Stochastic Battery SOC Model of EV Community for V2G Operations Using CTA-2045 Standards

Huangjie Gong, *Student Member, IEEE*, Rosemary E. Alden, *Student Member, IEEE*, and Dan M. Ionel, *Fellow, IEEE*
SPARK Lab, Department of Electrical and Computer Engineering, University of Kentucky, Lexington, KY, USA
huangjie.gong@uky.edu, rosemary.alden@uky.edu, dan.ionel@ieee.org

***Abstract*—An electric vehicle (EV) battery has large energy storage capacity in the context of residential total usage, and the potential to provide large energy reserves for Home energy Management (HEM) systems. In an electric distribution system, groups of EVs could provide vehicle-to-grid (V2G) service in response to control signals and enable virtual power plant (VPP) operation of the car batteries. The CTA-2045 standards were considered for integration of the EV controls into the HEM system for maximal interoperability with other appliances, such as residential battery, electric water heater, and heating, ventilation, and air conditioning (HVAC) system. The power distribution system under study was modeled based on a modified IEEE 123-bus feeder test case in OpenDSS software. The availability and state of charge (SOC) of EVs were calculated based on the national household travel survey (NHTS) data following a new procedure to create synthetic communities following experimental probability density functions (PDFs). Example case studies for long and short term V2G services were completed in this paper from the perspective of the distribution system. The power flow for the distribution system, the voltages on the buses, as well as the SOCs and available energies of the EVs were calculated following the control signals on an example day.**

***Index Terms* –** Electrical Vehicle (EV), Virtual Power Plant (VPP), Vehicle-to-Grid (V2G), CTA-2045, Stochastic, IEEE 123-bus, Electric Power Distribution, Home Energy Management (HEM), OpenDSS

I. INTRODUCTION

EV batteries provide large energy storage [1], enabling ancillary grid services such as peak power reduction and energy reserve assistance through vehicle-to-grid (V2G) connection. With V2G service, a virtual power plant (VPP) framework was enabled to smooth wind power output [2]. EVs increased the resilience of a microgrid with its own renewable generation and different types of loads [3]. The V2G service could also provide reactive power compensations, which is estimated to reduced the electric power losses up to 95% [4].

The CTA-2045 specifies the communication protocol with residential devices and provides a standard interface for signals to facilitate home energy management (HEM). The CTA-2045 standards has been used for the uniform control of residential battery, electric water heater, heating, ventilation, and air conditioning (HVAC) systems, and EVs. Laboratory evaluations for V2G operation were reported in [5] by the Electric Power Research Institute (EPRI) indicating the physical compatibility and capability of the EVs to connect to the residencies. The travel behavior of the American public is published in the national household travel survey (NHTS) [6]. In this source, personal and household travel were reported including the daily mileage, travel purpose, arrival home time, etc.

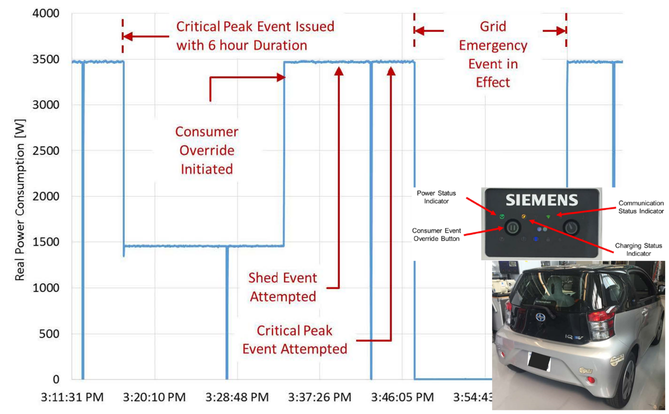

Fig. 1. The performance test results for CTA-2045 EV supply equipment published by Electric Power Research Institute (EPRI) [5]. Shown are the EV for testing, visual indicators and controls on electric vehicle service equipment EVSE, and results for different control signals.

In this paper, a community of 300+ homes with their distinct realistic residential loads was modeled in OpenDSS based on a modified IEEE 123-bus feeder system. The power flow and voltage on each bus were monitored during V2G services. The availability of EVs to connect to the home and the reserved energy from EV batteries were calculated based on the NHTS data. Two case studies were completed to proposed example operation and effects of long and short term V2G services.

II. CTA-2045 CONTROLS AND NHTS DATA ANALYSIS

The CTA-2045 communication signals can be applied to electric vehicle service equipment (EVSE) for the compatibility with other smart devices as part of HEM [5]. For a level-2 charger, the EV power is defined by the current as the voltage is fixed at 240V under ideal condition. The current for EV charging can be changed to respond to control signals from the grid. Example results from an EPRI report (Fig. 1) show the EV power responding to different control signals, which typically include normal operation, shed, critical peak, grid emergency, and variable, [5]. In this paper, V2G control was enabled by adding control signals with negative current, indicating reversed current draw from the battery to the grid.

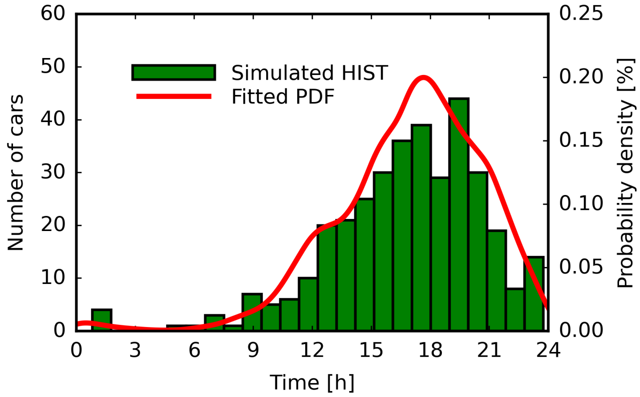

Fig. 2. Generated synthetic community of 353 EVs based on the National Household Travel Survey (NHTS) fitted probability density function (PDF) curve for home arrival time. A very large peak is expected in late afternoon/early evening due to work time schedules.

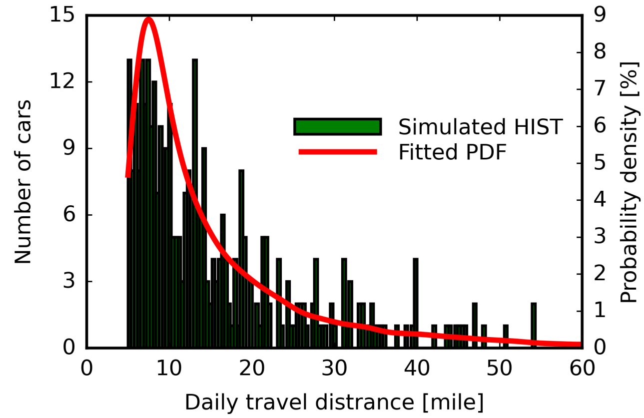

Fig. 3. The daily mileage for all 353 simulated EVs in the new community data set which is based on the NHTS data distribution. Most EVs had short daily commute distance.

Knowledge of the availability of an EV battery energy, i.e. if the vehicle is not being driven, is essential to plan for V2G service. At the community level, the aggregated behavior of EV owners is highly predictable as the randomness of individuals is smoothed out. Data from the National Travel Household Survey (NHTS) provides daily information from hundreds of thousands households and vehicles, including the home arrival time and daily driving mileage [6].

Firstly, the Gaussian Kernel Density Estimator was used to estimate of the probability distribution of home arrival time [7]. From this curve (Fig. 2), the arrival times of 353 EVs for the V2G case studies in this paper were generated. As shown in the NHTS data, the majority of the vehicles arrive home in the late afternoon. The distribution of daily mileage of EVs in the United States, was also estimated. Individual lengths driven were assigned to the 353 vehicles in a new synthetic dataset to match the PDF curve of the NHTs experimental drive length data. From this assignment, the SOCs of the new vehicles when they arrive at home was calculated as:

$$f(SOC_i^a) = \left(1 - \frac{d}{d_M}\right) \times 100\%, \tag{1}$$

$$d_M = E_C \cdot ECPM, \tag{2}$$

where d is the daily commute mileage; d_M, the maximum driving distance; E_C, EV battery energy capacity; $ECPM$, energy consumption per mile. A 100 kWh battery capacity and 3.33 mile/kWh energy usage were assumed in this paper.

It is important to note that the daily commute distance is short for the majority of the vehicles, resulting in high SOC when the EV returns home (Fig. 3). For this study, the EVs were modeled for three business days, starting with full charge and 100% SOC on a Monday morning. All EVs were assumed to have no further charging during the three day simulation time to representing periodical charging, and the last day is analyzed for VPP operations. After three days without charging, the EVs still returned with very high SOC and HEM system potential energy use, Fig. 4, due to low typical driving distances. The optimal time to apply VPP operations is in the evening because the total available energy increases as more EVs arrive at home over the day. This also corresponds to typical peak load across a residential community and the potential to substantially reduce strain on the utility.

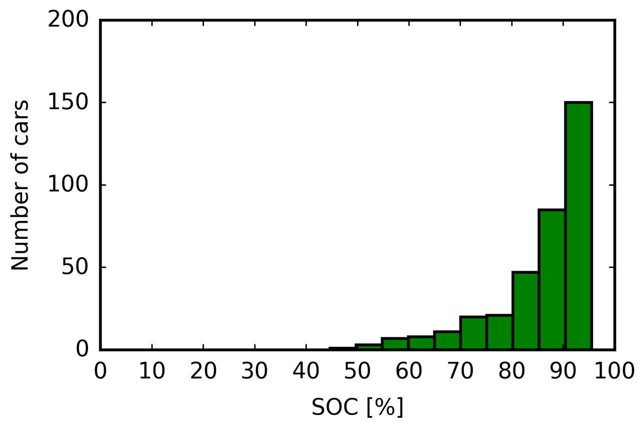

Fig. 4. The distribution of SOCs for the EVs upon home arrival calculated on the third weekday as calculated using the new proposed procedure. Almost half of the EVs, i.e., 150, considered in the study arrived at home with more than 90% SOC, due to the typical short commute distance identified through the NHTS experimental data.

III. VPP PROGRAM AND DISTRIBUTION POWER SYSTEM

The power distribution system for a residential community with EVs was modeled using the IEEE 123-bus feeder test (Fig. 5). Modification of the test system was as follows: for each phase of all the nodes, every 10 kW of existing load was replaced by a residence with a fixed power factor of 0.95 and a corresponding EV module. For example, phase-2 of bus-2 had 20kW of active power, therefore, two residences were connected to phase-2 of bus-2. Based on the original test case

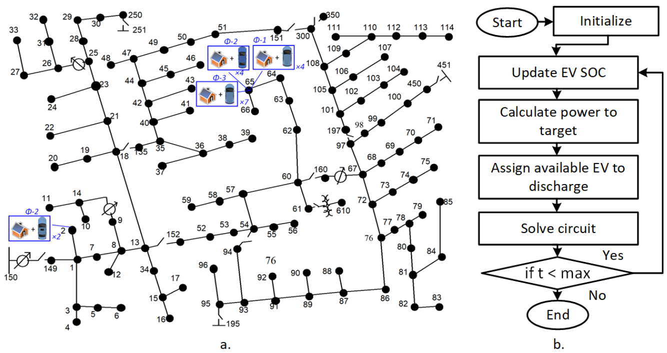

Fig. 5. A total of 353 residences were randomly generated with the new procedure described and connected together with associated EV as spot loads to a modified IEEE 123-bus feeder test case (a). A novel control scheme was implemented to select and assign a number of EVs to meet a target power at the feeder head (b).

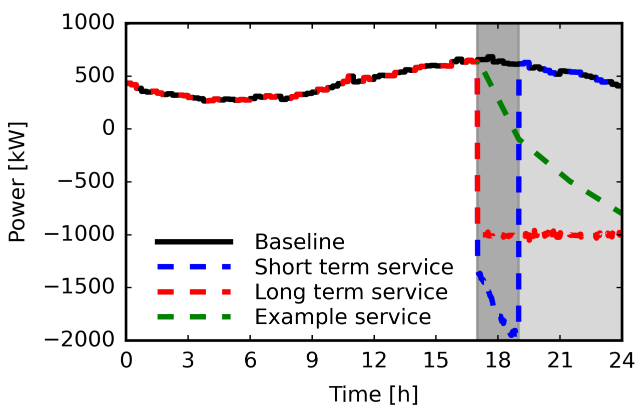

Fig. 6. Simulation results for the net aggregated power flow for the entire community in short, long, and example VPP case studies. Long term operation represents an extreme case and VPP example an alternative target profile. All result in a negative net power flow with absolute value much larger than the typical residential load.

active power load [8], a total number of 353 residences were connected. Each residences has its own distinctive load profile from the smart energy technologies (SET) project [9].

All available EVs at home in the distribution system with more than 50% SOC were considered eligible to participate in simulated VPP events through V2G connection. They operated with a current of -50A, i.e., discharging power of 12kW, a level-2 charger rate reversed. This discharge rate is intentionally larger than typical residential load to show the magnitude of EV battery energy reserves. Two cases representing maximal long term and short term V2G services in Fig. 6 find that EV's can provide significantly more power than residential load. The VPP controls may be used with other target profiles, an example of which is also included.

For the short term V2G service, all the available EVs were discharged between 17:00 and 19:00. At the beginning, approximately 2,000kW was supplied to the grid. As more EV arrived home, the aggregated discharging power increased.

For the long term service case, a target power of -1000 kW

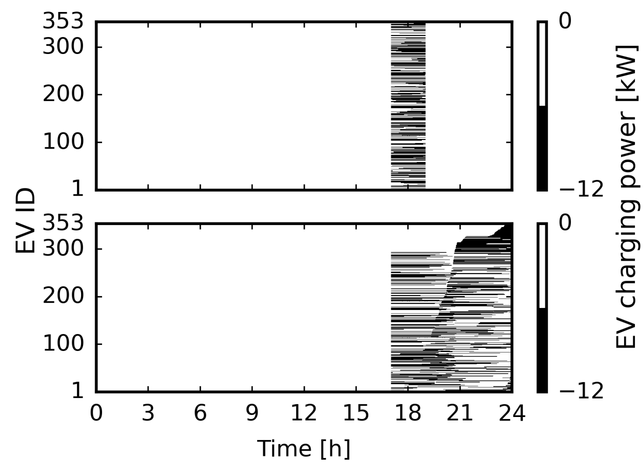

Fig. 7. The status of each EV for the simulated day during short term (top) and long term (bottom) control. EVs discharging the equivalent current as a level 2 charger: 50A.

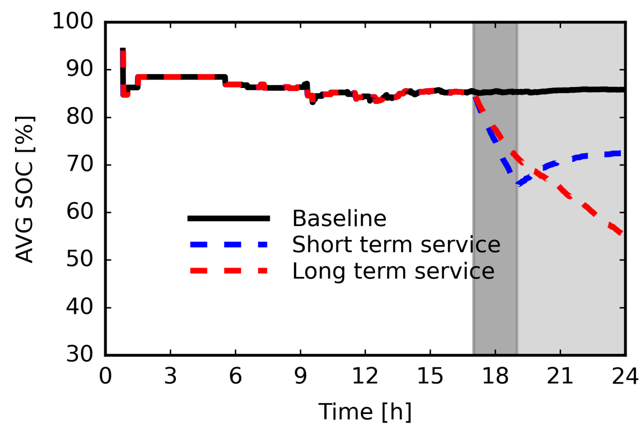

Fig. 8. The average SOC for all available EVs. The average SOC decreased during the short term service period, and increased afterwards as EVs with higher SOC arrived. No charging for EV was involved in this study.

through the feeder head was selected from 5pm to midnight. This reversal of power meets peak time load for the 353 residents and provides the power system with an additional 1000 kW. A number of EVs were selected to participate each minute so that the difference between the current power system output and the target power was near zero.

IV. Case Studies: Results and Discussion

In the exaggerated scenarios of this paper, EVs provided large negative net power flow with absolute value much larger than the typical residential load. With this coordination among EVs, the entire community operates as a VPP, providing constant power for a long period of time, as the long term service case documents. For this example VPP operation, the discharging power of each individual EV that is aggregated together to benefit the grid are shown in Fig.7.

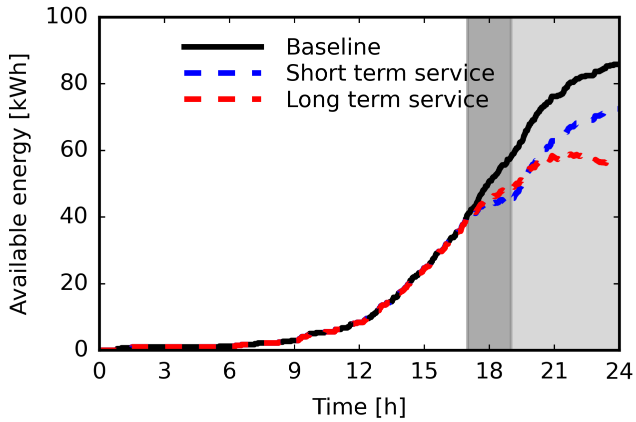

Fig. 9. The average available energy in an EV battery across the community, which increases even during VPP operation as more EVs with high SOC of batteries arrived home.

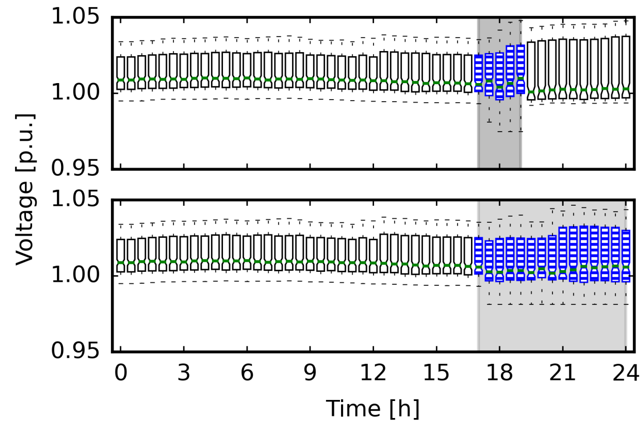

Fig. 10. The voltage for all buses for the simulated day for top: with short term DR, bottom: with long term DR. Samples were taken for every 30 minutes. There were virtually no violation for the simulated daily case.

Details for the short and long term service including community average SOC for all EVs, available energy in the power system, and bus voltages were analyzed. The average SOC for all available EVs in the neighborhood was recorded (Fig. 8) to show the equivalent energy storage available for the VPP. No SOC was recorded before the first EV arrived home. During the DR period for short term service, the average SOC decreased, and increased afterwards as EVs with higher SOC arrived. It is worth noting that EVs were likely to arrive home with high SOC (Fig. 4). Therefore, even without charging, the average SOC for all EVs in the community increased after the short term DR period.

The long term case had the largest impact and drained the communal energy storage level down to 50%, representing the maximal usage case. For the individual EVs with 50% SOC, the owners could still make the probable short distance trips to work or the store, and the EV could be charged the next day at work or at home when no DR events happen. The average available energy [kWh] of an EV battery across the community increased during the example day as more EV arrived home, even during the short term VPP duration (Fig. 9).

The voltage on all buses were within the variation tolerance of 5% for the entire simulated day (Fig. 10) even after controls to the target power flow.The reversed large power flow caused by EVs resulted in larger variation of voltage as expected, and no voltage violations from VPP operations of EVs were indicated in the example distribution system.

V. Conclusion

In this paper, V2G case studies of a power distribution system for an example community with high EV penetration were performed. The EVs provided community long time VPP support for constant aggregated net power, in this case, through the entire night. In both cases, EVs were guaranteed more than 50% SOC of the battery, which is more than able to cover the typical daily commute.

The EVs were modeled based on the NHTS driving PDFs and all EV controls comply with CTA-2045 standards for level 2 bi-directional chargers. Under the extreme studies, voltage regulation was not a major issue as no violation were observed in simulation. The assessed example energy capacity of EVs was extremely large, substantially exceeding the load of the community.

Acknowledgment

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