Electric Vehicle Energy Storage as a Solution to the Duck Curve Problem

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1. Introduction

Home owners in California have begun adopting residential solar systems at very high rates in recent years. As of 2017, 11.8% of the power generated in California is Solar [1], and by 2050 the state is planning to mandate that 50% of the energy produced by its electricity retailers be renewable. This transition is estimated to lower greenhouse gas emissions in the state by 35.8 million metric tons of carbon dioxide equivalent [2], but that comes with some caveats, those reductions in emission are projected to add 15% to the cost of electricity for users, and issues with grid instability can get worse without investing in energy storage solutions [3].

Due to the intermittent and unpredictable nature of renewable energy sources [4], a mismatch between daily mean and peak energy demand is becoming larger, this difference, often represented by a duck shaped daily demand plot, is expected to become more exaggerated over time [5]. The use of centralized energy storage solutions maintained by the electricity supplier is a possible solution, but that will come at a cost which carries over to the users in their utility bills. Another trend that is expected to help with this problem is a time of use rate [6], if users had a deterrent driving them to reduce usage during peak periods, electricity demand and production can get more balanced [7], but that can only help to a limited degree with no local storage or alternative energy solutions available to the users.

With no energy storage, solar peak production happens around noon which coincides with low residential electricity demand as people are out at work or in school, and if they have a thermostat schedule, their HVAC system would have a setback during that time as well. Around 5 or 6 PM, people start getting back from work, turning on their HVAC system, increasing the plug loads, and electricity usage, this coincides with a drop in solar energy production, which adds to the gap between peak and average demand.

Multiple studies have proposed vehicle to grid energy storage as a possible solution to the grid instability problem [8, 9]. the proposed usage case for EV owners is to charge their cars from the grid at off peak hours or during peak solar production, while at work, or at night, and then to use an inverter connected to the car and discharge the battery to provide energy during the peak demand period [10, 11]. Prior work investigated the drawbacks of vehicle to grid storage from the perspective of its users, such as the negative effect on the vehicle battery life [12]. Other studies also looked at possible solutions to that problem, like a peak demand electricity surcharge [13].

2. Objectives

This study aims to evaluate vehicle to grid energy storage as a possible solution to the demand instability problem by analyzing its possible effects on the grid and assessing the associated costs to prospective users.

3. **Methodology**

3.1. Simulating Residential Units and Recreating a Problematic Daily Demand Curve:

A total of six residential units in LA county, California were modeled using BEOpt. Three of the six units were modeled with oversized PV panels to simulate grid solar buyback, the other three were modeled with no solar generation. Four distinct layouts were used to reflect L.A. housing size distribution, which, according to the US Census bureau [14], shows that 71% of all houses in LA are 4, 3 and 2-bedroom homes. 1-bedroom homes are also common (19%) but those are more likely to be attached units since 49.3% in L.A. are. This study excludes attached units / apartment complexes as the ability to install and utilize V2G technology requires the units to be owner occupied.

One of the modeled layouts is a 2670 sq. ft, 4- bedroom, 2-story home [Figure 1], the layout was used twice, once with a 3kWh solar panel, and once without. A 14 SEER heat pump was modeled in those two units and the cooling/heating setpoint schedules were set to have a setback from 9 to 5 PM on weekdays. The heating setpoint was set to 71 F with a 65 F setback, while the cooling setpoint was set to 76 F with an 85 F setback. Washer/Dryer usage was setup with a modified schedule to only occur after 8 PM, and the kitchen appliance schedule was set to have a peak at 6PM.

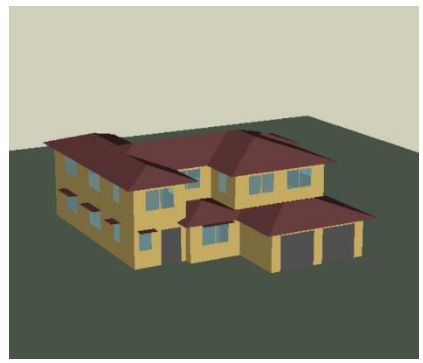

Figure 1: Four-Bedroom House Model

A 1320 Sq. ft, 3-bedroom, 1-story home was modeled with the same cooling and heating schedules, A 13 SEER AC with a furnace, and the same washer/dryer usage schedule and kitchen appliance schedule. The 3-bedroom layout was also simulated with/without a 2.5 kWh PV panel.

Two layouts for a 2-bedroom house were modeled [Figure 2]. One of them is a small 990 sq. ft layout modeled with a 1.5 kWh solar cell, the other is a two-story 2460 sq. ft layout modeled with no solar generation. Both have a fixed setpoint schedule (71 in heating and 76 in cooling), a single stage AC unit with gas heat, and they share the same kitchen appliance and washer/dryer schedules as the 4 and 3-bedroom units.

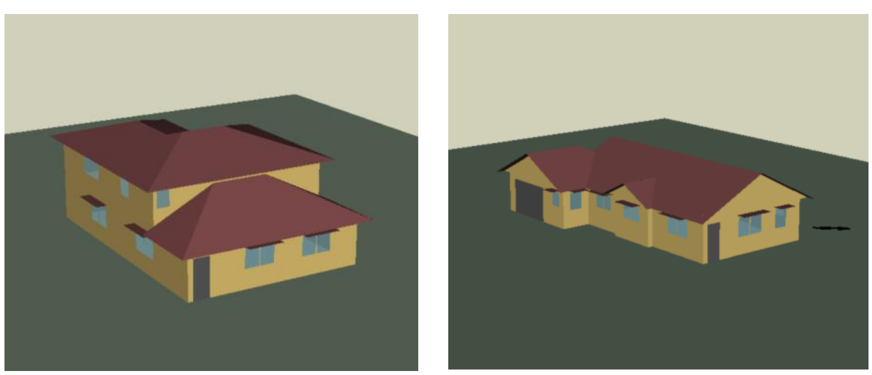

Figure 2: Two-Bedroom House models

The six houses were simulated for one year and an hour by hour electricity demand usage and solar production data were exported to an excel sheet using BEOpt. MATLAB was then used to process the data and calculate the mean daily demand, mean solar production and the mean net demand for each house. The mean daily demand is calculated for a grid connected to 6000 homes with the 6 layouts distributed evenly (6x1000), the grid demand calculation accounts for solar buyback from homes with oversized PV panels, and assumes no line losses in either direction.

3.2. Simulating Battery degradation over time:

Accelerated lithium ion battery degradation for electric vehicles is a concern that could prevent high adoption rates of vehicle to grid technology [12]. The charge/discharge schedule can be optimized to have a minor effect on battery life, and in some cases, even improve it when predictive partial charging techniques are used [15]. Lithium-ion batteries can be modeled using a semi-empirical degradation model [16]. A semi empirical model can be off by 10% on data it was calibrated on and 30%-60% off on uncalibrated test data [17], those models have downsides when compared to more detailed models like the finite element electrochemical ALST model [18], but they are much simpler and faster to run. Semi-empirical degradation models also requires a fewer number of parameters compared to regression models [19, 20]. The semi empirical model developed by Wang, et al [20] was used in this study.

$$QLoss = B.\exp\left(\frac{-31500 + 370\ x\ CRate}{R\ x\ T}\right).Ah^{0.552}$$

Where:
QLoss: The percentage of capacity loss
B: The pre-exponential factor.
CRate: Measure of the rate at which a battery is discharged relative to its maximum capacity.
*R: T*he gas constant
*T: T*he absolute temperature
*Ah: T*he total charge throughput of the cell

$$Ah\ =\ (DepthofDischarge).(ChargeCycles).(FullCellCapacity)$$

To simulate EV battery discharge due to driving, a driving distance of 12,000 mile per year is assumed. The annual mileage is divided into two daily commutes, a morning commute that happens between 8 and 9AM and an evening commute between 5 and 6 PM. The distance driven for each commute has some noise injected to simulate day to day variation. The discharge rate is calculated assuming a combined 0.28 kWh per mile car efficiency, and an average speed of 30MPH +- 5MPH of noise. The driving discharge simulation was repeated for each of the 6 houses. Two charging and discharging behaviors were modeled and analyzed using MATLAB. Both assume a 40 kWh EV battery capacity:

Unoptimized charging with no V2G usage: In this case, the user charges their car after they get back home. The charge starting time is set to be between 5 and 9PM with uncertainty. The charger used is assumed to be a 16A single phase charger with a charging rate of 3.7 kW. Charging time and energy will depend on the length of the two commutes in this case.

Optimized charging with V2G usage: In this case, the car determines when to charge or discharge itself to power the house while plugged depending on the house demand. To do that, the real time mean demand is calculated as a 48-hour time average approximated using a low pass filter. If the current demand is lower than the mean in off peak hours, the car charges itself at a rate that equalizes the demand with the mean (Up to the 3.7 kW charger limit). If the current house demand is higher than the mean demand at peak hours, the car will discharge its battery through the inverter (Up to 5kW) to reduce the load on the grid and get the demand closer to its mean. Peak hours are set to be between 5 PM and 0 AM. The car battery is not allowed to go below 25% to power the house.

$$if\ \big((On\ Peak) \cap (StateOfCharge > 25\%)\big) \rightarrow\ Discharge\ at\ a\ rate = \min\big(5\ , (Demand - MeanDemand)\big)$$

$$if\ \big((off\ peak)\ \cap (StateOfCharge < 100\%)\big) \rightarrow\ Charge\ at\ a\ rate = \min\big(3.7, (MeanDemand - Demand)\big)$$

Both unoptimized and optimized charging with V2G usage were simulated on all 6 houses, and MATLAB was used to calculate the updated house mean daily demand, and daily net demand for the houses. The grid demand baselines were also calculated.

The semi empirical battery model was used to predict the degradation level in each scenario. Battery replacement was assumed to occur at a 20% capacity reduction level, and from that, the predicted battery life with/without V2G usage is calculated for each of the six house models.

3.3. Calculating V2G adoption costs and a time of use electric utility schedule to balance it out:

The cost for EV battery replacement is assumed to be $7,500. This cost is divided over the life of the battery, so if the battery lasts for 10 years, the annual battery degradation cost is calculated as $7,500/10 = $750. To quantify the effect of V2G usage on EV batteries, the predicted battery life without V2G is used as a baseline:

$$Cost\ of\ V2G\ On\ Battery = \frac{7{,}500}{BatteryLife_{V2G}} - \frac{7{,}500}{BatteryLife_{No\ V2G}}$$

The cost for buying and installing a 5kW inverter is assumed to be $2,500. The battery degradation and inverter costs are calculated for each house.

To encourage adoption, the electric utility rate should be set to at least recover the cost of using V2G on the user. Users save money when they charge their cars at a low rate and discharge it to the house when the rate is higher. The total power transferred from the high to low rate multiplied by the price difference is the total amount the user saves. Making that saving equal to the cost gives the minimum difference between peak and off-peak electricity rate:

$$Rate\ Difference = \frac{Cost\ of\ V2G\ (\$)}{Total\ V2G\ Energy\ Transfered\ (kWh)}$$

The difference is distributed over the peak and off-peak periods:

$$Off\ Peak\ Rate = BaselinePrice - \frac{Rate\ Difference\ x\ Peak\ Hours\ in\ a\ Day}{24}$$

$$Peak\ Rate = BaselinePrice + \frac{Rate\ Difference\ x\ OffPeak\ Hours\ in\ a\ Day}{24}$$

4. **Results and Discussion**

4.1. Daily demand curve with no EV Charging:

Figure 3 shows the mean daily demand of a 2-bedroom house with solar generation. The net demand here is the solar generation subtracted from the house demand on an hour by hour basis, then averaged over the full year. Note the exaggerated dip in net demand occuring towards the middle of the day and the peak coinciding with people getting back home after 6 PM, both features are charectaristic of the duck curve.

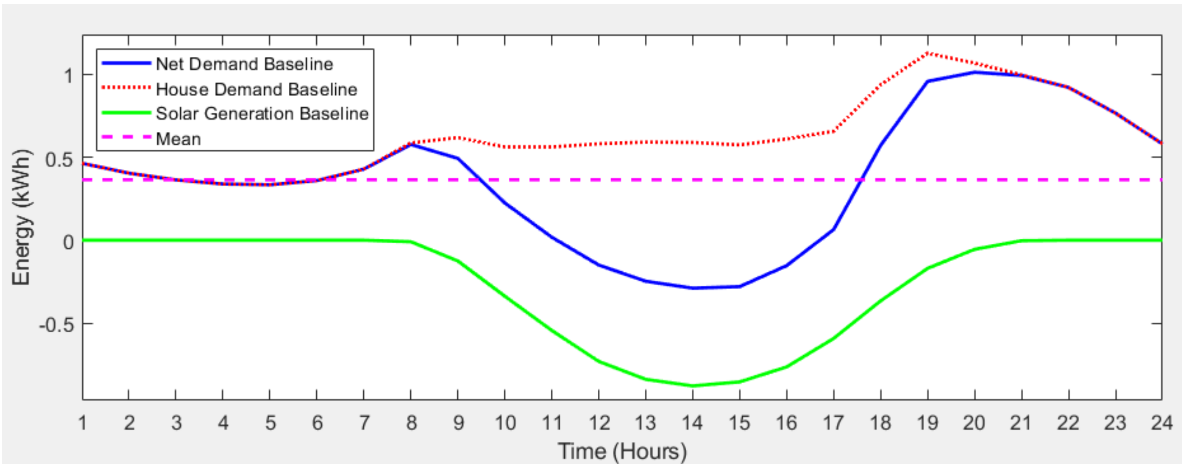

Figure 3: Mean daily demand of a 2 Bedroom house with solar generation and no EV charging

Figure 4, shows the mean daily demand of a 3-bedroom house with no solar generation. The net demand matches the house demand in this case as there is no solar generation. Having no solar generation removes the dip in net demand centered at peak solar production, however, the demand still peaks arround the same time, after people get back home arround 6 PM. This is due to the increase in appliance usage schedueled in the BEOpt simulation, and due to the increase in conditioning equipment load which needs to recover from the schedueled setback.

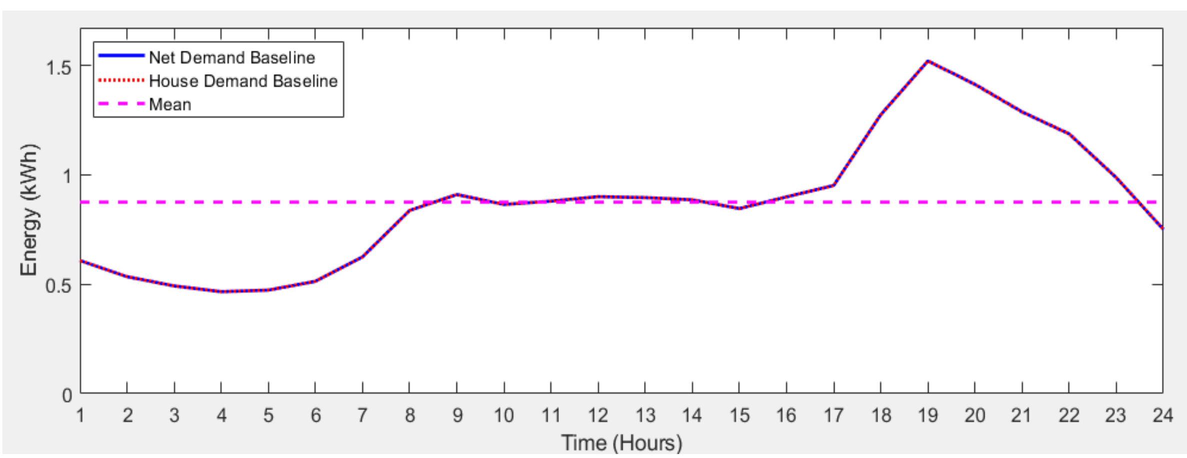

Figure 4:Mean daily demand of a 3 Bedroom house with no solar generation and no EV charging

The mean daily demand for the grid made up of 6000-home evenly distributed house models can be seen in figure 5. The demand matches the shape of an exaggerated duck curve, with a dip close to noon and a peak between 6 and 7 PM. Note the second, flatter dip centered around 4 am and extending over midnight to the early morning hours. The shape of this curve can be used to find the time to apply peak rate electricity pricing. The 7-hour period between 5PM and midnight was selected for peak pricing.

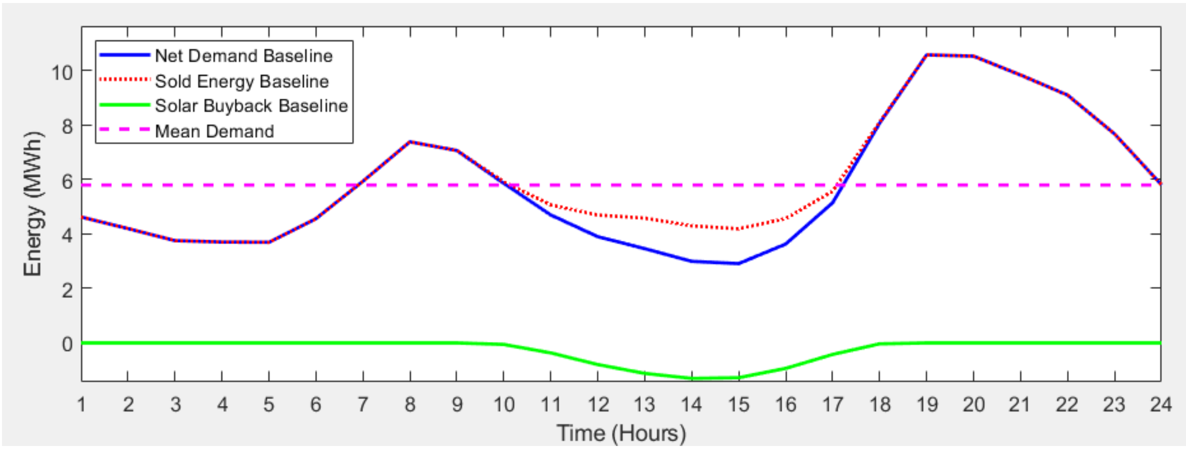

Figure 5: Grid mean daily demand with no EV charging

4.2. Daily demand curve with unoptimized EV Charging:

Figure 6 shows the mean daily demand and EV battery level of a 4-bedroom house with solar generation and EV charging. The demand was split between house demand (in blue) and EV charging demand (yellow). Charging in this case was set to occur after people get back home, which coincides with the house demand peak, this causes the net demand peak to be exaggerated further. Note the two distinct drops in EV battery life after 8 AM in the morning, and after 5 PM in the evening, corresponding to the two simulated daily commutes.

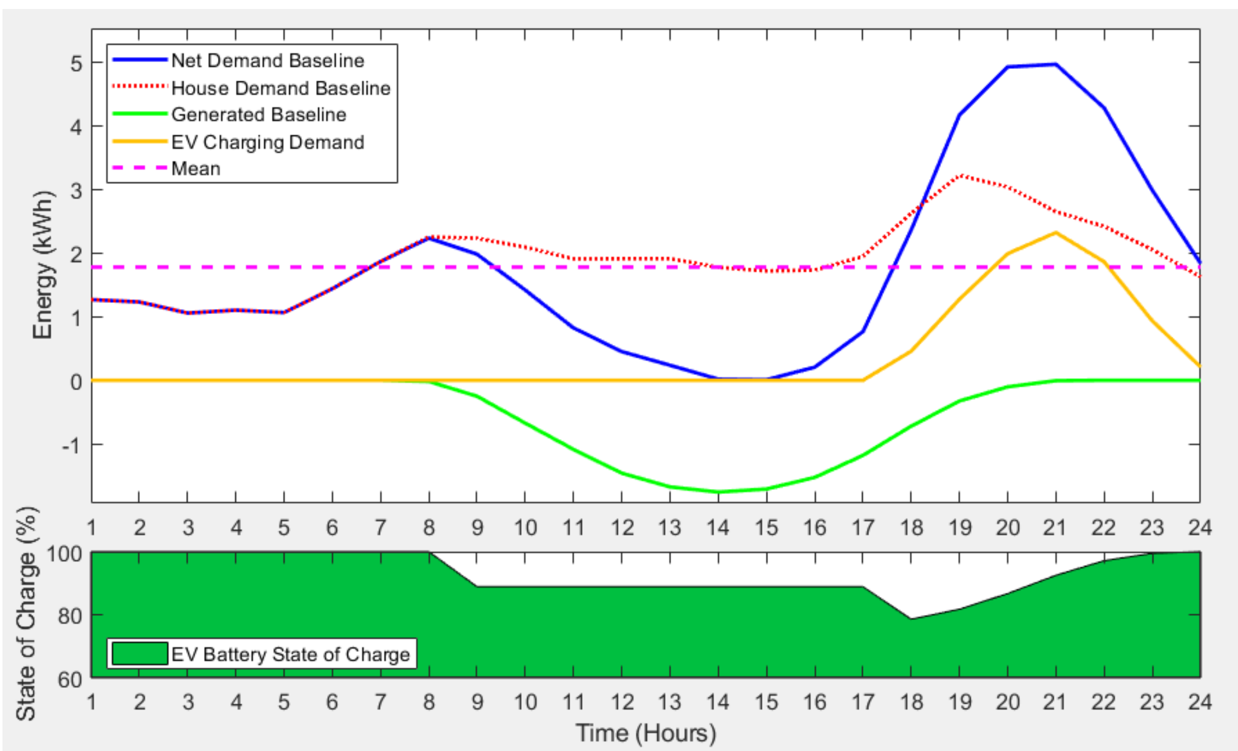

Figure 6: Mean daily demand and battery state of charge of a 4-bedroom house with solar generation

Figure 7 shows the mean daily demand and EV battery level of a 2-bedroom house with EV charging and without solar generation. The demand was again split between house demand (in blue) and EV charging demand (yellow). Charging behavior and commute timing was set in a similar manner to figure 6. The exaggerated net demand peak is more prominent here as the baseline house demand is relatively low for the 990 sq. ft. house.

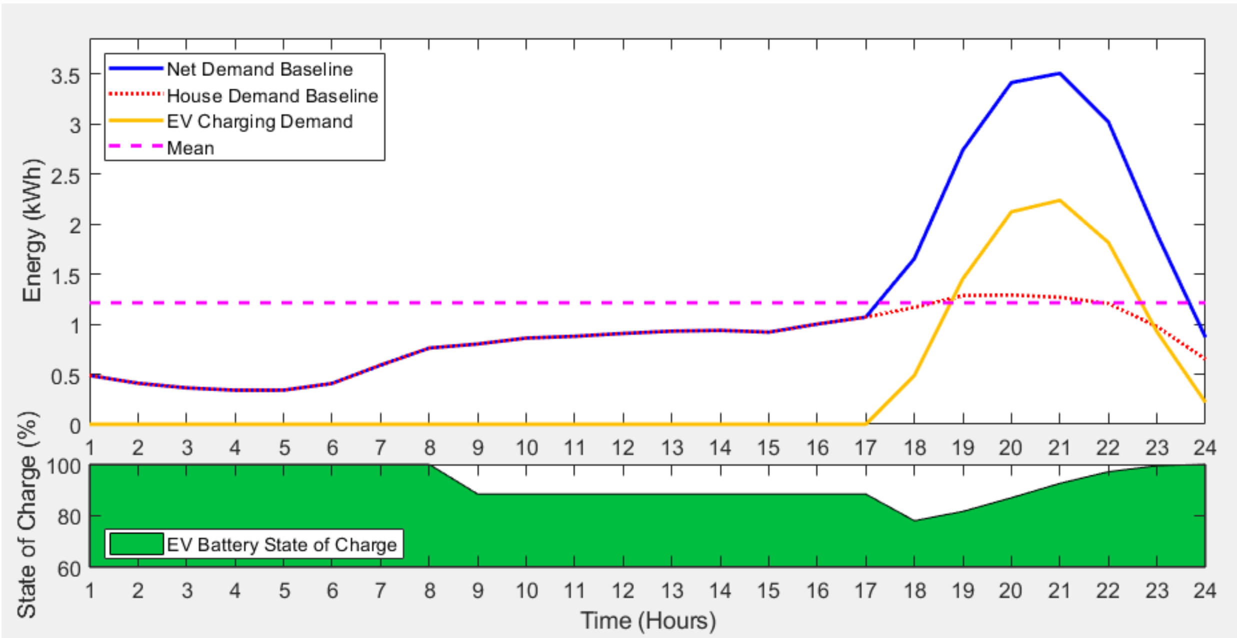

Figure 7: Mean daily demand and battery state of charge of a 2-bedroom house with no solar generation

The net load on the grid updated to include EV charging demand is shown in figure 8. Although the timing for the peak did not change by much, the amplitude increased significantly compared to figure 5. The difference between peak and mean demand went from 5 MWh to 15 MWh, this was more significant than expected, but it reflects the assumed 100% EV adoption rate with a very distinct shared charging times between all users.

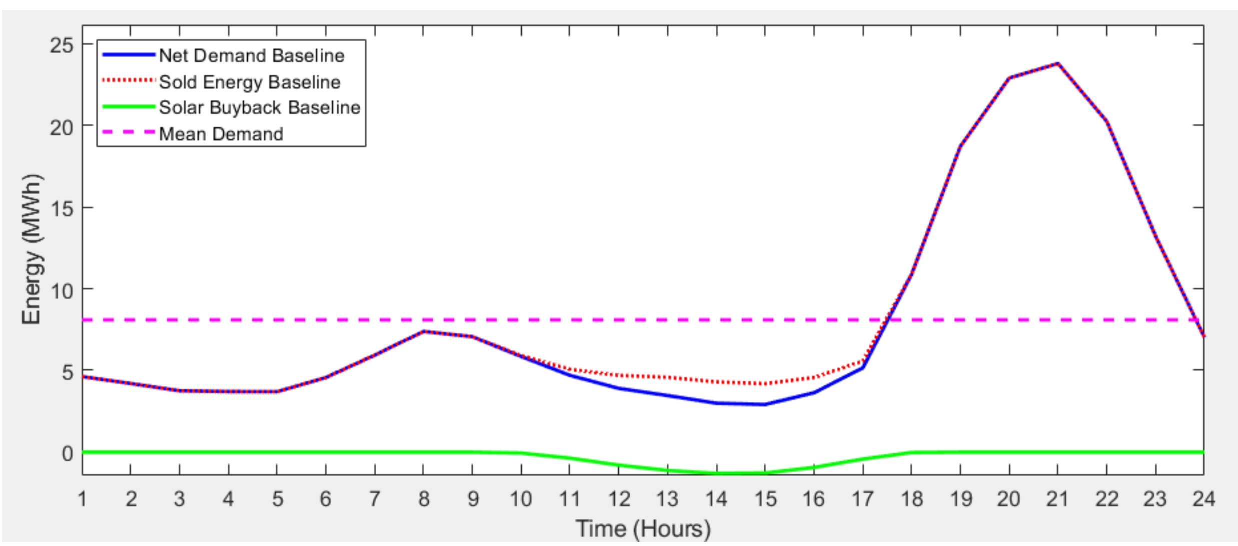

Figure 8: Grid mean daily demand with unoptimized EV charging

4.3. Daily demand curve with optimized EV Charging and V2G usage:

Figure 9 shows the mean daily demand and EV battery level of a 3-bedroom house with solar generation and optimized EV charging/V2G usage. V2G energy provided at peak times was added to the plot (black line). Although the average state of charge plot shown indicates that battery level stays over 75%, the battery level does drop below that, but taking the average over a year of simulated data evens the curve out.

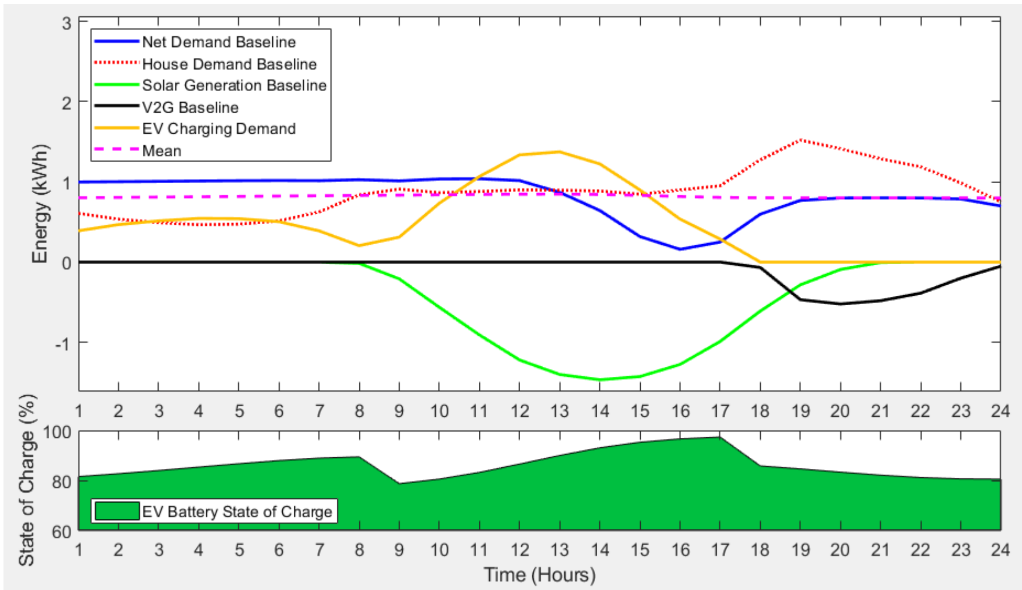

Figure 9: Mean daily demand and battery state of charge for a 3-bedroom house with solar generation and V2G usage

Figure 10 shows the mean daily demand and EV battery level of a 3-bedroom house with no solar generation and optimized EV charging/V2G usage.

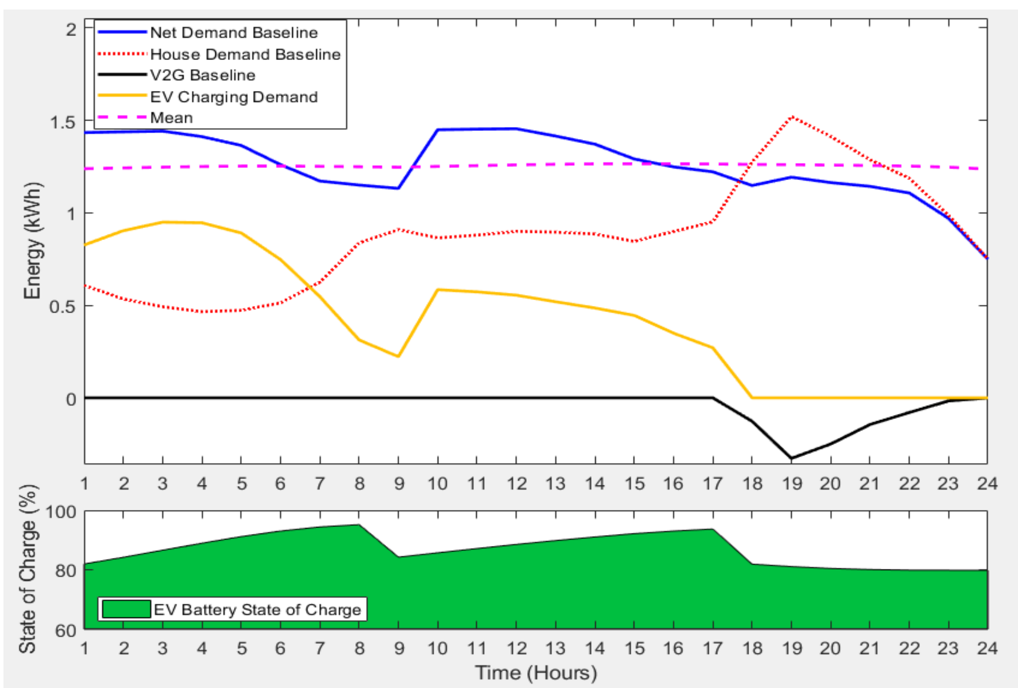

Figure 10: Mean daily demand and battery state of charge for a 3-bedroom house with solar generation and V2G usage

Figures 9 and 10 both show the significantly reduced difference between peak and mean demand resulting from optimized V2G use adoption. Note that the peak occurring after 5 PM is no longer there, and that charging has been shifted towards off-peak hours. The updated grid demand curve is shown in figure 11. The mean to peak demand difference drops from 15 MWh with unoptimized charging to about 2MWh with optimized V2G usage.

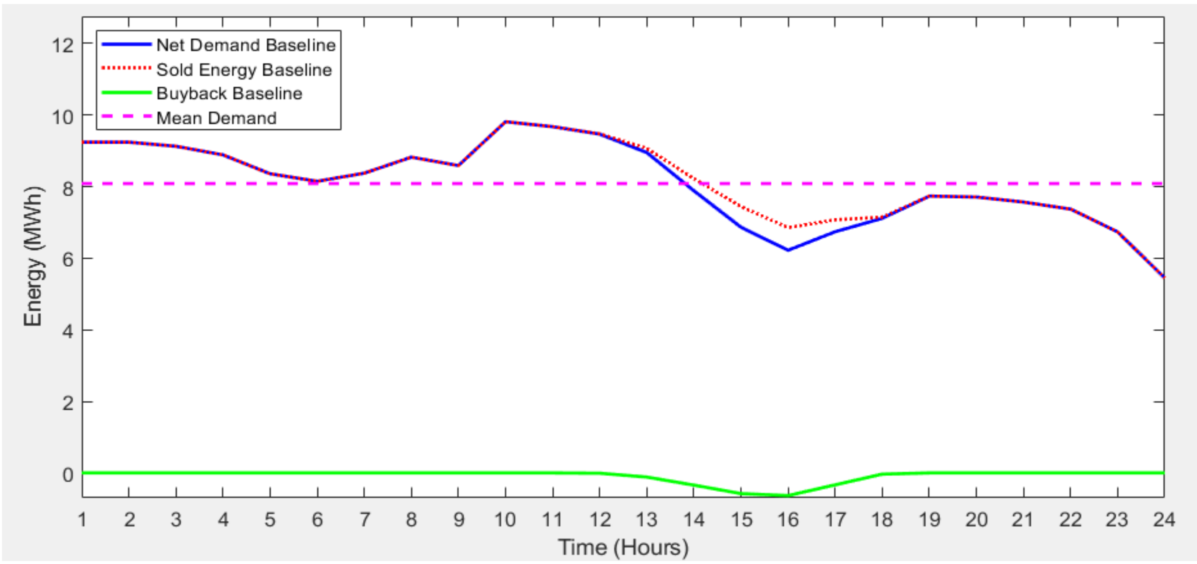

Figure 11: Grid mean daily demand with optimized EV charging and V2G use

To highlight the difference between no EV use, unoptimized charging use, and optimized V2G use on the grid, the three grid net demands are plotted on the same graph in figure 12.

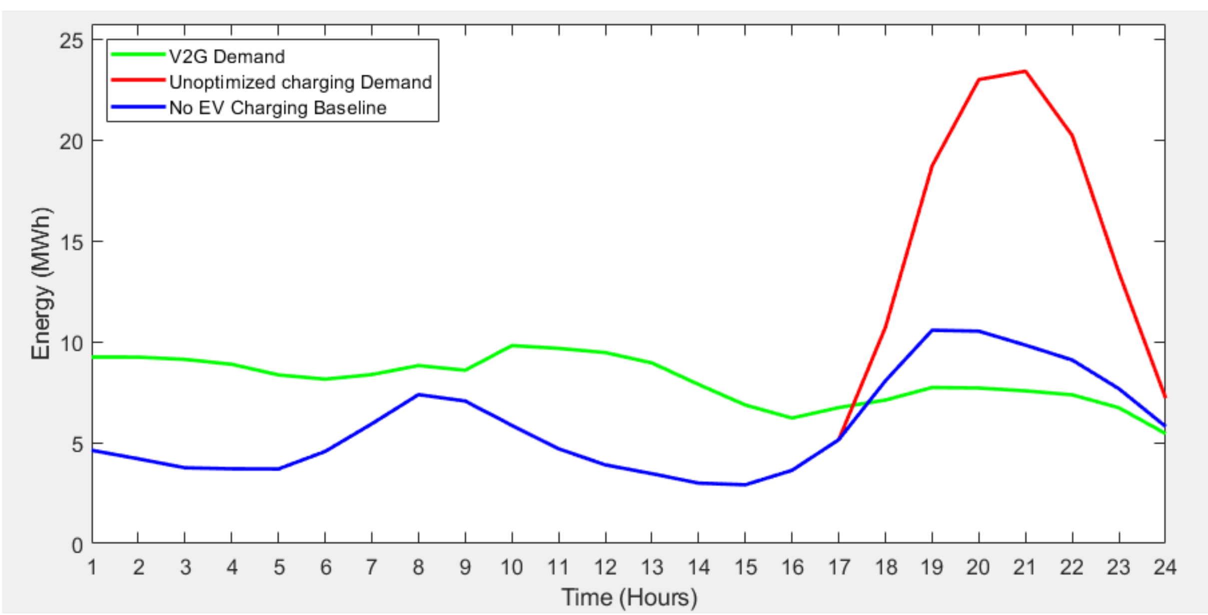

Figure 12: Grid mean net demand compared.

Clement-Nyns, et al did a study that compared the impact of unoptimized / optimized EV charging on the grid [11], the study assumed a 30% EV charging adoption rate, it also assumed the use of a 4kWh charger (Compared to the 3.7 kWh used in this study), and focused on plug in hybrids with a smaller battery size of 11 kWh (compared to 40 kWh assumed in this study). When normalized to the same adoption rate, the results presented here are in agreement with those of Clement-Nyns. Table 1 shows the results from table V in the paper [11] compared to the results from the BEOpt + MATLAB simulation.

Source	Parameter	Without charging	Unoptimized charging	Optimized charging
Clement-Nyns, et al (11), table V	Peak Load @ 30% adoption	23 kVA	36 kVA	25 kVA
	Normalized to No EV charging @ 30% adoption	1.00	1.57	1.09
BEOpt + MATLAB Simulation Results	Peak Load @ 100% adoption	10.5 MWh	23.5 MWh	9.8 MWh
	Normalized to No EV charging @ 100% adoption	1.00	2.24	0.93
	Normalized to No charging @ 30% adoption	1.00	1.37	0.98

Table 1: Result comparison of EV Charging Impact on Grid

4.4. Battery degradation and cost analysis results:

The results for battery degradation and cost analysis are summarized in table (2). The table also shows the results from another paper by David Richardson [6]. That study assumed a constant depth of discharge and a constant 95$ per year battery degradation cost due to shallow charging. The cost difference per kWh at a similar peak hour percentage was close to the calculated value in this study.

Parameter	2 Bed with PV	3 Bed with PV	4 Bed with PV	2 Bed No PV	3 Bed No PV	4 Bed No PV	Mean BEOpt + MATLAB Sim	Richardson [6]
Unoptimized Charging Battery Life (Years)	9.9	9.9	9.9	9.8	9.8	9.7	9.8	NA
Optimized V2G Use Battery Life (Years)	10.7	7.7	6.3	10.1	8.5	8.6	8.65	NA
Battery Degradation Annual Cost ($ per year)	-57	216	433	-22	117	99	131	95
Annual V2G Adoption Cost ($ per year)	-32	241	458	2	142	124	156	NA
Total V2G Energy Moved from Peak (kWh)	437	798	1824	152	343	797	725	NA
Min peak to off-peak price difference ($)	-0.07	0.303	0.251	0.015	0.414	0.155	0.178	227.3 $ per MWh (0.227 $ per kWh)

Table 2: V2G Cost analysis summary

Note that in some cases, battery life improved slightly with V2G usage, even though the number of cycles and the total amount of energy going through the battery increased. The cases where there was an improvement in battery life were for the 2 bedroom homes (with/without PV). This is due to the small required charge rate needed to balance the house load; since the battery degradation model used panelizes high charge rates, even though the amount of energy going through the battery increased, the improvement in battery life due to the lower charge rate balanced that out. With the calculated time of use minimum price difference, the electricity rate for the peak (5PM to 0AM) and off-peak (0AM to 5PM) periods is calculated with an assumed $0.18 per kWh base rate in California:

$$RateAtPeak = 0.18 + 0.178 * 17/24 = \$\, 0.305\ per\ kWh$$

$$RateOffPeak = 0.18 - 0.178 * 7/24 = \$\, 0.128\ per\ kWh$$

5. Conclusion

Based on the results of this study, at high adoption rates, vehicle to grid technology has the potential to completely eliminate the duck curve problem, and significantly improve grid stability, however, the use of V2G moves the burden and cost of energy storage to EV owners, who will have to pay for the increased battery degradation and other associated costs (Inverter + installation). With no proper incentives to balance adoption costs, the use of V2G technology will be financially unwise, and adoption rate may not be high enough by the time electric vehicles become more common. To solve that problem, the study proposes a time of use electric utility rate schedule designed to exactly balance out the costs associated with V2G usage for the average user.

The study found that in some cases, specifically for houses with a relatively small load, the use of V2G technology with optimized charging can improve EV battery life compared to unoptimized charging done at a faster rate. This observation means that in some cases, and even with a fixed electricity rate, the use of V2G has no to very low costs to the user over the life of their vehicle.

The analysis does show that using a time of use electricity rate as the only way to compensate users may not be feasible in areas with already low electricity prices. A price difference of 17 cents per kWh may be high in L.A. California with an 18 cent per kWh base rate, but it is completely infeasible in areas like Oklahoma and Texas where the average base rate is closer to 10 cents.

The main takeaway from this study however, is that a high EV and home charging adoption rate can make the grid much worse unstable in the future if no active measures are taken. Those measures could be more centralized solutions like a fast responding energy storage facility maintained by the grid, or more distributed solutions like dedicated home batteries or V2G usage.

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