SMART CHARGE

Charging Electric Vehicles to Support a Low Carbon Grid

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Utilizing Flexible EV Charging to Mitigate Renewable Energy Curtailment and Support a Low Carbon Grid

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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Abstract

To meet its climate change and air quality targets, California is rapidly electrifying its transportation sector. For electric vehicles' (EVs) climate benefits to be fully achieved, the electricity that charges their batteries must come from renewable resources. If EV charging is left unmanaged, charging will likely occur in peak periods, with less renewables providing electricity, and increased demand increasing strain on the electrical grid. With the ability of EVs to change when and where they charge, utilities are investigating managed charging strategies that induce drivers to charge using California's excess solar energy supply that is often curtailed in the middle of the day. This project developed an economic model that uses pricing, technology, and communication interventions to simulate changes in EV charging for non-residential markets. Our study found these interventions successfully reduce charging demand during peak periods, but limitations exist on shifting charging to midday. Shifting a third of peak charging demand to midday can reduce emissions up to 30%, but a lack of charging infrastructure and communication informing drivers on price limits this shift. While more research is required on EV driver demand response, our project offers insights into strategies for managing charging in non-residential locations.

Keywords: electric vehicles, electric vehicle charging, managed charging, climate change, electricity, electrical grid, curtailment, demand response

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Acronyms and Abbreviations

CAISO	California Independent System Operator
CEC	California Energy Commission
CPUC	California Public Utilities Commission
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
DER	Distributed Energy Resources
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
GHG	Greenhouse Gas
GWP	Global Warming Potential
IHD	In-Home Display
IOU	Investor Owned Utility
kW	Kilowatt
kWh	Kilowatt-hour
MW	Megawatt
MWh	Megawatt-hour
NOx	Nitrous Oxide
PM	Particulate Matter
SDG&E	San Diego Gas and Electric
SCE	Southern California Edison
SMUD	Sacramento Municipal Utility District
TOU	Time-of-Use

Executive Summary

Introduction

Transportation accounts for 40% of California's greenhouse gas (GHG) emissions.[1] To significantly reduce these emissions, the state is incentivizing the electrification of the transportation sector and setting aggressive targets to increase electric vehicle (EV) adoption. In 2018, there were an estimated 570,000 zero-emission vehicles (ZEV) in California.[2] The most recent ZEV target seeks to increase that number to 5 million by 2030.[3] Yet, EVs' full potential to reduce GHG emissions is most realized when the electricity that charges their batteries comes from renewable resources. If these new EVs charge in the middle of the day, they could take advantage of California's solar energy and fully capitalize on their potential to reduce GHG emissions. They could also help balance supply and demand on the electric grid and ultimately keep ratepayer costs low. However, if they charge in the evenings, they will further contribute to a period of peak electricity demand that is met through carbon-intensive fossil fuel resources. If this type of unmanaged charging occurs, EVs will not achieve their full GHG reduction potential.

Purpose and Goals

Southern California Edison (SCE), the primary electricity provider for much of Southern California, is investigating ways to incentivize EV drivers to shift their charging to the middle of the day. To complement that work, we develop models to estimate the extent to which various interventions can encourage drivers to charge in the middle of the day at long-dwell locations (workplaces, destination centers, fleets, multi-unit dwellings [MUDs]). To help visualize our results and make them accessible to a range of stakeholders, we develop a web-based tool that allows users to interact with and run our model; this tool is freely available online: https://smartcharge.shinyapps.io/smartcharge/.

Methods

Our model considers how economic, technical, and communication interventions can shift EV charging to different periods of the day, and how this shift impacts human health, the environment, and the electric grid.

Following economic theory, self-, cross-, and average elasticities represent how individuals' electricity demand changes in response to price changes at any point in the day. Because few studies have tackled these challenges for EV charging, carefully-estimated self- and cross-price elasticities for all 24 hours of the day for non-residential EV charging locations do not yet exist in the literature. Until they are estimated empirically, elasticities from other segments provide a

[1] "California's Greenhouse Gas Emission Inventory."
[2] "Sales Dashboard."
Zero-emission vehicles (ZEV) consist of full battery electric, hydrogen fuel cell, and plug-in hybrid electric vehicles. Both plug-in hybrid and full battery electric vehicles comprise the plug-in electric vehicle (PEV) category. PEVs constitute the majority of ZEVs.
[3] "Zero-Emission Vehicles"; "Zero Emission Vehicle (ZEV) Program."

reasonable proxy for estimating how changes in price over the course of the day impact demand. With these estimated elasticities we consider three potential price interventions, including a change in the entire rate schedule, a discount, and a rebate.

Our model considers two other non-price interventions: throttling and communication. Throttling represents a 50% forced reduction in load, which occurs when the utility physically reduces power to the charger. A communication intervention involves notifying EV drivers about a price change or the impact of charging on air pollution. We assume that EV drivers have some sense of their pricing schedule and thus our price communication intervention is simply about providing an additional reminder. Studies on how these communication strategies impact residential electricity usage are used to inform this aspect of our model.

Using this information, we can model the change in EV charging demand over the course of the day under any package of interventions. We then consider the impacts of these changes on climate, health, solar curtailment, and customer finances. We create hourly fuel mixes and emission factors for 2018 and 2030 to determine the GHG and air pollution impacts, and then translate those values into dollars using the social costs associated with carbon dioxide equivalents (CO_2eq) and nitrogen oxide (NOx). Curtailment, or the removal of solar energy from the grid, occurs when there is too much energy supply, reducing the benefits we get from adding solar to the grid. This is a key reason EVs may be able to charge more economically midday. We consider how any change in EV charging behavior may impact curtailment by considering the relevant proportion of demand likely to be powered through solar energy during the curtailment window (8:00 a.m. - 6:00 p.m.) and calculating the change in curtailed solar in kilowatt-hours (kWh).

Lastly, our model incorporates contextual information, such as the number of chargers, baseline demand profile, and baseline price schedule, as provided by our client, SCE.

Findings

We run a variety of scenarios for each segment to determine what is most likely to induce a shift in consumption into the middle of the day. **We find that interventions can reduce, increase, or shift demand. However, more load is reduced than shifted, most likely due to the methods we employ. As a result, the interventions considered here reduce GHG and air pollution emissions, but we need to go farther to induce the kind of behavior shift needed to ensure EVs full climate benefits are captured.**

We also find the following:

Interventions

- Raising or lowering the price can decrease or increase demand, respectively.
- Discounts and rebates can induce drivers to shift charging from/to another period.

- The 2019 time-of-use rate schedule may reduce demand during the evening peak period and increase demand midday.
- Additional communication about price and air pollution can amplify behavior response up to 12%.

Impacts

- Price, communication, and throttling can reduce demand in the evening peak period by up to 93%, and increase midday demand by up to 37%.
- Under all considered interventions, GHG and air pollution emissions fall. Daily emissions decrease by no more than 34% (GHG) and 37% (NOx), while evening emissions may fall as much as 93% (GHG) and 99% (NOx). While this does not fully reduce emissions, reducing emissions by one-third is significant, particularly on a clean grid such as the one in California.
- Reducing and shifting load as modelled has a negligible impact on NOx emissions released in California-designated disadvantaged communities (DACs).
- Under current EV growth rates and projected charger adoption rates for long-dwell segments, limiting these charger's availability to target windows would only allow them to meet 8-32% of daily EV charging demand. If charging during the target windows at long-dwell locations is encouraged, additional chargers and/or extending demand response efforts into the residential sector may be required.
- The interventions modelled here change only small amounts of load and therefore do not have a significant impact on curtailment, when we consider curtailment to be a potential problem from 8:00 a.m. to 6:00 p.m.
- The magnitude of the impacts in 2018-19 may be minimal since the number of chargers is relatively low compared to the number of EVs on the road in California. As more chargers are installed, impacts will increase.
- Communication to end users is a huge barrier. Unlike SCE's pilot, our model assumes that all EV drivers have some knowledge of the original price schedule. Thus, our model likely overestimates demand response because drivers do not make decisions about charging based on the electricity rate schedule. We test this assumption when we compare our model results to SCE pilot results.

Key Recommendations

We offer the following key recommendations for SCE to consider:

- *Close the Communication Gap:* Develop a communication and education outreach strategy to help site hosts communicate to their end users; consider requiring or incentivizing site hosts to pass costs or communication along to EV drivers.
- *Test Other Strategies:* Craft segment-differentiated strategies and align prices and throttling periods more closely with behavior in each segment. Consider alternative strategies, such as subscription charging, graduated pricing, and limited morning throttling.

- *Expand the Program:* Include residential segments in demand response programs or install more chargers in long-dwell segments.
- *Research Driver Behavior:* Consider tracking how and why drivers shift their charging from residential to non-residential segments. Conduct a robust economic study of how EV drivers respond to changes in price in non-residential segments and then derive the self and cross-price elasticities. Elasticities derived from an experiment in these segments may reveal that load shifting is more prevalent than appears in our modeled results.

Project Significance

Transportation accounts for 40% of California's greenhouse gas (GHG) emissions.[4] To significantly reduce these emissions, the state is incentivizing the electrification of the transportation sector and setting aggressive targets to increase electric vehicle (EV) adoption. The most recent zero-emission vehicle target seeks to increase that number to 5 million by 2030.[5] Yet, EVs' full potential to reduce GHG emissions is most realized when the electricity that charges their batteries comes from renewable resources. California has a significant amount of underutilized midday solar energy that may be a resource which EV drivers can take advantage of. If EVs shift their charging into off-peak, solar-abundant hours they will use clean energy and fully capitalize on the potential for EVs to reduce GHG emissions. However, if they charge in evening, peak periods, they will further contribute to a period of peak demand that is reliant on fossil fuel peaker plants and will not achieve their full GHG reduction potential.

When people charge their EVs in the middle of the day, they use clean solar energy that otherwise might be wasted or sold to other states *and* reduce their reliance on the fossil fuel-based power that would be used to charge their cars in the evening. Not only does this enable EVs to reduce GHG emissions, but it also helps balance the supply and demand of the electrical grid for California utilities and ultimately keeps ratepayer costs low.

Southern California Edison (SCE), the primary electricity provider for Southern California, is currently investigating ways to incentivize EV drivers to shift their charging to the middle of the day. This project complements that work by designing models that estimate the extent to which various interventions encourage drivers to charge in the middle of the day at workplaces, destination centers, fleets and multi-unit dwellings (MUDs). Creating this model and analyzing the data from SCE's Charge Ready Demand Response Pilot can help SCE determine the GHG emission and cost reductions associated with these demand response interventions and explore the scalability of these methods. This project's analysis provides insight into other potential strategies that use California's large quantity of midday solar energy to meet the growing demand for EVs. Overall, a greater understanding of EV consumer behavior and effective ways to communicate demand response information to customers is central to this project. Renewable energy production and EVs are both important solutions to climate change goals, and this project focuses on examining the strategies where the two complement each other.

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4 "California's Greenhouse Gas Emission Inventory."

5 "Zero Emission Vehicle (ZEV) Program"; "Zero-Emission Vehicles."

Project Objectives

This project determines how various economic, technical, and communication interventions can shift EV charging to different periods of the day, and how this shift impacts human health, the environment, and the electrical grid. EV charging for this project is analyzed in 4 long-dwell market segments (workplaces, destination centers, fleets, MUDs) within SCE's territory. This project produces a model that can simulate the impacts of any intervention and advise SCE on effectively implementing a managed charging strategy.

Specifically, this project aims to accomplish the following:

1. Model how EV charging load changes over the course of a day in response to price, throttling, and communication interventions.
2. Analyze the consequences of EV load reduction and load shifting on public health, the environment, and grid stability for different EV adoption rates in 4 long-dwell market segments (fleets, destination centers, MUDs, workplaces).
3. Review the performance of SCE's Charge Ready Demand Response pilot program events by (a) quantifying the economic, human health, and environmental costs and benefits of the events; (b) evaluating the effectiveness of interventions on participation; and (c) evaluating methods to effectively communicate the information to EV owners and increase participation.

Chapter I. Background

This chapter provides background on power generation in California, the two challenges associated with the growing EV demand in California, and the opportunities created to address these challenges with demand response and managing EV charging. General information about utility's interest in EVs and the SCE pilot program is also provided.

Power Generation Challenges in California: The Duck Curve

To understand the impact EVs will have on power generation and GHG emissions, we must first understand how demand and supply are met over the course of the day via the electrical grid. Figure 1 offers an average demand curve for a summer day in California.[6] As shown, demand varies over the course of the day. Demand is typically highest in the evening "peak" period, when people come home from work, and lower in the middle of the night and the day.[7]

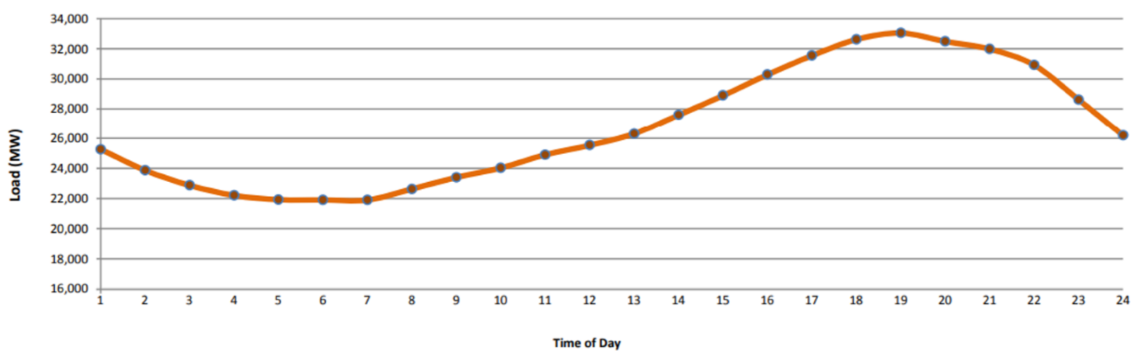

Figure 1. Hourly Electricity Demand in California on July 1, 2018 (CAISO)

Variability in demand means that grid operators must manage the energy that power generators produce over the course of the day. Sometimes they have to respond to sudden peaks in demand by quickly ramping resources up and down. Some power resources are dangerous or expensive to ramp up or down, while others are only available during certain periods of the day. Resources that cannot be easily turned off or on, like nuclear, hydro, and most electricity imported from other states, are considered "baseload" power. These resources run nearly 100% of the time. "Load-following" resources, can be turned on or off easily and cheaply, like natural gas and most renewables. Lastly, the grid uses "peaker" plants when demand rises quickly, as these plants are the easiest to turn on or off, but are very expensive to run. They are generally natural gas based and are the most inefficient and dirtiest resources in California.[8]

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6 "Renewables Watch_20180701."

7 Herman K. Trabish, "Inside California's Rate Restructuring Plan and the Battle for Fixed Charges Looming over It."

8 Fero, "Achieving California's 2030 Renewable Portfolio Standard and Electricity Sector Greenhouse Gas Emission Reduction Target"; "Turning Down the Gas in California"; John, "Dueling Charts of the Day."

Matching supply and demand poses a larger challenge as we strive to create a clean energy grid and as electricity demand rises overall. California's clean energy goals are primarily met through solar energy. Solar electricity production varies geographically and temporally with changes in solar irradiance and cloud cover (by hour, day, and season). Solar power plants reach peak generation in the middle of the day, when solar irradiance is highest, but when demand is low. Figure 2 begins to explore this mismatch between renewable energy availability and electricity demand.[9] Similar to Figure 1, the top graph in Figure 2 shows the total load and "net load" (total load minus energy provided by renewables). The bottom graph in Figure 2 shows wind and solar generation. We see that wind and solar provide zero-carbon electricity in the middle of the day, but they are not directly available to meet demand during the primary peak period, 4:00 - 9:00 p.m. Instead, the grid relies on load-following natural gas plants and peaker plants during this time because of their ability to ramp up and down quickly.[10]

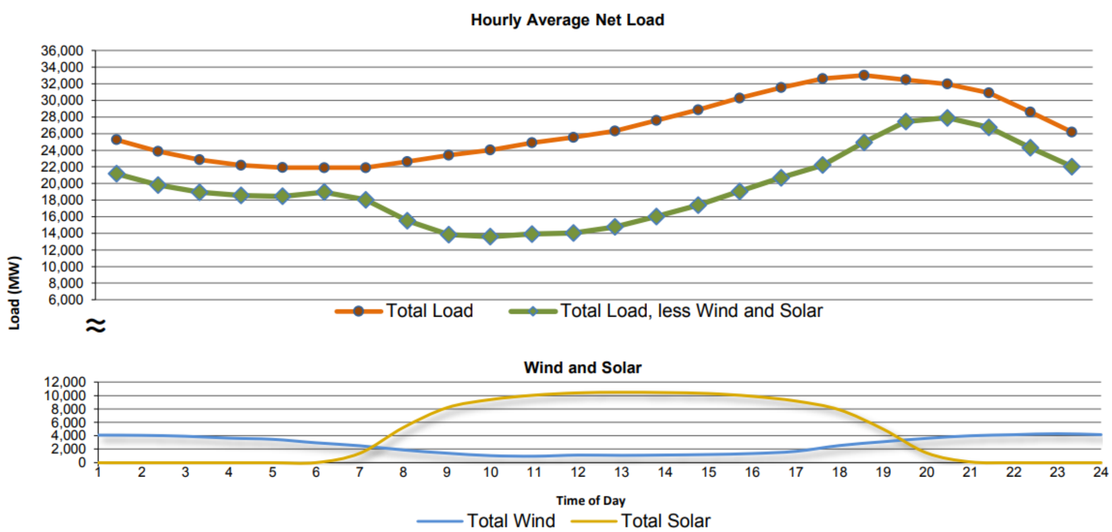

Figure 2. Hourly Average Net Load in California on July 1, 2018 (CAISO)

Solar's midday availability reduces the demand for traditional fuel resources, like natural gas, in the middle of the day, but it also exacerbates this "ramping" in the evening. It creates a steeper demand curve as solar resources shut down and peaker plants turn on. The intermittency of solar coupled with this "ramping" of demand in the evenings is known as the "Duck" curve, as seen in Figure 3.[11] This graph shows current and projected net demand (total demand – renewables). In the middle of the day, solar can easily provide enough power and, in fact, sometimes provides too much power (overgeneration). As the sun sets and evening demand spikes, fossil fuel resources are required to ramp up. The steepness of that ramp is problematic for grid operators trying to maintain equal supply and demand.

9 "Renewables Watch_20180701."

10 "Turning Down the Gas in California"; John, "Dueling Charts of the Day."

11 Denholm et al., "Overgeneration from Solar Energy in California. A Field Guide to the Duck Chart."

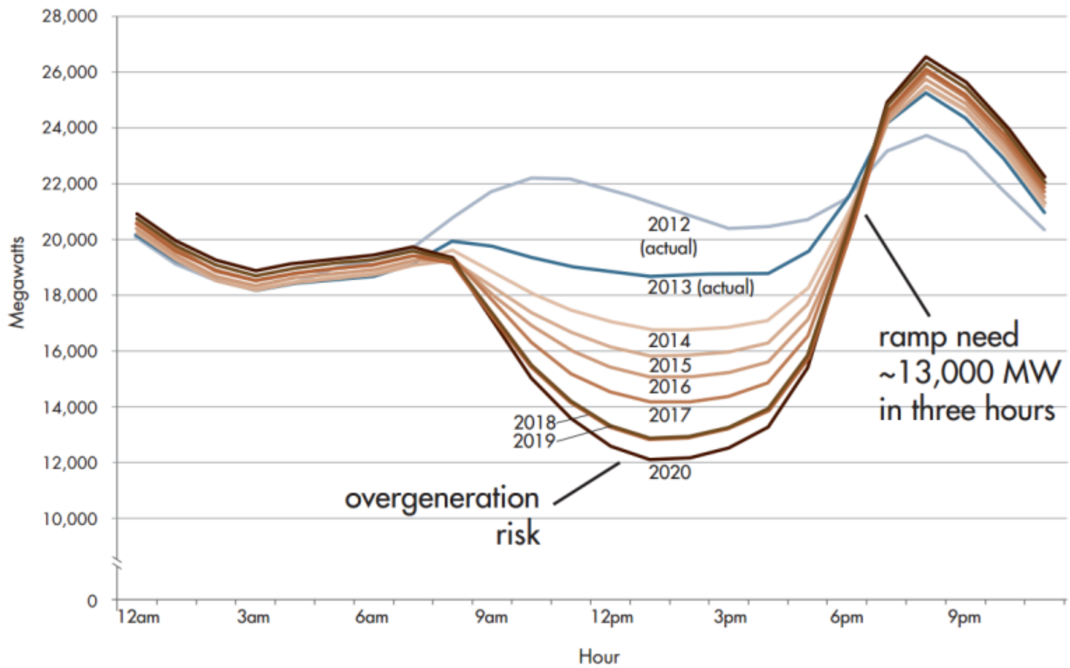

Figure 3. March 31, 2013 CAISO Duck Curve (NREL)

The duck curve is one of the underlying issues of concern when discussing load in California, including EVs, and generation, including renewable. Since we currently expect to see new EV drivers charging during the evening peak period,[12] EVs could exacerbate the duck curve and make the grid unstable. By 2025, EV chargers could add up to 1 gigawatt (GW) of load onto the grid during peak periods.[13] Figure 4 below details how EV charging demand on weekdays and weekends could align with and amplify the duck curve.[14]

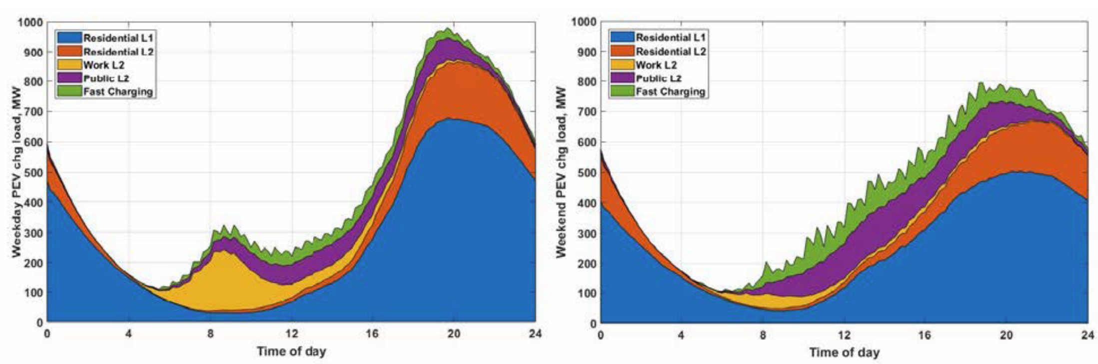

Figure 4. Projected EV Charging Load in 2025

12 Zhang, Markel, and Jorgenson, "Value to the Grid from Managed Charging Based on California's High Renewables Study"; Gavin Bade, "CEC."
13 Gavin Bade, "CEC."
14 Bedir et al., "California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025."

Greenhouse Gases and Peak Power Generation

GHG emissions from electricity generation vary across the day due to the temporal variability of resources. Solar energy accounts for most of California's renewable energy portfolio, particularly in the middle of the day. During the other periods of the day, California relies on other forms of energy, most notably natural gas. Figure 5 below shows the typical fuel mix over the course of the day for California.[15]

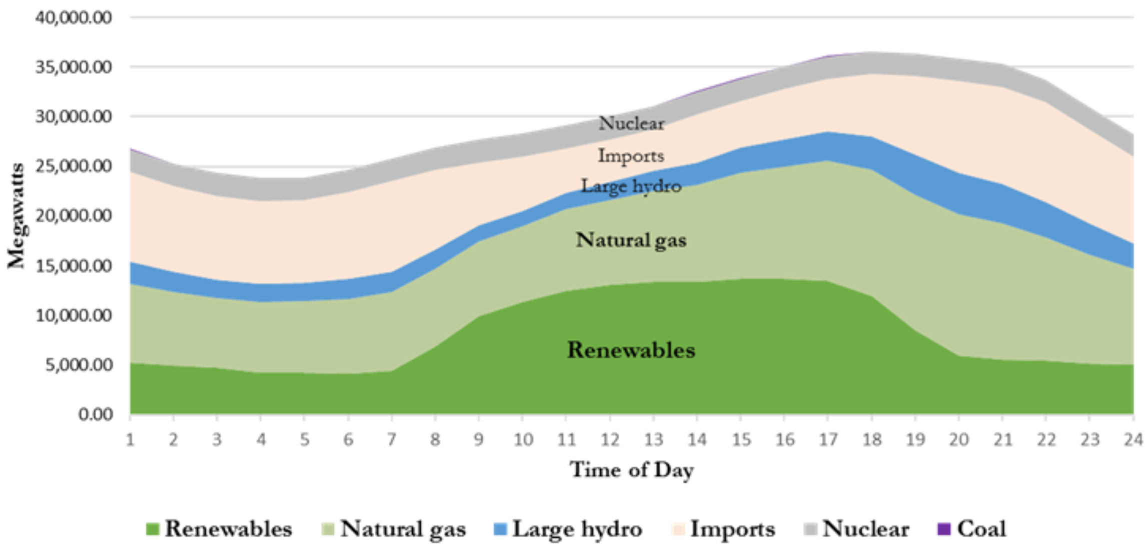

Figure 5. Average Hourly Electricity Production by Resource in California on July 1, 2018 (CAISO)

California's generation is provided by thermal (natural gas, coal, oil), hydro, nuclear, renewables, and a collection of imports.[16] As mentioned in the previous section, daylight, weather, and the ability of a resource to be turned on or off also determine when it is used. Wind and solar provide zero-carbon electricity in the middle of the day, but they cannot meet demand in the evenings. Instead, the grid relies on load-following natural gas and peaker plants because of their ability to ramp up and down quickly, but these resources are polluting.[17] The GHG and air pollutant emissions associated with this evening peak period are significantly higher compared to the emissions in the middle of the day when solar energy is abundant.

In other words, the time at which electricity is generated and simultaneously used determines the GHG emission impacts. If EVs are charged in the evenings when demand is already high, they consume electricity with a high emission factor. Since an EV is roughly equivalent to a full household's demand in a neighborhood, adding an EV can significantly increase overall demand

[15] This graph reflects the hourly fuel mix used in our model as adapted from CAISO data. "OASIS Database"; "Total System Electric Generation."
[16] "Total System Electric Generation."
[17] "Turning Down the Gas in California"; John, "Dueling Charts of the Day."

and thus overall GHG emissions.[18] However, if they are charged during periods of solar generation, they can limit the emissions associated with their use.[19] In order to capture the entire environmental benefit of EV growth, charging times must be managed. The ideal charging scenario is outlined in Figure 6 below.

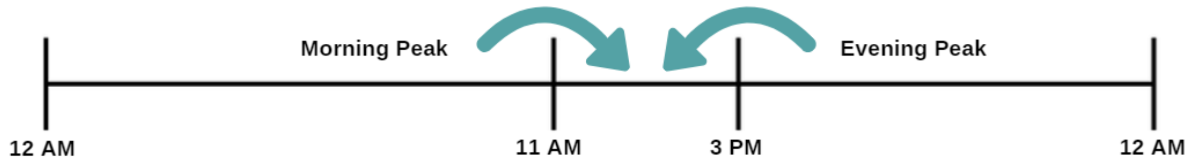

Figure 6. Ideal Demand Shifting Behavior to Ensure EVs GHG Reduction Potential is Fully Realized

[18] Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study." EVs consume 12.4kwh/day/EV on average (Zhang).

[19] Certain regions are required to source 25% of their power from natural gas at all times to meet local reliability standards (i.e., non-natural gas is far from these locations and sourcing natural gas ensures electricity demand is met), while CAISO *recommends* that 25% of all power at all times be sourced from natural gas and dispatchable hydro in order to ensure natural gas and hydro plants continue to be available during peak demand. To that end, no matter what time an EV goes on the grid, we assume that it will increase GHG load to some degree, at least for the next few years.

Fero, "Achieving California's 2030 Renewable Portfolio Standard and Electricity Sector Greenhouse Gas Emission Reduction Target"; Brinkman et al., "Low Carbon Grid Study."

Curtailment

The temporality of solar availability and California's efforts to reduce GHG emissions from the electricity sector has led to a related problem: overgeneration of solar energy. As part of its efforts to reduce GHG emissions from the electricity sector, the state has exponentially increased renewable energy capacity through a series of ambitious Renewable Portfolio Standards (RPS). The most recent RPS requires 50% of California's retail electricity sales to be sourced from eligible renewable energy technologies by 2030, and 100% by 2045.[20]

Despite the many benefits of California's high potential for generating solar electricity, California utilizes only 10% of existing utility-scale solar generation to meet its electricity demand.[21] SCE does slightly better than the state as a whole by utilizing 13% of its solar generation.[22]

A byproduct of this growth in renewable generation is overgeneration, which occurs when renewable energy supply exceeds electricity demand. As mentioned above, this occurs because most electricity demand occurs in the evening, while solar is available in the middle of the day. For safety reasons, demand must meet supply. Otherwise, the grid becomes unstable and unreliable.

To maintain a stable grid, grid operators, primarily the California Independent System Operator (CAISO), tell generators to "curtail" their generation, or operate at a lower capacity, when overgeneration occurs. Curtailment can occur in two ways:

- Economic curtailment: Another recipient takes the electricity at a low- or negative-price.
- Self-schedule cuts and exceptional dispatch: CAISO orders generators to reduce output.

These forms of curtailment are considered "market-based" because the CAISO's market automatically adjusts supply with demand.[23] For simplicity, "curtailment" is used within this project to refer to any curtailment type.

The problem of curtailment has been steadily worsening, as shown in Figure 7.[24] In 2016, 308,000 megawatt-hours (MWh) of solar and wind energy were curtailed, an increase from 187,000 MWh in 2015.[25] 2017 saw another rise, with 401,500 MWh curtailed; and 461,000 MWh were curtailed in 2018.[26] At certain times of the year, CAISO curtails between 20% and 30% of solar capacity;

20 "RPS Program Overview."
21 "Total System Electric Generation"; "California ISO - Managing Oversupply."
22 "California ISO - Managing Oversupply"; "2017 Power Content Label."
23 "California ISO - Managing Oversupply"; "Impacts of Renewable Energy on Grid Operations."
24 "California ISO - Managing Oversupply."
25 "California ISO - Managing Oversupply"; "Impacts of Renewable Energy on Grid Operations"; Paulos, "Too Much of a Good Thing?"
26 "California ISO - Managing Oversupply"; Temple, "California Is Throttling Back Record Levels of Solar—and That's Bad News for Climate Goals."

and as more renewables are added to California's grid, oversupply and curtailment will continue to increase.[27]

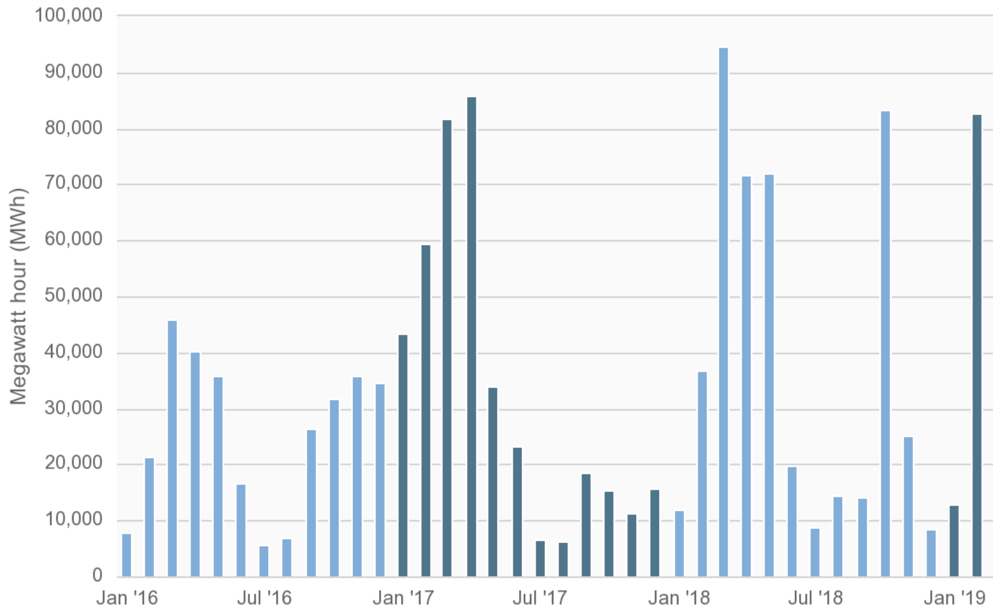

Figure 7. Wind and Solar Curtailment, January 2016 - February 2019.

This imbalance not only poses stability and reliability risks to the grid, but also represents a financial risk to potential developers. Since wind and solar projects have large capital costs but low marginal costs, their ability to recover capital expenses depends on maximizing energy output. When curtailment occurs, renewable developers lose money by selling less generated energy and foregoing the value of production tax credits. If curtailment increases beyond a cost-effective point, ~5% of California's renewable energy developers will face a significant risk of being unable to pay off loans for existing projects, or secure financing for future projects.[28] This may ultimately discourage investors and limit the potential for California to source 100% of its electricity from carbon free sources by 2045.

If electricity providers continue to increase their renewable energy generation without practical storage or demand response solutions, overgeneration and curtailment will continue to occur, limiting the amount of potential emissions reductions from the electricity sector.[29] Moving EV demand to the middle of the day may be able to address this excess supply of renewable energy in midday hours.

27 "Impacts of Renewable Energy on Grid Operations."
28 Golden and Paulos, "Curtailment of Renewable Energy in California and Beyond."
29 "Renewables Portfolio Standard (RPS)."

Demand Response

There are numerous supply and demand interventions that can be used to address overgeneration. On the supply side, when demand is low, power can be exported to other states in an Energy Imbalance Market at negative prices or curtailed by generators, as discussed in the previous section. Both of those solutions tend to be expensive. Energy could also be stored in utility scale storage facilities. Battery storage infrastructure has fallen in price and is quickly rising in adoption, with most new solar facilities in California being built with storage. But, as of 2019, there are a limited number of storage facilities. Utilities could also simply increase supply when demand is high, another expensive option. And of course, California could reduce solar energy development, but that would also reduce the state's ability to meet its overall climate goals.

On the demand side, rate structures like Time-of-Use (TOU) and Critical Peak Pricing (CPP) use price signals to shape load over time. Additional interventions such as rebates and discounts on electricity usage in certain hours can further incentivize customers to change their consumption habits in order to meet the balancing requirements of the grid. This demand side management, or "demand response," has traditionally been used as a strategy to reduce load at times of high demand, but more recently it has been considered a cost-effective way to shift demand to times of renewable overgeneration. The combination of reducing load in periods of high demand while simultaneously increasing load in periods of overgeneration is known as load shifting and has become an important topic in EV charging discussions.[30]

Providing the right incentive can influence EV owners to charge their vehicles at times of the day in which renewable electricity generation is high. This load shifting helps to utilize a larger proportion of the renewable resources that are available, while also reducing the electricity demand during periods that experience the highest demand. This demand response management, which we call managing charging, is the focus of this project.

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[30] "Impacts of Renewable Energy on Grid Operations."

SCE Pilot

Across California, utilities are looking at optimizing EV charging in order to capitalize on renewable energy overgeneration in the middle of the day and increase grid reliability. Since the California Public Utilities Commission (CPUC) lifted a 4-year ban on utilities investing in EV charging in 2015, numerous EV-charging investment plans have been proposed.[31] Through these charging plans, rate-based funds are used to support large-scale charger installation.[32]

In 2016, SCE launched their pilot program, Charge Ready. The program initially sought to incentivize the installation of 1,500 EV charge ports at four different long-dwell segments: workplaces, destination centers, fleet locations, and MUDs.[33] As a requirement of the pilot, site hosts were required to choose Electric Vehicle Supply Equipment (EVSE) vendors who provide chargers (charge ports) with demand response capabilities. Under this program, SCE installs and maintains the electrical infrastructure, while site hosts own and operate the chargers and receive a rebate to cover charger installation costs.[34] In 2018, SCE entered the second phase of their pilot and began calling "demand response events" at Charge Ready sites to explore how chargers may be used as a load shifting resource. These demand response events fall into two categories: load shift and load reduction, as outlined below. This project, Smart Charge, is designed to complement the pilot.[35]

Load Shift Events

Load shift events are intended to shift load into a targeted event window (11:00 a.m. - 3:00 p.m.) by providing a $0.05 per kWh discount on electricity rates during that time. Demand during these events is also excluded from demand charge calculations.[36] Half of these events are accompanied by "throttling," or a 50% cut in direct power to chargers in the hours before the event window. Load shift events are called during spring (March 1 – May 31) and winter (October 1 – December

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31 St. John, "California Utilities Seek $1B to Build Out Electric Vehicle Infrastructure."

32 St. John.

"Rate-based funds" are funds collected from rate-payers through their utility bills that are then used to support broader programs.

33 Long dwell-time segments are defined as locations where EVs are typically parked for at least four hours. This is adequate time for EV drivers to fully recharge their vehicles. The Charge Ready project also refers to these particular long-dwell segments as "non-residential." While a multi-unit dwelling is technically a residential building type (condominiums, apartment buildings, etc.) it is bundled into the non-residential market segment as it is not a private, single-home residence. SCE refers to this segment as non-residential and we maintain that language.

"Charge Ready and Market Education Programs: Pilot Report."

34 "Charge Ready and Market Education Programs: Pilot Report."

35 "SCE Advice 3773-E, 3773-E-A."

36 "SCE Advice 3773-E, 3773-E-A."

31), up to 10 times a year.[37] Figure 8 below uses a different target window, but outlines the general goal of a load shift event.[38]

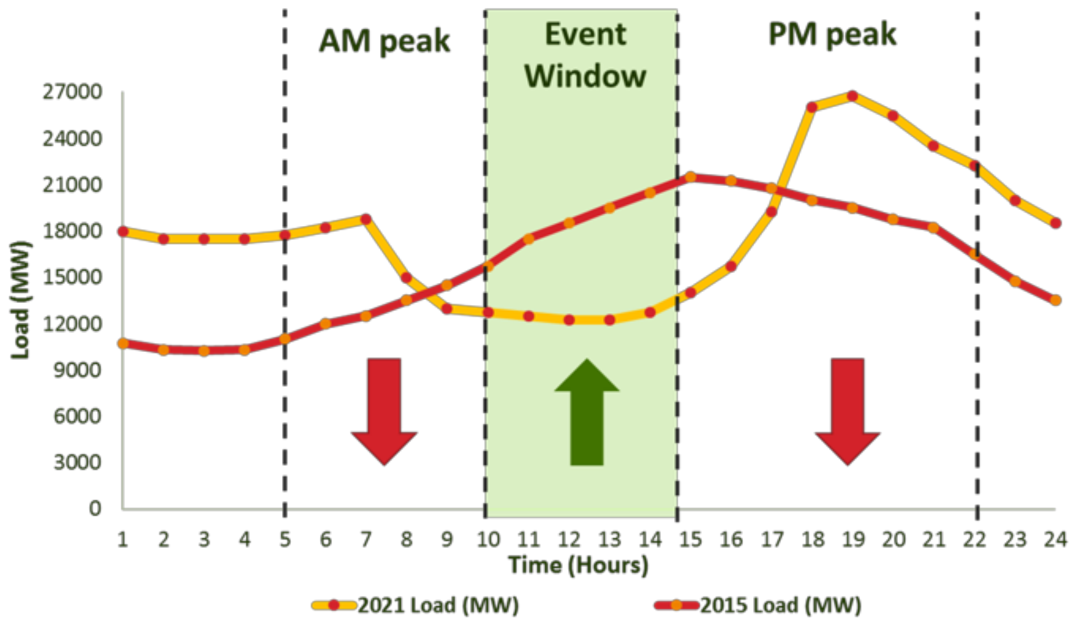

Figure 8. Current and Projected Hourly EV Load and Targeted Shift (SCE Pilot)

Load Reduction Events

Load reduction events are intended to decrease load during the evening peak (4:00 - 9:00 p.m.) by providing a $0.10 rebate (bill credit) for each kWh of energy reduced during this event period compared to a driver's typical demand. Half of these events may involve 50% throttling during the event window to force a reduction in demand. Load reduction events are called in the summer (June 1 – September 31), up to 10 times per year.[39]

Pilot Communication

In the Charge Ready pilot, there is a disconnect between the EV driver and the SCE customer who actually pays for the electricity consumed. The SCE customer is actually the owner of the charging site, such as a mall or a workplace, while the EV driver is an individual EV owner. Very few site hosts use energy-based fees to charge their drivers, and a large majority of site hosts offer EV charging as a perk and do not charge the driver any fee.[40] Therefore, the EV driver is insulated from price incentives, suggesting that price-based interventions may be less effective than if the EV customer was responsible for the entire electricity bill. This gap is further explored in our model.

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37 "SCE Advice 3773-E, 3773-E-A."
38 Southern California Edison (SCE), "Charge Ready DR Pilot Overview."
39 "SCE Advice 3773-E, 3773-E-A."
40 Southern California Edison (SCE), "Charge Ready DR Pilot Overview."

EV Market Segments

EV charging can be broadly categorized as occurring in two places – at home, or away-from-home. The Charge Ready pilot program tries to promote midday charging and increase access to charging infrastructure in those market segments that are away from private residences. As such, EV charging markets can be broken into two categories – residential and non-residential. Charge Ready is focused on the non-residential, long-dwell market segments of workplaces, destination centers, fleets, and MUDs. Note that SCE is solely focused on weekday behavior as weekend demand tends to be more variable.

Load Profiles

Current load profiles are provided for the segments of concern for this project in Figure 9. A summary of traditional charging behavior in key segments is also provided below.

Residential: This segment is unique in that it consists of private, single-family homes. The charging profile for residential is typically exemplified by a large evening peak on weekdays.[41]

Destination Centers: This can include a variety of buildings with long dwell-time parking (at least four hours) such as hotels, hospitals, sports venues, academic campuses, as well as city and county facilities. The charging profile for a destination center has a morning peak and slowly tapers throughout the day with minimal evening charging.

Workplaces: This segment includes buildings employees commute. The charging profile for workplaces displays a very high morning peak (when employees arrive at work and plug-in their vehicles), which plateaus before tapering off after the work day ends. There is also a slight afternoon peak, most likely representing employees returning from lunch and plugging in once again.

Multi-Unit Dwellings (MUDs): This segment consists of non-single home residences such as condominiums, townhomes, or apartment building complexes. The charging profile for a MUD is exemplified by a gradual rise from 11:00 a.m. to 6:00 p.m., then peaks around 8:00 p.m. and 11:00 p.m. before dropping off again.

[41] Bedir et al., "California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025."

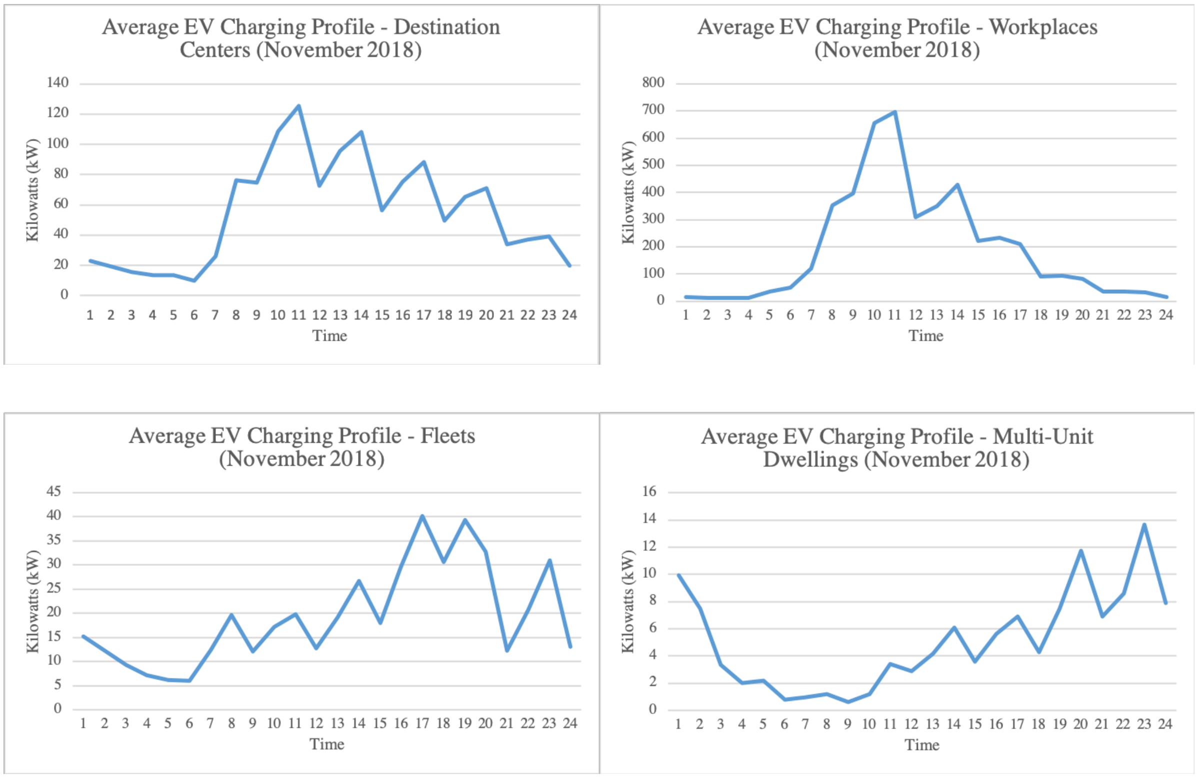

Figure 9. EV Charging Profiles - November 2018

Customer Charges

One of the most challenging aspects of incentivizing load shift in non-residential spaces is the lack of uniformity around pricing. While the utility may implement a fee schedule, how those fees get passed along to drivers varies drastically. Fee schemes take a variety of forms, but they typically include one or more of the following:[42]

- No fee
- Fee based on energy used ($/kWh)
- Fee based on time ($/minute)
- Fee based on parking

Workplaces, in particular, tend to allow users to charge for free as they consider charging to be an employment benefit. In 2017, more than half of sites in the Charge Ready pilot across all segments, allowed drivers to charge for free.[43] Of those that charged a fee, pricing systems included a fee based on time used, a fee based on energy used, some combination thereof, or an unknown fee structure.[44]

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42 Winn, "Electric Vehicle Charging at Work: Understanding Workplace PEV Charging Behavior to Inform Pricing Policy and Investment Decisions."

43 Southern California Edison (SCE), "Charge Ready DR Pilot Overview."

44 Southern California Edison (SCE).

Chapter II. Model Methodology

General Approach

The goal of this project is to determine how various interventions affect EV charging behavior. To do so, we build an economic model that allows users to enter different inputs (contextual and direct interventions) and receive outputs in the form of a new demand profile, as well as details on the relevant impacts of that demand on human health, climate change, and the electrical grid. Below is an outline of the approach we take to building this model and achieving the project objectives:

1) Evaluate

First, we evaluate what makes EV drivers change their charging behavior (i.e., charge at other times of the day) via a thorough literature review. This allows us to fully understand the problem, the solutions that exist, and the context for both.

2) Build

To determine the impacts of a change or shift in charging behavior, we build an economic model and implement it in a user-friendly web-based app. Users can input information on interventions and context and receive an output in the shape of a new demand profile. This new demand profile, when scaled up, can then provide insight into what effect inputs have on the electrical grid, climate change, and human health.

3) Compare

Our model relies primarily on values found in literature, but is also refined using SCE's Charge Ready pilot events. By analyzing the data from these demand response events, and more accurately understanding charging behavior within the target market segments, we enhance our model.

4) Create

Our completed model is available as a web-based application. In addition to providing SCE with the raw code and data, the app is a user-friendly tool enabling users to choose a variety of inputs and see the outcome. It can be run on any computer with an internet connection.

Model Framework

The core of this project is an economic model that determines the impacts of a change or shift in charging behavior.

Our model uses the elasticity of demand with respect to price in order to predict the demand for EV charging at each hour of the day given contextual information and interventions. The output generated from the model is a new demand profile that simulates what would happen to electrical load given the chosen inputs. This output is then analyzed to determine the implications of the intervention, including any changes in GHG emissions or curtailment.

The model relies primarily on values found in literature, but has also been refined using SCE's recent pilot events. The model is designed to allow for a variety of interventions to be tested together. It is cumulative, meaning that each intervention is layered on top of one another. Interventions can include a discounted price to incentivize more use at a certain time of day, a rebate to encourage less use during specific hours, throttling of charger output (direct load control), and communications strategies. Figure 10 outlines the simple framework of the model. The rest of this chapter provides details on the model inputs and outputs and the application that allows users to engage with the model.

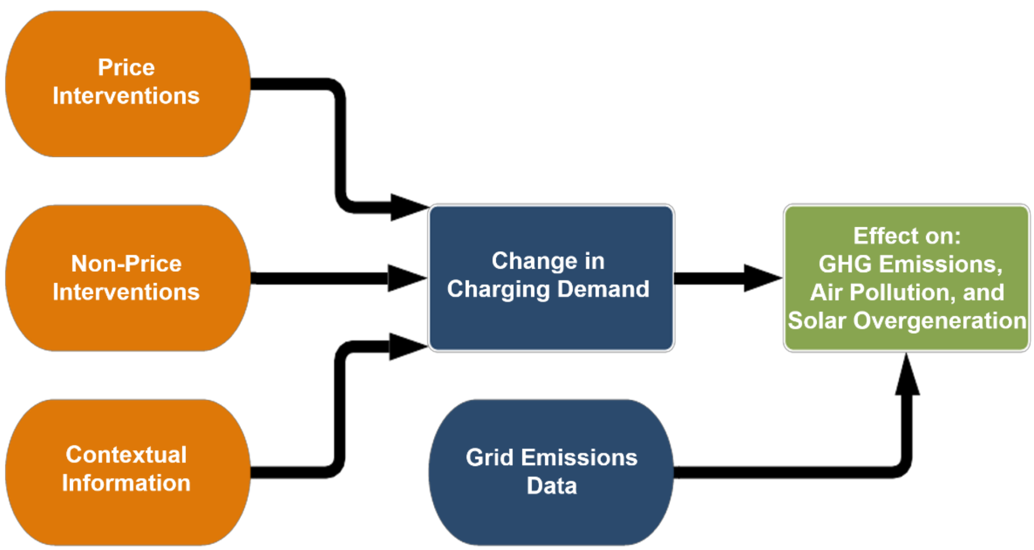

Figure 10. Model Framework

Model Inputs

Model inputs are broken into two categories: contextual, or basic background information about the context for the scenario or how EV drivers respond to various interventions, and interventions, or the inputs tested in the scenario. Table 1 summarizes these inputs and their sources. The following two sections detail each input.

Table 1. Model Inputs

Input	Values	Source[45]
Contextual		
Market Segment	Workplaces, Destination Centers, Fleets, MUDs	SCE
Baseline Load Profiles	Hourly Demand (varies by scenario)	Users
Baseline Price Profiles	TOU-EV-4 2018 (Winter, Summer)	Users
Season	Summer (June – September), Winter (October – May)	Users
Technology	Level 2 Chargers (6.6 kW)	SCE
Price Elasticities: Average	-0.04 to -0.80	Faruqui et al. [46]
Price Elasticities: Self	12 sets (Table 3)	SDG&E Pilot Study[47]
Communication Modifiers: Air Pollution	8.2%	Delmas et al.[48]
Communication Modifier: Price	3.5%	Jessoe and Raspson [49]
Throttling Amount	50%	SCE
Baseline Number of Chargers	Set by Segment and Season	Users
Theoretical Max	Calculated based on # Chargers	Users
Curtailed Energy	Varies by month	CAISO
Intervention		
Price	Discount, Rebate, TOU Rate, and Time	User
Throttling Time	Time	User
Communication	None, Air Pollution, Price	User

45 "User" here denotes inputs that vary based on the scenario run and are thus selected by the model operator.
46 Faruqui et al., "Will Smart Prices Induce Smart Charging of Electric Vehicles?"
47 Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study."
48 Asensio and Delmas, "Nonprice Incentives and Energy Conservation."
49 Jessoe and Rapson, "Knowledge Is (Less) Power."

Contextual

There are a variety of baseline and "contextual" inputs that feed into the model. Each of these inputs may be changed for each run of the model.

a) Market Segment and Baseline Load Profiles

Demand, or load, profiles represent the amount of electricity consumed for EV charging at each hour, aggregated as averages per hour per month. The four long-dwell market segments analyzed in our model have varying demand profiles that we have extrapolated from SCE's baseline usage data for the sites they have installed chargers at under their initial pilot. The demand profile of each market segment is what is manipulated in each model run. It is the starting point, or base data, to which we apply interventions.

b) Baseline Price Profile

The initial rate structure associated with most baseline load profiles in the SCE Charge Ready Pilot is TOU-EV-4. This rate is designed for separately metered, EV charging at non-residential facilities where monthly load is between 20 and 500 kilowatts (kW).[50] The details of the rate structure are included in Appendix II. TOU-EV-4 also varies by season (summer, winter). In our model we assume all baseline demand had a TOU-EV-4 price schedule.

c) Month

Our model aggregates data by month. Average month hour data is considered, or the average load in any hour in each month. By selecting by month, our model normalizes for the number of chargers installed in that month and for variation in charging behavior on any day or week in any month. Since most of the behavior change is between seasons and not months, any winter month also represents a typical winter month, and similarly for summer. Per SCE's breakdown, June through September are considered summer; and October through May are winter.[51]

d) Technology

Our model assumes only Level 2 chargers are in use, and that these chargers have a 6.6 kW power rating. Unlike Level 1 Chargers, which operate with standard 120-volt household outlets, Level 2 Chargers use 240-volt outlets, like the ones used for clothes washers and dryers. Level 2 chargers deliver 15-25 miles of range per hour of charging.

e) Price Elasticities

Our model fundamentally relies on price elasticities to predict the demand for EV charging at each hour of the day. Price elasticities reflect the responsiveness of customers to a change in price and

[50] "SCE Advice Letter 3648-E: Schedule TOU-EV-4."
[51] January - February are not classified for the pilot, as events are not called during that period. We choose to include them as winter.

indicate the percentage change in demand that would result from a 1% change in price.[52] Negative values indicate that as price increases, demand decreases, while positive values indicate that as price increases, demand increases. For example, an elasticity of -0.5 means that a 1% increase in price would result in a 0.5% decrease in demand.

Elasticity values are affected by the availability of substitutes, the necessity of the good or service, as well as the duration of the price change.[53] Elasticities can also be short- or long-term. Short-term elasticities refer to how demand responds to price in the short-term (1-5 years), while long-term elasticities account for demand responsiveness over longer periods of time (>5 years).[54] In the energy realm, these values are typically different due to technology adoption. Demand will be more elastic in the long-term because individuals have more time to determine how to successfully adapt their behavior and to purchase technologies that support a change in demand.[55] This model relies only on short-term elasticities and does not consider the adoption of new technology.

For EVs, elasticity values are rather uncertain since the market is growing and human response to EV charging pricing is not fully understood. EV-focused economists agree that EVs are likely to be more elastic, or more responsive to price changes, than other electricity markets.[56] How much more is still unknown.

This model considers three types of elasticity: average, self, and cross, as examined below. To account for a range of possible elasticity values, we use 12 sets of self-elasticities from a residential EV charging study, make assumptions about load shifting since we do not have robust cross-price elasticities, and use a range of average elasticities estimated for EVs. Until self- and cross- price elasticities for all 24 hours of the day for EV long-dwell markets can be estimated empirically, these elasticities provide a reasonable proxy for estimating how changes in price over the course of the day impact demand.

Due to the uncertainty associated with these numbers, this model uses three different methods to incorporate these elasticity values and averages across them. More on this is provided in the Model Outputs section below.

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[52] Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study."

[53] Neenan and Eom, "Price Elasticity of Demand for Electricity: A Primer and Synthesis."

[54] Neenan and Eom.

[55] Neenan and Eom.

[56] Typically, electricity demand is relatively inelastic. In other words, people continue to demand the same amount of energy regardless of price. Yet, EVs are a more flexible load and thus, drivers are more likely to respond to price.

Faruqui et al., "Will Smart Prices Induce Smart Charging of Electric Vehicles?"

Average Elasticity

The "average" elasticity refers to how customers respond to a change in the average daily price of electricity. Literature suggests that some customers respond to the change in average daily price that results from rate changes in any specific hour.[57] To that end, this model considers the average price elasticity associated with demand for EV charging.

Despite the growing interest in EVs, there is limited information available on average EV elasticities. Our model considers a range of average elasticities, from near inelastic (-0.04) to near elastic (-0.80).[58] These values are drawn from a 2011 study. Faruqui et al. analyzed average elasticities associated with non-EV dynamic pricing and TOU rates in over 100 studies and derived an elasticity of -0.04. Based on those studies and their understanding of EVs, they estimated a wide range of elasticities that could apply to EVs, which we use here.

Self and Cross-Price Elasticities

Since this model examines EV charging over the course of the day, it must also consider how people respond to a price change at any point in the day. In other words, EV drivers choose when to charge based on the cost at every hour of the day and the convenience of charging at specific hours. For example, a driver might choose to charge at 11:00 a.m. for a price of $0.10/kWh if the price at 12:00 is $0.40/kWh, but might choose to wait if the price at 12:00 is $0.05/kWh. "Self-" and "cross-" price elasticities account for this relationship.[59] Self-elasticities represent the change in demand within the hour when there is a price change. Cross-elasticities, or substitution elasticities, indicate how demand changes in other hours relative to the change in price at the hour of intervention.

These self- and cross- price elasticity values should capture the true flexibility of EV drivers and their willingness to substitute EV charging at one time of day for another time of day.

Self-elasticities for this model are taken from San Diego Gas & Electric Company's (SDG&E) 2-year Pricing and Technology Study, which investigated how residential EV drivers respond to price changes from 2012 to 2013.[60] In their 2014 final evaluation of the project, Cook, Churchwell, and George calculated price elasticities for residential EV drivers participating in the pilot project.

SDG&E randomly assigned 430 pilot participants to one of three EV TOU rate schedules, each with different price ratios between the most expensive ("on-peak"), middle ("off-peak"), and least

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57 Ito, "Do Consumers Respond to Marginal or Average Price?"

58 Faruqui et al., "Will Smart Prices Induce Smart Charging of Electric Vehicles?"

59 Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study"; Neenan and Eom, "Price Elasticity of Demand for Electricity: A Primer and Synthesis."

60 Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study."

expensive ("super off-peak") rates.[61] These three rate schedules also varied seasonally, with different summer and winter seasons and associated ratios. Non-residential charging behavior for these drivers was not considered. Within this study, the on-peak period ran from 1:00 to 8:00 p.m., the off-peak from 9:00 p.m. to midnight, and 6:00 a.m. to noon, and the super off-peak from 1:00 to 5:00 a.m. These price schedules are in Table 2 below.

Table 2. SDG&E Rate Schedules

	Period	**SDG&E Study Rates ($/kWh)**		
		EPEV-L	**EPEV-M**	**EPEV-H**
Summer	Peak	$0.25	$0.28	$0.36
	Off-peak	$0.16	$0.17	$0.14
	Super Off-peak	$0.13	$0.07	$0.06
Winter	Peak	$0.17	$0.23	$0.32
	Off-peak	$0.16	$0.16	$0.13
	Super Off-peak	$0.13	$0.08	$0.07

Drivers' response to these prices were tracked, which facilitated a calculation of price elasticities, as listed in Table 3 below.[62] From the SDG&E study, 12 sets of elasticities were reported, since there are 6 price schedules and 2 time periods (weekdays and weekends).

Table 3. Self-Elasticities from SDG&E

Day Type	**Elasticity**	**Summer**			**Winter**		
		EPEV-L	**EPEV-M**	**EPEV-H**	**EPEV-L**	**EPEV-M**	**EPEV-H**
Weekday	**Peak**	-0.41	-0.37	-0.35	-0.43	-0.38	-0.36
	Off-peak	-0.44	-0.41	-0.40	-0.45	-0.42	-0.41
	Super Off-peak	-0.23	-0.27	-0.29	-0.22	-0.26	-0.28
Weekend	**Peak**	-0.47	-0.46	-0.45	-0.48	-0.46	-0.46
	Off-peak	-0.46	-0.44	-0.43	-0.46	-0.45	-0.44
	Super Off-peak	-0.26	-0.31	-0.32	-0.25	-0.29	-0.31

While SDG&E reported both self- (or own) and cross-price elasticities, we did not use their cross-price elasticities. As detailed in the methods outputs below, the values used in this study for cross-price elasticities do not clearly apply to our non-residential scenario. Instead, our model sets the cross-price elasticities to zero and uses the average elasticities and other mathematical tools to determine how demand changes in all hours in response to a price change in any one hour.

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61 These ratios are important as they can determine how responsive drivers are to a change in price. When this ratio is larger (i.e., there is a larger gap between the peak and off-peak price), demand response is often greater. As our model uses all elasticities, we do not directly consider the importance of this ratio. (Hansen, Braithwait, and Armstrong, "Statewide Time-of-Use Scenario Modeling for 2015 California Energy Commission Integrated Energy Policy Report.")

62 Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study."

Since our model considers behavior on a 24-hour scale, we interpolated self-elasticities from these three block periods for all hours of the day.

As the idea of managed EV charging behavior is new, very few field studies have analyzed EV charging load shifting. There is a full body of literature on how consumers respond to incentives attempting to reduce electricity consumption (by turning off appliances or lights). However, EV load shifting is interested in *shifting,* not strictly reducing demand, and we believe EVs are not comparable to other home appliances. For that reason, we chose a study with the same goal we had, even though our project locations do not align. While only *residential* charging was studied in SDG&E's program and we are concerned with predominantly commercial usage, interpolating elasticities based on the time periods instead of specific hours adjusts for this issue. Moreover, all EV drivers owned a residential Level 2 home charger. All drivers owned or leased an electric Nissan Leaf, which was equipped to set charging times, as are most electric vehicles.[63] SDG&E's study also assume drivers are fully aware of price. This communication scenario is accounted for in our communication input, as discussed below. Lastly, SDG&E's study predominantly involved early EV adopters, whose behavior may not fully reflect that of the average EV driver in the future. In short, until additional studies can be conducted and elasticities then calculated empirically, the SDG&E elasticities offer a viable proxy for self-elasticities.

f) Communication Modifiers

Communication is an intervention that can have a significant effect on EV driver behavior.[64] Communication signals can notify the end user, the EV driver, as to the status of a dynamic rate schedule or a real-time price change. If that driver's utility offers demand response event incentives, such as discounts or rebates to shift EV load, then a communication signal to that driver can affect that driver's price responsiveness, or elasticity.

While we intended to model three communication areas - communications on GHG impacts, charging price, and health impacts - to see which one could have the largest impact on EV drivers, the literature only yielded reliable data on the impact of price and air pollution communications. These values come from studies on residential electricity consumption, as the EV field is too new to have robustly studied this effect.

For the impact of price communications, our best proxy comes from a 2014 study of home energy use, in which one of the key findings is that informing consumers who are provided with real time data on their energy use increases their elasticity of demand.[65] This study found that when informed about price only (through text, phone and/or email), consumers typically respond 0-7% more (average of 3.5%). This price communication modifier is intended to represent the impact

[63] Tuttle, "Data on Communications of Managed Charging."
[64] Fischer, "Feedback on Household Electricity Consumption: A Tool for Saving Energy?"
[65] Jessoe and Rapson, "Knowledge Is (Less) Power."

of an additional notification about price, i.e., it assumes that drivers already know their baseline price schedule.

For the impact of communication on air pollution, our proxy comes from a different 2014 study of home energy consumption in a neighborhood in Los Angeles.[66] The target population was young and technology minded. In a controlled study, messaging about the health and air pollution impacts of energy use reduced users' consumption by 8.2% relative to their baseline. Given the location and mindset of the study participants we use this value as a proxy for the impact of air pollution communication on EV drivers.

g) Throttling Elasticities

To encourage EV owners to charge during the off-peak period (11:00 a.m. - 3:00 p.m.), a 50% reduction in power to the chargers may be implemented during other periods of the day (6:00 - 11:00 a.m., 4:00 - 9:00 p.m.). This throttling is directly applied as a 50% cut in demand during the selected period.

h) Baseline: Number of EVs and EV Chargers

Each baseline load profile varies based on the number of chargers installed at the time. Including the number of chargers in our model allows us to model future load profiles, when there will be additional EVs on the road and chargers installed. The model does this first by scaling the baseline load profile to a per charger demand profile and then multiplying it by the total number of chargers input into the model, resulting in a total load profile.

While users of the model can manipulate this value on their own, we run scenarios based on current adoption projections. California has a goal of installing 250,000 chargers by 2025, in order to meet the state goal of 5 million ZEVs on the road by 2030.[67] As part of this, SCE intends to support the development of at least 50,000 chargers by 2025.[68]

i) Boundary: Theoretical Max

It is essential to know the exact amount of electricity that could be shifted, and the effects that has for the electrical grid, if all chargers were utilized from 11:00 a.m. to 3:00 p.m. as a result of effective demand response. We refer to this number as our "Theoretical Maximum." This maximum represents every charger being used during the midday load shift window of 1:00 a.m. to 3:00 p.m. and is the absolute upper boundary of demand shift that could be achieved.

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66 Asensio and Delmas, "Nonprice Incentives and Energy Conservation."

67 Gavin Bade, "CEC"; "Zero-Emission Vehicles"; "Zero Emission Vehicle (ZEV) Program"; Bedir et al., "California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025."

68 Griffo, "Edison Shares Vision for Clean Energy Future at Global Summit."

To calculate this, we need the number of chargers, the average power rating for every charger (kW), and the amount of time in our window (4 hours). Each model run calculates this per hour theoretical maximum using the following formula:

$$\#\ \text{Chargers} * \text{kW power rating} * 1\ \text{hour} = \text{Theoretical Max (kWh) per Hour}$$

Each model run calculates the theoretical maximum for the entire period as follows:

$$\#\ \text{Chargers} * \text{kW power rating} * 4\ \text{hours} = \text{Theoretical Max (kWh)}$$

Initial calculations considering the current number of chargers installed under the SCE pilot are as follows: As of November 2018, the Charge Ready Pilot had a total of 948 Level 2 Chargers installed across all four market segments. Table 4 table displays the maximum amount of electricity that could be drawn for each hour for each market segment as well as the total across all segments.

Table 4. Theoretical Maximum Electricity Used if all Chargers in the SCE Charge Ready Pilot were Used for an Entire Hour

Market Segment	Installed Chargers	Power Rating (kW)	Theoretical Max per hour (kWh)
Workplace	596	6.6	3,934
Destination Center	234	6.6	1,544
Fleet	83	6.6	548
MUD	35	6.6	231
Total	948	6.6	6,257

In order to find the theoretical max for a 4-hour window, such as the load shift target window, we multiply the number of hours by the final Theoretical Max column to see how much electricity could be drawn during that timeframe:

$$\text{SCE Pilot Theoretical Max} = 948\ \text{Chargers} * 6.6\ \text{kW power rating} * 4\ \text{hours} = 25{,}027.2\ \text{kWh}$$

Within the model, this theoretical max is used as to bound the amount of energy that could be shifted.

j) Curtailed Electricity

To determine the relevant impacts of managed charging on curtailment, the amount of curtailed energy during each seasonal-hour is input into the model. Since specific values for SCE overgeneration are confidential, specifically the pricing of curtailed renewable electricity, we use CAISO's 2018 Production and Curtailment data as a proxy. To focus our scope to SCE's territory, a ratio of SCE's electricity load (30%) was incorporated into the analysis.[69] While there are minor differences between California's aggregated data and SCE's, they are relatively similar.

For 2018, we use California's raw production data and curtailment for June 2017 to July 2018. For 2030, we pull projected curtailment data from literature, specifically from the National Resource Energy Laboratory.[70]

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[69] This 30% was calculated based on the percent of powerplants serving SCE's territory compared to those in California overall.
US EPA, "Emissions & Generation Resource Integrated Database (EGRID)."
[70] Brinkman et al., "Low Carbon Grid Study"; "Investigating a Higher Renewables Portfolio Standard in California"; Zhang, Markel, and Jorgenson, "Value to the Grid from Managed Charging Based on California's High Renewables Study."

Interventions

The interventions are the specific inputs which are applied in an attempt to manage charging. This includes the following:

- Price: Discount, Rebate, TOU Rate
- Non-price: Throttling, Communication

a) Price

Prices are the market signals that induce demand response. The most basic form of time variant pricing is a TOU rate, in which rates vary based on the time of day, the type of day (weekday or weekend), and even the season. This model considers TOU schedules because of their ability to influence EV drivers,[71] and because SCE is in the process of rolling out new TOU rates specifically for EV drivers.[72]

The other pricing interventions modelled are discounts and rebates, which are the basis of the SCE Charge Ready pilot demand response events and common tools in programs designed to change electricity usage. The ability to model these results can prove beneficial when comparing them to the demand response event data that we received from SCE. Additionally, we want to model a range of price changes in order to view the effect of a smaller or larger discount or rebate. Details on the specific values for each of these price interventions are below.

Discount

The discount encourages customers to use electricity during the target window to capitalize on surplus solar energy generated midday. This intervention tries to induce *load shift*. Under the current SCE pilot, it is a $0.05 discount during the load shift window from 11:00 a.m. - 3:00 p.m. For example, if this discount is applied to the 2018 TOU EV-4 price structure, the price falls from $0.12 to $0.07 per kWh for 11:00 a.m. - 12:00 p.m. and $0.29 to $0.25 for the rest of the hours in this window (12:00 - 3:00 p.m.).[73]

Rebate

The rebate is a pricing incentive that is intended to induce *load reduction* during target periods. Under the current pilot, SCE provides customers a $0.10 rebate on their electric bill in exchange for a reduction in demand between the hours of 4:00 - 9:00 p.m., the load reduction window, otherwise known as the time of peak demand.

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71 Cook, Churchwell, and George, "Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study."
72 "SCE Advice 3853-E."
73 Sisto, "Existing EV Rate Structures."

TOU Rate

The majority of Charge Ready participants are on TOU-EV-4, but some are on TOU-EV-3.[74] The periods associated with these rates "generally confine the lowest-cost charging periods to late-night hours," making it difficult for commercial and industrial customers who charge during the daytime periods to take advantage of these low evening rates.[75] New commercial TOU-EV rates will be rolled out in 2019 within SCE's service territory, which fundamentally change the on-peak, off-peak and super off-peak periods to reflect the needs of these customers as well as the grid.[76] The 2019 rate most applicable to Charge Ready sites is TOU-EV-8. The model can explore the impact of the difference in TOU rates for 2018 and 2019. All TOU rates are listed in Appendix II.

b) Non-price

Throttling

Throttling is a technological intervention that directly limits drivers' ability to charge. Throttling reduces the power sent to the EV charger by 50% with the intention of discouraging charging during throttling hours and encouraging charging in other periods. This intervention is modelled because it is being used as part of the SCE Charge Ready pilot and allows us to analyze the value of direct load control. For our model scenarios, we are incorporating throttling in two periods: 6:00 - 11:00 a.m. and 4:00 - 9:00 p.m.

Communication

Communication is another critical input that in integrated into our model. A large portion of demand response signals are not fully communicated to the end user, the EV driver. The Charge Ready pilot, for instance, is limited in its capacity to reach the end user since it can only communicate to the site hosts during demand response events. There is no guarantee that the hosts are informing EV drivers (whether they are customers, employees, or tenants) of a demand response event, or even charging any fee for the charge sessions. SCE does have a Demand Response Mobile App,[77] but that does not guarantee that every EV driver that might encounter a Charge Ready pilot charger is using the app. This model allows us to see what would happen if communication was directed to the end user.

The communication notifications options considered are as follows:

1) None
2) Communication about Price
3) Communication about Air Pollution

74 "Electric Vehicle Rates, Rebates and Incentives."
75 "SCE Advice 3853-E."
76 "SCE Advice 3853-E."
77 "Demand Response Mobile App."

Model Outputs

This project seeks to quantify the amount of electricity conserved or shifted as a result of various interventions on EV charging behavior. The model also considers the impacts of shifting EV charging behavior in terms of GHG emissions, environmental justice, and economic impacts.

Change in Demand

To model the change in demand over the course of a day, we first consider the impact of communication, then that of price, and finally that of throttling. The final output from this part of the model is an average expected change in demand. Figure 11 below outlines this order and output.

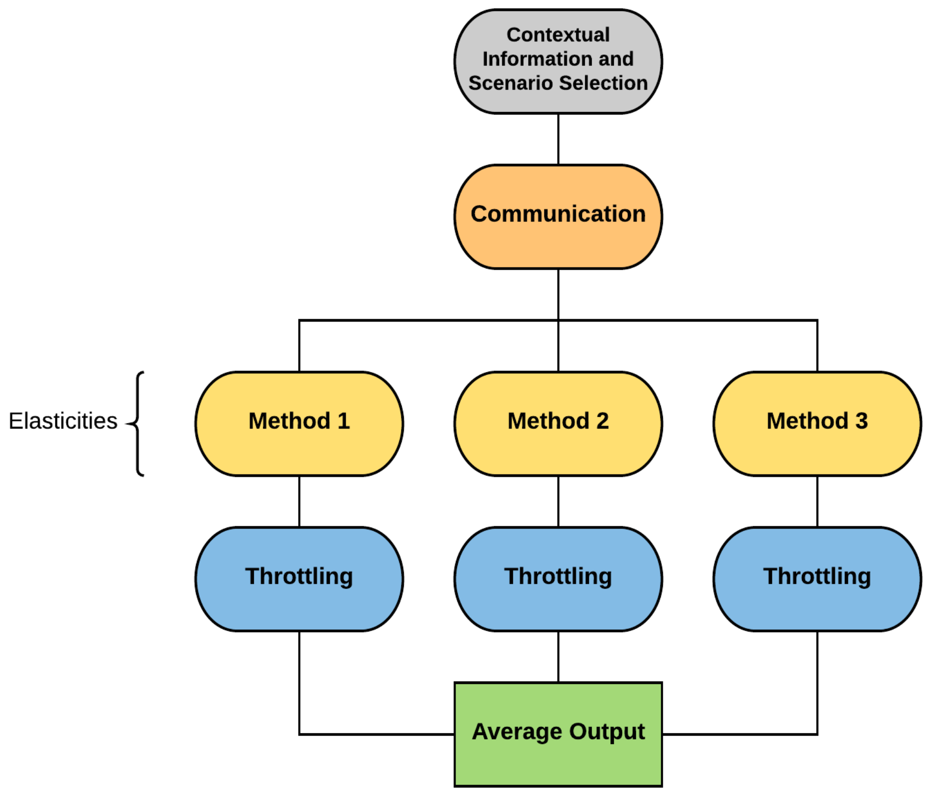

Figure 11. Model Flowchart for Change in Demand

Communication Intervention

We assume that the effect of communication about a price reaching an EV driver is similar to a change in the price. The following formula outlines this modification:

$$\textit{Original Price} + (\textit{Change in Price} * \textit{Communication Effect}) = \textit{Communication Modified Price}$$

For example, if there is a \$0.05 discount applied between 11:00 a.m. and 3:00 p.m. and we then assume all of that discount is being conveyed to the end user (100% communication), then the discounted price would be as follows:

$$\$0.29 + (-\$0.05 * 1) = \$0.24$$

But, when we incorporate a 20% communication effect (meaning 80% of that price signal does not reach the end user), then it is as if only 20% of that discount is conveyed and the resulting price is higher:

$$\$0.29 + (-\$0.05 * 0.2) = \$0.28$$

Even though a \$0.05 discount is being applied to both scenarios above, altering the price with the communication effect essentially indicates *less* of a discount occurs with *less* communication.

Any communication intervention that occurs in our model is relative to the SDG&E study since this is the source of our self-elasticity values. We assume that all the EV drivers in the SDG&E study are fully informed because they receive communications and thus have a communication modifier value of 1 (or 100%). We also assume that SCE's communication gap is 96.5%.[78] That means about 3.5% of the price signal is *not* being received by the EV driver.

Since communication acts as a price modifier, its impact is incorporated first into our model.

[78] We make this assumption because no price notification is reaching the EV end users. The general communication barrier between EV drivers and SCE is not directly quantified in our model, as discussed in the assumption and limitations section.

Price Intervention & Price Elasticities

Determining how demand changes in response to price typically only involves the self- and cross-price elasticities. For EVs, this would require data on the self- and cross-price elasticities at each hour of the day, to form a 24- by 24-hour matrix.[79] Unfortunately, that information has not been estimated in the literature. However, we included this method in the tool we built so if a 24- by 24-hour matrix becomes available, this method can be run.

Given this data gap, our model takes a different approach to determining how demand changes in response to price. Our model focuses on using self-elasticities to determine the change in demand in the hours when a price intervention occurs. We then use a variety of methods to determine how demand changes in the non-intervention hours. Given the uncertainty around EV price elasticities, this model considers three approaches to determining the impact of a price change. Through these three methods, we vary the self- and cross-price elasticities, along with the average elasticity, to model how demand changes in response to price. By running three methods, and then averaging across their results, we represent the range of possible outcomes arising from the uncertainty in these elasticity values.

Method 1 assumes that users only respond to a price change in the hour that the price changes (intervention hours) and do not change their behavior in the other hours (non-intervention hours). In other words, there is no load shifting, and cross-price elasticities are zero. Method 2 assumes that users only shift their load based on a price signal, and thus there is no net increase in load. Here, there is only load shifting. And, lastly, Method 3 assumes that users change their behavior in response to price changes in the intervention hours and how that changes the average price over the day. A summary of these methods is provided in Table 5 below.

[79] When developing that matrix, elasticities must be found for *each* hour. Extrapolating individual hour elasticities from other time categories (such as taking the periods of the day and extrapolating to a 24-hour scale) may overestimate the relationship between price changes during periods of low demand, like the middle of the night, and periods of high demand.

Table 5. Price Intervention Methods.

Method	Steps *Find load change in…*	Step Details	Potential Load Outputs	Assumptions
1	1. Intervention Hours	Self-elasticities	Change: Yes Shift: No	When price changes at any hour of the day, demand only changes in that hour
	2. Non-Intervention Hours	Assume zero		
	3. The Entire Day	Sum of Change in intervention and non-intervention hours		
2	1. Intervention Hours	Self-elasticities	Change: No Shift: Yes	A change in price at only one or some hours of the day leads to a shifting of demand so that net demand is zero
	2. The Entire Day	Assume zero		
	3. Non-Intervention Hours	Equal to the value needed to maintain zero net change in load, given the self-elasticities		
3	1. Intervention Hours	Self-elasticities	Change: Yes Shift: Yes	When price changes at any of the day, demand in that hour responds to that price change; demand in all other hours responds in a way to ensure that the average elasticity remains true
	2. The Entire Day	Average elasticity		
	3. Non-Intervention Hours	Equal to the value needed to maintain the net load set by the average elasticity given the self-elasticities		

The following explains each of these methods and how they are incorporated into one output. One example (Workplaces, November 2018 Baseline Load and Chargers, 2018 TOU-EV-4, Weekdays Only, $0.05/kwh Discount from 11:00 a.m. - 3:00 p.m., No Throttling, No Air Pollution or Price Communication) is provided for each method to highlight how they vary. These examples are listed after each method description.

Method 1

This method assumes that a change in price in an hour *only* impacts demand at that hour and has no spillover effect into other hours. Here, we use the self-elasticities to determine the change in demand during the hours when price changes, and assume the cross-price elasticities are zero. Since cross-price elasticities are not considered and all self-elasticities are negative, this method will always lead to a net increase in load.

In our model, this method draws from the 12 elasticities reported in the SDG&E study (Table 3). This method weights those sets of elasticities equally. Thus, this method yields 12 potential new demand curves.

Step 1. Find Change in Demand in Individual Intervention Hours

We first find the percent change in demand at each hour due to the percent change in price at that hour using the self-elasticities:

$$\%\Delta X_i = \varepsilon_{i,i} * \%\Delta P_i$$

$$where$$
$$\%\Delta X_i = percent\ change\ in\ demand\ in\ hour\ i$$
$$\%\Delta P_i = percent\ change\ in\ price\ in\ hour\ i$$
$$\varepsilon_{i,i} = elasticity\ of\ demand\ in\ hour\ i\ with\ respect\ to\ a\ price\ change\ in\ hour\ i\ (self - elasticity)$$

We then find the actual change in demand by multiplying that percentage change by the initial demand, as follows:

$$\Delta X_i = \%\Delta X_i * X_{0,i}$$

$$where$$
$$\Delta X_i = change\ in\ demand\ in\ hour\ i$$
$$\%\Delta X_i = percent\ change\ in\ demand\ in\ hour\ i$$
$$X_{0,i} = initial\ demand\ in\ hour\ i$$

Step 2. Assume Change in Load in All Non-intervention Hours is Zero

Since we assume the cross-price elasticity is zero, there is no change in demand in non-intervention hours.

Thus, the total change in daily demand is the sum of the change in demand in our intervention hours.

Method 1 Example

Step 1. Find Change in Demand in Individual Intervention Hours

When lowering the price from 11:00 a.m. - 3 p.m. by $0.05 and use the self-elasticities from Table 3, the following changes in demand will be seen in these hours:

$$\%\Delta X_{ih,12} = -0.42 * -55.6\% = 23\%$$
$$\%\Delta X_{ih,13} = -0.38 * -45\% = 17\%$$
$$\%\Delta X_{ih,14} = -0.38 * -45\% = 17\%$$
$$\%\Delta X_{ih,15} = -0.38 * -45\% = 17\%$$

Assuming all hours started with the initial demands listed below, the magnitude of demand will change as follows:

$$\Delta X_{12} = 0.23 * 407 = 94\ kWh$$
$$\Delta X_{13} = 0.17 * 459 = 78\ kWh$$
$$\Delta X_{14} = 0.17 * 563 = 96\ kWh$$
$$\Delta X_{15} = 0.17 * 290 = 49\ kWh$$

Step 2. Assume Change in Demand in All Non-intervention Hours is Zero

Since the price does not change at hours 3:00 p.m. - 11:00 a.m., there is no percent change in demand in these 20 non-intervention hours.

Thus, our total change in demand is only contingent on the intervention hours and would be as follows:

$$\Delta X_{12-15} = 94 + 78 + 96 + 49 = 317\ kWh$$

The blue line in Figure 12 below demonstrates this change.

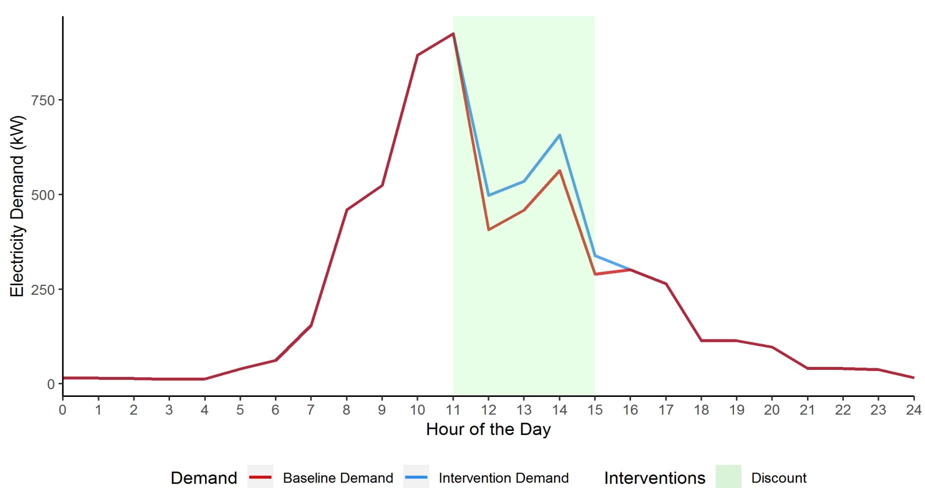

Figure 12. Method 1 Example Result

Method 2

Method 2 again uses the self-elasticities from the literature and assumes all cross-elasticities are zero, but it goes one step further than Method 1 and assumes that *all* load is shifted. In other words, this method builds in the assumption that there is zero change in daily load. This is done by using the self-elasticities to determine the change in load in the target window and then distributing that change across the other hours of the day based on the initial load profile. Thus, we treat the intervention hours (when a price change occurs) differently from the non-intervention hours (when a price change does not occur). The following details the steps in this method.

In our actual model, this method is also run with 12 sets of self-elasticities and thus yields 12 potential new demand curves.

<u>Step 1. Find Change in Demand in Individual Intervention Hours</u>

As in Method 1, we use the self-elasticities as follows to find the percent change in demand:

$$\%\Delta X_{ih,i} = \varepsilon_{i,i} * \%\Delta P_i$$

$$\begin{aligned}&\mathit{where}\\ \%\Delta X_{ih,i} &= \mathit{percent\ change\ in\ demand\ in\ intervention\ hour\ i}\\ \%\Delta P_i &= \mathit{percent\ change\ in\ price\ in\ intervention\ hour\ i}\\ \varepsilon_{i,i} &= \mathit{elasticity\ of\ demand\ in\ hour\ i\ with\ respect\ to\ a\ price\ change\ in\ hour\ i}\ (\mathit{self} - \mathit{elasticity})\end{aligned}$$

We find the actual change in demand by multiplying that percentage change by the initial demand:

$$\Delta X_{ih,i} = \%\Delta X_{ih,i} * X_{0,ih,i}$$

$$\begin{aligned}&\mathit{where}\\ \Delta X_{ih,i} &= \mathit{change\ in\ demand\ in\ intervention\ hour\ i}\\ \%\Delta X_{ih,i} &= \mathit{percent\ change\ in\ demand\ in\ intervention\ hour\ i}\\ X_{0,ih,i} &= \mathit{initial\ demand\ in\ intervention\ hour\ i}\end{aligned}$$

<u>Step 2. Find Change in Demand in All Intervention Hours</u>

We then sum those results to find the total change of demand in all intervention hours:

$$\Delta X_{ih,t} = \sum \Delta X_{ih,i}$$

$$\begin{aligned}&\mathit{where}\\ \Delta X_{ih,t} &= \mathit{total\ change\ in\ demand\ in\ intervention\ hours}\\ \Delta X_{ih,i} &= \mathit{change\ in\ demand\ in\ intervention\ hour\ i}\end{aligned}$$

<u>Step 3. Assume Net Change in Demand is Zero.</u>

<u>Step 4. Determine Change in Demand in All Non-intervention Hours</u>

Since we assume that the net change in load is zero, any change in demand in the intervention hours must have a corresponding change in demand in non-intervention hours. For example, if demand increased in the intervention hours as a result of a price decrease in the intervention hours, then demand must decrease by a corresponding amount across the non-intervention hours. Thus, the change in all non-intervention hours is as follows:

$$\Delta X_{ih,t} + \Delta X_{oh,t} = 0$$
$$\Delta X_{oh,t} = 0 - \Delta X_{ih,t}$$

$$where$$
$$\Delta X_{ih,t} = total\ change\ in\ demand\ in\ intervention\ hours$$
$$\Delta X_{oh,t} = total\ change\ in\ demand\ in\ non\ intervention\ hours$$

<u>Step 5. Determine Change in Demand in Individual Non-intervention Hours</u>

From the total change in load in non-intervention hours, we find the change in demand in individual non-intervention hours. We assign a portion of total change in load to each hour based on how much load that hour represents across the non-intervention hours in the baseline scenario. In other words, we maintain the general load curve in non-intervention hours. The following formula outlines this for one non-intervention hour:

$$\Delta X_{oh,i} = \Delta X_{oh,t} * \frac{X_{0,oh,i}}{X_{0,oh,t}}$$

$$where$$
$$\Delta X_{oh,i} = change\ in\ demand\ in\ non\ intervention\ hour\ i$$
$$\Delta X_{oh,t} = total\ change\ in\ demand\ in\ non\ intervention\ hours$$
$$X_{0,oh,i} = initial\ demand\ in\ non\ intervention\ hour\ i$$
$$X_{0,oh,t} = total\ initial\ demand\ in\ non\ intervention\ hours$$

Method 2 Example

Step 1. Find Change in Demand in Individual Intervention Hours

As this is the same methodology as that used in Method 1, we would see the same results in our example. When lowering the price in hours 11:00 a.m. to 3:00 p.m. by $0.05, demand changes by 23% from 11:00 a.m. to 12:00 p.m. and 17% in each hour between 12:00 and 3:00 p.m.

Step 2. Find Change in Demand in All Intervention Hours

As in Method 1, our total change in demand in the intervention hours is 317 kWh.

Step 3. Assume Net Change in Demand is Zero.

Step 4. Determine Change in Demand in All Non-intervention Hours

As the change in intervention hours is +317 kWh, the change in our non-intervention hours is -317 kWh.

Step 5. Determine Change in Demand in Individual Non-intervention Hours

In our example, we can determine the percentage of load at each hour and then determine the change in load at each of these hours. Examples of how this can be done for three non-intervention hours are listed:

$$\Delta X_{oh,1} = -317 * 0.004 = -1.27\ kWh$$
$$\Delta X_{oh,8} = -317 * 0.11 = -35.50\ kWh$$
$$\Delta X_{oh,11} = -317 * 0.225 = -71.33\ kWh$$

These changes can be seen in Figure 13 below.

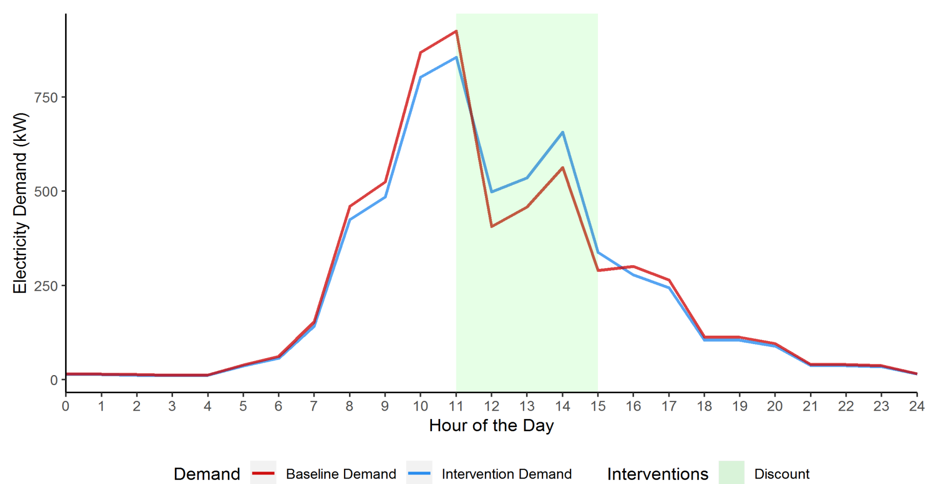

Figure 13. Method 2 Example Result

Method 3

Like Methods 1 and 2, Method 3 considers the self-elasticities from the literature and considers the cross-elasticities to be zero. However, it also uses the average elasticity to determine the net change in load. Self-elasticities determine the load increase in the intervention window, while the average determines the net change over the day. Together these values allow us to find the change in the non-intervention window.

In our actual model, this method is run with 12 sets of self-elasticities and average elasticities ranging from -0.04 to -0.85 in increments of -0.01.

<u>Step 1. Find Change in Demand in Individual Intervention Hours</u>

We use the same self-elasticity method as Methods 1 and 2 to find the change in demand (percentage and magnitude) in the intervention hours:

$$\%\Delta X_{ih,i} = \varepsilon_{i,i} * \%\Delta P_i$$

$$where$$
$$\%\Delta X_{ih,i} = percent\ change\ in\ demand\ in\ intervention\ hour\ i$$
$$\%\Delta P_i = percent\ change\ in\ price\ in\ intervention\ hour\ i$$
$$\varepsilon_{i,i} = elasticity\ of\ demand\ in\ hour\ i\ with\ respect\ to\ a\ price\ change\ in\ hour\ i\ (self - elasticity)$$

$$\Delta X_{ih,i} = \%\Delta X_{ih,i} * X_{0,ih,i}$$

$$where$$
$$\Delta X_{ih,i} = change\ in\ demand\ in\ intervention\ hour\ i$$
$$\%\Delta X_{ih,i} = percent\ change\ in\ demand\ in\ intervention\ hour\ i$$
$$X_{0,ih,i} = initial\ demand\ in\ intervention\ hour\ i$$

<u>Step 2. Find Change in Demand in All Intervention Hours</u>

We then sum those results to find the total change of demand in all intervention hours:

$$\Delta X_{ih,t} = \sum \Delta X_{ih,i}$$

$$where$$
$$\Delta X_{ih,t} = total\ change\ in\ demand\ in\ intervention\ hours$$
$$\Delta X_{ih,i} = change\ in\ demand\ in\ intervention\ hour\ i$$

<u>Step 3. Determine Total Daily Change in Demand</u>

Unlike in Method 2, we do not assume the change in demand over the course of the day is zero. Instead, we assume that the average elasticity associated with EV charging determines the total change in demand over the course of the day.

$$\%\Delta X_t = \varepsilon_a * \%\Delta P_a$$

$$where$$

$$\%\Delta X_t = percent\ change\ in\ demand\ over\ the\ entire\ day$$
$$\%\Delta P_a = percent\ change\ in\ daily\ average\ price$$
$$\varepsilon_a = average\ elasticity\ of\ demand\ over\ the\ entire\ day$$

To determine that percent change in demand, we need the percent change in average price as a result of the intervention. This is found by determining the average price paid for each kW of electricity consumed under the initial price and load schedule, as detailed below:

$$\%\Delta P_a = \frac{P_1 - P_0}{P_0}$$

$$P_1 = \frac{Initial\ Price\ at\ Each\ Hour * Initial\ Demand\ Each\ Hour}{Total\ Daily\ Demand} = \frac{\sum_{i=1}^{24}(X_{0,i} * P_{1,i})}{\sum_{i=1}^{24} X_{0,i}}$$

$$P_0 = \frac{New\ Price\ at\ Each\ Hour * Initial\ Demand\ Each\ Hour}{Total\ Daily\ Demand} = \frac{\sum_{i=1}^{24}(X_{0,i} * P_{0,i})}{\sum_{i=1}^{24} X_{0,i}}$$

where

$$\%\ \Delta P_a = change\ in\ daily\ average\ price$$
$$P_1 = average\ price\ with\ intervention$$
$$P_0 = average\ initial\ price$$
$$X_{0,i} = initial\ demand\ at\ hour\ i\ in\ kWh$$
$$P_{0,i} = initial\ price\ at\ hour\ i\ in\ \$/kWh$$
$$P_{1,i} = intervention\ price\ at\ hour\ i\ in\ \$/kWh$$

From the percent change in price, we can find the percent change in demand using our standard elasticity equation, as listed above.

From our percent change in demand, we calculate the magnitude of the daily change in demand:

$$\Delta X_t = \%\Delta X_t * X_{0,t}$$

where

$$\Delta X_t = change\ in\ demand\ over\ the\ entire\ day$$
$$\%\Delta X_t = percent\ change\ in\ demand\ over\ the\ entire\ day$$
$$X_{0,t} = initial\ demand\ over\ the\ entire\ day$$

Step 4. Determine Change in Demand in All Non-intervention Hours

From the daily change in demand due to the average elasticity and the total change in demand in the intervention hours, we can determine how much load must change in the non-intervention hours, using the same method as that in Method 2. Thus, the change in all non-intervention hours is as follows:

$$\Delta X_{ih,t} + \Delta X_{oh,t} = \Delta X_t$$
$$\Delta X_{oh,t} = \Delta X_t - \Delta X_{ih,t}$$

$$where$$
$$\Delta X_{ih,t} = total\ change\ in\ demand\ in\ intervention\ hours$$
$$\Delta X_{oh,t} = total\ change\ in\ demand\ in\ non\ intervention\ hours$$
$$\Delta X_t = total\ change\ in\ demand\ over\ the\ entire\ day$$

Step 5. Determine Change in Demand in Individual Non-intervention Hours

We can use the same process as in Method 2 to find the change in individual non-intervention hours. We want to know how much of the total change in load in non-intervention hours can be assigned to each non-intervention hour. We assign this load to each hour based on how much load that hour represents across the non-intervention hours before the intervention. Thus, we maintain the general load curve in non-intervention hours. The following formula outlines this for one non-intervention hour.

$$\Delta X_{oh,i} = \Delta X_{oh,t} * \frac{X_{0,oh,i}}{X_{0,oh,t}}$$

$$where$$
$$\Delta X_{oh,i} = change\ in\ demand\ in\ non\ intervention\ hour\ i$$
$$\Delta X_{oh,t} = total\ change\ in\ demand\ in\ non\ intervention\ hours$$
$$X_{0,oh,i} = initial\ demand\ in\ non\ intervention\ hour\ i$$
$$X_{0,oh,t} = total\ initial\ demand\ in\ non\ intervention\ hours$$

Method 3 Example

Step 1. Find Change in Demand in Individual Intervention Hours

As this is the same methodology as that used in Methods 1 and 2, we see the same results in our example. When lowering the price in hours 11:00 a.m. to 3:00 p.m. by $0.05, demand changes by 23% from 11:00 a.m. to 12:00 p.m. and 17% in each hour between 12:00 and 3:00 p.m.

Step 2. Find Change in Demand in All Intervention Hours

As in Method 1 and 2, our total change in demand in the intervention hours is 317 kWh.

Step 3. Determine Total Daily Change in Demand

In our example, our average elasticity is –0.4 and our average percent change in price is –15.9%. Thus, we can determine the percent change in demand over the entire day as follows:

$$\%\Delta X_t = -0.4 * -.159 = 6\%$$

That percent change in demand can be translated into a magnitude of change in daily demand:

$$\Delta X_t = 0.06 * 5830 = 350\ kWh$$

Step 4. Determine Change in Demand in All Non-intervention Hours

The change in non-intervention hours is the difference between the daily and intervention hour totals:

$$\Delta X_{oh,t} = 350 - 317 = 43\ kWh$$

Step 5. Determine Change in Demand in Individual Non-intervention Hours

We can then determine the change in load at each non-intervention hour based on the percentage of load each hour is responsible for. A few hours are listed below to elucidate this relationship:

$$\Delta X_{oh,1} = 43 * 0.004 = 0.17\ kWh$$
$$\Delta X_{oh,8} = 43 * 0.11 = 4.86\ kWh$$
$$\Delta X_{oh,11} = 43 * 0.225 = 9.68\ kWh$$

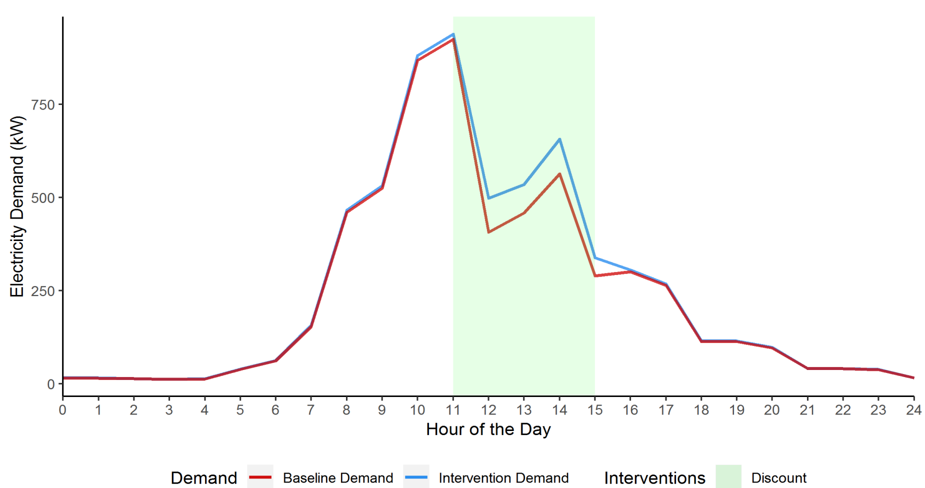

Figure 14. Method 3 Example Result

Final Average

Our model weights each of these methods equally, regardless of the number of underlying elasticities they may consider. Through a Monte Carlo simulation, we run each method 33.3% of the time. For each full model run, we run our simulation 1000 times. We then average the results from the three methods. Our final results present the averaged output from the three methods. Through our application, discussed below, users can further look into the trends associated with each method.

Figure 15 below shows the change in demand for this scenario and all methods for our featured example.

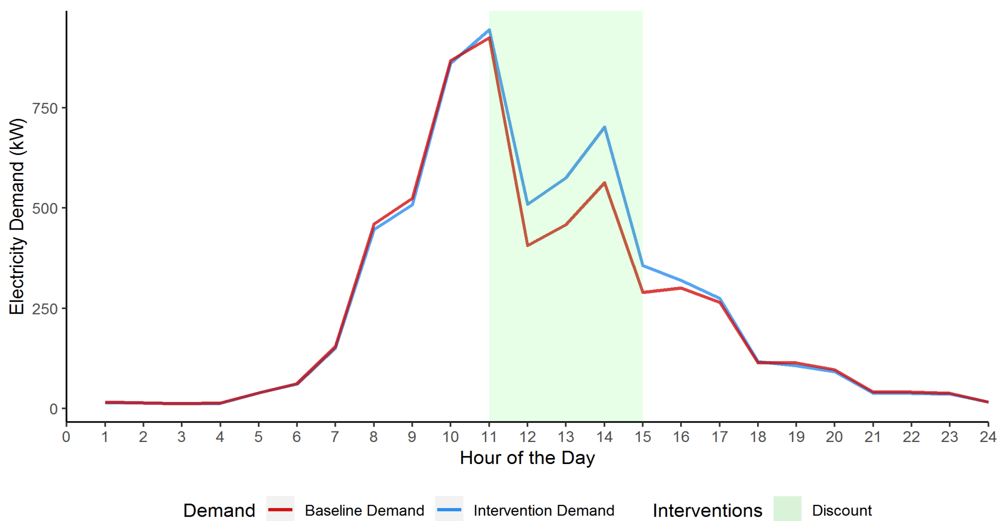

Figure 15. Methods 1-3 Example Result

Throttling Intervention

Throttling is layered onto the demand profile produced by a price modification. Throttling is a direct cut to the power available during a set hour. To that end, 50% throttling directly cuts the kWh demanded during the throttling window, as outlined in the following equation:

*Baseline Demand (kWh) * 0.50 = Demand with Throttling*

We considered applying throttling to the elasticities, but found an attempt to incorporate throttling into the model severely overestimated its value, as compared to SCE's pilot. See discussion under model refinement below. Throttling is also applied to each method before it is averaged with the other three methods, so our model produces a final averaged output, not an averaged output that we then modify.

Curtailment Impact

To determine the relevant impacts of managed charging on curtailment, the change in energy demanded is compared to the theoretical maximum curtailment reduction. Curtailment can occur from 8:00 a.m. to 6:00 p.m., so we must look at it over this period. First, we determine what percentage of the change in load could come from solar energy. To be conservative, we assume that the percentage of marginal solar energy will be the same as that in the total fuel mix. For example, if solar energy accounts for 30% of the baseline load at 10:00 a.m., then solar will also account for 30% of any change in demand. These solar percentages were drawn from the fuel mix discussed in the subsequent section.

In one place we varied our methodology. In 2018, we assume that 75% of any change in demand during the 11:00 a.m. to 3:00 p.m. window comes from solar energy.[80] We made this assumption since we know that curtailment values during this period are large and additional load will predominantly come from solar. In 2030, we did not need to make this assumption as solar is already forecast to provide at least 70% of energy.

To determine the modelled change in curtailment, we multiply the change during our target window by the percent of solar as follows:

*% Solar * Change in Load (kWh) = Modelled Change in Curtailment at Each Hour*

If this number is positive, then curtailment is reduced; if negative, curtailment is exacerbated. We then compare this number to the theoretical maximum change in curtailment calculated as part of our inputs. The theoretical maximum represents the total curtailed energy that could *theoretically* be avoided. In other words, it is the upper bound of any change in curtailment that our modelled scenario can cause. If the modelled change in curtailment is less than the theoretical, then the modelled change represents the change in curtailment. If the modelled change is more than the theoretical maximum, than the theoretical maximum is substituted in and represents the change in curtailment. The equations below outline this relationship:

If Modelled Change in Curtailment < Theoretical Maximum Change in Curtailment:
Change in Curtailment = Modelled Change in Curtailment

If Modelled Change in Curtailment > Theoretical Maximum Change in Curtailment:
Change in Curtailment = Theoretical Maximum Change in Curtailment

[80] More on this numerical breakdown can be found in the GHG emission section below. In general, this number is based on the assumption that any change in energy from 11:00 a.m. to 3:00 p.m. will predominantly involve turning on or off solar, but since natural gas is also a load-following resource, it will likely be manipulated to meet this load as well.

Our model reports the impact on curtailment as a percent, not a magnitude (i.e., the percentage reduction in curtailment).

Our model also seeks to make a rough estimate of the financial benefit associated with reducing curtailment. The cost of curtailing energy, for the utility, varies based on the reason for curtailment and the market. When curtailment requires paying electricity generators not to produce electricity, CAISO allows costs to go as high as $150/MWh, or $0.15/kWh.[81] In other words, generators agree to curtail their electricity based on a bid up to that value. This value was set at such a high point as an attempt to ensure that wind generators who receive tax credits for generating power are also incentivized to curtail energy when required.[82] This value does not fully capture the cost of curtailment. In some instances, it may overestimate the cost and in others it may underestimate the cost. However, it is our best proxy value. We can use that number as follows to estimate the savings from reducing curtailment or costs from exacerbating it:

*Curtailment Cost * Change in Curtailment (kWh) = Impact ($)*

81 Wells, "Self-Schedules Bid Cost Recovery Allocation and Bid Floor Addendum to Draft Final Proposal"; "Self-Schedules Bid Cost Recovery Allocation and Lower Bid Floor Draft Final Proposal: Comments from DMM."

82 Bird, Cochran, and Wang, "Wind and Solar Energy Curtailment."

Customer Cost

Our model also considers the impact of shifting demand on customer costs. To do so, we determine how much site hosts paid for charging under the baseline scenario and then how much they would pay under the modelled scenario. We apply the following formula at each hour and then sum the values across all hours:

*Demand (kWh) * Price at That Hour ($) = Customer Cost at That Hour ($)*

Greenhouse Gases and Air Pollution

Currently, most of the electricity generated in the middle of the day in California comes from solar resources, while a mix of natural gas, hydro, nuclear, imports, and other renewables supply power during the rest of the day.[83] Since energy resources vary over the course of the day, this means that GHG and air pollution emissions associated with that generation also varies at different times of the day.

Given the variability in fuel supply over the day, we are interested in understanding the emissions associated with generating a unit of electricity (kWh) for customers within SCE's territory at each hour of the day. In other words, we want to know the annual average hourly "emission factor." The GHG electricity emission factor is defined as the amount of GHG emissions per unit of generation measured in metric tons carbon dioxide equivalent per megawatt hour of electricity generation (MT CO_2eq/MWh).[84] The air pollution emission factor is defined as the amount of NOx released per unit of generation measured in metric tons of NOx per megawatt hour of electricity generation (MT NOx/MWh). With these hourly emissions factors we can complete the following key elements in our research:

- Estimate baseline emission levels associated with EV charging behavior in SCE's territory.
- Quantify the change in emissions after applying different interventions.
- Quantify the financial impact of a change in emissions.

We are specifically interested in GHG emissions because one of the goals of EVs is a reduction in GHG emissions. We are also interested in NOx emissions because we want to understand the impact of changing EV driving behavior on air pollution. NOx contributes to the creation of smog and acid rain. Inhalation of these smog particles can worsen lung function, exacerbate asthma and respiratory diseases, and even lead to premature death.[85] NOx is the primary air pollutant associated with the combustion of natural gas, and the main fossil fuel currently used in California. For that reason, this model uses NOx as its primary indicator of air pollution impacts.

The following sections outline how we find hourly emissions factor and how they are used to provide emissions outputs.

Finding an Hourly Emission Factor

Many factors affect electricity's emissions factors, including the quantity and fuel source of the electricity. The electricity emissions factor for the SCE service territory depends on the percentage of electricity from each source and emissions factor of each source in a given year.

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[83] "2017 Annual Report on Market Issues and Performance."

[84] Anders, Silva-Send, and Gu, "Estimating Annual Average Greenhouse Gas Emission Factors for the Electric Sector: A Method for Inventories."

[85] "Levelized Cost of Energy 2017."

We need to determine the fraction of electricity supplied by each fuel source (natural gas, solar, etc.) at each hour, and then generate a total emissions factor for each hour by weighting each fuel source's emissions factor based on its fraction of the supply. The equation below outlines this formula for an example hour:

$$Hourly\ Emission\ Factor = \ Supply\ Fraction_1 * EF_1 + \cdots + Supply\ Fraction_n * EF_n$$

To find our 24 hourly emission factors, we had to determine the hourly fuel mix and the emission factors for each resource. The following two sections detail these calculations. Since our model is intended to calculate impacts for both 2018 and 2030 and we expect grid resources to change over this period, we determine a fuel mix and emission factors for both years. Appendix III lists the hourly supply fractions.

SCE 2018 Fuel Mix: Supply Fractions

Since SCE's current hourly fuel mix is not publicly available, we adapt publicly available data on the entire state's fuel mix. CAISO reports the amount of each fuel used at each hour of the day across the entire state.[86] From that data, we calculate the percentage of each fuel used at each hour. We assume that SCE, whose territory accounts for roughly one-third of all electricity demand in the state, has a similar hourly fuel mix.

The CAISO numbers, however, lack sufficient detail for us to determine all resources. As of 2017, 29% of California's power is imported from the north- and south-west.[87] CAISO lists power imported as "imports," without providing details on what fuel resources provide this imported power. We use the California Energy Commission's 2017 breakdown of imported fuel resources to determine the fraction of imports coming from each fuel resource.[88] Together the CAISO and CEC data provide a good estimation of the hourly fuel mix.

Yet, a significant portion of the overall electricity supply still cannot be traced to its original fuel sources and is categorized as "unspecified source of power."[89] This poses a challenge for determining relevant emission factors, as discussed below.

SCE 2030 Fuel Mix: Supply Fractions

Since an SCE specific 2030 projected fuel mix is not readily available, we adapt the National Renewable Energy Lab's (NREL) projections for California's 2030 fuel mix.[90] We consider two projections: diverse and conservative. While both scenarios are projected to meet California's RPS

86 "OASIS Database."
87 "Total System Electric Generation."
88 "Total System Electric Generation."
89 California Public Utilities Code Section 398.2(a), (c), & (d).
90 Brinkman et al., "Low Carbon Grid Study."

goals, the diverse scenario assumes even more renewables will be integrated and accompanied by battery storage.

The following summarizes the two scenarios:

- Due to the expected decommissioning of Diablo Canyon Power Plant in 2026, in-state nuclear generation disappears; however, California is expected to continue to import nuclear energy.
- Energy from oil and coal are excluded in 2030 in both projected fuel mix. As California shifts to a zero-carbon fuel mix, this most polluting technologies will be displaced first.
- Both scenarios include natural gas, and project that natural gas generation will be needed through at least 2030 to aid grid stability and flexibility.[91] Our conservative scenario still assumes a minimum of 25% local natural gas generation in each hour to address flexibility and local capacity requirement concerns in California.[92] The diverse scenario does not have this assumption built in, but still sees natural gas percentages ranging from 18-25% in most hours. However, natural gas is not used from 9:00 a.m. to 4:00 p.m. in our diverse scenario. High renewable penetration with imports in the diverse scenario will satisfy electricity demand during these daylight hours.
- A minimum of 1.5 GW of battery storage is required in both scenarios to meet California Public Utility Commission's requirements.[93] Based on the literature, we expanded the diverse fuel mix to 3.5 GW to increase dispatch flexibility during high demand periods.

The differences across scenarios can be seen in Figures 16 and 17 below.

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[91] "Turning Down the Gas in California."
[92] Local capacity requirements are very important for ensuring grid reliability and currently met through natural gas. The literature projects that utility scale batteries can address grid flexibility issues (ramping up and down) and substantially reduce gas plant usage.
"Turning Down the Gas in California."
[93] "Decision 13-10-040: Decision Adopting Energy Storage Procurement Framework and Design Program."

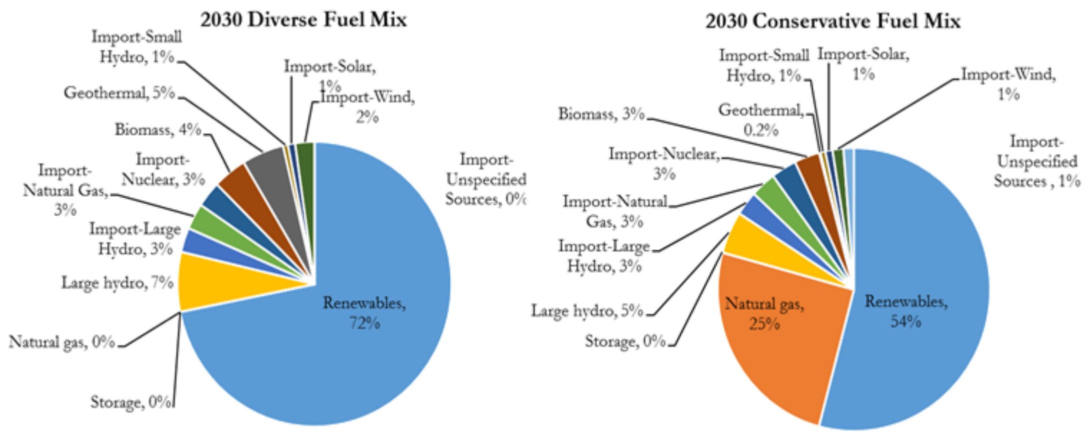

Figure 16. 2030 Hourly Fuel Mix Projection for 12:00 - 1:00 p.m.

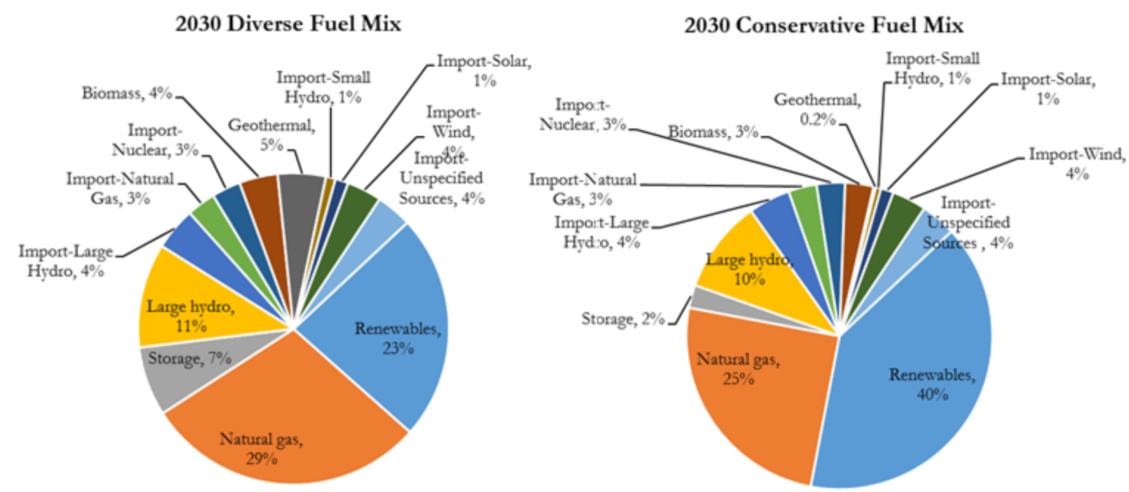

Figure 17. 2030 Hourly Fuel Mix Projection for 6:00 - 7:00 p.m., a peak demand hour

For our model, we use the conservative fuel mix to account for our baseline GHG and air quality hourly emissions. We use the diverse fuel mix to account for our marginal GHG and air pollution emissions. In short, we assume that our marginal power is more renewable than our baseload, an idea we also use for our 2018 calculations.

As NREL's projected fuel mix uses slightly different categories than those set by CAISO and thus used for our 2018 calculations, we had to modify the fuel mixes from NREL. We re-categorized wind, solar PV, and solar thermal as renewables, and combustion turbine, combined cycle, and combined heat and power as natural gas.

2018 and 2030 Supply Emission Factors

As this model is concerned with electricity generated to serve SCE's customers, we need emissions factors for the electricity actually generated within SCE's territory. For example, we want to know the emissions associated with natural gas generated in SCE's territory, not any generic natural gas plant. Yet, we are unable to obtain precise, internal emission factors. Instead, we use reliable data sources to generate a proxy. These proxies provide a more location specific number than a generic emission factor associated with each fuel resource, but caution should be used when taking them out of this context.

To determine the emissions factor from each fuel, we use data on the emissions and net generation at each plant serving SCE territory. Our basic methodology involves dividing the total emissions reported from plants in each fuel source by the total electricity generated by that fuel source. The equation below outlines this process for the GHG emission factor:

$$Emission\ Factor\ \left[\frac{CO_2\ eq\ MT}{MWh}\right] = \frac{Emissions\ [CO_2 eqMT]}{Net\ Generation\ [MWh]}$$

An example of the GHG emission factor calculation is given below:

$$Emission\ Factor = \frac{428{,}515.20[CO_2 eqMT]}{769{,}748.02[MWh]} \times \frac{1000kg}{MT} \times \frac{MWh}{1000kWh} = 0.556\frac{CO_2 eqkg}{kWh}$$

Electricity generated by solar, wind, and hydro is assumed to have zero emissions and thus a zero-value for the emission factor since we are only considering the power generation phase and not the entire life cycle.[94]

We calculated emission factors for all natural gas plants and their sub-categories of "load-following" and "peaker" as we are interested in the specific contributions of these plants when we apply an intervention.[95]

All resources, besides unspecified resources are calculated with the equation above. Since it is impossible to determine the origin of unspecified resources, we use the default emission factor used by the Mandatory Reporting of GHG emissions from California Air Resource Board (CARB).[96]

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[94] Anders, Silva-Send, and Gu, "Estimating Annual Average Greenhouse Gas Emission Factors for the Electric Sector: A Method for Inventories."
[95] Within SCE's territory there are 10 operating Peaker Plants.
"2015 General Rate Case, Exhibit SCE-02 Vol. 09"; "California Power Map — Beta."
[96] Regulation for the Mandatory Reporting of Greenhouse Gas Emissions.

Table 6. Emission Factors by Fuel Source

Resource	CO_2 eq (kg/kWh)	NOx (kg/kWh)
Natural Gas - Load Following and Peaker	0.431	0.0014
Natural Gas - Load Following	0.119	0.003
Natural Gas - Peaker Plants	0.580	0.0002
Coal (Refined)	0.528	0.001
Geothermal	0.398	0
Biomass	0.092	0.004
Biogas	0.548	0.144
Imports[97]	0.475	0.029
Unspecified Resources	0.428	0.0035

The same emission factors, as listed in Table 6, are used for both 2018 and 2030, for simplicity and comparison across model runs. By 2030, some power plants in SCE's territory may shut down or upgrade their pollution control mechanisms. Our model does not account for any of those potential changes.

The primary data source for conversion and emission factors is the Emission and Generation Resource Integrated Database (eGRID) 2016 data.[98] Issued by the U.S Environmental Protection Agency, eGRID reports annual net generation (MWh), CO_2 emissions (tons), N_2O emissions (lbs), and CH_4 emissions (lbs) for all power plants. Based on the Utility Service Territory, Plant Operator Name, and Balancing Authority, we located the power plants serving SCE's territory. To allow comparison of the global warming impacts of different gases, we use the global warming potential over a standard time horizon of a 100 years (GWP100). eGRID reports CO_2, CH_4, N_2O together as CO_2 equivalency and calculates them using GWP100 from the IPCC Fourth Assessment Report.[99] This assessment method characterizes emission based on the power mix for Southern California Edison. NOx emissions data are also taken from eGRID, which uses the EPA's Air Market Program Data to source air pollutant information.

Total Emissions

These hourly emission factors are put into the model to determine the emissions associated with a demand profile.

Baseline Demand

To find the emissions associated with the baseline demand, the average emissions generated by SCE are used for each hour as follows:

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97 The emission factor for imports is an average for all fuel resources that are imported. The emission factors for imports currently uses the same resource-specific emission factors used for SCE.

98 The latest version of eGRID was published in February 2018, but provides data for the year 2016. US EPA, "Emissions & Generation Resource Integrated Database (EGRID)."

99 "Global Warming Potential Values."

*Σ (Baseline Hourly Load * Hourly Emission Factor) = Baseline Kg Pollutant Released*

Marginal Demand

The change in emissions associated with the intervention are calculated differently. When the amount of electricity demanded is reduced or increased, the most expensive, and often the dirtiest, electricity generators (peakers) are turned off first. Thus, we are looking for the hourly *marginal* emission factor, not the hourly average emission factor.

For 2018, this model assumes there are three key periods of the day that can be grouped: 11:00 a.m. - 3:00 p.m., the target window when we assume solar is likely to be turned on or off; 4:00 - 9:00 p.m., the evening peak period when peakers are going to be turned on or off to accommodate demand; and all other hours when there is not a clear marginal resource and we can use the average emission factor. Note that 25% of generation is recommended to come from natural gas at all times, and traditionally we see 25-30% of natural gas consistently on the grid. So, to be conservative, even during the middle of the day the marginal emission factor relies on 25% natural gas.[100] Table 7 outlines these groups and emission factors:

Table 7. 2018 Marginal Emission Factors

Time	CO_2 eq (kg/kWh)	NOx (kg/kWh)	Fuel Mix
11 am - 3 pm	0.108	0.0004	25% Natural Gas, 75% Solar
4 - 9 pm	0.442	0.001	30% Natural Gas, 70% Peakers
Other	Varies by Hour	Varies by Hour	Average Hourly Mix

For 2030, we use the diverse fuel mix to calculate our marginal emission factors with a slight modification. We assume that from 10:00 a.m. to 4:00 p.m. no natural gas is being used. Instead, solar and other renewables and imports account for this load. Table 8 summarizes this:

Table 8. 2030 Marginal Emission Factors

Time	CO_2 eq (kg/kWh)	NOx (kg/kWh)	Fuel Mix
10 am - 4 pm	Averages 0.050 (Varies by Hour)	Averages 0.0002 (Varies by Hour)	0% In-State Natural Gas, 71% Solar, 29% Other Renewables, Imported Natural Gas and Imported Nuclear
Other	Varies by Hour	Varies by Hour	Average Hourly Mix

100 Certain regions are required to source 25% of their power from natural gas at all times to meet local reliability standards (i.e., non-natural gas is far from these locations and sourcing natural gas ensures electricity demand is met), while CAISO *recommends* that 25% of all power at all times be sourced from natural gas and dispatchable hydro in order to ensure natural gas and hydro plants continue to be available during peak demand. To that end, no matter what time an EV goes on the grid, it will increase GHG load to some degree.
Fero, "Achieving California's 2030 Renewable Portfolio Standard and Electricity Sector Greenhouse Gas Emission Reduction Target"; Brinkman et al., "Low Carbon Grid Study."

From these marginal emission factors, we can find the change in GHG and air pollution emissions associated with the intervention as follows:

$$\Sigma\ \textit{(Change in Hourly Load} \times \textit{Hourly Emission Factor)} = \textit{Change in Kg Pollutant Released}$$

Final Demand

With the marginal change calculated above, we find the total emissions released under the new demand profile:

$$\textit{Baseline Emission} + \textit{Change in Emission} = \textit{New Kg Pollutant Released}$$

Impact of Emission Change

The change in emissions value can then be used to calculate a few final indicators.

For both GHG and air pollution, we can determine the financial cost associated with emissions. For CO_2-eq, we use the US Social Cost of Carbon at a 3% inflation rate in 2020, translated to 2018 dollars.[101] This translates to $0.05/kWh.

In Los Angeles County, NOx emissions from natural gas plants are expected to have external impacts of $21,927.48 per metric ton in 2018 dollars.[102] This number reflects the monetary value of the impact of NOx emissions on human health, timber and crop harvest, recreation and visibility, and decay of buildings and materials.[103] Mortality and morbidity account for the majority of this impact.[104] This number is based on a $6 million value of statistical life.[105]

101 "Social Cost of Carbon."
102 "LCOE with Environmental Costs."
103 Holland et al., "Environmental Benefits from Driving Electric Vehicles?"
104 Rhodes et al., "New U.S. Power Costs: By County, with Environmental Externalities."
105 Rhodes et al.

Environmental Justice

As with most energy and environmental projects, managed charging has the potential to have distributional effects. Much literature has focused on the affordability and accessibility of EVs and EV charging. SCE's initial Charge Ready pilot focused on installing EV chargers in various communities, with a large percentage focused on "disadvantaged communities" (DACs), as defined by California law.[106] This project is focused strictly on EV charging behavior and assumes EV adoption and charger installation will continue along current trends. Thus, its direct distributional impacts follow another vein.

As discussed in the previous section, this project has the potential to change air pollution within SCE's territory. By shifting demand into the middle of the day when solar is generated, managing charging should reduce demand in the evenings, when fossil-fuel based power plants provide the majority of the power. While air pollution travels, turning on or off specific plants could have an impact on specific communities. In SCE's territory, 70% percent of peaker plants are in DACs.[107] But, from 2015 to 2017, those 7 plants only accounted for 25% of all peaker capacity. The other 75% of peaker capacity was met by the 3 plants in non-DACs and the majority by a single plant. If we maintain that split while assuming that 70% of peak load is provided by peakers in 2018, as mentioned above, then the following outlines how much of emissions from each scenario during the peak window can be assigned to DACs:

$$\textit{Peaker Emissions in DACs} = 0.25 * 0.70 * \textit{Emissions During Peak Windows}$$

Beyond the direct NOx emissions, we must also consider how frequently peaker plants exacerbate poor air quality days. Peaker plants in DACs operate 3.29 times as much on high PM days and 2.08 times as often on high ozone days than plants not in DACs.[108] Thus, even small changes in NOx emissions in DACs may actually have large impacts. These impacts are out of the scope of this project and something to consider in future analyses.

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106 "Charge Ready and Market Education Programs: Pilot Report"; Monserrat, "SB 535 Disadvantaged Communities."
107 "California Power Map — Beta."
108 "California Power Map — Beta."

Shiny Application

Visualization and accessibility of our model is a key part of our project. To that end, we have built a “Shiny application.” Shiny is a package in the R coding language that makes it easy to create interactive web applications. The application gives the user an easy way to interact with the model. Through this app, they can change contextual and intervention inputs and view the resulting load profile of each segment on a graph. The load profile graphs have one line representing the baseline load profile and a second line representing the change in demand resulting from a chosen intervention. The application also automatically calculates and displays the reduction or increase in emissions due to the shift in demand.

The application consists of four tabs: Overview, Simulation Graphs, Modeling Methods, and Instructions. The “Overview” tab provides background on the project and why the app was developed, while the “Instructions” tab provides a walkthrough of the sidebar widgets and contextual information on the inputs that can be selected. The primary tab for modeling non-residential EV charging demand is the “Simulation Graphs” tab (Figure 18). The sidebar on the left allows users to choose which inputs they want to enter in the model. Changing inputs creates *reactive* outputs within the main panel on the right, meaning as users increase or decrease a number or percentage, or switch between segments, number of simulations, or dates, the graphs and table change in real time.

To access the app, visit https://smartcharge.shinyapps.io/smartcharge/.

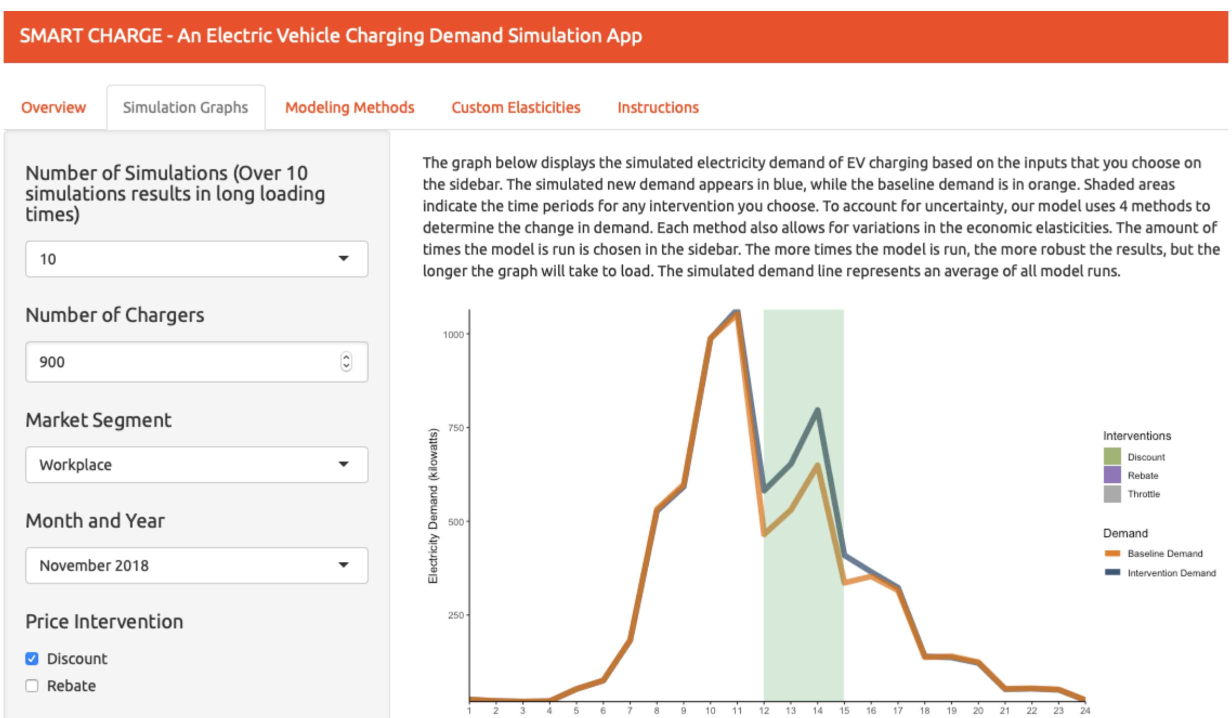

Figure 18. Shiny Application Simulation Tab

Chapter III. Model Results

Segment Scenarios

Our model allows users to examine the likely consequences of one or more interventions on EV charging behavior. There can be multiple combinations of interventions; any combination of interventions is known as a scenario. While we can run hundreds of different scenarios, we critically examine several that are the most relevant. We consider scenarios under the present 2018-2019 conditions and under projected 2030 charger adoption rates.[109] All of these scenarios are run for one single day and thus the results indicate how demand might change if interventions are called on one single day.

We considered more than the scenarios reported below. These are simply those that we think show the most promise for inducing behavior change that reduces climate, health, and grid challenges.

[109] Each scenario follows a similar naming convention. W denotes Workplaces, D denotes Destination Centers, F denotes Fleets, while M denotes Multi-Unit Dwellings. The number denotes the scenario number. For example, W2 is the second scenario run on Workplaces. If an F follows this number, that indicates a future scenario. For instance, the scenario W5-F increases the number of chargers to 31,435 (the number projected to be installed in 2030) and uses a new TOU rate (2019), compared to a present day scenario like W2 that would only model 596 chargers.

Workplaces

Workplaces are targeted for load shifting (discounts), given their high morning peak and the simple fact that most people's vehicles sit for up to eight hours during the workday. To that end, we considered five scenarios that couple a midday discount with a new TOU rate, communication, and throttling. Below and in Tables 9-10 is a summary of these scenarios. The following pages provide numerical details on the impacts of each scenario.

Across the board, a **discount** successfully increases demand in the midday target window, and decreases demand in the peak period.

A new 2019 **TOU rate** can have a substantial impact. The TOU 2019 price scenario (W2) induces more charging in the target midday window than the TOU 2018 scenario (W1) (32% compared to 19%), while dropping more load in the evening window (75% compared to 2%). The new TOU rate also leads to the largest reduction in **costs to consumers** (55%) since energy demand falls most in hours of high demand and high price.

Communication is shown to have a minor effect. Scenario W1 which includes a price notification results in a slightly higher increase in demand in the intervention period (1%) than Scenario W4 which eliminates the price notification. Demand in the peak period is similar across both scenarios, but demand in all other hours falls more when communication is applied. Together, this leads to a larger decrease in daily GHG and air pollution emissions.

Morning throttling (6:00 - 11:00 a.m.), as applied in Scenario W2, results in decrease in demand in the peak period (75%). Without this throttling, demand over the entire day can actually increase, the midday demand change may be minimal, and GHG and air pollution emission reductions may not be seen.

Additional **chargers**, as applied in our future scenario (W5-F), lead to a similar proportional impact while magnifying the magnitude of the impact to the point of significance.

Under a discount, **curtailment** and its associated costs increase in all scenarios except the one that does not include throttling (W3), since demand over the entire day falls in these scenarios. Since solar energy is being produced in the morning hours (8:00 - 11:00 a.m.), there is often curtailment in these hours. By reducing any usage during those hours, curtailment can increase. SCE seeks to smooth the load curve, but they should be wary of throttling in hours where there is the potential for curtailment. Instead, throttling may be better suited to evening hours when solar energy is low and it is critical to reduce demand.

GHG and air pollution emissions fall across all scenarios. Under a new TOU, discount, and communication, emissions can fall up to 99% in the peak period and 33% across the entire day.

Despite these proportional impacts, the magnitudes of emission changes are typically small and the impact on DACs is negligible.

In sum, a discount, communication, throttling, and new TOU (Scenario W2 for 2018 and W5-F for 2030), create a load curve most like what SCE hopes to achieve. Demand increases in the midday period and falls in the peak, while costs fall overall.

Table 9. Workplace Scenarios' Demand and Cost

	Interventions						Load and Cost Impacts				
							Demand				
	Discount (5¢) (11 am - 3 pm)	Price Comm.	Air Pollution Comm.	Throttling (6 - 11 am)	TOU	Chargers	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily	Customer Cost	Curtailment
W1	X	X		X	2018	596	19%	-2%	-21%	-36%	0.08%
W2	X	X		X	2019	596	32%	-75%	-24%	-53%	0.05%
W3	X	X			2019	596	19%	-2%	4%	-14%	-0.06%
W4	X			X	2018	596	18%	-2%	-21%	-36%	0.09%
W5-F	X	X	X	X	2019	31,435	34%	-80%	-24%	-55%	0.79%

Table 10. Workplace Scenarios' Emissions

	Interventions						Emission Impacts					
							GHG			NOx		
	Discount (5¢) (11 am - 3 pm)	Price Comm.	Air Pollution Comm.	Throttling (6 - 11 am)	TOU	Chargers	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily
W1	X	X		X	2018	596	12%	-4%	-23%	11%	-3%	-24%
W2	X	X		X	2019	596	20%	-93%	-32%	19%	-95%	-33%
W3	X	X			2019	596	12%	-4%	1%	11%	-3%	1%
W4	X			X	2018	596	11%	-3%	-42%	11%	-2%	-42%
W5-F	X	X	X	X	2019	31,435	21%	-93%	-32%	20%	-99%	-33%

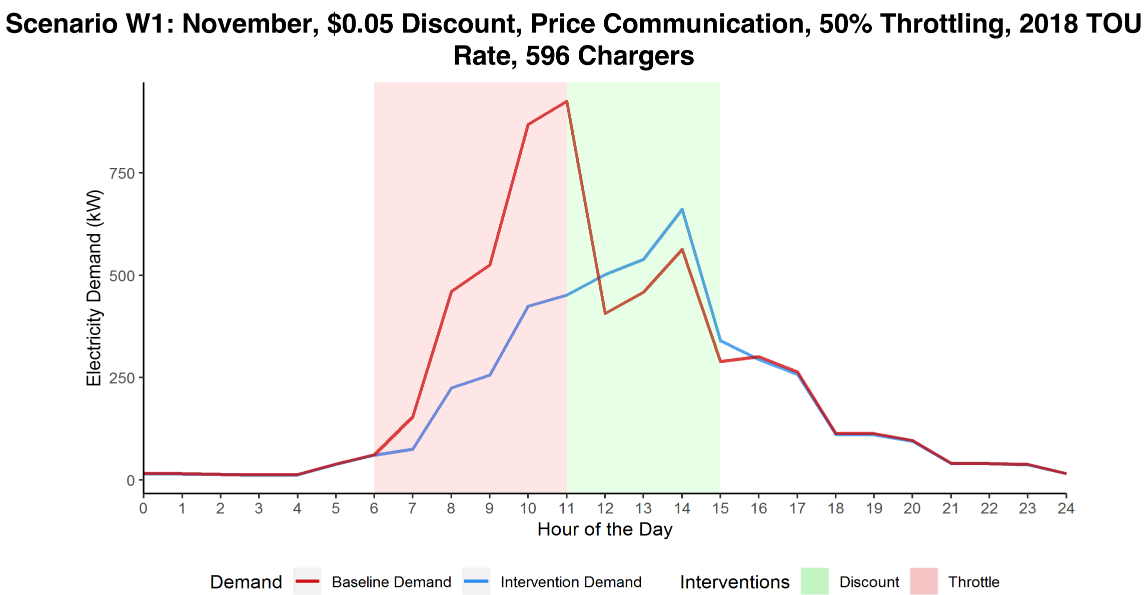

Figure 19. W1 Demand Graph

Table 11. W1 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	1,718	2,042	19%
Peak (4 - 9 pm)	629	615	-2%
Other	3,483	1,972	-43%
Total	5,830	4,628	-21%

Table 12. W1 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	299.80	334.67	12%	1.07	1.19	11%	N/A
Peak (4 - 9 pm)	136.37	130.58	-4%	0.49	0.48	-3%	0
Other	675.79	388.24	-57%	2.47	1.42	-43%	N/A
Total	1,111.96	853.50	-23%	4.03	3.08	-24%	0

Scenario Highlights

- Midday demand rises due to the discount, while morning demand falls due to throttling.
- Demand falls over the entire day, mainly due to the morning decline.
- The decline in daily demand mildly exacerbates curtailment (0.08%), costing $47.81.
- GHG and air pollution emissions fall moderately, leading to a $12.92 and $20.79 social benefit, respectively.
- The impact on air pollution in DACs is negligible.
- Consumer costs decrease by 36%, from $540.91 to $344.51.

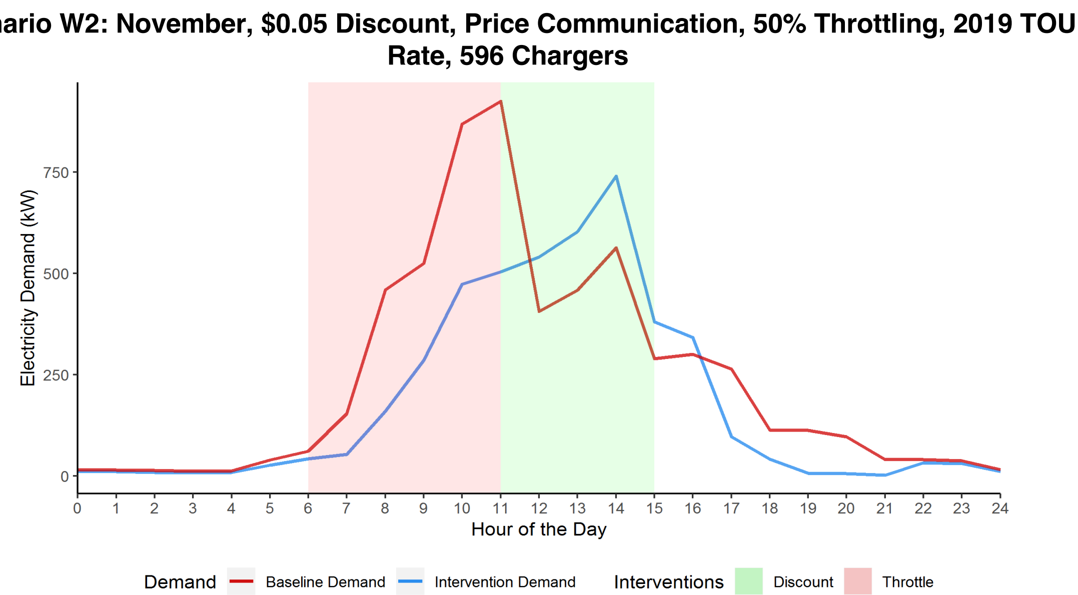

Figure 20. W2 Demand Graph

Table 13. W2 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	1,718	2,264	32%
Peak (4 - 9 pm)	629	155	-75%
Other	3,483	2,001	-43%
Total	5,830	4,419	-24%

Table 14. W2 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	299.80	358.59	20%	1.07	1.27	19%	N/A
Peak (4 - 9 pm)	136.37	9.14	-93%	0.49	0.02	-95%	-0.08
Other	675.79	385.26	-43%	2.47	1.38	-87%	N/A
Total	1,111.96	752.99	-32%	4.03	2.70	-33%	-0.08

Scenario Highlights

- Midday demand rises due to the discount, while peak demand falls significantly due to the new TOU and morning demand falls due to throttling.
- Demand falls over the entire day, increasing curtailment by 0.05% and costing $27.37.
- GHG and air pollution emissions fall almost to zero in the peak period, resulting in a $17.95 and $29.25 reduction in costs respectively.
- Air pollution impacts in DACs are small, but the initial NOx emissions are also minimal.
- Consumer costs decrease by 53%, from $540.91 to $253.99.

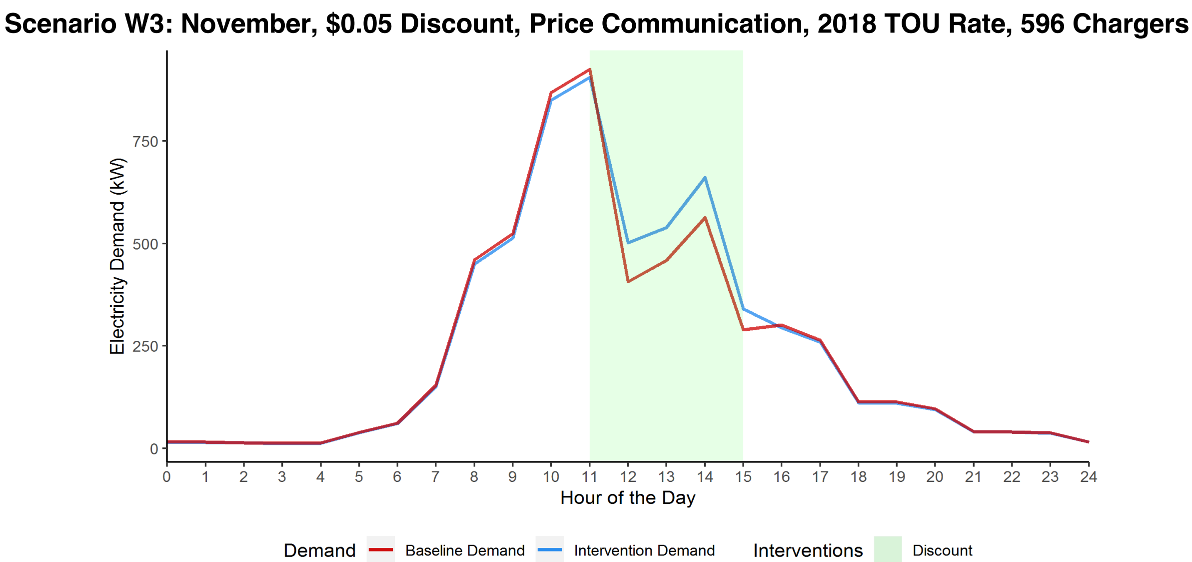

Figure 21. W3 Demand Graph

Table 15. W3 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	1,718	2,042	19%
Peak (4 - 9 pm)	629	615	-2%
Other	3,483	3,409	-2%
Total	5,830	6,066	4%

Table 16. W3 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	299.80	334.69	12%	1.07	1.19	11%	N/A
Peak (4 - 9 pm)	136.67	131.81	-4%	0.49	0.48	-3%	0
Other	675.79	661.40	-2%	2.47	2.42	-2%	N/A
Total	1,111.96	1,126.90	1%	4.03	4.08	1%	0

Scenario Highlights

- As the only price intervention applied is a discount, midday demand, and thus total demand increases, reducing curtailment 0.06% and yielding a financial benefit of $32.10.
- GHG and air pollution impacts are negligible,[110] as are the impacts in DACs.
- Consumer costs decrease by 14%, from $540.91 to $464.84.

[110] Social and health benefits of $5 or less are considered negligible.

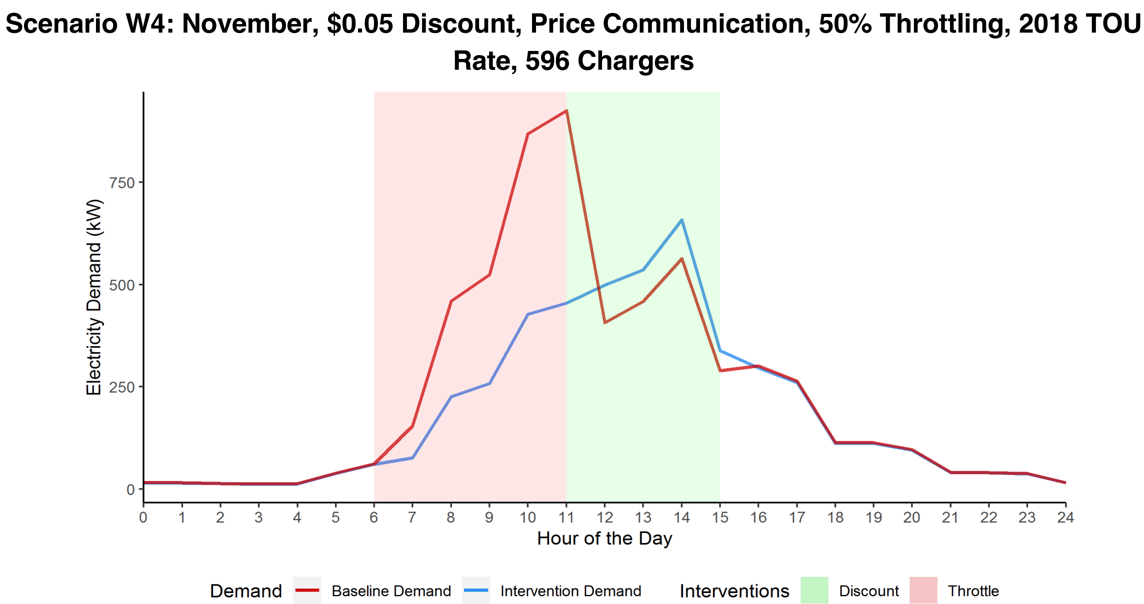

Figure 22. W4 Demand Graph

Table 17. W4 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	1718	2031	18%
Peak (4 - 9 pm)	629	618	-2%
Other	3483	1983	-43%
Total	5830	4633	-21%

Table 18. W4 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	299.80	333.52	11%	1.07	1.18	11%	N/A
Peak (4 - 9 pm)	136.37	132.05	-3%	0.49	0.48	-2%	0
Other	675.79	390.48	-42%	2.47	1.43	-42%	N/A
Total	1,111.96	856.05	-23%	4.03	3.09	-23%	0

Scenario Highlights

- Midday demand rises due to the discount, while morning demand falls due to throating.
- The decline in daily demand, mainly due to the morning decline, increases curtailment by 0.09%, with an associated cost of $48.92.
- GHG and air pollution emissions fall moderately, with a $12.80 and $20.62 reduction in social costs, respectively.
- The impact on air pollution in DACs is negligible.
- Consumer costs decrease by 36%, from $540.91 to $345.26.

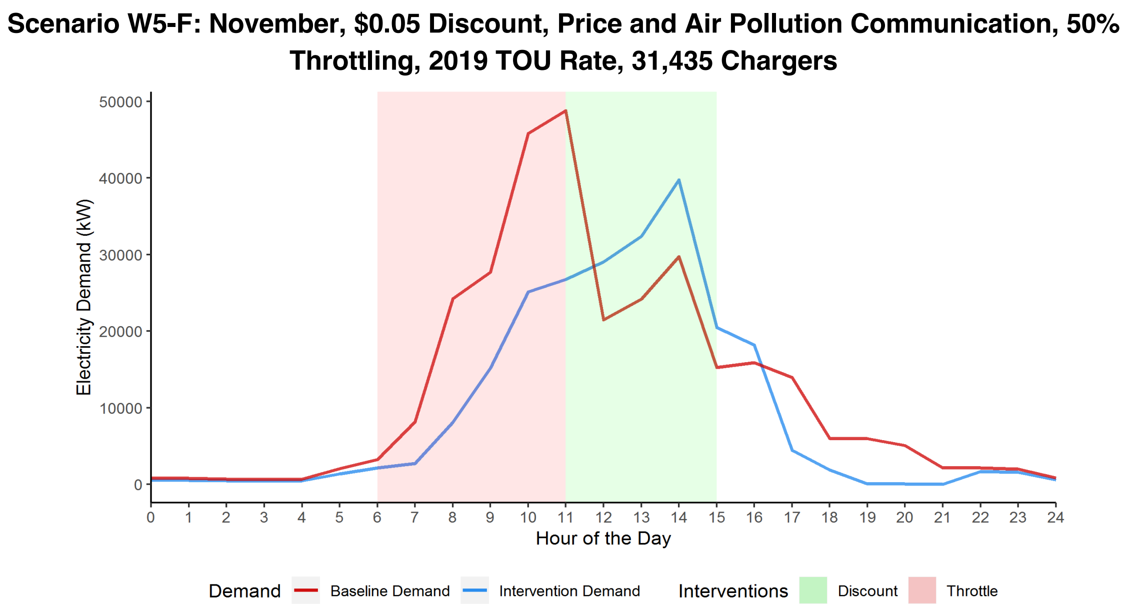

Figure 23. W5-F Demand Graph

Table 19. W5-F Demand Impacts

Time	Demand		
	Initial (kWh)	**New (kWh)**	**Change**
Intervention (11 am - 3 pm)	90,630	121,653	34%
Peak (4 - 9 pm)	33,155	6,527	-80%
Other	183,697	105,408	-42%
Total	307,482	233,589	-24%

Table 20. W5-F Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	**New (kg)**	**Change**	**Initial (kg)**	**New (kg)**	**Change (all)**	**Change (DACs) (kg)**
Intervention (11 am - 3 pm)	15,812.56	19,157.65	21%	56.52	67.75	20%	N/A
Peak (4 - 9 pm)	7,192.67	478.28	-93%	25.82	0.29	-99%	-4.47
Other	35,643.20	20,252.53	-43%	130.18	73.73	-43%	N/A
Total	58,648.43	39,888.46	-32%	212.52	141.77	-33%	-4.47

Scenario Highlights

- Demand increases in the target window due to the discount, but falls by a larger proportion in the evening peak period due to the new TOU.
- The magnitude of the increase in overall daily demand, due predominantly to the number of chargers, increases curtailment by 0.79%, with a cost of $1,633.55.
- GHG and air pollution emissions fall significantly in the peak period, and moderately through the entire day, resulting in a $938.00 and $1,551.58 cost reduction respectively.
- Air pollution in DACs falls.
- Consumer costs decrease by 55%, from $28,529.54 to $12,914.52.

Destination Centers

Destination Centers are characterized by a high morning charging peak with small peaks across the day that taper off during the evening. These variable peaks are due to the variety of buildings that compose the segment, which include theme parks, sports arenas, hotels, university campuses, hospitals, city/county facilities, and similar locations where vehicle dwell times are at least four hours. Because of this variety and the unique characteristics of each type, this segment is more dynamic and difficult to predict. We considered 3 scenarios to determine how communication, throttling, and discounts might shift the morning peak and increase usage in the target window of 11:00 a.m. - 3:00 p.m. Below and in Tables 21-22 is a summary of these scenarios. The following pages provide numerical details on the impacts of each scenario.

In general, we see that a **discount** increases demand in the midday target window, regardless of the additional interventions applied. It also reduces customer costs and has a negligible impact on curtailment. However, the total change in GHG emissions and the reduction in demand in the peak window is heavily contingent on other interventions, most notably the **TOU rate**.

D3-F looks forward to vary the number of chargers, but it also changes the TOU rate. TOU 2019 reduces demand in the peak window substantially more than TOU 2018. This leads to a significant fall in GHG (89%) and in air pollution (98%) emissions in the peak window, with an overall fall over the course of the day of 34% and 37% respectively.

Communication has a minor impact in the target window and overall, but it does vary demand outside the target windows, as seen when comparing Scenarios D1 and D2. Without communication, demand in the target window increases only 20% (D2), compared to 22% under a full communication scenario (D1).

Throttling is applied in all scenarios and successfully drops demand in the morning period, but does not necessarily lead to significant load shifting. In all scenarios, the **curtailment** impacts are minimal, since the magnitude of demand changes minimally.

GHG and air pollution emissions fall across all scenarios run. Under a new TOU, discount, and communication, emissions can fall up to 98% in the peak period and 37% across the entire day. Despite these proportional impacts, the magnitudes of emission changes are typically small and the impact on DACs is negligible.

In short, destination centers respond reasonably well to a discount and throttling, but respond best when these interventions are coupled with new TOU rates, as seen in D3-F. Communication has a small but nearly negligible effect on shifting demand. While none of the scenarios create any notable impacts on environmental justice impacts, they are effective in creating a load shift to the middle of the day.

Table 21. Destination Center Scenarios' Demand and Cost

	Interventions						Load and Cost Impacts				
							Demand				
	Discount (5¢) (11 am - 3 pm)	Price Comm.	Air Pollution Comm.	Throttling (6 - 11 am)	TOU	Chargers	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily	Customer Cost	Curtailment
D1	X	X	X	X	2018	234	22%	-2%	-11%	-26%	0%
D2	X			X	2018	234	20%	-2%	-12%	-26%	0%
D3-F	X	X	X	X	2019	4,378	37%	-81%	-26%	-43%	0.04%

Table 22. Destination Center Scenarios' Emissions

	Interventions						Emission Impacts					
							GHG			NOx		
	Discount (5¢) (11 am - 3 pm)	Price Comm.	Air Pollution Comm.	Throttling (6 - 11 am)	TOU	Chargers	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily	Intervention (11 am - 3 pm)	Peak (4 - 9 pm)	Daily
D1	X	X	X	X	2018	234	14%	-4%	-14%	13%	-3%	-14%
D2	X			X	2018	234	12%	-3%	-14%	11%	-2%	-14%
D3-F	X	X	X	X	2019	4,378	23%	-89%	-34%	22%	-98%	-37%

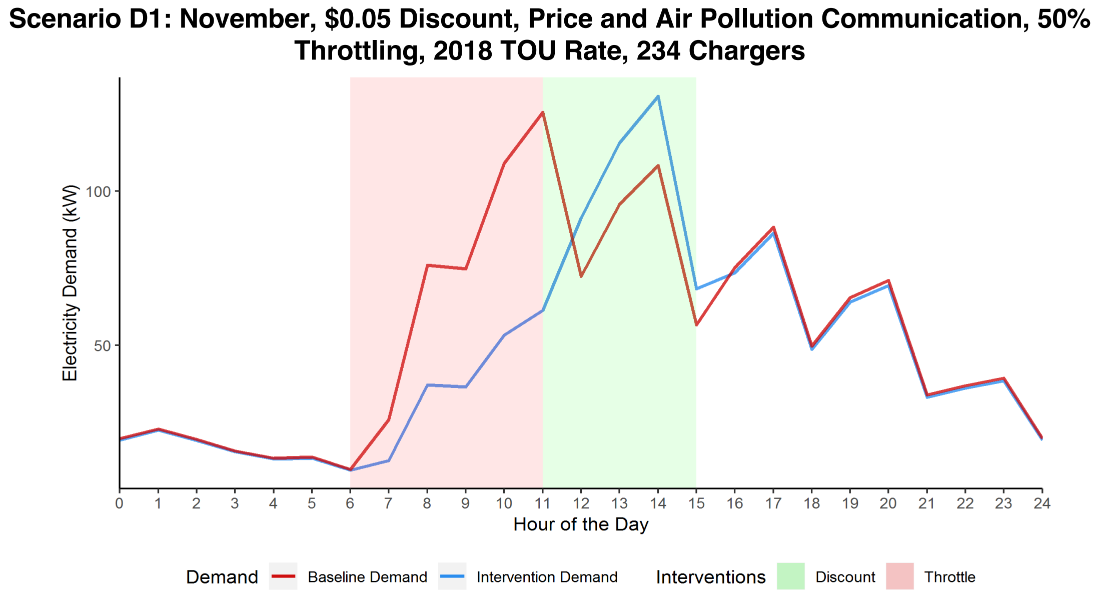

Figure 24. D1 Demand Graph

Table 23. D1 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	333	406	22%
Peak (4 - 9 pm)	309	302	-2%
Other	678	462	-32%
Total	1,319	1,169	-11%

Table 24. D1 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	58.10	65.98	14%	0.21	0.23	13%	N/A
Peak (4 - 9 pm)	69.62	66.91	-4%	0.25	0.24	-3%	0
Other	140.43	98.69	-30%	0.51	0.36	-30%	N/A
Total	268.15	231.58	-14%	0.97	0.84	-14%	0

Scenario Highlights

- Midday load increases slightly, while morning load falls due to throttling.
- The minimal reduction the magnitude of daily demand has a minimal impact on curtailment.
- GHG and air pollution emission fall mildly overall, but the social monetary benefit is negligible.
- The change in air pollution in DACs is negligible.
- Consumer costs decrease by 26%, from $121.70 to $90.55

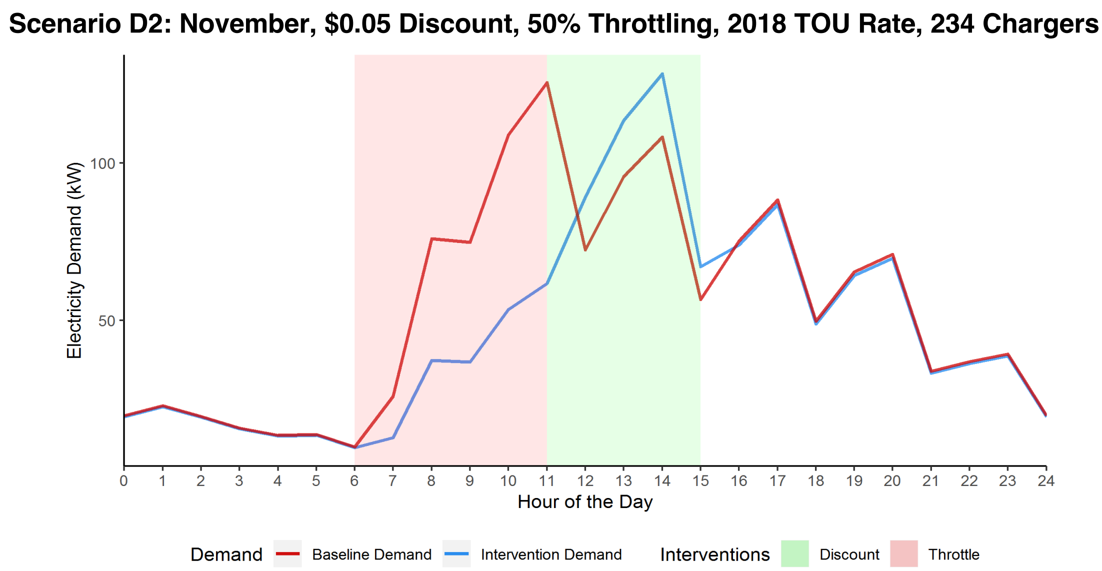

Figure 25. D2 Demand Graph

Table 25. D2 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	333	398	20%
Peak (4 - 9 pm)	308	303	-2%
Other	678	464	-32%
Total	1,319	1,166	-12%

Table 26. D2 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	58.10	65.14	12%	0.21	0.23	11%	N/A
Peak (4 - 9 pm)	69.62	67.51	-3%	0.25	0.25	-2%	0
Other	140.43	99.18	-29%	0.51	0.36	-29%	N/A
Total	268.15	231.83	-14%	0.97	0.84	-14%	0

Scenario Highlights

- Midday demand increases due to the discount, while morning demand falls due to throttling.
- Daily demand decreases, with a magnitude too small to have an impact on curtailment.
- GHG and air pollution emissions fall slightly, with negligible social monetary benefits.
- The impact on DACs is negligible.
- Consumer costs decrease by 26%, from $121.70 to $90.47.

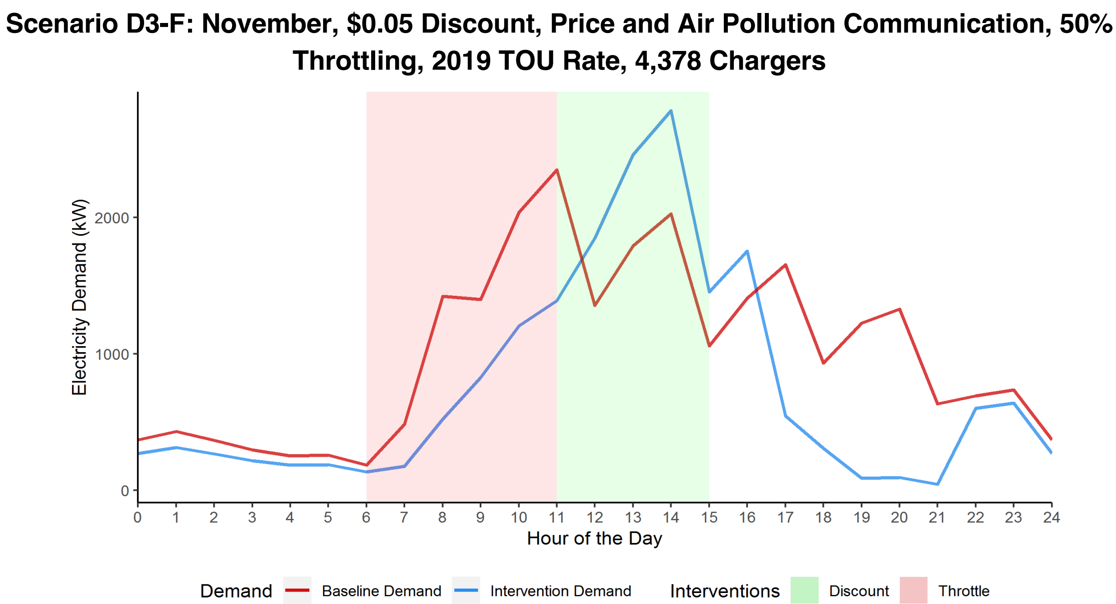

Figure 26. D3-F Demand Graph

Table 27. D3-F Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention (11 am - 3 pm)	6,229	8,548	37%
Peak (4 - 9 pm)	5,772	1,078	-81%
Other	12,682	8,694	-31%
Total	24,683	18,320	-26%

Table 28. D3-F Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	1,087.00	1,337.05	23%	3.89	4.72	22%	N/A
Peak (4 - 9 pm)	1,302.57	142.62	-89%	4.69	0.07	-98%	-0.81
Other	2,627.35	1,802.32	-31%	9.63	6.59	-22%	N/A
Total	5,016.93	3,281.00	-34%	18.20	11.38	-37%	-0.81

Scenario Highlights

- Midday demand increased slightly due to the discount, while morning demand falls due to throttling, and evening demand falls due to the new TOU.
- The overall decline in daily demand increases curtailment by 0.04%, with an $89.34 cost.
- GHG and air pollution emissions fall significantly, with an $86.74 and $149.52 social benefit respectively.
- Air pollution in DACs falls.
- Consumer costs decrease by 43%, from $2,276.99 to $1,303.30.

Fleets

Fleets have static and predictable demographics and characteristics, with vehicles typically deployed throughout the work day and charging in the evenings. Since we want to reduce evening peak demand, a rebate is the intervention we chose to examine most closely. As listed in Tables 29-30, we consider 3 scenarios for fleets to compare the impact of new TOU rates and increase in the number of chargers.

Rebates and **price communication**, under all TOUs, reduce demand and emissions in the peak. When we layer a new **TOU rate** on top of this (Scenario F2), load in the peak window falls 39% more than under a scenario without the new TOU rate. A new TOU rate also causes **customer costs** to fall instead of rise.

When **more chargers** are installed, as predicted for 2030 and modelled in Scenario F3-F, the same pattern emerges. Two-thirds of the GHG and NOx emissions in the target window are eliminated, resulting in a $36 social carbon benefit and $66 reduction in NOx costs. Customer costs once again fall, and we begin to see a mild curtailment impact.

All scenarios led to a reduction in **GHG and air pollution emissions**, both in the peak period and overall.

In sum, a rebate paired with a TOU rate reduces GHG and air pollution emissions; however, all scenarios yield negligible impacts on grid curtailment despite the mild load shift that takes place as a result of the TOU rate.

Table 29. Fleets Scenarios' Demand and Cost

	Intervention				Load and Cost Impacts			
					Demand			
	Rebate (10¢) (4 - 9 pm)	Price Comm.	TOU	Chargers	Intervention / Peak (4 - 9 pm)	Daily	Customer Cost	Curtailment
F1	X	X	2018	83	-23%	-7%	-13%	0%
F2	X	X	2019	83	-62%	-12%	-8%	0%
F3-F	X	X	2019	4,378	-63%	-11%	-9%	-0.45%

Table 30. Fleets Scenarios' Emissions

	Intervention				Emission Impacts			
					GHG		NOx	
	Rebate (10¢) (4 - 9 pm)	Price Comm.	TOU	Chargers	Intervention / Peak (4 - 9 pm)	Daily	Intervention / Peak (4 - 9 pm)	Daily
F1	X	X	2018	83	-42%	-17%	-30%	-11%
F2	X	X	2019	83	-77%	-27%	-72%	-24%
F3-F	X	X	2019	4,378	-67%	-24%	-67%	-24%

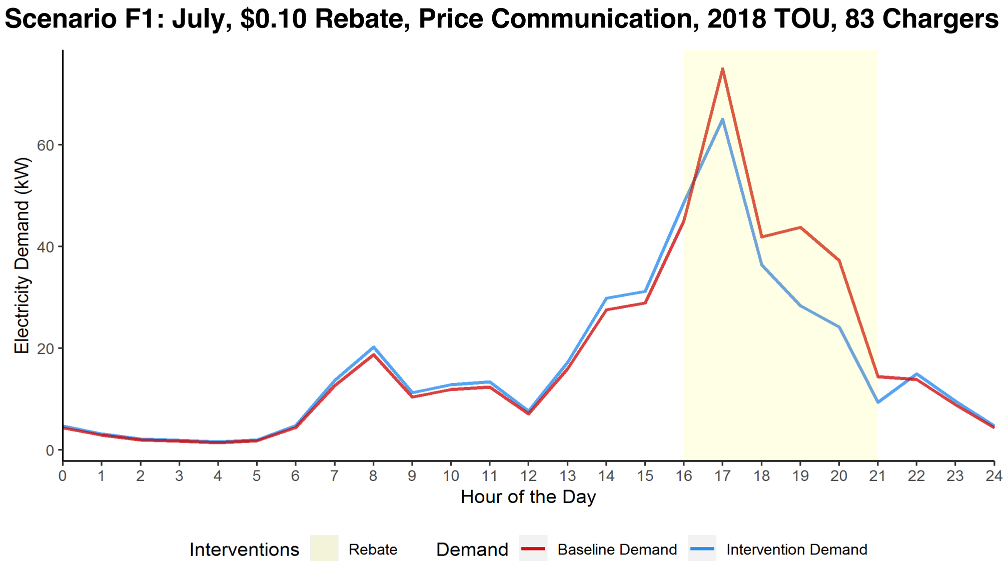

Figure 27. F1 Demand Graph

Table 31. F1 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention / Peak (4 - 9 pm)	212	163	-23%
Other	232	251	8%
Total	444	414	-7%

Table 32. F1 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	46.64	27.04	-42%	0.17	0.12	-30%	-0.01
Other	46.43	49.77	7%	0.17	0.18	7%	N/A
Total	93.08	76.81	-17%	0.34	0.30	-11%	-0.01

Scenario Highlights

- Demand in the evening period falls as a result of the rebate.
- As demand in the middle of the day changed little, the impact on curtailment is negligible.
- While GHGs and air pollution emissions fall, the impacts are financially negligible.
- Air pollution in DACs falls slightly.
- Consumer costs decrease by 13%, from $101.01 to $89.60.

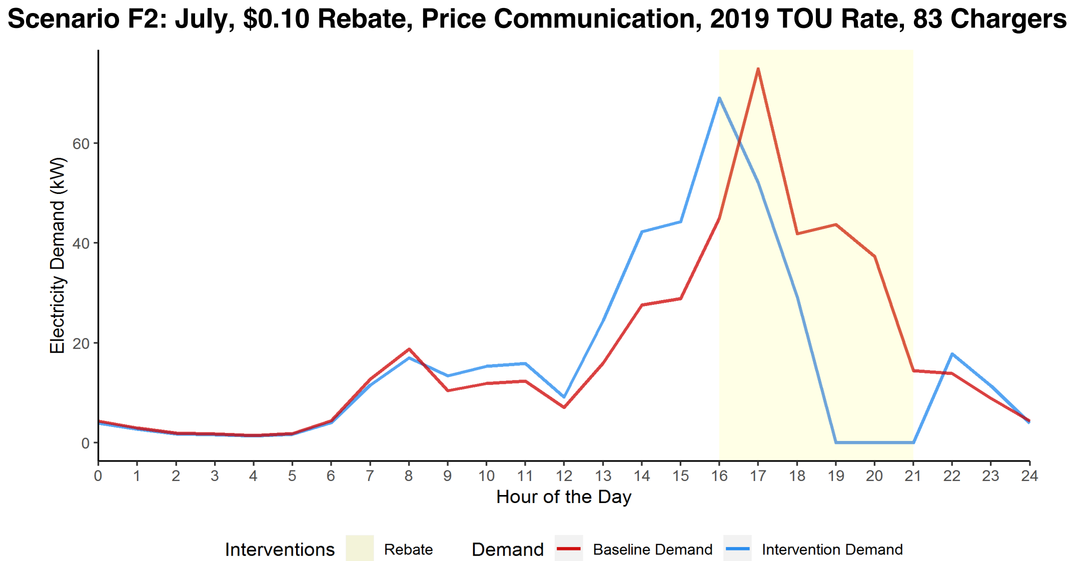

Figure 28. F2 Demand Graph

Table 33. F2 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention / Peak (4 - 9 pm)	212	81	-62%
Other	232	309	33%
Total	444	390	-12%

Table 34. F2 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	93.08	68.41	-77%	0.17	0.05	-72%	-0.02
Other	46.43	57.71	24%	0.17	0.21	23%	N/A
Total	93.08	68.41	-27%	0.34	0.25	-24%	-0.02

Scenario Highlights

- Peak demand falls by almost two-thirds, with some of that demand shifted earlier in the day, due to the new TOU price.
- The magnitude of the overall change in daily demand has no impact on curtailment.
- GHG and air pollution emissions fall, but the small magnitude of the change leads to negligible social monetary benefits.
- Air pollution emissions in DACs fall slightly.
- Consumer costs decrease by 8%, from $89.60 to $82.41.

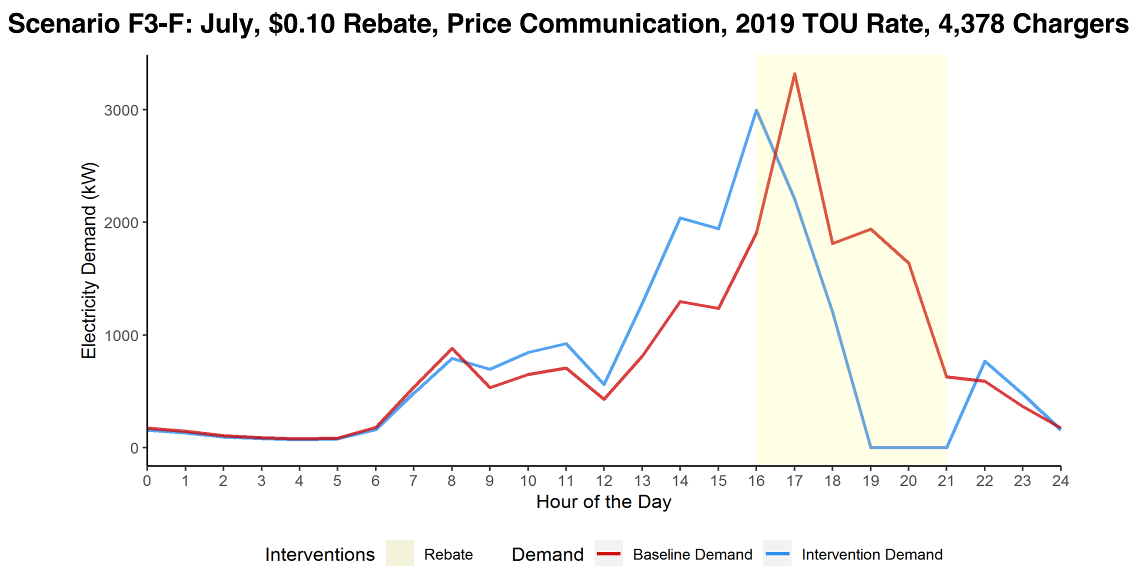

Figure 29. F3-F Demand Graph

Table 35. F3 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention / Peak (4 - 9 pm)	9,342	3,412	-63%
Other	10,804	14,679	35%
Total	20,146	17,992	-11%

Table 36. F3 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	1,377.77	460.01	-67%	5.82	1.90	-67%	-0.69
Other	1,609.82	1,799.30	12%	6.87	7.79	13%	N/A
Total	2,987.60	2,260.21	-24%	12.70	9.69	-24%	-0.69

Scenario Highlights

- Load in the peak period falls due to the rebate and new TOU.
- With the increase in chargers projected for 2030 under this scenario, the total decrease in demand leads to a small decline in curtailment (0.45%), and thus a benefit of $163.05.
- GHG and air pollution emissions fall, with a $36.37 and $65.82 cost reduction respectively.
- Air pollution emissions in DACs fall.
- Consumer costs decrease by 9%, from $4,024.54 to $3,670.16.

Multi-Unit Dwellings (MUDs)

Since most residents of MUDs are assumed to be away from their residence in the middle of the day, we only consider interventions that are intended to change behavior in the evening hours. We consider and compare three scenarios for MUDs that allow us to examine the impact of a rebate, along with communication since we imagine this audience might be easier to communicate with than other segments. Throttling is not considered as it is not typically applied to MUDs since people have less flexibility. These three scenarios are summarized in Tables 37-38 and below. The following pages provide numerical details on the impacts of each scenario.

As with fleets, a **rebate** and **communication** about price successfully reduce demand in the peak evening period. While demand does not completely disappear, the majority of demand for fossil-fuel based power does. This intervention does not fully shift demand into the middle of the day and thus does not directly address grid **curtailment**, but it can be useful at peak shaving.

The new **2019 TOU rate** further drops demand in the peak period, both with the current number of chargers (Scenario F2) and predicted number in 2030 (Scenario F3-F).

In all scenarios, **GHG and air pollution emissions** fall. **Curtailment** varies minimally even in the scenario with additional charges due to the minimal change in the magnitude of demand.

In short, the new TOU rates are the strongest indicator of a decrease in demand in the evening periods for MUDs. This fall can have significant impacts on GHGs and air pollution.

Table 37. MUDs Scenarios' Demand and Cost

	Intervention				Load and Cost Impacts			
					Demand			
	Rebate (10¢) (4 - 9 pm)	Price Comm.	TOU	Chargers	Intervention / Peak (4 - 9 pm)	Daily	Customer Cost	Curtailment
M1	X	X	2018	35	-29%	-8%	12%	0%
M2	X	X	2019	35	-79%	-20%	-7%	0%
M3-F	X	X	2019	4,378	-80%	-17%	-4%	0%

Table 38. MUDs Scenarios' Emissions

	Intervention				Emission Impacts			
					GHG		NOx	
	Rebate (10¢) (4 - 9 pm)	Price Comm.	TOU	Chargers	Intervention / Peak (4 - 9 pm)	Daily	Intervention / Peak (4 - 9 pm)	Daily
M1	X	X	2018	83	-45%	-16%	-34%	-11%
M2	X	X	2019	83	-77%	-23%	-86%	-27%
M3-F	X	X	2019	4,378	-80%	-17%	-83%	-23%

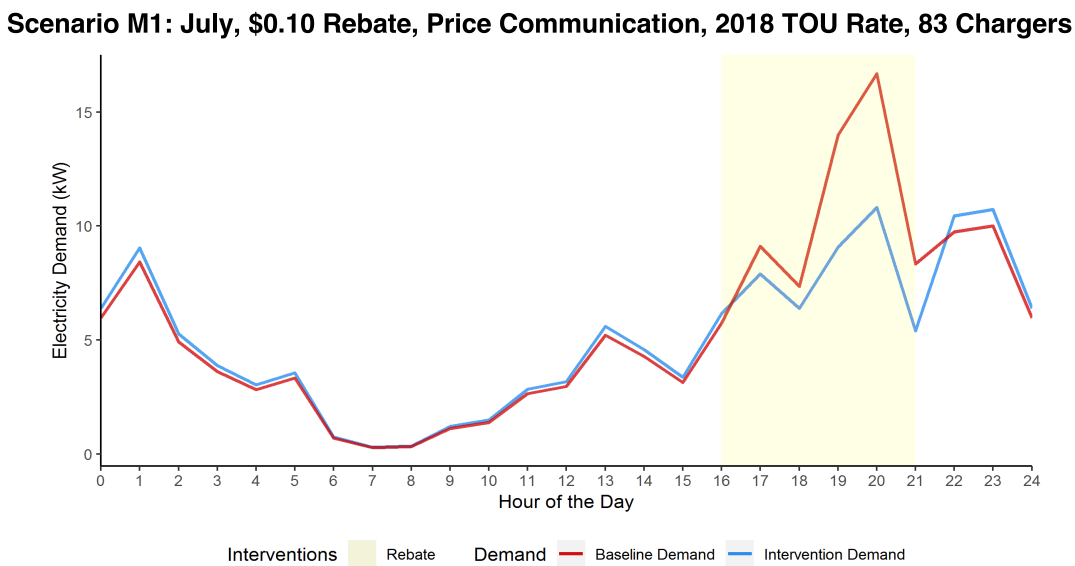

Figure 30. M1 Demand Graph

Table 39. M1 Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention / Peak (4 - 9 pm)	55	40	-29%
Other	77	82	7%
Total	132	122	-8%

Table 40. M1 Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	12.98	7.16	-45%	0.05	0.03	-34%	0
Other	17.09	18.25	7%	0.06	0.07	7%	N/A
Total	30.07	25.40	-16%	0.11	0.10	-11%	0

Scenario Highlights

- Demand in the peak period decreases, with minor shifting into other hours in the day.
- Daily demand falls, with a negligible impact on curtailment.
- GHG and air pollution emissions fall slightly, with a negligible reduction in costs.
- Air pollution in DACs does not change.
- Consumer costs increase 12%, from $19.65 total to $22.07.

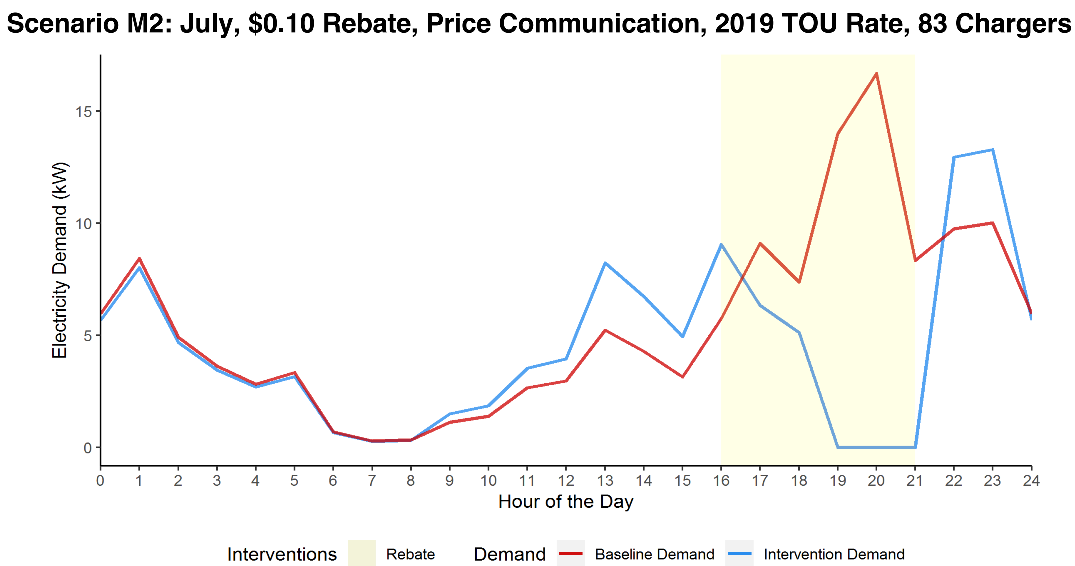

Figure 31. M2 Demand Graph

Table 41. M2 Demand Impacts

Time	**Demand**		
	Initial (kWh)	**New (kWh)**	**Change**
Intervention / Peak (4 - 9 pm)	55	11	-79%
Other	77	95	24%
Total	132	106	-20%

Table 42. M2 Emissions and Environmental Justice Impacts

Time	**GHGs**			**NOx**			
	Initial (kg)	**New (kg)**	**Change**	**Initial (kg)**	**New (kg)**	**Change (all)**	**Change (DACs) (kg)**
Intervention / Peak (4 - 9 pm)	12.98	2.92	-77%	0.05	0.01	-86%	-0.01
Other	17.09	20.18	18%	0.06	0.07	18%	N/A
Total	30.07	23.11	-23%	0.11	0.08	-27%	-0.01

Scenario Highlights

- Demand in the peak period decreases significantly, with some load shifting.
- Demand over the entire day falls, with a negligible impact on curtailment.
- GHG and air pollution emissions fall significantly in the target window, but the magnitude change is small and thus the monetary benefits are negligible.
- Air pollution in DACs falls slightly.
- Consumer costs decrease by 7%, from $19.65 to $18.29.

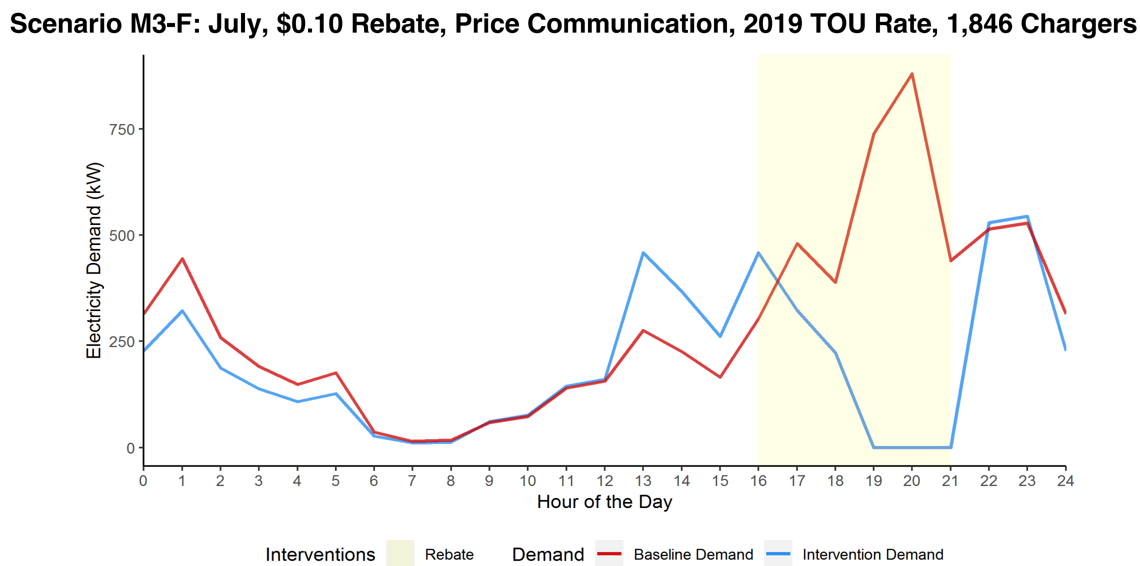

Figure 32. M3-F Demand Graph

Table 43. M3-F Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change
Intervention / Peak (4 - 9 pm)	2,926	584	-80%
Other	4,042	5,208	30%
Total	6,968	5,791	-17%

Table 44. M3-F Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change	Initial (kg)	New (kg)	Change (all)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	1,075.10	820.20	-80%	4.73	3.66	-83%	-0.28
Other	633.22	741.19	29%	2.82	3.34	18%	N/A
Total	1,075.10	820.20	-17%	4.73	3.66	-23%	-0.28

Scenario Highlights

- Demand in the evening peak falls significantly, while some load shifting occurs.
- The decline in demand over the entire day has a negligible impact on curtailment.
- GHG and air pollution emissions fall significantly in the evening peak, with a $12.75 reduction in social carbon costs and $23.40 in NOx costs.
- Air pollution emissions in DACs fall.
- Consumer costs increase 5%, from $537.65 to $677.02.

Assumptions and Limitations

Below are the general caveats associated with using this model. Assumptions and limitations associated with specific model inputs and data sources are listed in those sections above.

Assumptions

Our model assumes that self-elasticity values from the literature regarding residential EV charging can be applied to our EV market segments. Generally, these elasticity values are likely negative, but may vary from the literature values if empirically studied. Empirical values different from the literature values may result in our model containing a bias estimation of the change in electricity demand during the intervention period.

Additionally, our model relies on three methods that use three different assumptions about behavior change outside the intervention window. Method 1 assumes that there is no change in demand outside of the intervention period. This assumption results in cross-elasticity values of zero in the calculation of demand. Method 2 assumes that all of the change that occurs within the intervention period is offset by the opposite change in hours outside the intervention period. This method assumes that the net daily demand for electricity for vehicle charging is unchanged by a price intervention at one point of the day. This method also assumes that the change that occurs within the intervention period is distributed among the hours outside the intervention window according to the proportion of demand in each hour outside of the intervention window. In other words, hours that have higher overall demand will be shifted more by a price intervention. Method 3 assumes that the overall demand for EV charging changes based on the overall change in average electricity price throughout the day. The same assumptions hold for demand change within the intervention window. But to model how demand changes outside of the intervention window, we use the average elasticity to determine how changing the price in the intervention windows affects the daily change in demand and then use that change proportionately as in Method 2.

Our communication interventions reflect the impact of a *notification* about price or air pollution. Thus, our model assumes that the end user has some baseline knowledge of their price schedule. For much of the baseline data that our results are based on, it is likely that the end user is unaware of the price of electricity that the site host is paying. This unawareness exists in two ways. First, many site hosts do not charge drivers to park their EVs in parking spots based on electricity usage. Additionally, when a price intervention occurs, many end users are likely unaware of the event, because information about the event is only sent to the site hosts. Therefore, many of the interventions tested result in a price change that occurs without the knowledge of the end user. It is reasonable to assume that if the intervention is occurring, but the end user is completely unaware, we would see no significant change in usage behavior due to the intervention. Since our model has this underlying assumption that all EV drivers have some knowledge of the original price schedule, it likely overestimates behavior response. However, this communication barrier may be smaller in fleets, since fleets are typically owned by a company that itself receives the electricity bill.

We use month-hour averages for our baseline usage and assume this is representative of the segment as a whole. This may not be true as some days may have external events that determine charging behavior (conferences, weather, holidays, etc.) and we do not normalize for any difference in these events across months.

All chargers in the program are on TOU electricity rates; however, there are multiple TOU options that customers can choose from (mainly TOU-EV-3 and TOU-EV-4). TOU-EV-3 and TOU-EV-4 have the same time windows for peak and off-peak hours, but TOU-EV-3 is designed to support customers that use less than 20 kW of demand at any point in each month. The majority of chargers in the Charge Ready Program are on TOU-EV-4, but some minority are on TOU-EV-3. It is not possible with the data available to identify what portion of the chargers are on which TOU rate or what portion of the demand comes from each rate. Due to this uncertainty, and for modelling simplicity, we assume that all chargers are on TOU-EV-4. This implies that baseline data is a result of chargers facing this TOU rate structure and that any price interventions in model scenarios are applied to the TOU-EV-4 rate structure.

Limitations

Since this is a growing field, none of our model inputs perfectly reflect the reality in each of our segments. Instead, they were pulled from literature on either residential EV charging or residential electricity use. We would expect that because of the different load profiles among market segments, elasticity values would differ across segments for hours that have differing demand across segments Thus, our model may not fully capture the flexibility or price responsiveness of EV drivers in long-dwell segments.

Given data and time constraints, this model does not consider how load may be switched across non-residential segments or between non-residential and residential segments. Yet, we expect that drivers may substitute across these segments. We found no existing research that provided a method of estimating the substitution of charging in residential and non-residential segments. Additional research and experimental data would be required to find the cross-price elasticity between residential and non-residential in order to quantify how the two charging methods may act as substitutes for one another.

The preferred method to predict demand for each hour of the day would be to do so using a cross-price elasticity for each hour of the day, resulting in a 24- by 24-hour elasticity matrix with which to estimate the effect of a price change in one hour on the demand of every other hour of the day. Empirical estimates of such a 24 by 24-hour matrix do not currently exist. Additional research should be completed using a randomized controlled trial of price interventions to measure the effect of a price change on each hour of the day's demand and develop a 24- by 24-hour matrix that could be used to robustly predict the effect on demand of any given price intervention.

Lastly, this model does not consider how drivers may respond differently to a change in price for a one-off event than a daily change in the pricing schedule. In short, we do not consider the impact of learning behavior.

Pilot Event and Model Refinement

Before crafting our model, we analyze the interventions used in SCE's Charge Ready Pilot events. Specifically, we look at the impact of throttling in these events. While throttling is a direct cut to load of 50%, it could feasibly reduce load by a larger proportion since users may dislike the idea of throttling. However, the initial pilot results show that throttling acts as a direct 50% cut in load. Thus, our model does the same.

To then test and refine our model, we compare its outputs to those from SCE's Charge Ready Pilot. As of February 2019, SCE ran 8 pilot events – 4 of them as load reduction (rebates) and 4 as load shifting (discounts).

After running model scenarios with baseline data that corresponds to the month in which a pilot event occurs, we compare the results to the event data to see if our model accurately predicts the response seen in pilot events.

Because most EV drivers participating in the pilot events do not pay for charging, our model overpredicts driver's response to price-based interventions. As basic knowledge about price is required for any pricing model, we do not adjust our model based on this difference.

Although there were 8 pilot events in each segment, we compare only on event per segment to specified model scenarios, for a total of 4 comparisons. Below is a summary of these 4 comparisons.

Full analysis of all pilot events is provided in Appendix IV.

Workplaces

November 14, 2018 Event vs. W1

The November 14th Workplace Load Shift event can be compared to Scenario W1. Both apply throttling in the morning hours and a discount in the target window. Scenario W1 has price communication incorporated, as discussed below. Table 45 summarizes the differences between these scenarios.

Table 45. Modelled Workplace Scenario vs. Event Comparison

Time	November 14th Event			W1		
	Demand Change	GHG Change	NOx Change	Demand Change	GHG Change	NOx Change
Intervention (11 am - 3 pm)	2%	1%	1%	19%	12%	11%
Peak (4 - 9 pm)	-4%	-48%	-29%	-2%	-4%	-3%
Other	-5%	-2%	-8%	-43%	-57%	-43%
Total	-5%	-7%	-4%	-21%	-23%	-24%

We would expect the pilot event to yield similar results to W1, especially with regards to the throttling period, but the pilot results do not correspond to our expectations. Scenario W1 predicts a larger reduction in demand in the peak hours and a larger increase in the midday target window. As a result of these differences in demand change, Scenario W1 also predicts larger declines in GHG and NOx emissions than seen in the pilot event.

While we expected to see mild differences between the two outputs due to the communication intervention applied in Scenario W1, these differences exceed anything that may be attributable to that intervention. First this suggests that our model does not fully account for the communication barrier between EV drivers and SCE. In addition, the larger demand in the W1 "other hours," which includes throttling hours, compared to the pilot suggests throttling does not have the intended 50% reduction effect in the pilot. However, the pilot event and the modelled scenario are compared to the average baseline demand. It is possible that the demand on the specific event day was much higher than the average and we cannot see what the load would have been without throttling on that day.

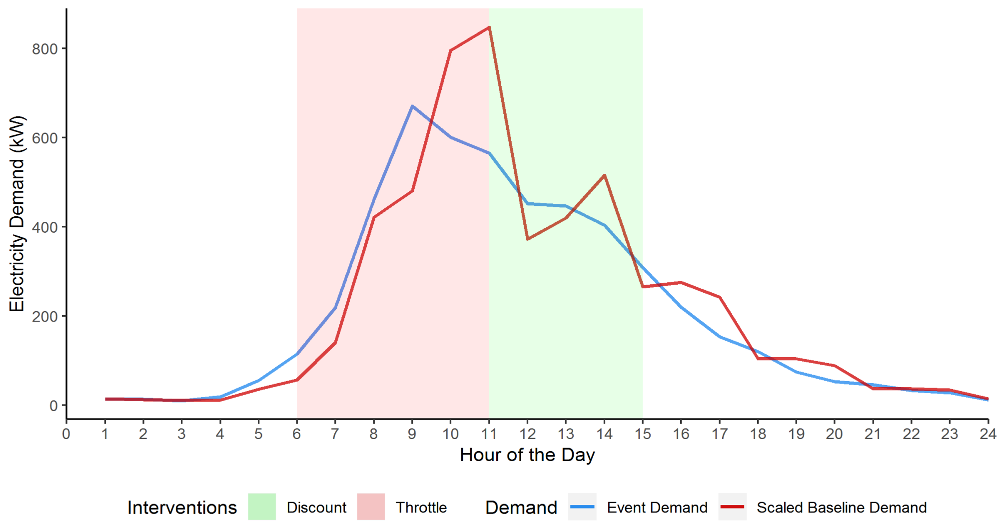

Figure 33. November 14, 2018 Workplace Load Shift Event Demand Graph

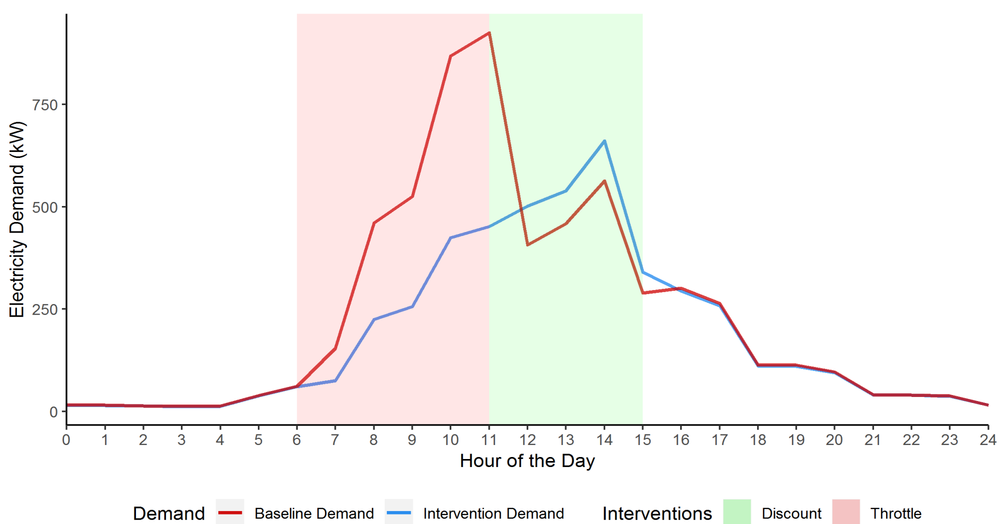

Figure 34. Model Scenario W1 Demand Graph

Destination Centers

November 14, 2018 Event vs. Model Scenario D2

The November 14th Destination Center Load Shift event can be compared to our modeled D2 scenario. Both scenarios use a $0.05 discount in the target window (11:00 a.m. - 3:00 p.m.) and throttling between 6:00 - 11:00 a.m. A summary of these two events is provided in Table 46.

Table 46. Modelled Destination Scenario vs. Event Comparison

Time	November 14th Event			D2		
	Demand Change	GHG Change	NOx Change	Demand Change	GHG Change	NOx Change
Intervention (11 am - 3 pm)	-11%	-7%	-6%	20%	-45%	-34%
Peak (4 - 9 pm)	38%	55%	47%	-2%	7%	7%
Other	-21%	-17%	-17%	-32%	-16%	-11%
Total	5%	3%	1%	-12%	-14%	-14%

Scenario D2 affects demand differently in the target and intervention window than the pilot event. Despite the same interventions being applied, Scenario D2 predicts an increase in demand in the target window and a decline in demand in the peak window, while the November 14th event saw the exact opposite result. However, load reduction in the time periods outside the event and peak windows ("other hours") is in the same order of magnitude in the same direction, which suggests throttling in the pilot and in our scenarios had a similar effect.

As expected with these changes in demand, GHG and air pollution impacts also varied in direction and magnitude between the pilot event and the scenario. The November 14th pilot event saw an increase in emissions, while Scenario D2 predicted a decrease.

This large disparity between the pilot events and our modelled event is likely due to the difficulty associated with predicting destination centers' load. While we have average monthly load profiles, destination centers demand changes drastically day to day. Thus, our modelled results are inevitably going to be different from the pilot event.

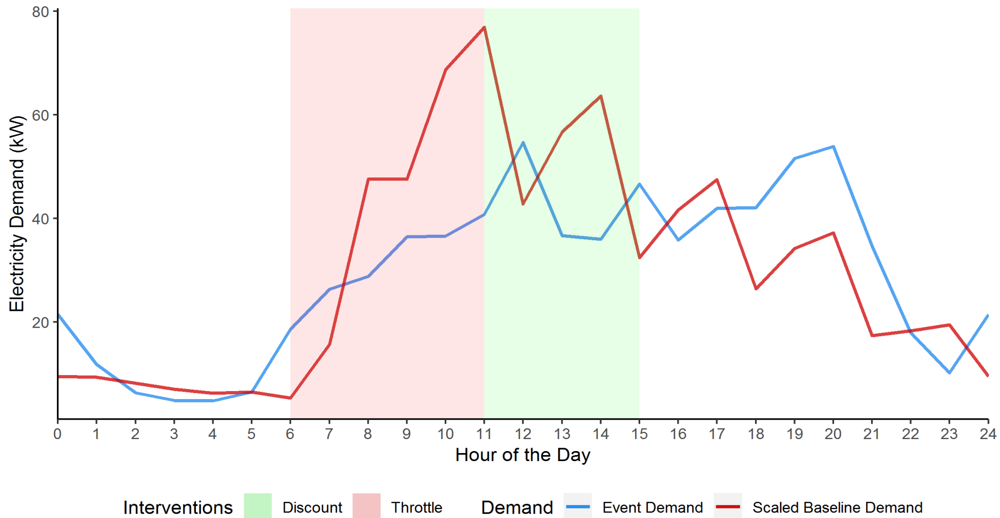

Figure 35. November 14, 2018 Destination Center Load Shift Event Demand Graph

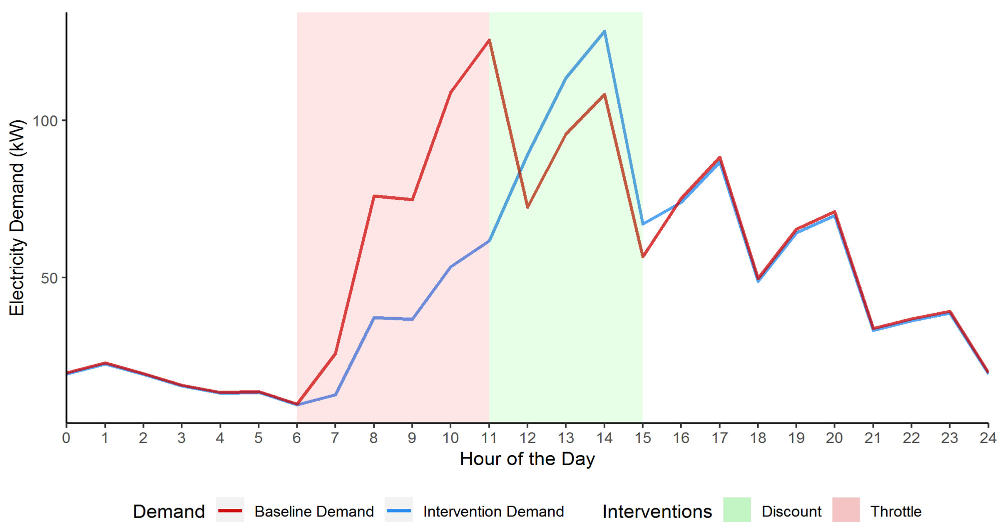

Figure 36. Model Scenario D2 Demand Graph

Fleets

July 31, 2018 Event vs. F1 Model Scenario

The July 31st event can be most easily compared to our modeled F1 scenario, despite their differences. Both scenarios use a $0.05 discount in the target window (11:00 a.m. - 3:00 p.m.), but the pilot event employed 50% throttling from 4:00 – 9:00 p.m. and Scenario F1 did not. Scenario F1 also included full price communication as an intervention during the target window. Table 47 below compares the outputs of these two scenarios.

Table 47. Modelled Fleet Scenario vs. Event Comparison

Time	July 31st Event			F1 Model Scenario		
	Demand Change	GHG Change	NOx Change	Demand Change	GHG Change	NOx Change
Intervention / Peak (4 - 9 pm)	25%	33%	32%	-23%	-42%	-30%
Other	75%	64%	63%	8%	7%	7%
Total	51%	49%	48%	-7%	-17%	-11%

Given the difference in throttling applications between these two scenarios, we would expect the event demand to fall below the baseline in the intervention window because of the direct impact of throttling, and for the F1 scenario intervention demand to be slightly below the baseline in the intervention window due to the effect of a $0.10 rebate, but not as significantly as the reduction due to throttling. However, we see the opposite.

The pilot event resulted in an increase in demand in the throttling and rebate period, while the F1 scenario rebate resulted in a demand decrease in the intervention window. This is likely due to some inflexibility on the day of the event or limited communication about the event.

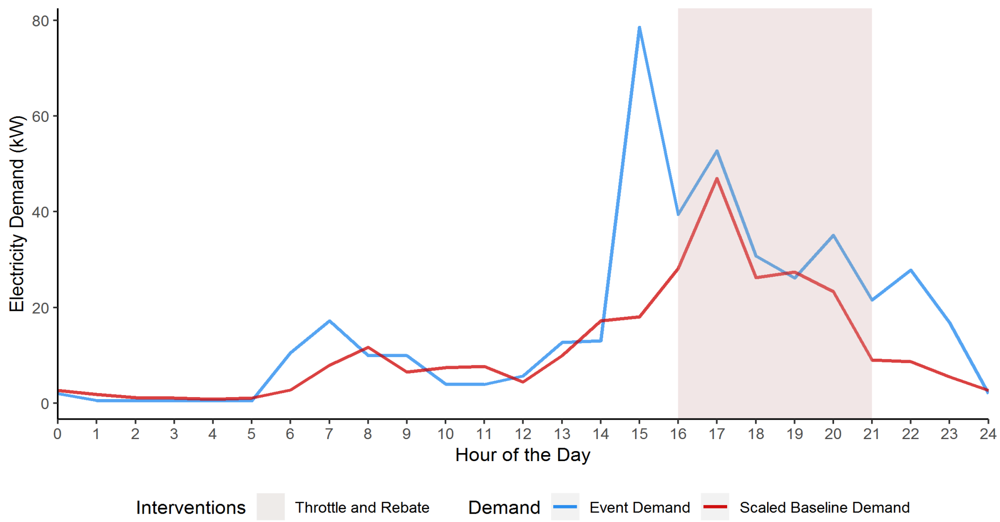

Figure 37. July 31, 2018 Fleets Load Reduction Event Demand Graph

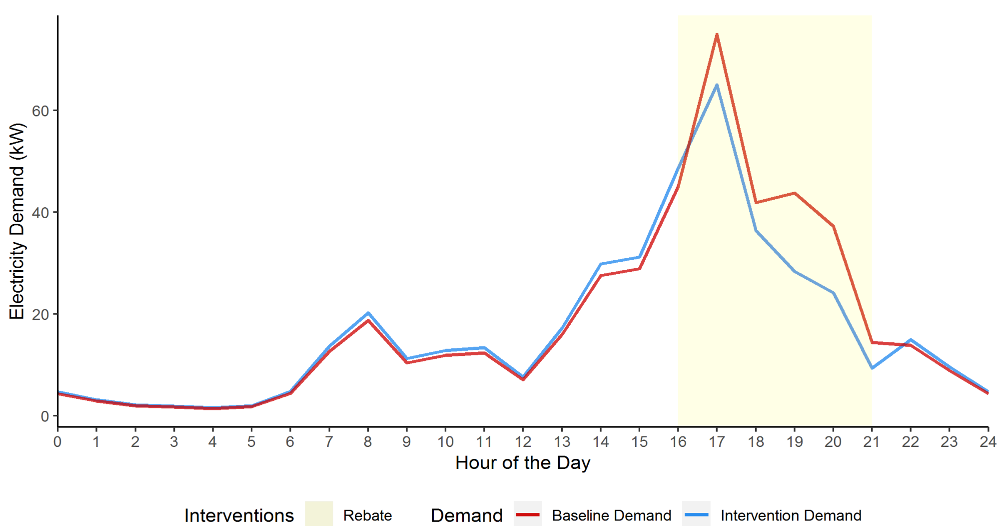

Figure 38. Model Scenario F1 Demand Graph

Multi-Unit Dwellings (MUDs)

July 31, 2018 Event vs. M1

The July 31st event can be compared to our modeled M1 scenario. Both scenarios use a $0.10 rebate in the target window (4:00 – 9:00 p.m.) but the pilot event uses throttling while the model scenario does not. Table 48 below outlines the differences in these two scenarios.

Table 48. Modelled MUDs vs. Event Comparison

Time	July 31st Event			M1		
	Demand Change	GHG Change	NOx Change	Demand Change	GHG Change	NOx Change
Intervention / Peak (4 - 9 pm)	65%	98%	77%	-29%	-45%	-34%
Other	-7%	-14%	-15%	7%	7%	7%
Total	18%	26%	18%	-8%	-16%	-11%

The pilot event increased demand in the evening period, despite the throttling and rebate, while our modelled rebate scenario reduced demand. As such, the pilot event increased GHG emissions by 26% and NOx emissions by 18%. This tells us that pilot customers are very price inelastic and have no choice but to charge their cars in that period *or* they are simply unaware of the rebate. As we imagine that the latter is true, a communication strategy directed at this segment could make MUDs ideal to induce load shift from the evening to late-night hours.

The load profile for this month does also support potential reduction in curtailment. There is a spike in the midday hours between 11:00 a.m. - 3:00 p.m., likely due to drivers coming home for lunch and plugging in their cars. It may not be realistic to shift all charging into these hours, but drivers should be financially encouraged to charge in these times when they can.

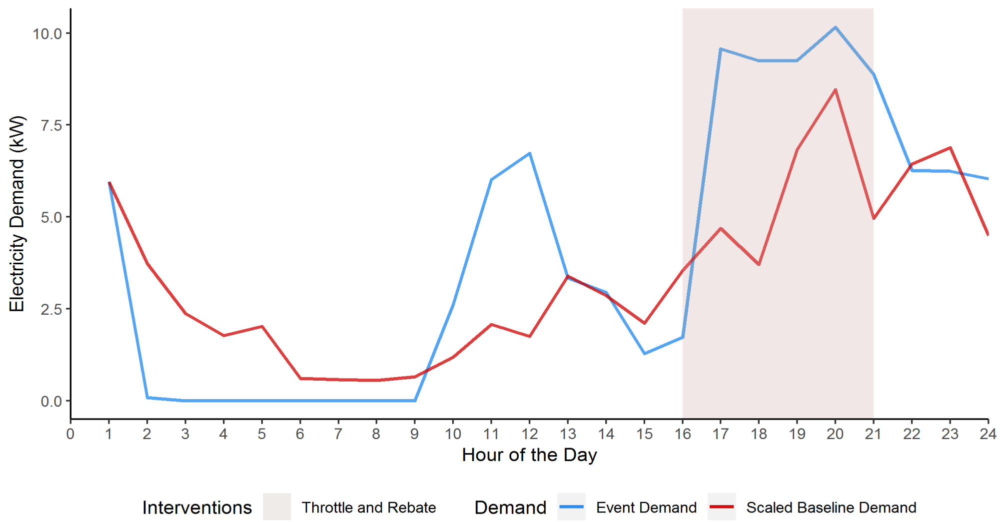

Figure 39. July 31, 2018 MUDs Load Reduction Event Demand Graph

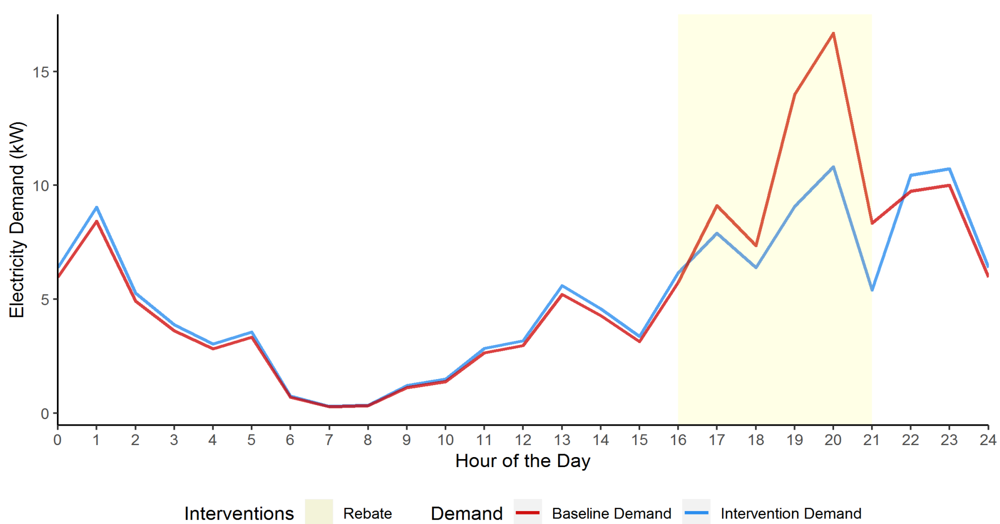

Figure 40. Model Scenario M1 Demand Graph

Chapter IV. Hypotheticals

In addition to the specific scenario outputs listed above, we calculate the theoretical impact of shifting charging under specific situations. Given the limitations in our model, these theoretical impacts provide some sense of the scope of the potential impact of load shifting. In other words, we build out the theoretical maximum discussion already in the model. These hypotheticals are for 2030, the year when California intends to have 5 million zero-emission vehicles on the road.[111] To support that goal, SCE intends to support the installation at least 50,000 long-dwell public chargers by 2025.[112] We use those chargers as a proxy for the number of non-residential chargers that will be available in 2030. We do not model any future dates since by 2045, all electricity in California is slated to be sourced by zero-carbon resources and thus shifting will be less relevant to climate goals.[113]

Two general categories of hypotheticals are examined:

1. *Target Charging Only*. Shifting all charging into the target midday window (11:00 a.m. - 3:00 p.m.)
2. *No Charging Before 11*. Shifting 50% of charging into the target midday window (11:00 a.m. - 3:00 p.m.) and 50% into the off-peak evening window (11:00 p.m. - 3:00 a.m.).

To determine how much load these chargers can absorb in 2030, we first need to understand what load will look like in 2030. SCE currently projects that daily average EV load in their territory will be 10,330 MWh and yearly it will be 3,770,876 MWh.[114] Figure 41 below outlines this projected daily load profile. This includes all EVs charging at all locations (home level 1 and level 2, work level 2, public level 2, fast charging).

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[111] Gavin Bade, "CEC"; "Zero-Emission Vehicles"; "Zero Emission Vehicle (ZEV) Program"; Bedir et al., "California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025."
[112] Griffo, "Edison Shares Vision for Clean Energy Future at Global Summit."
[113] De Leon, SB-100. California Renewables Portfolio Standard Program: emissions of greenhouse gases., 100.
[114] "SCE TAC Hourly Results 2027-2030."

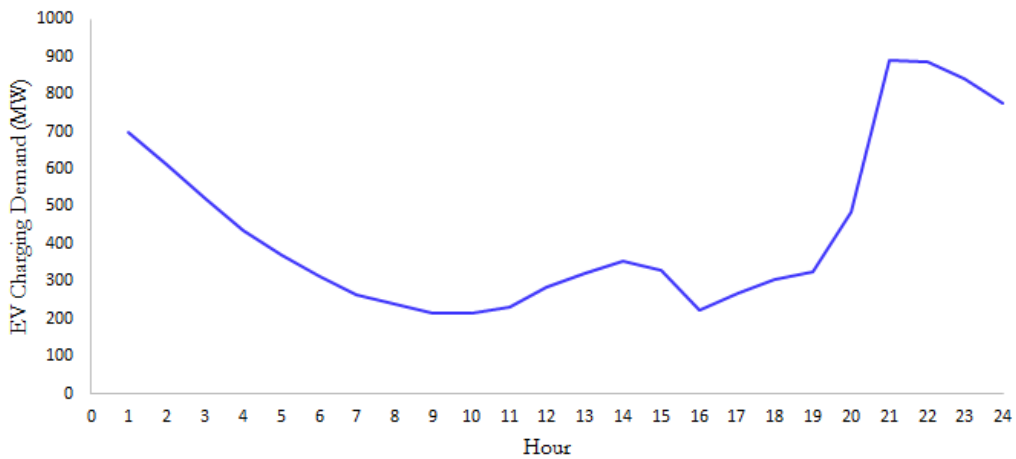

Figure 41. Projected SCE 2030 Hourly EV Demand

We then determine the maximum amount of load that could be absorbed by the long-dwell chargers in California in 2030 under our hypothetical charging behaviors. This is done by calculating the "theoretical maximum" as we did in our model above, defined as the amount of load the chargers could absorb if they were at full capacity during the target window:

$$6.6\ kW\ charger\ power * \#\ hours * \#\ chargers = Theoretical\ Max\ (kWh)$$

Table 49 summarizes the potential impacts of each of these hypothetical scenarios. Given the forecasted daily EV demand of 10,331 MWh, this number of long-dwell chargers could meet 8-26% of demand under the potential load shifting requirements.

Table 49. Potential Load Impacts of "Target Charging Only" and "No Charging Before 11" of Long-dwell Chargers in 11:00 a.m. - 3:00 p.m. and 11:00 p.m. - 3:00 a.m. in 2030.

Load Shift Window	Segment	Chargers	Load Availability (MWh)	% Daily Demand Could Meet
11 am - 3 pm	Workplaces	31,435	830	8%
11 am - 3 pm	All	50,000	1,650	13%
11 am - 3 pm *and* 11 pm - 3 am	Workplaces	31,435	1,660	16%
11 am - 3 pm *and* 11 pm - 3 am	All	50,000	3,300	26%

Table 50 summarizes the GHG and NOx emission impacts of these hypothetical scenarios. Assuming a conservative estimate that 25% of energy in the target window is provided by natural gas and using an average 2030 emissions factor for the grid for the entire day (0.16 kg CO_2eq/kwh and 0.0007 kg NOx/kWh), shifting demand reduces daily GHG emissions associated with EV charging by 2-8% and NOx emissions by 4-12%. If we instead assume that 100% solar is displaced, daily emissions would fall 8-26% for GHGs and NOx.

Table 50. Potential Emission Impacts of "Target Charging Only" and "No Charging Before 11" of Long-dwell Chargers in 11:00 – 15:00 and 23:00 – 03:00 in 2030.

Load Shift Window	Segment	GHG Change		NOx Change	
		All Day	Load Shift Window	All Day	Load Shift Window
11 am - 3 pm	Workplaces	-2%	-30%	-4%	-47%
11 am - 3 pm	All	-4%	-30%	-6%	-47%
11 am - 3 pm *and* 11 pm - 3 am	Workplaces	-5%	-30%	-8%	-47%
11 am - 3 pm *and* 11 pm - 3 am	All	-8%	-30%	-12%	-47%

To shift all load and eliminate all GHG and air pollution emissions associated with EV charging, additional long-dwell chargers would be needed and/or additional segments would need to be included in the shift.

Chapter V. Discussion and Recommendations

Results Discussion

EV adoption in California has the potential to offer significant climate and health benefits. But charging behavior must be managed to ensure that grid strain during peak demand conditions is not exacerbated and to ensure that EVs fully capture their GHG reduction potential.

This project responds to Southern California Edison's growing interest in managing EV charging behavior. We seek to determine how various economic, technical, and communication interventions shift EV charging to different periods of the day, and how this shift impacts human health, the environment, and the electrical grid. To do so, we develop models that can simulate the impact of any combination of selected interventions. We run a variety of scenarios on our four target, long-dwell market segments (workplaces, destination centers, fleets, multi-unit dwellings [MUDs]]) and also develop a web-based interface for users to run the model for alternative scenarios.

When we look across all scenarios considered in our model, we can see the impact of various interventions, as summarized below:

- Lowering the price of electricity through a **discount** increases demand in that window and over the course of the day. Raising the price in peak periods through a **rebate** reduces demand in that target period and over the whole day.
- Discounts and a rebates can induce load shifting. This conclusion is based on our model's elasticity values; segment-specific cross-price elasticities may show that load shifting is larger under a rebate or discount.
- The new **TOU 2019** rate schedule may have a significant impact on reducing load during the evening peak period and increasing load in the midday.
- **Throttling**, as a command and control activity, drops load considerably when applied.
- According to our model, **additional communication about price and air pollution** can amplify behavior response up to 12%. It is unlikely that this benefit will be achieved in SCE's pilot given the communication gap between EV drivers and SCE. Under the pilot, EV drivers often do not know the actual price of electricity, let alone receive the types of notifications in our model about price changes. This communication barrier makes it challenging to induce EV drivers to respond as desired. However, if communication is improved, more than a 12% improvement may be possible.
- Scaling up the **number of chargers** scales up the response.

From our scenarios and hypotheticals, we can draw some general conclusions about the value of these interventions in achieving grid stability, reducing curtailment, and reducing the impact of electricity consumption on climate change and air pollution.

Our modelled interventions can successfully reduce **demand** in the evening period by up to 93%. Our interventions are less effective at load shifting and increase midday demand by up to 37%. These changes in load are based on the elasticities used in our model, which do not consider cross-price elasticities. Thus, the magnitude of load shifting is less than that of load reduction. These elasticities are also pulled from residential segments and do not consider the availability of different segments' drivers at different times and thus do not consider the flexibility, or inflexibility, of drivers. To that end, these results are likely overestimates. But this projected emphasis on load reduction and not shifting contributes to the impacts we see on cost, emissions, and curtailment, as detailed below.

This change in demand typically reduces daily **GHG emissions and air pollution emissions** associated with EV charging by up to 34% and 37% respectively. Emissions in the peak evening period can fall by up to 93% for GHGs and 99% for NOx. While we do not eliminate all emissions in our modeled scenarios, reducing emissions by one-third is substantial, particularly on a clean grid such as the one in California. Our modeled emissions values are also limited by the assumptions we make about marginal electricity resources: Our model is conservative and assumes that any change in load comes partially from non-zero carbon resources, even in the middle of the day. The minimal magnitude of change in emissions means that the financial benefits of these changes are also minimal.

In general, changing load behavior as predicted also has a negligible impact on NOx emissions in California-designated **disadvantaged communities.** This is because we only consider the marginal impact on DACs and the initial NOx emissions associated with the current low number of chargers. However, even a minor change in load in DACs may be significant since that load is more likely to occur on days when air quality is already low. Thus, these reductions *may* be significant. Additional analysis is needed.

Our model predicts negligible changes in **curtailment**, but this does not imply that shifting EV charging may not impact curtailment or grid stability. Our model predicts negligible changes because 1) we predominantly considered the impact of changing behavior associated with less than 1,000 chargers. The magnitude of this potential change is low (maximum 1,400 kWh), especially when considered to the high amount of curtailment happening (up to 482,000 kwh). Even under our 2030 scenarios, the highest change in curtailment we would see is 4,000 kWh. If we consider load shifting beyond these segments and thus include more chargers and more of the load that the grid may be forced to absorb by 2030, curtailment impacts may rise. 2) We assume curtailment is happening from 8:00 a.m. to 6:00 p.m. Thus, any change in behavior during that window can affect curtailment. If we only considered curtailment to be of concern from 11:00 a.m. to 3:00 p.m., we would expect to see larger decreases in curtailment.

Our model periodically predicts an increase in curtailment. This is because our model typically predicts changes in demand more than it predicts load shifting and thus predicts a net decline in demand. Again, since we assume curtailment can happen over most of the daylight hours, a reduction in daily demand exacerbates curtailment.

Relatedly, our interventions generally cause **customer costs** to fall anywhere from 8 to 55%.

Lastly, it is important to note that all of models only consider the change in demand from a one-day event. Thus, the magnitude of the impacts is naturally limited.

It is also interesting to compare the output from our modeled interventions to that of our hypothetical. Under current charger projected adoption rates for long-dwell segments and overall EV adoption rates in Southern California, limiting charger use to target windows would only allow us to meet 8-32% of load in 2030. If we shift this percentage of load, we could reduce daily GHG emissions by up to 8% and NOx emissions by 12%.[115] In other words, if we want to shift everyone to charging in our target windows and at these long-dwell segments, we would need to install more chargers.[116] Alternatively, we could also consider the importance of residential charging.

A summary of specific impacts by segment are listed below.

- **Workplaces** respond as SCE desires most to a discount, communication, throttling, and 2019 TOU.
- **Destination centers** respond to a discount, throttling, and communication. 2019 TOU rates have the potential to further change charging demand as intended.
- **Fleets and MUDs** exhibit similar initial behavior and thus response, as both segments are typically away from their chargers during the day and plug-in in the evening. A rebate, paired with the 2019 TOU rates, is the most effective intervention in these segments.

[115] This is based on conservative 25% natural gas assumptions. If we assume that 100% solar was displaced instead, daily emissions would fall 8-26% for GHG and NOx.
[116] This conclusion builds on recent studies suggesting that California has not installed enough EV chargers to date. (Nicholas, Hall, and Lutsey, "Quantifying the Electric Vehicle Charging Infrastructure Gap across U.S. Markets.")

Recommendations

We offer the following recommendations for SCE to consider:

Close the Communication Gap

- Develop a communication and education outreach strategy to help site hosts communicate to their end users; consider requiring or offering incentives to site hosts to pass costs or communication along to end users.
- Reconsider messaging: If California is aiming to have a zero-carbon grid by 2045, changing charging behavior may become less about GHG emissions and more about grid stability and thus messaging about demand response should reflect these infrastructure concerns.

Test Other Strategies

- Work with site hosts to eliminate free charging and to instead offer graduated pricing, free charging only during specific windows, or some other mechanism that allows price and price incentives to be passed along to drivers.
- If solar curtailment is the primary concern, consider aligning TOU prices to match the midday solar period, instead of setting one on-peak and one off-peak price.
- Craft segment-differentiated strategies. Each market segment in the Charge Ready Pilot has different characteristics and load profiles so different demand response strategies are needed for each segment. For example, SCE has already identified workplaces as an appropriate segment to call load shift events because drivers have access and ability to adjust the time at which their car charges while they are at work. So, instead of calling load reduction (rebate) events in the evening when employees have left work and there is no load, it might be more beneficial to change the time of the load reduction events to earlier in the morning when peak load occurs.
- Limit the time frame of morning throttling. Solar energy may be curtailed in morning periods so reducing the amount of charging in those periods by throttling may adversely impact curtailment and actually increase costs. Limiting the hours in which throttling occurs to only those where negative prices and curtailment *do not occur* (i.e., in the early morning hours, 6:00 - 8:00 a.m.) could reduce curtailment costs.
- Consider changing pricing from a dollar per kWh to a time-based subscription model. Under this model, users could be charged a predetermined fee for a set amount of electricity during a set time, like early mornings. If they then exceed that usage in that time, they face an additional charge.
- Consider alternative strategies, such as subscription charging or incorporating local site storage. These were outside of the scope of this project, but are discussed briefly in Appendix I.
- Make timer capability or compatibility a requirement for charger vendors.

Expand the Program

- Include residential segments or install more chargers in long-dwell segments; otherwise we will not be able to fully support midday charging.

Research Driver Behavior

- Consider tracking how drivers shift their charging from residential to non-residential segments and what incentivizes them to do so.
- Conduct a robust economic study of how EV drivers respond to changes in price in non-residential segments and then derive the self and cross-price elasticities. These values could then be entered into our project's web-based tool and more robust results could be calculated. Our chosen elasticity methods do not reveal much load shifting. Elasticities derived from an experiment in our segments may reveal that load shifting is more prevalent.
- Consider running our model with other interventions. We reported on the ones that are traditionally applied in these segments, but more may be of interest.
- Compare the impact of periodic events with price changes against changing long-term electricity rates.

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Glossary

Baseload Power	Electricity resources that cannot be easily turned off or on, like nuclear and hydro.
Demand/Load Profile	Demand for electricity (kWh) over the course of a day.
Duck Curve	Term used to refer to the phenomenon where there is low demand in the middle of the day for fossil fuel based electricity (due to the availability of solar energy), followed by a rapid and large demand for fossil fuels in the evenings.
Load Reduction	A reduction in electricity demand at any point.
Load Shift	A shift in electricity demand from one period of the day to another.
Peaker	Power resources that can easily be turned off or on. These are typically natural gas or oil and are expensive.
Peak Shaving	A reduction in electricity demand during the peak period (normally 18:00 – 21:00) through either load reduction or load shift.

Appendix I. Alternative Strategies

The SCE Charge Ready Pilot follows the tradition of modifying the price per kWh to change electricity usage. However, this is just one of many strategies that have the potential to shift charging behavior or help shape supply and demand. Below is a summary of the challenges of a price per kWh incentive and potential alternate strategies.

Challenges Associated with price/kWh

The primary challenge associated with using a price per kWh incentive to change demand is that most drivers in our target segments do not pay for charging on a price per kWh scale. Site hosts pay the utility bills and thus pay the price per kWh fee. Drivers do not. Most of them pay either nothing, a fee for parking, or a fee for time used. Thus, incentivizing their behavior shift with a price per kWh incentivize is challenging.[117] Communication about this price shift thus becomes key.

But since the current incentives given to site hosts are relatively minimal on a dollar per kWh basis, communication about that metric may not be substantial enough to motivate site hosts to encourage their drivers to comply. If, instead, SCE is able to communicate about the overall energy savings in dollars for a month or even an entire year, they may be able to encourage site hosts to incentivize their own drivers to change their behavior. For example, "you could save up to $200 per month/year if you encourage drivers to charge from 11:00 a.m. to 3:00 p.m.," may be more valuable than stating "you will get $0.05 discount on the price per kwh if you increase consumption between 11:00 a.m. to 3:00 p.m."

Subscriptions

Rate design has always been at the center of the utility business model, and it is becoming even more important as new distributed energy resources (DERs) like EVs come onto the grid. Time of Use rates have been crucial in aligning traditional demand with new, variable forms of generation such as solar, but they may not be adequate to manage the growing load from EVs. There are some EV rate structures currently available for non-residential locations to help minimize the cost of electricity to the site host, but each market segment has a different load profiles and these new rates may or may not align with their particular charging availability. Moreover, demand charges are based on a site's peak usage and this billing feature discourages many non-residential site costs from installing chargers because they are concerned EVs will increase their peak usage and therefore demand charges.[118]

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117 We are not advocating removing all pricing. Setting a price for charging is typically needed if a behavior change is desired. (Winn, "Electric Vehicle Charging at Work: Understanding Workplace PEV Charging Behavior to Inform Pricing Policy and Investment Decisions.")

118 Fehrenbacher, "Report"; "Demand Charges 101."

In 2018, PG&E realized that many of these current rate structures are no longer appropriate for this realm of electricity consumption, and proposed subscription-style EV charging rates.[119] These rates would allow the customer (i.e. a non-residential site host) to choose how much power they will need for their charging stations per month and pay a fee according to that number. This method would avoid the challenge of demand charges and encourage more investment in charging infrastructure. In addition, this type of billing could work in tandem with the fee structure already in use by EVSE vendors, thereby increasing the possibility of price pass through to the end driver. As SCE continues to look for new strategies to manage charging, they may want to consider their rate designs and specifically subscription style charging.[120]

Managed Charging (by Utility)

In addition to traditional demand response which incentivizes drivers to change their behavior, "managed charging" has been proposed as a way to change charging behavior.[121] Managed charging considers EVs as a resource for the utility to shave peak load, reduce grid constraints, and allow more efficient and effective use of excess energy produced by renewable energy resources.[122] It enables the utility to harness direct control over the chargers (much like throttling in our model), but for all periods of the day. Drivers plug in their vehicles as usual, but the utility determines when the vehicle actually gets to charge, based on grid conditions.[123]

In other words, it should perfectly create the load charging profile that SCE is trying to produce. While this policy could be found to be politically contentious and expensive to implement, it is a notable alternative strategy.

Storage

A common reaction to the complexity of charging EVs using renewable power is to simply store the solar energy and deploy it later. Even with battery costs dropping, shaping demand through demand response provides the benefit of not having to invest in additional generating capacity for utilities. TOU rates is a strategy to help shape demand, but it does not address the issue of "clustering" and the "timer peaks"[124] associated with drivers adapting to TOU schedules. In a

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119 Lillian, "PG&E Proposes Subscription-Style EV Charging Rates."
120 Lillian.
121 Cohn, "Managed Charging."
122 Zhang, Markel, and Jorgenson, "Value to the Grid from Managed Charging Based on California's High Renewables Study."
123 "Managed Charging" is also referred to as V1G (unidirectional electricity flow from the grid into the battery), intelligent charging, adaptive charging, or smart charging.
Myers, "Utilities and Electric Vehicles: The Case for Managed Charging."
124 Clustering is when loads, such as EVs, are aggregated within a specific location, causing stress on the transformer and infrastructure serving that location. Timer peaks occur when EV drivers adapt to TOU schedules by setting timers or changing behavior to charge at the onset of a period with lower rates,

study examining the impacts of DERs like EVs within Sacramento Municipal Utility District's (SMUD) service territory it was found that such clustering and poor management could lead to 17% of SMUD's transformers potentially being replaced by 2030 due to transformer overload from EVs, at an average cost of $7,400 per transformer.[125]

If transformer stress becomes a localized issue for utility providers, localized strategies might need to be deployed. One option is to identify these clustered "hot spots," areas where transmission infrastructure is particularly stressed from EV overloading, and pair these vulnerable transformers and substations with energy storage.[126] As battery costs continue to decline, incentives could be provided to site hosts that exhibit high peak loads despite pricing interventions. Essentially, if areas are identified where pricing strategies do not seem to be influencing charging behavior, the utility may want to consider storage in those critical areas.

While storage might proactively address the problem of stressed infrastructure, it still does not address the issue of grid curtailment. It also does not address the more foundational causes, such as influencing charging behavior.

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resulting in peaks at the start of those periods. Both of these have been found to create stress on utility infrastructure.

[125] "Beyond the Meter: Planning the Distributed Energy Future, Volume II: A Case Study of Utility Integrated DER Planning from Sacramento Municipal Utility District."

[126] Engel et al., "The Potential Impact of Electric Vehicles on Global Energy Systems."

Appendix II. Rate Structures

The following tables list the primary Time-of-Use rates for EVs in SCE's territory in 2018, as well as the rate to be rolled out in late 2019.

Table AII-1. TOU EV-4 (2018) (21-500 kw/month)[127]

Hour Ending	Period	Summer	Winter
1	Super Off Peak	0.05	0.06
2	Super Off Peak	0.05	0.06
3	Super Off Peak	0.05	0.06
4	Super Off Peak	0.05	0.06
5	Super Off Peak	0.05	0.06
6	Super Off Peak	0.05	0.06
7	Super Off Peak	0.05	0.06
8	Super Off Peak	0.05	0.06
9	Off Peak	0.12	0.09
10	Off Peak	0.12	0.09
11	Off Peak	0.12	0.09
12	Off Peak	0.12	0.09
13	On Peak	0.29	0.11
14	On Peak	0.29	0.11
15	On Peak	0.29	0.11
16	On Peak	0.29	0.11
17	On Peak	0.29	0.11
18	On Peak	0.29	0.11
19	Off Peak	0.12	0.09
20	Off Peak	0.12	0.09
21	Off Peak	0.12	0.09
22	Off Peak	0.12	0.09
23	Off Peak	0.12	0.09
24	Super Off Peak	0.05	0.06

127 "SCE Advice Letter 3648-E: Schedule TOU-EV-4."

Table AII-2. TOU EV-3 (2018) (<20 kw/month)[128]

Hour Ending	Period	Summer	Winter
1	Super Off Peak	0.09	0.10
2	Super Off Peak	0.09	0.10
3	Super Off Peak	0.09	0.10
4	Super Off Peak	0.09	0.10
5	Super Off Peak	0.09	0.10
6	Super Off Peak	0.09	0.10
7	Super Off Peak	0.09	0.10
8	Super Off Peak	0.09	0.10
9	Off Peak	0.17	0.14
10	Off Peak	0.17	0.14
11	Off Peak	0.17	0.14
12	Off Peak	0.17	0.14
13	On Peak	0.36	0.16
14	On Peak	0.36	0.16
15	On Peak	0.36	0.16
16	On Peak	0.36	0.16
17	On Peak	0.36	0.16
18	On Peak	0.36	0.16
19	Off Peak	0.17	0.14
20	Off Peak	0.17	0.14
21	Off Peak	0.17	0.14
22	Off Peak	0.17	0.14
23	Off Peak	0.17	0.14
24	Super Off Peak	0.09	0.10

128 "SCE Advice Letter 3648-E: Schedule TOU-EV-3."

Table AII-3. TOU EV-8 (2019) (21-500 kw/month)[129]

Hour Ending	Summer Period	Summer	Winter Period	Winter
1	Super Off Peak	0.13	Off Peak	0.13
2	Super Off Peak	0.13	Off Peak	0.13
3	Super Off Peak	0.13	Off Peak	0.13
4	Super Off Peak	0.13	Off Peak	0.13
5	Super Off Peak	0.13	Off Peak	0.13
6	Super Off Peak	0.13	Off Peak	0.13
7	Super Off Peak	0.13	Off Peak	0.13
8	Super Off Peak	0.13	Off Peak	0.13
9	Super Off Peak	0.13	Super Off Peak	0.07
10	Super Off Peak	0.13	Super Off Peak	0.07
11	Super Off Peak	0.13	Super Off Peak	0.07
12	Super Off Peak	0.13	Super Off Peak	0.07
13	Super Off Peak	0.13	Super Off Peak	0.07
14	Super Off Peak	0.13	Super Off Peak	0.07
15	Super Off Peak	0.13	Super Off Peak	0.07
16	Super Off Peak	0.13	Super Off Peak	0.07
17	On Peak	0.42	On Peak	0.29
18	On Peak	0.42	On Peak	0.29
19	On Peak	0.42	On Peak	0.29
20	On Peak	0.42	On Peak	0.29
21	On Peak	0.42	On Peak	0.29
22	Super Off Peak	0.13	Off Peak	0.13
23	Super Off Peak	0.13	Off Peak	0.13
24	Super Off Peak	0.13	Off Peak	0.13

[129] "SCE Advice 3853-E."

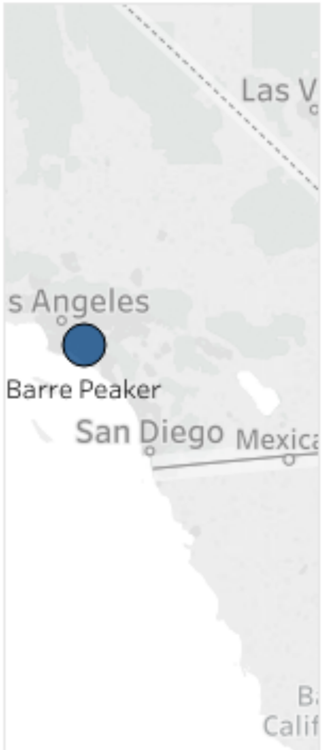
Appendix III. Emission Factors

Peaker Operation and Demographic Data

The following figures provide operational information on the 10 peaker plants in SCE's territory, including the percentage of power produced on high ozone zones and PM days compared to other power plants. Demographic information for the community living within one-mile of each plant is also listed. All figures were gathered from the California Power Map.[130]

[130] "California Power Map — Beta."

Barre Generating Station



Capacity (MW)	49
Generation (MWh)	32,675
Capacity factor	8%
Annual CO2 emissions (tons)	18,910
Annual NOx emissions (tons)	2.1
CO2 emissions rate (tons/MWh)	0.58
NOx emissions rate (lbs/MWh)	0.13
Heat rate (MMBtu/MWh)	9.7
% MWh high ozone	23%
% MWh high PM	3%
Annual operational hours	908
Annual starts	206
Average run hours per start	4
Age (years)	11
EIA ID	56474
Latitude	33.8073
Longitude	-117.9830

Figure AIII-1. Barre Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
Barre Peaker

Radius (miles)
1

Population data: 1-mile radius

Census tract	6059087803
Plant latitude	33.8073
Plant longitude	-117.9830
Tract CalEnviroScreen percentile	87
Population characteristics percentile	76
Pollution burden percentile	87
Total population in selected radius	35,120
CalEnviroScreen percentile	75
Median income	$52,591
% Below poverty line	23%
% American Indian/Native Alaskan	0%
% Asian	23%
% Black	2%
% Hispanic/Latino	53%
% Native Hawaiian/Pacific Islander	1%
% Other	0%
% Two or more	2%
% White	19%

Demographics

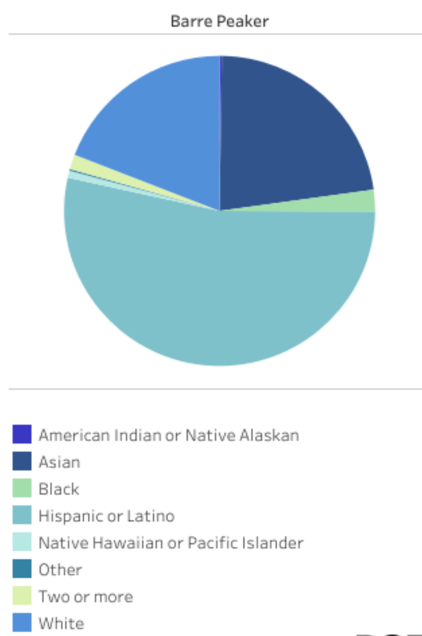
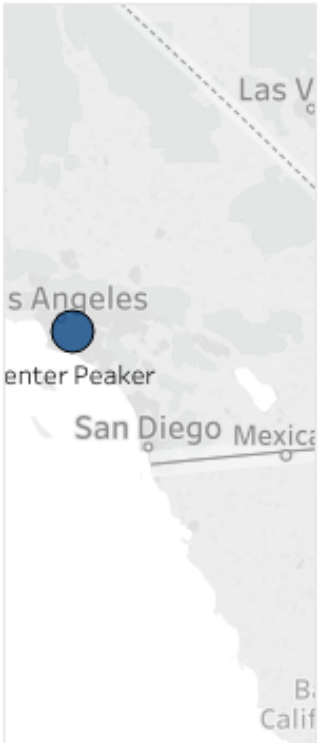


Figure AIII-2. Barre Generating Station Demographic Information

Center Generating Station



Capacity (MW)	49
Generation (MWh)	27,389
Capacity factor	6%
Annual CO2 emissions (tons)	16,014
Annual NOx emissions (tons)	1.6
CO2 emissions rate (tons/MWh)	0.58
NOx emissions rate (lbs/MWh)	0.11
Heat rate (MMBtu/MWh)	9.8
% MWh high ozone	32%
% MWh high PM	2%
Annual operational hours	839
Annual starts	189
Average run hours per start	4
Age (years)	11
EIA ID	56475
Latitude	33.9296
Longitude	-118.1044

Figure AIII-3. Center Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
Center Peaker

Radius (miles)
1

Population data: 1-mile radius

Census tract	6037550300
Plant latitude	33.9296
Plant longitude	-118.1044
Tract CalEnviroScreen percentile	85
Population characteristics percentile	66
Pollution burden percentile	92
Total population in selected radius	22,892
CalEnviroScreen percentile	78
Median income	$67,912
% Below poverty line	12%
% American Indian/Native Alaskan	0%
% Asian	7%
% Black	3%
% Hispanic/Latino	71%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	1%
% White	17%

Demographics

Center Peaker

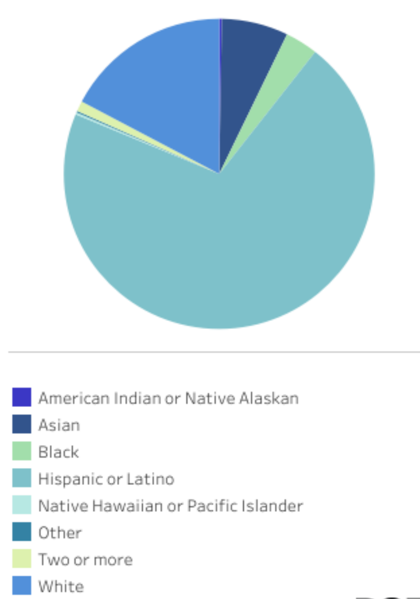
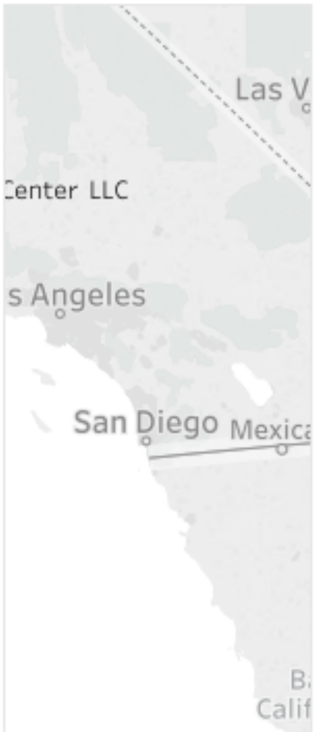


Figure AIII-4. Center Generating Station Demographic Information

Delano Energy Center, LLC



Capacity (MW)	50
Generation (MWh)	16,632
Capacity factor	4%
Annual CO2 emissions (tons)	10,798
Annual NOx emissions (tons)	1.7
CO2 emissions rate (tons/MWh)	0.65
NOx emissions rate (lbs/MWh)	0.20
Heat rate (MMBtu/MWh)	10.9
% MWh high ozone	43%
% MWh high PM	6%
Annual operational hours	687
Annual starts	137
Average run hours per start	5
Age (years)	5
EIA ID	58122
Latitude	35.7910
Longitude	-119.2946

Figure AIII-5. Delano Energy Center Annual Average Operations (2015-2017)

Filters

Plant name
Delano Energy Center LLC

Radius (miles)
1

Population data: 1-mile radius

Census tract	6107004300
Plant latitude	35.7910
Plant longitude	-119.2946
Tract CalEnviroScreen percentile	89
Population characteristics percentile	87
Pollution burden percentile	78
Total population in selected radius	1,860
CalEnviroScreen percentile	96
Median income	$44,895
% Below poverty line	3%
% American Indian/Native Alaskan	0%
% Asian	0%
% Black	30%
% Hispanic/Latino	46%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	0%
% White	23%

Demographics

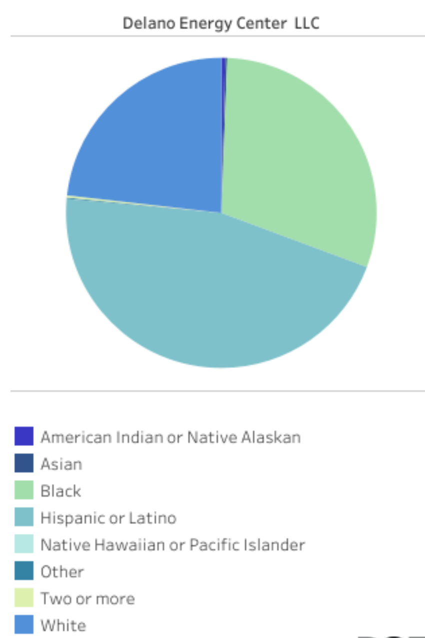
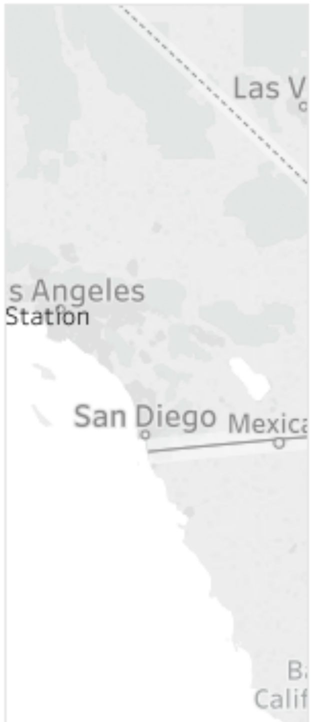


Figure AIII-6. Delano Energy Center Demographic Information

Ellwood Generating Station



Capacity (MW)	57
Generation (MWh)	6,352
Capacity factor	1%
Annual CO2 emissions (tons)	
Annual NOx emissions (tons)	
CO2 emissions rate (tons/MWh)	
NOx emissions rate (lbs/MWh)	
Heat rate (MMBtu/MWh)	14.0
% MWh high ozone	
% MWh high PM	
Annual operational hours	
Annual starts	
Average run hours per start	
Age (years)	44
EIA ID	8076
Latitude	34.4313
Longitude	-119.9000

Figure AIII-7. Ellwood Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
Ellwood Generating Station

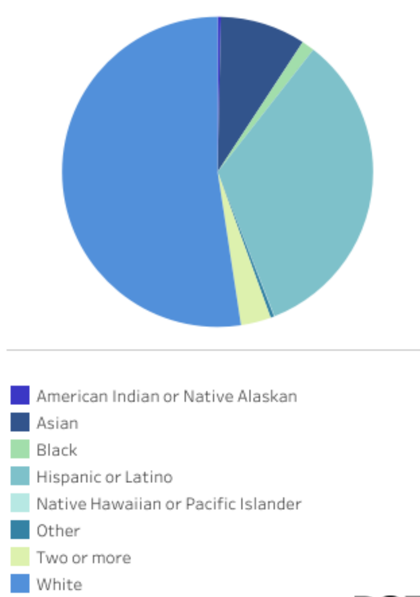
Radius (miles)
1

Population data: 1-mile radius

Census tract	6083002930
Plant latitude	34.4313
Plant longitude	-119.9000
Tract CalEnviroScreen percentile	12
Population characteristics percentile	18
Pollution burden percentile	12
Total population in selected radius	9,357
CalEnviroScreen percentile	10
Median income	$86,995
% Below poverty line	9%
% American Indian/Native Alaskan	0%
% Asian	9%
% Black	1%
% Hispanic/Latino	34%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	3%
% White	52%

Demographics

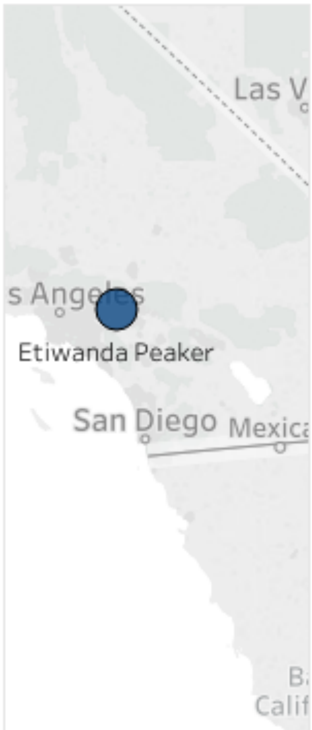
Ellwood Generating Station



PSE

Figure AIII-8. Ellwood Generating Station Demographic Information

Grapeland/Etiwanda Generating Station



Capacity (MW)	49
Generation (MWh)	27,263
Capacity factor	6%
Annual CO2 emissions (tons)	15,842
Annual NOx emissions (tons)	1.9
CO2 emissions rate (tons/MWh)	0.58
NOx emissions rate (lbs/MWh)	0.14
Heat rate (MMBtu/MWh)	9.8
% MWh high ozone	30%
% MWh high PM	1%
Annual operational hours	853
Annual starts	193
Average run hours per start	4
Age (years)	11
EIA ID	56472
Latitude	34.0904
Longitude	-117.5340

Figure AIII-9. Grapeland/Etiwanda Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
Etiwanda Peaker

Radius (miles)
1

Population data: 1-mile radius

Census tract	6071002207
Plant latitude	34.0904
Plant longitude	-117.5340
Tract CalEnviroScreen percentile	76
Population characteristics percentile	44
Pollution burden percentile	98
Total population in selected radius	3,135
CalEnviroScreen percentile	76
Median income	$55,500
% Below poverty line	3%
% American Indian/Native Alaskan	0%
% Asian	1%
% Black	24%
% Hispanic/Latino	47%
% Native Hawaiian/Pacific Islander	0%
% Other	1%
% Two or more	0%
% White	26%

Demographics

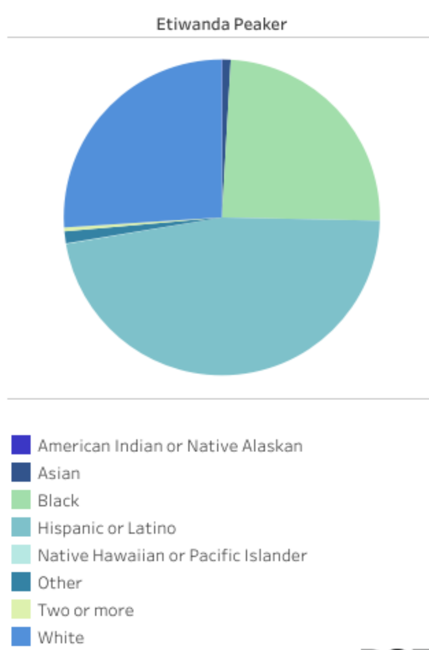
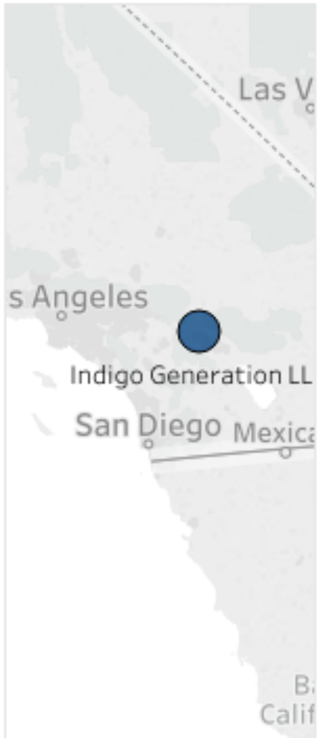


Figure AIII-10. Grapeland/Etiwanda Generating Station Demographic Information

Indigo Generating Station



Capacity (MW)	135
Generation (MWh)	58,062
Capacity factor	5%
Annual CO2 emissions (tons)	34,968
Annual NOx emissions (tons)	7.0
CO2 emissions rate (tons/MWh)	0.60
NOx emissions rate (lbs/MWh)	0.24
Heat rate (MMBtu/MWh)	10.1
% MWh high ozone	20%
% MWh high PM	1%
Annual operational hours	1,016
Annual starts	215
Average run hours per start	5
Age (years)	17
EIA ID	55541
Latitude	33.9112
Longitude	-116.5530

Figure AIII-11. Indigo Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
Indigo Generation LLC

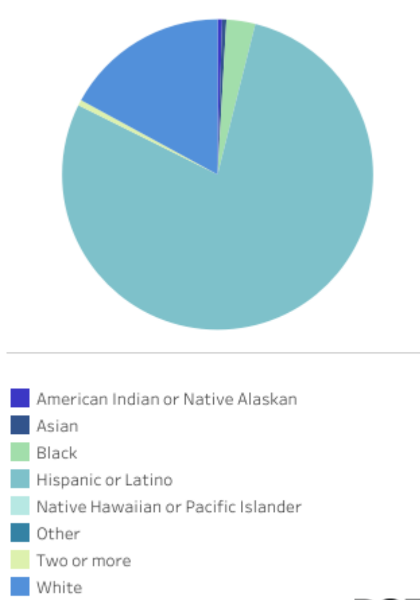
Radius (miles)
1

Population data: 1-mile radius

Census tract	6065044522
Plant latitude	33.9112
Plant longitude	-116.5530
Tract CalEnviroScreen percentile	32
Population characteristics percentile	48
Pollution burden percentile	16
Total population in selected radius	419
CalEnviroScreen percentile	32
Median income	$34,583
% Below poverty line	22%
% American Indian/Native Alaskan	0%
% Asian	0%
% Black	3%
% Hispanic/Latino	78%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	1%
% White	17%

Demographics

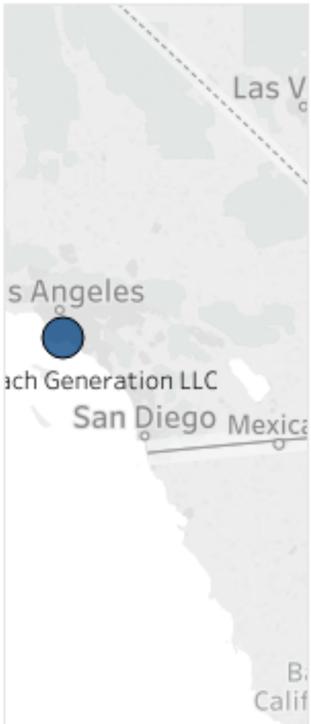
Indigo Generation LLC



PSE

Figure AIII-12. Indigo Generating Station Demographic Information

Long Beach Generating Station



Capacity (MW)	260
Generation (MWh)	26,006
Capacity factor	1%
Annual CO2 emissions (tons)	25,687
Annual NOx emissions (tons)	6.2
CO2 emissions rate (tons/MWh)	0.99
NOx emissions rate (lbs/MWh)	0.48
Heat rate (MMBtu/MWh)	16.6
% MWh high ozone	35%
% MWh high PM	3%
Annual operational hours	312
Annual starts	51
Average run hours per start	6
Age (years)	41
EIA ID	341
Latitude	33.7641
Longitude	-118.2248

Figure AIII-13. Long Beach Generating Station Annual Average Operations (2015-2017)

Filters

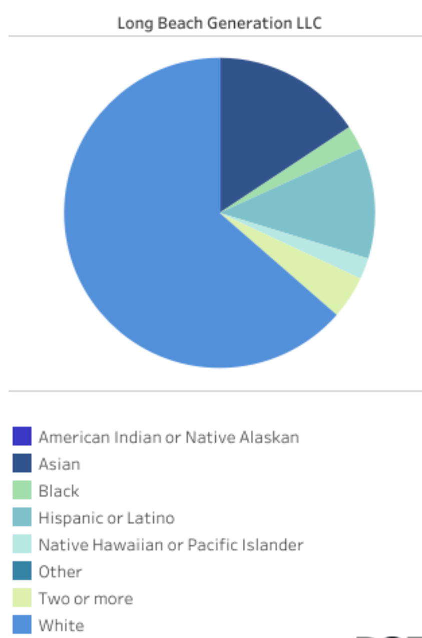
Plant name
Long Beach Generation LLC

Radius (miles)
1

Population data: 1-mile radius

Census tract	6037980033
Plant latitude	33.7641
Plant longitude	-118.2248
Tract CalEnviroScreen percentile	
Population characteristics percentile	
Pollution burden percentile	99
Total population in selected radius	38
CalEnviroScreen percentile	
Median income	$0
% Below poverty line	0%
% American Indian/Native Alaskan	0%
% Asian	16%
% Black	2%
% Hispanic/Latino	12%
% Native Hawaiian/Pacific Islander	2%
% Other	0%
% Two or more	4%
% White	64%

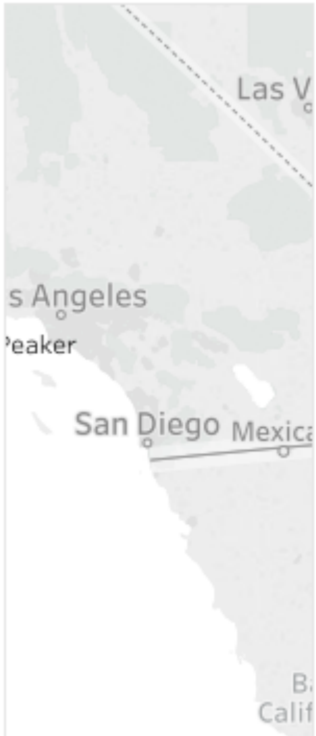
Demographics



PSE

Figure AIII-14. Long Beach Generating Station Demographic Information

McGrath Generating Station



Capacity (MW)	49
Generation (MWh)	40,559
Capacity factor	9%
Annual CO2 emissions (tons)	23,448
Annual NOx emissions (tons)	2.5
CO2 emissions rate (tons/MWh)	0.58
NOx emissions rate (lbs/MWh)	0.13
Heat rate (MMBtu/MWh)	9.7
% MWh high ozone	11%
% MWh high PM	0%
Annual operational hours	1,087
Annual starts	220
Average run hours per start	5
Age (years)	6
EIA ID	56471
Latitude	34.2056
Longitude	-119.2477

Figure AIII-15. McGrath Generating Station Annual Average Operations (2015-2017)

Filters

Plant name
McGrath Peaker

Radius (miles)
1

Population data: 1-mile radius

Census tract	6111002905
Plant latitude	34.2056
Plant longitude	-119.2477
Tract CalEnviroScreen percentile	89
Population characteristics percentile	70
Pollution burden percentile	94
Total population in selected radius	1,269
CalEnviroScreen percentile	34
Median income	$73,774
% Below poverty line	7%
% American Indian/Native Alaskan	0%
% Asian	2%
% Black	1%
% Hispanic/Latino	13%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	3%
% White	81%

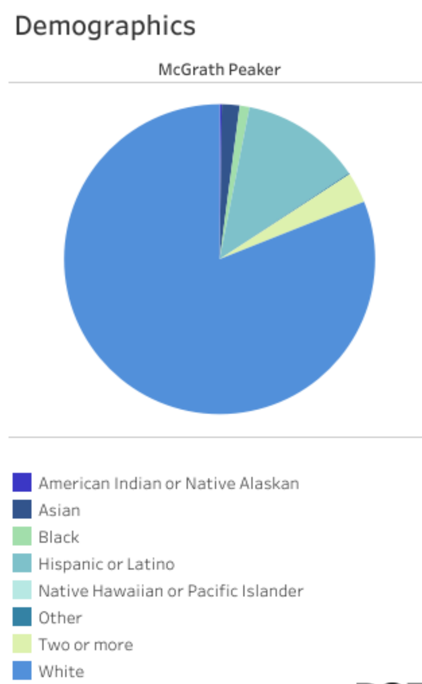
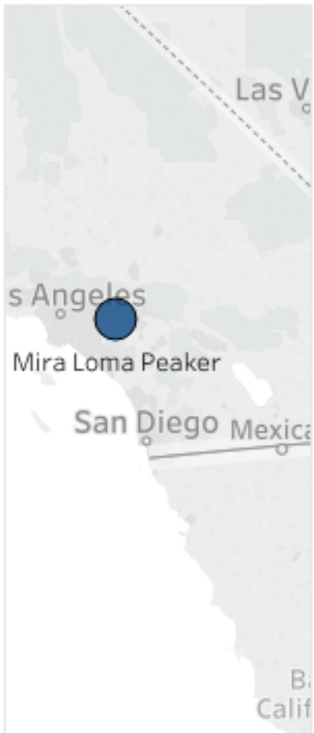


Figure AIII-16. McGrath Generating Station Demographic Information

Mira Loma Generating Station



Capacity (MW)	49
Generation (MWh)	28,537
Capacity factor	7%
Annual CO2 emissions (tons)	16,731
Annual NOx emissions (tons)	2.0
CO2 emissions rate (tons/MWh)	0.59
NOx emissions rate (lbs/MWh)	0.14
Heat rate (MMBtu/MWh)	9.9
% MWh high ozone	25%
% MWh high PM	2%
Annual operational hours	826
Annual starts	193
Average run hours per start	4
Age (years)	11
EIA ID	56473
Latitude	34.0053
Longitude	-117.5607

Figure AIII-7. Mira Loma Generating Station Annual Average Operations (2015-2017)

Filters

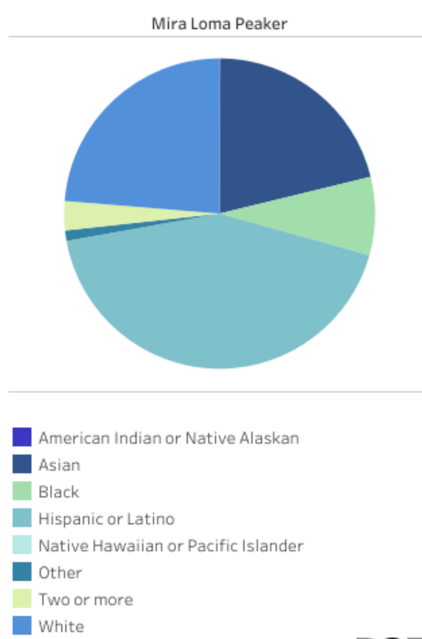
Plant name
Mira Loma Peaker

Radius (miles)
1

Population data: 1-mile radius

Census tract	6071001906
Plant latitude	34.0053
Plant longitude	-117.5607
Tract CalEnviroScreen percentile	79
Population characteristics percentile	56
Pollution burden percentile	93
Total population in selected radius	660
CalEnviroScreen percentile	79
Median income	$87,770
% Below poverty line	8%
% American Indian/Native Alaskan	0%
% Asian	21%
% Black	8%
% Hispanic/Latino	43%
% Native Hawaiian/Pacific Islander	0%
% Other	1%
% Two or more	3%
% White	24%

Demographics



PSE

Figure AIII-8. Mira Loma Generating Station Demographic Information

Sentinel Energy Center, LLC

Capacity (MW)	800
Generation (MWh)	530,955
Capacity factor	8%
Annual CO2 emissions (tons)	316,130
Annual NOx emissions (tons)	28.7
CO2 emissions rate (tons/MWh)	0.60
NOx emissions rate (lbs/MWh)	0.11
Heat rate (MMBtu/MWh)	10.0
% MWh high ozone	12%
% MWh high PM	1%
Annual operational hours	2,886
Annual starts	422
Average run hours per start	7
Age (years)	5
EIA ID	57482
Latitude	33.9367
Longitude	-116.5772

Figure AIII-17. Sentinel Energy Center Annual Average Operations (2015-2017)

Filters

Plant name
Sentinel Energy Project CPV

Radius (miles)
1

Population data: 1-mile radius

Census tract	6065044522
Plant latitude	33.9367
Plant longitude	-116.5772
Tract CalEnviroScreen percentile	32
Population characteristics percentile	48
Pollution burden percentile	16
Total population in selected radius	53
CalEnviroScreen percentile	32
Median income	$34,583
% Below poverty line	22%
% American Indian/Native Alaskan	0%
% Asian	0%
% Black	2%
% Hispanic/Latino	55%
% Native Hawaiian/Pacific Islander	0%
% Other	0%
% Two or more	0%
% White	43%

Demographics

Sentinel Energy Project CPV

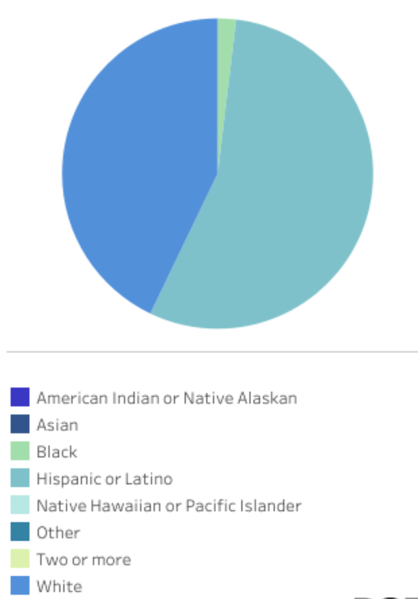


Figure AIII-18. Sentinel Energy Center Demographic Information

Hourly Fuel Mixes

Table AIII-1. Hourly Fuel Mix 2018[131]

2018 Fuel Mix																								
Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Renewables	20%	20%	19%	18%	18%	17%	17%	26%	36%	40%	43%	44%	43%	41%	40%	39%	37%	33%	23%	17%	16%	16%	17%	18%
Natural gas	29%	29%	29%	30%	30%	31%	31%	29%	27%	27%	28%	28%	29%	30%	32%	32%	34%	35%	37%	40%	39%	37%	35%	34%
Large hydro	9%	8%	8%	7%	8%	8%	8%	7%	6%	5%	6%	6%	7%	7%	7%	8%	8%	9%	11%	12%	11%	11%	10%	9%
Nuclear	8%	9%	9%	10%	10%	9%	9%	8%	8%	8%	8%	8%	7%	7%	7%	6%	6%	6%	6%	6%	6%	7%	7%	8%
Coal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Other	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Import-Coal	5%	5%	5%	5%	5%	5%	5%	4%	3%	3%	2%	2%	2%	2%	2%	2%	2%	2%	3%	4%	4%	4%	4%	4%
Import-Large Hydro	2%	2%	2%	2%	2%	2%	3%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	2%	2%	2%	2%	2%	2%
Import-Natural Gas	3%	3%	4%	4%	4%	4%	4%	3%	2%	2%	2%	1%	1%	2%	1%	1%	2%	2%	2%	3%	3%	3%	3%	3%
Import-Nuclear	3%	3%	3%	4%	3%	4%	4%	3%	2%	2%	2%	1%	1%	1%	1%	1%	1%	2%	2%	3%	3%	3%	3%	3%
Import-Oil	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
mport-Other (Petroleum Coke/Waste Heat	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Import-Biomass	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Import-Geothermal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Import-Small Hydro	1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
Import-Solar	2%	2%	2%	2%	2%	2%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	2%	2%	2%	2%	2%
Import-Wind	6%	6%	6%	6%	6%	6%	6%	5%	4%	3%	3%	2%	2%	3%	2%	2%	3%	3%	4%	4%	5%	5%	5%	5%
Import-Unspecified Sources	11%	11%	11%	11%	11%	11%	11%	9%	7%	6%	5%	5%	4%	5%	4%	5%	5%	5%	7%	8%	9%	9%	10%	10%
Average Import	3%	3%	3%	4%	3%	4%	4%	3%	2%	2%	2%	1%	1%	1%	1%	1%	1%	2%	2%	3%	3%	3%	3%	3%

131 "OASIS Database"; "Total System Electric Generation."

Table AIII-2. Conservative Hourly Fuel Mix 2030[132]

2030 Conservative Fuel Mix																								
Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Renewables	31%	32%	31%	31%	31%	31%	31%	38%	46%	48%	51%	52%	54%	52%	51%	48%	46%	43%	40%	35%	35%	34%	33%	34%
Natural gas	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%
Storage	3%	3%	4%	4%	3%	3%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	2%	2%	2%	2%	3%	3%	3%
Large hydro	8%	8%	7%	7%	7%	8%	8%	7%	6%	6%	6%	5%	5%	5%	7%	8%	8%	9%	10%	11%	11%	10%	10%	9%
Import-Large Hydro	7%	7%	7%	7%	7%	7%	7%	6%	5%	4%	3%	3%	3%	3%	3%	3%	3%	4%	4%	5%	6%	6%	6%	6%
Import-Natural Gas	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Import-Nuclear	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Import-Biomass	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Import-Geothermal	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%
Import-Small Hydro	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Import-Solar	0%	0%	0%	0%	0%	2%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Import-Wind	6%	6%	6%	6%	6%	6%	6%	4%	3%	3%	2%	1%	1%	3%	2%	2%	2%	3%	4%	4%	4%	5%	5%	5%
Import-Unspecified Sources	9%	9%	10%	10%	10%	9%	9%	7%	4%	3%	3%	2%	1%	2%	1%	3%	3%	4%	4%	8%	8%	7%	7%	7%

Table AIII-3. Diverse Hourly Fuel Mix 2030[133]

2030 Diverse Fuel Mix																								
Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Renewables	28%	28%	27%	27%	27%	26%	25%	34%	44%	48%	71%	72%	72%	71%	72%	71%	37%	33%	23%	17%	16%	16%	17%	18%
Natural gas	21%	21%	21%	22%	22%	23%	23%	21%	19%	19%	0%	0%	0%	0%	0%	0%	26%	27%	29%	32%	31%	29%	27%	26%
Storage	2%	2%	2%	2%	3%	3%	3%	1%	0%	0%	0%	0%	0%	0%	0%	0%	5%	6%	7%	9%	9%	8%	9%	9%
Large hydro	10%	10%	10%	9%	8%	8%	8%	7%	6%	6%	6%	6%	7%	7%	7%	8%	8%	9%	11%	11%	11%	10%	10%	9%
Import-Large Hydro	7%	7%	7%	7%	7%	7%	7%	6%	5%	4%	3%	3%	3%	3%	3%	3%	3%	4%	4%	5%	6%	6%	6%	6%
Import-Natural Gas	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Import-Nuclear	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Import-Biomass	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%
Import-Geothermal	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%
Import-Small Hydro	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Import-Solar	0%	0%	0%	0%	0%	0%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Import-Wind	6%	6%	6%	6%	6%	6%	6%	5%	4%	3%	3%	2%	2%	3%	2%	2%	2%	3%	4%	4%	5%	5%	5%	5%
Import-Unspecified Sources	10%	10%	11%	11%	11%	11%	10%	8%	5%	3%	2%	0%	0%	0%	0%	0%	2%	2%	4%	6%	7%	9%	10%	11%

132 Brinkman et al., "Low Carbon Grid Study."
133 Brinkman et al.

Appendix IV. Pilot Event Impacts

As of February 2019, SCE had run 8 pilot events, 4 of them as load reduction (rebates) and 4 as load shifting (discounts). Here we summarize the demand, GHG, air pollution, curtailment, and costs impacts of each of these events. For simplicity, we provide full details on 4 events per segment (2 load reduction and 2 load shift). We provide graphs of the load change for all other events.

Note that pilot results are aggregated over an entire segment, so results may not be representative of individual sites. Each event is compared to a baseline average for the corresponding month. These baseline averages are aggregated by month hour and have been scaled for the number of chargers that "participated" during each event. There may be a different number of chargers in each segment participating in an event because site hosts have the option to opt out of demand response events. The baseline data also excluded weekends in order to be consistent with the days on which events were called.

Workplaces

Load Reduction Events (July 31 and July 11)

As expected, load reduction in the intervention window of 4:00 - 9:00 p.m. is minimal, as workplaces traditional load profile is not well suited to respond to rebates. In the July 31st event, an overall increase in usage suggests that load reduction efforts did not work. In the July 16th a mild increase in the target reduction window further suggests that load reduction in the afternoons is ineffective. Instead, workplaces may be more responsive to morning load reduction events.

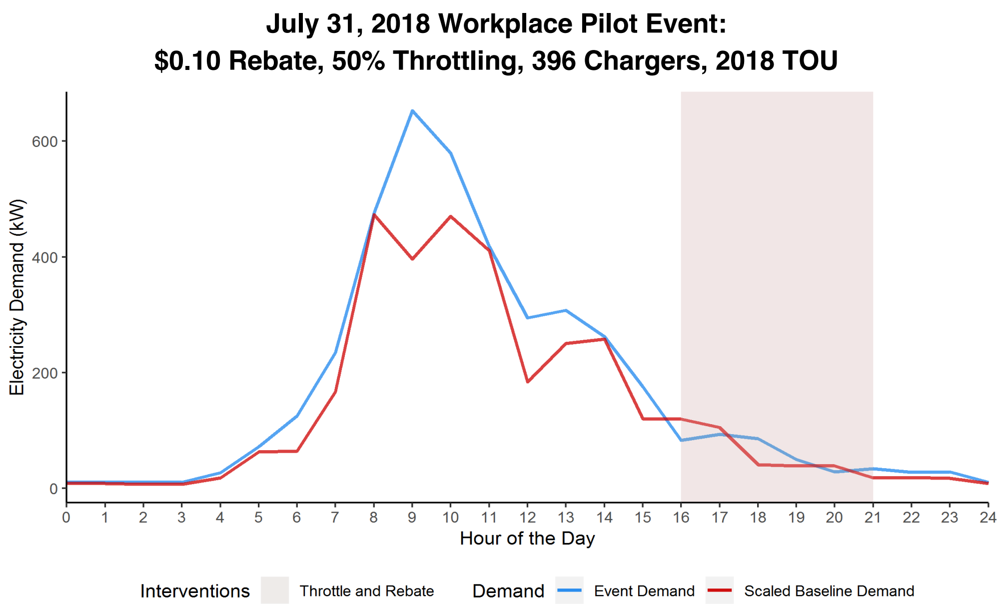


Figure AIV-1. July 31, 2018 Workplace Load Reduction Event Graph

Table AIV-1. July 31, 2018 Workplace Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention / Peak (4 - 9 pm)	242	292	21%
Other	3,062	3,807	24%
Total	3,304	4,099	24%

Table AIV-2. July 31, 2018 Workplace Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	52.55	68.03	29%	0.19	0.24	27%	0.01
Other	595.54	728.46	22%	2.17	2.66	22%	N/A
Total	648.09	796.49	23%	2.36	2.89	23%	0.01

Event Highlights

- A load increase in the target window suggests evening throttling and price incentives are not effective.
- GHG and air pollution emissions rose, causing a $7.42 social carbon cost and $11.70 NOx cost. The impact in DACs was negligible.
- Consumer costs rose from $491.35 to $542.86, a $51.51 increase.

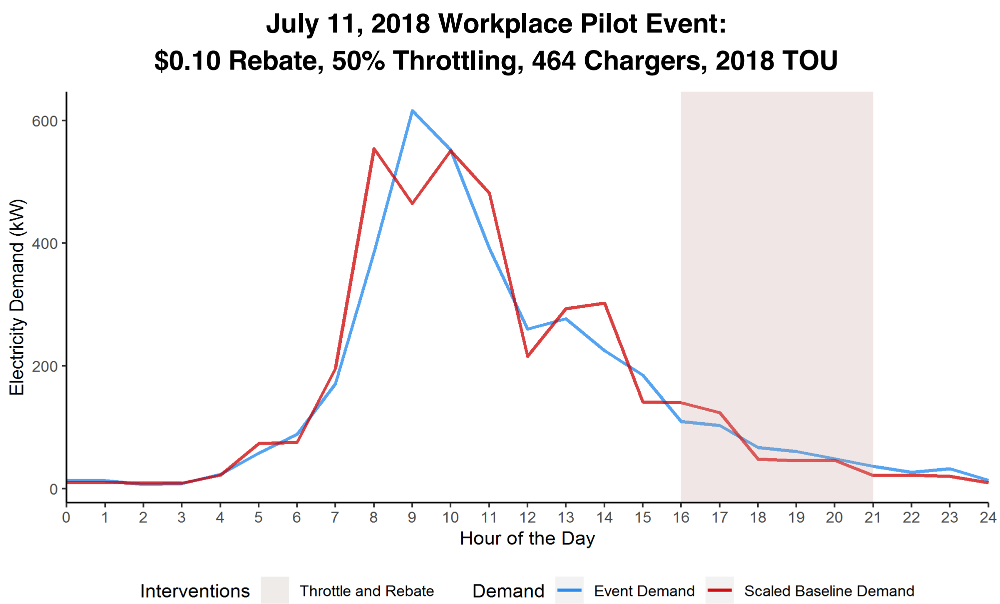


Figure AIV-2. July 11, 2018 Workplace Load Reduction Event Graph

Table AIV-3. July 11, 2018 Workplace Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention / Peak (4 - 9 pm)	284	315	11%
Other	3,588	3,441	-4%
Total	3,872	3,755	-3%

Table AIV-4. July 11, 2018 Workplace Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	61.57	69.07	12%	0.22	0.25	14%	0.01
Other	697.81	666.50	-5%	2.55	2.43	-5%	N/A
Total	759.38	735.57	-3%	2.77	2.68	-3%	0.01

Event Highlights

- An increase of 30.85 kWh in the target window (4:00 – 9:00 p.m.) suggests throttling and price incentives were not effective.
- GHGs and NOx fell slightly, with negligible social financial benefit.
- The impact on DACs was negligible.
- Consumer costs fell $62.03, from $575.72 to $513.70.

Load Shift Events (November 14 and 28)

Load shift events have the potential to impact workplace load more significantly because they operate in the period of time when most people are at work. In both November scenarios below we can see the impact of throttling happening in the morning periods (6:00 – 11:00 a.m.) and a slight load shift into the target window (11:00 a.m. - 3:00 p.m.). Although there was a 36 kWh increase in usage between those midday hours, we are still skeptical that the discount had an impact on drivers' behavior since we know that they were not receiving that price incentive. Overall it seems that the November 14th and 28th events follow the general workplace usage pattern, but decreased overall usage slightly, most likely due to throttling.

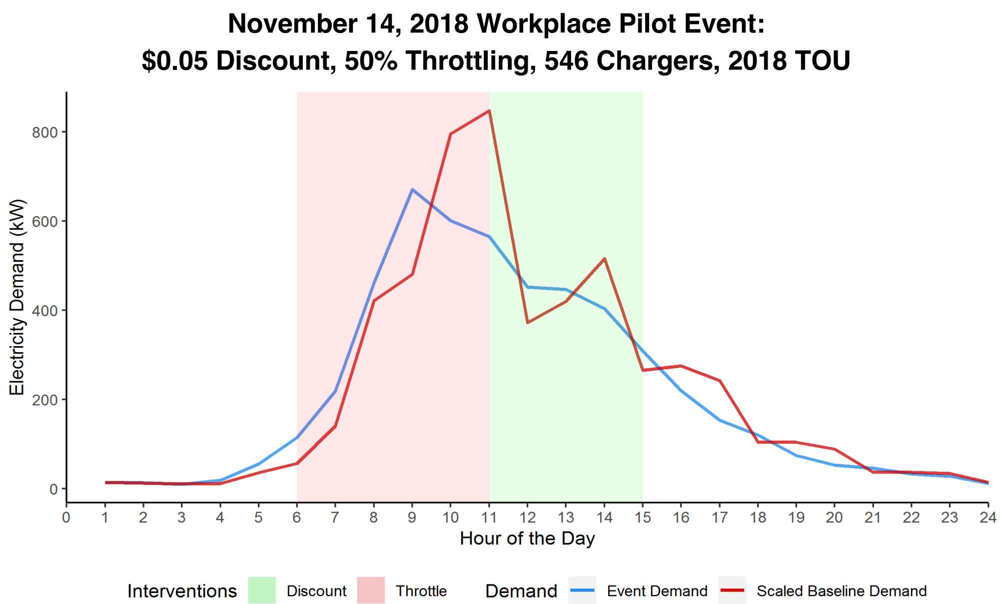


Figure AIV-3. November 14, 2018 Workplace Load Shift Event Demand Graph

Table AIV-5. November 14, 2018 Workplace Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11am - 3pm)	1,574	1,610	2%
Peak (4 - 9 pm)	576	448	-4%
Other	3,191	3,039	-5%
Total	5,341	5,097	-5%

Table AIV-6. November 14, 2018 Workplace Load Shift Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11am – 3pm)	274.65	278.54	1%	0.98	0.99	1%	N/A
Peak (4 - 9 pm)	124.93	65.04	-48%	0.45	0.32	-29%	-0.02
Other	619.09	608.24	-2%	2.26	2.23	-8%	N/A
Total	1,018.67	951.83	-7%	3.69	3.54	-4%	-002

Event Highlights

- There was an increase in demand in the target window of 36 kWh, and a decrease in the peak period of 128 kWh. The overall decline in daily demand increased curtailment by 0.04%, costing $21.88.
- GHG emissions and NOx emission fell slightly, with a negligible reduction in social costs.
- Consumer costs fell from $495.53 to $383.69, a $111.84 reduction.

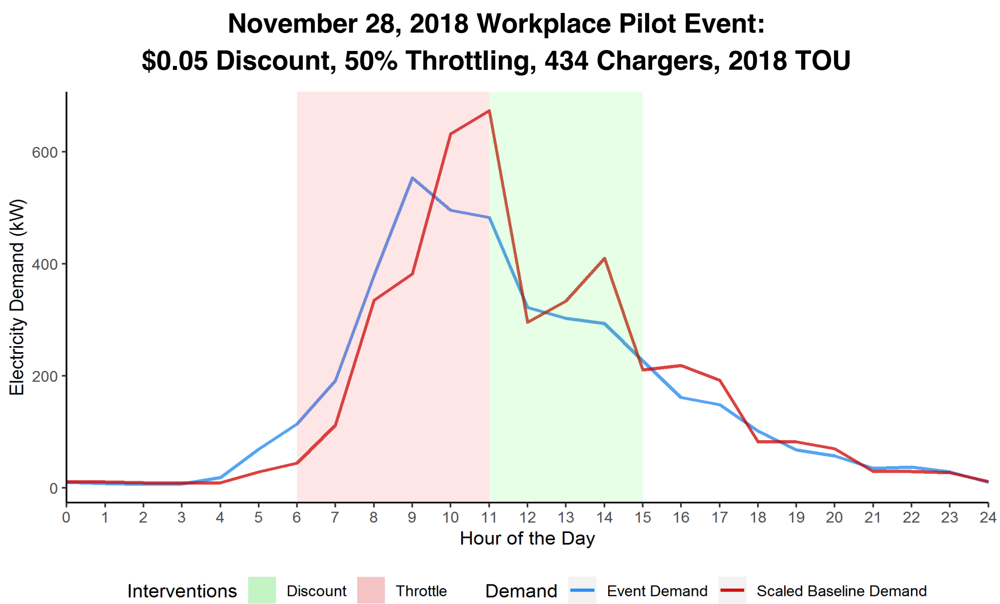


Figure AIV-4. November 28, 2018 Workplace Load Shift Event Demand Graph

Table AIV-7. November 28, 2018 Workplace Load Shift Event Demand Impacts

Time	**Demand**		
	Initial (kWh)	**New (kWh)**	**Change (%)**
Intervention (11 am - 3 pm)	1,251	1,145	-9%
Peak (4 - 9 pm)	458	412	-10%
Other	2,536	2,567	1%
Total	4,245	4,124	-3%

Table AIV-8. November 28, 2018 Workplace Load Shift Event Emissions and Environmental Justice Impacts

Time	**GHGs**			**NOx**			
	Initial (kg)	**New (kg)**	**Change (%)**	**Initial (kg)**	**New (kg)**	**Change (all) (%)**	**Change (DACs) (kg)**
Intervention (11am – 3pm)	218.31	206.89	-5%	0.78	0.74	-5%	N/A
Peak (4 - 9 pm)	99.30	76.68	-23%	0.36	0.31	-14%	-0.01
Other	492.10	516.69	5%	1.80	1.90	6%	N/A
Total	809.71	800.26	-1%	2.93	2.95	0%	-0.01

Event Highlights

- There was an increase in demand in the target window of 121 kWh, and a decrease in the peak period of 46 kWh. The overall decline in daily demand increased curtailment by 0.04%, $26.67
- GHG emissions and NOx emission fell slightly, with a negligible reduction in social costs.
- Consumer costs fell by $79.49, from $393.88 to $314.39.

Additional Events

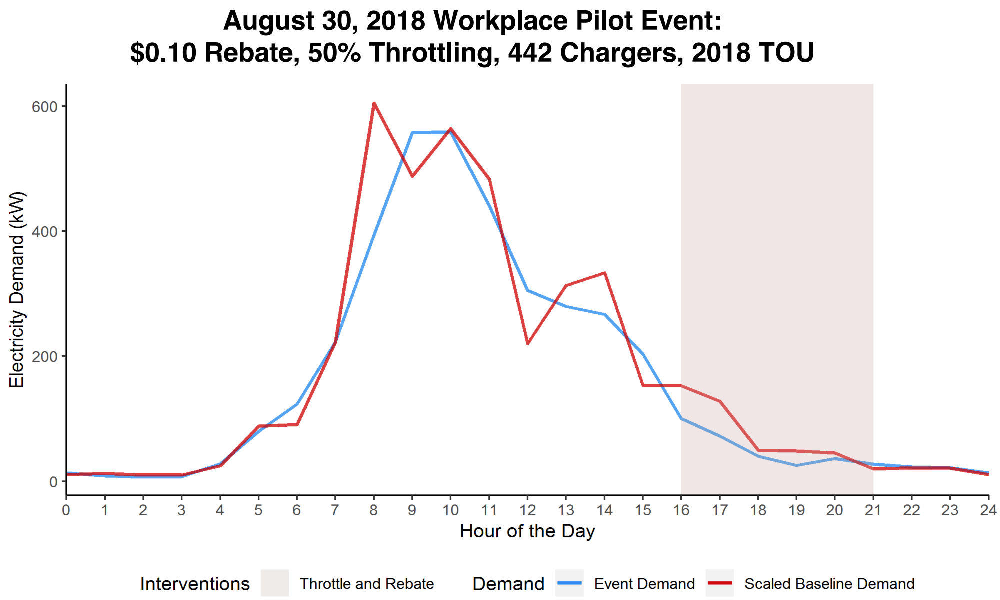


Figure AIV-5. August 30, 2018 Workplace Load Reduction Event Graph

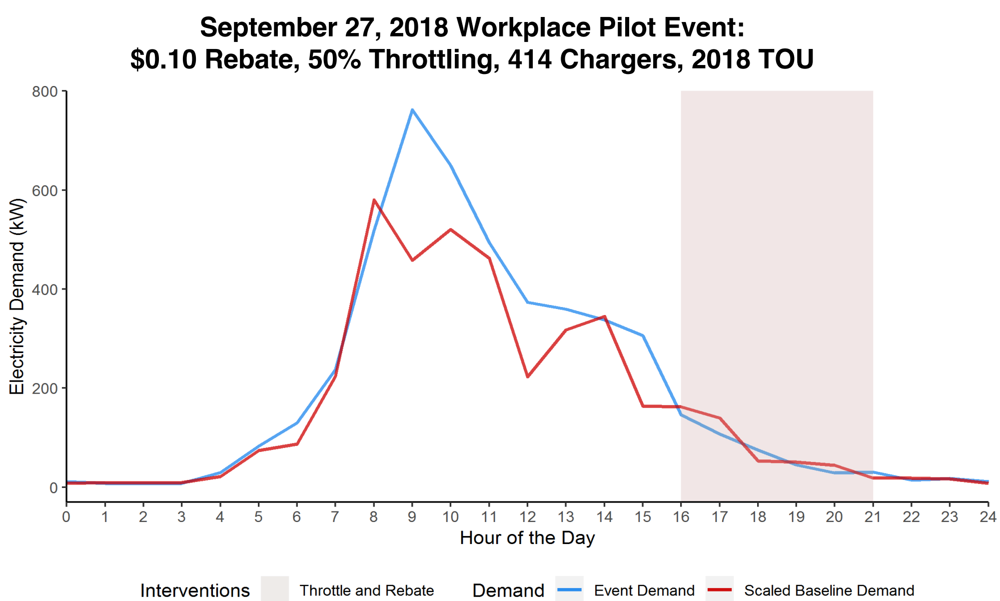


Figure AIV-6. September 27, 2018 Workplace Load Reduction Event Graph

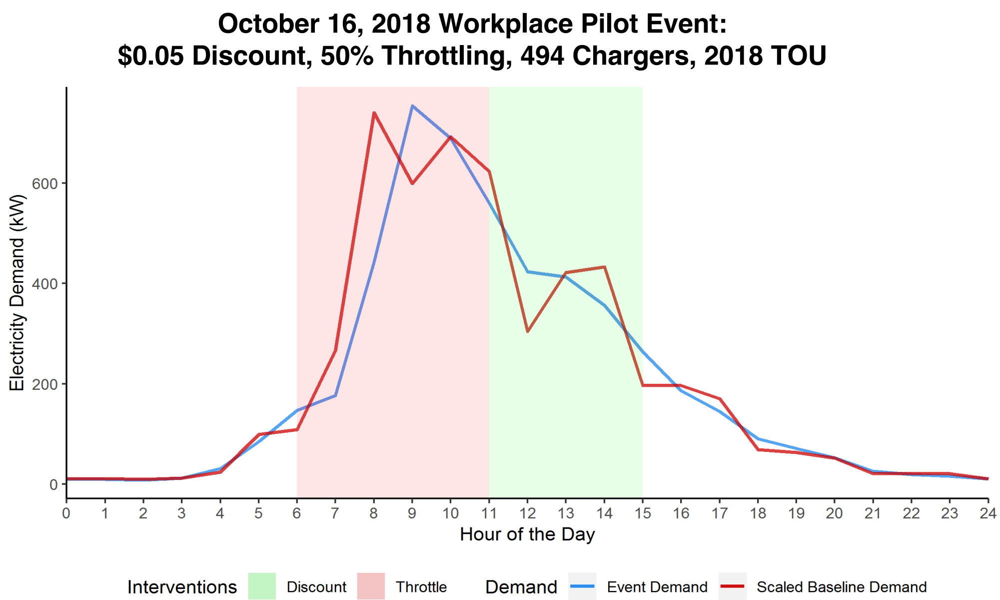


Figure AIV-7. October 16, 2018 Workplace Load Shift Event Graph

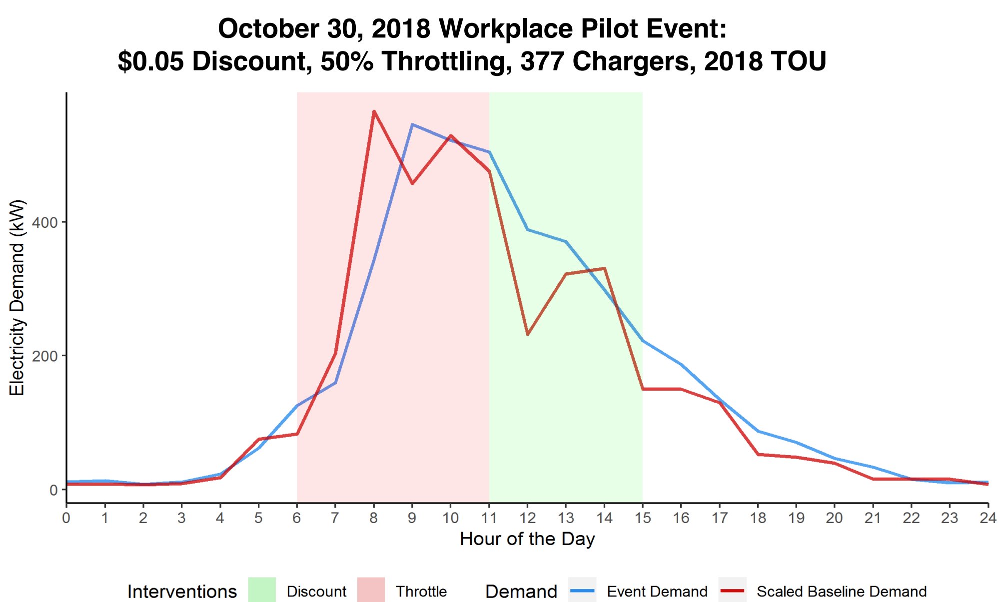


Figure AIV-8. October 30, 2018 Workplace Load Shift Event Graph

Destination Centers

When moving from workplaces to destination centers, it is important to notice the change in scale. Peak usage in workplaces varies between 600 and 800 kW; destination centers have much smaller peak usage, ranging from 60 to 100 kW because they have fewer chargers. Destination centers seem to be much more variable in their load profile because the types of locations they include and the behaviors of people charging at these locations are not always consistent or predictable. However, there does seem to still be a peak period in the morning hours, and then three to four other smaller peaks throughout the rest of the day.

Load Reduction Events (July 11 and July 31)

In the July 11th event, demand in the intervention hours (4:00 – 9:00 p.m.) increased about 10 kWh and in the July 31st event, demand decreased in these hours by 20 kWh. These different responses suggest that the rebate and throttling may not be very effective at inducing demand response from EV drivers since load in these hours is relatively low. It is difficult to know how much demand was actually reduced on that day without knowing the baseline demand during those hours on the day of the event, but compared to the monthly baseline, these days did not respond according to our predictions.

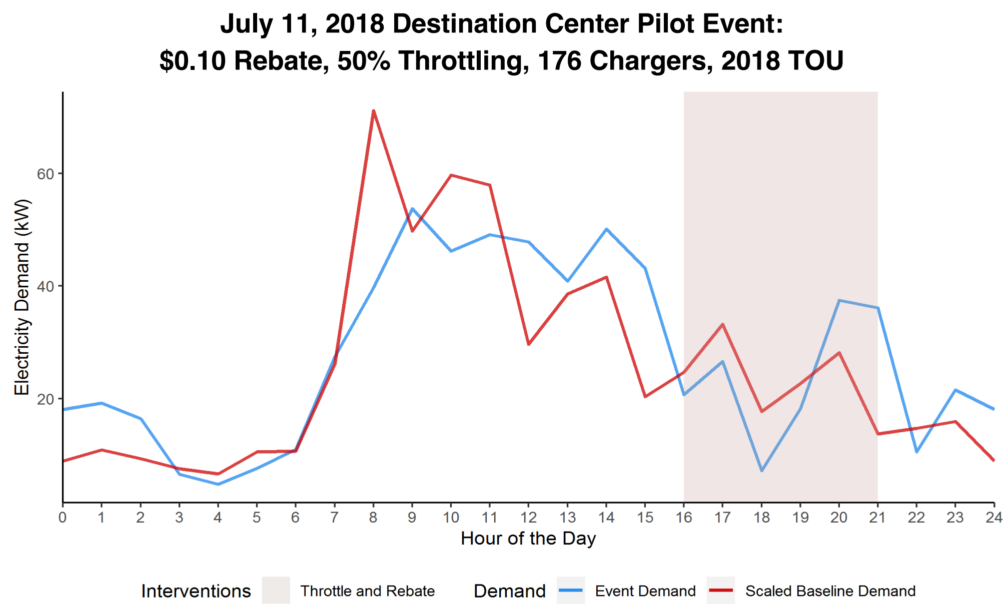


Figure AIV-9. July 11, 2018 Destination Center Load Reduction Event Demand Impacts

Table AIV-9. July 11, 2018 Destination Center Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention / Peak (4 - 9 pm)	115	126	9%
Other	515	535	4%
Total	630	660	5%

Table AIV-10. July 11, 2018 Destination Center Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	26.12	21.51	-18%	0.09	0.10	11%	0
Other	103.51	103.37	~0%	0.38	0.38	-1%	N/A
Total	129.63	124.88	-4%	0.47	0.48	2%	0

Event Highlights

- There was an increase in demand in the intervention/peak period of 11 kWh. The overall increase in daily demand reduced curtailment by 0.01%, saving $2.87.
- GHG and air pollution emissions decreased slightly, with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs decreased by 2.7%, from $94.20 to $91.62.

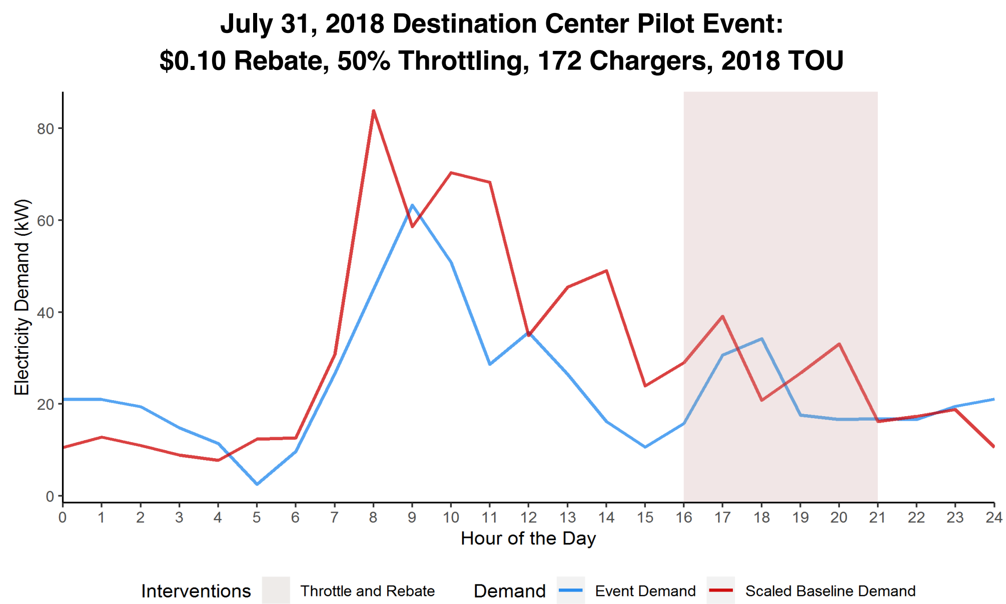


Figure AIV-10. July 31, 2018 Destination Center Load Reduction Event Demand Graph

Table AIV-11. July 31, 2018 Destination Center Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	**New (kWh)**	**Change (%)**
Intervention / Peak (4 - 9 pm)	136	116	-15%
Other	606	455	-25%
Total	742	571	-23%

Table AIV-12. July 31, 2018 Destination Center Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	**New (kg)**	**Change (%)**	**Initial (kg)**	**New (kg)**	**Change (all) (%)**	**Change (DACs) (kg)**
Intervention / Peak (4 - 9 pm)	30.78	21.67	-30%	0.11	0.09	-18%	0
Other	121.94	99.11	-19%	0.45	0.36	-18%	N/A
Total	152.72	120.77	-21%	0.56	0.46	-18%	0

Event Highlights

- There was an reduction in demand in the intervention/peak period of 20 kWh. The overall decrease in daily demand increased curtailment by 0.04%, a $13.77 cost.
- GHG emissions fell by 21% and air pollution emissions fell by 18%. The reduction in social costs was negligible. There was also negligible impact in DACs.
- Consumer costs decreased by 32.5%, from $110.90 to $74.85.

Load Shift Events (November 14 and 28)

Load shift events may be more appropriate for the destination center segment because this segment often has a morning peak. In the November 14th event we can see the effect of throttling between the hours of 6:00 and 11:00 a.m. There does appear to be an increase in load directly after this throttling period around 12:00 p.m., and that spike is inconsistent with general load profile patterns for that month, suggesting that there may have been a shift from the morning to afternoon period. The November 28th event shows a similar reduction in load in the morning period compared to the monthly baseline, however there is no increase in demand in the following target period meaning that load was not shifting as intended. Both events closely reflect our modeled scenarios (D2 and D3-F) in the morning period which would be expected because of the direct nature of throttling. It seems that destination centers are good candidates for morning throttling, but because there is not a consistent increase in the following target period, other strategies outside of a price discount should be considered.

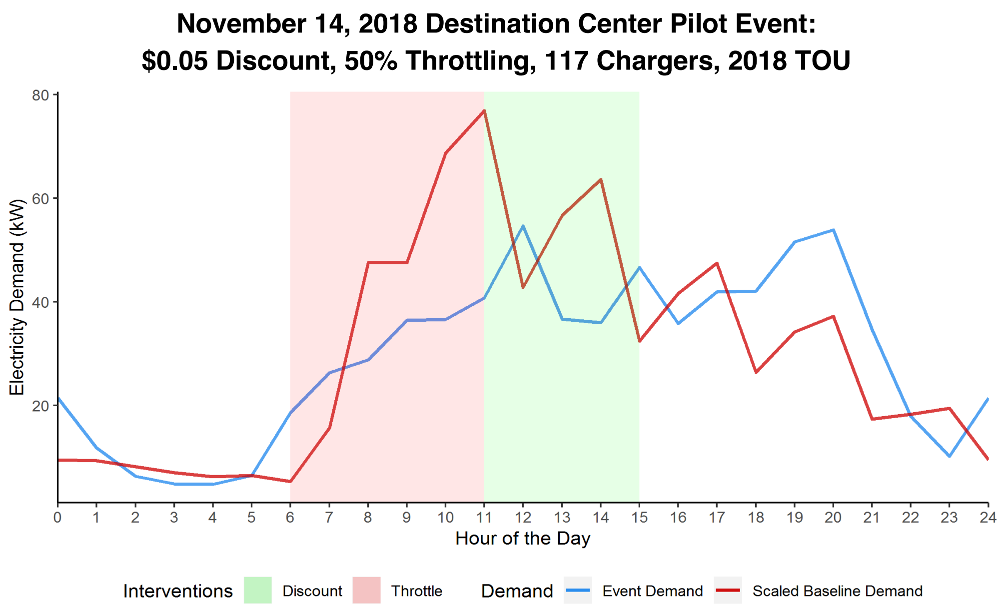


Figure AIV-11. November 14, 2018 Destination Center Load Shift Event Demand Graph

Table AIV-13. November 14, 2018 Destination Center Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11 am - 3 pm)	195	174	-11%
Peak (4 - 9 pm)	163	224	38%
Other	388	307	-21%
Total	745	705	-5%

Table AIV-14. November 14, 2018 Destination Center Load Shift Event Demand Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	34.08	31.77	-7%	0.12	0.11	-6%	N/A
Peak (4 - 9 pm)	36.62	56.77	55%	0.13	0.19	47%	0.01
Other	79.25	65.56	-17%	0.29	0.24	-17%	N/A
Total	149.94	154.10	3%	0.54	0.55	1%	0.01

Event Highlights

- There was an 11% decrease in demand in the target window, and a 38% increase in the peak period. The overall 5% decline in daily demand increased curtailment by 0.01% and costs by $8.05.
- GHG and air pollution emissions increased slightly, with a negligible impact on social costs. There was minimal impact in DACs.
- Consumer costs reduced by 19.4%, from $68.99 to $55.63

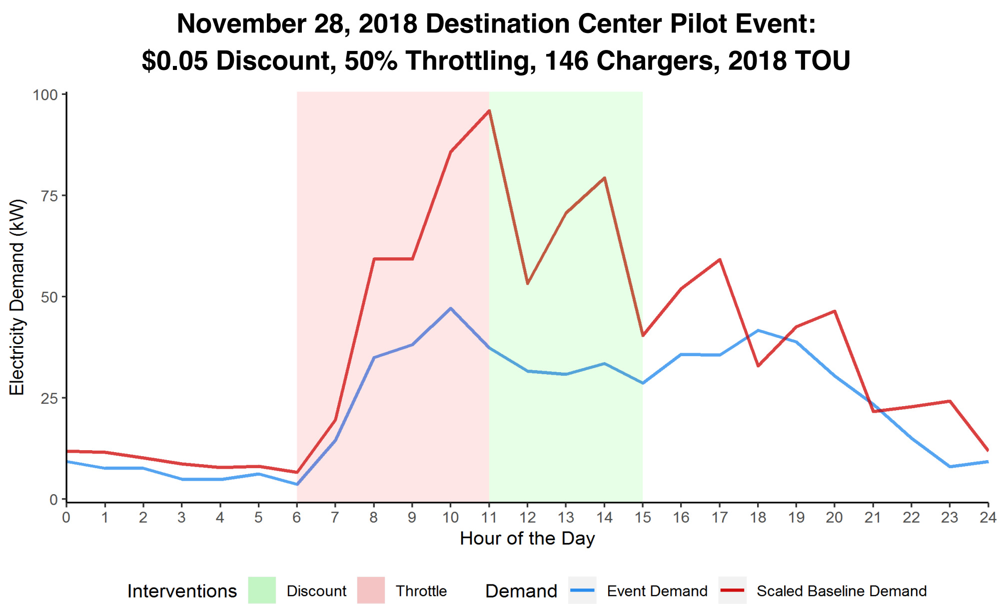


Figure AIV-12. November 28, 2018 Destination Center Load Shift Event Demand Graph

Table AIV-15. November 28, 2018 Destination Center Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11 am - 3 pm)	244	125	-49%
Peak (4 - 9 pm)	203	170	-16%
Other	484	276	-43%
Total	930	570	-39%

Table AIV-16. November 28, 2018 Destination Center Load Shift Event Demand Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	42.52	29.68	-30%	0.15	0.11	-28%	N/A
Peak (4 - 9 pm)	45.70	30.48	-3%	0.16	0.13	-20%	-0.01
Other	98.89	57.04	-42%	0.36	0.31	-42%	N/A
Total	187.10	117.20	-37%	0.68	0.45	-34%	-0.01

Event Highlights

- There was an 49% decrease in demand in the target window, and a 16% decrease in the peak period. The overall 39% decline in daily demand increased curtailment by 0.04%, costing $23.71.
- GHG and air pollution emissions decreased by about 35% each, with a negligible decrease in social carbon costs and a $5.03 decrease in NOx costs. There was minimal impact in DACs.
- Consumer costs decreased by 46%, from $86.09 to $46.36

Additional Events

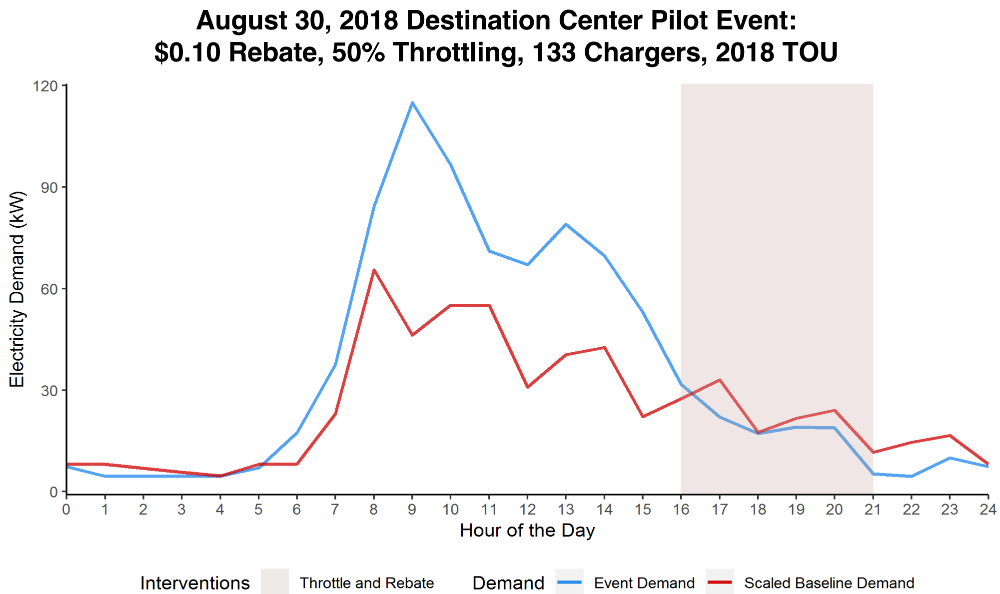


Figure AIV-13. August 30, 2018 Destination Center Load Reduction Event Demand Graph

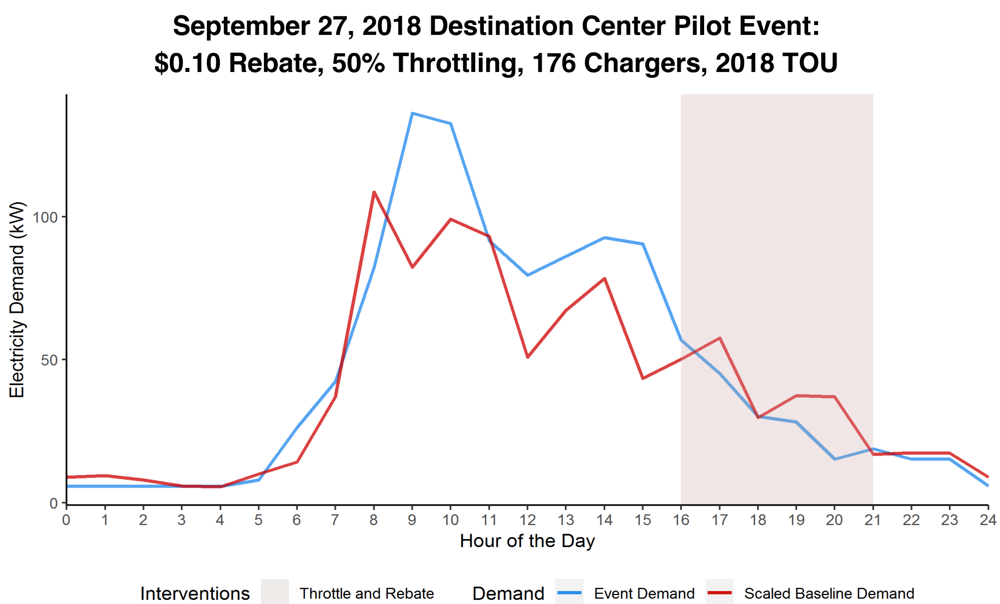


Figure AIV-14. September 27, 2018 Destination Center Load Reduction Event Demand Graph

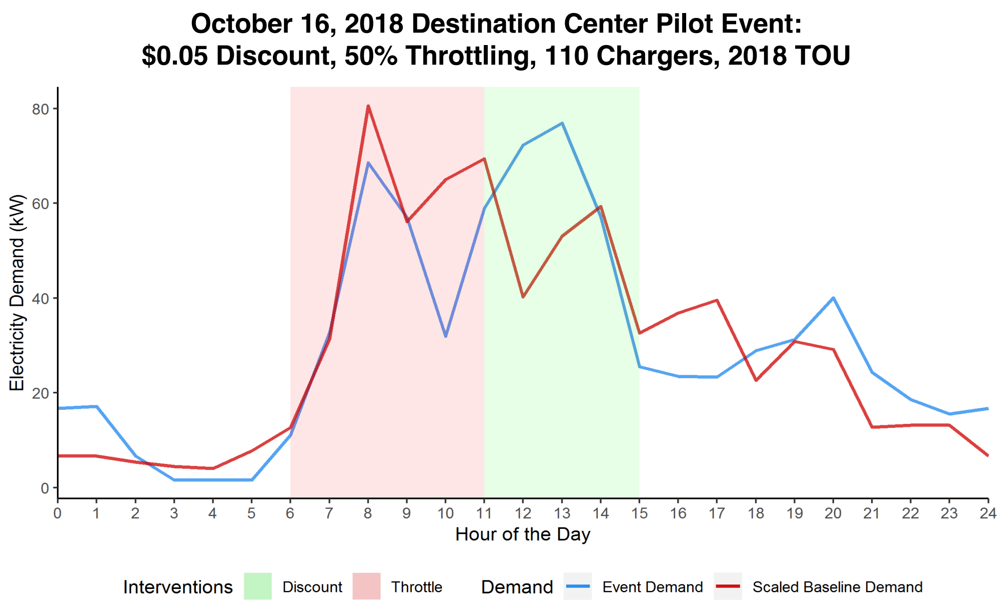


Figure AIV-15. October 16, 2018 Destination Center Load Shift Event Demand Graph

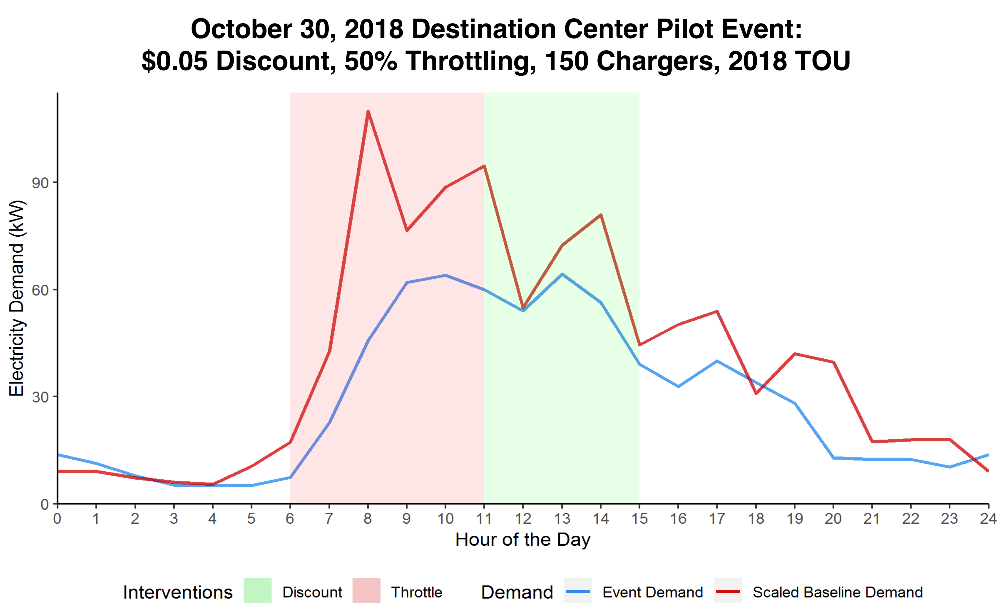


Figure AIV-16. October 30, 2018 Destination Center Load Shift Event Demand Graph

Fleets

Fleets are similar to destination centers in that their peak usage ranges between 30 and 80 kW, but they differ with regard to when that peak load occurs. Peak load generally occurs in the evening hours when fleet vehicles return from working that day, but there is also a small increase in the morning hours, probably from vehicles charging before they leave for the day.

In general, load increases across all hours for these events during load shifting events and load reduction events. This may be because fleets have more limitations in terms of when they are working and when they can charge, so they may have very different elasticities compared to other segments. Utilities might consider additional price incentives or other communication or technological strategies to encourage load shifting from late afternoon to middle of the night because it seems fleets have that flexibility.

Load Reduction Events (July 11 and July 31)

In the July 11th load reduction events it is obvious to see where throttling occurred based on the flattening of load between 4:00 and 9:00 p.m. This throttling has a significant effect on peak shaving; however, overall load in this period actually increases by 8.82 kWh. This fact begs the question: does SCE truly want a reduction in demand in the 4:00 - 9:00 p.m. period, or for the current load to just be smoother? If it is the latter, then throttling could be a very effective strategy. Unfortunately, the opposite occurs in the July 31st event which suggests that throttling may not have been as effective. Overall load in the July 31st event increased by 142 kWh versus 22 kWh in the July 11th event so strategies currently implemented for fleets may need to be reconsidered.

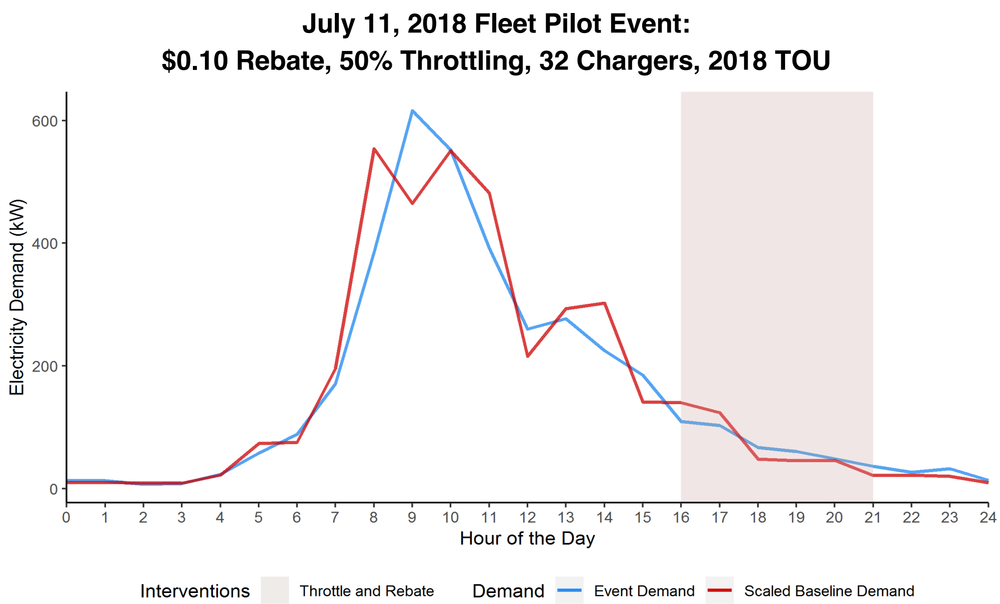


Figure AIV-17. July 11, 2018 Fleets Load Reduction Event Demand Graph

Table AIV-17. July 11, 2018 Fleets Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention / Peak (4 - 9 pm)	82	91	11%
Other	89	102	14%
Total	171	193	13%

Table AIV-18. July 11, 2018 Fleets Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	17.98	16.46	-8%	0.06	0.07	14%	0
Other	17.90	19.61	10%	0.06	0.07	9%	N/A
Total	35.88	36.07	1%	0.13	0.14	12%	0

Event Highlights

- There was an 11% increase in demand in the target window. The overall 13% increase in daily demand increased curtailment negligibly.
- GHG increased slightly and air pollution emissions increased by 12%, with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 8.2%, from $34.54 to $31.70.

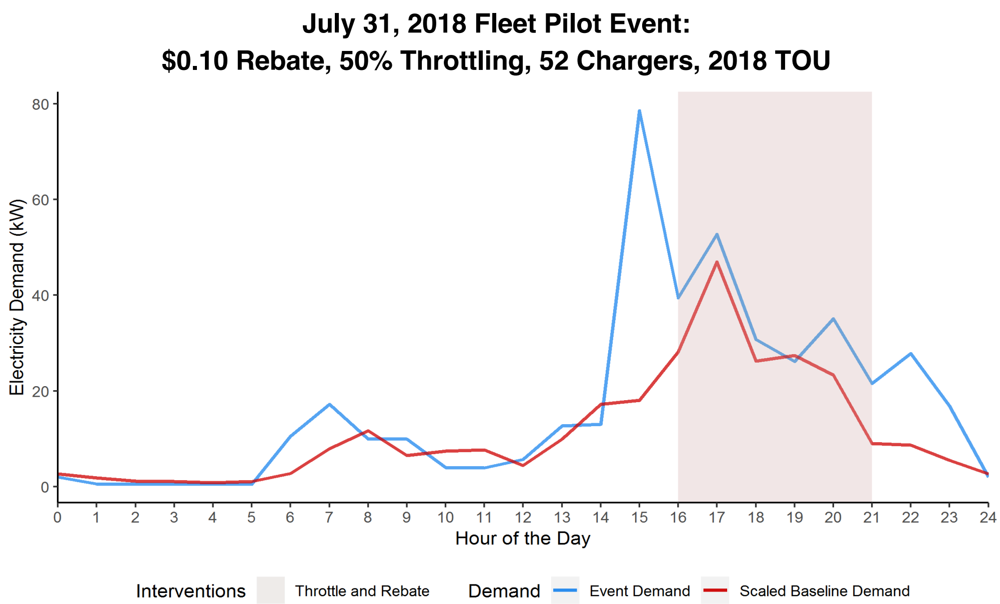


Figure AIV-18. July 31, 2018 Fleets Load Reduction Event Demand Graph

Table AIV-19. July 31, 2018 Fleets Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention / Peak (4 - 9 pm)	133	166	25%
Other	145	255	75%
Total	278	421	51%

Table AIV-20. July 31, 2018 Fleets Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention / Peak (4 - 9 pm)	29.22	38.87	33%	0.11	0.14	32%	0.01
Other	29.09	47.74	64%	0.11	0.17	63%	N/A
Total	58.31	86.60	49%	0.21	0.31	48%	0.01

Event Highlights

- There was an *25%* increase in demand in the target window. The overall 51% increase in daily demand increased curtailment by 0.02%, costing $8.23.
- GHG and air pollution emissions increased significantly in terms of proportion, but there was a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 44%, from $56.14 to $80.70.

Load Shift Events (November 14 and 28)

Because there is such little load in the morning and early afternoon periods, load shifting strategies do not seem to be very effective for fleets.

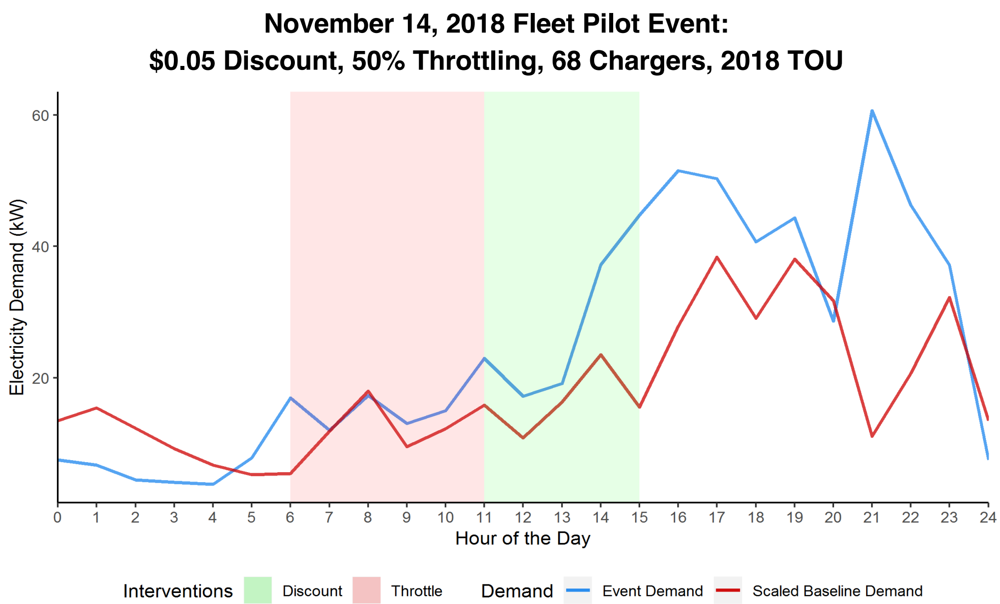


Figure AIV-19. November 14, 2018 Fleets Load Shift Event Demand Graph

Table AIV-21. November 14, 2018 Fleets Load Shift Event Demand Impacts

Time	**Demand**		
	Initial (kWh)	**New (kWh)**	**Change (%)**
Intervention (11 am - 3 pm)	66	118	79%
Peak (4 - 9 pm)	148	225	51%
Other	216	267	24%
Total	431	610	42%

Table AIV-22. November 14, 2018 Fleets Load Shift Event Demand Impacts

Time	**GHGs**			**NOx**			
	Initial (kg)	**New (kg)**	**Change (%)**	**Initial (kg)**	**New (kg)**	**Change (all) (%)**	**Change (DACs) (kg)**
Intervention (11 am - 3 pm)	11.63	17.24	48%	0.04	0.06	45%	N/A
Peak (4 - 9 pm)	33.32	46.87	41%	0.12	0.20	64%	0.01
Other	48.80	59.50	22%	0.18	0.22	21%	N/A
Total	93.74	123.61	32%	0.34	0.48	39%	N/A

<u>Event Highlights</u>

- There was an *25*% increase in demand in the target window and a 51% increase in the peak period. The overall 51% increase in daily demand increased curtailment by 0.02%, costing $8.23.
- GHG and air pollution emissions increased slightly, with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 32.3%, from $38.84 to $51.40.

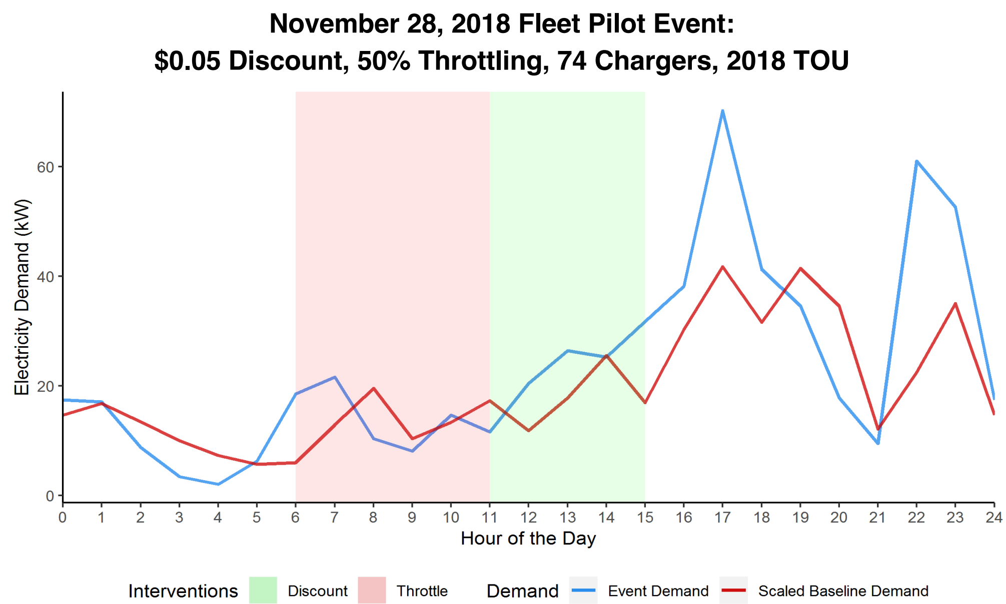


Figure AIV-20. November 28, 2018 Fleets Load Shift Event Demand Graph

Table AIV-23. November 28, 2018 Fleets Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11 am - 3 pm)	72	104	44%
Peak (4 - 9 pm)	161	173	7%
Other	235	292	24%
Total	469	569	21%

Table AIV-24. November 28, 2018 Fleets Load Shift Event Demand Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	12.66	16.08	27%	0.05	0.06	25%	N/A
Peak (4 - 9 pm)	36.26	42.61	18%	0.13	0.14	9%	0
Other	53.10	67.88	28%	0.20	0.25	28%	N/A
Total	102.02	126.57	24%	0.37	0.45	21%	0

Event Highlights

- There was an 44% increase in demand in the target window and a 7% increase in the peak window. The overall 21% increase in daily demand decreased curtailment by 0.02%, reducing costs by $9.36.
- GHG and air pollution emissions increased, with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 32%, from $38.84 to $51.40.

Additional Events

August 30, 2018 Fleet Pilot Event:

$0.10 Rebate, 50% Throttling, 10 Chargers, 2018 TOU

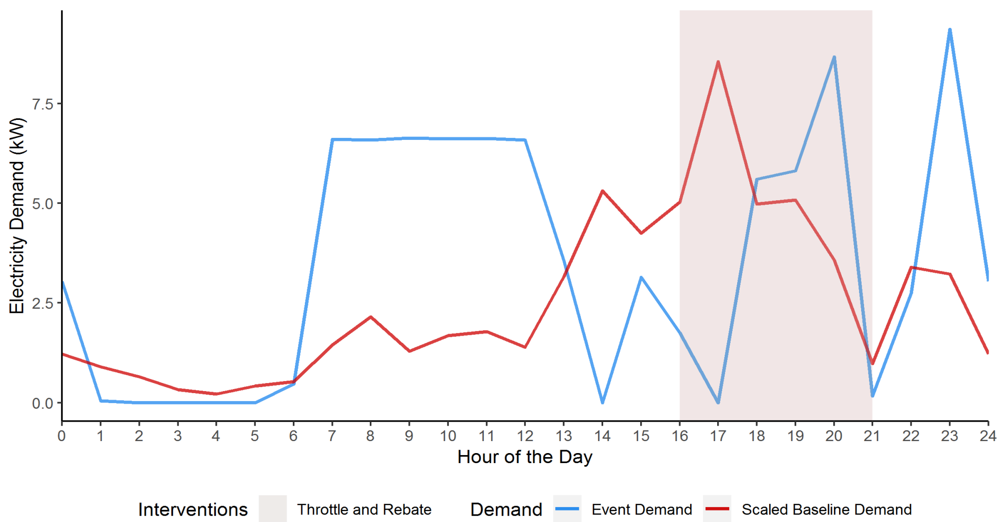


Figure AIV-21. August 30, 2018 Fleets Load Shift Event Demand Graph

September 27, 2018 Fleet Pilot Event:

$0.10 Rebate, 50% Throttling, 24 Chargers, 2018 TOU

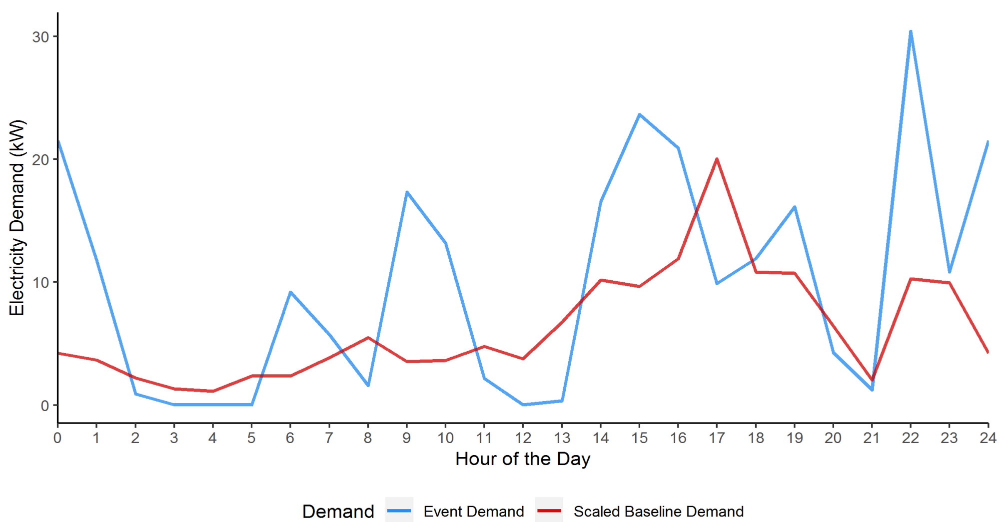


Figure AIV-22. September 27, 2018 Fleets Load Reduction Event Demand Graph

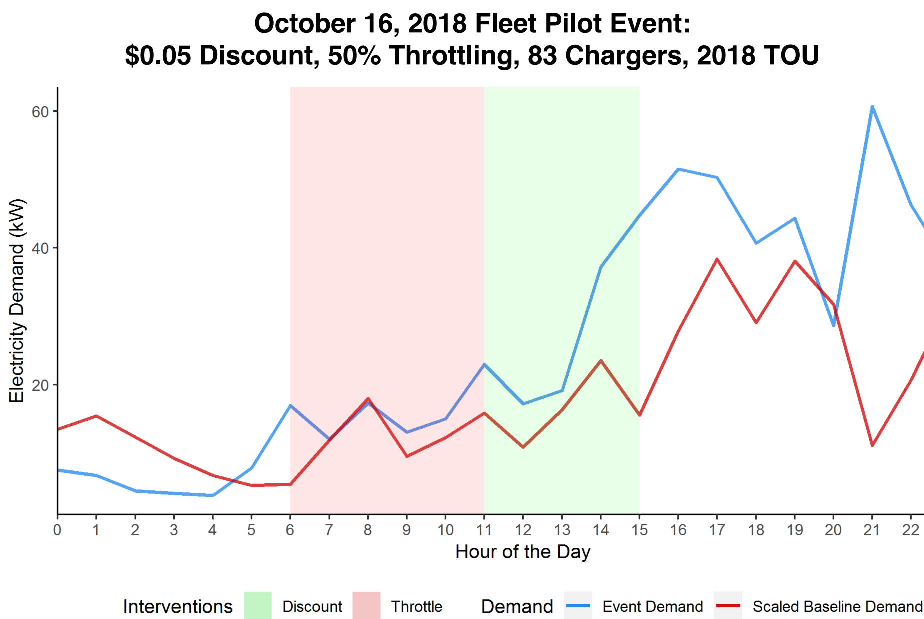


Figure AIV-23. October 16, 2018 Fleets Load Shift Event Demand Graph

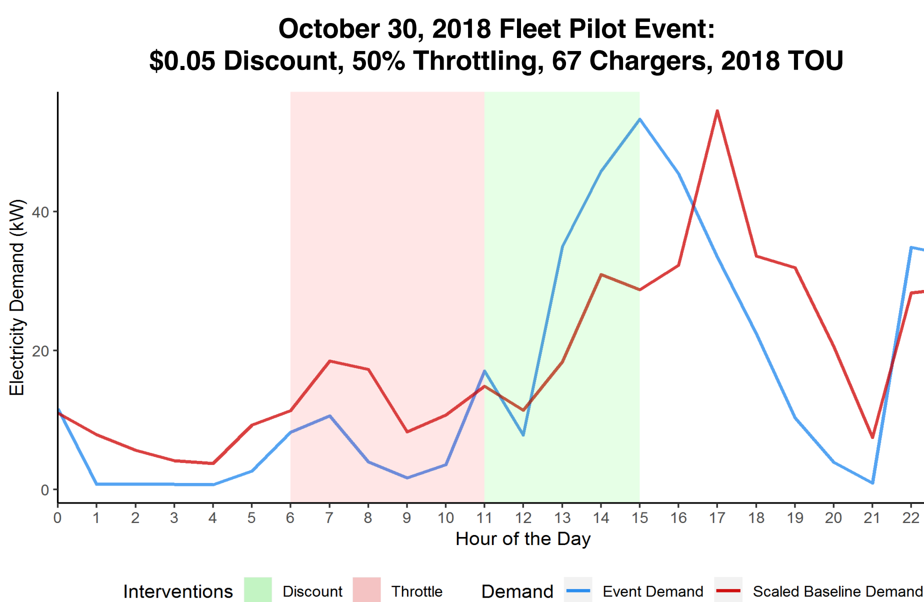


Figure AIV-24. October 30, 2018 Fleets Load Shift Event Demand Graph

Multi-Unit Dwellings (MUDs)

Although there are many less chargers and much less usage in MUDs compared to other segments, we can still get a sense for the daily habits of EV drivers who use these facilities. The event data reveals several peaks throughout the day (mainly lunchtime) and then a much larger peak in the evening when drivers come home from work.

Load Reduction Events (July 11 and July 31)

The July 11th event follows the general trend of MUD average monthly usage, but we can see the effect of throttling in the evening period by the dip in usage that occurs around 7:00 p.m. Again, it is unclear how much the rebate affects their decision to charge as compared to 50% throttling, but based on the fact that the usage is about half that of the baseline, it seems that the price incentive did not have much of an impact. In the July 31st event, usage increased by almost 20 kWh, suggesting throttling and the rebate had little to no effect on customer behavior probably because of a lack of information.

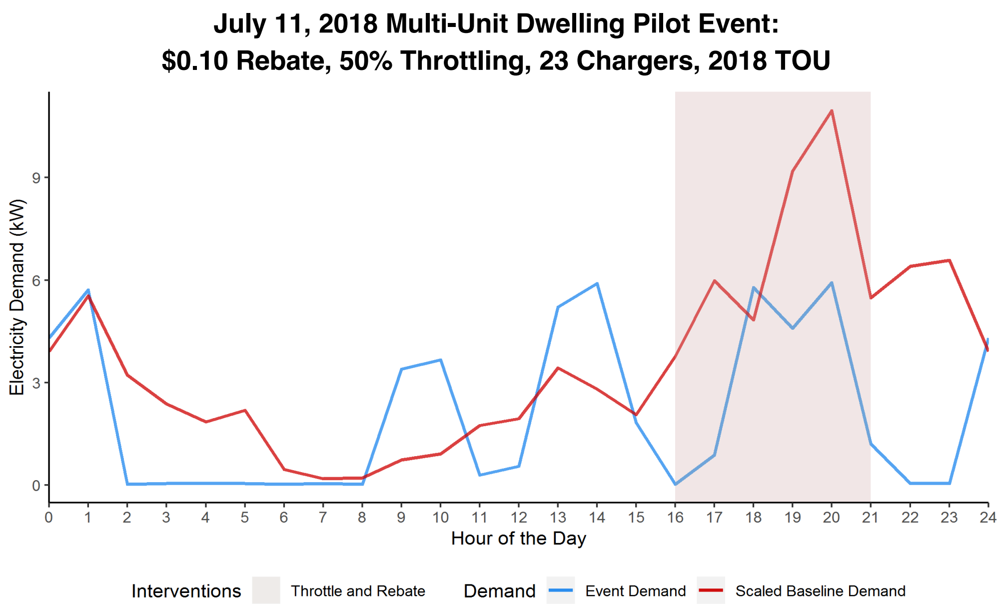


Figure AIV-25. July 11, 2018 MUDs Load Reduction Event Demand Graph

Table AIV-25. July 11, 2018 MUDs Load Reduction Event Demand Impacts

Time	Demand		
	Initial (kWh)	**New (kWh)**	**Change (%)**
Intervention / Peak (4 - 9 pm)	36	18	-49%
Other	50	31	-38%
Total	87	50	-43%

Table AIV-26. July 11, 2018 MUDs Load Reduction Event Emissions and Environmental Justice Impacts

Time	GHGs			NOx			
	Initial (kg)	**New (kg)**	**Change (%)**	**Initial (kg)**	**New (kg)**	**Change (all) (%)**	**Change (DACs) (kg)**
Intervention / Peak (4 - 9 pm)	8.53	2.29	-73%	0.03	0.01	-59%	0
Other	11.23	6.03	-46%	0.04	0.02	-47%	N/A
Total	19.76	8.32	-58%	0.07	0.03	-52%	0

Event Highlights

- There was an 49% decrease in demand in the target window. The overall 43% decrease in daily demand had a negligible impact on curtailment and associated costs.
- GHG and air pollution emissions decreased significantly proportionately, but with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs decreased by 39%, from $12.91 to $7.90.

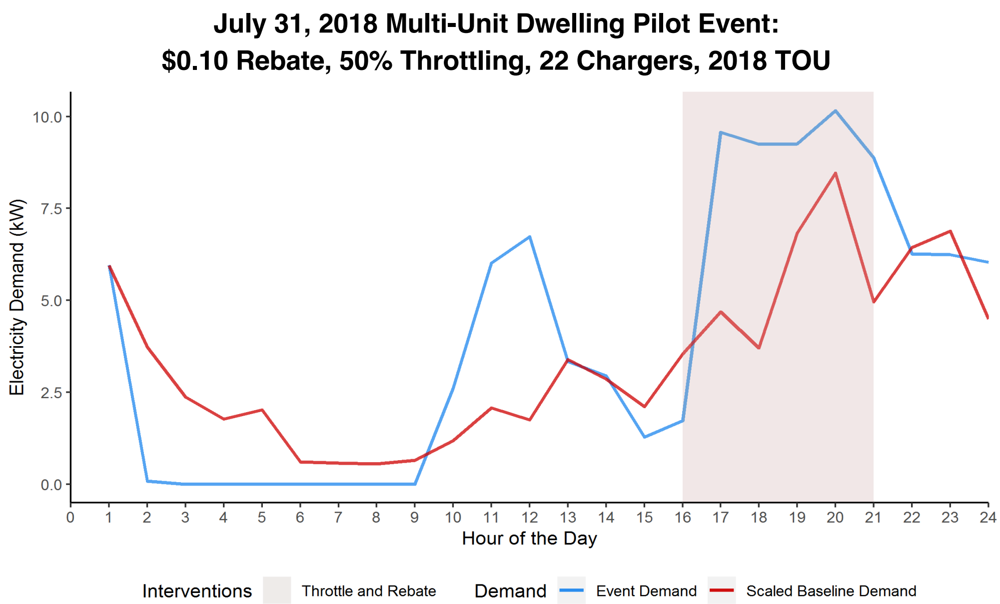


Figure AIV-26. July 31, 2018 MUDs Load Reduction Event Demand Graph

Table AIV-27. July 31, 2018 MUDs Load Reduction Event Demand Impacts

Time	**Demand**		
	Initial (kWh)	**New (kWh)**	**Change (%)**
Intervention / Peak (4 - 9 pm)	29	47	65%
Other	53	49	-7%
Total	82	96	18%

Table AIV-28. July 31, 2018 MUDs Load Reduction Event Emissions and Environmental Justice Impacts

Time	**GHGs**			**NOx**			
	Initial (kg)	**New (kg)**	**Change (%)**	**Initial (kg)**	**New (kg)**	**Change (all) (%)**	**Change (DACs) (kg)**
Intervention / Peak (4 - 9 pm)	6.72	13.28	98%	0.02	0.04	77%	0
Other	11.84	10.16	-14%	0.04	0.04	-15%	N/A
Total	18.56	23.45	26%	0.07	0.08	18%	0

<u>Event Highlights</u>

- There was an 65% increase in demand in the target window. The overall 18% increase in daily demand had a negligible impact on curtailment.
- GHG and air pollution emissions increased significantly proportionately, but with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 32%, from $11.69 to $15.50.

Load Shift Events (November 14 and 28)

The limited number of MUDs participating in these events makes it difficult to draw general conclusions. It is very difficult to determine a shift in load from the morning to early afternoon period because of the low amount of demand in the November 14th event. The November 28th event also does not show any evidence of load shift, further evidencing the fact that these events are not being properly advertised and drivers charging at MUDs may not be very flexible in terms of their charging habits.

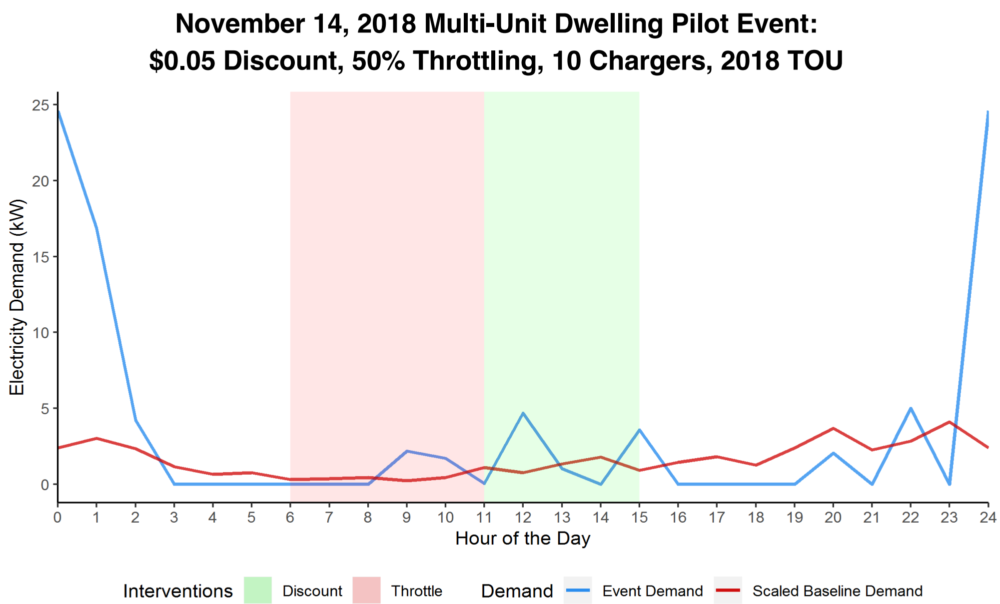


Figure AIV-27. November 14, 2018 MUDs Load Shift Event Demand Graph

Table AIV-29. November 14, 2018 MUDs Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11 am - 3 pm)	5	9	93%
Peak (4 - 9 pm)	11	2	-82%
Other	22	55	153%
Total	38	66	75%

Table AIV-30. November 14, 2018 MUDs Load Shift Event Demand Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	0.84	1.33	58%	~0	~0	~0%	N/A
Peak (4 - 9 pm)	2.69	0	-100%	0.01	0	-100%	0
Other	5.10	13.14	158%	0.02	0.05	150%	N/A
Total	8.63	13.95	62%	0.03	0.05	67%	0

Event Highlights

- There was an 93% increase in demand in the target window and a 82% reduction in the peak period. The overall 75% increase in daily demand had negligible effects on curtailment.
- GHG and air pollution emissions increased significantly proportionately, but with a negligible impact on social costs. There was no impact in DACs.
- Consumer costs increased by 30%, from $3.23 to $4.19.

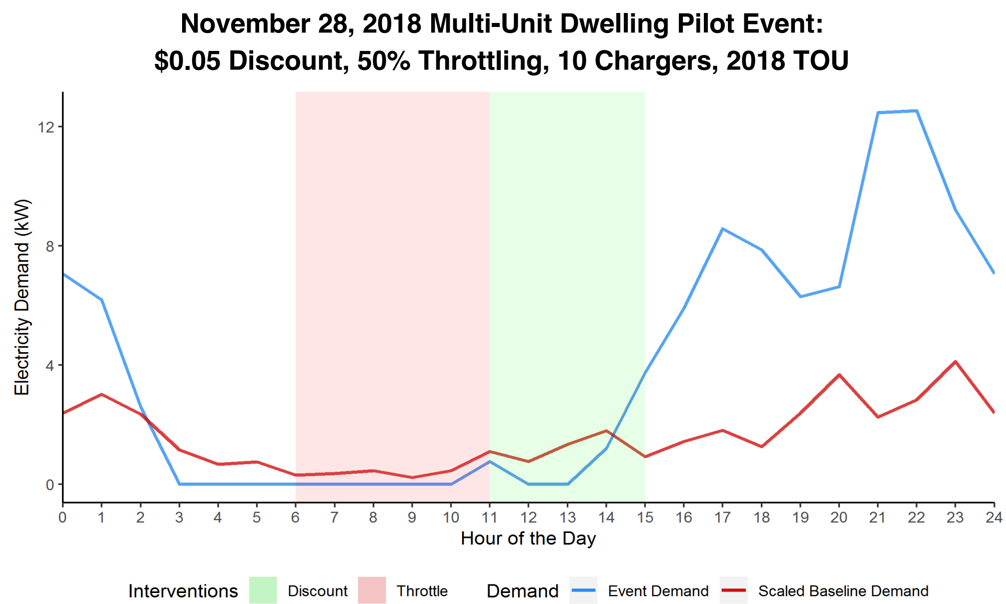


Figure AIV-28. November 28, 2018 MUDs Load Shift Event Demand Graph

Table AIV-31. November 28, 2018 MUDs Load Shift Event Demand Impacts

Time	Demand		
	Initial (kWh)	New (kWh)	Change (%)
Intervention (11 am - 3 pm)	5	5	3%
Peak (4 - 9 pm)	11	42	268%
Other	22	44	105%
Total	38	91	140%

Table AIV-32. November 28, 2018 MUDs Load Shift Event Demand Impacts

Time	GHGs			NOx			
	Initial (kg)	New (kg)	Change (%)	Initial (kg)	New (kg)	Change (all) (%)	Change (DACs) (kg)
Intervention (11 am - 3 pm)	0.84	0.85	2%	0.003	0.003	2%	N/A
Peak (4 - 9 pm)	2.69	11.98	346%	0.01	0.04	218%	0.01
Other	5.10	10.61	108%	0.02	0.04	107%	N/A
Total	8.63	23.46	172%	0.03	0.08	162%	0.01

Event Highlights

- There was an 3% increase in demand in the target window and a 268% increase in the peak period. The overall 140% increase in daily demand had negligible effects on curtailment and associated costs.
- GHG and air pollution emissions increased significantly proportionately, but with a negligible impact on social costs. There was minimum impact in DACs.
- Consumer costs increased by 148%, from $3.23 to $8.01.

Additional Events

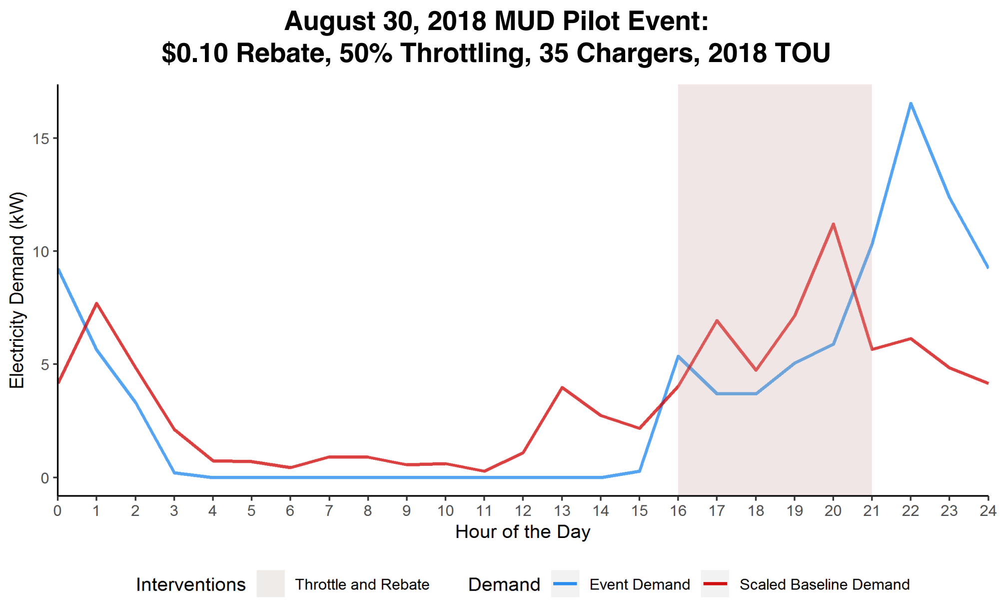


Figure AIV-29. August 30, 2018 MUDs Load Shift Event Demand Graph

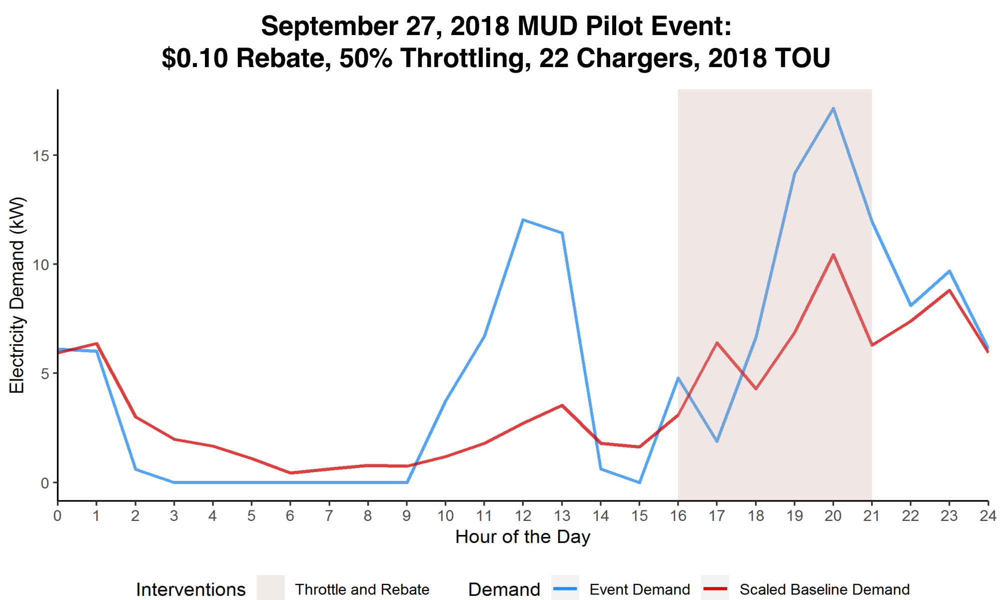


Figure AIV-30. September 27, 2018 MUDs Load Shift Event Demand Graph

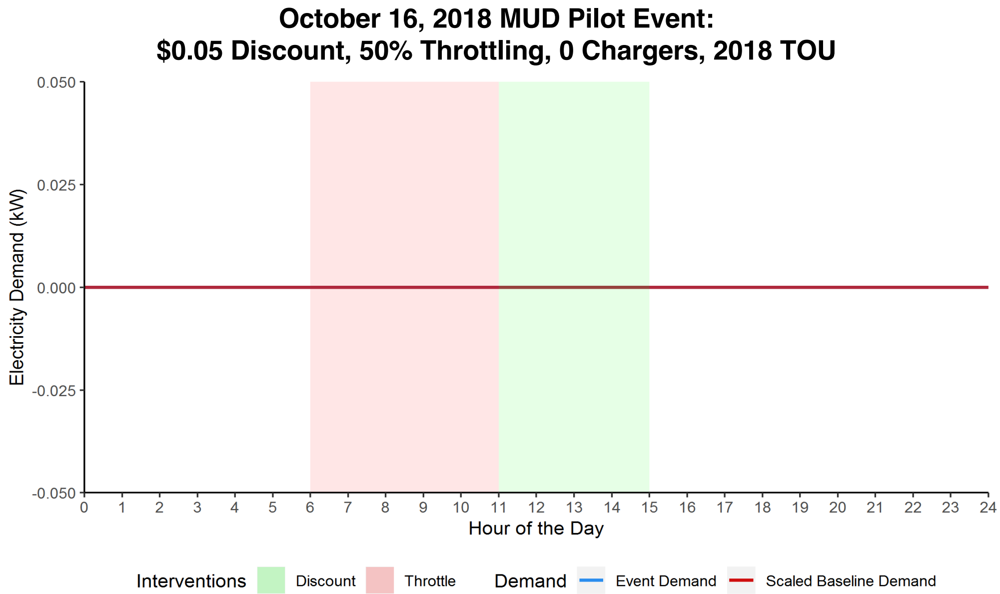


Figure AIV-31. October 16, 2018 MUDs Load Shift Event Demand Graph

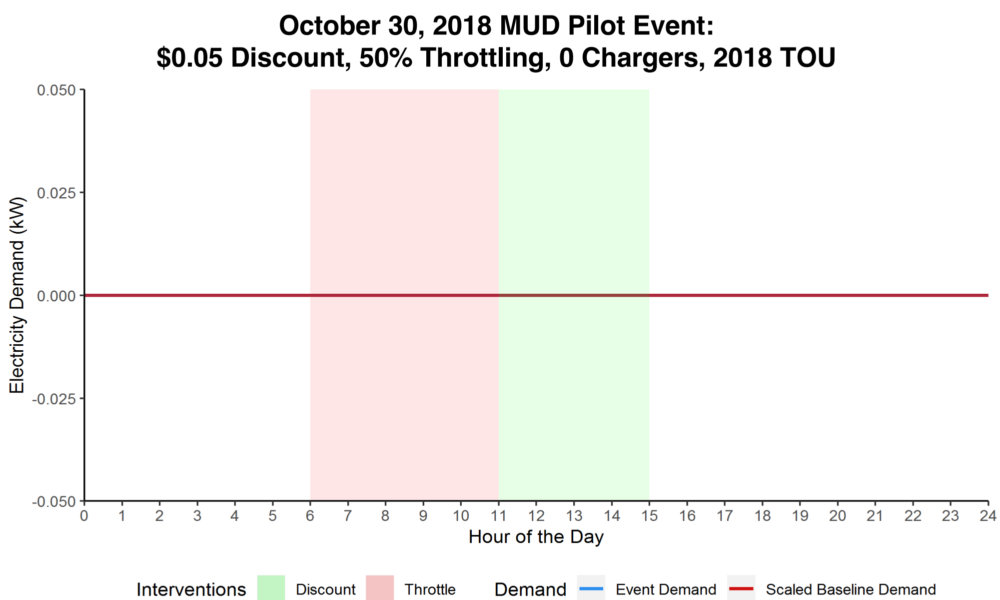


Figure AIV-32. October 30, 2018 MUDs Load Shift Event Demand Graph