Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services

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Abstract

The risk of accelerated electric vehicle battery degradation is commonly cited as a concern inhibiting the implementation of vehicle-to-grid (V2G) technology. However, little quantitative evidence exists in prior literature to refute or substantiate these concerns for different grid services that vehicles may offer. In this paper, a methodology is proposed to quantify electric vehicle (EV) battery degradation from driving only vs. driving and several vehicle-grid services, based on a semi-empirical lithium-ion battery capacity fade model. A detailed EV battery pack thermal model and EV powertrain model are utilized to capture the time-varying battery temperature and working parameters including current, internal resistance and state-of-charge (SOC), while an EV is driving and offering various grid services. We use the proposed method to simulate the battery degradation impacts from multiple vehicle-grid services including peak load shaving, frequency regulation and net load shaping. The degradation impact of these grid services is compared against baseline cases for driving and uncontrolled charging only, for several different cases of vehicle itineraries, driving distances, and climate conditions. Ten-year degradation simulation results show that frequency regulation and peak load shaving at power rates typical for vehicle charging and discharging will not significantly accelerate battery degradation in comparison to the degradation incurred from driving and calendar aging.

Keywords: electric vehicle, battery degradation, vehicle-to-grid, powertrain

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1. Introduction

Electrification of transportation is commonly believed as a promising path to meet climate goals around the world [1], and prior studies have established the ability for today's commercially available EVs to meet the daily travel needs of the vast majority of drivers [2]. Moreover, if EVs can feed energy back to the grid to provide "vehicle-to-grid (V2G)" services, it will bring multiple benefits to different stakeholders including both power systems and EV owners. These benefits might include frequency regulation, peak load shaving, enhancing the integration of solar and wind energy, and providing distributed energy resources to deal with unexpected outages [3]. The authors in [4] provided quantitative methods to estimate the cost and revenue of implementing V2G in four major electricity markets. The results showed that implementing V2G can increase the reliability of power grids, reduce system costs, and lower the prices of storage devices and reserves for renewable energy integration. The authors in [5] proposed a V2G algorithm to optimize the scheduling of energy, regulation and spinning reserves based on the Electric Reliability Council of Texas system. The simulation results demonstrated that V2G can bring substantial benefits to both aggregators and customers. In [6, 7, 8], the authors showed that the controlled charging of EVs can increase the use of renewable energies in both distribution and transmission levels by mitigating the intermittency of solar and wind power generation.

Despite these benefits, the concern on battery degradation incurred by V2G services is one of the major hurdles to its widespread deployment [9]. Batteries will lose irreversible capacity with cycling and calendar aging. The battery pack has to be replaced, if it degrades to sufficient levels. It is traditionally assumed that batteries will reach their end-of-life (EOL) once they lose 20-30% of their original storage capacity [10]. Therefore, a quantitative methodology to estimate the EV battery degradation is the basis of evaluating the financial and technical feasibility of V2G services.

Many researchers have studied the degradation mechanisms of lithium-ion batteries which are widely used in today's EVs [11]. Capacity loss may be caused by irreversible electrochemical side-reactions(e.g. electrolyte reduction). It can also result from the

30 loss of active electrode materials due to phase transition, particle isolation, or other degradation mechanisms [12]. Based on these prior studies, it is generally understood that capacity loss is related to time, temperature, discharge rate and depth of discharge (DOD). Different battery degradation models have been proposed based on several aging mechanisms including parasitic side reactions [13], solid electrolyte interphase
35 (SEI) formation [14], and resistance increase [15]. Characterization of battery degradation from driving or grid services requires a huge experimental matrix to cover all combinations of different factors, and acquiring the test data to individually isolate and quantify each degradation mechanism is intractable.

Furthermore, evaluating EV battery degradation is even more complex due to the
40 variability of EV battery working conditions. Battery temperature is influenced by multiple factors including solar radiation, environmental temperature, heat generated when it is charging or discharging, and the battery's thermal management system. In addition, DOD, current input/output and heat generated by the battery are determined by EV driving patterns, like trip distance and frequencies, acceleration, speed, road
45 grade, etc. The authors in [16] presented mathematical correlations of battery wear for different conditions of charging/discharging, ambient temperature, DOD, but they did not extend their work to consider the influences of driving patterns on battery degradation. The authors in [17] quantified the impact on battery degradation while providing bulk energy and ancillary services. However, battery working temperature is assumed
50 to have a constant value which is insufficient given that prior literature [11, 12, 13, 14] has emphasized the importance of temperature upon battery degradation.

To the best of our knowledge, this paper is the first work to present a methodology to quantify EV battery degradation from driving vs. V2G services, incorporating a detailed thermal model, travel patterns and EV powertrain model. Battery degradation
55 caused by multiple V2G services including emergency DR, frequency regulation and load shaping for renewable integration, are simulated under various travel and charging itineraries, with different charger levels, and at different climate conditions.

The reminder of the paper is organized as follows. Section 2 stresses the specific objectives of this paper. The methodology is presented in Section 3. In Section 4,
60 we explain the V2G services simulated in this paper. Simulation results are shown in

Section 5. Conclusions and future work are in Section 6.

2. Specific objectives

Vehicle grid integration (VGI) presents a tremendous opportunity to benefit both the electricity grid and the transportation sector, yet concerns about accelerated battery degradation in vehicles that provide grid services remains an obstacle. The lack of a quantitative evaluation method for EV battery degradation amplifies people's anxiety on V2G cost and hinders stakeholders to price V2G services. Therefore, this study aims to quantify the magnitude of battery degradation that is incurred from normal driving and uncontrolled charging of vehicles versus degradation in vehicles that are driving plus offering grid services. In order to comprehensively examine the validity of concerns about battery degradation from VGI, we quantify battery degradation for several different grid services, under various travel and charging itineraries, and at different ambient temperature and solar radiation levels. This work will also provide reference for pricing or making compensation policies for different V2G services.

3. Methodology

3.1. Battery capacity fade model

Lithium-ion batteries slowly lose storage capacity with calendar aging and cycling. These capacity losses mainly result from lithium inventory loss due to irreversible electrochemical side-reactions [18]. There are often two distinct, but inter-related ways that are used to measure the life of lithium-ion batteries: calendar life and cycle life. Calendar life represents how long the battery might be expected to last in terms of calendar years, while cycle life is typically expressed in terms of number of charge and discharge cycles. A recent research [19] developed a semi-empirical model to calculate the capacity losses caused by both cycling and calendar aging for a particular lithium ion chemistry. It takes into account four important experimental parameters including temperature, time, depth of discharge (DOD) and charge/discharge rate. Moreover, this model decouples the capacity loss caused by cycling and calendar aging. Total capacity loss can be calculated by adding them together during any time horizon.

Calendar aging is strongly affected by temperature (T) and time (t). Capacity loss of a battery cell induced by calendar aging is expressed as [19]:

$$Q_{loss}^{calendar} = f e^{-E_a/RT} t^{1/2} \quad (1)$$

where $Q_{loss}^{calendar}$ is the percentage of capacity loss induced by calendar aging, f is the pre-exponential factor, which is $14876 \text{ day}^{-1/2}$. E_a is the activation energy, which is $24.5 \text{ kJ} \cdot \text{mol}^{-1}$. R is the gas constant, which is $8.314 \text{ J} \cdot \text{mol}^{-1} \text{ K}^{-1}$. T is the absolute temperature in K.

Cycle life loss is related to temperature, charge/discharge rate and energy throughput. The effects of discharge rates can be captured by an exponential function. Therefore, capacity loss of a battery cell induced by cycling is expressed as [19]:

$$\begin{aligned} Q_{loss}^{cycle} &= B_1 \cdot e^{B_2 \cdot I_{rate}} \cdot A_h \\ B_1 &= a \cdot T^2 + b \cdot T + c \\ B_2 &= d \cdot T + e \end{aligned} \quad (2)$$

where Q_{loss}^{cycle} is the percentage of capacity loss induced by cycling. Both the pre-exponential factor B_1 and exponential factor B_2 are functions of temperature. The values of a , b , c are $8.89 \times 10^{-6} \text{ Ah}^{-1} \text{ K}^{-2}$, $-0.0053 \text{ Ah}^{-1} \text{ K}^{-1}$, 0.7871 Ah^{-1} , respectively. I_{rate} is the charge/discharge rate in C-rate. A_h is the Ah-throughput, which is expressed as $A_h = (\text{cycle number}) \times (\text{DOD}) \times (\text{full cell capacity})$. Alternatively, A_h can be expressed as the cumulative charge throughput, i.e. the integral of I_{rate} . At each C-rate, Ah-throughput is directly proportional to time.

Combining (1) and (2), the general function of battery capacity loss is:

$$Q_{loss}^{total} = (a \cdot T^2 + b \cdot T + c) e^{(d \cdot T + e) \cdot I_{rate}} \cdot A_h + f \cdot e^{-E_a/RT} \cdot t^{1/2} \quad (3)$$

It should be noted these equations are obtained from the experiments on the commercially available 18650 cylindrical cells [19] which have been considered as a viable candidate for vehicular applications. Other batteries can degrade differently.

From (1) - (3), we can see that battery capacity loss is a continuous function of temperature, current and time. It is convenient to use (3) to calculate the battery degradation at a fixed working condition. However, the current and temperature of EV battery

pack keep changing when the vehicle is driving. In order to capture the degradation under a practical working condition, we need to discretize both calendar life and cycle life equations. Discretizing the calendar life loss equation (1), the incremental degradation from calendar aging at time $\hat{t}$ is

$$\Delta Q_{loss}^{calendar}(\hat{t}) = \frac{\partial Q_{loss}^{calendar}(t)}{\partial t} \Big|_{t=\hat{t}} \Delta t = 0.5Ae^{-E_a/RT} t^{-0.5} \Delta t \quad (4)$$

Ah-throughput can be interpreted as total energy in Ah which is output from the battery. For a constant charging rate which lasts for time Δt , it can be expressed as

$$A_h(\Delta t) = I_{rate} \times \Delta t \quad (5)$$

Discretizing the cycle life loss equation (2), the incremental degradation from cycling at time $\hat{t}$ is:

$$\Delta Q_{loss}^{cycle}(\hat{t}) = \frac{\partial Q_{loss}^{cycle}(t)}{\partial t} \Big|_{t=\hat{t}} \Delta t = B_1 \cdot e^{B_2 \cdot I_{rate}} \cdot I_{rate} \Delta t \quad (6)$$

Thus, the total capacity loss Q_{loss} of battery by time t is the sum of all capacity losses at all contributing time steps

$$Q_{loss}(t) = \sum_{\hat{t}=0}^t (Q_{loss}^{cycle}(\hat{t}) + Q_{loss}^{calendar}(\hat{t})) \quad (7)$$

110 3.2. EV battery temperature model

From the battery capacity fade model, we can see that temperature is one of the dominant factors. Therefore, it is necessary to provide an accurate estimate of battery temperature. A car-level lumped capacitance thermal network approach [20] is utilized for calculating both cabin heating, ventilation and air conditioning (HVAC) loads and
115 battery temperature. Equations (8) - (9) define the lumped capacitance thermal network of the battery and its environment.

$$M_c \frac{dT_c}{dt} = K_{ac}(T_a - T_c) + K_{bc}(T_b - T_c) + q_{rad} + q_{hvac} \quad (8)$$

$$M_b \frac{dT_b}{dt} = K_{ab}(T_a - T_b) + K_{bc}(T_c - T_b) + q_{btms} + Q \quad (9)$$

where T_a is the ambient temperature, T_b is the battery temperature, T_c is the cabin temperature. K_{ab} is the effective heat transfer coefficient between ambient and battery; K_{ac} is the effective heat transfer coefficient between ambient and cabin; K_{bc} is the effective heat transfer coefficient between battery and cabin. M_c is the thermal mass of vehicle cabin; M_b is the thermal mass of battery. q_{rad} is the solar radiance, which depends on time and location. q_{hvac} is the heat added to or removed from the cabin by the HVAC system. q_{btms} is the heat added to or removed by the battery thermal management system. Q is the heat generated by the battery. Ambient temperature and solar radiation data are sourced from historical databases. The values of parameters are calculated to fit the response of this model to test data [20]. They are listed in Table. 1

Table 1: Values of parameters in the EV thermal model.

Parameter	Value
K_{ab}	4.343 WK ⁻¹
K_{ac}	22.6 WK ⁻¹ ($T_c < T_a$) 22.6+1500 WK ⁻¹ ($T_c > T_a$, key-on)
K_{bc}	3.468 WK ⁻¹
M_b	182,000 JK ⁻¹
M_c	101,771 JK ⁻¹
q_{hvac}	+4 kW ($T_c < 292$, key-on) -4.5 kW ($T_c > 297$, key-on)

How to calculate Q is a key question before using this temperature model. The heat generated from the battery is:

$$Q = I^2 \times R \quad (10)$$

where I is the current input/output, R is the internal resistance. Intuitively, the current is related to speed and acceleration. High speed and acceleration usually require high current output to power the vehicle. Therefore, we should consider the EV powertrain model, which can provide the detailed battery parameters when it is in use for any driving conditions.

3.3. Acquisition of battery working parameters

As discussed above, we need to acquire the time-resolved current and internal resistance in order to calculate the heat generated from the battery while it is cycling for driving or V2G services. In addition, current input/output and real-time SOC are also required for calculating cycle life loss as shown in (3).

A simulation tool called "V2G-Sim", which we developed previously [2, 9, 21, 22], is applied in this study to obtain detailed EV information and battery working parameters. In this work, V2G-Sim is provided with travel itinerary input data from the National Household Travel Survey (NHTS) [23], which contains 159,844 representative samples of weekday and weekend vehicle usage for drivers in the United States. It conveys the detailed information on each trip, including trip distances, start and end times, and types of locations (e.g. home, work, etc.). Table. 2 shows an example of the travel itinerary information input into V2G-Sim from the NHTS dataset.

Table 2: An example of travel itinerary information provided to V2G-Sim

Start time	End time	Event type	Distance/charger level	Location
0:00	8:45	Plugged in	L1	Home
8:45	9:45	Driving	39.6 mi	N/A
9:45	16:30	Parked	L2	Work
16:30	17:00	Driving	5.0 mi	N/A
17:00	17:30	Parked	N/A	Restaurant
17:30	18:00	Driving	5.0 mi	N/A
18:00	21:00	Parked	L2	Work
21:00	22:00	Driving	39.6 mi	N/A
22:00	0:00	Plugged in	L1	Home

For each activity (e.g. plugged-in, driving or parked) in the travel itineraries listed in Table. 2, V2G-Sim calls relevant sub-models which tracks energy consumption and other parameters in the vehicle powertrain. The term powertrain describes the main components that generate power and deliver it to the road surface. This includes the transmission, engine, differentials, drive shafts, drive wheels, etc. A detailed pow-

150 ertrain model, similar to Autonomie powertrain model [24], is developed to predict the energy consumption of any vehicle make/model on any trip-specific drive cycle (including terrain considerations), and with any level of ancillary power loading (e.g. from a vehicle's HVAC system). In this paper, we use the powertrain specifications for a "Nissan Leaf" [9].

155 When a vehicle parks and plugs into a certain type of charger (e.g. L1 charger at 1.4 kW, L2 charger at 7.2 kW, or super charger at 120kW), charging sub-models are used to calculate the power transfer from the electricity grid to that vehicle. When the vehicle is driving, a trip-specific drive cycle profile and the terrain during the trip will be input into the detailed powertrain simulation. In this paper, we generate the drive
160 cycles from the US Environmental Protection Agency (EPA) standard drive cycles for city (UDDS), highway (HWFET), and aggressive driving (US06), as shown in Fig. S1 in the supplementary material, however the models can be provided with any real world drive cycle.

Since the battery degradation model in Section 3.1 is for individual cell, we need
165 to transfer the pack-level parameters to cell level. It is assumed that the temperature and SOC in the battery pack is homogeneous. That means the SOC and temperature of all battery cells are the same as the pack-level values. In this paper, we use the configurations of "Nissan Leaf" battery package which has 48 modules in series. Each module is formed by connecting 4 cells in a 2-series, 2-parallel formation. Therefore,
170 the current through each cell is half of the current input/output from the whole battery package.

In this manner, each vehicle's SOC, current and internal resistance are computed on a second-by-second basis.

3.4. *Simulation flow*

175 After obtaining temperature data and other working parameters, we can calculate the battery degradation according to (4) - (7). As shown in Fig. 1, given EV itineraries and V2G strategies, V2G-Sim will specify all driving/charging/discharging/idle events and assign a drive cycle to each trip. After setting charging/discharging parameters, all information will be imported into the detailed powertrain model. Then, we can acquire

180 SOC, current, and internal resistance. Values of internal resistance and current will further go to the temperature module where solar radiation and ambient temperature are sourced from historical data. Battery temperature will be used to calculate calendar life loss according to (4). Current, SOC and temperature will be used to calculate cycle life loss according to (6). Finally, we add them together and get the total capacity loss.

Figure 1: The whole framework of quantifying EV battery degradation.

It should be noted that the proposed method is ex-post and simulation-based. Given a specific strategy and itinerary, we can calculate battery degradation second-by-second. If the replacement price of the EV battery is known, we can further translate the irreversible capacity loss to the EV cost from providing grid services, according to specific End-of-Life criterion of EV battery. The cost of battery degradation for an individual EV C_{ev} for a grid service event will be:

$$C_{ev} = \frac{Q_{loss}^{gs}}{\eta} \cdot P_b \quad (11)$$

185 where Q_{loss}^{gs} % is the capacity loss in a grid service event. η % is the end-of-life threshold which is commonly (though arbitrary in nature [9]) set to be between 20-30%. If the battery loses its capacity by η %, it reaches the end of life. P_b is the price of the whole battery pack (e.g. the cost to replace a pack).

4. Simulated grid services

190 In this paper, we explore the EV battery degradation in four different cases. They are uncontrolled charging, peak load shaving, frequency regulation and net load shaping. In all these cases, we ensure that the grid services offered by each vehicle does not compromise the mobility needs of each driver.

4.1. Driving and uncontrolled charging (*Base case*)

195 In the base case, all EVs are used only for driving. They do not provide any grid services. It is assumed that EVs can charge either at home or workplace. Once they arrive at home or workplace, they start to charge immediately. The charging process will not end until the battery pack is full or the EV has to start the next trip. We show the weekday charging load of 17805 vehicles in California from NHTS dataset in Fig. 200 S2 in the supplementary material. The total load profile has two peaks. The first one happens around 9:00am when most of EVs arrive at workplaces. The second peak occurs between 6:00pm-7:00pm, after most people get home from work. This case is considered as the base case to evaluate the extra battery degradation caused by V2G services in the following sections.

205 4.2. Peak load shaving

Peak load spikes endanger the safety and reliability of electric power networks. Shaving the load peak can not only alleviate the shortage of supply and strengthen the stability of power systems, but also enable a lower transmission capacity, thereby reducing the capital cost of transmission infrastructure. During peak load times, curtailment of EV charging load can provide a quick-responsive resource. If V2G is 210 enabled, EVs can also feed energy back to the grid during these periods. Examples of the

charging load profiles in both V1G and V2G cases are shown in Fig. S3 in the supplementary material. EVs shift their charging demand from 17:00-21:00 to other time periods. Negative charging load means the vehicles are discharging at that time. Peak
215 load shaving may be required when extreme hot or cold weather results in the power demand peak. In addition, since the electricity price is usually higher during the load peak time, people may be also interested in permanent load shifting to do arbitrage.

4.3. Frequency regulation

Frequency regulation is a service that corrects for short-term changes in electricity
220 use that might affect the stability of the power system. It helps match generation and demand and adjusts generation output to maintain the desired electrical frequency for the grid to function normally. EVs can respond to the frequency regulation signal and act as demand-side regulating resources. It is often believed that frequency regulation is one of the most lucrative V2G services. The pilot project led by University of Delaware
225 demonstrated that Electric BMW Minis can earn approximately \$100 per month per car by following PJM frequency regulation signals [27].

In the PJM regulation market, a fast response regulation signal (RegD) is separated from the traditional regulation signal (RegA). Compared with RegA signal, RegD is derived with a high-pass filter, thereby having much faster movement. An example of
230 PJM regulation signals including RegA and RegD is shown in Fig. S4 in the supplementary material. Since EV batteries are able to ramp from zero to full power output within a very short period, they can provide the fast response regulation service which is more lucrative. In addition, RegD signal is symmetrical, which requires zero net energy over a 15-min time period. This favorable characteristics reduces the amount
235 of obligated reserved energy in the EV battery pack. In this paper, we simulate the scenario that vehicles can precisely follow the RegD signal.

4.4. Net load shaping

Since EVs can be either flexible loads or power sources, they have the potential to enable high penetration of renewables by balancing loads with intermittent generation. In this paper, we study the EV battery degradation from performing net load shaping,

which aims to mitigate the fluctuation of net load. A distributed optimal charging algorithm [28] has been built into V2G-Sim. The objective (12) is to minimize the variance of net load.

$$\min_u \sum_{t=1}^T (D^t + \sum_{n=1}^N u_n^t)^2 \quad (12)$$

where N is the number of EVs; T is the time horizon; u_n^t is the charging rate of EV n at time t ; D^t is the net load at time t (total load minus renewable generation). u_n^t is the decision variable. An EV is charging if $u_n^t > 0$, while it is discharging if $u_n^t < 0$. There are also power and energy constraints, which guarantee the charging/discharging power does not exceed the power limits and all EVs have enough energy for the drivers' desired travels.

A load shaping case for the so-called California "Duck Curve" is given in Fig. S5 in the supplementary material. Due to the features of wind and solar generation, the net load reaches a deep valley in the daytime and a high peak at 19:00. The short and steep ramps require the operator to bring on or shut down generation resources to meet an increasing or decreasing electricity demand quickly, over a short period of time. Uncontrolled charging even makes the situation worse. If V1G control is performed, vehicles opt for charging during the daytime valley, but it cannot help lower the load peak. However, in V2G case, EVs will charge during valley time and discharge during peak time. It can be seen that the fluctuation of net load is significantly mitigated.

5. Results and Discussions

In this section, we quantify the EV battery degradation from each grid service defined in Section 4. Parametric simulations are conducted for different travel and charging itineraries, different grid service durations, different charging/discharging rates, and different ambient temperature and solar radiation levels.

5.1. Driving + uncontrolled charging

We firstly study the battery capacity loss from normal driving and uncontrolled charging. To get the general results which can cover different itineraries, drive cycles and travel distances, we randomly pick up 100 vehicles from NHTS dataset and assume

all EVs repeat the same daily travel itineraries for 10 years. EVs can charge either at home or workplace. Once they arrive at home or workplace, they start to charge immediately. The charging process will not end until the battery pack is full or the EV has to start the next trip. We assume all EVs use level charger (1.44kW) at home and level charger (7.2kW) at work locations. Ambient temperature [25] and solar radiation [26] data from Phoenix, San Francisco and Minneapolis, which represent three typical climates, are used to show the battery degradation caused by cycling and calendar aging. We can see from Fig. 2 (a) that the degradation incurred by calendar aging is fast in the beginning and slows down as time progresses, since it follows a $time^{0.5}$ relationship according to (1). Calendar aging is also related to the battery temperature. It can be seen that the battery calendar aging in Minneapolis is minimal because of the cold ambient temperature. However, the battery degradation caused by cycling in Minneapolis is much more than that in other cities. Fig. 2 (b) shows that the 10-year battery capacity loss caused by cycling in Minneapolis is over 25%. It should be noted that we do not consider an active heating system here. If the heating system can warm up the battery before cycling, the degradation in cold cities will be significantly reduced, however this will cause a larger penalty in the EV travel range. After understanding the influences of temperature and solar radiation, we use the climate data of San Francisco to perform the sensitive analysis for other factors in the following simulations.

For the "Driving + uncontrolled charging" case, we also simulate the 10-year average battery degradation of 100 EVs in four different scenarios of charging, including level 1 (1.44kW) or level 2 (7.2kW) charging at home and work locations. Fig. 3 shows that in the case of driving only with uncontrolled charging, typical EV batteries lose around 31% capacity after ten years. Using an L2 charger has only minor effects on the battery degradation compared to using L1 charger. In the following simulations, the battery degradation curve with L1 charger at home and L2 charger at work location will be used as the baseline to evaluate the impacts of different grid services.

5.2. Peak load shaving

Next we simulate the battery degradation caused by providing peak load shaving, which is defined in Section 4.2. Both V1G and V2G scenarios are considered. Sensi-

Figure 2: Capacity loss incurred by (a) calendar aging and (b) cycling, in 3 typical climate cities. The results are the average values over 100 vehicles. Calendar life loss is fast in the beginning and slows down as time progresses. Although low temperature is helpful to slowing down the calendar aging, it will result in more cycle life loss.

tivity analysis on the time length of peak shaving event and charging/discharging rate is conducted. Fig. 4 (a) shows the average degradation of 100 vehicles by performing the peak load shaving from 19:00-21:00 every day for ten years. In the V1G case, all vehicles avoid charging during this period. Different charger combinations only make a slight difference on the battery degradation. In the V2G scenario, the grid service results in more capacity loss than that in V1G scenario. Since most vehicles are at home from 19:00-21:00, using an L2 charger at home in the V2G scenario will greatly increase the energy fed back to the grid, thereby accelerating the battery degradation. It can be seen that the 10-year capacity loss by using an L2 charger at home is over 45%, which is 9% more than that by using an L1 charger at home.

Fig. 4 (b) shows the battery degradation with different peak shaving hours. Here we assume L1 charger is used at home and L2 charger is used at work location. If vehicles

Figure 3: Average battery degradation of 100 EVs with different charger availability in driving + uncontrolled charging case. Using an L2 charger just has minor impacts on the battery degradation. Capacity loss after ten years is about 31%.

perform permanent peak load shaving every day for ten years, the total capacity losses by performing one to four hour services are 34.2%, 37.0%, 38.8%, 41.1%, respectively.

The above results show the capacity losses if EVs perform permanent peak shaving every day. It also helps people who are interested in utilizing EV for energy arbitrage to understand the magnitude of battery degradation from permanent load shifting. However, based on the emergency demand response programs of utility companies [29], peak load shaving may just be called 20 times per year in emergency events. Here we choose the 20 hottest days of a year and calculate the battery capacity losses if EVs provide peak load shaving (V2G) from 19:00-21:00 on these days. As shown in Table. 3, the V2G emergency peak load shaving increases the capacity losses by 0.38% with L1 charger at home and 0.82% with L2 charger at home after ten years, compared to the base case. Average capacity losses from each peak shaving event are 0.0019% and 0.0041%. If the replacement price of the whole battery pack is \$6000 and 30% is the end of life, the battery degradation cost from the 2-hour emergency providing peak load

Figure 4: Average 10-year battery degradation of 100 EVs for providing peak load shaving with (a) different charger availability; (b) different peak shaving hours.

shaving (V2G) would be \$0.38 using L1 charger at home and \$0.82 using L2 charger at home. These results provide reference for pricing or making compensation policies for emergency peak load shaving. EV owners can also be aware of the monetary cost

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Table 3: Battery capacity loss if EVs provide emergency peak load shaving (V2G) from 19:00-21:00 on 20 hottest days every year for ten years. The 10-year degradation in the driving and uncontrolled charging (base case) is 31.41%.

Charger level	Total capacity loss after ten years (%)	Average degradation from each event (%)	Battery cost for each event (\$)
Home L1 Work L2	31.79	0.0019	0.38
Home L2 Work L2	32.23	0.0041	0.82

if their EVs are used for this V2G grid service.

5.3. Frequency regulation

In the frequency regulation case, we also discuss the influence of charging/discharging rate and length of grid service time. Fig. 5 (a) shows the 10-year average capacity loss of 100 EVs with different charging/discharging levels. It is assumed that all EVs can accurately follow the frequency regulation signal from 19:00-21:00 and repeat for ten years. The result shows that for the V2G frequency regulation, the battery will lose 42.56% capacity if L2 charger is deployed at home, while the capacity loss will be about 35.03% if L1 charger is used at home. This compares with 31.41% capacity loss in the baseline scenario of the same vehicles simply driving and charging in an uncontrolled manner.

In the electricity market, regulation service periods are determined by the day-ahead bidding and economic dispatch. However, the power economics are beyond the scope of this paper. Here we simulate four different scenarios with different regulation service hours including all day regulation, work time regulation (9:00am-5:00pm), home time regulation (5:00pm-9:00am) and 4-hour peak time regulation (5:00pm-9:00pm). It can be seen from Fig. 5 (b) that all day regulation will increase 33% capacity loss after ten years, compared with the baseline. For the work time regulation scenario, the ten-year capacity loss is 51%, which is 20% more than that in the base case. Even though the work time is shorter than the home time, the work-time degradation is more due to a higher discharging rate.

It should be noted that the above results are very "extreme", because we assume

Figure 5: Average 10-year battery degradation of 100 EVs for providing V2G frequency regulation with (a) different charger availability; (b) different regulation hours.

these EVs provide the frequency regulation service every day for ten years. It is obvious that the battery degradation will be slower if EVs are called for fewer times. In Table. 4, we show the 10-year battery capacity losses with different numbers of frequency regulation events per year. The results are the average values over 100 EVs,

Table 4: Increase in the battery capacity loss when EVs provide the frequency regulation service (V2G) for different numbers of days every year. 10-year degradation in the driving and uncontrolled charging (base case) is 31.41%. The regulation period is from 19:00 to 21:00.

		10-year battery capacity loss (%)	
		Home L1 Work L2	Home L2 Work L2
Times of frequency regulation events per year	20 times	31.62	31.88
	50 times	31.93	32.55
	100 times	32.40	33.73
	200 times	33.41	36.01
Average degradation in each event (%)		0.0010	0.0023
Battery cost for each event (\$)		0.2	0.46

and we assume the regulation period is from 19:00-21:00. It can be seen that the average capacity losses in each frequency regulation event are 0.0010% and 0.0023% with different charger availability at home or work locations. If we assume the replacement price of the whole battery pack is \$6000 and 30% is the end of life, the battery degradation cost from the 2-hour frequency regulation (V2G) would be \$0.2 using L1 charger at home and \$0.46 using L2 charger at home.

5.4. Net load shaping

In this case, EVs are used to mitigate the fluctuation of net load caused by the high renewable energy penetration. Fig. 6 shows the average 10-year degradation of 100 EVs in both V1G and V2G scenarios. In the V1G scenario, since all EVs only adjust their charging periods to avoid charging during peak hours, it will not cause extra degradation. However, in the V2G scenario, even using L1 charger at home will significantly accelerate the battery degradation.

To clearly illustrate what happens to an individual EV, we use Fig. 7 to show the SOC of a sample vehicle when performing this grid service. It can be seen in the V1G scenario, using L1 or L2 charger at home will not make any difference on the SOC profile. The vehicle avoids charging in the evening when the net load is high. In the V2G scenario, both SOC profiles reach two valleys. For the sake of filling the net load

Figure 6: Average battery degradation of 100 EVs in the net load shaping case. In V1G scenarios, using different chargers at home and work locations does not cause different degradation results. These curves are almost overlapped. In V2G scenarios, using L2 charger at home will significantly increase the battery degradation.

valley, the vehicle has to discharge from 5:00am - 9:00 am. From 6:00pm-9:00pm, the vehicle discharges in order to shave the peak. We can also see that the SOC valleys are deeper when using L2 charger at home. If L1 charger is used at home, limited by the maximum charging/discharging rate, the vehicle is not able to discharge as much as possible to make room to store the energy for the upcoming charging event. Therefore, using L1 charger at home causes less battery degradation because of less energy output from the battery.

The above results show the battery degradation if EVs provide general net load shaping service every day for ten years. However, extreme "duck curve" may only happen on a couple of days per year in reality. Here, we assume that EVs are called to perform the net load shaping service on 20 days of a year, and calculate the battery capacity losses incurred by the V2G service. As shown in Table. 5, the V2G net load shaping increases the capacity losses by 1.18% with L1 charger at home and 2.60%

Figure 7: Battery SOC profiles of an individual EV when performing load shaping service. The SOC profiles in V1G scenarios are overlapped. The vehicle avoids charging during the load peak time. In V2G scenarios, using L2 charger at home causes more energy output from the battery. The battery keeps charging and discharging almost whole day.

with L2 charger at home after ten years, compared to the base case. Average capacity losses from each peak shaving event are 0.0059% and 0.013%. If the replacement price
 380 of the whole battery pack is \$6000 and 30% is the end of life, the battery degradation cost from the net load shaping (V2G) for one day would be \$1.18 using L1 charger at home and \$2.60 using L2 charger at home.

5.5. Comparisons across different grid services

After discussing each of these grid services, we put them together and compare to
 385 the baseline. Since V1G services do not result in extra battery degradation, we show the battery capacity losses from V2G services here. The average capacity loss of 100 EVs over 10 years for different grid services are shown in Fig. 8. V2G service hours for the peak load shaving and frequency regulation are from 7:00pm-9:00pm. For the three extreme cases, each vehicle offers the chosen grid service daily for ten years.
 390 The increases in capacity loss from performing the frequency regulation and peak load

Table 5: Average battery capacity losses of 100 EVs if they provide the net load shaping (V2G) on 20 days per year for ten years. The 10-year degradation in the driving and uncontrolled charging (base case) is 31.41%.

Charger level	Total capacity loss after ten years (%)	Average degradation from each event (%)	Battery cost for each day (\$)
Home L1 Work L2	32.59	0.0059	1.18
Home L2 Work L2	34.01	0.013	2.60

shaving are 3.62% and 5.60%, compared with the capacity loss in the driving and uncontrolled charging case. In the net load shaping case, because EVs keep charging and discharging almost whole day, the capacity loss is much more than the base case. However, in real cases, the emergency peak load shaving and extreme "duck curve" only
395 happen a couple of times per year. We simulate the cases that 100 EVs provide these services 20 times per year for ten years. The results show that the V2G services only have minor impacts on the battery degradation. For the peak load shaving, frequency regulation and net load shaping, the 10-year average capacity losses are 0.38%, 0.21% and 1.18% more than that in the base case, respectively. If we assume 30% as the end
400 of life, these grid services will shorten the life time of the battery by 0.25, 0.19, 0.51 years.

It should be noted that we focus on quantifying the battery degradation caused by different grid services in this paper. The profits of V2G for both EV owners and power grids, which depend on the system operation conditions and market mechanisms, are
405 beyond the scope of this paper. In the future work, we will continue to evaluate the benefits of V2G and profit allocation among different stakeholders.

6. Conclusions

In this paper, we present a methodology to quantify EV battery degradation caused by driving and V2G services. A semi-empirical battery degradation model is utilized
410 to calculate battery capacity loss induced by both calendar aging and cycling. Since the temperature is a key factor which effects battery degradation, we integrate an EV

Figure 8: Average capacity losses of 100 EVs by performing different V2G services for ten years. In the extreme cases, all EVs provide the chosen grid service every day. The ten-year capacity losses from peak load shaving, frequency regulation and net load shaping increase by 3.62%, 5.6% and 22.6% compared to the base case, respectively. In the more realistic cases, EVs provide V2G services for 20 times per year. The ten year capacity losses increase by 0.38%, 0.21% and 1.18%, respectively.

thermal model. Battery working parameters, including current, SOC and internal resistance, are acquired by employing the detailed EV powertrain model. Following the proposed methodology, the second by second degradation results can be obtained, with respect to time-varying working conditions of EV batteries. This methodology captures the interactions among thermal model, EV powertrain and drive cycles. Even though we use this specific semi-empirical capacity fade model in this paper, the method is not limited to this model. If there are other capacity fade models for different chemistries and battery designs, they can be also implemented into the proposed framework.

We use the proposed method to simulate the battery degradation impacts from multiple vehicle-grid services including frequency regulation, peak load shaving, net load shaping with high renewable energy penetration. The degradation impacts of these grid services are compared against the baseline case for driving plus uncontrolled charging. The simulation results lead to the following broadly applicable findings:

1. Frequency regulation and peak load shaving at power rates typical for vehicle

charging and discharging will not significantly accelerate battery degradation in comparison to the degradation incurred from driving and calendar aging. Even in the "extreme" cases in which we assume all EVs provide grid services from 7:00pm-9:00pm every day for ten years, the capacity losses from frequency regulation and peak load shaving only increase by 3.62% and 5.6%, respectively.

2. If EVs are only utilized to provide the V2G services occasionally (e.g. in emergency events), which is more realistic, then the impacts on the battery degradation will be minor. The 10-year average capacity losses are 0.38%, 0.21% and 1.18% more than that in the base case, if EVs provide peak load shaving (V2G), frequency regulation (V2G) and net load shaping (V2G) for 20 times per year.
3. The battery degradation cost of each V2G service is estimated. If we assume the cost of the whole battery pack is \$6000 and the end of life is 30%, battery degradation costs of 2-hour peak load shaping and frequency regulation are \$0.38 and \$0.20, respectively per event. Since the batteries are used for whole day in the net load shaping case, the degradation cost for a day is \$1.18.
4. Unidirectional grid services (V1G), which only adjust the charging periods, will not cause extra degradation on EV batteries.
5. Using L2 fast charger at home just has minor impacts on the battery degradation in the base case and V1G cases. However, it will significantly accelerate the capacity loss in V2G cases because of more energy output from the battery.
6. Compared with other grid services, the battery degradation from the net load shaping case is relatively higher, since the batteries keep charging and discharging almost for the whole day. Instead, we can consider other strategies, which have limited service time, to utilize EVs to help the integration of renewable energies. Using EVs to manage the steep ramping of the net load caused by renewable energies might be a prospective direction.

Acknowledgements

This work was supported with funding from the Department of Energy Vehicle Technologies Office, under the Grid Modernization Lab Consortium. Further sup-

455 port was provided by the Laboratory Directed Research & Development program at
Lawrence Berkeley National Laboratory, by the Director, Office of Science, of the
U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

The vehicle-to-grid simulator (V2G-Sim), which was developed and applied in this
study. V2G-Sim provides a valuable research, development, and deployment platform
460 for users to understand how different vehicles will perform for different drivers, and
how different vehicles will interact with the electricity grid. Stakeholders benefiting
from V2G-Sim include engineers, scientists, researchers, policy makers, analysts, and
investors across the automotive industry, electricity grid industry, policy and regulatory
sectors, and end users. More information is available at <http://v2gsim.lbl.gov>.

465 **References**

- [1] J. H. Williams, A. DeBenedictis, R. Ghanadan, A. Mahone, J. Moore, W. R. Mor-
row, S. Price, M. S. Torn, The technology path to deep greenhouse gas emissions
cuts by 2050: the pivotal role of electricity, *Science* 335 (6064) (2012) 53–59.
- [2] S. Saxena, J. MacDonald, S. Moura, Charging ahead on the transition to electric
470 vehicles with standard 120V wall outlets, *Applied Energy* 157 (2015) 720–728.
- [3] S. B. Peterson, J. Apt, J. Whitacre, Lithium-ion battery cell degradation resulting
from realistic vehicle and vehicle-to-grid utilization, *Journal of Power Sources*
195 (8) (2010) 2385–2392.
- [4] W. Kempton, J. Tomić, Vehicle-to-grid power fundamentals: calculating capacity
475 and net revenue, *Journal of Power Sources* 144 (1) (2005) 268–279.
- [5] E. Sortomme, M. A. El-Sharkawi, Optimal scheduling of vehicle-to-grid energy
and ancillary services, *Smart Grid, IEEE Transactions on* 3 (1) (2012) 351–359.
- [6] A. Y. Saber, G. K. Venayagamoorthy, Resource scheduling under uncertainty in
a smart grid with renewables and plug-in vehicles, *Systems Journal, IEEE* 6 (1)
480 (2012) 103–109.

- [7] A. Schuller, C. M. Flath, S. Gottwalt, Quantifying load flexibility of electric vehicles for renewable energy integration, *Applied Energy* 151 (2015) 335–344.
- [8] D. P. Birnie, Solar-to-vehicle (S2V) systems for powering commuters of the future, *Journal of Power Sources* 186 (2) (2009) 539–542.
- 485 [9] S. Saxena, C. Le Floch, J. MacDonald, S. Moura, Quantifying ev battery end-of-life through analysis of travel needs with vehicle powertrain models, *Journal of Power Sources* 282 (2015) 265–276.
- [10] E. Wood, M. Alexander, T. H. Bradley, Investigation of battery end-of-life conditions for plug-in hybrid electric vehicles, *Journal of Power Sources* 196 (11)
490 (2011) 5147–5154.
- [11] J. Vetter, P. Novák, M. Wagner, C. Veit, K.-C. Möller, J. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, A. Hammouche, Ageing mechanisms in lithium-ion batteries, *Journal of power sources* 147 (1) (2005) 269–281.
- [12] J. Purewal, J. Wang, J. Graetz, S. Soukiazian, H. Tataria, M. W. Verbrugge,
495 Degradation of lithium ion batteries employing graphite negatives and nickel–cobalt–manganese oxide+ spinel manganese oxide positives: Part 2, chemical–mechanical degradation model, *Journal of Power Sources* 272 (2014) 1154–1161.
- [13] G. Ning, B. N. Popov, Cycle life modeling of lithium-ion batteries, *Journal of The Electrochemical Society* 151 (10) (2004) A1584–A1591.
- 500 [14] R. Spotnitz, Simulation of capacity fade in lithium-ion batteries, *Journal of Power Sources* 113 (1) (2003) 72–80.
- [15] J. Christensen, J. Newman, Effect of anode film resistance on the charge/discharge capacity of a lithium-ion battery, *Journal of the Electrochemical Society* 150 (11) (2003) A1416–A1420.
- 505 [16] C. Zhou, K. Qian, M. Allan, W. Zhou, Modeling of the cost of EV battery wear due to V2G application in power systems, *Energy Conversion, IEEE Transactions on* 26 (4) (2011) 1041–1050.

- [17] J. D. Bishop, C. J. Axon, D. Bonilla, M. Tran, D. Banister, M. D. McCulloch, Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV, *Applied Energy* 111 (2013) 206–218.
- [18] M. Palacín, A. de Guibert, Why do batteries fail?, *Science* 351 (6273) (2016) 1253292.
- [19] J. Wang, J. Purewal, P. Liu, J. Hicks-Garner, S. Soukazian, E. Sherman, A. Sorenson, L. Vu, H. Tataria, M. W. Verbrugge, Degradation of lithium ion batteries employing graphite negatives and nickel–cobalt–manganese oxide+ spinel manganese oxide positives: Part 1, aging mechanisms and life estimation, *Journal of Power Sources* 269 (2014) 937–948.
- [20] J. Neubauer, E. Wood, Thru-life impacts of driver aggression, climate, cabin thermal management, and battery thermal management on battery electric vehicle utility, *Journal of Power Sources* 259 (2014) 262–275.
- [21] S. Saxena, J. MacDonald, D. Black, S. Kiliccote, Quantifying the flexibility for electric vehicles to offer demand response to reduce grid impacts without compromising individual driver mobility needs, Tech. rep., SAE Technical Paper (2015).
- [22] T. Markel, A. Meintz, K. Hardy, B. Chen, T. Bohn, Multi-lab EV smart grid integration requirements study, 2015.
- [23] U.S. Department of Transportation, National Household Travel Survey, 2009, <<http://nhts.ornl.gov>>.
- [24] R. V. Gopal, A. P. Rousseau, System analysis using multiple expert tools, Tech. rep., SAE Technical Paper (2011).
- [25] National centers for environmental information, <<http://www.ncdc.noaa.gov/>>.
- [26] National solar radiation data base, <http://rredc.nrel.gov/solar/old_data/nsrdb/>.

- [27] W. Kempton, V. Udo, K. Huber, K. Komara, S. Letendre, S. Baker, D. Brunner,
535 N. Pearre, A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system, <<http://www1.udel.edu/V2G/resources/test-v2g-in-pjm-jan09.pdf>>, 2009.
- [28] C. Le Floch, F. Belletti, S. Moura, Optimal charging of electric vehicles for load
540 shaping: a dual splitting framework with explicit convergence bounds, Transportation Electrification, IEEE Transactions on, 2 (1) (2016) 190 - 199.
- [29] P. Siano, Demand response and smart grids a survey, Renewable and Sustainable Energy Reviews 30 (2014) 461–478.