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Probabilistic Estimation of Aggregated Power Capacity of EVs for Vehicle-to-Grid Application

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Abstract—Electric Vehicles (EVs) have emerged as a promising solution to reduce oil dependency and environmental impacts from the transportation segment. They can also be used as distributed energy resources providing ancillary services to the Grid through Vehicle-to-grid (V2G). EV availability estimation is the first step in determining the capacity for V2G operation. The main challenges in determining the Aggregate Power Capacity (APC) lies in the prediction of the vehicle availability and the plug-in probability. While the vehicle availability solely depends on the driving pattern of the EV owner, the plug-in probability depends on the availability of plugs at car park and plug-in human behavior. This paper models the stochastic mobility and plug-in probability of a fleet of EVs. The Aggregator model is realized using an infrastructure of contracted car parks at offices, recreational places and dispersed EVs at homes. Mobility is modeled using Trip Chaining and EV Driving patterns are profiled based on data from survey conducted, employment pattern and vehicular statistics. The Availability Probability Table (APT) is plotted to track the availability of each EV, considering EV reliability and traffic congestion index. The proposed models are tested and analyzed using Singapore data.

Index Terms— Electric Vehicle (EV), Vehicle-to-Grid (V2G), Aggregator, SOC, Driving pattern, Aggregate power capacity.

I. NOMENCLATURE

EV	Electric Vehicle
APC	Aggregate Power Capacity
SOC	State of Charge
SOC_{start}	SOC at beginning of each trip
ISO	Independent System Operator
N	Number of EVs
α_t	Traffic congestion index
R_i	Reliability of i_{th} EV
P_l	Power Limit
p	Parking location type
d	Trip distance
d_{max}	Driving range/ mileage of the EV
ρ_x	Plug-availability at location x
ρ_{xavg}	Average plug-availability of parking location type x
P_x	Probability of occurrence of Event x
i	EV counter

II. INTRODUCTION

Electric Vehicles are one of the routes to sustainable future. While wide adoption of EVs promises reduced environmental impacts from the transportation segment, it increases the grid dependency. These distributed loads, however, have one attribute that makes them most distinct, i.e., the storage capability in their batteries that can act as energy storage infrastructure for the grid. The plug-in electric vehicles, when connected to grid, can interact intelligently with existing power systems providing ancillary services, referred to as Vehicle-to-grid (V2G) [1] and seen as one of the key elements of future smart grids. In addition, coordinated charging can prevent them from becoming additional loads on the existing grids. Advanced Smart Grid technologies will facilitate the implementation of the required infrastructure. V2G proposes significant solutions for power markets in the form of load smoothing (peak shaving, valley filling, etc.) and ancillary services like frequency regulation and reserves [2]-[4]. An intermediate body called Aggregator will be required, since a single EV capacity is too small on the large grid scale. The main sources of revenues for an Aggregator will be from the markup of the electricity sold during EV charging and the percentage from the profit generated by providing V2G services to the ancillary service markets [2], [4].

The current deregulated power markets operate as day ahead and real time balancing markets. In order to bid in either of the markets, a bidder should be well aware of the power capacity it can deliver, prior to the actual service delivery. Thus an Aggregator needs a firm estimation of the aggregate power capacity at any time, while the individual EVs connect or disconnect from the V2G infrastructure. Upon winning the contract, the Aggregator would receive service commands within the range of contracted power capacity (CPC) and the payment being proportional to it. Also failing to meet the contract will result in suspension of the contract partially or fully and a penalty imposed on the Aggregator [5].

The authors in [5] determine APC using binomial distribution by clustering EVs into groups with similar plug-in probability and power capacity thus presenting scenarios for maximizing profit under penalty imposed to the V2G Aggregator. References [6]-[8] use different methods to estimate vehicle availability at different locations. Reference

[6] uses stochastic modeling to generate driving profiles using a survey data to determine trip distance and location of EVs. Location types are classified into: *home*, *work*, *leisure* and *shopping*, and three charging strategies are evaluated to generate load profiles on different day types assessing energy stored in EV batteries and available storage capacities for V2G potential. However, a plug-in probability of 80% is assumed uniformly at different car parks, which is impractical in real world scenario. Reference [7] uses Monte-Carlo techniques to determine probabilities of EV in "parked" or "movement" state and identifies events based on parking locations in *residential*, *industrial* and *commercial* areas to evaluate the impact of massive EV integration on the distribution grid. But usage of only transition probabilities between different states misses the main attributes of trip chain, thus presenting an unclear overall scenario.

Reference [8] uses nonhomogeneous semi-Markov process (NHSMP) defining three states of being *at home*, *at work* and *elsewhere* to analyze EV availability at these car parks and loading due to EV charging. NHSMP addresses the problem of time dependency which was missing in [7]. Still, detailed driving patterns remain a critical issue in determining vehicle availability, as it largely depends on personal needs and travel preferences of the EV driver. Also, most of the present literature on V2G uses Trip Datasets to determine driving patterns, which do not trace a car for trip chains over a longer period of time. Reference [9] presents a more realistic mobility model, describing different trip chain possibilities by classifying drivers as per their employment pattern etc., to evaluate parking and charging behavior.

However, with low EV penetration and charging infrastructure still in its infancy, it will take a while till the V2G infrastructure is fully realized. During this period, there will be frequent mismatches between the required plug availability and the installed plug accessibility at the contracted car park. Instances of a random car park not being under a V2G contract when a contracted EV driver parks, may also occur, forcing the underutilization of the EV availability. Thus a detailed analysis for plug-in probability is required to assess the net EV availability for V2G, and a probabilistic estimation would be necessary to evaluate the overall APC, owing to the temporal and spatial randomness in EV locations and respective plug availabilities. A firm APC would minimize the risk and in turn the penalties incurred by the Aggregator.

In this paper, we approach the APC analysis from a different standpoint. The proposed model has 3 parts. First, the detailed driving patterns have been simulated for different trip chain possibilities, with probabilities assigned to each trip chain in accordance with the Singapore driving pattern, to estimate the EV availability in car parks. Second, an infrastructure is mapped with varying plug availabilities and linked to each EV driver to obtain APT. Finally APC is obtained using APT and power capacity.

The paper is organized as follows: Section III presents the methodology, framework and the data used in the work. Section IV introduces the mathematical modeling. Finally simulation results are presented in Section V and conclusions are drawn in Section VI.

III. METHODOLOGY

A. Aggregator Model

An Aggregator is supposed to contract with different car parks and individual EV owners to build up its capacity. The business model, as shown in Fig.1, will be very similar to the typical supply chains in the existing markets where smaller entities such as car parks at malls, offices and other recreation centers will be selling their capacities to the main Aggregator in contract with the ISO.

Fig. 1. Aggregator framework model

In V2G markets, the Aggregator will be under a contract with the EV owners, hence it will become an obligation for the EV owner to plug-in when not driving. However this will not affect the driving freedom of the EV owner. It will also be in the best interest of the EV owner as more availability generates more revenues for him. Since the entire business model of the Aggregator relies on the EVs, their availability cannot be left under the total spirit of the EV owners. Upon entering the contract, the Aggregator will have the right to penalize the EV owners who fail to plug-in when not driving, which may be in the form of deducting penalty amounts from the earned incentive. Agents like EV owner, EV charging point manager or the contracted car park owner and the Aggregator will confirm the plugged-in status. Thus the plug-in human behavior will no more be a limitation. Hence it is safe to assume that the plug-in probability will solely depend on the plug availability. The work reported in this paper uses Singapore statistics for the analysis. In Singapore, the recreational car parks are mainly attached to shopping malls. A plug-availability database was created, as shown in Fig.2, with 20 car parks each at offices, lunch places, recreational centers and grocery stores. Each of these infrastructures was linked to the EV drivers during profiling.

B. EV Owner Profiling

The EV driving pattern looks too haphazard when realized from a holistic viewpoint but becomes quite ordered once it is brought down to each driver level and his preferences. EV driver profiling is used to model the driving pattern of each driver who signs up a V2G contract with the Aggregator. The Aggregator uses an online database to determine the default usage profile of the EV [10]. This database tracks the driver's travel preferences, favorite locations, timings and other details as shown in Fig.2. And this online tool can also be used to keep

a track of changing habits or job timings of drivers. Profiling helps the Aggregator to determine the most probable location of the EV and its respective plug-in-probability. Since the EV earns decent incentives for the EV owner under a contract with the Aggregator, he will be obliged to update these details. Using this profiling, the Aggregator populates his availability probability table depending on EV availability and plug-in-probability to determine the net aggregate capacity to bid in the power market. 10,000 hypothetical EV drivers were profiled, using Singapore employment data from [11], vehicle statistics from [12] and the survey conducted, representing around 2% EV penetration in Singapore.

1) Survey Data

A survey was conducted to determine travel preferences [13]. Only responses of employed and unemployed respondents owning a vehicle were used. An average of 50% replied that they take lunch outside office, and more than 75% replied that they are more than 50% likely or almost certain to go to the same store for shopping groceries. The average distance to the grocery store was around 3 km. Individuals go home directly from work almost 80% of the time while for the remaining 20% time, take recreational trips and then drive back home. More than 80% of people had their most visited recreational place between 5 and 25 km. Travel preferences on weekends were 20% between 8 am-12 pm, 25% between 12 pm-4 pm, 40% between 4 pm-8 pm and 15% for 8 pm-midnight and later.

C. Mobility Model

The concept of trip chain has been utilized to model the driving pattern of each EV. A trip is characterized by purpose, source, destination, arrival and departure times and trip duration [14]. Each trip chain typically starts from the same point every day (e.g. home) and terminates at the same point and every trip chain is unique as it contains different sets of trips and locations. We have classified the possible parking locations as *Home (H)*, *Office (O)*, *Lunching outside office (L)*, *Recreation (R)* or *Grocery shopping (G)* related. Shopping groceries was classified separately because it's a regular trip that happens irrespective of working day or holidays even if there are no recreational trips occurring on weekdays.

The estimated average daily mileage for private cars in Singapore was 52 km in 2010 [12]. Under the assumption that 10,000 of these private cars were EV, the EV drivers were categorized into 3 groups depending on their employment pattern in [11]. 92% of the employees work full-time for 9 hours daily, either from 8 am to 5 pm, 8.30 am to 5.30 pm or 9 am to 6 pm, including 1 hour lunch break which falls in the respective middle hour. 4% of the employees work part time with an average of 5 hours per day. The remaining 4% work either from home or are on leave on any given day. Full working days and holidays are analyzed because full-time employees follow the pattern of part-time employees on half shift days working in morning or afternoon shifts.

Table I shows some of the trip chain possibilities for different employment status and day types. However, the average number of trips in Singapore in 2010 was around 3 trips per day. Hence in the simulation model, lower probabilities have been assigned to trip chains with number of

trips other than 3. The average driving speeds in Singapore are estimated around 30 km/h in arterial roads and 60 km/h on Expressways [12]. Any trip was assumed to contain a minimum of 10 km of arterial roads. Thus the travel time, in minutes, was determined by (1).

TABLE I. TRIP CHAIN POSSIBILITIES

Employment Status	Day type	Trip Chain
Full time	Working Day	HO-OH HO-OR-RH HO-OL-LO-OH HO-OR-RG-GH HO-OH-HG-GH HO-OL-LO-OR-RH
		HO-OH HR-RO-OH HO-OR-RH HO-OH-HG-GH
Working from Home/ On leave	Working Day	HR-RH HG-GH HR-RG-GH
Any	Holiday	HR-RH HG-GH HR-RG-GH HR-RR-RH HR-RH-HG-GH

$$T(x) = \begin{cases} (10+2x)(1+\frac{\alpha_i}{100}); x \leq 10 \\ (20+x)(1+\frac{\alpha_i}{100}); x > 10 \end{cases} \quad (1)$$

x being the distance in km, 10 min considered as buffer to park and plug-in and α_i the traffic congestion index. Distances between home, office and recreational places were assumed to be normally distributed with a mean distance of 15 km and standard deviation of 10 km. Distances for lunching outside office and buying groceries were assumed to be normally distributed with a mean distance of 3 km and standard deviation of 1 km.

D. EV Reliability & Traffic Congestion Index

The availability of a car for V2G in the expected hour also depends on its reliability and the mobility model being congestion free. The reliability of an EV varies as per its make, manufacturer and age.

TABLE II. EV MODELS

EV Model	Battery (kWh)	Range in km (EPA cycle)	VDS PP100
Mitsubishi i-MiEV	16	100	178
Nissan Leaf 2013	24	135	137
Toyota RAV4	41.8	166	112
Tesla Model S	60	335	126 ^a

^a. Industry average used in absence of data for Tesla

Table II lists the four pure battery EV (BEV) models considered in the present work to represent subcompact, compact, SUV and sedan categories and are assumed to have equal share in total number of cars. The range of the respective EVs are determined from [15] on EPA cycle. The Reliability is

determined from the 2013 U.S. Vehicle dependability study (VDS) [16]. PP100 represents the number of problems experienced per 100 vehicles in a year, with a lower score reflecting higher quality. An average downtime of 5 hours/failure was assumed for every problem reported. It is assumed that the batteries are typically operated between 20% and 80% SOC, called as "long life mode" by the EV manufacturers, because lithium ion batteries suffer high stress at both ends of the SOC and this also meets the goal of EV battery cycle life (1000 cycles to 80% DoD) made by USABC [17],[18].

In megacities like Singapore, with high population density, there are more chances of traffic congestions especially in the peak hours when most of the driving happens. The congestion index compares travel time during non-congested periods (free flow) with travel times in peak hours. The difference is expressed as a percentage increase in travel time, representing the congestion level [19]. Congestion level varies with day of week, time of day, weather condition, special events etc. 6 AM to 11AM and 4 PM to 9 PM are considered as peak hours with average congestion index of 20% for weekdays and 10% for holidays and travel times are computed accordingly.

Fig. 2. Control flow of simulation, EV Driver Profiling and Plug- Availability Database

IV. MATHEMATICAL MODEL

Let X,Y be the trip events defined as follows:

Event X: *Going to Office, lunching outside, Recreational place or Grocery store*

Event Y: *Going to the favorite or most visited location*

$$APT_{i,t} = [P_{i,X}(P_{i,Y} \cdot \rho_{p_{fav}} + (1 - P_{i,Y}) \cdot \rho_{p_{avg}}) + (1 - P_{i,X}) \cdot \rho_{p'}] \cdot R_i \quad (2)$$

Thus the availability probability for i_{th} EV at time t is obtained from (2). For instance, a shopping trip from home to a grocery store, with a probability of occurrence of trip $P_{i,X}=0.5$ and probability of going to favorite store $P_{i,Y}=0.5$, the possible

parking locations in the given time are either home or the grocery store. Hence $\rho_{p_{fav}}$ and $\rho_{p_{avg}}$ represent the plug availabilities of the favorite store and the average of all the grocery stores respectively, while $\rho_{p'}$ represents the plug availability of home. Similarly for a trip to office on a working day, $P_{i,X}=1$, $P_{i,Y}=1$ ruling out any other case.

Under the assumption that the SOC drops linearly with distance travelled, SOC at time t can be calculated by (3),

$$SOC_{i,t} = SOC_{START} - \left(\frac{d}{d_{max}} \right) \times 100\% \quad (3)$$

The variation of SOC due to charging and discharging during V2G operations is not considered in the present work, as it will largely depend on the strategy of the Aggregator and will be studied in future research. In addition, the overall energy dispatched for regulation is only a fraction of the capacity procured and is usually balanced between regulation up and down such that it adds up to zero. The reserve contracts have limited number and duration of calls and are paid for the capacity, i.e., the amount of energy kept ready and available for the time they are procured for, even though there is no energy or much lesser energy actually being transferred.

In spite of the varying battery capacities, the power transfer capacities are actually limited by the rating of the onboard chargers (or inverters) and the voltage and the rated current capacity of the power line at the contracted infrastructure. A uniform Level 2 charging infrastructure consisting of 240 V, 20 A was considered, limiting power transfer to approximately 5kW. Fig.2 shows the control flow of the simulation, in determining APT and APC. Eqn.4 was used to compute the APC at any time t .

$$APC_t = \sum_{i=1}^N APT_{i,t} \cdot P_i \quad (4)$$

V. SIMULATION RESULTS

The model was simulated with a time resolution of 1 minute for EV availability, APT, APC and SOC for working day and holiday scenarios.

A. EV Availability

Fig. 3. EV availability on working day

Fig.3 shows the number of EVs parked at different types of parking locations on a working day. It can be observed that the number of cars parked in offices gradually increases as the drivers start reaching office in the morning. The afternoon dip occurs as the EV drivers take a trip of lunching outside office which results in a corresponding peak in the 'other' curve. The second peak in 'other' reflects the recreational and grocery shopping trips post office hours. It can also be concluded that more than 50% of the EVs are parked at any given time. And particularly the daytime period of 9 am to 5 pm and nighttime period of midnight to 6 am offers maximum availability.

B. Availability Probability Table

In order to illustrate the model, the plug-availabilities in the database were set between 0.7-0.8 for offices, 0.5-0.6 for lunching car parks, 0.3-0.4 for recreational and grocery car parks. A plug availability of 1 was assigned to all the 10,000

homes owing to the fact that it is highly probable that every EV owner will have a dedicated charging point in home. The output of the simulation were two 10000×1440 matrices, one each for working day and holiday respectively, with rows representing the EVs and the columns representing time of the day. Table III shows a sample APT.

TABLE III. SAMPLE AVAILABILITY PROBABILITY TABLE

EV\Time	1	2	3	4	5	6
EV1	0.9990	0.9990	0.9990	0.7492	0.7992	0.5494
EV2	0.9992	0.7994	0.7994	0.7494	0.8720	0.7494
EV3	0.9994	0.9994	0.9994	0.7495	0.7995	0.7495
EV4	0.9993	0.9993	0.7994	0.8322	0.8656	0.7495
EV5	0.9990	0.7992	0.7992	0.7492	0.8715	0.7492
EV6	0.9992	0.9992	0.9992	0.8421	0.8735	0.7494

C. SOC

The best case and the worst case scenarios were analyzed for the residual SOC status of the 4 EV types over a working day. It was assumed that the EVs charge overnight, to be fully charged at 80% SOC by 6 am. The best case constitutes shortest trip chain HO-OH, while the worst case constitutes one of the longest trip chain HO-OL-LO-OR-RH-HG-GH, being least probable.

Fig. 4. SOC variation over a working day

The average SOC plots, from 2300 driving profiles each, for different EV types, of full time employees, are shown in Fig.4. The top plot corresponds to the longest trip chain with average driven distance of 60.56 km. It can be observed that, even for Mitsubishi i-MiEV with a driving range of merely 100 km, the SOC falls to only 19.44%. In the bottom plot, for the shortest trip chain, the SOC for i-MiEV falls to only 44.78%. It can be concluded that, under normal driving conditions, most of the EVs in Singapore will not be requiring intermediate charging and thus overnight charging will be sufficient for daily use. A high V2G opportunity can be realized from the stored energy in these Electric Vehicles.

D. APC

P_i was set to 5kW and using APT obtained earlier, APC output shown in Fig.5 was obtained from the simulation model. It can be observed that more than 20 MW capacity is available

at any given time. It also gives an insight on which infrastructure the Aggregator should focus on in order to increase the aggregate capacity; such as it is more beneficial to contract office car parks as they offer maximum availability during day time.

Fig. 5. APC for different day types

In the absence of any direct data from plug-in EVs, as they are just getting introduced to the Singapore market, we did not have an actual APC value to compare with, for the validation of the proposed method. Fig.6 presents a comparison between APC values obtained from the EV availability with and without consideration of plug-in probability on a working day.

Fig. 6. Comparison of APC with and without consideration of plug-in probability on a working day

VI. CONCLUSIONS

A method to obtain the aggregate power capacity (APC) from EV availability, varying plug-in probability and power capacity has been described and implemented. Though we considered only BEVs in the present study, the model works fine for Plug-in hybrid EVs (PHEV) too, having much smaller battery capacities. Future studies will present a more detailed analysis considering a combination of EVs (BEVs and PHEVs) and the variation of SOC during V2G operations under Aggregator strategies to participate in various power markets.

The results can be summarized as follows:

- Individual driving pattern plays a key role in the net vehicle availability at any location.
- A mere 2% EV penetration in Singapore can offer storage capacity up to 50 MW and battery capacities as low as 16 kWh is enough for meeting the daily driving requirement, without any intermediate charging.
- The home and office car parks have maximum availability; hence the infrastructure should be well suited to offer maximum plug availability to utilize V2G potential fully.

The simulation results provide valuable information for a profitable Aggregator design, which is a crucial step in realizing V2G business model. Higher incentives to an EV owner, through increased vehicle availability, will lead to reduced ownership costs, thus increasing EV acceptance and overall penetration. The intelligent integration of vehicles and power systems can potentially limit the use of fossil fuels, leading to sustainable transportation and generation systems.

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