Vehicle-to-Aggregator Interaction Game

Chenye Wu, *Student Member, IEEE*, Hamed Mohsenian-Rad, *Member, IEEE*, and Jianwei Huang, *Senior Member, IEEE*

***Abstract*—Electric vehicles (EVs) are likely to become very popular worldwide within the next few years. With possibly millions of such vehicles operating across the country, one can establish a distributed electricity storage system that comprises of the EVs' batteries with a huge total storage capacity. This can help the power grid by providing various ancillary services, once an effective vehicle-to-grid (V2G) market is established. In this paper, we propose a new game-theoretic model to understand the interactions among EVs and aggregators in a V2G market, where EVs participate in providing frequency regulation service to the grid. We develop a smart pricing policy and design a mechanism to achieve optimal frequency regulation performance in a *distributed* fashion. Simulation results show that our proposed pricing model and designed mechanism work well and can benefit both EVs (in terms of obtaining additional income) and the grid (in terms of achieving the frequency regulation command signal).**

***Index Terms*—Aggregator, electric vehicle, frequency regulation, game theory, Nash equilibrium, optimization, smart grid.**

I. Introduction

A. Background

RECENT studies have shown that about 70% of the total oil extracted worldwide is consumed in various transportation systems [1]. With rising oil prices, the United States and many other countries have set long-term plans to electrify the transportation sector and manufacture electric vehicles (EVs) to reduce oil consumption. It is predicted in [1] that by 2013, approximately 700 000 grid-enabled electric vehicles will be on the road in the United States. Such plans will provide great opportunities for the power grid, as the batteries of millions of EVs can be used to boost distributed electricity storage. Currently, the only noticeable electricity storage units in most power grids are the pumped storage systems which may store only around 2.2% of the total generated power [2]. The fast development of the vehicle-to-grid (V2G) systems can significantly increase the capacity of distributed storage.

Manuscript received February 26, 2011; revised July 23, 2011; accepted August 14, 2011. Date of publication October 25, 2011; date of current version February 23, 2012. This work was supported in part by the new faculty startup support by Texas Tech University, the National Basic Research Program of China Grants 2007CB807900 and 2007CB807901, and the National Natural Science Foundation of China under Grant 61033001, 61061130540, and 61073174. Paper no. TSG-00081-2011.

C. Wu is with the Institute for Interdisciplinary Information Sciences, Tsinghua University, Beijing, 100084, China (e-mail: wucy05@mails.thu.edu.cn).

H. Mohsenian-Rad is with the Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409 USA (e-mail: hamed.mohsenian-rad@ttu.edu).

J. Huang (corresponding author) is with the Network Communications and Economics Lab, Department of Information Engineering, The Chinese University of Hong Kong, Shatin, New Territories, Hong Kong (e-mail: jwhuang@ie.cuhk.edu.hk).

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/TSG.2011.2166414

Electric storage can help both consumers and power grid. At a consumer's side, distributed storage can help residential consumers to store electricity at off-peak hours and consume it at peak hours to reduce energy cost (e.g., [3]–[7]). This may also bring some additional income. For example, it is estimated that an EV owner may obtain approximately 2500 to 3000 dollars each year by participating in V2G systems [8]. At the grid's side, distributed storage can provide various ancillary services (e.g., [9], [10]). In particular, V2G systems (e.g., [11], [12]) can contribute in *frequency regulation* to fine-tune the frequency and voltage of the grid by matching generation to load demand [13], [14]. Currently, frequency regulation is achieved mainly by turning large generators on and off [12], which is significantly costly. Alternatively, if several EVs are connected to the grid, frequency regulation can be done by charging the EVs' batteries when generation exceeds load demand and by discharging them when load demand exceeds generation.

A key challenge in distributed EV-assisted frequency regulation systems is to provide *incentives* for the EVs to participate in such programs. Tackling this challenge is the focus of our paper. Although we only address frequency regulation, the solutions can be generalized to facilitate other ancillary services that can be provided by a large number of EVs.

B. Related Work

Most related literature on V2G systems have only appeared in the last few years. In [12], Kempton *et al.* studied the economic and social advantages of V2G systems and markets. Considering the distributed storage capacity of V2G systems, Han *et al.* designed an optimal centralized control strategy for frequency regulation in presence of aggregators in [15], [16]. Deployment of aggregators, which act as interfaces between the grid and a group of EVs, was also addressed in [17]–[19]. In [20], Kamboj *et al.* employed a multiagent system approach to explain how a coalition of several EVs can better represent them in V2G systems. However, the work in [20] did not take into account the impact of price variations on EVs' behavior or the potential for the EVs to sell electricity back to the grid. Peterson *et al.* examined the economic implications of distributed storage systems in [21]. Sortomme *et al.* demonstrated an optimal charging strategy for unidirectional V2G systems in [22]. In [23], the authors analyzed how to charge the EVs in the V2G market to minimize the power losses in distribution lines. To the best of our knowledge, our work is the first to consider EVs as *active players* in V2G markets and design a mechanism to encourage EVs' participation in frequency regulation through smart pricing.

Another body of related literature focus on game theoretical analysis of power grid networks. Mohsenian-Rad *et al.* used game theory to address demand response management via price predication and optimal energy consumption scheduling in [3]–[6]. Ibars *et al.* proposed a distributed load management scheme to control the power demand at peak hours by modeling the system as a congestion game in [24]. Ma *et al.* introduced the Nash Certainty Equivalence principle to "valley-fill" charging control in [25]. Vytelingum *et al.* introduced an agent based approach for micro-storage management in [26]. Wei *et al.* extended this approach to a learning agent based model in [27]. Different from the work in [3]–[6], [24]–[27], here, we use game theory to analyze a V2G market through understanding the vehicle-to-aggregator interactions to provide frequency regulation service to power grids.

C. Our Contributions

In this paper, we consider a realistic scenario where each EV is controlled by a software agent representing the interests of the EV owner (e.g., as in [3], [5]). An aggregator [9], [17]–[19], [28] coordinates a large number of EVs to take part in frequency regulation service to the grid. We want to answer the following key question: *How should an aggregator and its corresponding EVs interact in order to achieve optimal frequency regulation performance across the grid?*

The contributions in this paper are summarized as follows.

- *Vehicle-to-Aggregator Interaction Model:* We propose a new game theoretical model to characterize the interactions among EVs and the aggregator in a V2G system.
- *Smart Pricing:* We introduce a new pricing policy that encourages EVs to participate in frequency regulation.
- *Theoretical Performance Guarantee:* By analyzing the Nash equilibrium in vehicle-to-aggregator interaction games, we show that our proposed decentralized mechanism is guaranteed to achieve the optimal performance, i.e., same as in a centralized controlled system.
- *Benefiting Both Consumers and the Grid:* Simulation results show that our mechanism works well over a long-term period and benefits both consumers and power grids. The consumer will obtain additional income by providing regulation services, and the power grid will achieve the frequency regulation and save on the infrastructural cost.

The rest of this paper is organized as follows. We introduce the system model in Section II. Section III demonstrates an optimal centralized design. The vehicle-to-aggregator interaction game model is developed in Section IV. We analyze the theoretical properties of the game in Section V. Simulation results are presented and assessed in Section VI. The future work and concluding remarks are discussed in Section VII.

II. System Model

Consider a V2G system as shown in Fig. 1. We can identify *three* main components in this system: power grid, several aggregators, and several EVs. Each aggregator serves as an interface between the grid and a group of EVs. As demonstrated in Fig. 1, the communications among EVs, aggregators, and grid can go through a two-way digital communications (wired or wireless) infrastructure, which is foreseen to be available in the future smart grid (cf. [29]–[32]). We assume that a large number of EVs in the system are interested in participating in frequency regulation by charging or discharging their batteries. To facilitate EVs' participation, each aggregator signs a contract with the grid based on the expected storage capacity of its associated EVs. Frequency regulation is formally defined as follows [33]:

Fig. 1. The vehicle-to-grid system model considered in this paper.

Definition 1: Frequency regulation is used to maintain continuous balancing between power generation and power load within the grid during normal operating conditions.

Frequency regulation needs to be done frequently, e.g., once every few seconds [13], [14]. Thus, we can divide the daily operation of the grid into several *time slots*, each one corresponding to one frequency regulation attempt. At each time slot, the grid informs each aggregator with the amount of frequency regulation it expects the aggregator to provide. The total frequency regulation provided by all aggregators should match the frequency regulation needed in the system. As one approach, the grid can distribute the frequency regulation job among aggregators *based on the number of EVs of each aggregator*. There can be many other distribution possibilities as well, but detailed are out of the scope of this paper.

Consider one of the aggregators in the system, and let G denote the *frequency regulation command signal* that this aggregator receives at the current time slot. Note that G can be either *positive* or *negative*. If G is negative, the grid needs the aggregator to *inject* some power into the grid. If G is positive, the grid needs the aggregator to *consume* some power. Such power exchange is expected to be provided by discharging or charging the batteries of the EVs' connected to the aggregator.

Let $\mathcal{N}$ denote the set of N EVs associated with the aggregator at this time slot. We define three subsets of $\mathcal{N}$:

- $\mathcal{N}_c$: EVs that choose to charge their batteries.
- $\mathcal{N}_d$: EVs that choose to discharge their batteries.
- $\mathcal{N}_n$: EVs that choose to remain idle.

Here, $\mathcal{N} = \mathcal{N}_c \bigcup \mathcal{N}_d \bigcup \mathcal{N}_n$ and $N_c + N_d + N_n = N$, where N_c, N_d, and N_n are the cardinalities of sets $\mathcal{N}_c$, $\mathcal{N}_d$, and $\mathcal{N}_n$. Let r denote the rate at which an EV is charged or discharged. The total discharged power by the EVs in set $\mathcal{N}_d$ is rN_d. Similarly, the total charged power by the EVs in set $\mathcal{N}_c$ is rN_c. Without loss of generality, for the rest of this paper, we assume that the charging/discharging rate is normalized to $r = 1$.

In order for the aggregator to reach the frequency regulation command signal G requested by the grid, it is needed to have

$$G + N_d - N_c = 0. \tag{1}$$

That is, the total power discharged by EVs' batteries in set $\mathcal{N}_d$ minus the total power charged by the EVs' batteries in set $\mathcal{N}_c$ should match the total charging or discharging level requested by the power grid to achieve frequency regulation. However, equality (1) may *not* hold in every time slot if the EVs do not cooperate with the aggregator or if there are not enough EVs available to participate in frequency regulation.

To overcome this problem, we assume that each aggregator is equipped with a *backup battery bank* (BBB) to assure achieving frequency regulation target G for those cases where (1) does not hold. For example, if G is very large such that there are not enough EVs to discharge their batteries, then the aggregator needs to discharge BBB to satisfy G. Thus, at each time slot the *net change* in the aggregator's BBB's energy level is obtained as

$$\Delta = G + N_d - N_c. \tag{2}$$

Of course, Δ can take both positive and negative values.

Let E_{current} denote the current energy level in the aggregator's BBB at the beginning of a time slot. Also let E_{next} denote the resulting energy level in the aggregator's BBB by the end of the time slot. Clearly, we have

$$E_{\text{next}} = E_{\text{current}} + \Delta. \tag{3}$$

In fact, depending on the value of G and the number of EVs that charge or discharge their batteries, the energy level at the aggregator's BBB may change to different values at different time slots during the daily operation of the system.

Given the system model explained above, the design objective for an aggregator is to achieve the frequency regulation command signal G while minimizing the usage of its own BBB. Clearly, if frequency regulation always requires charging or discharging the aggregator's BBB (instead of using EVs' batteries), then there will be no advantage in having a V2G-based storage infrastructure. Note that BBB is usually expensive and is intended to be used *rarely*. Next, in Sections III and IV, we explain how such design objective can be achieved in centralized and decentralized fashions, respectively.

III. Centralized Design

As a benchmark case, we consider a centralized control system where the aggregator aims to schedule charging and discharging of its associated EVs' batteries in order to solve the following optimization problem:

$$\begin{aligned} \underset{N_c, N_d}{\textbf{minimize}}\ & |E_{\text{current}} + G + N_d - N_c - E_{\text{desired}}| \\ \textbf{subject to}\ & N_d + N_c \leq N, \\ & N_d\, N_c = 0, \\ & N_d \geq 0, N_c \geq 0. \end{aligned} \tag{4}$$

From (2) and (3), the objective function in optimization problem (4) is to minimize $|E_{\text{next}} - E_{\text{desired}}|$, where E_{desired} is the energy level that the aggregator wants to *constantly maintain* in its BBB. For example, E_{desired} can be equal to half of the BBB's total storage capacity. The first constraint in (4) indicates that the total number of EVs that perform charging and discharging should not exceed the total number of EVs. The second constraint indicates that charging and discharging should *not* be performed simultaneously. Otherwise the EVs cancel out each other's efforts in terms of frequency regulation.

Assuming that the aggregator has *full control* over EVs' charging and discharging, it can solve problem (4) and decide on how many EVs should charge their batteries or how many EVs should discharge their batteries. However, in practice, the aggregator does *not* have any direct control on EVs as they are owned by individual consumers. Therefore, there is a need for a decentralized control mechanism as we will explain next.

IV. Decentralized Design Using Game Theory

We would like to design a decentralized mechanism in the described V2G system, such that we can achieve the same optimal performance as the centralized mechanism introduced in Section III. Our mechanism considers the fact that the EVs are *independent decision makers*. Therefore, it encourages efficient resource management through *pricing*.

A. Smart Pricing Policy

At each time slot, the aggregator determines two prices p_d and p_c, which indicate how much *the aggregator pays to an EV* for the EV's participation in frequency regulation by charging or discharging their batteries, respectively. Each of these prices can take either *positive* or *negative* values. We have

$$p_c = w_c + v_c\,(E_{\text{current}} + G + N_d - N_c - E_{\text{desired}}), \tag{5}$$
$$p_d = w_d - v_d\,(E_{\text{current}} + G + N_d - N_c - E_{\text{desired}}), \tag{6}$$

where w_c, w_d, $v_c \geq 0$ and $v_d \geq 0$ are design parameters with the following physical meanings: w_c and w_d are the base prices and v_c and v_d affect how much the prices would vary based on different values of E_{current}, E_{desired}, G, as well as EVs' behavior such as N_d and N_c. The intuition behind the proposed pricing models in (5) and (6) is as follows.

- If EVs' collective decisions of charging or discharging their batteries lead to an energy level in BBB that *exceeds* the desired level E_{desired}, i.e., $E_{\text{current}} + G + N_d - N_c - E_{\text{desired}} > 0$, then the charging price p_c is larger than the base price w_c and the discharging price p_d is smaller than the base price w_d (and may eventually become negative). This encourages EVs to *charge* their batteries, helping to reduce the BBB's energy level back to E_{desired}.
- If EVs' collective decisions lead to an energy level in BBB *less* than the desired level E_{desired}, i.e., $E_{\text{current}} + G + N_d - N_c - E_{\text{desired}} < 0$, then the pricing mechanism encourages EVs to *discharge* their batteries, helping to increase the BBB's energy level back to E_{desired}.

B. EVs' Payoff Functions

For each EV $i \in \mathcal{N}$, let a_i denote its decision, where $a_i = 1$ indicates discharging, $a_i = -1$ indicates charging, and $a_i = 0$ indicates remaining idle. EV i's payoff function is

$$f_i(a_i, a_{-i}) = \begin{cases} p_d(a_i, a_{-i}), & \text{if } a_i = 1, \\ 0, & \text{if } a_i = 0, \\ p_c(a_i, a_{-i}), & \text{if } a_i = -1, \end{cases} \tag{7}$$

where a_{-i} denotes the strategies of all EVs *other than* EV i. EV i's payoff is the payment it receives from the aggregator due to participation in frequency regulation. Note that prices p_c and p_d are given in (5) and (6), which depend on all EVs' behaviors (a_i, a_{-i}) as well as parameters G and E_{current}.

C. Vehicle-to-Aggregator Interaction Game

We can now formally define a *vehicle-to-aggregator interaction game* in a V2G frequency regulation system as follows:

- ***Players***: The set $\mathcal{N}$ of all EVs.
- ***Strategies***: For each EV, choosing to charge or discharge battery or to remain idle in the current time slot.
- ***Payoffs***: EV i receives payment $f_i(a_i, a_{-i})$ as in (7).

Note that the above game is played among the EVs. The aggregator is *not* a player and simply *coordinates* the game. That is, given the number of EVs that decide to charge or discharge their batteries or remain idle, the aggregator sets the prices p_c and p_d based on the model in (5) and (6).

V. Analytical Performance Evaluation

In this section, we explain how the vehicle-to-aggregator interaction game is played and what is the frequency regulation performance at the equilibrium of such game in a V2G system.

A. Best Response and Nash Equilibrium

We first consider the concept of *best response strategy*, which is an EV's best choice to maximize its own payoff function assuming that other EVs' strategies are fixed. For EV $i \in \mathcal{N}$, its best response strategy is defined as[1]

$$a_i^{\text{best}}(a_{-i}) = \underset{a_i \in \{-1,0,1\}}{\arg\max} \; f_i(a_i, a_{-i}). \tag{8}$$

Next, we consider the solution concept of Nash equilibrium, which is a vector of all players' strategies such that no player has an incentive to deviate *unilaterally*. For our game, a Nash equilibrium is defined as follows.

Definition 2: A Nash equilibrium of a vehicle-to-aggregator game is a strategy profile $\boldsymbol{a} = \{a_i^*, \forall i \in \mathcal{N}\}$ where

$$f_i(a_i^*, a_{-i}^*) \geq f_i(a_i, a_{-i}^*), \forall i \in \mathcal{N}, a_i \in \{-1, 0, 1\}.$$

A Nash equilibrium is also a fixed point of all players' best responses, i.e., $a_i^{\text{best}}(a_{-i}^*) = a_i^*$ for all $i \in \mathcal{N}$. It represents a stable solution of the game. In the vehicle-to-aggregator interaction game, we want to develop a mechanism such that the Nash equilibrium of this game has an optimal frequency regulation performance, i.e., it solves Problem (4).

[1]For simplicity, we assume that there is a unique a_i maximizer in (8), which is true for our problem. In general, best response can be a set.

B. Pricing Parameters

Recall that for the price models in (5) and (6), the values of parameters w_c, w_d, v_c, and v_d need to be selected. In this section, we consider a simple model where the charging price p_c and discharging price p_d follow a *linear* relationship

$$p_c = -\delta p_d, \tag{9}$$

with $0 < \delta \leq 1$. Note that the two prices take opposite signs. When $p_d > 0$ and $p_c < 0$, the aggregator encourages the EVs to discharge their batteries, and penalizes EVs for charging their batteries. When $p_d < 0$ and $p_c > 0$, EVs are encouraged to charge and penalized for discharging. For the rest of this section, we only focus on designing the discharging price p_d. Then, p_c is obtained from p_d using (9).

As an illustrating example, consider a case where there are only $N = 2$ EVs connected to an aggregator. We can calculate EVs' payoffs under different choices of strategies. The payoff matrix for such 2-player game is shown in Table I. In this table, different rows indicate various choices of the first EV, i.e., $a_1 \in \{-1, 0, 1\}$, and different columns indicate choices of the second EV, i.e., $a_2 \in \{-1, 0, 1\}$. Note that we have defined a new parameter u to make the table more compact

$$u \doteq w_d - v_d(E_{\text{current}} + G - E_{\text{desired}}). \tag{10}$$

Since there are only 2 EVs in the system, the maximum power that they can provide by discharging their batteries or the maximum power they can consume by charging their batteries at each time slot has an absolute value of 2, which may not always be enough to balance the BBB's energy level. Next, we will discuss different possible scenarios based on a newly defined parameter h, where

$$h \doteq E_{\text{desired}} - (E_{\text{current}} + G). \tag{11}$$

From (10) and (11), $u = w_d + v_d h$. Note that h indicates the amount of charging/discharging needed from the EVs' batteries such that the energy level at the aggregator's BBB reaches E_{desired} while the frequency regulation command signal G is also satisfied. If we normalize G, E_{current}, and E_{desired} such that they *only take integer values*, the term h in (11) will also always take an integer value, i.e., $h \in \{\ldots, -3, -2, -1, 0, 1, 2, 3, \ldots\}$. We are now ready to choose pricing parameters w_d and v_d to achieve an optimal performance based on different amounts of parameter h:

- If $h \in \{2, 3, \ldots\}$, then we want both EVs to discharge their batteries. Thus, the Nash equilibrium should be $(a_1 = 1, a_2 = 1)$. To achieve this, we need to set $w_d > 0$. This can be derived directly from Definition 2. That is $f_i(a_i = 1, a_{-i} = 1) \geq f_i(a_i = 0 \text{ or } -1, a_{-i} = 1)$ for $i = 1, 2$. Therefore, from Table I, we have

$$u - 2v_d \geq 0 \text{ and } u - 2v_d \geq -\delta u. \tag{12}$$

Moreover, we expect that the EVs receive positive payments in response to their contribution in providing frequency regulation. Thus, we should also have

$$u - 2v_d > 0. \tag{13}$$

From (12) and (13), we can conclude that to achieve a desirable behavior by the EVs at Nash equilibrium in this sce-

TABLE I
PAYOFF MATRIX FOR THE GAME WITH ONLY TWO EVS

(f_1, f_2)	$a_2 = 1$	$a_2 = 0$	$a_2 = -1$
$a_1 = 1$	$(u-2v_d, u-2v_d)$	$(u - v_d, 0)$	$(u, -\delta u)$
$a_1 = 0$	$(0, u - v_d)$	$(0,0)$	$(0, -\delta(u + v_d))$
$a_1 = -1$	$(-\delta u, u)$	$(-\delta(u+v_d), 0)$	$(-\delta(u+2v_d), -\delta(u+2v_d))$

nario, we need to set the pricing parameter $w_d > 0$. The other four scenarios below can be analyzed similarly.

- If $h = 1$, then we want *only one* EV to discharge its battery while the other EV remains idle. The desirable Nash equilibrium is either $(a_1 = 1, a_2 = 0)$ or $(a_1 = 0, a_2 = 1)$. To achieve this, we set $0 < w_d < v_d$ and $v_d > 0$.
- If $h = 0$, then we want both EVs remain idle. The desirable Nash equilibrium is $(a_1 = 0, a_2 = 0)$. To achieve this, we set $-v_d < w_d < v_d$ and $w_d \neq 0$.
- If $h = -1$, then we want *only one* EV to charge its battery while the other EV remains idle. The desirable Nash equilibrium is either $(a_1 = -1, a_2 = 0)$ or $(a_1 = 0, a_2 = -1)$. To achieve this, we set $-v_d < w_d < 0$.
- If $h \in \{-2, -3, \ldots\}$, then we want both EVs to charge their batteries. The desirable Nash equilibrium is $(a_1 = -1, a_2 = -1)$. To achieve this, we set $w_d < 0$.

The above analysis provides a system of inequalities that can be solved to obtain the following choices of pricing parameter w_d to achieve an optimal performance in *all* five scenarios:

$$\begin{aligned} w_d &= \theta\, v_d \operatorname{sgn}(h) \\ &= \theta\, v_d \operatorname{sgn}(E_{\text{desired}} - (E_{\text{current}} + G)), \end{aligned} \tag{14}$$

where $0 < \theta < 1$, $v_d > 0$, and

$$\operatorname{sgn}(x) = \begin{cases} 1, & \text{if } x \geq 0, \\ -1, & \text{otherwise.} \end{cases} \tag{15}$$

Based on (14), the optimal discharging and charging prices are

$$\begin{aligned} p_d = {} & \theta\, v_d \operatorname{sgn}(E_{\text{desired}} - (E_{\text{current}} + G)) \\ & - v_d \times (E_{\text{current}} + G + N_d - N_c - E_{\text{desired}}), \end{aligned} \tag{16}$$

and

$$p_c = -\delta p_d. \tag{17}$$

Clearly, more than one value for θ and v_d can assure optimal frequency regulation performance at Nash equilibrium.

We next generalize the discussions of the two-player game, and prove the existence and optimality of Nash equilibria in a system with $N \geq 2$ EVs under such a pricing policy.

C. Characterizing Nash Equilibria

Consider the vehicle-to-aggregator interaction game in Section IV-C. For a Nash equilibrium $\{a_i^*, \forall i \in \mathcal{N}\}$, we define

$$\mathcal{N}_d^* = \{i \mid i \in \mathcal{N}, a_i^* = 1\}, \tag{18}$$

$$\mathcal{N}_c^* = \{i \mid i \in \mathcal{N}, a_i^* = -1\}. \tag{19}$$

The cardinalities of the above sets are defined as N_d^* and N_c^*, respectively. We want to show that N_d^* and N_c^* form an optimal solution for problem (4). To prove this, the first step is to characterize all Nash equilibria of the vehicle-to-aggregator interaction game for different values of h in (11).

Theorem 3: We can show that:

- If $h > 0$, then the Nash equilibrium of the vehicle-to-aggregator interaction game satisfies:

$$N_d^* = \min\{h, N\} \quad \text{and} \quad N_c^* = 0. \tag{20}$$

- If $h = 0$, then all Nash equilibria of the vehicle-to-aggregator interaction game satisfy:

$$N_d^* = 0 \quad \text{and} \quad N_c^* = 0. \tag{21}$$

- If $h < 0$, then all Nash equilibria of the vehicle-to-aggregator interaction game satisfy:

$$N_d^* = 0 \quad \text{and} \quad N_c^* = \min\{-h, N\}. \tag{22}$$

The proof for Theorem 3 is given in Appendix A. Theorem 3 can easily be generalized to the case where only a subset of EVs are capable of charging and another subset may only discharge their batteries. This can be the case when some EVs' batteries are below certain energy level or well charged. We skip the details for the general case due to space limitation.

D. Optimality

We are now ready to provide the key optimal result.

Theorem 4: The Nash equilibria of the vehicle-to-aggregator interaction game using the pricing model in (16) and (17) coincide with the optimal solutions of problem (4).

The proof for Theorem 4 is given in Appendix B. The idea is to show that N_d^* and N_c^* in (20)–(22) minimize the objective function in problem (4) for every possible value of h.

E. Choice of Nash Equilibrium

Depending on system parameters, there can be multiple optimal solutions for optimization problem (4), and thus multiple Nash equilibria for the vehicle-to-aggregator interaction game. These multiple Nash equilibria achieve the same frequency regulation performance within the time slot under consideration. However, different Nash equilibria may result in different *long-term* performance over *several* time slots. For example, assume that at a time slot, the optimal solution of problem (4) indicates that five out of ten EVs should discharge their batteries. But as far as solving the one-time slot optimization problem (4) is concerned, it does not matter which five EVs discharge. However, different selections of the EVs may affect the number of EVs to be available for discharging in the next time slot, depending on the battery levels of different EVs.

It will be interesting to extend our design to consider a long-time horizon (where each time slot corresponds to one instance of the game studied in this section) when formulating optimization problem (4) and the vehicle-to-aggregator interaction game. In that case, the choice of equilibrium in each time slot may become important. A precise analysis of this dynamic game involves the theory of competitive Markov decision processes [34], and is out of the scope of this paper. Nevertheless, our simulations in Section VI show that our proposed *per-time slot* pricing policy can still achieve a good frequency regulation performance over a long period of time.

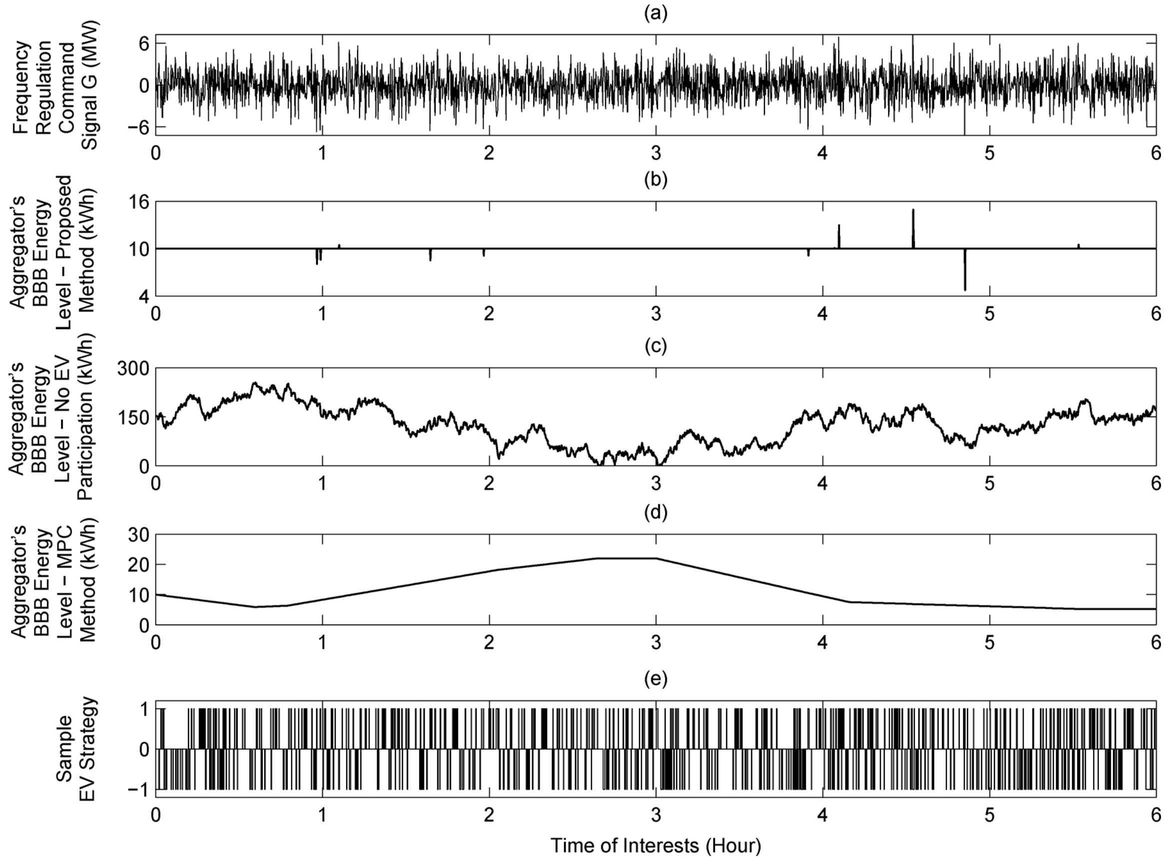


Fig. 2. Simulation results for a vehicle-to-grid system with an aggregator and $N = 1000$ EVs. (a) The frequency regulation command signal G. (b) The aggregator's backup battery bank's energy level where frequency regulation involves EVs using the proposed smart pricing policy. (c) The aggregator's backup battery bank's energy level without involving EVs in frequency regulation. (d) The aggregator's backup battery bank's energy level based on Model Predictive Control. (e) A sample path of the strategy for one of the EVs in the vehicles-to-aggregator interaction game.

VI. Simulation Results

We describe the message passing mechanism in the formulated game model at a particular time slot as follows:

- The aggregator receives the frequency regulation command signal G, and announces it to all EVs.
- The aggregator computes all possible Nash equilibria of the game (in closed-form) based on Theorem 3. It then selects one Nash equilibrium randomly[2] and announces its choice to all EVs in the system. Since the announcement is a Nash equilibrium, EVs will simply follow it.[3]
- The aggregator collects EVs' responses and satisfies the grid's frequency regulation command signal G using the backup battery bank based on the difference Δ. It also records EVs' profits given the price values and metering.

The signalling and information exchanged among aggregator and EVs is handled using the available V2G communications infrastructure. An overview on different wired and wireless technologies for V2G communications and corresponding data transmission protocols can be found in [36].

[2]We consider a complete information game scenario [35], where the aggregator and all EVs know everyone's payoff function. Thus the aggregator as well as each EV can directly compute the Nash equilbria at each time slot. We plan to study the game with incomplete information in the future.

[3]The aggregator serves as a nonenforcing coordinator and the equilibrium achieved is related to the concept of *correlated equilibrium*, which is a generalization of Nash equilibrium in advanced game theory [35]. The discussions on correlated equilibrium is beyond the scope of this paper.

Simulation results for a vehicle-to-aggregator system with $N = 1000$ EVs are shown in Fig. 2. For each EV, we consider the normalized maximum charging/discharging rate to be 7.68 kW which is compatible with Level 2 charging standard in North America [37]. As a result, the maximum power that can be provided by all 1000 EVs at each time is up to 7.68 MW. For the aggregator of interest, the maximum capacity of the internal BBB is assumed to be 20 kWh. Therefore, we set $E_{\text{desired}} = 10$ kWh. The initial energy level of the BBB is set to be E_{desired}. The frequency regulation command signal G follows a shifted binomial distribution[4] with parameters 3×10^6 and 0.5. The value of G is updated by the grid every 10 s using the available V2G communications infrastructure. Its trend is shown in Fig. 2(a).

The trend of the energy level in the aggregator's BBB when users' participation in frequency regulation is facilitated by the proposed smart pricing policy is shown in Fig. 2(b). We can see that the energy level in the BBB rarely deviates from E_{desired}, and the amount of deviation is at most 5 kWh. That is, almost all charging and discharging needed to support frequency regulation are provided by the EVs once the proposed pricing policy is used. The energy level in the BBB *without* utilizing any EVs is shown in Fig. 2(c), where the deviation from E_{desired} can be as high as 150 kWh. In this case, we need a BBB with maximum capacity of 300 kWh.

[4]Binomial distribution is a good approximation for Gaussian distribution in a discrete case. A shifted binomial distribution has zero mean.

The energy level in the BBB based on Model Predictive Control (MPC) [38] is shown in Fig. 2(d). We assume perfect prediction for command signal G such that the aggregator can accurately predict the grid's frequency regulation needs. We define an MPC multiple-horizon cost function J as

$$J = \sum_{h=1}^{H} \left(G^h + N_d^h - N_c^h\right)^2. \tag{23}$$

To obtain the MPC solution, we minimize the cost function J subject to EV charging/discharging constraints: EVs with empty batteries cannot discharge their batteries to inject power into the grid; EVs with full batteries cannot charge provide power to consume power from the grid; and the number of EVs participating in frequency regulation cannot exceed the amount of available EVs in the system. The prediction with perfect information guarantees the best performance of MPC. Nevertheless, as shown Fig. 2(d), in order to minimize the command signal cost function J, this MPC method still needs a slightly larger capacity BBB compared with our proposed policy. In addition, an MPC-based approach would essentially be centralized different from our proposed decentralized solution that can better encourage user participation.

Finally, Fig. 2(e) shows one (out of a thousand) EV's charging/discharging strategy during the 6 hours of participating in frequency regulation under the smart pricing policy. The total payment to each user is obtained as around 1000 v_d for 6 hours, which for a proper choice of v_d will become comparable with the expected 2500 to 3000 dollars annual profit for user participation in frequency regulation [8].

VII. Future Work and Conclusions

This paper considers the problem of providing frequency regulation ancillary service to power grid using several electric vehicles' batteries as distributed power storage system. We propose a vehicle-to-aggregator interaction game, where vehicles are independent players making charging/discharging decisions, and the aggregator serves as a coordinator. By adopting a smart pricing policy as part of the game, we showed that the distributed behaviors of self-interested electric vehicles can achieve the same optimal performance as if they are in a centrally controlled system. Moreover, our design provided a new model explaining how a *backup battery bank* can be deployed in an aggregator to maintain a *stable* regulation capacity.

This paper can be extended in various directions. For example, one can design an optimal *frequency regulation duty distribution* method among different aggregators. In addition, we can incorporate EVs' own charging targets, e.g., reaching 80% of its full battery level when leaving the power grid, into the formulated game model. Note that we did not consider this issue explicitly; instead, we simply assumed that an automated demand side management technique, e.g., [3], [6], can separately coordinate achieving the EVs' charging needs.

Appendix

A. *Proof of Theorem 3*

Here, we only provide the detailed proof for the case where $h > 0$. The proofs for the cases where $h = 0$ and $h < 0$ are similar. Since $h > 0$, we have $\operatorname{sgn}(h) = 1$. Therefore, the pricing policy in (16) can be simplified as

$$p_d = \theta\, v_d + v_d(h - (N_d - N_c)), \tag{24}$$

where h is defined in (11). Next, in addition to sets $\mathcal{N}_d$ and $\mathcal{N}_c$ which are already defined in (18) and (19), we also define

$$\mathcal{N}_n = \{i \,|\, i \in \mathcal{N}, a_i = 0\}. \tag{25}$$

The proof includes *two* steps. First, we show that strategy profiles where $N_d^* = \min\{h, N\}$ and $N_c^* = 0$ are Nash equilibria. Then, we show that they cover all the Nash equilibria of this game, i.e., there is no other Nash equilibrium.

To prove the first step, we will show the following cases according to the definition of Nash equilibrium in Definition 2.

- *Case 1.1:* No EV in $\mathcal{N}_d^*$ will switch to be idle.
- *Case 1.2:* No EV in $\mathcal{N}_d^*$ will switch to charge its battery.
- *Case 1.3:* No EV in $\mathcal{N}_n^*$ will switch to charge its battery.
- *Case 1.4:* No EV in $\mathcal{N}_n^*$ will switch to discharge its battery.

Case 1.1: We want to show that no EV in set $\mathcal{N}_d^*$ will switch to be idle. By Definition 2, it is sufficient to show that the current payoff function of an EV $i \in \mathcal{N}_d^*$, i.e., $f_i(a_i^* = 1, a_{-i}^*)$, is no worse than its payoff function after switching to be idle, i.e., $f_i(a_i = 0, a_{-i}^*)$. Mathematically,

$$\begin{aligned} f_i(a_i^* = 1, a_{-i}^*) &= p_d(a_i^* = 1, a_{-i}^*) \\ &= \theta v_d + v_d(h - (N_d^* - N_c^*)) \\ &= \theta v_d + v_d(h - N_d^*) \\ &\geq \theta v_d \\ &> 0 = f_i(a_i = 0, a_{-i}^*), \end{aligned}$$

where the first inequality is due to $N_d^* = \min\{h, N\}$, and the second inequality is due to the fact that $0 < \theta < 1$ and $v_d > 0$.

Case 1.2: We show that no EV in set $\mathcal{N}_d^*$ will choose to charge. That is, the current payoff of an EV $i \in \mathcal{N}_d^*$, i.e., $f_i(a_i^* = 1, a_{-i}^*)$, is no worse than its payoff if it chooses to charge its battery, i.e., $f_i(a_i = -1, a_{-i}^*)$. Let us denote the strategy profile after the change as (N_d', N_c', N_n'). We have

$$\begin{aligned} f_i(a_i^* = 1, a_{-i}^*) &= p_d(a_i^* = 1, a_{-i}^*) \\ &> 0 \geq -\delta p_d(a_i^* = 1, a_{-i}^*) \\ &= -\delta(\theta v_d + v_d(h - (N_d^* - N_c^*))) \\ &\geq -\delta(\theta v_d + v_d(h - (N_d' - N_c'))) \\ &= -\delta p_d(a_i = -1, a_{-i}^*) = f_i(a_i = -1, a_{-i}^*). \end{aligned}$$

The inequality in the fourth line is because $N_d' = N_d^* - 1$ and $N_c' = N_c^* + 1 = 1$; thus, $N_d' - N_c' < N_d^* - N_c^*$.

Case 1.3: We show that no EV in $\mathcal{N}_n^*$ will choose to charge its battery. Note that if $N_d^* = N$, then set $\mathcal{N}_n^*$ is empty. Therefore, this case may occur only if $N_d^* = h < N$. Next, we show that the current payoff function of an EV $i \in \mathcal{N}_n^*$, i.e., $f_i(a_i^* = 0, a_{-i}^*)$ is no worse than its payoff function after changing to charge, i.e., $f_i(a_i = -1, a_{-i}^*)$. Denote the strategy profile after the change to be (N_d', N_c', N_n'). We have

$$\begin{aligned} f_i(a_i^* = 0, a_{-i}^*) &= 0 \\ &> -\delta p_d(a_i^* = 1, a_{-i}^*) \\ &= -\delta(\theta v_d + v_d(h - (N_d^* - N_c^*))) \\ &\geq -\delta(\theta v_d + v_d(h - (N_d' - N_c'))) \\ &= -\delta p_d(a_i = -1, a_{-i}^*) = f_i(a_i = -1, a_{-i}^*). \end{aligned}$$

The inequality in the fourth line is because $N_d' = N_d^*$ and $N_c' = N_c^* + 1 = 1$, thus $N_d' - N_c' < N_d^* - N_c^*$.

Case 1.4: We show that no EV in $\mathcal{N}_n^*$ will choose to discharge its battery. That is, the current payoff function of an EV $i \in \mathcal{N}_n^*$, i.e., $f_i(a_i^* = 0, a_{-i}^*)$, is no worse than its payoff function after changing to discharge, i.e., $f_i(a_i = 1, a_{-i}^*)$. Denote the strategy profile after the change to be (N_d', N_c', N_n') as before. Then, we can show that

$$\begin{aligned} f_i(a_i^* = 0, a_{-i}^*) &= 0 \\ &> \theta v_d - v_d \\ &= \theta v_d + v_d(h - ((h+1) - 0)) \\ &= \theta v_d + v_d(h - (N_d' - N_c')) \\ &= p_d(a_i = 1, a_{-i}^*) = f_i(a_i = 1, a_{-i}^*). \end{aligned}$$

The equality in the fourth line is because $N_d^* = h < N$, $N_d' = N_d^* + 1 = h + 1$ and $N_c' = N_c^* = 0$.

Combining the above results, the the first step is proved.

To prove the second step, we show that any strategy profile $(N_d', N_c') \neq (N_d^*, N_c^*)$ is *not* a Nash equilibrium. We will discuss three cases depending on the value of N_c' and N_d'.

- *Case 2.1:* Any strategy profile where $N_d' - N_c' > N_d^* - N_c^*$ is not a Nash equilibrium.
- *Case 2.2:* Any strategy profile where $N_d' - N_c' < N_d^* - N_c^*$ is not a Nash equilibrium.
- *Case 2.3:* Any strategy profile where $N_d' - N_c' = N_d^* - N_c^*$ and $N_c^* > 0$ is not a Nash equilibrium.

Case 2.1: Any strategy profile where $N_d' - N_c' > N_d^* - N_c^*$ is not a Nash equilibrium. We want to show that any EV in $\mathcal{N}_d'$ can simply choose to be idle for a better payoff. Mathematically, we have

$$\begin{aligned} f_i(a_i' = 1, a_{-i}') &= p_d(a_i' = 1, a_{-i}') \\ &= \theta v_d + v_d(h - (N_d' - N_c')) \\ &\le \theta v_d + v_d(h - (h+1)) \\ &\le \theta v_d - v_d \\ &< 0 = f_i(a_i = 0, a_{-i}'), \end{aligned}$$

where the first inequality is due to $N_d' - N_c' > N_d^* - N_c^*$ and $N_c^* = 0$, which implies $N_d' > N_d^*$. Since $N_d' \le N$ and $N_d^* = \min\{h, N\}$, we have $N_d^* = h$. Thus $N_d' - N_c' > N_d^* = h$, which implies $N_d' - N_c' \ge h + 1$.

Case 2.2: Any strategy profile where $N_d' - N_c' < N_d^* - N_c^*$ is not a Nash equilibrium. If $N_c' > 0$, then for any EV $i \in \mathcal{N}_c'$, we can show that it can choose to be idle for a better payoff. Mathematically, we have

$$\begin{aligned} f_i(a_i' = 1, a_{-i}') &= -\delta(\theta v_d + v_d(h - (N_d' - N_c'))) \\ &< -\delta(\theta v_d + v_d(h - (N_d^* - N_c^*))) \\ &< 0 = f_i(a_i = 0, a_{-i}'). \end{aligned}$$

If $N_c' = 0$, since $N_d' < N_d^* \le N$, we have $\mathcal{N}_n' \neq \emptyset$. We want to show that an EV in $\mathcal{N}_n'$ can choose to discharge for a better payoff. Mathematically, we have

$$\begin{aligned} f_i(a_i' = 0, a_{-i}') &= 0 \\ &< \theta v_d + v_d(h - (N_d^* - N_c^*)) \\ &\le \theta v_d + v_d(h - (N_d' + 1 - N_c')) \\ &= p_d(a_i = 1, a_{-i}') = f_i(a_i = 1, a_{-i}'), \end{aligned}$$

where the second inequality is due to N_d' and N_d^* are integers, hence $N_d' < N_d^*$ implies $N_d' + 1 \le N_d^*$.

Case 2.3: Any strategy profile where $N_d' - N_c' = N_d^* - N_c^*$ and $N_c' > 0$ is not a Nash equilibrium. We want to show that any EV in $\mathcal{N}_c'$ can simply choose to be idle for a better payoff. Mathematically, we have

$$\begin{aligned} f_i(a_i' = -1, a_{-i}') &= -\delta p_d(a_i' = -1, a_{-i}') \\ &= -\delta p_d(a_i^*, a_{-i}^*) \\ &< 0 = f_i(a_i = 0, a_{-i}'). \end{aligned}$$

■

B. *Proof of Theorem 4*

With h, we can first simplify the objective function of the optimization problem (4)

$$|E_{\text{current}} + G + N_d - N_c - E_{\text{desired}}| = |N_d - N_c - h|. \quad (26)$$

If $h > 0$, a Nash equilibrium of the game has the form of $(N_d^*, N_c^*) = (\min\{h, N\}, 0)$. We want to prove that a Nash equilibrium with such a form achieves the optimal objective value of the optimization problem.

Case I: If $h \le N$, then $N_d^* = h$ and $N_c^* = 0$. We have

$$|N_d - N_c - h| \ge 0 = |N_d^* - N_c^* - h|. \quad (27)$$

Case II: If $h > N$, then $N_d^* = N$ and $N_c^* = 0$. Noting $N_d + N_c \le N$, we have

$$\begin{aligned} |N_d - N_c - h| &= h - N_d + N_c \\ &\ge h - N = |h - N_d^* + N_c^*|. \quad (28) \end{aligned}$$

Thus, we have proved when $h > 0$, every Nash equilibrium of the game achieves the optimization problem. Cases of $h = 0$ and $h < 0$ can be proved similarly. ■

REFERENCES

[1] "Electrification roadmap: Revolutionizing transportation and achieving energy security," Nov. 2009 [Online]. Available: http://www.electrificationcoalition.org/reports/EC-Roadmap-screen.pdf, Electrification Coalition

[2] Energy Information Administration, "Inventory of electric utility power plants in the United States 2000" U. S. Department of Energy, Washington, DC, DOE/EIA-0095 (2000), 2002, Table I.

[3] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120–133, Sep. 2010.

[4] A.-H. Mohsenian-Rad, V. Wong, J. Jatskevich, and R. Schober, "Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid," in *Proc. Innov. Smart Grid Technol. (ISGT)*, Jan. 2010, pp. 1–6.

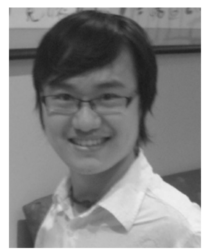
[5] P. Samadi, A. Mohsenian-Rad, R. Schober, V. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *Proc. 1st IEEE Int. Conf. Smart Grid Commun.*, Oct. 2010.

[6] A. H. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

[7] M. Galus and G. Andersson, "Demand management of grid connected plug-in hybrid electric vehicles (PHEV)," in *Proc. Energy 2030 Conf.*, Nov. 2008.

[8] W. Kempton, J. Tomic, S. Letendre, A. Brooks, and T. Lipman, "Vehicle-to-grid power: Battery, hybrid, and fuel cell vehicles as resources for distributed electric power in California," Tech. Rep. UCD-ITS-RR-01-03, 2001.

[9] A. N. Brooks, *Vehcile-to-Grid Demonstration Project: Grid Regulation Ancillary Service With a Battery Electric Vehicle*. San Dimas, CA: AC Propulsion Inc., Dec. 2002.
[10] C. Quinn, D. Zimmerle, and T. H. Bradley, "The effect of communication architecture on the availability, reliability, and economics of plug-in hybrid electric vehicle-to-grid ancillary services," *J. Power Sources*, vol. 195, no. 5, pp. 1500–1509, 2010.
[11] W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," *Transp. Res. D, Transp. Environ.*, vol. 2, no. 3, pp. 157–175, 1997.
[12] W. Kempton and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, 2005.
[13] B. J. Kirby, "Frequency regulation basics and trends," Oak Ridge National Laboratory, Tech. Rep., 2004.
[14] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *J. Power Sources*, vol. 144, no. 1, pp. 280–294, 2005.
[15] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–72, Jun. 2010.
[16] S. Han, S. Jang, K. Sezaki, and S. Han, "Quantitative modeling of an energy constraint regarding V2G aggregator for frequency regulation," in *Proc. 9th Int. Conf. Environ. Electr. Eng. (EEEIC)*, May 2010.
[17] C. Guille and G. Gross, "Design of a conceptual framework for the V2G implementation," in *Proc. IEEE Energy 2030*, Atlanta, GA, Nov. 2008.
[18] J. R. Pillai and B. Bak-Jensen, "Vehicle-to-grid for islanded power system operation in bornholm," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, Minneapolis, MN, Jul. 2010.
[19] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," *Proc. IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011.
[20] S. Kamboj *et al.*, "Exploring the formation of electric vehicle coalitions for vehicle-to-grid power regulation," in *AAMAS Workshop Agent Technol. Energy Syst. (ATES)*, Oct. 2010.
[21] S. B. Peterson, J. Whitacre, and J. Apt, "The economics of using plug-in hybrid electric vehicle battery packs for grid storage," *J. Power Sources*, vol. 195, no. 8, pp. 2377–2384, 2010.
[22] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.
[23] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011.
[24] C. Ibars, M. Navarro, and L. Giupponi, "Distributed demand management in smart grid with a congestion game," in *Proc. 1st IEEE Int. Conf. Smart Grid Commun.*, Oct. 2010.
[25] Z. Ma, D. Callaway, and I. Hiskens, "Decentralized charging control for large populations of plug-in electric vehicles: Application of the nash certainty equivalence principle," in *Proc. IEEE Int. Conf. Control Appl. (CCA)*, Sep. 2010, pp. 191–195.
[26] P. Vytelingum, T. D. Voice, S. D. Ramchurn, A. Rogers, and N. R. Jennings, "Agent-based micro-storage management for the smart grid," in *Proc. 9th Int. Conf. Auton. Agents Multiagent Syst.*, May 2010.
[27] C. Wei, H. Hu, Q. Chen, and G. Yang, "Learning agents for storage devices management in the smart grid," in *Proc. Int. Conf. Comput. Intell. Softw. Eng. (CiSE)*, Dec. 2010.
[28] C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid implementation," *Energy Policy*, vol. 37, no. 11, pp. 4379–4390, 2009.
[29] A. Ipakchi and F. Albuyeh, "Grid of the future," *IEEE Power Energy Mag.*, vol. 7, no. 2, pp. 52–62, Mar. 2009.
[30] A. Vojdani, "Smart integration," *IEEE Power Energy Mag.*, vol. 6, no. 6, pp. 71–79, Nov. 2008.
[31] U. S. Department of Energy, "The smart grid: An introduction," 2008.
[32] S. M. Amin and B. Wollenberg, "Toward a smart grid: Power delivery for the 21st century," *IEEE Power Energy Mag.*, vol. 3, no. 5, pp. 34–41, Sep. 2005.
[33] California Independent System Operator, "Settlements guide, ancillary services overview," [Online]. Available: http://www.caiso.com
[34] J. Filar and K. Vrieze, *Competitive Markov Decision Processes*. New York: Springer-Verlag, 1997.
[35] D. Fudenberg and J. Tirole, *Game Theory*. Cambridge, MA: MIT Press, 1991.
[36] C. Wu, H. Mohsenian-Rad, and J. Huang, *Vehicle-to-Grid Systems: Ancillary Services and Communications, Book Chapter in Smart Grid Communications and Networking*. Cambridge, U.K.: Cambridge Univ. Press, 2011.
[37] M. Kisacikoglu, B. Ozpineci, and L. Tolbert, "Examination of a phev bidirectional charger system for V2G reactive power compensation," in *Proc. 25th Annu. IEEE Appl. Power Electron. Conf. Expo. (APEC)*, Feb. 2010, pp. 458–465.
[38] M. Khalid and A. Savkin, "Model predictive control based efficient operation of battery energy storage system for primary frequency control," in *Proc. 11th Int. Conf. Control Autom. Robot. Vis. (ICARCV)*, Dec. 2010, pp. 2248–2252.



Chenye Wu (S'11) received the B.S. degree in electronic engineering from Tsinghua University, China, in 2005. Currently, he is working toward the Ph.D. degree supervised by Prof. Andrew Yao in the Institute for Interdisciplinary Information Sciences at Tsinghua University.

He was a Research Assistant at the Chinese University of Hong Kong in 2010 and 2011, respectively. He was also a visiting research assistant at Texas Tech University in 2011. His research interests lie in the general theoretical computer science such as algorithm design and complexity analysis. Currently, he is working on the design, optimization, and game-theoretic analysis of smart power systems.

Mr. Wu is the receipt of the honorary academic rising star in 2011, and the national scholarship in 2008 both from the Ministry of Education of People's Republic of China.

Hamed Mohsenian-Rad (S'04–M'09) received the M.S. degree in electrical engineering from Sharif University of Technology in 2004 and the Ph.D. degree in electrical and computer engineering from the University of British Columbia, Canada, in 2008.

Currently, he is an Assistant Professor at the Department of Electrical and Computer Engineering at Texas Tech University. He is an Associate Editor of the *International Journal of Electronics and Communication* and the TPC Co-chair of the first *IEEE International Workshop on Smart Grid Communications and Networking*. His research interests include design, optimization, and game-theoretic analysis of communication networks and smart power systems.

Jianwei Huang (S'01–M'06–SM'11) received the Ph.D. degrees in electrical and computer engineering from Northwestern University, Evanston, IL, in 2005.

He is an Assistant Professor in the Department of Information Engineering at the Chinese University of Hong Kong. He worked as a Postdoc Research Associate in the Department of Electrical Engineering at Princeton University during 2005–2007. He currently leads the Network Communications and Economics Lab (http://ncel.ie.cuhk.edu.hk), with main research focus on network economics, cognitive radio networks, and smart grid.

Dr. Huang is the recipient of the IEEE Marconi Prize Paper Award in Wireless Communications in 2011, the IEEE GLOBECOM Best Paper Award in 2010, the IEEE ComSoc Asia-Pacific Outstanding Young Researcher Award in 2009, and Asia-Pacific Conference on Communications Best Paper Award in 2009. He has served as Editor of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS—Cognitive Radio Series, Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, Guest Editor of IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS special issue on "Economics of Communication Networks and Systems," Lead Guest Editor of the IEEE JOURNAL OF SELECTED AREAS IN COMMUNICATIONS special issue on "Game Theory in Communication Systems." He has served as Vice Chair of IEEE Multimedia Communications Technical Committee, and the TPC Co-Chair of several conferences including IEEE WiOpt 2012, GameNets 2009, IEEE GlOBECOM Wireless Communications Symposium 2010, and IWCMC Mobile Computing Symposium 2010.