Vehicle-to-Grid Service Potential with Price Based PEV Charging/Discharging

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***Abstract*—In this paper the operation of distributed charging infrastructure of plug-in electric vehicles (PEVs) is characterized. Charging and discharging pattern is optimized according to price variations to maximize the social benefit of PEV participation as energy storage in the electricity market. 2009 US National Household Travel Survey (NHTS) data set has been used in several ways to probabilistically quantify the PEVs' status in order to characterize the real time mobility behavior. Grid regulation ancillary service potential of the vehicle fleet is calculated based on the results of optimization problem.**

***Index Terms*-- V2G, aggregator, regulation power, driving behavior, profit optimization, smart grid.**

I. NOMENCLATURE

acc	Plug accessibility vector
c_{el}	Market electricity price
E_{bat}	Aggregated Energy level of PEV batteries
E_{max}	Maximum Aggregated capacity of PEV batteries
E_{min}	Minimum Aggregated capacity of PEV batteries
E_{cns}	Aggregated energy consumption of PEVs
P_c	Power absorbed from the grid
P_d	Power supplied to the grid
r_c	(Dis)Charging rate of battery
R_{up}	Up regulation power
R_{dwn}	Down regulation power
η_{bat}	Battery efficiency
η_{chg}	Charger efficiency
η_{cnv}	Conversion efficiency
η_{rnd}	Round-trip efficiency

II. INTRODUCTION

SMART grids provide opportunities for the implementations of the advanced communications, automation and intelligent appliance control techniques to improve system efficiency. The capability for two way energy flow and two way communications from a vehicle to the electrical grid under control of grid operator's signal known as vehicle to grid (V2G) is one of the features that can be achieved in a smart grid environment. Furthermore, the distributed energy storage devices have been proposed to provide ancillary services for power grids and to accrue revenue [1]. Plug-in electric vehicles (PEVs) have huge power capacity both as loads and energy storage devices. 25% penetration level of PEVs in the U.S. light vehicle fleet has more generation power than the electric generation system with a reaction time of milliseconds and a power price comparable with peak load prices [2]. Therefore, PEVs responsiveness to the power grid may be critical for reliable operation of electric power system. PJM/Better Place study finds unmanaged charging of one million electric cars could add $750M in annual wholesale energy costs [3].

Fortunately, PEVs are likely to have onboard embedded intelligence and communications (like the Nissan LEAF™ in-car telematics system called CARWINGS®); they are *smart-loads* that can be directly controlled and monitored within a smart grid. Intelligent charging of PEVs can significantly limit the charging burden and potentially improve the power system operation [4]-[7]. PEVs coordinated discharging could provide emergency reliability and ancillary services along with load frequency control to help overcome the difficulties enhanced by intermittent wind and solar resources and provide an incentive for customers. This scenario could potentially smooth the load curve, leading to better prices, lower losses and resource utilization improvements [8]-[12].

The most prevalent strategies currently being pursued to implement intelligent charging are labeled as *uncontrolled off-peak charging, price-based charging and fleet aggregator based charging* [13]. Using characteristics of PEVs currently being developed allows considering practical constraints for the V2G model. To harness the full potential of renewable energy sources, initiatives to smoothen the charging demand are essential, i.e., wide access to charging stations will play a critical role in surpassing the need for sudden change in PEV charging load profile. Unlike fast charging stations, the distributed infrastructure can choose the charging periods more freely and is capable of discharging power to the grid.

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The difficulties in achieving above objectives arise because the charging load of PEVs and the potential battery capacity for discharging depends completely on the usage pattern. Their functions will also depend on the actual infrastructure developed. PEVs are essentially dynamic and mobile assets which make their real-time interaction with the system inevitable. In this work the charging/discharging problem is formulated considering the mobility behavior of vehicle fleet and the potential of PEVs as power regulating service is estimated. 2009 National Household Travel Survey (NHTS) was analyzed statistically to derive parameters which model vehicles trips and are used to predict the movement and energy consumption pattern of vehicle fleet over one week. While these results are preliminary and system specific, more suited for systems that are naturally bounded, it provides a foundation to optimally derive the charging/discharging pattern and regulating power capacity considering vehicles' commuting behavior.

Section III describes the transportation analysis adopted for this work. Section IV presents the problem formulation and optimization procedure that will be used to support the participation of vehicle fleet in the market. Furthermore, the mechanism to evaluate the power regulation service based on the results of optimization process is presented. Finally, conclusions are presented in section V.

III. COMMUTING PATTERN ANALYSIS OF PEVS

One of the most important inputs for determining the potential of PEV fleet as system energy storage is their commuting pattern, which requires historical transportation data. The transportation data from 1995 to 2009 in U.S.A were collected by the NHTS [14]. For the purpose of PEV studies, data related to vehicle and daily trips was primarily considered [15]. Therefore, two MS Excel files of the 2009 NHTS: VEHV2PUB and DAYV2PUB are utilized to extract useful information. The *BESTMILE* attribute developed by Oak Ridge National Lab, gives out the best estimate of annual miles driven by each vehicle. The average daily mileage is found to be 29 miles which is consistent with the formerly reported 33 miles average miles driven in major U.S. metropolitan areas [16]. The NHTS data are used in this study for modeling of PEVs commuting pattern. The relevant data sets of the 2009 NHTS are filtered out for the purpose of this study. It is assumed that the advent of PEVs will not affect daily travel pattern and lifestyles in general; therefore, the driving behaviour of PEV owners will remain similar to the behaviour of drivers of conventional vehicles.

A PEV can only be available for charging/discharging service when it is in a parking lot. Therefore the distribution of the parked cars in 24 hours is studied from the NHTS. The trips in progress are first extracted from the NHTS. Date of travel day (YYYYMM) from April 2008 until April 2009, day of the week and time of the day (hourly) filtered out. The number of trips is found to have a peak in the morning when people leave their home and another peak in the afternoon which is mainly representative of education related trips and getting-back home trips. The proportion of parked cars for 24 hours is obtained as shown in Fig. 1. The dominant trend of parked pattern is shown for weekdays and weekends for one deterministic case. The shares of the parked cars are very high; therefore, the availability of PEVs for V2G services is very high.

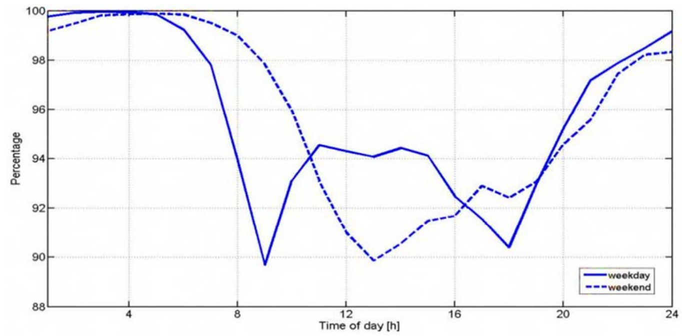

Figure 1. Proportion of parked cars

The WHYTRP1S attribute in DAYV2PUB file as shown in Table I, summarized the trip purposes and is utilized to extract the *plug accessibility* (acc) vector. This vector is used to estimate how likely it is that the PEV will be able to plug in when parked. This is done by allocating a constant probability of an available plug to each type of trip. The plug accessibility in a given hour can be determined from multiplying the plug probability with the share of the cars parked for the ten different purposes based on (1).

TABLE I. TRIP PURPOSE SUMMARY WITH PLUG PROBABILITY

Purpose	Probability
Home	1
Work	0.5
School/Daycare/Religious activity	0.3
Medical/Dental services	0.3
Shopping/Errands	0.3
Social/Recreational	0.3
Family personal business/Obligations	0.1
Transport someone	0.1
Meals	0.1
Other reason	0.1

$$acc(t) = \sum_{i=1}^{10} \frac{purpose(i,t) \times probability(i)}{\sum_i purpose(i,t)} \quad t = 1,2,\dots,168 \quad (1)$$

The plug accessibility vectors for each hour of each day from Monday to Sunday during the period of 12 month are shown in Fig. 2. The minimum value of each hour is used as the input data for optimization problem. In the distributed architecture, we assume that individual vehicles will be available to perform ancillary services whenever they are connected to the grid. Under this assumption, the availability of the vehicle to perform ancillary services is equal to the average fraction of a day that the vehicle is present at a V2G charging station.

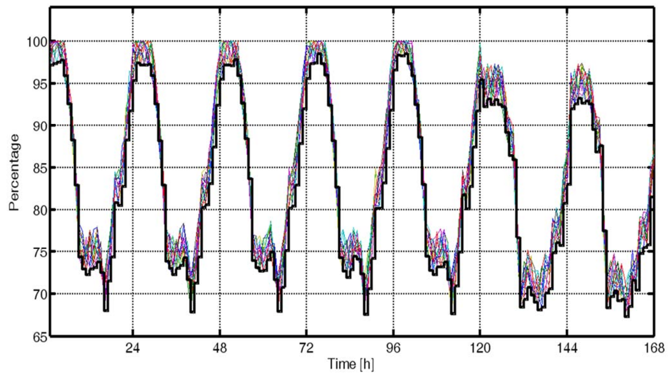

Figure 2. Plug accessibility vector (acc)

As it is expected the availability of vehicles is very high from 2359-0500. During the day, the availability of vehicles decreases as they drive to work or other locations. Between 0800 and mid-afternoon, more than 25% of vehicles are not available to perform V2G services. The minimum vehicle availability in weekdays is 68.44%, and the averaged vehicle availability is 85.51%. These values for weekends decrease to 67.11% and 82.97% respectively.

IV. Problem Formulation

The energy surplus in PEV batteries in power system operation can be effectively used due to the relation between power consumption and electricity price. Optimizing the charging/discharging times of vehicle batteries based on price variation is essential to prevent negative impacts on the supply side during peak demand periods. In this study the charging/discharging of 100,000 PEVs in response to hourly electricity prices is optimized and V2G regulating power potential is estimated by a dynamic optimization approach. The proposed optimization process is performed by deterministic method under the assumption of perfect forecasts. Although uncertain values were chosen conservatively, it does not take into account the stochastic nature of input data, e.g., electricity prices and trip behavior. This issue is not the focus of this paper. References [17]-[19] describe the appropriate models for forecasting in the context of electric vehicles.

The distributed infrastructure is not constrained by low battery capacity and the choice of charging periods can be free. In vehicle-grid interaction, the power flow is limited by connection rather than battery specification or power electronics limitations. So it is assumed that the battery charge and discharge rate given a constant value of 0.5 C and is independent of the state of charge (SOC). The PEV fleet is regarded as one aggregated battery from the power system viewpoint instead of having to consider each individual vehicle separately. On the other hand, since we want to evaluate the entire PEV potential, an aggregated battery capacity and an average driving range and consumption pattern is assumed for all the vehicles. A conservative average connection of 3.5 kW is assumed to investigate the effect on the charging/discharging pattern and energy potential. In this study the PEVs are only price takers i.e., they will not affect the market price when they are connected to the grid.

A. *Input Parameters*

Optimal charging/discharging schedule depends on many factors such as real time market clearing price, PEV consumption pattern etc. The Elspot market data in western Denmark from Monday the 1st to Sunday the 7th of August 2011 has been used. Nord Pool market data is used in the simulations since wind power constitute a high share of power generation in Nordic countries which directly affects power price and gives large imbalances that have to be corrected by regulating power [20]. It should be noted that applying the transportation data from U.S. and the Nordpool spot market data from Europe is only to illustrate the proposed procedure. The results will be used to determine the impacts of PEVs charging load and how appropriate they are for providing ancillary services.

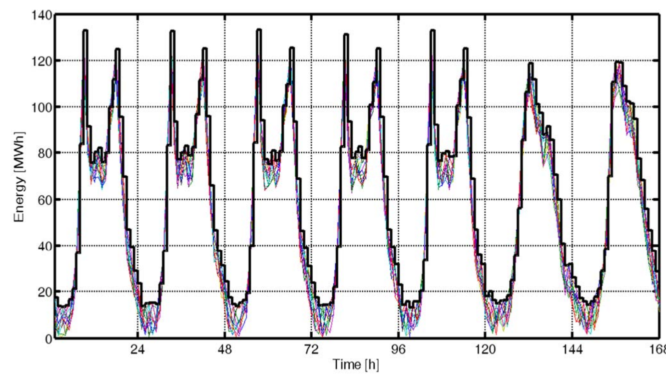

Figure 3. PEV fleet driving consumption (E_{cns})

Market Clearing Price (c_{el}) is the basis for the optimization process. Hourly electricity demand pattern is quite similar on weekdays and weekends due to similar daily pattern of energy consumption. The driving consumption is calculated from the average daily driving distance, the number of PEVs and the driving pattern, which is determined from the parking pattern described earlier. Fig. 4 shows the aggregated energy consumption (E_{cns}) of the vehicle fleet. The maximum value of each hour is used as the input data for optimization problem to account for worst case scenario. $r_{c_{max}}$ is the multiplication result of average connection capacity and number of vehicles.

The average battery capacity and average energy consumption of currently available PEVs are found to be 25 kWh and 0.23 kWh/km respectively [21]. Average driving distance is assumed to be 50 km. The program determines a total driving consumption for a day, from the total number of PEVs, and distributes this consumption via the driving pattern. Batteries are not allowed to discharge less than 10% of the full capacity. It is assumed that the efficiencies of charger and battery (round-trip) are 95% [7] and 92% [22] respectively. Thus η_{cnv} and η_{bat} can be obtained.

$$\eta_{bat} = \sqrt{\eta_{rnd}} = 0.96 \tag{2}$$

$$\eta_{cnv} = \eta_{chg} \times \eta_{bat} = 0.95 \times 0.96 = 0.91 \quad (3)$$

B. Optimization formulation

The objective of the problem is to schedule the power supplied to and absorb from the grid to minimize the system cost considering all relevant constraints. The objective function F of the problem is:

$$Min \quad F = \sum_{t=1}^{168} c_{el}(t) \times (P_c(t) - P_d(t)) \quad (4)$$

Subject to the following constraints:

Energy balance constraints:

$for\ t > 1$:

$$E_{bat}(t) = E_{bat}(t-1) + \left[P_c(t).\eta_{cnv} - \frac{P_d(t)}{\eta_{cnv}}\right].\Delta t - E_{cns}(t) \quad (5)$$

$if\ t = 1$:

$$E_{bat}(t) = E_{min} + \left[P_c(t).\eta_{cnv} - \frac{P_d(t)}{\eta_{cnv}}\right].\Delta t - E_{cns}(t) \quad (6)$$

Battery capacity constraint:

$$E_{min} \leq E_{bat}(t) \leq E_{max} \quad (7)$$

Charging/discharging rate limits:

$$P_c(t).\eta_{cnv} \leq r_{c_{max}}.acc(t) \quad (8)$$

$$\frac{P_d(t)}{\eta_{cnv}} \leq r_{c_{max}}.acc(t) \quad (9)$$

Plug accessibility constraints:

$$P_c(t).\eta_{cnv} \leq acc(t).(E_{max} - E_{bat}(t)) \quad (10)$$

$$\frac{P_d(t)}{\eta_{cnv}} \leq acc(t).(E_{bat}(t) - E_{min}) \quad (11)$$

$$t \in \{1,2,\ldots,168\} \quad (12)$$

(5) and (6) show the energy balance of the aggregated battery, keeping track of energy consumed from and supplied to the battery, including the demand for driving purposes. Since this is a minimization problem the state of charge (SOC) will be at minimum at the last period in the optimization, therefore the initial charge is set to be at the value of 5 kWh for each vehicle. The variable $E_{bat}(t)$ in constraint (7) is limited to the range between the minimum and maximum values. Constraints (8) and (9) make sure that the power absorbed by the batteries does not exceed the maximum. The vector $acc(t)$ estimates the availability of the aggregated battery as explained earlier. A similar rate constraint makes sure that the variable $P_d(t)$ does not violate the same rates. Constraints (10) and (11) ensure the fact that the plugged vehicles, cannot charge for the driving ones. They dictate that in any given hour the energy charged to the batteries cannot exceed the available capacity of the aggregated battery multiplied with the share of cars that are assumed parked and plugged. Again a similar constraint is constructed for the variable $P_d(t)$ that assumes the energy available for discharging is the extractable energy from the aggregated battery multiplied with the vector $acc(t)$.

C. Preliminary Results

The linear optimization problem is solved using CPLEX under GAMS on an MS windows-based server. All variables are observed at the power system level. The charge and discharge pattern determined by the optimization process and energy level variation of the aggregated battery with 3.5 kW connections for each vehicle are shown in Fig. 4 and Fig. 5.

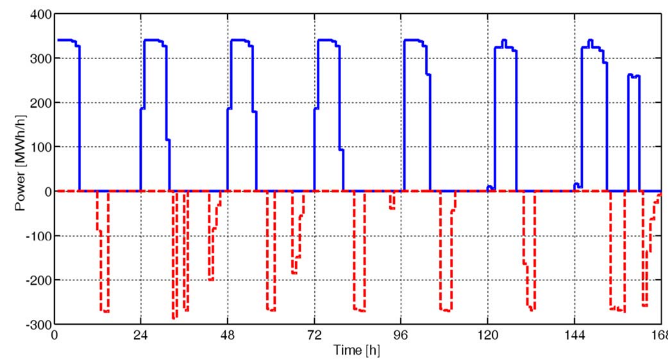

Figure 4. PEV charging and discharging pattern with 3.5 kW average connections

It can be seen that the battery is charged during low price period and discharged during high price and parked period of the day time. Since the charging pattern is closely related to the market clearing prices, an increased PEV consumption is observed when power production gets close to power overflow and the prices are low.

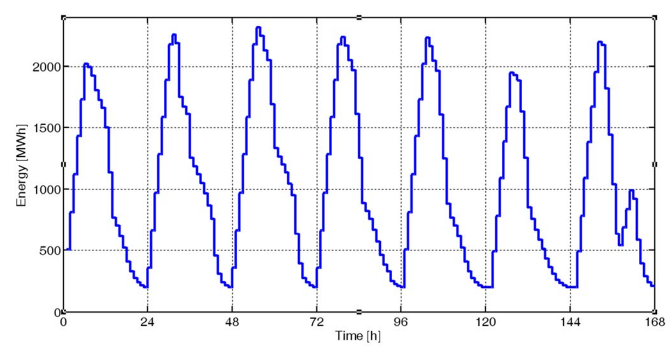

Figure 5. Energy variations in aggregated PEV battery with 3.5 kW average connections

The potential to provide regulating power is shown in Fig. 6 during the simulated week. It clearly shows that the distributed infrastructure has huge potential to provide balancing power, although it is not able to provide same kind of regulation in every hour. Obviously it cannot supply down regulation when fully charging, but has a huge potential to provide up regulation. The same is true for up regulation and discharging. There are hours where no regulating power can be supplied. This means that other sources of regulating power must be available. The regulating power potential of the aggregated battery at time t is estimated based on the energy that a PEV battery can supply or absorb. Therefore up and down regulations which depend on the capacity, charging/discharging rate and energy level of aggregated battery at time t are respectively calculated from the optimization results based on maximum regulation participation. Furthermore, if the battery is charging, changing charging current can also be a way of providing regulating power. The same is true for discharging. Considering plug accessibility and grid connection limits, the potential to provide up and down regulation in each hour is given in (13) and (14) respectively.

$$R_{up}(t) = min \begin{cases} [(E_{bat}(t) - E_{min}).acc(t)] \\ \left(r_{c_{max}}.\ acc(t) - \dfrac{P_d(t)}{\eta_{cnv}} \right).\eta_{cnv} + P_c(t) \end{cases} \quad (13)$$

$$R_{dwn}(t) = min \begin{cases} \dfrac{(C_{batt} - E_{batt}(t))}{\eta_{cnv}}.acc(t) \\ \dfrac{r_{c_{max}}.\ acc(t) - P_c(t).\eta_{cnv}}{\eta_{cnv}} + P_d(t) \end{cases} \quad (14)$$

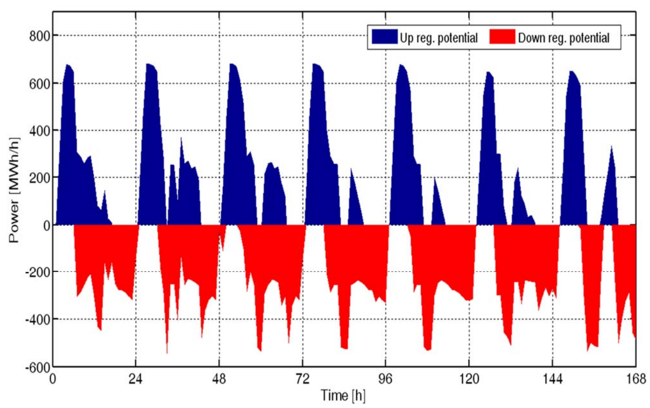

Figure 6. Potential regulating power with 3.5 kW PEVs average connections

V. CONCLUSION

A price based charging schedule scheme has been used to perform the charging schedule for all PEVs based on the forecasted driving pattern. Furthermore, the predicted PEV availability and the charging schedules are used to estimate the possible regulating power capacity from PEVs for both up and down regulation. The results of the regulating power capacity study show that the regulating power capacity from PEV grid integration are promising to meet the regulating power requirements in future power systems with high renewable energy penetration. The effectiveness of the PEVs participation in the market is found to depend on the range of electricity price variations. PEVs are considered to support the variability of the renewable generation. This may be feasible if the renewable generation has sufficient impact on the price. Regulations and incentives should be introduced to promote the best utilization of the PEVs.

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