Bidirectional Electric Vehicle Charging to Reduce Grid Impact of Deep EV Penetration

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***Abstract*—As the penetration of electric vehicles (EVs) and renewable energy sources like wind and solar PV deepen, we will begin to see increased challenges for the grid. In this paper, we explore the effect of bidirectional EV charging on the energy balance on the grid. We first create a simplified 3-bus grid model with a similar resource profile to the grid that CAISO operates. We then optimize the bi-directional EV charging with high EV penetration to determine the amount of ramping needed when we electrify a high percentage of vehicles. We end up with a model that shows a 3-fold economic advantage for EV drivers who choose to discharge in the evening peak hours. We also determine charging/discharging behavior that both maximizes the profits for drivers while reducing the need for fossil fuel peaking plants.**

***Index Terms*—Electric Vehicles, Bidirectional Charging, Vehicle-to-Home, Vehicle-to-Grid, Duck Curve**

I. Introduction

The goal of this project is to model a portion of the California electric grid with a portion of electric vehicle charging modeled as bidirectional chargers. As solar penetration increases in California, we are seeing a more exaggerated ”duck curve” in the net load profile for CAISO. In 2020, for example, between the hours of 4pm when the sun starts setting and 9pm when demand begins to drop for the night, there was a 13,000 MW net load ramp that required fossil fuel based generators to increase production and batteries to discharge [10]. This problem is set to become more dramatic as PV production increases and net load during the day decreases and as more people adopt EVs and begin to charge their vehicles when they return home during the evening.

By modeling a portion of the California electric grid, we hope to determine scenarios in which bidirectional EV charging can help reduce the total load ramping that occurs in the evening hours. We will work off of projected penetration of EVs and PV in CA in the future decades and model their effects of charging on our simplified grid model. We will then consider cases where EV owners have access to bidirectional charging and analyze the effects of this compared to our base case model.

II. Background and Literature Review

A. The Need for Charging Management for Grid Health

In a world where there is high penetration of EVs and where a high percentage of electricity generation is from renewable sources, the generation ramping needed in the evening hours when people get home from work will increase dramatically. It is currently around 13,000 MW in 5 hours in the CAISO area [10].

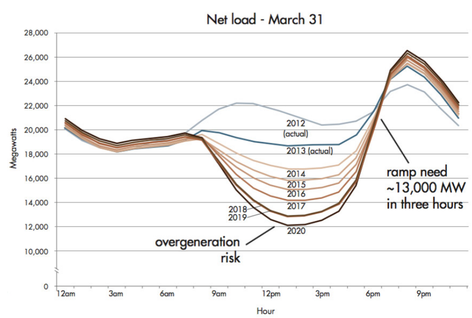


Fig. 1. The CAISO duck curve. Notice the 13,000 MW ramp in the evening

The hope with having widespread bidirectional EV charging is that vehicles can act as distributed energy resources that utilities can then dispatch when plugged into a charger to support resource adequacy goals.

B. Bidirectional EV Charging Systems

There are a couple of different types of bidirectional EV charging systems that exist today. The two main types that exist in 2023 are vehicle-to-home (V2H) and vehicle-to-grid (V2G). In this project we will focus on V2G bidirectional charging systems as we can more easily make assumptions about their use and the system operator's ability to control the discharge of their vehicle into the larger grid to reduce net load.

V2H charging is seen in systems like the Ford/Sunrun system that can be installed along when one purchases the F-150 Lightning EV. Sunrun claims their system is an 80 amp system that can provide up to 9.6 kW of electricity and can power a house for up to 3 days depending on the load and capacity of battery in the truck [11]. V2H bidirectional charging is very useful for areas which lose grid power frequently, are entirely off-grid, or who have advanced power systems controls installed at their home. These systems are specialized and expensive. It is also difficult to predict when EV owners will choose to discharge their vehicle to their house. For this reason we choose to leave the case for V2H for future study and will focus on V2G instead.

V2G systems discharge the battery of an EV into the larger electric grid. For V2G to work on a scale which will have an impact on net load in areas with high peak loads like CA, the technology will need to be very efficient and high power, likely using Galium Nitride (GaN) based power electronics that are still in development. We will also need utilities and system operators to have advanced control systems and access to charge/discharge EVs into the grid. For V2G to work, the vehicles must be accessible as a distributed battery system that can be dispatched when needed [12].

C. Existing Literature

Much of the inspiration for this project was taken from Siobhan Powell's papers in *Nature* and *Science Direct*. In *Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption*, Powell describes different charging behaviors that people may adopt as they use electric vehicles. She then applies these behaviors to the Speech model of the grid that her team developed in order to explore the effects of 50% to 100% EV adoption in CA [3].

Similar to this paper, in *Scalable probabilistic estimates of electric vehicle charging given observed driver behavior*, Powell also explores driver charging behavior on a large scale in California using statistical methods to capture uncertainty in driver behavior. The estimates in peak charging demand ranged from 4 GW to 8.75 GW depending on driver behavior and penetration of EVs [2].

Our analysis differs from this existing literature because rather than trying to come up with a statistical model that captures driver charging behavior, we create a simple set of rules for charging and discharging vehicles that most reasonable EV drivers would accept. Rather than having a model that cannot easily be shifted onto different populations (people who work during the day vs. people who work at night, etc.), we come up with optimal charging behavior that benefits both the driver and the utility.

III. Methodology

We begin our modeling by creating a 3 bus transmission network. At each node we have solar production and loads that are all time dependent. We run the optimization for the 24 hours on one representative day on May 24, 2023. For our method, we also assumed to use Level 2 chargers where the maximum charging level is 6.6 kW and the maximum discharging is 3.3 kW. To compare how well EV bidirectional charging works in the grid, we created 2 cases. Case 0 is where we have no EVs and no storage in the system while in Case 1 we have have EVs and their parameters such as charging rate limits.

A. Data Sources

PV production data was generated using PVWatts assuming different DC capacities installed in various regions around Northern California on May 24, 2023 [13]. PV system sizes were arbitrarily estimated with the hope of making the overall generation profile look similar to the generation mixes that CA

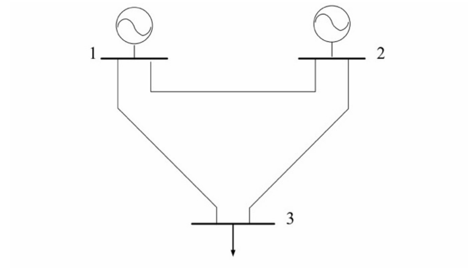


Fig. 2. The 3 bus topology we are dealing with. Each bus has PV generation and loads that are not pictured here.

seems on a daily basis. Load data for Bus 1 was generated from CAISO's Demand Outlook portal using actual demand data from May 24, 2023 [14]. For Bus 2 and 3, we added a Gaussian noise with zero mean and .01 variance to each hour to create some variation in demand for each bus. For Bus 2, we increased the total load during the daytime hours and in Bus 3 we increased the total load in the morning and decreased it in the evening. With our approach we intended to make a model that can work for different regions for the state of California. Figure 3 gives a visualization of the data that forms the basis for the load and PV generation portions of the datasets.

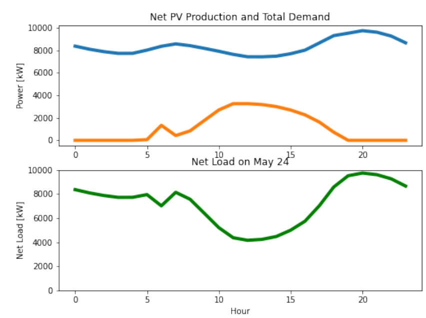


Fig. 3. Total PV production and demand at all buses. Net Load minus the PV production. (For labels, blue line represent demand, orange represent PV, and green represent demand minus the PV.)

B. Case 0: No Electric Vehicles

In this case, we create a CVX optimization problem in which we take the 3 bus system with PV and load data and optimize the power generation at the dispatchable generators Buses 1 and 2. Our problems consists of the following cost equation and constraints:

$$\forall \text{ hour, minimize } \sum C(G_1) + C(G_2) + C(G_3)$$

$$\text{s.t at each bus: } P_{ik} = B(\theta_i - \theta_k)$$

$$P_{gen_1,min} \leq P_{gen_1} \leq P_{gen_1,max}$$

$$P_{gen_2,min} \leq P_{gen_2} \leq P_{gen_2,max}$$

$$P_{gen_3,min} \leq P_{gen_3} \leq P_{gen_3,max}$$

C. Case 1: Bidirectional Charging and Grid Ramping

Parameters:

Adding bidirectional charging complicates the model and requires additional parameters and variables in order to build EVs into the model.

Parameter	Description
PV_b	PV production profiles for all $b \in B$
D_b	Demand profiles for all $b \in B$
$Y_{\mathrm{bus}_{b_1,b_2}}$	Admittance matrix for all $b_1, b_2 \in B$
$B_{\mathrm{bus}_{b_1,b_2}}$	Admittance imaginary matrix for all $b_1, b_2 \in B$
$\mathrm{gen\_cost}_b$	Generation costs for all $b \in B$
$\mathrm{gen\_max}_b$	Maximum generation limits for all $b \in B$
num_EVs	Number of electric vehicles
charge_limit	Charging limit for EVs
discharge_limit	Discharging limit for EVs
P_s	Start time of peak hours
P_{end}	End time of peak hours
peak_price	Peak price
offpeak_price	Off-peak price
R_c	charge_rate_limit in kW for each EV
R_d	discharge_rate_limit in kW for each EV
B_e	Battery capacity for each EV

Variable	Description
$P_{t,b}$	Power injection at each bus for all $t \in T$, $b \in B$
$\theta_{b,t}$	Voltage angles at each bus for all $b \in B$, $t \in T$
$\mathrm{gen\_bus}_{b,t}$	Generator power output for each bus for all $b \in B$, $t \in T$
$\mathrm{EV\_charge}_{e,t}$	EV charging/discharging power for all $e \in E$, $t \in T$

Set	Description
T	Set of time periods
B	Set of buses
E	Set of electric vehicles

The most notable variables and parameters that affect the function of our model are the peak pricing periods, charge and discharge rate limits on the vehicles, and the SOC levels at which a vehicle can be discharged. The SOC parameters are the parameters that influence our driver's charging behaviors, as is a car is below the SOC threshold, it cannot be discharged and can only be charged. This is a reasonable assumption as people will want their vehicles to have a charge when they go to work in the morning.

Objective Function

In our model we are trying to minimize the sum of running the generators while also minimizing the charging/discharging price that EV drivers see.

$$\begin{aligned} \mathrm{obj} = &\sum_{b\in B}\sum_{t\in T} \mathrm{gen\_cost}_b \cdot (\mathrm{gen\_bus}_{b,t})^2 \\ &+ \mathrm{peak\_price} \cdot \sum_{t\in T} \max(0, P_{t,1} - P_{t,2}) \\ &+ \mathrm{offpeak\_price} \cdot \sum_{t\in T} \max(0, P_{t,1} - P_{t,2}) \end{aligned}$$

Constraints

The power flow, generator limits, and energy balance constraints for each node remain the same as in Case 0. We add a series of EV charging/discharging constraints so that drivers can expect reasonable charging/discharging of their vehicles while they are plugged in. We also add constraints so that the actual charging/discharging rates are realistic for the technology that exists today.

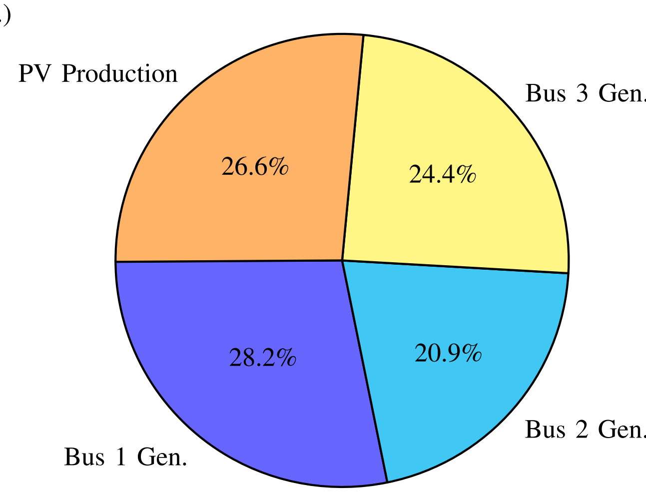
- Power flow constraints:
  - $\theta_{0,t} = 0$, for all $t \in T$
  - $P = -Y_{\mathrm{bus}} \cdot \theta$
  - $P_{t,b} = \mathrm{D}_b - \mathrm{PV}_b - \mathrm{gen\_bus}_{b,t} + \sum_{e\in E} \mathrm{EV\_charge}$, for all $b \in B$, $t \in T$
- Generator capacity constraints:
  - $0 \le \mathrm{gen\_bus}_{b,t} \le \mathrm{gen\_max}_b$, for all $b \in B$, $t \in T$
- EV charging and discharging constraints:
  - $\mathrm{EV\_charge}_{e,t} \ge 0$, if $\mathrm{initial\_SOC}_e < \mathrm{charge\_limit}$, for all $e \in E$, $t \in T$
  - $\mathrm{EV\_charge}_{e,t} \le 0$, if $\mathrm{P}_s \le t \le \mathrm{P}_{\mathrm{end}}$ and $\mathrm{initial\_SOC}_e > \mathrm{discharge\_limit}$, for all $e \in E$, $t \in T$
  - $\mathrm{R}_{c,e,t} \le 6.6$ kW
  - $\mathrm{R}_{d,e,t} \ge -3.3$ kW
  - hour x $\mathrm{EV\_charge}_{e,t} \le B_e$
- Energy neutrality constraint:
  - $\sum_{e\in E} \mathrm{EV\_charge}_{e,t} = P_{t,1} - P_{t,2}$, for all $t \in T$

IV. Results

A. Case 0 Results

After running the optimization to schedule the firing of gas generators in our 3 bus network, the total production breakdown is as follows:

In the pie chart, we can see the generation resources broken down by percentage. The differences between generators are based on cost of operation and the maximum power that they can produce. (Note: The pie chart can be referred as Figure 9.)



The results from Case 0 validate that our model is running as expected. We see that generators are being scheduled based on price and availability. Gen. 1 is being used the most due to its cheaper operating cost, while Gen. 3 is used second most due to its high generation capacity that can be dispatched when Gen. 1 and 2 are at maximum production. The resulting total generation ramp that is needed in this base case is nearly 3,300 kW in roughly 5 hours. This will be the value that we compare the one-directional and bidirectional charging values to in the future cases.

B. Case 1 Results

When we ran the optimization to include EVs, we obtained optimal schedule for the generators as we can see in Figure 4. The buses generate the minimum during the middle of day. The clipping that we see in Generator 1 and 2 is due to the capacity constraints that we placed on these gensets. This optimal scheduling minimizes the total cost of running the generators while still meeting the demand for the EVs that are required to be charged due to the SOC. (Note: Due to the indexing convention in Python, Bus 0 here refers to Bus 1, Bus 1 refers to Bus 2, Bus 2 refers to Bus 3 as seen in Case 0. There are still a total of 3 buses.)

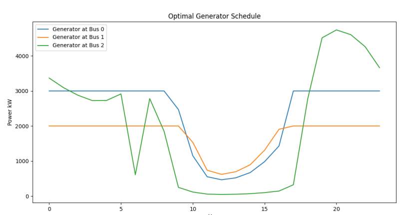


Fig. 4. Optimal Schedule for Generators. X-label is for hour of the day and Y-label is the power in kW.

As we can further observe, simulating 100 EVs to investigate the discharging behavior during peak hours starting from 4:00pm, we can see vehicles starting to contribute to the grid as we can see in Figure 5. As the peak pricing hours continue, and cars continue to be discharged in order to maximize the profits that drivers see and also to minimize the power output and costs of the gensets. As we reach the end of peak hours, we see a few different phenomena that result in total power discharge to flatten out:

- Total demand begins to drop so less production is needed.
- SOC on vehicles begins to drop below 0.7 so they can no longer discharge under our constraints
- Peak pricing drops at 9:00pm so there is less incentive for drivers to discharge their vehicles.

For learning purposes, to help validate how our model would do with new sets of data, we tried using a similar validating approach used by Powell in [2]. Our first step, was to simulate new data, and then use the optimal variables obtained in the optimization to predict the overall behavior of discharging times. We used random forest and support vector

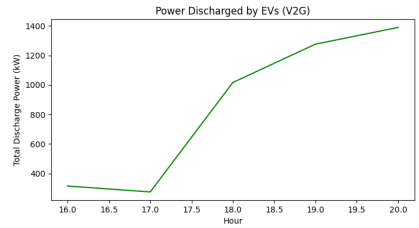


Fig. 5. Power from Vehicle to Grid.

machine because these two can deal with our particular data (SVM needed more modification, by modifying it we are also assuming it works with non linear data). We first trained using 80 percent of randomly selected data, and then we used the rest 20 percent to test. We obtained results where the Root Square Mean Errors for random forest and support vector machine are 0.1368 and 0.1365, respectively. This comparison is seen in Figure 6. This result is consistent with Figure 5 where the optimal times to discharge EVs is during the peak hours.

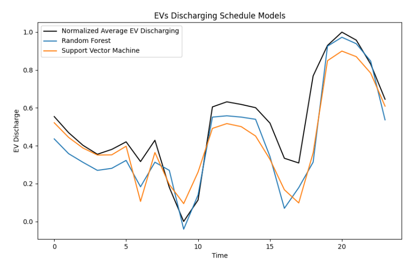


Fig. 6. Comparing results with machine learning models.

Furthermore, in addition to helping reduce emissions by contributing to the grid during peak hours, EV owners can also benefit from a profit perspective as we can see in Figure 7. By discharging during peak hours, EV owners in our model can make \$3.5 per day vs other drivers who only make \$1 per day. The model to generate this profit observation has been adjusted to only represent a maximum discharge up to 3.3 kW.

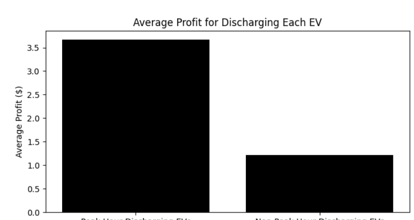


Fig. 7. Profit benefits from discharging.

We also found in Figure 8 that the optimal charging behavior for vehicles was during the off peak hours in the middle of the day. This is for the following reasons:

- PV production is high in the middle of the day and net demand is low.
- Cost of electricity is low during off peak hours.

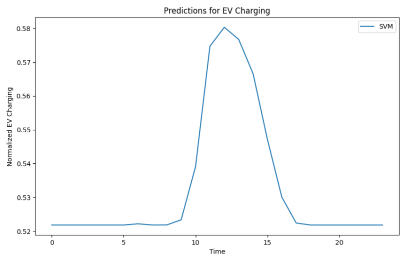


Fig. 8. Optimal charging times for vehicles as generated from Support Vector. X-axis is hour of day and Y-axis is for Normalized EV Charging.

Figure 8 shows that the best solution for drivers and for the grid is to charge during the day. The benefit also extends to the fact that these vehicles that charge during the day will also have a higher SOC so that they are able to discharge in the evening where drivers can profit and fossil fuel consumption can be reduced.

V. Discussion

The results we obtained are insightful because we created a model that is fast compared to models in literature. For example, to run a simulation of 100 EVs in Powell's paper for scheduling for 1 directional charging, the expected running time is approximately 10 minutes in Apple M1, 2020. This computational time grows exponentially by increasing the number of EVs. However, running our optimization model only takes approximately 3 seconds for bidirectional charging. Our model is good if we want to make a quick demonstration for the benefits of bidirectional charging. However, we are also aware that more parameters and constraints might be needed to make it more realistic.

In addition, we were not only able to create a discharging schedule for EVs during the day, but we were able to show the profits that an EV owner would get if they chose to discharge. Showing that there is an economic incentive is important because utilities and grid operators cannot control when and if EV drivers decide to plug their car in and make it accessible as a distributed energy resource that can be dispatched for resource adequacy.

Another advantage of our model over a more complex model that uses statistical modeling to create driver behavior profiles is that our model determines the optimal driver charging behavior based on vehicle SOC at any time of the day. This means that for drivers who may not fit the model of working during the day and being home at night, our model will still determine the best charging/discharging strategy for them and for the grid.

Finally, by using support vector and random forest to generate optimal charging behavior based on different SOC values for the 100 cars that we simulated, we have shown that our model is good and profitable for a wide series of driver profiles. We trained these models based on the optimal solution found by our CVX model and after changing the vehicle parameters, we are finding consistent results about what times of day are best for drivers to charge and discharge.

VI. Conclusion and Future Work

In this project we have built a simple yet functional 3-bus power system model that incorporates renewable generation, dispatch-able fossil fuel generation, and bidirectional EV charging. We showed that drivers are encouraged to discharge during peak electrical hours and to charge during the non-peak hours. Not only does behavior benefit drivers, but it also supports the grid and minimized generator costs. Additional constraints can easily be added to our model in order to capture driver behavior in a more nuanced manner that is still generalized. The timescale can also easily be increased or decreased to capture smaller time steps or seasonal differences in renewable generation and loads.

It would be interesting for this model to be expanded to cover a larger geographic area and to include more buses/a more complex distribution system. As of now, our model limits the charging and discharging of EVs to the levels that Level 2 chargers can handle, but what would happen if we limited it to Level 1 chargers while at home? More work could be done to better capture the reality of the current charging landscape and to build in real electric constraints like distribution transformers, home electrical panels, and local distribution lines. All of these aspects will likely need to be upgraded in the future to accommodate high EV penetration, but it would be interesting to look at the current electrical infrastructure and see what effect bidirectional charging could have on the grid and for drivers.

Acknowledgment

The inspiration for this project came largely from Siobhan Powell's papers in *Nature* [3] and *Applied Energy* [2]. We are grateful for the work that she and her team did to document their model of the CA electric grid and EV charging. We used pieces of her code for inspiration, particularly in our use of random forest and support vector machine to generate an optimal charging behavior for a wide class of drivers. We are grateful for the mentorship of Dr. Ram Rajagopal and his teaching of power systems in CEE 272R. We are also very grateful for the time and support of Sonia Martin for her help in our modeling process and for her feedback on our model, poster, and paper.

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