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Online Scheduling for Vehicle-to-Grid Regulation Service

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Abstract—Electric vehicle (EV) fleets can provide ancillary services, such as frequency regulation, to the utility grid, if their charging/discharging schedules are coordinated appropriately. In this paper, a multi-level architecture for bidirectional vehicle-to-grid regulation service is proposed. In this architecture, aggregators coordinate the charging/discharging schedules of EVs in order to meet their shares of regulation demand requested by the grid operator. Based on this architecture, the scheduling problem of V2G regulation is then formulated as a convex optimization problem, which in turn degenerates to an online scheduling problem for charging/discharging of EVs. It requires only the current and past regulation profiles, and does not depend on the accurate forecast of regulation demand. A decentralized algorithm, which enables every EV to solve its local optimization problem and obtain its own schedule, is applied to solve the online scheduling problem. Based on the household driving pattern and regulation signal data from the PJM market, a simulation study of 1,000 EVs has been performed. The simulation results show that the proposed online scheduling algorithm is able to smooth out the power fluctuations of the grid by coordinating the EV schedules, demonstrating the potential of V2G in providing regulation service to the grid.

I. INTRODUCTION

Electric vehicles (EVs) can provide ancillary services, such as regulation services, to the utility grid if their charging/discharging schedules are coordinated appropriately. Therefore, the scheduling problem for EV charging/discharging is an important research topic in recent years. Most research on this topic falls into two categories: EV charging control and vehicle-to-grid (V2G) scheduling.

Studies on EV charging control regard the EV charging load as controllable load. Research on smart/coordinated EV charging can be categorized as centralized control [1], [2], and decentralized control [3], [4]. They try to determine the optimal EV charging schedules to minimize the distribution system losses by flattening the total load without sacrificing the charging needs of EVs. However, the centralized algorithms proposed in [1], [2] are inadequate due to high computational complexity as the number of EVs scales up. This is one of the key reasons why the decentralized control strategies [3], [4], which distribute the computation to EVs and allow them to determine their schedules locally, are preferred, since the penetration of EVs is expected to be high in the future. We regard the formulation and algorithms proposed in [1]–[4] as forecast-based, since they all require accurate forecasts of the base load or non-EV load to perform the optimal EV charging control.

V2G seeks to utilize the battery packs installed on EVs as energy storage to provide energy and ancillary services to the grid [5]. It can be both unidirectional when EVs provide ancillary services by modulating their charging rates, and bidirectional when EVs are also allowed to discharge their batteries to inject energy back to the grid. Most research efforts on V2G ancillary services focus on frequency regulation service. Frequency regulation is a zero-energy service that compensates the minute-to-minute fluctuations of generation and demand [6]. Distributed control strategies based on local frequency measurement have been proposed in [7], [8]. The control strategy proposed in [7] ensures that an EV will be charged to a desired level of state-of-charge (SOC), but it cannot achieve the global optimum among the EV fleet since the control is for a single EV and the discharging/charging schedules of EVs are not coordinated. In [8], each EV decides its own charging/discharging schedule in response to its locally measured frequency deviation, but there is no guarantee on charging needs. Again, global optimum is not achievable. In [9], [10], centralized scheduling is employed where an aggregator acts as the central controller. They try to optimize the schedules of the EV fleets so as to maximize the revenue of regulation service. However, they do not consider whether the EVs are adequately charged. The concept of EV aggregators is applied in [9], [10], but no existing work has clearly specified the structure or architecture of the V2G system consisting of the utility grid, aggregators, and EVs. Moreover, the functions and relations of different parts of the system have not been well defined.

In this paper, we try to tackle the problems of V2G scheduling mentioned above. In Section II, we first propose a multi-level architecture for bidirectional V2G regulation service with three types of operation protocols. The scheduling problem is then formulated as a convex optimization problem which may be operated online with guarantees of adequate charging for EVs in Section III. A decentralized algorithm is designed to solve the optimization problem in Section IV. Simulation results are presented and discussed in Section V. Finally, Section VI draws the conclusions.

II. System Architecture

In this section, we propose a multi-level system architecture, the schematic diagram of which is shown in Fig. 1, for the provision and operation of bidirectional V2G frequency regulation service. The architecture consists of three key components: the grid operator, the aggregators, and a set of EVs. It has a hierarchical structure with multiple levels of nodes. The utility grid operator is the root node. The aggregators directly connected to the grid operator are called *level-1 aggregators*. An aggregator directly connected to a group of level-$(l+1)$ aggregators is called a *level-l aggregator*, where $l = 1, 2, \cdots, N_L$, and N_L is the number of aggregator levels in the system. For convenience, the aggregators directly connected to EVs are called *aggregators of EVs*. Correspondingly, all the other aggregators are called *aggregators of aggregators*. Each aggregator node can be viewed as the "root node" of a subtree of aggregators and EVs. The size of a subtree is determined by the size of its subordinate EV fleets and other geographical, economic, and/or technical factors, such as the communication radius, delay, and cost between nodes at different levels. For instance, a parking lot or a certain area of a large parking lot can install an aggregator of EVs. A number of such parking areas can be controlled by an aggregator of aggregators.

As illustrated in Fig. 1, there are three types of operation protocols, namely, grid operator-aggregator protocol, aggregator-aggregator protocol, and aggregator-EV protocol. Each protocol operates between a node and its immediate subordinate nodes. The grid operator-aggregator protocol governs how the grid operator assigns the regulation requests to and coordinates the level-1 aggregators to meet regulation demand. The regulation requests are the aggregators' shares of regulation demand according to their signed contracts for regulation service. The aggregator-aggregator protocol governs how an aggregator of aggregators coordinates its immediate subordinate aggregator to meet regulation requests. The aggregator-EV protocol specifies the process and algorithm for an aggregator of EVs to coordinate its connected EVs to decide their charging/discharging schedules. In other words, the aggregators act as the interface between the utility grid and EV fleets so that the grid operator does not need to care about the individual charging/discharging profiles of EVs. These EVs can collectively form a massive energy storage system to provide regulation service. In this paper, the focus is on the design of the aggregator-EV protocol.

III. Problem Formulation

The scheduling problem of EVs, which determines the charging/discharging scheduling of EVs, is the most important problem for the operation of the proposed architecture for the V2G regulation service. In this section, we focus on the design of the aggregator-EV protocol and derive a practical formulation of the online scheduling for V2G frequency regulation for an aggregator of EVs. The proposed formulation jointly considers the provision of regulation service and the charging
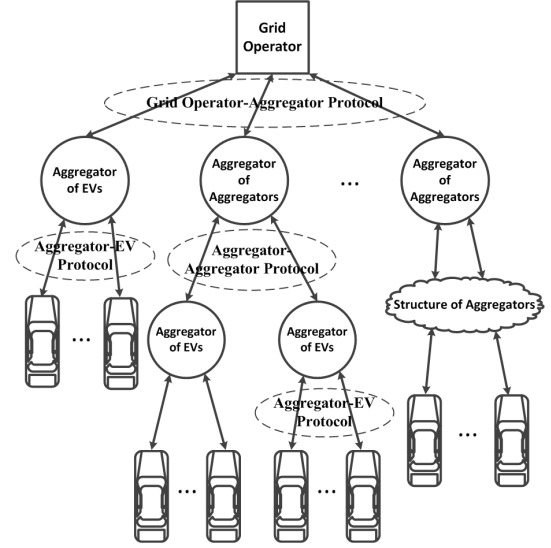

Fig. 1. Multi-level Architecture of Bidirectional V2G.

guarantees for EVs, and does not depend on the accurate forecast of regulation demand.

A. Model and Constraints

Consider a scenario where an aggregator of EVs coordinates N_{EV} EVs to schedule their charging/discharging profiles to meet the share of regulation demand assigned to the aggregator and fulfill the charging requirements of the EVs over a participation period $[T_{begin}, T_{end}]$, which is divided equally into N_T time slots of length Δt. Let $\mathcal{T} := \{T_k | k = 1, 2, \ldots, N_T\}$ be the set of the slotted participation period, $R(T_k)$ be the assigned share of regulation demand at time slot T_k, and $P_n(T_k)$ be the charging/discharging power of EV n at T_k, for $T_k \in \mathcal{T}$ and $n \in \mathcal{N} := \{1, 2, \ldots, N_{EV}\}$. We assume that the share of regulation demand of an aggregator accounts for a fixed proportion of the total regulation demand in the grid during $\mathcal{T}$. $R(T_k) > 0$ means that the aggregator should coordinate the N_{EV} EVs to provide regulation up or deliver active power to the grid. Similarly, $R(T_k) < 0$ provides regulation down or absorbs excessive power from the grid. When $P_n(T_k) > 0$, EV n is charging or consuming power. When $P_n(T_k) < 0$, it is discharging its battery or delivering power back to the grid. Denote the plug-in time and plug-out time of EV n as $T_{n,in}$ and $T_{n,out}$, respectively. Define the lower bound $\underline{P_n}(T_k)$ and upper bound $\overline{P_n}(T_k)$ of $P_n(T_k)$ for $T_k \in \mathcal{T}$ and $n \in \mathcal{N}$ as:

$$\underline{P_n}(T_k) := \begin{cases} P_{n,discharge} & \text{if } T_k \in [T_{n,in}, T_{n,out}] \\ 0 & \text{if } T_k \notin [T_{n,in}, T_{n,out}] \end{cases} \quad (1)$$

and

$$\overline{P_n}(T_k) := \begin{cases} P_{n,charge} & \text{if } T_k \in [T_{n,in}, T_{n,out}] \\ 0 & \text{if } T_k \notin [T_{n,in}, T_{n,out}] \end{cases} \quad (2)$$

where $P_{n,discharge}$ and $P_{n,charge}$ denote the limits of discharging power and charging power of EV n, respectively.

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Thus

$$\underline{P_n}(T_k) \leq P_n(T_k) \leq \overline{P_n}(T_k), t \in \mathcal{T}, n \in \mathcal{N} \qquad (3)$$

Let $SOC_{n,0}$, $SOC_n(T_k)$, and C_n be the initial SOC, SOC at the end of T_k, and capacity of the battery pack of EV n, respectively. We propose two constraints for the SOC of the battery pack during the plugged-in period of EV n, where $n \in \mathcal{N}$ as follows:

$$SOC_n(T_{N_T}) \geq SOC_{n,MinCharged} \qquad (4)$$

$$SOC_{n,min} \leq SOC_n(T_k) \leq SOC_{n,max}, T_k \in \mathcal{T} \qquad (5)$$

From (4), $SOC_{n,MinCharged}$ denotes the minimum value of SOC that EV n needs to reach before it is plugged out. The minimum amount of energy to charge for EV n before it is plugged out, $E_{n,min}$, can be expressed as:

$$E_{n,min} := C_n \left(SOC_{n,MinCharged} - SOC_{n,0} \right) \qquad (6)$$

From (5), $SOC_{n,min}$ and $SOC_{n,max}$ denote the lower and upper SOC limits, respectively, of EV n for all $T_k \in \mathcal{T}$. This constraint is to avoid deep-discharging or over-charging of the battery so as to protect the longevity of the battery.

B. Formulation of the Scheduling Problem

According to the model in Section III-A, an aggregator receiving a regulation request $R(T_k)$ would coordinate its managed EVs to determine their charging/discharging power to smooth out the fluctuation by minimizing:

$$|R(T_k) + \sum_{n \in \mathcal{N}} P_n(T_k)| \qquad (7)$$

or

$$(R(T_k) + \sum_{n \in \mathcal{N}} P_n(T_k))^2 \qquad (8)$$

We call the term $\sum_{n \in \mathcal{N}} P_n(T_k)$ in (7) and (8) the aggregated EV power at $T_k \in \mathcal{T}$. Since (7) is non-convex, it entails a higher computational complexity for optimization than the convex one (8). Thus, we choose (8) instead and introduce a forecast-based or offline formulation of the scheduling problem over the participation period $\mathcal{T}$. Assume that, before the participation period $\mathcal{T}$, the aggregator receives the forecasting profile of its assigned regulation demand $\{R(T_k)|T_k \in \mathcal{T}\}$. Then, it coordinates the EVs to determine the optimal schedule by the following optimization:

$$\min_{\{P_n(T_k)|n \in \mathcal{N}, T_k \in \mathcal{T}\}} \sum_{T_k \in \mathcal{T}} (R(T_k) + \sum_{n \in \mathcal{N}} P_n(T_k))^2 \qquad (9)$$

The optimization result of the forecast-based formulation (9) provides the best possible schedule if the forecasting profile of $\{R(T_k)|T_k \in \mathcal{T}\}$ is accurate. However, in reality, the forecast of regulation demand is highly inaccurate and unreliable because regulation demand is vulnerable to forecasting errors of generation and load. Therefore, the forecast-based formulation is not appropriate or practical for frequency regulation.

Considering that regulation demand is derived from the regulation signals measured in real time, an online formulation, which schedules the EV power in response to the real-time input of $R(T_k)$, is more realistic. At time slot T_k, the aggregator receives the real-time signal of $R(T_k)$. It then coordinates a group of EVs to update their schedules from T_k to T_{N_T} by the following optimization:

$$\min_{\{P_n(T_i)|n \in \mathcal{N}, k \leq i \leq N_T\}} (R(T_k) + \sum_{n \in \mathcal{N}} P_n(T_k))^2$$
$$+ \sum_{i=k+1}^{N_T} (\mathbb{E}(R(T_i) \mid \{R(T_j)|1 \leq j \leq k\}) + \sum_{n \in \mathcal{N}} P_n(T_i))^2 \qquad (10)$$

Although (10) allows for real-time update of the schedules and does not need accurate forecast of regulation demand, it still requires the calculation of the conditional expectation of every future regulation request, i.e., the term $\mathbb{E}\left(R(T_i)|\{R(T_j)|1 \leq j \leq k\}\right)$, for $i = k+1, k+2, \cdots, N_T$. Unfortunately, this calculation requires the distribution of regulation demand which is not known a priori. Nonetheless, since frequency regulation is a zero-energy service, which means the expectation of the total energy that the regulation service requires is zero over a long period of time, we can make the following assumption:

$$\mathbb{E}(\sum_{T_k \in \mathcal{T}} R(T_k)) = 0 \qquad (11)$$

By applying the Cauchy Inequality, we can derive a lower bound of the second summation in the objective function of (10) when $k \leq N_T - 1$ as follows:

$$\sum_{i=k+1}^{N_T} (\mathbb{E}(R(T_i) \mid \{R(T_j)|1 \leq j \leq k\}) + \sum_{n \in \mathcal{N}} P_n(T_i))^2$$
$$\geq \frac{1}{N_T - k}(\mathbb{E}(\sum_{i=k+1}^{N_T} R(T_i) \mid \{R(T_j)|1 \leq j \leq k\}) + \sum_{n \in \mathcal{N}} FP_n(T_i))^2 \qquad (12)$$

where

$$FP_n(T_k) := \sum_{i=k+1}^{N_T} P_n(T_i) \qquad (13)$$

is the sum of future charging/discharging profile of EV n.

By (11), the conditional expectation of the sum of the future regulation requests in (12) can be calculated as:

$$\mathbb{E}(\sum_{i=k+1}^{N_T} R(T_i) \mid \{R(T_j)|1 \leq j \leq k\}) = -\sum_{j=1}^{k} R(T_j) \qquad (14)$$

Let $Q_n(T_k) := (P_n(T_k), FP_n(T_k))$ be the schedule of EV $n \in \mathcal{N}$, and $Q(T_k) := (Q_1(T_k), Q_2(T_k), \ldots, Q_{N_{EV}}(T_k))$ denote the schedules of all EVs at time slot $T_k \in \mathcal{T}$. We apply the lower bound derived in (12) and propose the formulation of online scheduling for V2G frequency regulation as follows. For any $T_k \in \mathcal{T}$,

$$\min_{Q(T_k)} U(Q(T_k)) \qquad (15)$$

such that

$$P_n(T_k) + FP_n(T_k) \geq \frac{E_{n,min}}{\Delta t} - \sum_{i=1}^{k-1} P_n(T_i) \qquad (16)$$

$$P_n(T_k) \geq \frac{C_n}{\Delta t} \left(SOC_{n,min} - SOC_n(T_{k-1}) \right) \qquad (17)$$

$$P_n(T_k) \leq \frac{C_n}{\Delta t} \left(SOC_{n,max} - SOC_n(T_{k-1}) \right) \qquad (18)$$

$$\underline{P_n}(T_k) \leq P_n(T_k) \leq \overline{P_n}(T_k) \qquad (19)$$

$$\sum_{i=k+1}^{N_T} \underline{P_n}(T_k) \leq FP_n(T_k) \leq \sum_{i=k+1}^{N_T} \overline{P_n}(T_k) \qquad (20)$$

where

$$U(Q(T_k)) := \begin{cases} (\sum_{n \in \mathcal{N}} P_n(T_{N_T}) + R(T_{N_T}))^2 & \text{if } k = N_T \\ (\sum_{n \in \mathcal{N}} P_n(T_k) + R(T_k))^2 + \frac{1}{N_T - k} \cdot \\ \quad (\sum_{n \in \mathcal{N}} FP_n(T_k) - \sum_{j=1}^{k} R(T_j))^2 & \text{otherwise} \end{cases} \qquad (21)$$

The constraint set (16) – (20) is a simple transformation of the definitions and constraints (1) – (6) introduced in Section III-A.

It can be shown that the objective function (21) and the set of feasible solutions under the constraint set (16) – (20) are both convex. Therefore, the proposed formulation (15) – (21) is a convex optimization problem. Although (15) only seeks to optimize a lower bound of (10), it is tractable and more practical than (10). In addition, (15) requires much lower computational complexity than (9) and (10) since it reduces the number of variables needed significantly.

IV. DECENTRALIZED SCHEDULING ALGORITHM

In this section, we propose a decentralized algorithm to solve the proposed convex optimization problem (15) – (21) for V2G scheduling.

Let $\langle \cdot, \cdot \rangle$ represent the dot product operation and $\|\cdot\|$ denote the Euclidean norm. The proposed algorithm is presented in Algorithm 1, which is inspired by the decentralized algorithm proposed in the work of the optimal EV charging control [3].

The stopping criterion of Algorithm 1 can be based on the number of iteration performed, and/or the convergence of the control signal s^m within the convergence tolerance. At each iteration, each EV $n \in \mathcal{N}$ solves an convex optimization problem with only two variables $P_n(T_k)$ and $FP_n(T_k)$. Hence, Algorithm 1 requires very low computational cost. In addition, user information privacy can be preserved since the data related to the driving patterns of the EV owner, including the SOC of the EV's battery, the plug-in time, and plug-out time, do not need to be reported in advance to the aggregator.

Theorem 1. *The schedule Q^m converges to the optimal solution for the convex optimization problem* (15) – (21) *as* $m \to \infty$.

The proof of Theorem 1 is similar to that of Theorem 3 in [3]. Therefore, we skip the proof due to the constraint in space.

V. CASE STUDY

In this section, the performances of the proposed online formulation and decentralized algorithm are studied by simulation. We first outline a set of scheduling algorithms for the provision of the V2G regulation service, followed by a performance metric introduced for the comparison of the scheduling algorithms. The simulation setup is then specified. Finally, the simulation results are presented and discussed.

Algorithm 1 Online Scheduling

Input: At any time slot $T_k \in \mathcal{T}$, the aggregator knows the total number of time slots, N_T, and the number of EVs, N_{EV}, and it has received the requests of regulation demand $\{R(T_i)|1 \leq i \leq k\}$. Each EV $n \in \mathcal{N}$ knows about its own constraint set (16) – (20) and the constraint parameters.

Output: Schedule $Q(T_k) = (Q_1(T_k), \ldots, Q_{N_{EV}}(T_k))$.
Choose a parameter β satisfying $0 < \beta < \frac{1}{2N_{EV}}$.
Initialize the schedule $Q_n^0(T_k)$ of every EV $n \in \mathcal{N}$ as:

$$Q_n^0(T_k) := \begin{cases} (0,0) & k = 1 \\ (0, FP_n(T_{k-1})) & \text{otherwise} \end{cases} \qquad (22)$$

Set the iteration number $m \leftarrow 1$, repeat Steps 1) – 3).

1) The aggregator calculates the control signal $s^m(T_k)$ as follows. When $k \neq N_T$:

$$\begin{aligned} s^m(T_k) &:= \beta \left(\frac{\partial U(Q(T_k))}{\partial (\sum_{n \in \mathcal{N}} P_n(T_k))}, \frac{\partial U(Q(T_k))}{\partial (\sum_{n \in \mathcal{N}} FP_n(T_k))} \right) \\ &= 2\beta \Big(R(T_k) + \sum_{n \in \mathcal{N}} P_n^{m-1}(T_k), \\ &\quad \frac{1}{N_T - k} \Big(\sum_{j=1}^{k} R(T_j) + \sum_{n \in \mathcal{N}} FP_n^{m-1}(T_k) \Big) \Big) \end{aligned} \qquad (23)$$

When $k = N_T$:

$$\begin{aligned} s^m(T_{N_T}) &:= \beta \left(\frac{\partial U(Q(T_{N_T}))}{\partial (\sum_{n \in \mathcal{N}} P_n(T_{N_T}))}, 0 \right) \\ &= 2\beta \Big(R(T_{N_T}) + \sum_{n \in \mathcal{N}} P_n^{m-1}(T_{N_T}), 0 \Big) \end{aligned} \qquad (24)$$

Then, it broadcasts the control signal $s^m(T_k)$ to all EVs.

2) Each EV $n \in \mathcal{N}$ calculates a new schedule $Q_n^m(T_k)$ as:

$$\begin{aligned} Q_n^m(T_k) := \arg \min_{Q_n(T_k)} (&\langle s^m(T_k), Q_n(T_k) \rangle \\ &+ \frac{1}{2} \|Q_n(T_k) - Q_n^{m-1}(T_k)\|^2) \end{aligned} \qquad (25)$$
$$\text{s.t. (16), (17), (18), (19), (20) hold}$$

and reports $Q_n^m(T_k)$ to the aggregator.

3) If the stopping criterion is not met, set $m \leftarrow m + 1$ and go to Step 1).

Return $Q_n(T_k) = Q_n^m(T_k), \forall n \in \mathcal{N}$.

A. V2G Scheduling Algorithms

The forecast-based scheduling and the online scheduling will be studied.

As indicated in Section III-B, the forecast-based or offline formulation (9) will provide the best possible scheduling results only when the forecast profile of the regulation requests is accurate. The performance of the forecast-based scheduling with inaccurate forecast will also be tested. The forecast error $e(t)$ is introduced to the actual regulation request $R(t)$ as:

$$R(t) = (1 + e(t))R_f(t), t \in \mathcal{T} \qquad (26)$$

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where $e(t) \sim N(0, 0.3)$ and $R_f(t)$ is the forecast regulation profile. The forecast-based scheduling will be solved by the algorithm *Optimal Decentralized Charging* proposed in [3].

In order to show that the proposed online formulation (15) – (21) can jointly handle provision of regulation service and charging requirement of EVs, a so-called "myopic" online scheduling which only considers the current regulation demand is introduced as follows:

$$\min_{\{P_n(T_k) | n \in \mathcal{N}\}} (\sum_{n \in \mathcal{N}} P_n(T_k) + R(T_k))^2 \tag{27}$$
$$\text{s.t. (16), (17), (18), (19), (20) hold}$$

Both the proposed online scheduling and the myopic online scheduling (27) will be studied. They will be solved by the proposed decentralized scheduling algorithm, Algorithm 1.

B. Performance Metric

First, we define the total power $P_{total}(t)$, which is the sum of the regulation request and the aggregated EV power, as follows:

$$P_{total}(t) := R(t) + \sum_{n \in \mathcal{N}} P_n(t), t \in \mathcal{T} \tag{28}$$

The variance of the total power profile, $\text{Var}(P_{total}(t))$, is used as the performance metric, which is defined as follows:

$$\text{Var}(P_{total}(t)) := \frac{1}{N_T} \sum_{k=1}^{N_T} P_{total}(T_k)^2 - \frac{1}{N_T^2} (\sum_{k=1}^{N_T} P_{total}(T_k))^2 \tag{29}$$

A smaller variance $\text{Var}(P_{total}(t))$ indicates a more flattened profile of the total power, which means that the fluctuations of the regulation requests are better absorbed by the aggregated EV power, resulting in a better scheduling performance.

C. Simulation Setup

The simulation scenario is an aggregator coordinating 1,000 EVs to decide their schedules from 19:00 on a weekday to 7:00 on the following day. This 12-hour period of time is divided equally into $N_T = 144$ slots of length $\Delta t = 5$ minutes. All the EVs are assumed to have been contracted to provide V2G regulation, either unidirectionally or bidirectionally. $\theta_{bi} \in [0, 1]$ denotes the proportion of the EVs that participate in bidirectional V2G. According to the standard Level 2 charging in the U.S.A [11], we assume that the power of the EVs that participate in bidirectional and unidirectional V2G can vary from -4.0 kW to 4.0 kW and from 0 to 4.0 kW, respectively. According to [12], the distribution of plug-in time of EVs is close to a normal distribution. Hence, in the simulation, the plug-in time of the EVs is assumed to follow a normal distribution with the mean at 19:00 and the standard deviation is equal to 1 hour. In addition, the plug-out time is also assumed to follow a normal distribution with the mean at 7:00 and the standard deviation is equal to 1 hour. Any plug-in time before 19:00 and plug-out time after 7:00 is set to be 19:00 and 7:00, respectively. The profiles of frequency regulation demand used in the simulation are scaled data of the fast response regulation signal of the PJM market [13] from 19:00 on Monday, 14 January 2013 to 7:00 on Tuesday,
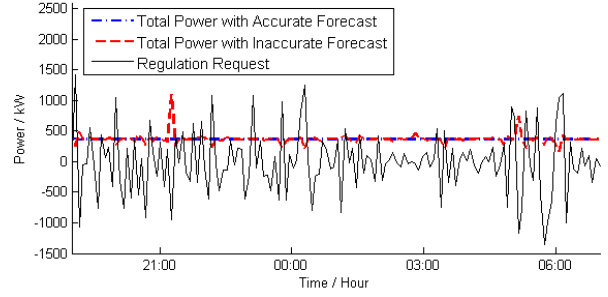

Fig. 2. Simulation results of forecast-based scheduling when $\theta_{bi} = 1$.

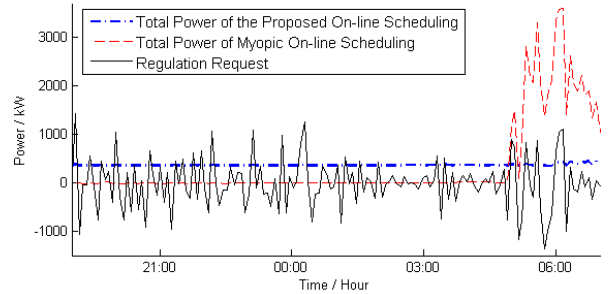
Fig. 3. Simulation results of online scheduling when $\theta_{bi} = 1$.

15 January 2013, because the regulation signal and regulation demand are related linearly [14].

D. Simulation Results

The results of the forecast-based or offline scheduling in (9) are shown in Fig. 2. The proportion θ_{bi} of bidirectional V2G is 1, which means all the EVs participate in bidirectional V2G. It can be observed that, ideally, the total power profile with accurate forecast (the dash-dotted curve) is flat indicating that the power fluctuations are smoothed out. We note that the dash-dotted curve is close to a constant positive load of about 366 kW. This phenomenon is due to the charging requirement of the EVs. Because of the zero energy assumption (11) of regulation demand, the constant positive load is approximately equal to the power consumption for satisfying the charging needs of EVs. The total power profile with inaccurate forecast (the dashed curve) reflects a more realistic case. Since the schedules obtained by the offline scheduling are not able to react to the change of real-time regulation demand, the total power profile has frequent and significant fluctuations.

The simulation results of the proposed online scheduling (15) and the myopic scheduling (27) when $\theta_{bi} = 1$ are shown in Fig. 3. Since the myopic scheduling just tries to meet the current regulation request at each time slot without considering the influence of the EVs' charging requirements, it results in a huge peak load (the dashed curve) for charging the EVs during the last two hours of the simulation period. The proposed online scheduling outperforms the myopic scheduling and the offline scheduling with forecasting errors. The total power profile (the dash-dotted curve in Fig. 3) of the proposed online
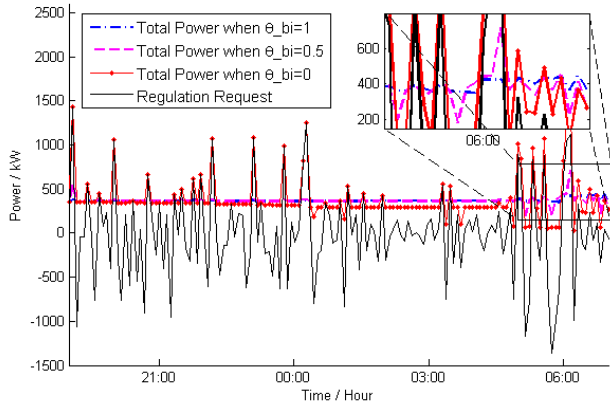
5

Fig. 4. Influence of θ_{bi} on the proposed online scheduling.

TABLE I
PERFORMANCE OF VARIOUS SCHEDULING ALGORITHMS WHEN $\theta_{bi} = 1$

Algorithm	Forecast-Based		Online	
	Accurate	Inaccurate	Proposed	Myopic
$\mathrm{Var}(P_{total}(t))$	1.7	6765.6	296.1	696955.7

scheduling is almost as flat as that (the dash-dotted curve in Fig. 2) of the offline scheduling with accurate forecast, although it has some minor fluctuations during the final one hour because the EVs start to be plugged out and thus become unavailable for providing regulation.

Table I compares the performance of the forecast-based scheduling and the online scheduling when $\theta_{bi} = 1$ based on the $\mathrm{Var}(P_{total}(t))$ metric. It again shows that our proposed online scheduling algorithm can perform nearly as well as the forecast-based scheduling with accurate forecasts, and outperforms the forecasting-based scheduling with forecast errors and the myopic online scheduling.

Fig. 4 presents the influence of the participation ratio θ_{bi} of bidirectional V2G on the performance of the proposed online scheduling. The total power profile (the pointed curve) when $\theta_{bi} = 0$, which means that all the EVs participate in unidirectional V2G, has many positive spikes concurrent with the regulation up requests because the EVs cannot discharge the batteries to provide energy back to the grid. The total power curve (the dashed curve) when $\theta_{bi} = 0.5$ is similar to that (the dash-dotted curve) when $\theta_{bi} = 1$, except for the performance degradation in the final two hours of the simulation period. Such small performance degradation suggests that it may not always be necessary to have all EVs enabled with bidirectional V2G and there may exist a minimum θ_{bi} to satisfy the regulation requests. Considering the high infrastructure cost of bidirectional V2G, it is desired to determine the minimum θ_{bi}. However, due to the constraint in space, we skip the discussion in this paper.

VI. CONCLUSIONS

A multi-level architecture for bidirectional V2G regulation service is proposed. Based on the three types of operation

protocols introduced for this architecture, the EV fleets are able to provide frequency regulation service to the utility grid under the coordination of the aggregators. Focused on the design of the aggregator-EV protocol, an online formulation for the EV charging/discharging scheduling problem is then proposed. We apply a decentralized algorithm to solve the proposed scheduling problem. Our simulation results show that the proposed online scheduling algorithm can perform nearly as well as offline scheduling with accurate forecasts of regulation requests and outperforms off-line scheduling with inaccurate forecasts. Future work will focus on the algorithm design of the grid operator-aggregator protocol and the aggregator-aggregator protocol for the distributed control of regulation demand.

REFERENCES

[1] K. Clement-Nyns, E. Haesen, and J. Driesen, "The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid," *IEEE Transactions on Power Systems*, Vol. 25, No. 1, pp. 371–380, Feb. 2010.

[2] E. Sortomme, M. Hindi, S. MacPherson, and S. Venkata, "Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses," *IEEE Transactions on Smart Grid*, Vol. 2, No. 1, pp. 198–205, Mar. 2011.

[3] L. Gan, U. Topcu, and S. H. Low, "Optimal Decentralized Protocol for Electric Vehicle Charging," *IEEE Transactions on Power Systems*, Vol. 28, No. 2, pp. 940–951, May 2013.

[4] 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," *Proceeding of IEEE CCA 2010*, pp. 191–195, Sep. 2010.

[5] W. Kempton and J. Tomić, "Vehicle-to-Grid Power Implementation: From Stabilizing the Grid to Supporting Large-Scale Renewable Energy," *Journal of Power Sources*, Vol. 144, No. 1, pp. 280–294, Jun. 2005.

[6] B. J. Kirby, "Frequency Regulation Basics and Trends," Oak Ridge National Laboratory, Tech. Rep., Dec. 2004.

[7] Y. Ota, H. Taniguchi, T. Nakajima, K. Liyanage, J. Baba, and A. Yokoyama, "Autonomous Distributed V2G (Vehicle-to-Grid) Satisfying Scheduled Charging," *IEEE Transactions on Smart Grid*, Vol. 3, No. 1, pp. 559–564, Mar. 2012.

[8] H. Yang, C. Y. Chung, and J. Zhao, "Application of Plug-In Electric Vehicles to Frequency Regulation Based on Distributed Signal Acquisition Via Limited Communication," *IEEE Transactions on Power Systems*, Vol. 28, No. 2, pp. 1017–1026, May 2013.

[9] S. Han, S. Han, and K. Sezaki, "Development of an Optimal Vehicle-to-Grid Aggregator for Frequency Regulation," *IEEE Transactions on Smart Grid*, Vol. 1, No. 1, pp. 65–72, Jun. 2010.

[10] E. Sortomme and M. El-Sharkawi, "Optimal Scheduling of Vehicle-to-Grid Energy and Ancillary Services," *IEEE Transactions on Smart Grid*, Vol. 3, No. 1, pp. 351–359, Mar. 2012.

[11] *SAE Electric Vehicle and Plug-in Hybrid Electric Vehicle Conductive Charge Coupler*, SAE Std. J1772, 2010.

[12] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid Integration of Electric Eehicles and Demand Response with Customer Choice," *IEEE Transactions on Smart Grid*, Vol. 3, No. 1, pp. 543–550, Mar. 2012.

[13] "Fast response regulation signal," PJM, Feb. 2013. [Online]. Available: http://www.pjm.com/markets-and-operations/ancillary-services/mkt-based-regulation/fast-response-regulation-signal.aspx]

[14] Y. Rebours, D. Kirschen, M. Trotignon, and S. Rossignol, "A Survey of Frequency and Voltage Control Ancillary Services — Part I: Technical Features," *IEEE Transactions on Power Systems*, Vol. 22, No. 1, pp. 350–357, Feb. 2007.