



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

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## Motivation

As Electric Vehicle EV penetration deepens in California, the “Duck Curve” effect and need for generation ramping in the evening hours is set to increase dramatically. Currently, we see a need to ramp generation by 13,000 MW in roughly 5 hours to meet evening demand.

As demonstrated in Siobhan Powell’s papers on EV driver charging behavior in CA, traditional charging during the day can increase the health of the grid. If many drivers were to participate in vehicle-to-grid charging, could the current grid be adequate for an electrified future and the need for new generation/transmission systems be avoided?

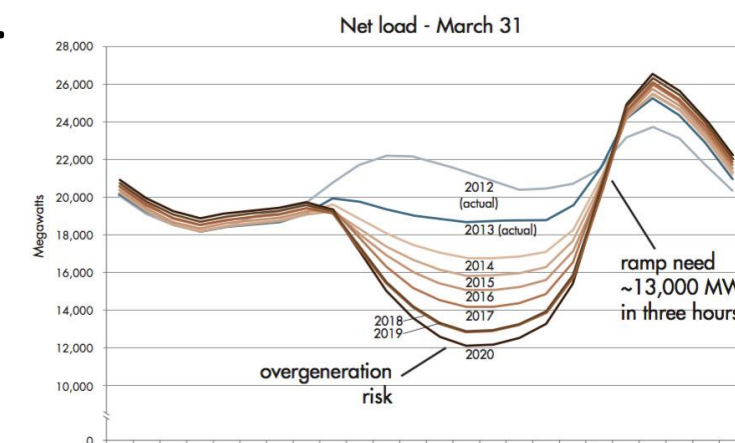


Figure 1: Duck curve in California.

## Model

Our model is a 3 bus system with PV generation and variable loads at each node. All of the nodes also contain dispatchable gas generation that can be ramped quickly from hour-to-hour in order to meet the total demand of the system.

The optimization problem is formulated to minimize the total generation cost while giving optimal values such as when to charge/discharge EVs focusing on peak hours from 4pm-9pm in California.

Objective Function
The objective function is defined as follows:
$\text{obj} = \sum_{b \in B} \sum_{t \in T} \text{gen\_cost}_b \cdot (\text{gen\_bus}_{b,t})^2 + \text{peak\_price} \cdot \sum_{t \in T} \max(0, P_{t,1} - P_{t,2}) + \text{offpeak\_price} \cdot \sum_{t \in T} \max(0, P_{t,1} - P_{t,2})$
Constraints
The constraints of the problem are defined as follows:
<ul style="list-style-type: none"><li>Power flow constraints:<ul style="list-style-type: none"><li><math>\theta_{b,t} = 0</math>, for all <math>t \in T</math></li><li><math>P = Y_{\text{bus}} \cdot \theta</math></li><li><math>P_{t,b} = \text{demand}_{t,b} - \text{PV}_b - \text{gen\_bus}_{b,t}</math>, for all <math>b \in B, t \in T</math></li></ul></li><li>Generator capacity constraints:<ul style="list-style-type: none"><li><math>\text{gen\_bus}_b \leq \text{gen\_max}_b</math>, for all <math>b \in B, t \in T</math></li></ul></li><li>EV charging and discharging constraints:<ul style="list-style-type: none"><li><math>\text{EV\_charge}_{e,t} \geq 0</math>, if <math>\text{initial\_SOC}_e &lt; \text{charge\_limit}</math>, for all <math>e \in E, t \in T</math></li><li><math>\text{EV\_charge}_{e,t} \leq 0</math>, if <math>\text{peak\_start\_time} \leq t \leq \text{peak\_end\_time}</math> and <math>\text{initial\_SOC}_e &gt; \text{discharge\_limit}</math>, for all <math>e \in E, t \in T</math></li></ul></li><li>Energy neutrality constraint:<ul style="list-style-type: none"><li><math>\sum_{e \in E} \text{EV\_charge}_{e,t} = P_{t,1} - P_{t,2}</math>, for all <math>t \in T</math></li></ul></li></ul>

**Case 1:** Our model runs as expected, with our most expensive generator behaving like a peaking generator and ramping its production in the evening to match demand. The total fossil fuel ramping was 7,833 kW in this case.

### Parameters

The parameters used in the problem are defined as follows:

- PV production profiles:  $\text{PV}_b$ , for all  $b \in B$
- Demand profiles:  $\text{demand}_b$ , for all  $b \in B$
- Admittance matrix:  $Y_{\text{bus}_{b,b_2}}$ , for all  $b_1, b_2 \in B$
- Admittance imaginary matrix:  $B_{\text{bus}_{b,b_2}}$ , for all  $b_1, b_2 \in B$
- Generation costs:  $\text{gen\_cost}_b$ , for all  $b \in B$
- Maximum generation limits:  $\text{gen\_max}_b$ , for all  $b \in B$
- Number of electric vehicles:  $\text{num\_EVs}$
- Charging limit for EVs:  $\text{charge\_limit}$
- Discharging limit for EVs:  $\text{discharge\_limit}$
- Start time of peak hours:  $\text{peak\_start\_time}$
- End time of peak hours:  $\text{peak\_end\_time}$
- Peak price:  $\text{peak\_price}$
- Off-peak price:  $\text{offpeak\_price}$

### Variables

The variables used in the problem are defined as follows:

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

### Sets

The sets used in the problem are defined as follows:

- Set of time periods:  $T$
- Set of buses:  $B$
- Set of electric vehicles:  $E$

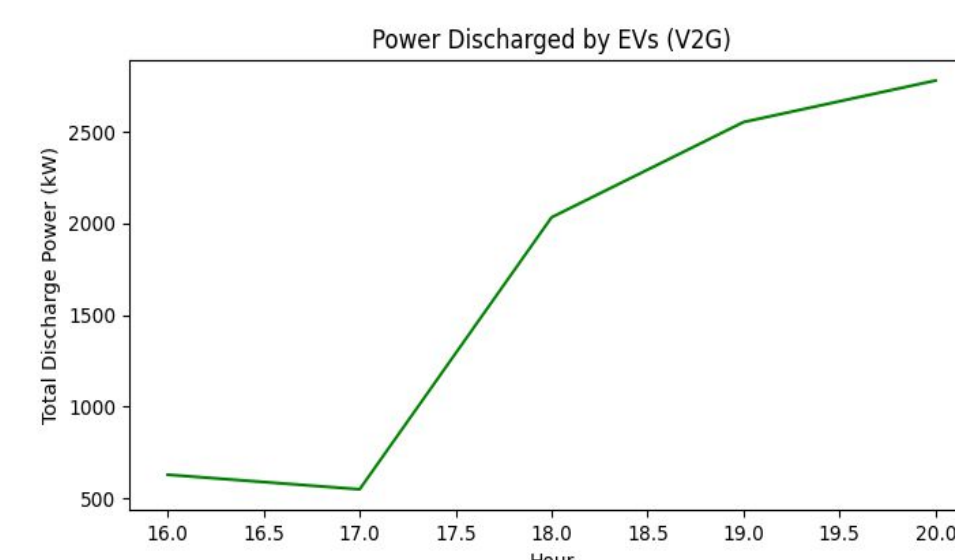


Figure 2: EVs discharging from optimization results.

In Figure 2, we can see the times to discharge EVs if their state of charge (SOC) is above .7 and stop discharging if it reaches SOC of 0.5.

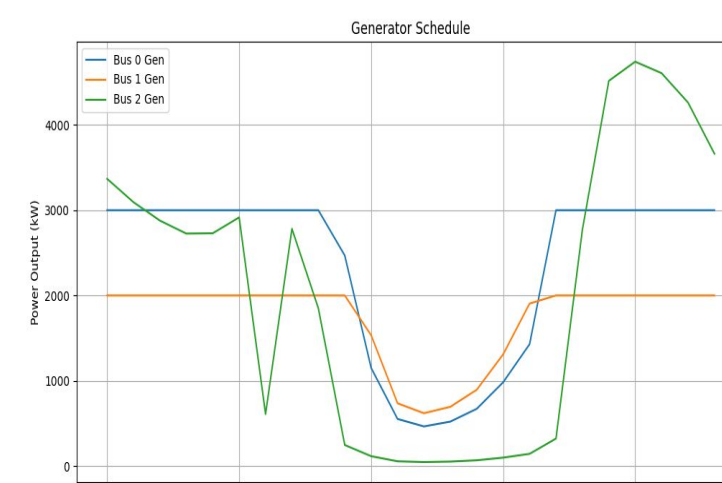


Figure 3: Generation by each bus.

## Conclusions

Our model found it most cost efficient to have large groups of cars charging/discharging at the same time. Due to the cost structure of charging your car at peak/non-peak hours, the financial incentives encourage drivers to discharge their vehicles during peak hours with a higher average economic benefit as seen in Figure 6.

**Acknowledgments:** The inspiration for this project came largely from Siobhan Powell's papers. 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 are also grateful for the mentorship of Dr. Ram Rajagopal and Sonia Martin during the course of this project.

### REFERENCES

- Phillip L. Swagel, “Emissions of Carbon Dioxide in the Transportation Sector”, <http://www.cbo.gov/publication/58861#footnote-015>. Accessed: May 05, 2023.
- Siobhan Powell, Gustavo Vianna Cezar, Ram Rajagopal, “Scalable probabilistic estimates of electric vehicle charging given observed driver behavior”, Applied Energy, Volume 309, 2022, 118382, ISSN 0306-2619, <https://doi.org/10.1016/j.apenergy.2021.118382>.
- Powell, S., Cezar, G.V., Min, L. et al. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. Nat Energy 7, 932–945 (2022). <https://doi.org/10.1038/s41560-022-01105-7>.
- Bo, L., Bissan Ghaddar, Jatin Nathwani “Electric Vehicle Routing with Charging/Discharging under Time-variant Electricity Prices.” Elsevier, 2021. <https://doi.org/10.1016/j.tre.2021.103285>.
- Sina Bahrami, Mehdi Nourinejad, Ghareh Amirjamshidi, Matthew J. Roorda, “The Plugin Hybrid Electric Vehicle routing problem: A power-management strategy model”, Transportation Research Part C: Emerging Technologies, Volume 111, 2020, Pages 318–333, ISSN 0968-090X, <https://doi.org/10.1016/j.trc.2019.12.006>.
- J. Barco, A. Guerra, L. Muñoz, N. Quijano, “Optimal Routing and Scheduling of Charge for Electric Vehicles: A Case Study”, Mathematical Problems in Engineering, vol. 2017, Article ID 859783, 16 pages, 2017. <https://doi.org/10.1155/2017/859783>.
- Aghajani-Eskaveri, S., Azad, S., Nazari-Heris, M., Amali, M.T., Asadi, S. Charging and Discharging of Electric Vehicles in Power Systems: An Updated and Detailed Review of Methods, Control Structures, Objectives, and Optimization Methodologies. Sustainability, 2022, 14(4):2137. <https://doi.org/10.3390/su14042137>.
- U. Qureshi, A. Ghosh and B. K. Panigrahi, “Real-Time Control for Charging Discharging of Electric Vehicles in a Charging Station with Renewable Generation and Battery Storage”, 2021 International Conference on Sustainable Energy and Future Electric Transportation (SEFET), Hyderabad, India, 2021, pp. 1–6, doi: 10.1109/SEFET48154.2021.9375717.
- Vingawade, S. V. (2021). Bidirectional Wireless EV Charging and Smart Grid Integration. Technical Articles. <https://eepower.com/technical-articles/bidirectional-wireless-ev-charging-and-smart-grid-integration/#/FullText.pdf>
- <https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables...>
- <https://www.caiso.com/Today/Outlook/Pages/default.aspx>

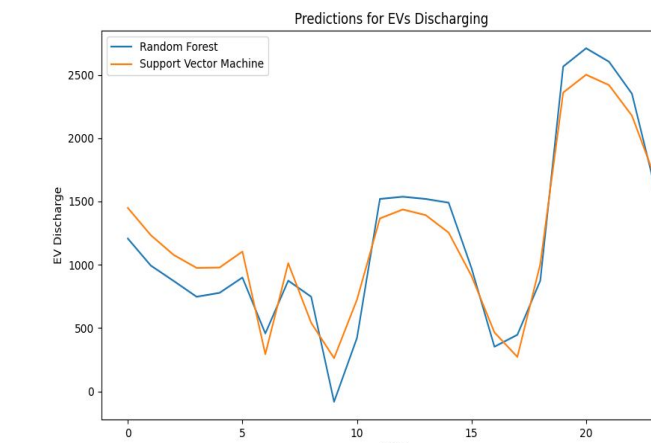


Figure 4: Models demonstrating the times to discharge EVs.

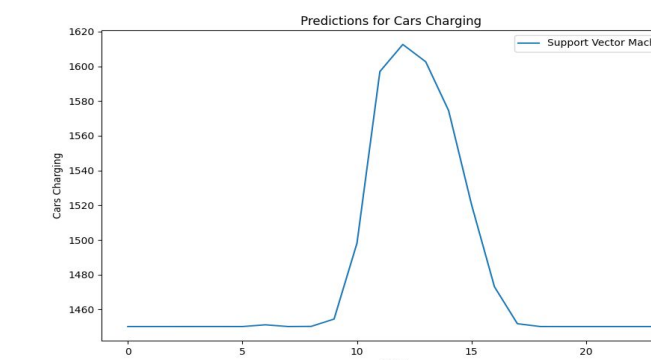


Figure 5: Charging times for EVs.

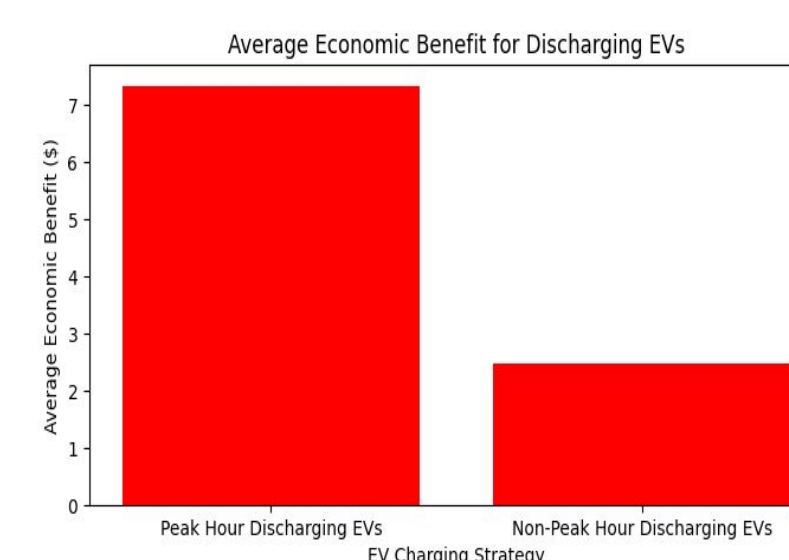


Figure 6: Average economic benefit of discharging for EVs during a day.

## Methodology

We obtained sample PV generation data from 3 different cities in CA using PVWatts to generate hourly datasets of production. We then used the CAISO Demand Outlook database to take total demand from May, which we then scaled and modified so that the loads at different buses looked slightly different from each other.

We also used data from Pecan Street and from the Powell’s papers on EV charging behaviors to provide ourselves with an understanding of how driver’s tend to behave around charging their cars.

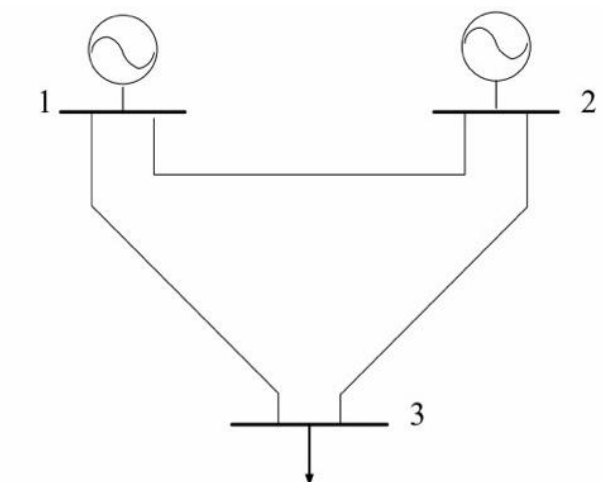


Figure 6: Bus system

Finally, we run our CVX model to optimize the generator outputs and minimize the cost of EV charging/discharging. This leaves us with a large set of V2G charging behaviors for our 3 bus system that we can then use to train an SVR model and a random forest model to predict the optimal V2G behavior for a single car in our model.

## Modeled Scenarios

**Case 1:** Here we model our 3 bus system with generators at each bus and no storage in the system. This scenario tests our model and gives us a control to compare our EV charging models against.

**Case 2:** We look at the case where vehicles can be both charged and discharged to and from the grid. We add in charging/discharging and battery SOC evolution constraints into the model in order to capture driver behavior that we found in Powell’s papers and on Pecan Street.

This case makes the most assumptions as driver behavior cannot accurately be predicted. To combat this, we added constraints to eliminate V2G discharging if an EV was below a certain SOC. This one constraint allows us to eliminate a bulk of impractical charging behavior in our model while still finding a solution that helps the 3-bus system in our model.