International Journal of Automotive Technology, Vol. 16, No. 5, pp. 827−837 (2015)
DOI 10.1007/s12239−015−0085−3

pISSN 1229−9138/ eISSN 1976−3832

OPTIMIZING THE PERFORMANCE OF VEHICLE-TO-GRID (V2G) ENABLED BATTERY ELECTRIC VEHICLES THROUGH A SMART CHARGE SCHEDULING MODEL

Z. LI[1)], M. CHOWDHURY[1)*], P. BHAVSAR[2)] and Y. HE[3)]

[1)]Glenn Department of Civil Engineering, Clemson University, Clemson 29634, USA
[2)]Department of Civil Envrionmental Engineering, Rowan University, Glassboro 08080, USA
[3)]Development Department, Mathworks, Natick 01760, USA

(Received 21 January 2014; Revised 4 June 2014; Accepted 26 June 2014)

ABSTRACT−A smart charge scheduling model is presented for potential (1) vehicle-to-grid (V2G) enabled battery electric vehicle (BEV) owners who are willing to participate in the grid ancillary services, and (2) grid operators. Unlike most V2G implementations, which are considered from the perspective of power grid systems, this model includes a communication network architecture for connecting system components that supports both BEV owners and grid operators to efficiently monitor and manage the charging and ancillary service activities. This model maximizes the net profit to each BEV participant while simultaneously satisfying energy demands for his/her trips. The performance of BEVs using the scheduling model is validated by estimating optimal annual financial benefits under different scenarios. An analysis of popular BEV models revealed that one of the existing BEVs considered in the study can generate an annual regulation profit of $454, $394 and $318 when the average daily driving distance is 20 miles, 40 miles and 60 miles, respectively. All popular BEV models can completely compensate the energy cost and generate a positive net profit, through the application of the scheduling model presented in this paper, with an annual driving distance of approximately 15,000 miles. Simulation analysis indicated that the extra load distribution from the optimized BEV charging operations were well balanced compared to the unmanaged BEV operations.

KEY WORDS : Battery electric vehicle, Vehicle to grid, Smart grid, Charge scheduling

1. INTRODUCTION

The real-time connectivity between elements of a transportation system supports different Intelligent Transportation System (ITS) applications, such as providing decision support to drivers (Bhavsar *et al*., 2008), optimizing energy consumption of Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and conventional vehicles (He *et al*., 2012), and improving safety (Bohm and Jonsson, 2008). The recent evolution in the connected vehicle technology (CVT) which is a part of ITS can enhance these applications further by assessing and predicting real-time traffic conditions (Ma *et al*., 2012; Ma *et al*., 2009). Furthermore, recent studies suggests that energy management and optimization of Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) can contribute to a sustainable future and improve quality of life in developed countries as well as developing countries, if the source of electricity is renewable (Begley, 2011; Aggeri *et al*., 2008; Beaume and Midler, 2009; Wu *et al*., 2012; Gu *et al*., 2013). CVT can also enhance the operations of EVs by providing real-time connectivity between EVs, charging stations and electricity grid (Johnson *et al*., 2013).

Although it is envisioned that one million EVs will be on the road by 2015 (Department of Energy, 2011), the EV market is growing quite slowly, with several major deficiencies currently hindering widespread commercial adoption, the most significant of which entails the charging of these vehicles. Table 1 shows the battery features of several popular Battery Electric Vehicle (BEV) models in the EV market. While the Environmental Protection Agency's (EPA's) certified all-electric falls within the range of 62-82 miles, the U.S. weighted average daily driven distance of 39.5 miles (U.S. Department of Transportation, 2009) indicates that BEV owners are likely to recharge their vehicles frequently in order to meet their daily driving demands. Unlike gasoline refueling, however, BEV charging takes time, requiring as much as 7 hours to fully charge a Nissan Leaf BEV using a level two home charging dock with a 240-volt supply, and 3.5 hours for a Ford Focus Electric using a similar charging station. Furthermore, the high initial manufacturing cost of BEVs, most particularly due to the high battery cost offsets any advantages of the

**Corresponding author.* e-mail: mac@clemson.edu

inexpensive electrical energy used to power them. Currently the average price of an EV lithium-ion battery pack is at \$800/kWh with a lifetime of approximately 1000 complete charge-discharge cycles before degrading to 80% of its initial full charge capacity (Cluzel and Douglas, 2012) which is equivalent to a capital cost of approximately \$19,200 for a Nissan Leaf battery. Therefore, replacing the battery before the end of the service life of the vehicle, should that be required, would greatly increase the total cost of ownership.

A variety of federal and state incentives (i.e. tax credits, rebates, free parking and access to the HOV lanes) for EVs and charging stations have been introduced to reduce their prohibitive costs. For example, consumers purchasing EVs after December 31, 2008 were eligible for a \$2,500 to \$7,500 tax credit depending upon battery size, and with an accompanying BEV infrastructure tax credit of 30%, up to \$1,000 (Department of Energy, 2013a). Also, new research on the integration of BEV energy storage systems with vehicle-to-grid (V2G) technology has determined the feasibility of rerouting excess electricity from this V2G technology back to the grid (Kempton *et al*., 2008). A V2G-enabled BEV can not only draw the electricity from the grid to recharge the battery but also reverse the flow and provide a variety of ancillary services to ease the grid imbalance. With such a technology, BEV owners would have the opportunity to profit quite nicely when the vehicle is connected to the bi-directional charger to provide ancillary services to the power industry. However, estimates on how much profit BEV owners may earn from the surplus power are unclear based upon simple assumptions that disregard driving plans and other personalized user inputs. Though scattered BEVs in a certain area must be aggregated to enter the ancillary service market with sufficient power, very little research has been undertaken to develop methods for efficiently controlling and managing those mobile storage resources, and little research has been attempted to optimize the profit margins from V2G programs through scheduling of a sound charge and discharge plan encompassing smart grid technologies. Consequently, building a smart charge scheduling model in which BEV participants may maximize their V2G profits while ensuring adequate battery supply for driving demands, are important for the viability of BEV-supported ancillary services.

Table 1. Battery features of popular BEV models in the market (Department of Energy, 2013b).

BEV model	Nissan Leaf	Ford Focus Electric	Honda Fit EV	Mitsubishi i-MiEV
Battery type	lithium-ion	lithium-ion	lithium-ion	lithium-ion
Battery capacity (kWh)	24	23	20	16
EPA label range (miles)	73	76	82	62
EPA combined (kWh/100 mi)	34	32	29	30
EPA combined MPGe rating	99	105	118	112
On-board charger (kW)	3.3	6.6	6.6	3.3

This paper presents a charge scheduling model for V2G-enabled EVs that appropriately arranges charge and ancillary service activities to

- maximize net profits ,
- meet energy demand for driving, and
- help grid operators to leverage the additional load from EV charging.

A review of available ancillary services for BEVs along with current strategies for optimizing the V2G implementation is presented in the following section. In the subsequent section, a charge scheduling model that facilitates communications among system components and maximizes the net profits to BEV participants by providing an automatically generated charge/discharge schedule while simultaneously accommodating driving demands is presented. The scheduling problem is modeled as a binary integer programming problem. The performance of BEVs with the proposed scheduling model is evaluated in the next section.

2. ANCILLARY SERVICES FOR V2G-EQUIPPED BEVS

Ancillary services in the U.S. electrical power system are the support services that maintain reliable and secure grid operations. These services are controlled and monitored by organization such as independent system operators (ISOs) and regional transmission organizations (RTOs) (Kempton and Tomic, 2005; Kempton *et al*., 2008). BEVs can be treated and deployed as distributed mobile storage resources and would be competitive for the following four ancillary services (Kempton *et al*., 2008).

(1) Frequency regulation service. To synchronize generation assets in the power system, the desired system frequency must be maintained within defined limits. This service in the open market is designed in response to ISO signals for rapidly correcting frequency deviations that can adversely affect electric equipment and appliances.
(2) Spinning reserve service activates the backup energy resources to deliver electricity back in response to major outages.
(3) Peak load leveling service typically occurs within a single hour of the day at peak demand times.
(4) Backup supply service is engaged during power outages.

Of these four ancillary services, frequency regulation appears to be the most appropriately suited for V2G-enabled BEVs (Kemtpon *et al*., 2008; Brooks, 2002; De Los Rios *et al*., 2012) because unlike spinning reserve and peak load leveling, frequency regulation requires no high battery capacity and allows for a shallow charge/discharge cycling instead of deep depth of discharge (DoD), a measurement of indicating battery capacity, that is likely to degrade the lifecycle of the battery. The number of cycles of a lithium-ion battery can be estimated as a function of DoD, making it obvious that lowering DoD can prevent from fast battery degradation (De Los Rios *et al*., 2012). Therefore, providing frequency regulation services with lower DoD to the BEV will experience less impact on the battery cycle lifetime. While the power fluctuations of frequency regulation may change the battery's state of charge (SOC), a fuel guage for measuring current capacity of the battery, in a short time, the energy storage level is nonetheless retained over a certain period as opposed to other ancillary services that could drain the battery. In the United States, ancillary services account for 5-10% of total electricity cost as $12 billion/year, 80% of which are for regulation and spinning reserve with an average value of $30-$45/MW per hour and $10/MW per hour respectively (Kempton *et al*., 2008).

A vehicle can be V2G available for the majority of the day. According to 2009 National Household Travel Survey, in the US at least 70% of vehicles are parked and available for plug in even during peak hours (U.S. Department of Transportation, 2009). Although the uncertainty of a BEV's battery SOC and plug-in duration may adversely affect the reliability of the BEV that is supposed to augment regulation resources, a group of BEVs in the same region can constantly provide an adequate energy level to participate in the frequency regulation market. In this paper, BEVs are assumed to be participants in the frequency regulation market, serving as the energy storage resources.

Currently frequency regulation is largely provided by generators specifically designed for this purpose. Replacing these generators with V2G-enabled BEVs as energy storage resources could save ISO/RTO substantial resources. Since V2G-equipped BEVs can transmit the power flow bi-directionally, both "regulation up" and "regulation down" services representing power delivery to and from the grid respectively can be accessed as necessary. The gross revenue of frequency regulation services consists of two main parts: the capacity value and the energy value. The capacity value is contracted based upon the vehicle's available power capacity and the energy value is the sum of the hourly regulation up and regulation down prices. Though regulation up and regulation down can be procured separately, ISO may call for equal quantities of both services in a certain time to prevent discharge of EV batteries (Kempton *et al*., 2008). The model presented in this paper assumes that the amount of energies for both regulation up and regulation down at hourly intervals would yield a zero net energy delivered to the grid.

Several studies were undertaken to calculate the potential revenue of offering ancillary services for EVs and plug-in hybrid electric vehicles (PHEVs) when V2G power transfer is enabled. A report from the California Air Resources Board and the California Environmental Protection Agency shows that frequency regulation results in an annualized gross value of $967 to $5038 to BEV owners when a BEV is assumed as plugged in for 94.2 percent of the day (Brooks, 2002). Tomic and Kempton found that the annual net profit of 252 Toyota RAV4 fleets ranged from $135,000 to $450,000 when both up and down regulation services are provided, assuming they are available for V2G power delivery from 3PM to 8AM, or either 17 hours per day (Tomic and Kempton, 2007). Similarly, in their investigation of the maximum average revenue for PHEVs in Sweden and Germany, Andersson et al. found that each PHEV in the German market generated 30 to 80 euros per month while the Swedish market provided no profit via grid ancillary services (Anderson *et al*., 2010). All of these studies, however, considered neither the driving demands nor the dynamic regulation pricing, and they oversimplified available V2G hours as a consecutive time frame. Indeed, the BEV charging process must consider a real-time variation of regulation prices so that they may provide the regulation services when the prices are relatively high and recharge the battery otherwise, thereby maximizing the profits. This paper explores the potential benefits and costs of V2G-equipped BEVs in the United States by intelligently arranging charging events (charging, regulation, driving and do nothing) through real-time communication with grid operators.

Though the grid scheduling problem, which includes V2G-enabled vehicles, was the subject of recent studies, it has been done so only from the perspective of power systems. In their particle swarm optimization based approach for the distribution network scheduling problem, Soares et al. minimized the total generation cost for the power generators (Soares *et al*., 2011). Though they considered the V2G resources and driving pattern impacts on the smart grid, BEVs were only treated as discharge resources and they did not explore the potential of BEVs to act as ancillary service resources (Soares *et al*., 2011). Guille and Gross proposed a conceptual framework to integrate the aggregated battery vehicles which acted as distributed energy resources within the power grid (Guille and Gross, 2009). They developed strategies to construct the information layer and design an incentive program for V2G implementation, however, they neither validated the performance of the conceptual framework, nor did they consider the charge/discharge scheduling problem for aggregators and the management of customized BEV input (Guille and Gross, 2009). Clearly, much more research must be undertaken to accommodate individual BEVs. In that regard, Mal et al. presented a charge scheduling system to optimize charge/V2G activities in a parking garage using profiles of the vehicles (Mal *et al*., 2013). However, they only optimized the charge scheduling between the arrival and the departure times in the parking lot, and did not consider vehicles that may have been possibly plugged and unplugged multiple times a day. Such a scheduling optimized for the next few hours may not be the best solution compared to the optimal scheduling on a 24-hour basis involving driving behaviors. In addition, some variable factors, such as the hourly changed regulation service market rate and the battery features of different EV models, haven't been considered in the paper.

In an effort to fully explore the potential of V2G-equipped BEVs to enhance their performance, the authors developed a smart charge scheduling model that is specifically designed for both BEV owners and grid operators in the distributed energy network. Under such a scheme, BEV owners are expected to become more motivated to participate in such V2G programs. The scheduling model is developed to effectively enhance real-time communication and coordination among BEVs, aggregation servers and the ISO/RTO, and rapidly arrange the charge and ancillary service activities over a 24-four hour period.

3. CHARGE/DISCHARGE SCHEDULING MODEL

Figure 1 depicts the components and communication flow of the smart charging architecture in which BEVs get to control and switch the charging status automatically at optimal time by monitoring both the time varying pricing data and the ISO/RTO dispatch signals. BEVs can be plugged in either at home or public charging stations with each belonging to a single aggregation server that is connected through a wireless network or wired network. To provide a greater power-on-demand reserve for use in the ancillary service market, BEVs in a certain area are aggregated as a centralized resource so that the ISO/RTO can interact with aggregation servers representing BEVs rather than thousands of individual vehicles. An aggregation server is responsible for collecting, storing and processing all the data regarding BEV charging activities as well as communicating with the ISO/RTO. The dynamic pricing for ancillary services can make ancillary services more attractive when the demand is high, while the time-of-use (TOU) electricity rates that are released by ISO/RTO can ease the load during peak hours. Aggregation servers can acquire the past and real-time price information for electricity and ancillary services to support the bidding and scheduling strategies. After determining the aggregated available capacity in a given time frame, each aggregation server submits its ancillary service bid with the rate per MWh and the total capacity it offers to the ISO/RTO which controls all electrical transmissions in a region. Once the bid is accepted, all the involved BEVs are placed on a

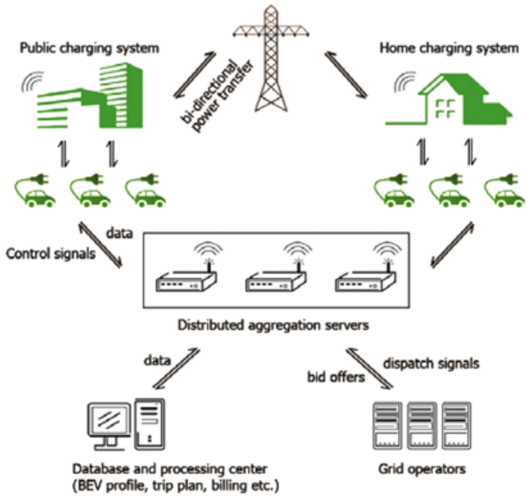

Figure 1. Components and communication architecture in the smart charging system.

standby mode to respond automatically to dispatch signals sent by the ISO/RTO through aggregation servers.

Since multiple BEVs are likely to share the home and public charging system, the communications architecture should encompass an ID authentication sub-system for personal configuration and billing purposes. In this architecture, each BEV has an onboard radio-frequency identification (RFID) tag to provide a unique ID when connected with the power grid system. The aggregation server then retrieves specific information (e.g. the user profile, scheduling preference, trip plan and billing history) from the database using the RFID reader. A corresponding optimal charge/regulation schedule is determined for each BEV based on the associated information on the server side. Once all the schedules are updated, the aggregation server calculates the total available capacity for the next time interval and submits the bid offer to the ISO/RTO ancillary service market.

In this architecture, BEV owners are provided continuous access to the information management system from which they can monitor the battery status, update BEV settings and upcoming trip plans, and access charging and billing histories via web browsers and mobile devices. Should any of the changes affect the coefficients or variables in the scheduling model, the aggregation server instantly updates the optimal scheduling to ensure a constant accuracy of the total available capacity.

To help BEV owners maximize their potential benefits and simultaneously satisfy driving energy demands, a smart charge scheduling model that optimizes and updates the schedule in a timely manner based on the time varying data is necessary. Since last-minute trip changes are always likely, aggregation servers must have the capability to update the charge/discharge schedule right before the start of each time interval. In this way, both aggregated servers and BEV participants can benefit from acquiring accurate optimal charge/discharge scheduling information.

In the scheduling model, the charge/discharge plan of an individual BEV is optimized for the next 24 hours. Every hour is defined as a time interval in which one BEV is either sitting idle, in use, being recharged or providing regulation services when parked and plugged in. Although the objective is to maximize the net profit for BEV owners by providing regulation services, several constraints impede unlimited regulation supply in that BEVs will lose energy after driving and must recharge to prevent a battery drain. Optimizing the BEV charging schedule is considered as a binary linear programming problem. The objective is described as:

Maximize

$$\sum_{j=1}^{24}(P_l * R_{cj} * X_{2j} + E * P_l * (R_{uj}+R_{dj}) * X_{2j}/2 - P_v * R_{sj} * X_{1j})$$

Where:

j: index of time intervals. for hourly optimization, $j = 1, 2, \ldots, 24$

$$x_{1j} = \begin{cases} 1 & \text{if BEV is charging at time interval j} \\ 0 & \text{otherwise} \end{cases}$$

$$x_{2j} = \begin{cases} 1 & \text{if BEV is providing regulation at time interval j} \\ 0 & \text{otherwise} \end{cases}$$

P_v : Power of vehicle in kW

R_{cj} : Regulation capacity price at the time interval j in \$/kW-h

P_l : Power of line in kW

R_{uj} : Regulation up price at the time interval j in \$/kWh

R_{dj} : Regulation down price at the time interval j in \$/kWh

R_{sj} : Electricity selling price at the time interval j in \$/kWh

E : Dispatched energy ratio

In this binary problem, the net profit in the next 24 hours is defined as the total ancillary service profit subtracted from the charging cost. The first item of the objective function is the capacity value of frequency regulation while the second item is the energy value of frequency regulation. The dispatched energy ratio in the energy value part is defined as the ratio of the dispatched energy for regulation to the contracted power and time. As mentioned in the previous section, the energy delivered for regulation up and from regulation down in each hour is assumed as equal. Therefore, the energy value is projected as the sum of the 30-minute regulation up rate and the 30-minute regulation down rate in each time interval.

The constraints of this problem are expressed as:

$$X_{1j} + X_{2j} \leq 1 \,\forall j$$
$$X_{1k} + X_{2k} = 0 \,\forall k$$

$$\sum_{i=1}^{j} DIS_i * M/Bat - \sum_{i=1}^{j} X_{1i} * \mu * P_v/Bat \leq SOC_i - SOC_b \,\forall j$$

$$\sum_{i=1}^{j} X_{1i} * \mu * P_v/Bat - \sum_{i=1}^{j} DIS_i * M/Bat \leq SOC_t - SOC_i \,\forall j$$

Where:

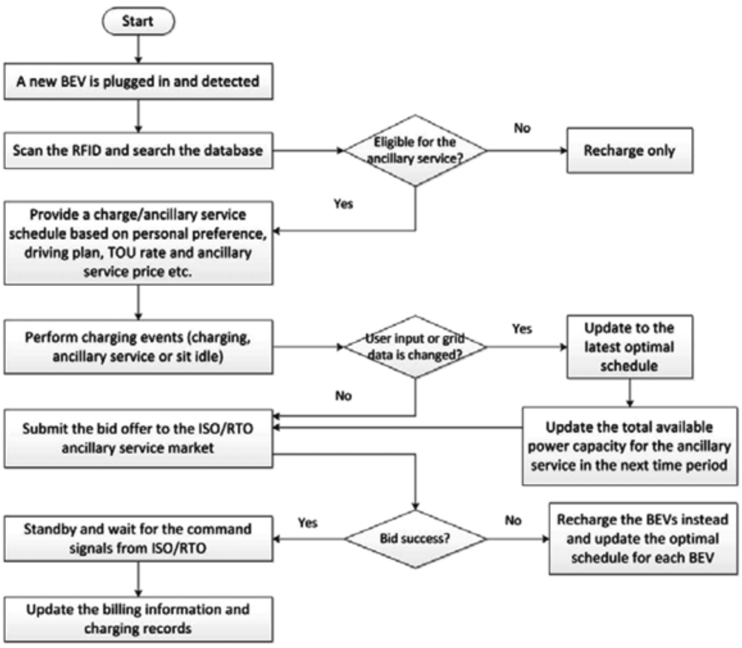

Figure 2. Event sequence diagram of the smart charge scheduling model.

k : index of unavailable time intervals. $k \in j$
DIS_j : Driving distance at the time interval j in mile
μ : Charging efficiency
M : MPGe in kWh/mile
Bat : Battery Capacity in kWh
SOC_i : Initial SOC
SOC_b : SOC window minimum
SOC_t : SOC window maximum

The first two constraints indicate that a single BEV might be unavailable to plug in during several time intervals (e.g. in use with no equipment in proximity for grid connection). Both the charging binary value and regulation binary value are projected as zero under the circumstances. The last two constraints suggest that the SOC of battery must fall in the allowed SOC window at any time, the lower limit of which is typically more than 20% and the upper limit up to 90%. The authors do not suggest 0% to 100% availability, however, as a complete charge-discharge cycle will slightly diminish the battery capacity and a valid SOC window can potentially extend the lifetime of the battery as mentioned in the previous section. BEV participants may then determine both the lower and upper limit of the SOC window through the information management system with additional constraints that are applicable based upon the user configurations. The scheduling model can adapt to various changes. For example, in the Great Britain, grid balancing market data is released every 30 minutes, for which the scheduling model can split each day into 48 time intervals (i.e. $j = 1, 2, \ldots, 48$) for optimization instead of the 24 time intervals considered in this paper. Similarly, the coefficients of this binary integer programming problem may vary over time as the TOU rates and dynamic ancillary service market prices can be measured hourly. The problem will be updated and solved iteratively at the beginning of each time interval to provide the latest optimal charge/discharge schedule according to the user preferences, driving plans and other information in the next 24 hours. If the solution cannot be determined, charging settings must be changed to make the schedule possible, such as adjusting excessive driving mileages or trying to connect to the charging station before the trip. It's also beneficial for BEV participants to be aware if their driving plan can be satisfied so as to relieve the concerns of range anxiety. The event sequence diagram in Figure 2 shows the processes of the scheduling model.

4. EVALUATION OF THE BEV PERFORMANCE IN THE SCHEDULING MODEL

To evaluate the performance of the proposed charge scheduling model for BEVs, the Nissan Leaf model was chosen in the initial analysis, the battery specifications of which are illustrated in Table 2. In this paper, the EV energy consumption was simulated using the EV model in the platform of Matlab-Simulink, assuming that vehicles precisely follow the Urban Dynamometer Driving Schedule (UDDS) drive cycle. The scheduling model has to retrieve associated information, such as the TOU electricity rate, the regulation capacity price and the regulation up/down prices, from the database before yielding the optimal charge/discharge plan through the aggregation server for which the authors performed several simulations using the data provided by Electric Reliability Council of Texas (ERCOT) market for the year of 2009 (Electric Reliability Council of Texas, 2013).

Table 2. Nissan Leaf model specifications.

Base total weight	3385 lbs
Maximum speed	90 mph
Maximum torque	210 ft·lb
Battery size	24 kWh lithium-ion battery
Miles per gallon equivalent (MPGe)	34 kWh/100 miles
Maximum range	73 miles
Electric motor	80 kW
On-board charger	3.3 kW
Lithium battery modules	48

In our experiments, it is assumed that on a typical work day, a Nissan Leaf is plugged in a public charging station and connected to the aggregation server that will derive a new charge/discharge schedule for the BEV. The driver uses the vehicle twice in a subsequent 24 hour period: it is disconnected from the power system between 5:00 PM and 7:00 PM for a trip of 22 miles, and again between 8 a.m. and 9 a.m. the following day for another trip of 18 miles. Total driving distance in that 24-hour period is 40 miles, quite close to the U.S. average daily driving distance of 39.5 miles. The total available plug-in parking time is 21 hours with a 240V and 30 Amps, i.e. 7.2 kW power of electrical circuit. The SOC window is between 20% and 90% with an initial SOC of 50%, and a charging efficiency set at 90%. A value of 0.10 is applied for the dispatched energy ratio as provided in data released by the California ISO (CAISO) (Kempton and Tomic, 2005). The hourly market prices for both the capacity and the ancillary services of the experiments conducted in this paper are provided in Table 3 with the solver yielding an optimal solution as shown in Figure 3. For purposes of comparison, another V2G-equipped BEV that does not use the scheduling model and follows a fixed charge/discharge schedule with the same setting is assumed to be parked and plugged in simultaneously. The fixed charge/discharge schedule involved recharging the battery to full status (90% SOC) after the TOU pricing of the nighttime hours starting at 10:00 PM, and then serving as the regulation resource for the remainder of the available time intervals. This fixed

Table 3. Hourly market clearing prices for capacity and frequency regulation (Electric Reliability Council of Texas, 2013).

Time	12:00	13:00	14:00	15:00	16:00	17:00
Capacity ($/MW-h)	9.85	8.82	9.73	8.50	8.79	13.01
Regulation up ($/MWh)	8.79	7.75	9.56	11.00	9.56	20.02
Regulation down ($/MWh)	10.9	9.89	9.89	6.00	8.01	6.00
Time	18:00	19:00	20:00	21:00	22:00	23:00
Capacity ($/MW-h)	25.39	40.61	23.01	17.88	11.12	20.00
Regulation up ($/MWh)	35.02	51.22	30.02	25.00	9.09	20.00
Regulation down ($/MWh)	15.76	30.00	16.00	10.75	13.15	20.00
Time	00:00	01:00	02:00	03:00	04:00	05:00
Capacity ($/MW-h)	16.01	8.46	6.05	6.00	7.07	9.47
Regulation up ($/MWh)	14.99	8.12	6.89	6.00	5.02	4.84
Regulation down ($/MWh)	17.02	8.80	5.20	5.99	9.12	14.10
Time	06:00	07:00	08:00	09:00	10:00	11:00
Capacity ($/MW-h)	26.02	29.35	21.70	18.10	11.76	9.05
Regulation up ($/MWh)	11.60	40.00	22.69	20.00	8.62	5.00
Regulation down ($/MWh)	40.43	18.70	20.70	16.20	14.89	13.10

Table 4. Overall result of the optimized vs. fixed schedule.

Charge/discharge schedule (from 12:00 PM 01/05/2009 to 12:00 PM 01/06/2009)	Optimized	Fixed
Regulation profit ($)	2.13	1.89
Charging cost ($)	1.20	1.35
Net profit ($)	0.93	0.54
Regulation hours (h)	16	15
Charging hours (h)	5	6
Unavailable hours (h)	3	3

charge/discharge schedule is also shown in Figure 3, with the overall result of the two charging schemes shown in Table 4.

As Table 4 indicates, it is clear that although the regulation hours and charging hours of both schedules are very close, the fixed charge/discharge schedule renders a net profit of $0.54 in the next 24 hours without paying for the energy consumed by driving. The net profit based on the optimized schedule is almost twice as much as that of the fixed schedule. It is also likely that BEV participants will increase their earnings if they choose to deploy the frequency regulation service during the nighttime hours rather than recharge the vehicles. The optimized schedule also ensures a sufficient SOC of battery for driving demands to mitigate any concerns of range anxiety.

The authors conducted a series of simulations to calculate the annual profits and costs under different circumstances to observe the sensitivity of each variable in the objective function. The authors first calculated the annual profits and costs for the Nissan Leaf model when the average daily driving distances are 20 miles, 40 miles and 60 miles, respectively. The driving hours are distributed mainly during rush hours in a day using 7.2 kW

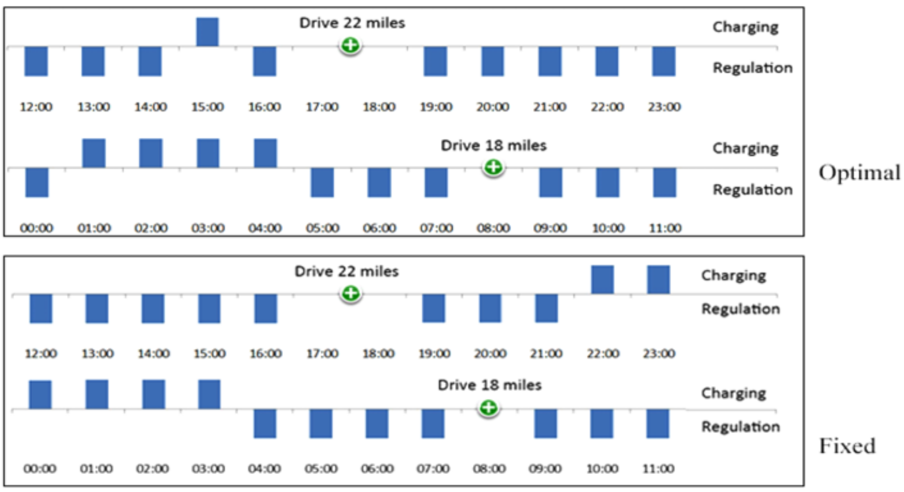

Figure 3. Comparison of optimized and fixed charge/discharge schedule in the next 24 hours.

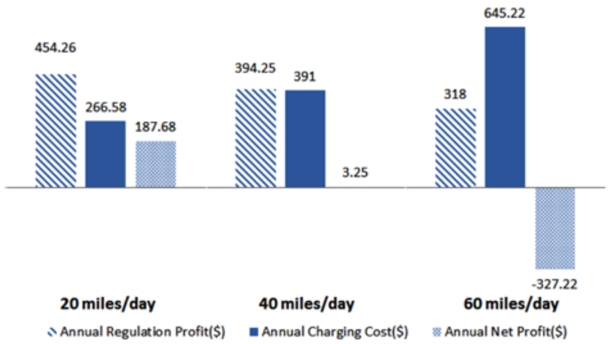

Figure 4. Annual charging profits and costs of the Nissan Leaf model with different average daily driving distance.

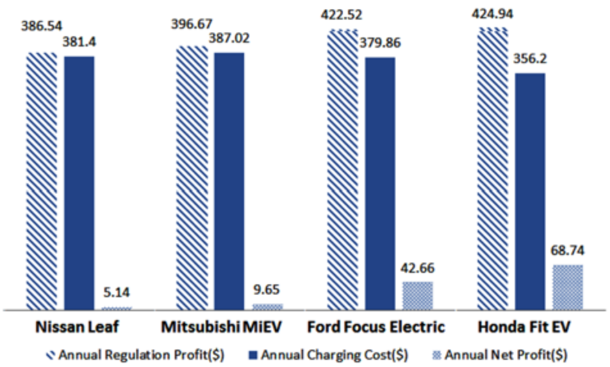

Figure 5. Annual charging profits and costs of BEV models with 7.2 kW power.

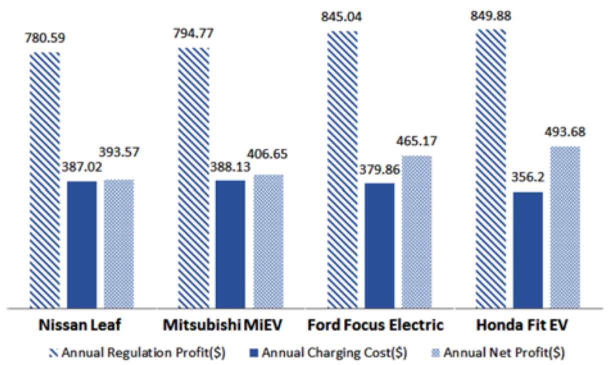

Figure 6. Annual charging profits and costs of BEV models with 14.4 kW power.

as the power capacity of the line in a level two charging station. The results are demonstrated in Figure 4. When the driver drives 20 miles per day on average, the EV is capable of earning $454.26 each year from providing the regulation service with an annual net profit of $187.68. As the daily driving distance goes up, the cost for recharging increases and the regulation profit decreases due to the reduction of available plug-in hours. The regulation profit can only compensate for the annual energy cost when the average driving distance reaches 40 miles per day, i.e. 14,600 miles per year.

The authors then considered the benefits and costs of all the BEV models in Table 1 which have different battery capacity and on-board chargers assuming an average daily driving distance of 40 miles associated with 7.2 kW power capacity of the line in a level two charging station. Here, as the results in Figure 5 indicate, the regulation service completely compensates for the energy cost with an annual driving distance of approximately 15,000 miles and all BEV models make a positive net profit through the application of the scheduling strategy. The regulation profit earned by V2G-enabled BEVs with 3.3 kW on-board chargers only offsets the energy payment for driving, while BEVs with 6.6 kW chargers earn approximately 7% more profits from regulation services since less time is required for battery recharge, thusly increasing the availability for deploying frequency regulation services.

One of the long-term goals for EV infrastructure is the fast charging capability which allows EV batteries to be fully recharged within a short time. However, the upgrade involves considerable investment and is not practical at the present time. As the power capacity of the electrical circuit is an important coefficient that affects objective profits, for the purpose of sensitivity analysis, the authors doubled the circuit's ampere capacity to 60 Amps (i.e. increased the electrical circuit power capacity to 14.4 kW) and estimated the potential benefits under the circumstances. The annual profits and costs of the same BEV models under the same conditions are shown in Figure 6. As it is evident, BEVs plugged in with the higher electrical circuit power capacity generate almost double profits compared to BEVs with a lower capacity while the energy cost remains at the same level. All the BEV models compensate the energy cost to generate a positive annual net profit between $393.57 and $493.68.

On the other hand, balancing the additional load from BEV charging can be challenging, in that the smart charging architecture is also designed to support the ISO/RTO with load leveling by adjusting prices through real-time communication and coordination among BEVs, aggregation servers and the ISO/RTO. To elucidate the merits of the architecture under load management, the authors conducted a simulation that utilized 2009 ERCOT data for Texas, most particularly in the determination that 21.4 million vehicles were registered in the state in 2009 (Texas Department of Motor Vehicles, 2010). The hourly trend of the ratio of the projected BEV regulation up and down capacity to the total regulation up and down demand in a typical day with an average power capacity of 7.2 kW and 14.4 kW is illustrated in Figure 7. This trend assumes a V2G-enabled BEV market penetration rate of 10 percent with an average of 80 percent of BEVs plugged in at any given time interval.

Here, the aggregated regulation up and down capacity provided by BEVs with 7.2kW power accounts for

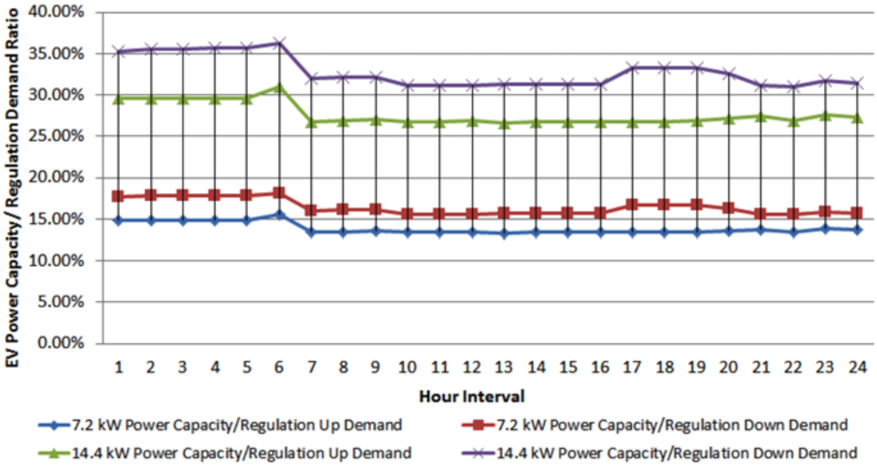

Figure 7. Hourly trend of the ratio of EV power capacity/total regulation demand.

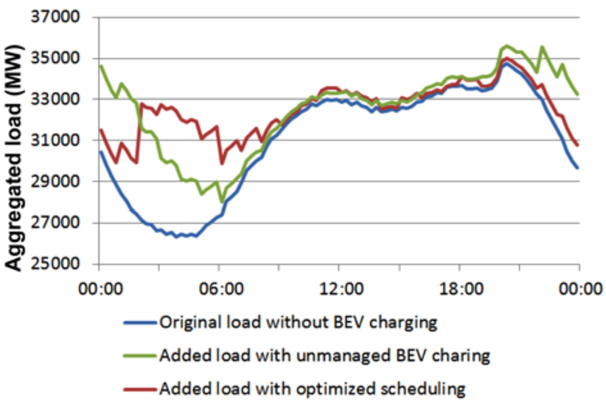

Figure 8. Comparison of added load distribution between unmanaged BEVs verses managed BEVs.

approximately 10% to 17% of total regulation demand if 80% of 21.4 million BEVs are deployed as regulation service resources in each hour interval. If the average power capacity of electrical circuits increases to 14.4kW, this supply share is doubled. As shown in Figure 6, there is a great demand for frequency regulation services in Texas. In this analysis, BEVs become a major regulation service supplier given a market penetration rate of 10%. However, it's worth noting that the regulation service hourly rate may be subject to change as the number of BEV participants expands. More possible sources of regulation can free up power plants for the energy market, which would eventually be reflected in reduced service rate offered by utilities (Peterson *et al*., 2010a).

The authors then simulated two scenarios, unmanaged BEVs without performing optimized schedules and managed BEVs following the optimized charge/regulation schedules, and added the additional load from BEV charging to the grid system assuming all chargers deliver 7.2 kW and the BEV penetration is 10%. The load distribution is presented in Figure 8. As shown in Figure 8, the added load under the managed scenario is particularly concentrated and the overall distribution is more balanced than that of the unmanaged distribution. While BEV owners without the charging guidance prefer to recharge their vehicles during off-peak hours when the TOU electricity pricing is the lowest of the day, excessive loads from 8 p.m. to midnight may be the result. Aggregation servers in charge of the BEVs within the region appeared more sensitive to the hourly changes of the TOU electricity price and the regulation up/down prices given that most additional load is allocated between 2 a.m. and 6 a.m. to fill the grid valley. This demonstrates that the managed scenario provided a well-balanced overall distribution compared to the unmanaged scenario and improved the utilization of power infrastructure during off-peak periods. The unique variance can help ISO/RTOs monitor and ease the load in real-time by adjusting the prices should the load exceed the capacity.

5. INCREMENTAL COST ESTIMATE

From the economic perspective it is essential to determine if the benefits of integrating V2G technology are worth the extra cost of developing and implementing such a scheduling model. In addition to the energy costs already considered in our charge/discharge scheduling model, costs for both equipment and battery are the major extra expenses BEV owners will incur to enable V2G capabilities. Key equipment components that must be installed are a power connection and an on-board inverter for V2G flow, an accurate on-board metering, and a communication system among vehicles, charging stations, aggregation servers and the ISO/RTO to receive and respond to the signals. The incremental cost of the on-board power electronics system and the on-board electric metering system designed for this purpose can be estimated as $400 and $50 respectively (Tomic and Kempton, 2007). In order to provide 1 MW of power on demand, assuming an average plug-in connection power of 10 kW with 80% of BEVs available, 125 BEVs with an estimated value of $150 for each are required to share a single aggregation server associated with other communication components, such as the RFID reader and the wireless network deployment (Del Los Rios *et al*., 2012). Thus the fixed total incremental cost for V2G support is equal to $600, while BEV owners can expect less extra cost as grid operators are likely to offer either price incentives or financial subsidies to encourage V2G solutions due to the savings on the ancillary-service-specific utilities.

The extra cycling of an EV battery as a storage device for the regulation service will adversely affect the battery life and result in additional depreciation cost. The capacity loss of an EV battery for a combined driving and V2G usage can be quite low, however, regardless of the DoD window experienced. Statistical analyses from a related study indicate that participating in the V2G application will lose 2.7x% of the capacity per normalized Wh or Ah processed compared to the loss of 6.0x% for the rapid cycling encountered while driving, and one year of driving/V2G incurs only 1% capacity loss no matter how much is used for V2G support (Peterson *et al*., 2010b). Though the simulation results presented in this paper show that approximately one-third of the total capacity loss is from V2G usage, it is not necessary to replace the battery before the vehicle breaks down. Cluzel and Douglas estimated an average price of battery pack to be $800 per kWh (Cluzel and Douglas, 2012). With 1 percent capacity loss each year, the total depreciation cost can be estimated as [(800*24*0.01)/(6.0 × 10-3/2.7 × 10-3)], which is equal to $86.4 per year for a 24 kWh battery pack (Cluzel and Douglas, 2012; Peterson *et al*., 2010b). Although current battery pack cost appears expensive, a recent study by Cluzel and Douglas estimated a 50 percent reduction in cost and 30 percent reduction in mass of the 30kWh battery pack for a medium sized BEV by the year 2020 (Cluzel and Douglas, 2012).

The annual fixed cost of enabling V2G capacities can be estimated as $600/10, which is equal to $60 per year if a BEV can last for ten years, bringing the total average yearly cost including the depreciation cost to be approximately ($86.4+$60.0), which is equal to $146.40. Since the profits earned by providing frequency regulation services and charge scheduling model presented in this paper, range from $386.54 to $424.94 for the 7.2 kW power and almost doubled for the 14.4 kW, V2G technologies are deemed beneficial for bringing a positive net profit to each BEV participant.

6. CONCLUSION

In this paper, the authors presented a smart charge scheduling model to boost the performance of V2G-enabled BEVs when the bi-directional power flow was available and in which each BEV provided the ancillary service to the grid system. Although the potential profit of a V2G-enabled BEV has been calculated by various researchers, many uncertain factors have not been considered. Unlike previous research that used simple assumptions that disregard driving plans and other personalized user inputs, this study evaluated the performance of BEVs by providing an estimate on the potential annual profit of a single BEV upon optimization of the scheduling using practical real-world data.

Our research focused on developing a charge scheduling model, in which BEVs were controlled and managed by the aggregation server and were eligible to bid their aggregated capacity into the ancillary service market. Through the assumed real-time communication interface, aggregation servers obtained a variety of dynamic data in a timely manner in order to develop the latest and optimized charge/discharge schedule for BEVs so that they could simply be parked and plugged in without manually controlling the charge/discharge processes. The scheduling model always yielded an optimal solution by solving the binary integer programming problem and thusly the net profit was maximized while the energy demand for driving was guaranteed in the meantime.

Through a series of simulation analyses, the study found that the regulation profits of the Nissan Leaf model (with the battery capacity of 24 kWh and the on-board charger of 3.3 kW), which used level two charging station, ranged between $318.00 and $454.26 when the average daily driving distance dropped from 60 miles to 20 miles. All BEV models in Table 1 completely compensated the energy cost to generate a positive net profit through the application of the scheduling model with an annual driving distance of approximately 15,000 miles.

The ISO/RTO could also benefit from the strategy presented in this paper in that they could save substantial revenue on investment in utilities specifically equipped for regulation services by authorizing and encouraging BEVs as ancillary service providers. With the availability of BEVs as an additional power regulation resource, the ISO/RTO could leverage the additional load from BEV charging by adjusting TOU electricity prices and frequency regulation prices to enhance both the reliability and robustness of the power grid system.

Optimizing the performance of any system is a key to sustainable future. The strategy provided in this paper optimizes V2G performance that can benefit both the consumers (i.e. users of BEVs) and the providers (i.e. ISO/RTO). The model presented in this study can be extended to identify regional benefits for different driving scenarios by using different local cost parameters. Policy makers could review these benefits and costs for the region to consider BEV related laws and incentives to help generate more interests in BEVs.

REFERENCES

Aggeri, F., Elmquist, M. and Pohl, H. (2008). Managing learning in the automotive industry– The race for hybridization. *Gerpisa 16th Int. Conf.*

Andersson, S. L., Elofsson, A., Galus, M., Göransson, L., Karlsson, S., Johnsson, F. and Andersson, G. (2010). Plug-in hybrid electric vehicles as regulating power providers: Case studies of sweden and germany. *Energy Policy* **38**, **6**, 2751−2762.

Begley, J. (2011). Priorities and practises for developing low carbon vehicle networks in small open economies. *Int. J. Automotive Technology and Management* **11**, **4**, 340−355(16).

Beaume, R. and Midler, C. (2009). From technology competition to reinventing individual ecomobility: New design strategies for electric vehicles. *Int. J. Automotive Technology and Management* **9**, **2**, 174−190.

Bhavsar, P., Chowdhury, M., Sadek, A., Sarasua, W. and Ogle, J. (2008). Decision support system for predicting traffic diversion impact across transportation networks using support vector regression. *Transportation Research Record: Journal of the Transportation Research Board* **2024**, **1**, 100−106.

Bohm, A. and Jonsson, M. (2008). Supporting real-time data traffic in safety-critical vehicle-to-infrastructure communication. *Local Computer Networks, 2008. LCN 2008. 33rd IEEE Conf. IEEE*, 614−621.

Brooks, A. N. (2002). Vehicle-to-grid demonstration project: Grid regulation ancillary service with a battery electric vehicle California Environmental Protection Agency, Air Resources Board, Research Division.

Cluzel, C. and Douglas, C. (2012). Cost and Performance of EV Batteries Final Report for the Committee on Climate Change. Element Energy Limited.

De Los Rios, A., Goentzel, J., Nordstrom, K. E. and Siegert, C. W. (2012). Economic analysis of vehicle-to-grid (V2G)-enabled fleets participating in the regulation service market. *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, 1−8.

Department of Energy (2011). http://www1.eere.energy. gov/vehiclesandfuels/pdfs1_million_electric_vehicles_ rpt.pdf

Department of Energy (2013a). http://www.afdc.energy. gov/laws

Department of Energy (2013b). http://www.fueleconomy. gov/feg/download.shtml

Electric Reliability Council of Texas (2013). http:// www.ercot.com/mktinfo

Gu, J., Ouyang, M., Lu, D., Li, J. and Lu, L. (2013). Energy efficiency optimization of electric vehicle driven by in-wheel motors. *Int. J. Automotive Technology* **14**, **5**, 763−772.

Guille, C. and Gross, G. (2009). A conceptual framework for the vehicle-to-grid (V2G) implementation. *Energy Policy* **37**, **11**, 4379−4390.

He, Y., Chowdhury, M., Ma, Y. and Pisu, P. (2012). Merging mobility and energy vision with hybrid electric vehicles and vehicle infrastructure integration. *Energy Policy*, **41**, 599−609.

Johnson, J., Chowdhury, M., He, Y. and Taiber, J. (2013). Utilizing real-time information transferring potentials to vehicles to improve the fast-charging process in electric vehicles. *Transportation Research Part C: Emerging Technologies*, **26**, 352−366.

Kempton, W. and Tomiæ, J. (2005). Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *J. Power Sources* **144**, **1**, 280−294.

Kempton, W., Udo, V., Huber, K., Komara, K., Letendre, S. and Baker, S. (2008). A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system. University of Delaware, Pepco Holdings, Inc PJM Interconnect, and Green Mountain College.

Ma, Y., Chowdhury, M., Sadek, A. and Jeihani, M. (2009). Real-time highway traffic condition assessment framework using vehicle–infrastructure integration (VII) with artificial intelligence (AI). *Intelligent Transportation Systems, IEEE Trans.* **10**, **4**, 615−627.

Ma, Y., Chowdhury, M., Sadek, A. and Jeihani, M. (2012). Integrated traffic and communication performance evaluation of an intelligent vehicle infrastructure integration (VII) system for online travel-time prediction. *Intelligent Transportation Systems, IEEE Trans.* **13**, **3**, 1369−1382.

Mal, S., Chattopadhyay, A., Yang, A. and Gadh, R. (2013). Electric vehicle smart charging and vehicle-to-grid operation. *Int. J. Parallel, Emergent and Distributed Systems* **28**, **3**, 249−265.

Peterson, S. B., Apt, J. and Whitacre, J. F. (2010b). Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. *J. Power Sources* **195**, **8**, 2385−2392.

Peterson, S. B., Whitacre, J. F. and Apt, J. (2010a). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *J. Power Sources* **195**, **8**, 2377−2384.

Soares, J., Sousa, T., Morais, H., Vale, Z. and Faria, P. (2011). An optimal scheduling problem in distribution networks considering V2G. *Computational Intelligence Applications in Smart Grid (CIASG), 2011 IEEE Symp.*

Texas Department of Motor Vehicles (2010). Vehicle Sales, Registration and Titling Fee Information: House Committee on Transportation, Senate Committee on Transportation & Homeland Security.

Tomic, J. and Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. *J. Power Sources* **168**, **2**, 459−468.

U.S. Department of Transportation (2009). http://nhts.ornl. gov

Wu, J., Zhang, C. H. and Cui, N. X. (2012). Fuzzy energy management strategy for a hybrid electric vehicle based on driving cycle recognition. *Int. J. Automotive Technology* **13**, **7**, 1159−1167.