Title	Capacity management of vehicle-to-grid system for power regulation services
Author(s)	Lam, AYS; Leung, KC; Li, VOK
Citation	The IEEE 3rd International Conference on Smart Grid Communications (SmartGridComm 2012), Tainan, Taiwan, 5-8 November 2012. In Proceedings of the 3rd SmartGridComm, 2012, p. 442-447
Issued Date	2012
URL	http://hdl.handle.net/10722/184989
Rights	Proceedings of the IEEE International Conference on Smart Grid Communications. Copyright © IEEE.

Capacity Management of Vehicle-to-Grid System for Power Regulation Services

Albert Y.S. Lam
Department of Computer Science
Hong Kong Baptist University
Kowloon Tong, Hong Kong
E-mail: albertlam@ieee.org

Ka-Cheong Leung and Victor O.K. Li
Department of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam Road, Hong Kong
E-mail: {kcleung, vli}@eee.hku.hk

***Abstract*—Due to green initiatives adopted in many countries, renewable energy will be massively incorporated into the future smart grid. However, the intermittency of the renewables may result in power imbalance, thus adversely affecting the stability of a power system. Voltage regulation may be used to maintain the power balance at all times. As electric vehicles (EVs) become popular, they may be connected to the grid to form a vehicle-to-grid (V2G) system. An aggregation of EVs can be coordinated to provide voltage regulation services. However, V2G is a dynamic system where EVs are connected to the grid according to the owners' habits. In this paper, we model an aggregation of EVs with a queueing network, whose structure allows us to estimate the capacities for regulation up and regulation down, separately. The estimated capacities from the V2G system can be used for establishing a regulation contract between an aggregator and the grid operator, and facilitate a new business model for V2G.**

I. INTRODUCTION

Global warning is one of biggest problems of the twenty-first century. It is becoming more evident that it has been accelerated by the greenhouse gas (GHG) emissions caused by human activities. Many countries and regions have set up policies to control such GHG emissions. For example, California has adopted the Global Warming Solutions Act of 2006 to reduce its GHG emissions to 80% of the 1990 levels by 2050. One of the main solutions to these goals is to make massive and effective use of renewable energy generation, e.g., solar, wind, and biomass.

For a reliable power system, power balancing needs to be maintained at all times; power generation and consumption must always be equal. Traditional power generations (e.g., thermal power stations) and the renewables serve in the day-ahead and hour-ahead markets [1]. One of the most challenging problems of incorporating the renewables into the power system is its intermittency, rendering it difficult to predict the amount of power generated from the renewables accurately. It is possible that the resulting generation from those markets are excessive or deficient compared with the predicted amount. The real-time market bridges the residual gap between the power generation and the actual demand, accomplished by the ancillary services, including voltage regulation, spinning reserve, supplemental reserve, replacement reserve, and voltage control [2]. According to the U.S. Federal Energy Regulatory Commission, ancillary services are "those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system" [3]. Regarding load balancing, spinning, supplemental reserve, and replacement reserves are for contingency purposes while voltage regulation tracks on a minute-to-minute basis. In this paper, we focus on the ancillary service given by voltage regulation.

There have been some studies about integrating renewables into the grid more reliably and efficiently, such as [4]. One proposed solution is the introduction of energy storage to *defer* the excess for the future deficient. Examples of energy storage include batteries, flywheels, and pumped water. In the near future, one of the most realistic forms is batteries. This can be justified by the expanding markets of plug-in hybrid electric vehicles or simply electric vehicles (EVs). For example, it is forecast that there will be 2.7 million EVs on the road in the U.S. by 2020 [5]. In California, it is expected that roughly 70% of new light-duty vehicles and 60% of the fleets will be EVs [1]. The integration of EVs into the power grid is called the vehicle-to-grid (V2G) system, which is depicted in Fig. 1.

Regulation requires power in the order of MW while each EV can only supply power around 10-20 kW [6]. In order to provide regulation service from the V2G system, an aggregation of EVs is necessary and an aggregator coordinates a group of EVs. The aggregators thus provide regulation services to the grid, which is controlled and coordinated by the gird operators. In general, an aggregator can be a parking infrastructure or a facility coordinating the EV activities of the households in a residential area.

To implement regulation in V2G, the aggregators need to make contracts with the grid operators. The V2G system can support both *regulation up* and *regulation down* services. The former means that the grid does not have enough power supply and extra power sources (e.g., V2G) provides the shortfall. The latter refers to the situation in which extra power loads are needed to absorb the excessive power.

One of charges for the regulation services is capacity payment [7]. It refers to the service charges due to the V2G system only guaranteeing power support when the grid requires regulation up or down. In other words, the V2G

978-1-4673-0911-0/12/$31.00 ©2012 IEEE

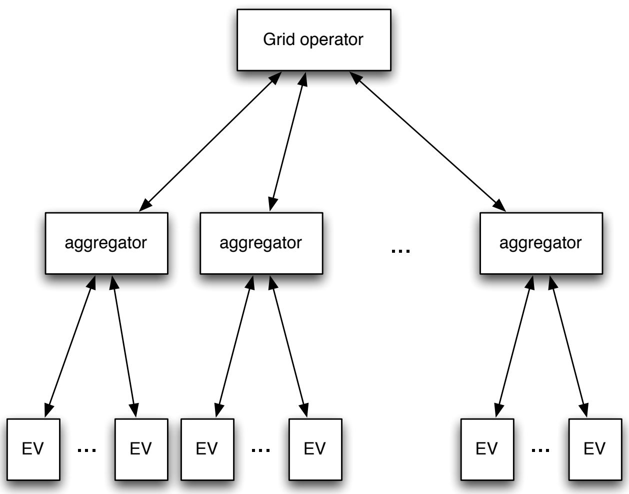

Fig. 1. The V2G system.

system gets paid even without any actual power transfer. The grid operator pays for the service according to the expected amount of power to be supplied and absorbed for regulation up and down, respectively. In this paper, we study the capacity management of the V2G system for an aggregator which can help estimate the total profit and set up the contract between an aggregator and the grid operator. Due to the dynamics of EVs and the similarities between the batteries of V2G (for power) and the buffers of the communication networks (for data packets), we estimate the V2G capacity for regulation with the queueing theoretic approach, which has been widely used for performance analysis in communication networks [8].

The rest of this paper is organized as follows. We give some related work of the V2G studies in Section II and a system overview in Section III. Section IV presents our analytical model and the capacities for both regulation up and down are derived. A performance study of the V2G system for the power regulation services is presented in Section V. Finally, Section VI concludes our work.

II. Related Work

There are many studies on V2G since it is expected to be a major component in the future smart grid. In [7] and [9], V2G was systematically introduced with some preliminary studies on the business model for V2G. They give information of different kinds of EVs and different power markets, including baseload power, peak power, spinning reserves, and regulation. The merits of V2G are quick response and high-value services with low capital costs, but V2G has shorter lifespans and higher operating costs per kWh. The most promising service for the V2G system in terms of regulation and spinning reserves are described next. They give some rough idea about the scale of V2G so as to make it comparable with the traditional regulation from generators. In [10], a simple $M/M/c$ queueing model for EV charging was devised. In [11], the capacity for regulation is also called *achievable power capacity*, but it does not consider separate capacities for regulation up and down. [11], [12], [13] are dedicated to studying V2G regulation. In [12], an optimal charging control scheme for maximizing the revenue of an EV was proposed. In [13], the problem was formulated as a quadratic program and an efficient algorithm considering discharge was devised. [11] considers the user pattern to develop an approximate probabilistic model for achievable power capacity. [14] suggests an $M/M/\infty$ queue with random interruptions to model the EV charging process and analyzes the dynamics with time-scale decomposition. V2G energy trading has been studied as an auction in [15]. To the best of our knowledge, there is no unified study on the capacity management for both regulation up and regulation down.

III. System Overview

Each EV is assumed to be autonomous. It can participate and leave the V2G system according to the schedule of the EV owner. Once an EV is connected or plugged to the system, it will be actively charged and/or support regulation until it departs. When actively charged, it pays for the amount of energy consumed. While it is supporting the regulation, it receives payment for providing the service. Regulation can result in either EV charging or discharging, depending on whether regulation up or down is requested. Thus, it is possible for an EV to get paid while it is being charged (i.e., in a regulation-down event), known as a charging event, in which an EV requests charging itself and supports regulation, *active charging* and *reactive charging*, respectively. A discharging event happens only when an EV participates in supporting regulation up. Both the residual energy stored in the battery of the EV at the time it arrives and the energy charged from active or reactive charging can be used to support regulation up. However, an EV cannot support regulation up when its battery is empty. Similarly, an EV cannot participate in supporting regulation down when its battery is full. Since the battery capacity is finite, the amount of energy stored in a battery affects its potential for supporting regulation up and regulation down services. In this paper, we aim to estimate the capacities of an aggregator for regulation services so that it will be beneficial for an aggregator to establish a contract with the grid operators. Hence, we only consider the events of active charging. The charging and discharging rates due to regulation are small enough so that the estimated capacities for regulation services are not affected by charging and discharging events due to regulation.

Now, we focus on a particular aggregator. We denote the set of EVs, each of which has registered at the aggregator for providing the regulation service, by $\mathcal{I}$. The events associated with each EV and among EVs are independent with each other. All EVs are assumed to be homogeneous such that each is equipped with a battery with the same capacity when fully charged. The state-of-charge (SOC) of an EV refers to the amount of energy stored in its battery normalized with the maximum capacity. We denote SOC of EV i at time t by $x_i(t)$. Without loss of generality, we assume $x_i(t) \in [0, 1], \forall i \in \mathcal{I}$. We also define the *target SOC* of EV i as the amount of energy, normalized with the maximum battery capacity, that the EV's owner aims to reach when it departs, given in a range $[\underline{x}_i, \overline{x}_i]$, where $\underline{x}_i$ and $\overline{x}_i$ are the lower and upper limits of the target SOC of EV i, and $0 \le \underline{x}_i \le \overline{x}_i \le 1$. In other words, if EV i leaves the system at time t', it aims to satisfy $\underline{x}_i \le x_i(t') \le \overline{x}_i$. If the target SOC is merely a value, we have $\underline{x}_i = \overline{x}_i$.

The lower SOC target threshold $\underline{x}_i$ represents the minimum targeted amount of energy, normalized with the maximum battery capacity, retained for EV i when it departs from the system. Hence, it is designed to meet the mobility pattern of EV i. For example, an EV which travels a lot in between two successive chargings requires a higher $\underline{x}_i$. If an EV can be charged quite frequently, a lower $\underline{x}_i$ may be sufficient to support its operation. On the other hand, $\overline{x}_i$ is defined for regulation. Recall that a fully charged EV cannot provide the regulation down service. $\overline{x}_i < 1$ means that EV i reserves room of size $(1 - \overline{x}_i)$ for later regulation-down opportunities or other purposes. At time t, if $x_i(t)$ is smaller than $\underline{x}_i$, active charging always happens in order to bring SOC to the target range. However, active charging must stop when $x_i(t)$ reaches $\overline{x}_i$, since no future regulation-up event is guaranteed to happen in order to bring SOC back to the target range.

Recall that regulation can result in charging or discharging to an EV. We can increase $x_i(t)$ by both active and reactive (i.e., regulation down) chargings, while we can only reduce $x_i(t)$ by regulation up. Hence, when EV i is still connected to the system, it will be in one of the three states according to the value of $x_i(t)$, each of which supports different voltage regulation services, as follows:

- State 1) $x_i(t) \le \underline{x}_i$:
  Only regulation down (reactive charging) is allowed.
- State 2) $\underline{x}_i < x_i(t) < \overline{x}_i$:
  Both regulation up and regulation down are allowed.
- State 3) $x_i(t) \ge \overline{x}_i$:
  Only regulation up (discharging) is allowed.

For simplicity in the analysis, we do not consider that the EVs are actually charged or discharged due to regulation in this paper. Let $r_i(t) \ge 0$ be the active normalized charging rate of EV i at time t and it is constant over time, i.e., $r_i(t) = r_i, t \ge 0$. Consider that EV i is plugged in at time t and its SOC is $x_i(t)$. If it is actively charged at rate r_i, after a time period Δt, we have $x_i(t + \Delta t) = x_i(t) + r_i \Delta t$.

From the standpoint of an EV owner, the primary concern is to charge its EV such that it has enough battery level to support its operation. The profit derived from providing the ancillary services is of secondary concern. In other words, an owner considers to provide the ancillary services from its EV only if the remaining energy (after discharging from providing the ancillary services) is enough to support its operation. Hence, we propose the following simple charging policy: When EV i arrives at the system with SOC below $\overline{x}_i$, it will be actively charged until $\overline{x}_i$ is reached. Otherwise, no active charging is required.

In fact, we can always set $\underline{x}_i = \overline{x}_i$ to simplify the system. EV i supports regulation down when $x_i(t)$ is below $\overline{x}_i$, and it supports regulation up when $x_i(t)$ goes above $\overline{x}_i$. However, suppose that $x_i(t) = \overline{x}_i$ supporting regulation (i.e., it can be actually charged or discharged due to regulation). When there exists a random sequence of regulation-up and regulation-down requests, the EV will be oscillating between States 1 and 3 previously discussed and this will make system unstable. The introduction of State 2 can help stabilize the system.

Note that we aim to perform capacity management by estimating the capacities for regulation to help construct the contract between an aggregator and a grid operator. There are different kinds of regulation contracts in the market:

- Regulation down only:
  An EV always absorbs power from the grid to provide the service. To maximize the profit, we can simply set $\underline{x}_i = \overline{x}_i = 0$ so as to reserve the largest room for energy absorption.
- Regulation up only:
  An EV always supplies power to the grid when providing the service. To maximize the profit, we can simply set $\underline{x}_i = \overline{x}_i = 1$ to preserve as much energy in the battery as possible for future discharging events.
- Regulation up and regulation down:
  Both regulation up and down are allowed. We would set $0 < \overline{x}_i < 1$ appropriately to balance the demand for regulation-up and -down.

In this paper, we consider the V2G system supporting both regulation up and regulation down. We can define two kinds of capacities for the V2G regulation services, namely, the *regulation-down capacity* and *regulation-up capacity*. The former refers to the total amount of energy that can be absorbed by the system to support regulation down. Similarly, the latter corresponds to the total amount of energy available from the system to support regulation up. Here, we focus on determining the regulation-up and regulation-down capacities of one particular aggregator. The capacity of the whole V2G system can then be seen as the sum of the capacities of the individual aggregators. In the next section, we propose an analytical model to estimate the two capacities of an aggregator for our charing policy.

IV. Analytical Model

In this section, we model an aggregator with a queueing network. We first define the settings of the model from the system discussed in Section III and give some assumptions. Then, we construct a queueing network, which is used to estimate the metrics of interest, i.e., the available capacities for regulation up and regulation down.

A. Settings

The V2G system is modelled as a queueing network with three queues, namely, the *regulation-down queue* (RDQ), *regulation-up-and-down queue* (RUDQ), and *regulation-up queue* (RUQ). When an EV is plugged in at time t, the decision to join which queue depends on its SOC $x_i(t)$. If it is in States 1, 2, and 3 (defined in Section III) at time t, it will join the RDQ, RUDQ, and RUQ, respectively. After joining a particular queue, the following will happen:

1) RDQ: Each EV i in this queue is actively charged at its own normalized charging rate r_i. If its SOC reaches $\underline{x}$ at time t', i.e., $x_i(t') = \underline{x}$, it will leave RDQ and join RUDQ. The duration is determined by:

$$\Delta t = t' - t = \frac{\underline{x}_i - x_i(t)}{r_i}, \quad x_i(t) < \underline{x}_i. \tag{1}$$

When an EV is actively charged, it gets served in the queue. It is also possible for it to depart from the queue before its SOC has reached $\underline{x}$. This represents the situation that it quits the system.

2) RUDQ: When EV i arrives at this queue, it will be actively charged at the normalized charging rate r_i until its SOC reaches $\overline{x}_i$. If the charging process starts at time t and the EV is charged to $\overline{x}_i$ at time t', the duration is given by:

$$\Delta t = t' - t = \frac{\overline{x}_i - x_i(t)}{r_i}, \quad \underline{x}_i < x_i(t) < \overline{x}_i. \tag{2}$$

If the EV joins from RDQ, we have:

$$\Delta t = t' - t = \frac{\overline{x}_i - \underline{x}_i}{r_i}. \tag{3}$$

After charging up to $\overline{x}_i$, the EV departs from this queue and goes to RUQ. Similar to RDQ, a departure of an EV from the queue before its SOC reaching $\overline{x}$ represents that the EV leaves the system.

3) RUQ: When an EV joins this queue, no active charging takes place. It will stay in this queue until it departs from the system.

B. Assumptions

We make the following assumptions to make the analysis mathematically tractable:

1) The events associated with each EV and among EVs are independent with each other. Each EV arrives at the system randomly, by following a Poisson process at rate λ. Among the EV arrivals, fractions p_1, p_2, and p_3 of EVs are in States 1, 2, and 3, respectively, where $p_1, p_2, p_3 \in [0, 1]$ and $p_1 + p_2 + p_3 = 1$.
2) There exists a smart charging mechanism M_{SC} : $(x_i(t), \underline{x}_i, \overline{x}_i) \mapsto r_i$, which assigns the normalized charging rate r_i to EV i according to its current SOC $x_i(t)$ upon its arrival at time t, and its target SOC thresholds $\underline{x}_i$ and $\overline{x}_i$. The durations of EVs in States 1 and 2 (refer to (1), and (2) and (3), respectively) are exponentially distributed at rates μ_1 and μ_2, respectively.
3) There exists a fraction q_1 of EVs in State 1 which will directly quit the system. This fraction represents those EVs whose SOCs do not reach their lower target SOC limits at their departures from the system. Similarly, we have a fraction q_2 of EVs to depart from the system in State 2. Note that q_1 and q_2 already capture those EVs which require fast charging. In other words, they may only stay in the system for a short period of time.
4) When an EV is in State 3, no charging would happen. It will remain on standby in the system for a period exponentially distributed with rate μ_3.

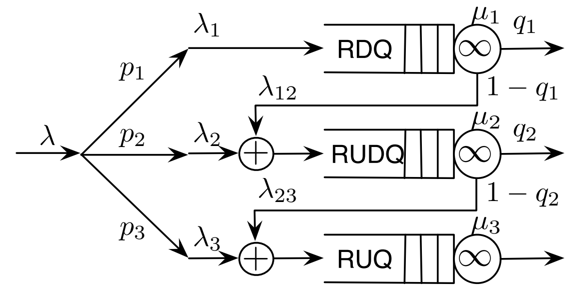

Fig. 2. The queueing model.

Poisson arrivals and exponentially distributed durations of EVs residing in the systems are assumptions. The values of p_1, p_2, q_1, and q_2 can be determined by statistical measurements from the operations of the charging facilities. The design of M_{SC} is out of the scope of this paper and we will consider it as part of the future work.

C. Model

Fig. 2 depicts the queueing model, where RDQ, RUDQ, and RUQ model the behaviours of EVs in States 1, 2, and 3, respectively. Assumption 1 states that we randomly split the EV arrival process into three subprocesses according to the probability distribution (p_1, p_2, p_3). Since random splitting results in independent Poisson subprocesses, the external arrivals at each queue constitute a Poisson process with rate λ_1 for RDQ, λ_2 for RUDQ, and λ_3 for RUQ, where $\lambda_1 = p_1\lambda$, $\lambda_2 = p_2\lambda$, and $\lambda_3 = p_3\lambda$.

When an EV enters RDQ, active charging starts immediately. In other words, all EVs in this queue can get served without queueing up. With Assumption 2, an EV resides in this queue with a duration exponentially distributed with rate μ_1. Hence, RDQ can be modelled as an $M/M/\infty$ queue with arrival rate λ_1 and service rate μ_1. According to [16], the probability $p_{1,n}$ of having n EVs in this queue in the steady state is:

$$p_{1,n} = \frac{(\frac{\lambda_1}{\mu_1})^n e^{-(\frac{\lambda_1}{\mu_1})}}{n!}. \tag{4}$$

The expected number L_1 of EVs charging in RDQ is:

$$L_1 = \sum_{n=1}^{\infty} n p_{1,n} = \frac{\lambda_1}{\mu_1} = \frac{p_1\lambda}{\mu_1}. \tag{5}$$

By Burke's theorem [17], the departure process of RDQ is a Poisson process with rate λ_1. With Assumption 3, this Poisson process is split randomly according to the probability distribution $(q_1, 1 - q_1)$. $(1 - q_1)$ of EVs enter RUDQ with rate $\lambda_{12} = (1 - q_1)\lambda_1$, which superposes with the Poisson subprocess for the external arrivals with rate λ_2. Since the superposition of Poisson processes is still a Poisson process, the combined arrivals to RUDQ constitute a Poisson process with rate $(\lambda_2 + \lambda_{12})$. Similar to RDQ, RUDQ can also be modeled as an $M/M/\infty$ queue with the arrival rate $(\lambda_2 + \lambda_{12})$ and the service rate μ_2. Hence, the probability $p_{2,n}$ of having

n EVs in this queue is:

$$p_{2,n} = \frac{(\frac{\lambda_2+\lambda_{12}}{\mu_2})^n e^{-\frac{\lambda_2+\lambda_{12}}{\mu_2}}}{n!}. \tag{6}$$

The expected number L_2 of EVs charging in RUDQ is given by:

$$L_2 = \frac{\lambda_2+\lambda_{12}}{\mu_2} = \frac{\lambda(p_1+p_2-p_1q_1)}{\mu_2}. \tag{7}$$

With Assumption 3, the departure process is Poisson with rate $(\lambda_2+\lambda_{12})$, which is split randomly according to the probability distribution $(q_2, 1-q_2)$. $(1-q_2)$ of EVs enter RUQ as a Poisson process with rate $\lambda_{23} = (\lambda_2+\lambda_{12})\cdot(1-q_2)$ for RUQ. The combined arrival process of RUQ is also a Poisson process with rate $(\lambda_3+\lambda_{23})$. With Assumption 4, RUQ can be modelled as an $M/M/\infty$ queue with arrival rate $(\lambda_3+\lambda_{23})$ and service rate μ_3. Therefore, the probability $p_{3,n}$ of having n EVs in this queue is:

$$p_{3,n} = \frac{(\frac{\lambda_3+\lambda_{23}}{\mu_3})^n e^{-\frac{\lambda_3+\lambda_{23}}{\mu_3}}}{n!}. \tag{8}$$

The expected number L_3 of EVs standing by in RUQ can be expressed as:

$$L_3 = \frac{\lambda_3+\lambda_{23}}{\mu_3} = \frac{\lambda(1-p_1q_1-p_1q_2-p_2q_2+p_1q_1q_2)}{\mu_3}. \tag{9}$$

The overall system departure process is a Poisson process superposed by three individual departure Poisson processes from the three queues. The overall departure process has rate:

$$\lambda = q_1\lambda_1 + q_2(\lambda_2+\lambda_{12}) + (\lambda_3+\lambda_{23}). \tag{10}$$

The duration of each regulation service Δt_{reg} is normally short, such as a few minutes [2], while EVs are expected to switch their states in a relatively much lower rate. Thus, the mean service times of the queues, $\frac{1}{\mu_1}$, $\frac{1}{\mu_2}$, and $\frac{1}{\mu_3}$ are generally much longer than a few minutes. This is justifiable as an EV cannot be charged up nor leave the system within a few minutes on the average. For each EV, the amount of power P_{EV} contributed for a regulation event can be determined with the amount of energy required Δx_{EV} by:

$$P_{EV} = \frac{\Delta x_{EV}}{\Delta t_{reg}}. \tag{11}$$

As an aggregator normally coordinates hundreds of EVs, P_{EV} contributed by a single EV is small. Hence, Δx_{EV} would be even smaller. For a particular regulation contract with the fixed regulation service duration Δt_{reg}, we can fix P_{EV} to be small enough such that the probability of having a state transition of an EV after an absorption or a removal of energy of Δx_{EV} for a regulation service is almost negligible.[1] Therefore, the capacities for the regulation services can be estimated based on the numbers of EVs available for regulation. Due to the types of regulation supported by EVs as described in Section III, the steady state capacity for regulation down C_{RD} can be computed as:

$$C_{RD} = P_{EV}(L_1+L_2). \tag{12}$$

Similarly, the steady state capacity for regulation up C_{RU} is given by:

$$C_{RU} = P_{EV}(L_2+L_3). \tag{13}$$

[1]Interested readers can refer to Section V for some numerical figures.

V. Performance Evaluation

We study a particular scenario in a parking infrastructure, where EVs arrive and leave independently. On the average, there are five EVs entering the parking structure per minute. 90% of EVs require charging, where their SOCs are below their upper target thresholds at their arrivals. One tenth of them do not, since they need parking only and their SOCs are above their respective upper target thresholds. Among those requiring a charge, two thirds have SOCs below the lower target thresholds (State 1). Hence, we have $p_1 = 0.6$, $p_2 = 0.3$, and $p_3 = 0.1$. For those EVs in State 1, they spend 40 minutes in this state on the average. When they exit State 1, 10% of them leave the system, while the other 90% of them transit to State 2 and continue to charge up their batteries to their upper target thresholds with a mean service time of 50 minutes. One fifth of them leave the system from State 2. Hence, we have $q_1 = 0.1$ and $q_2 = 0.2$. The rest of the EVs stay in State 3 (without charging) with the mean residence time equal to 30 minutes. Thus, RDQ, RUDQ, and RUQ in the model serve EVs with mean service times of 40 minutes, 50 minutes, and 30 minutes, respectively. By (5), (7), and (9), the expected numbers of EVs in States 1-3 are $L_1 = 120$, and $L_2 = 210$, and $L_3 = 115.8$ in the steady state.

We set $P_{EV} = 6$ kW and $\Delta t_{reg} = 1$ minute. Thus, each EV absorbs or delivers 0.1 kWh for each regulation service. When compared with the EV models already available in the market, such small charging and discharging rates of P_{EV} result in a regulation event where the involved EVs do not switch states when supporting regulation (i.e., no transition to other queues merely for regulation). For example, the Tesla Model S has a battery capacity ranging from 40 kWh to 85 kWh [18], and BYD e6 has a battery capacity of 60 kWh [19]. With (12) and (13), the expected capacities for regulation down and regulation up are:

$$C_{RD} = 6 \text{ kW} \times (120+210) = 1.98 \text{ MW} \tag{14}$$

and

$$C_{RU} = 6 \text{ kW} \times (210+115.8) = 1.9548 \text{ MW}. \tag{15}$$

We simulate the instantaneous numbers of EVs getting served in the queues for 2000 minutes. The simulation was done with SimEvents of Matlab. The results are exhibited in Fig. 3. The system is initially empty and it takes about 200 minutes to reach the steady state, where the numbers of EVs in the queues oscillate around our computed expected values.

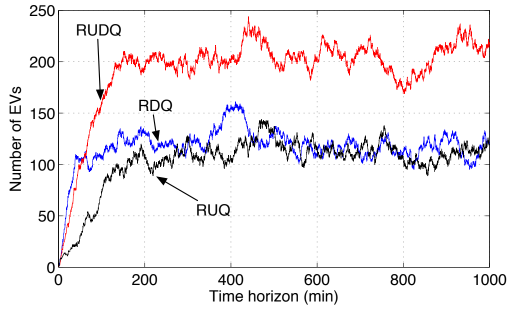

Fig. 3. Variations of the number of EVs in each queue.

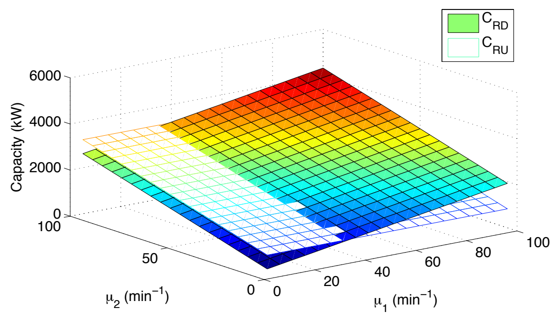

Fig. 4. Regulation capacities with various μ_1 and μ_2.

Most of the parameters in our model, including λ, (p_1, p_2, p_3), μ_3, q_1, and q_2, cannot be controlled generally but they can be determined from the scenario of study statistically. Recall that there exists a smart charging mechanism M_{SC}, which assigns the active charging rates to EVs. In other words, we can adjust μ_1 and μ_2 through proper design of M_{SC}. However, the values of μ_1 and μ_2 may affect the capacities C_{RD} and C_{RU}. Here, we adopt the settings identical to the previous case study, except for μ_1 and μ_2. Fig. 4 shows the capacities corresponding to different combinations of μ_1 and μ_2. From the figure, we can see that C_{RD} is more sensitive to the values of μ_1 and μ_2 than C_{RU}. If an aggregator makes a balanced contract between regulation up and regulation down with a grid operator, the values of μ_1 and μ_2 should be carefully set so that the expected capacities are close to each other. For example, $\mu_1 = \frac{1}{40}$ min^{-1} and $\mu_2 = \frac{1}{50}$ min^{-1} in our case study produce the near-balanced capacities $C_{RD} = 1.98$ MW and $C_{RU} = 1.9548$ MW.

VI. Conclusions

Due to high penetration of renewable energy generation in smart grid, the stochastic nature of the renewables will induce new challenges in matching the actual power consumption and supply. One measure to enforce power balance is through voltage regulation. Traditional regulation services are mainly run by power plants and very costly. The increasing social consensus on environmentally friendly transportation would lead to more reliance on EVs. With the embedded rechargeable batteries in EVs, a fleet of EVs can behave as a huge energy buffer, absorbing excessive power from the smart grid or supplying power to overcome the deficit. This implies that an aggregation of EVs is a practical alternative to support the regulation services of smart grid. However, V2G is a dynamic system. Each EV connects to and disconnects from the system independently. In this paper, we model an aggregation of EVs with a queueing network. The structure of the queueing network allows us to estimate the capacities for regulation up and regulation down separately. The estimated capacities can help set up the regulation contract between an aggregator and a grid operator so as to facilitate a new business model for V2G.

Acknowledgment

This research is supported in part by the Collaborative Research Fund of the Research Grants Council, Hong Kong Special Administrative Region, China, under Grant No. HKU10/CRF/10.

References

[1] "California's Energy Future: The View to 2050," *Technical Report, California Council on Science and Technology*, May 2011.
[2] B. J. Kirby, "Frequency Regulation Basics and Trends," *Technical Report TM2004-291, Oak Ridge National Laboratory*, Dec. 2004.
[3] Federal Energy Regulatory Commission [Online], Available: http://www.ferc.gov/market-oversight/guide/glossary.asp, May 2010.
[4] E. Bitar, K. Poolla, P. Khargonekar, R. Rajagopal, P. Varaiya, and F. Wu, "Selling Random Wind," *Proceedings of the 45th Hawaii International Conference on Systems Science*, pp. 1931-1937, Jan. 2012.
[5] T. A. Becker and I. Sidhu, "Electric Vehicles in the United States: A New Model with Forecasts to 2030," *Technical Report 2009.1.v.2.0, Center for Entrepreneurship and Technology, University of California, Berkeley*, Aug. 2009.
[6] C. Silva, M. Ross, and T. Farias, "Evaluation of Energy Consumption, Emissions and Cost of Plug-In Hybrid Vehicles," *Energy Conversion and Management*, Vol. 50, No. 7, pp. 1635-1643, Jul. 2009.
[7] W. Kempton and J. Tomic, "Vehicle-to-Grid Power Fundamentals: Calculating Capacity and Net Revenue," *Journal of Power Sources*, Vol. 144, No. 1, pp. 268-279, Jun. 2005.
[8] C.-H. Ng and B.-H. Soong, *Queueing Modelling Fundamentals: With Applications in Communication Networks*, 2nd Edition, Wiley, 2008.
[9] W. Kempton and J. Tomic, "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.
[10] R. Garcia-Valle and J. G. Vlachogiannis, "Letter to the Editor: Electric Vehicle Demand Model for Load Flow Studies," *Electric Power Components and systems*, Vol. 37, No. 5, pp. 577-582, Sep. 2009.
[11] S. Han, S. Han, and K. Sezaki, "Estimation of Achievable Power Capacity from Plug-In Electric Vehicles for V2G Frequency Regulation: Case Studies for Market Participation," *IEEE Transactions on Smart Grid*, Vol. 2, No. 4, pp. 632-641, Dec. 2011.
[12] ——, "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.
[13] ——, "Optimal Control of the Plug-In Electric Vehicles for V2G Frequency Regulation using Quadratic Programming," *Proceedings of IEEE PES Innovative Smart Grid Technologies*, Jan. 2011.
[14] S. J. Baek, D. Kim, S.-J. Oh, and J.-A. Jun, "Modeling of Electric Vehicle Charging Systems in Communications Enabled Smart Grids," *IEICE Transactions on Information and Systems*, Vol. E94-D, No. 8, pp. 1708-1711, Aug. 2011.
[15] A. Y. S. Lam, L. Huang, A. Silva, and W. Saad, "A Multi-Layer Market for Vechicle-to-Grid Energy Trading in the Smart Grid," *Proceedings of the First IEEE INFOCOM Workshop on Green Networking and Smart Grids*, Mar. 2012.
[16] D. Gross, J. F. Shortle, J. M. Thompson, and C. M. Harris, *Fundamentals of Queueing Theory*, 4th Edition, Wiley, 2008.
[17] D. P. Bertsekas and R. G. Gallager, *Data Networks*, 2nd Edition, Prentice Hall, 1992.
[18] Tesla Motors [Online], Available: http://www.teslamotors.com, May 2012.
[19] B. Berman, *Exclusive: Byd Announces Breakthrough U.S. Pricing for Chinese Long-Range Electric Cars*, plugincars, 9 Jan. 2011.