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Quantifying the Flexibility for Electric Vehicles to Offer Demand Response to Reduce Grid Impacts without Compromising Individual Driver Mobility Needs

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Abstract

Electric vehicles (EVs) enable improved vehicle efficiency and zero emissions in population centers, however the large loads from EV charging can stress grid systems during periods of peak demand. We apply detailed physics-based models of EVs with data on how drivers use their cars to quantify the ability for EVs to reduce their charging during periods of peak demand, i.e. as in a demand response program. A managed charging controller is developed and applied within the vehicle-to-grid simulator (V2G-Sim) which charges vehicles during demand response (DR) events only if charging is required to satisfy anticipated mobility needs for a given driver over the next 24 hours.

We find that up to 95% of EV charging loads can be removed during DR events without compromising the mobility needs of individual drivers. This value is found by comparing the charging loads of EVs using the managed charging controller against an uncontrolled charging case. Simulations are conducted with parametric sweeps of several important variables to understand the sensitivity of EV load reduction potential to these variables. For instance, demand response events are simulated at different times of day, and for different durations. It is shown that the EV charging load reduction potential is lower if DR events occur at later times of day; however the percentage reduction in EV charging load during these DR events is always above 75%. Further, we quantify the impact of uncertainty in the anticipated travel itineraries of individual drivers and it is shown that the DR load reduction potential from EVs decreases as greater levels of uncertainty must be accommodated. However, it is shown that even if managed charging for DR must accommodate substantial levels of uncertainty in individual travel itineraries, the DR load reduction potential is greater than 65%. Finally, we show that significant grid demand peaks are created if EV charging of many vehicles simultaneously resumes at the end of a DR event. We show that the post-DR peak from EV charging can be substantially reduced and pushed to later hours of the day if EV charging gradually resumes over a time window after the end of the DR event.

These findings show that EV loads are highly flexible, even while accommodating for highly uncertain individual travel needs, and that additional stress on the grid from EV charging is almost entirely eliminated during DR periods when EV charging is properly coordinated.

Introduction

Governments around the world have agreed to aggressive targets for greenhouse gas emissions reductions, however major studies have shown that meeting these targets requires widespread electrification of transportation [1]. Rapid deployment of plug-in vehicles (PEVs) soon and at significant scale will have large benefits in terms of increasing the energy efficiency of personal transportation, and decreasing harmful emissions. However, increased penetration of PEVs also has the potential to destabilize the grid at local scales (e.g. transformer overloads) or wholesale market scales by adding substantial loads at times when the grid is already stressed. For many household, commercial and industrial loads, demand response (DR) has been shown as an effective approach for reducing flexible loads at times when the grid is stressed [2, 3, 4, 5]. Flexible loads are energy consumers that can reduce or defer their operations while having little or no impact on people or facility operations. Given that reduction in demand from these flexible resources can help to ensure grid stability, several utilities and system operators have demand response programs in place where participants can be financially compensated for reducing their electricity demand during a DR event [5, 6, 7]. Participation in such programs often relies on automated response to DR signals, often using the OpenADR standard [8].

On the household scale, plug-in electric vehicles are a substantial load. As PEV adoption tends to occur in concentrated geographic areas, electrical utility-scale DR programs can help ensure the stability of distribution systems and can allow for upgrades of infrastructure to be deferred [9, 10, 11, 12]. However, participation of vehicles in DR programs can be challenging as failure to adequately charge a vehicle can leave a driver stranded during a trip. As a result of this risk, participation of PEVs in DR requires careful consideration of the individual travel itineraries of drivers with adequate margins for unexpected travel.

Several prior studies have examined the participation of PEVs in DR. For instance, several papers [13, 14, 15, 16] are dedicated to developing load control strategies for EVs. Shao et al. [13-14] propose a DR load control strategy for household appliances (including EVs) which introduces metrics for consumer choices and consumer comfort. Fan [15] and Lujano-Rojas et al. [16], further expand EV charging load controllers by factoring electricity pricing into their controllers. Additionally, on a conceptual level, Mallette et al. [17-18] explore the impact of PHEV market penetration on DR, describe financial incentives, and outline the most effective manner of using these resources. Several studies [19, 20, 21, 22, 23] have also examined load scheduling of EV charging from the perspective of aggregators, who will also likely leverage EV charging to enable other grid services such as regulation and renewables integration.

Despite the substantial magnitude of prior research in DR and grid services using EVs, to the authors' knowledge there has only been one study [24] which quantifies the flexibility of EVs for participating in DR events, and quantifies the amount of load reduction that can be achieved during DR events without adversely affecting driver mobility needs. The study by Finn et al. [24], developed a charging control algorithm that applied load shifting to the charging profiles of many vehicles to reduce demand peaks from EV charging. The study found that 34-56% of EV charging demand could be removed during peak demand hours by simply time-shifting the charging profile of a vehicle within a single charging session. Given that this study preserves the amount of energy delivered during each charging session (e.g. only power-time profiles are shifted), it is likely that further reductions in EV charging demand can be obtained by considering the actual travel needs of individual drivers. For instance, if a driver's travel itinerary only requires limited range, it is likely that an EV will not need to charge at all if a DR event were called during its charging session. The magnitude of reduced EV charging during DR events that can be obtained in this scenario can only be captured if the overall travel itinerary for each vehicle is considered, and this is the focus of the present paper.

Specific Objectives

This study quantifies the flexibility in EV charging to respond to DR events without adversely affecting individual driver mobility needs. A managed charging controller is created and integrated into the vehicle-to-grid simulator (V2G-Sim) [25-26], and several parametric simulations are run and analyzed to quantify how EV DR load reduction potential changes in response to several factors. Specifically, while preserving the ability for EVs to meet the mobility needs of drivers, this study quantifies:

1. The percentage reduction in EV charging loads during DR events that may occur at different times of day and with different DR event durations.
2. The percentage reduction in EV charging loads during DR events with different scenarios for workplace charging, in terms of both the number of vehicles that charge at work, and the type of charger (e.g. L1 or L2) that is used at workplaces.
3. The impact of accommodating different levels of uncertainty in individual travel itineraries upon the percentage reduction in EV charging loads during DR events.
4. The magnitude of post-DR peaks from EV charging that would occur if vehicles simultaneously resumed charging at the end of a DR event, and how much the peak can be reduced by gradually resuming EV charging over different durations after the end of DR events.

Percentage reductions in EV charging loads during DR events are quantified by running several parametric simulations using a DR managed charging controller in V2G-Sim and comparing the results against baseline cases where vehicles are charged in an uncontrolled way. In this context, uncontrolled charging means that a vehicle begins charging when it arrives at a location where a charger is available (e.g. at home) and does not finish charging until either it has a full battery or it departs on a new trip.

Methodology

Vehicle-to-Grid Simulator (V2G-Sim)

A simulation tool called the vehicle-to-grid simulator (V2G-Sim) [25-26] is created, validated and applied in this study to provide quantitative metrics to accomplish the above objectives. For this study, V2G-Sim is provided input data from the National Household Travel Survey (NHTS) [27], which provides a survey of the 24-hour vehicle usage profiles of a random sample of drivers across the United States, including trip start and end times, trip distances, and types of locations where vehicles are parked. Weekday travel itineraries from the San Francisco Bay Area portion of the NHTS are used within this study, resulting in 3,166 samples of weekday vehicle usage. Table 1 provides an example of the travel itinerary information provided to V2G-Sim from the NHTS data source.

Table 1. Example of travel itinerary information for a randomly selected vehicle provided to V2G-Sim. A total of 3,166 travel itineraries are provided for each V2G-Sim simulation in this format using data from the National Household Travel Survey.

Start time	**End time**	**Event type**	**Distance /Charge type** (Charger types are defined by assumptions)	**Location type**
12:00 am	7:50 am	Plugged in	L2	Home
7:50 am	8:50 am	Driving	27 mi	N/A
8:50 am	3:00 pm	Parked	N/A	Work
3:00 pm	3:10 pm	Driving	3 mi	N/A
3:10 pm	3:40 pm	Parked	N/A	Restaurant
3:40 pm	3:50 pm	Driving	3 mi	N/A
3:50 pm	7:00 pm	Parked	N/A	Work
7:00 pm	7:40 pm	Driving	27 mi	N/A
7:40 pm	12:00 am	Plugged in	L2	Home

For each type of activity (e.g. driving, plugged-in, or parked) in the travel itineraries listed in Table 1, V2G-Sim calls an appropriate sub-model which tracks energy consumption in the vehicle powertrain, or power transfer between the electricity grid and the vehicle. In this manner, each individual vehicle's battery state-of-charge (SOC) is computed on a second-by-second basis for a chosen time interval (e.g. 24 hours).

Predicting the energy consumption and battery SOC of a vehicle while it is on a given trip requires a trip-specific drive cycle of the vehicle's second-by-second velocity profile and the terrain during the trip. For the results presented in this paper, the trip-specific drive cycles are generated from EPA standard drive cycles for city, highway, and high speed driving, however trip-specific drive cycle generation methods have been built into V2G-Sim which enable drive cycles to be generated which consider traffic conditions, city or highway fractions within a single trip, etc.

For this study commercially available EVs, with specifications resembling a Nissan Leaf, are simulated in V2G-Sim to travel along the individual daily travel patterns specified by the NHTS data, using drive cycles for a specific trip. While driving, each vehicle's energy consumption and battery state-of-charge (SOC) is predicted using vehicle powertrain sub-models in V2G-Sim that are validated against measurement data [28], as shown in Figure 1. These powertrain models determine the EV's energy consumption during a trip while accounting for the high energy conversion efficiency of chemical to electrical energy in the battery, and electrical to kinetic energy in the motor.

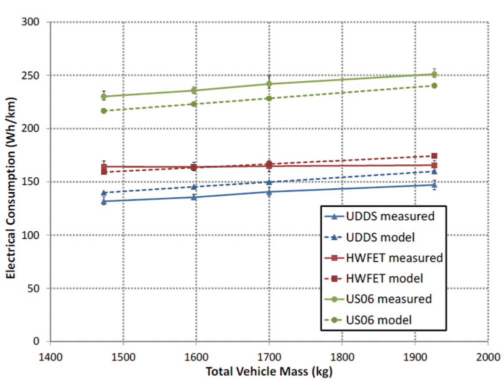

Figure 1. Comparisons of powertrain model predictions against chassis dynamometer measurement data.

Detailed powertrain models within V2G-Sim can be used 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). For this study, a single powertrain type (resembling a Nissan Leaf) is simulated on 3 drive cycles that are modified to fit trip-specific distance/duration targets specified by the NHTS input data. Thus, to enable rapidly executing simulations the detailed powertrain model is used to initialize a simpler model of energy consumption per unit distance travelled by each vehicle. Figure 2 illustrates the component-level dynamics that are considered in a detailed powertrain model of an EV, and Table 2 presents the powertrain specifications and averaged energy consumption values on the given drive cycles:

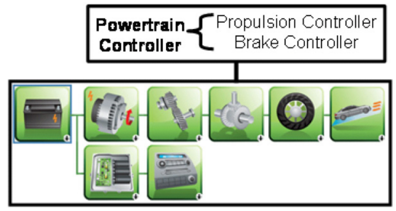

Figure 2. EV powertrain model architecture and included component-level models. Figure shows an example of a powertrain model from Argonne National Laboratory's Autonomie software. V2G-Sim can directly initialize, execute, and post-process powertrain models developed within Autonomie, or run one of several options of its own built-in powertrain models with varying levels of complexity and computationally efficiency.

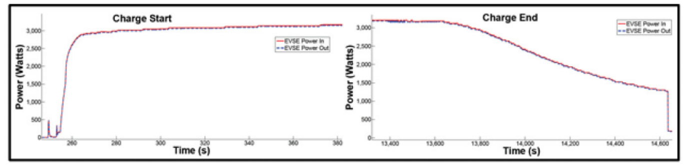

Figure 3. Measurement data of power transfer vs. time profile for a ChargePoint CT503 Level 2 charger. This data is used in calibrating the charger sub-models built into V2G-Sim for these simulations [29].

Table 2. Specifications of simulated vehicles

Vehicle & Powertrain Specifications	Vehicle mass (kg)	1550.0
	Traction motor	80 kW AC
	Total battery energy capacity (kWh)	23.83
	Usable SOC (%)	95-7.5%
	Useable battery capacity (kWh)	20.85
	Battery chemistry	Li-Ion
	Final drive ratio	7.9377
	Tire size	205/55R16
	Drag coefficient	0.285
	Frontal area (m2)	2.6
	Ancillary load (kW)	1.00
	Road Grade (%)	0%
Average Electrical Consumption while Driving (Wh/km)	EPA City (UDDS)	143.25
	EPA Highway (HWFET)	161.75
	EPA High Speed (US06)	220.60

When a vehicle parks at a location where it can plug into a certain type of charger (e.g. level 1 charger at 1.4 kW, level 2 charger at up to 7.2 kW, or fast charger), power transfer from the electricity grid to the vehicle is calculated using charging sub-models which are calibrated with measurement data, similar to the data illustrated in Figure 3 [29].

A managed charging controller is developed and applied in V2G-Sim to reduce the charging rate of each vehicle during prescribed demand response time windows, while ensuring the mobility needs of an individual driver are not compromised. The managed charging controller is described in the next sub-section.

EV Managed Charging Controller for Demand Response

V2G-Sim enables any user-specified charging or discharging control algorithm to be applied to vehicles which are simulated. With this capability, users can quantify the vehicle-level and grid-level impacts of their managed charging/discharging control algorithm. Any vehicle-grid service that requires modulated charging or discharging power profiles of individual vehicles can be simulated, including control for demand response, renewables integration, avoiding of demand charges, frequency regulation, etc. For this study, a charging control algorithm is created to simulate EVs reducing their charging during prescribed demand response periods throughout the day.

Establishing Charging Rate during a Demand Response Time Period

If a given vehicle's charging session falls within the prescribed demand response time window, the DR charging controller in V2G-Sim determines how much, if any, charging must occur for an individual vehicle during the DR time period in order to satisfy a drivers' anticipated mobility requirements. The following steps are used to calculate how much, if any, charging must occur during the DR time period:

1. The vehicle's 24 hour SOC profile, $SOC_{24\text{h}}$, is calculated using a driver's anticipated travel itinerary assuming that no charging occurred during the DR time period within the present charging session.
2. If the minimum of the 24 hour SOC forecast for the vehicle falls below an acceptable SOC level, $SOC_{\text{min allowable}}$, the vehicle must charge during the DR time period. For this study, $SOC_{\text{min allowable}}$ = 0.20 in most cases, but it is parametrically varied in a later section of this paper.

   Charging required during DR time window
   $$= \begin{cases} \text{Yes}, & \min\left(SOC_{24h}\right) < SOC_{\text{min allowable}} \\ \text{No}, & \min\left(SOC_{24h}\right) \geq SOC_{\text{min allowable}} \end{cases}$$
3. If charging is required during the DR time window, the magnitude of required charging during the DR time period is calculated as:
   $$E_{\text{req'd}} = \left(SOC_{\text{min allowable}} - \min\left(SOC_{24h}\right)\right) \times E_{\text{batt cap}}$$
   Where: $E_{\text{batt cap}}$ = 23.8 kWh, to resemble specifications for a Nissan Leaf
4. The charging power level required during the DR time period is calculated as:
   $$P_{\text{charge,DR}} = \frac{E_{req'd}}{t_{\text{DR end}} - t_{\text{DR start}}}$$
   Where $t_{\text{DR start}}$ and $t_{\text{DR end}}$ are the start and end times of the DR event.

This process is repeated for each charging event of each simulated vehicle within V2G-Sim.

Vehicle charging events that occur outside of the prescribed peak demand time window use the maximum allowable charging rate until a vehicle reaches a fully charged state.

Mitigating Demand Spikes from Vehicles Simultaneously Resuming Charging at end of Demand Response Time Period

Using the methods described in the previous section, all vehicles that are plugged in at the time $t_{\text{DR end}}$ will simultaneously resume charging at the maximum allowable rate, resulting in a sudden and sharp peak in grid demand. To mitigate this grid demand peak, vehicles are set to sequentially resume charging over a "resume charge time window" after the prescribed demand response end time, $t_{\text{DR end}}$. The time at which a given vehicle resumes charging during the resume charge time window is randomly assigned, while continuing to ensure that the mobility needs of drivers are not compromised. A later section of this paper examines the effectiveness of different settings for the duration of the resume charge time window for mitigating post-DR demand peaks.

Real World Implementation of the Proposed Managed Charging Controller

The proposed managed charging controller can be implemented on individual vehicles, on charging stations, on third party aggregation systems or at the utility or system operator level. Regardless of where the controller is implemented, it will require the following key features, information and actuation capability:

1. The ability for individual drivers to enter their planned travel itinerary and the minimum travel range they feel is acceptable to accommodate any unexpected travel.
2. The ability to modulate the charging of individual vehicles.
3. The ability to receive information on the time and duration of demand response events that are called by grid agencies.
4. The ability to verifiably determine how much charging load was shed during the DR event.
5. The location of a vehicle during a DR event, to verify it falls into a grid service territory where a DR event is called.

As an example, much of the implementation of this charging controller can be accomplished within the onboard powertrain controller of individual vehicles. A prompt within the vehicles' display panels could inform the driver of the estimated monetary benefits from entering their planned travel itinerary, and enable the driver to enter their travel itinerary and minimum acceptable range for unplanned trips. Through a communications system, the vehicle would learn about DR events throughout the day and respond by reducing charging if it deemed possible without interfering with the mobility needs of the driver. If the vehicle responds to the DR event, the powertrain controller would set the appropriate charging rate for its onboard charging systems. The vehicle's location during a DR event would be used as an important piece of information in determining whether it falls into a service area that requires DR load shedding, and how the driver will be compensated for the vehicle responding to the DR event. The powertrain controller could determine how much load it shed during the DR event by comparing its actual charging rates during the DR time window against the charging rates it would have used had it not responded to the DR event. The amount of load shedding by the vehicle during the DR event can be reported through a communication system to an aggregation service provider, utility, or some grid agency that handles the disbursement of payments for vehicles that responded to the DR event. A similar architecture could be applied for any other grid service offered by vehicles, including those which leverage bi-directional power transfer between the vehicle and grid systems.

Results

V2G-Sim and the managed charging controller described in the earlier section are applied in this study to quantify the magnitude of load reduction that can be obtained during demand response events without adversely impacting individual driver mobility needs. To quantify the load reduction potential, several parametric simulations are conducted with different times of day for DR events, for different DR event durations, for different workplace charging scenarios, and for different levels of uncertainty in travel itineraries. Additionally, a control strategy is developed to mitigate the demand peak that occurs if all vehicles simultaneously resume charging at the end of the DR period, and the effectiveness of this post-DR peak mitigation strategy is quantified through further parametric simulations. Table 3 lists the parametric simulations included in this study. The specific values in the parametric sweeps were chosen to explore a wide range of possible factors that could affect EV DR potential, while reflecting the realities of how EVs are charged at the time of this manuscript's publication.

EV Charging Load Reduction during Demand Response

EV Charging Load Profiles

Figure 4 shows the aggregate charging load for 3,166 vehicles in scenarios of uncontrolled charging and for managed charging with a demand response event occurring from 5-9 pm. The uncontrolled charging case offers a baseline comparison of the load profile before implementing demand response control of EV charging. By comparing the two plots, the percentage reduction in load from the managed charging controller can be quantified. As shown in the inset plot in Figure 4, the percentage reduction is calculated for each time step and the maximum, average, and minimum load reduction is determined during the DR period. Figures 5, 6, 7 show the results from parametric simulations by plotting the average percentage load reduction as the main data points, while the length of uncertainty bars indicate the maximum and minimum percentage load reduction during the DR event. Additionally, Figure 4 demonstrates that V2G-Sim quantifies the magnitude of the post-DR load peak if all vehicles resume charging simultaneously. The peak is unacceptably high, and therefore the final sub-section (with Figure 8) explores the effectiveness of strategies to reduce the post-DR peak by gradually resuming charging of vehicles over a pre-defined duration which is parametrically varied.

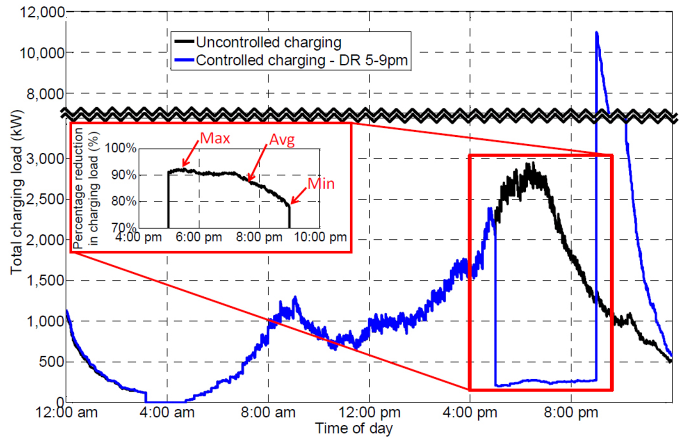

Figure 4. Total EV charging load profiles for 3,166 vehicles for uncontrolled charging scenario and managed charging for DR. DR scenario shows the maximum magnitude of load reduction that can occur for a DR event between 5:00-9:00 pm without adversely impacting driver mobility needs. The inset plot quantifies the percentage reduction in charging load during the DR time period, with labels for the maximum average and minimum percentage reduction in total charging load.

Table 3. Parametric simulations to quantify the flexibility of EVs to reduce charging loads during demand response

Parameter(s) of interest	Corresponding figure	Charging power level	Workplace charging scenario(s)	DR start time	DR event duration	Post-DR charge resumption duration	Minimum allowable SOC in DR control
DR start time and duration	5A	L2 Home, L1 Work	40% workplace charging	07:00 – 20:00	1, 2, 4 hours	0	20%
	5B	L2 Home, L2 Work					
Workplace charging scenarios	6A, 6B	L2 Home, L1 Work	Only req'd charging	07:00 – 20:00	2 hours	0	20%
		L2 Home, L2 Work	40% workplace charging				
			100% workplace charging				
Uncertainty in travel itinerary	7	L2 Home, L2 Work	40% workplace charging	07:00 – 20:00	2 hours	0	10%, 20%, 30%, 40%, 50%
Post-DR load peak	8A, 8B, 8C	L2 Home, L2 Work	40% workplace charging	16:00 – 18:00	1 hour	0, 30 min, 1 hour, 2 hours, 3 hours, 4 hours	20%

Charging Load Reduction during Different Demand Response Event Timings and Durations

Figure 5 quantifies the percentage reduction in EV charging load during DR events at different times of day, and spanning different DR event durations. Each simulation is for a case where the reserve SOC for unexpected trips in the DR charging control is 20%, vehicles resume charging right at the end of the DR period, and 40% of vehicles are charged at workplace locations. Figure 5(A) shows results for cases where vehicles charge on L1 chargers at workplaces, while Figure 5(B) shows results for cases where vehicles charge using L2 chargers at workplaces.

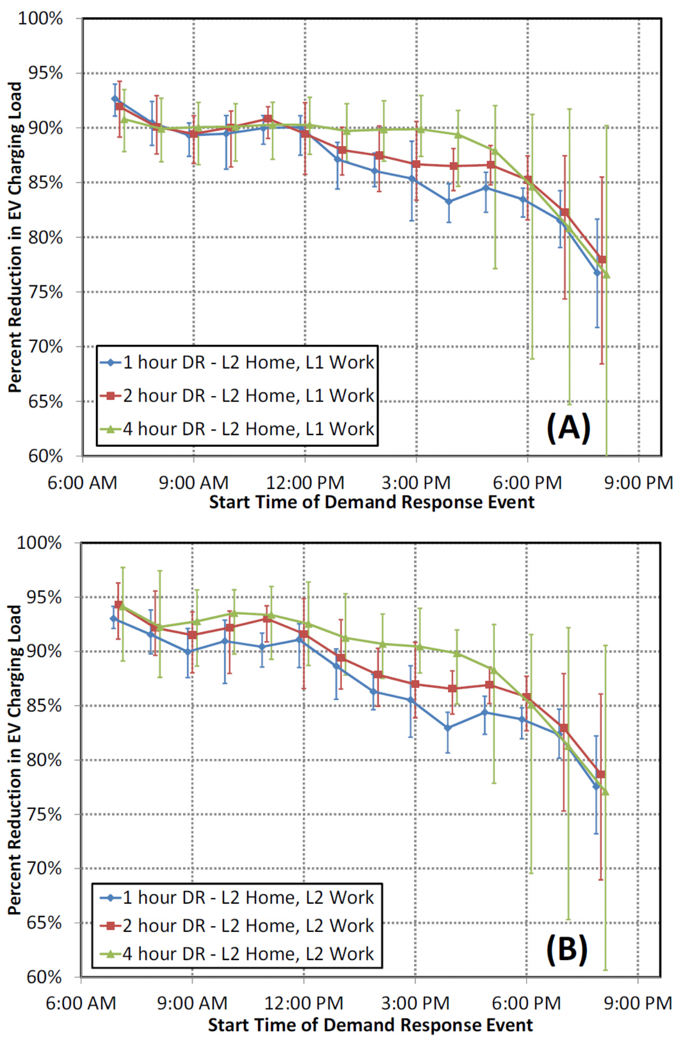

Figure 5. Percentage reduction in EV charging loads during DR events without adversely impacting driver mobility needs, for DR events occuring at different times of day and for different durations. DR controller settings: $SOC_{min,allow}$=20%, t_{resume}=0, 40% workplace charging scenario.

The results in Figure 5 show that DR load reduction potential decreases later into the day, but the average DR percentage load reduction is uniformly above 75% and as high as 95%. A 75% load reduction potential is particularly high and indicates that EV charging loads are highly flexible. The high load reduction potential result is especially noteworthy because this load reduction occurs without adversely affecting the mobility needs of individual drivers.

Figure 5 shows that the span between maximum and minimum load reduction potential during a single DR event increases as the DR event occurs later in the day, and as DR events span longer time durations. Furthermore, by comparing Figure 5(A) and Figure 5(B), it can be seen that the type of charging at workplaces (e.g. L1 or L2) does not have a significant impact on the magnitude of DR load reduction potential. Finally, Figure 5 shows that the percentage load reduction potential increases slightly when the load reduction is spread out over longer DR event durations.

Charging Load Reduction for Different Workplace Charging Scenarios

Figure 6 quantifies the percentage reduction in EV charging load during DR events at different times of day, and for different workplace charging scenarios. Each simulation is for a case where the reserve SOC in DR control is 20%, and vehicles resume charging right at the end of the DR period. Three workplace charging scenarios are simulated, including: 1) only EVs which require workplace charging are plugged in at work, 2) 40% of vehicles that go to work plug in at workplaces, 3) all vehicles that go to work are plugged in at workplaces. Figure 6(A) shows results with L1 chargers being used at workplaces, while Figure 6(B) shows results with L2 chargers being used at workplaces.

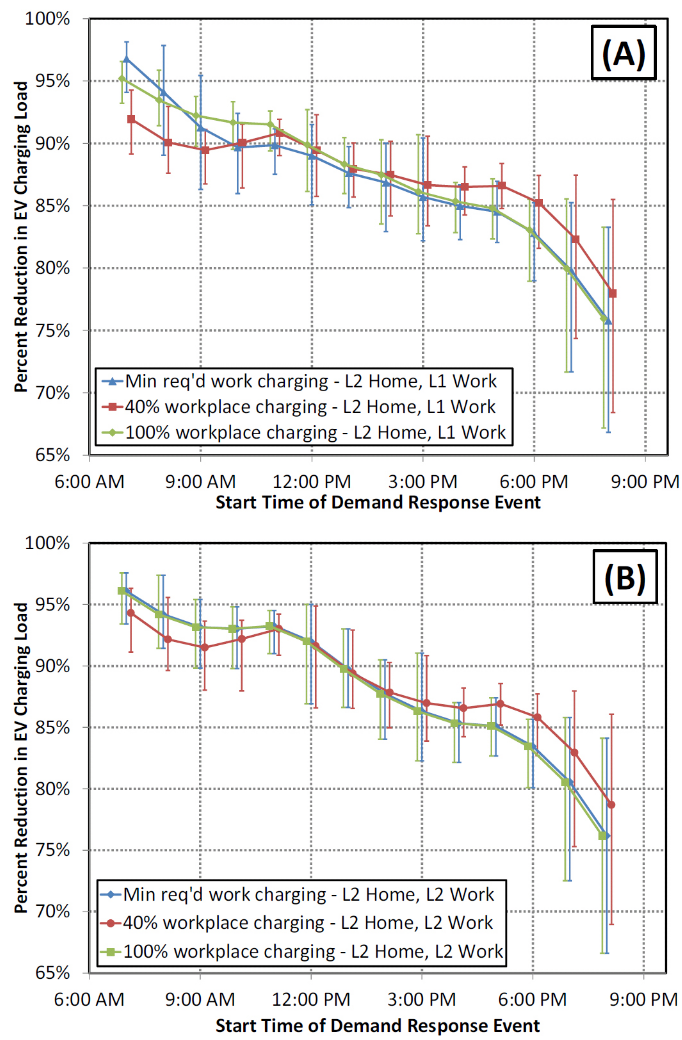

Figure 6. Maximum percentage reduction in EV charging loads during DR events without adversely impacting driver mobility needs, for different fractions of vehicles charging at work and for DR events occuring at different times of day. DR controller settings: $SOC_{min,allow}$=20%, t_{resume}=0, t_{DR}=1 hour

The results in Figure 6 show that the fraction of vehicles charging at work does not significantly impact the DR percentage load reduction potential. It is important to note, however, that the percentage reduction in load is also affected by the baseline load which is changing in each of the three workplace charging scenarios, with baseline loads being higher in cases with more vehicles plugged in at work. Consistent with Figure 5, Figure 6 shows that DR load reduction potential is lower when DR events occur later in the day.

Impact of Accommodating Larger Uncertainties in Travel Itinerary

Thus far the results and corresponding discussions are based on the availability of nearly perfect knowledge of each vehicle's travel itinerary over the upcoming 24 hours. However in the real world people will make unexpected trips leading to uncertainty in the travel itinerary. The impact of this uncertainty in travel itineraries can be quantified by setting the managed charging controller to charge vehicles during DR events so that higher reserve SOC is available for unexpected trips, corresponding with higher specified values for the controller's $SOC_{min\ allowable}$ parameter. With these higher reserve SOC settings, vehicles will have greater reserve range available to accommodate unexpected trips.

Figure 7 presents the results of parametric simulations to quantify how accommodating greater uncertainties in travel itinerary will impact percentage load reduction capabilities during DR events. Each simulation is for a case where vehicles resume charging right at the end of the DR period, and 40% of vehicles are charged at workplace locations using L2 chargers at home and at work, using 2 hour DR event durations.

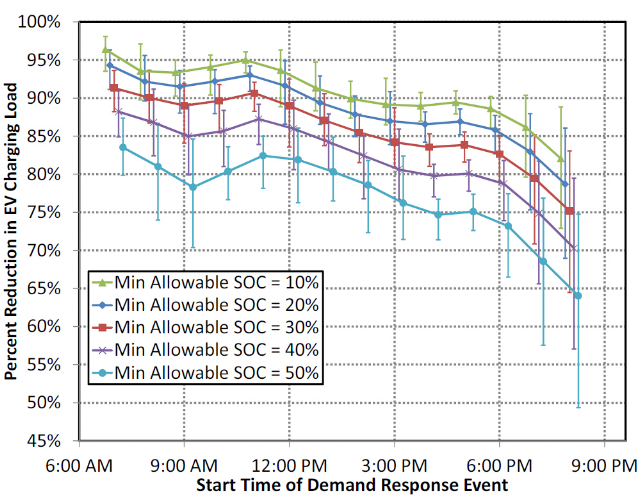

Figure 7. Maximum percentage reduction in EV charging loads during DR events without adversely impacting driver mobility needs, for different reserve SOC values and for DR events occuring during different times of day. Greater values in reserve SOC enable EVs to accommodate greater levels of uncertainty in travel itinerary. DR controller settings: t_{resume}=0, t_{DR}=2 hours, 40% workplace charging scenario.

The results in Figure 7 show that the DR percentage load reduction potential decreases as greater levels of uncertainty in vehicle travel itinerary must be accommodated. Though the DR reduction potential decreases, it is important to note that the magnitude of DR load reduction is still substantially high (>65%) even when the DR controller aims to preserve 50% reserve SOC for unexpected trips.

With 50% reserve SOC, vehicles will still be able to accommodate unexpected travel of substantial trip distances. From the results in Figure 7 it can be concluded that over 65% of EV charging load can be removed during DR events even if there is substantial uncertainty in trip itineraries.

Mitigating Post Demand Response Load Peaks

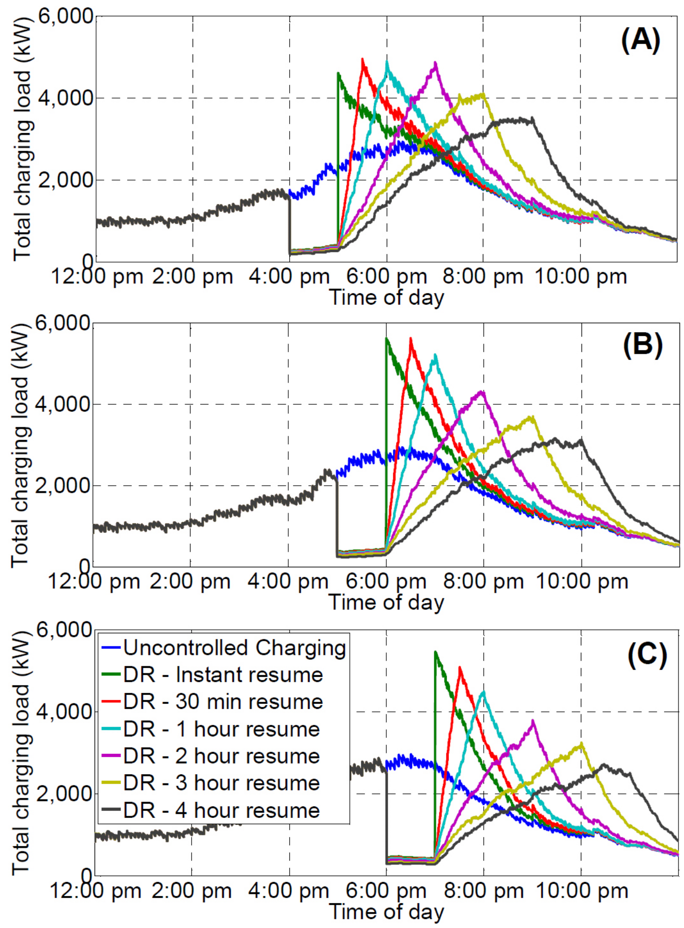

Figure 8. EV charging load profiles for 3,166 vehicles with demand response occuring at (A) 4-5 pm, (B) 5-6 pm, and (C) 6-7 pm. Different load profiles quantify the ability to reduce post-DR demand peaks by gradually resuming charging of EVs either instantly after the DR end time, over 30 minutes, 1 hour, 2 hours, 3 hours, or 4 hours.

As shown in Figure 4, there are substantial load peaks that result if vehicles simultaneously resume charging at the end of DR events. This section quantifies the effectiveness of a strategy to mitigate the post-DR load peak by gradually resuming the charging of vehicles over some duration after the end of the DR event. Vehicles are set up to resume charging at a randomly chosen time during a specified post-DR resume charging period. For instance, in a simulation where the DR event ends at 5 pm and where the post-DR resume charging period is set as 1 hour, each of the 3,166 simulated vehicles will resume charging at a randomly chosen time between 5-6 pm. Parametric simulation results are presented in this section to quantify the magnitude of peak reduction from different post-DR resume charging settings, from 30 minutes to 4 hours. Results quantifying the peak reduction potential are presented in Figure 8 for cases with a 1 hour DR event, 20% reserve SOC setting, and for a scenario with 40% workplace charging using L2 chargers. Figure 8(A) shows simulation results for DR occurring from 4-5 pm, Figure 8(B) shows DR from 5-6 pm, and Figure 8(C) for DR from 6-7 pm.

The results in Figure 8 show that offsetting the time for EVs to resume charging over some duration has mixed effects on post-DR peak reduction. Figure 8(A) shows that the post-DR peak actually increases as the resume charging duration increases up to 2 hours, but the decreases for a 3 hour or 4 hour resume charging window. Figure 8(B) and Figure 8(C), however, show that there is always a decrease in the post-DR peak as the resume charging duration increases - this is the trend that is expected. Figure 8(A) does not show the expected trend because too many cars arrive at home and begin charging between 5-7 pm, and thus the added load from charging the additional vehicles outweighs the reduced charging from distributing the resume charging time over longer durations. All three cases in Figure 8 show that the peak demand is moved to later hours with longer resume charging durations, and with a resume charging duration of 4 hours the magnitude of the post-DR peak is similar to the charging demand peak that occurs in the uncontrolled charging case.

Summary/Conclusions

This study quantifies the magnitude of EV charging that can be removed during demand response events, without compromising driver mobility needs. A simulation platform, called the vehicle-to-grid simulator (V2G-Sim), was developed and applied to predict the battery state-of-charge profile for N number of vehicles following different itineraries of when they drive, park, and charge. Vehicle usage itinerary data from the San Francisco Bay Area region of the National Household Travel Survey was used within V2G-Sim with the assumption that each vehicle had specifications similar to a Nissan Leaf. A managed charging controller was developed which, if a vehicle is plugged in during the demand response period, charges vehicles only if it is required to satisfy individual driver travel needs over the next 24 hours.

Simulations were run to quantify the percentage load reduction in EV charging that can be obtained without adversely impacting driver mobility needs, and parametric simulations were used to quantify how the load reduction potential changes with different factors. The parametric simulations included sweeps of the timing and duration of DR events, different workplace charging scenarios, and accommodating different levels of uncertainty in travel itineraries. Additionally, the peak demand that occurs if vehicles simultaneously resume charging at the end of a DR event is quantified, and the effectiveness of a strategy to reduce this peak by distributing the resume charging time over a specified duration is quantified. The simulation results lead to the following broadly applicable findings:

1. EV charging loads are highly flexible. For demand response events occurring at any time of day, with DR event durations as long as 4 hours, more than 75% of charging loads can be removed without adversely affecting individual driver mobility needs, with the potential load reduction being as high as 95% in some cases.
2. The percentage load reduction decreases as DR events are called later in the day.
3. The fraction of vehicles that charge at work locations and the type of charger (e.g. L1 or L2) used at work places does not substantially affect the percentage load reduction potential of EV charging during DR events.
4. The percentage load reduction potential is greatest if there is good knowledge of the future travel itinerary for individual vehicles. The load reduction potential decreases as greater uncertainty in travel itineraries must be accommodated. However, even in cases with substantial uncertainty in travel itineraries, over 65% of EV charging load can be shed during DR events without adversely impacting driver mobility needs.
5. Substantial demand peaks are created if EVs simultaneously resume charging at the end of a DR event. This post-DR demand peak can be mitigated by gradually resuming EV charging over some duration after the DR event. As the duration of this resume charging period is increased, the post-DR peak becomes smaller in magnitude and is shifted later. With a 4 hour resume charging window duration, the post-DR peak has a similar magnitude as the peak demand in an uncontrolled charging case.

The findings of this study show that with proper coordination in their charging, EV charging loads on the grid can be almost entirely eliminated during peak demand periods without compromising the mobility needs of drivers. These findings suggest that EVs are highly flexible loads and are very conducive for participation in demand response programs. An implementation approach is proposed which enables participation by EVs in demand response programs without compromising the mobility needs of individual drivers.

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The vehicle-to-grid simulator (V2G-Sim), which was developed and applied in this study, is available for use by all stakeholders. V2G-Sim provides a valuable research, development, and deployment platform 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.

Definitions/Abbreviations

ADR - Automated demand response

DR - Demand response

EPA - Environmental Protection Agency

EV - Electric vehicle

HVAC - Heating ventilation and air conditioning

NHTS - National household travel survey

PEV - Plug-in electric vehicle

SOC - State-of-charge

V2G - Vehicle-to-grid

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