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ENERGY RESEARCH AND DEVELOPMENT DIVISION

FINAL PROJECT REPORT

SCRIPT: Smart Charging Infrastructure Planning Tool

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PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission, and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation, and bring ideas from the lab to the marketplace. The EPIC Program is funded by California utility customers under the auspices of the California Public Utilities Commission. The CEC and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas and Electric Company, and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

For more information about the Energy Research and Development Division, please visit the CEC's research website (www.energy.ca.gov/research/) or contact the Energy Research and Development Division at ERDD@energy.ca.gov.

ABSTRACT

Transportation is one of the key contributors to greenhouse gas emissions and is recognized as one of the main factors contributing to climate change. California is at the forefront of setting aggressive transportation clean energy goals that will accelerate electric vehicle adoption. For California to reach these goals, understanding the impacts that increased adoption of electric vehicles will have on the electrical system, and the infrastructure required to support it, is paramount to ensuring a smooth transition. This project developed the Smart Charging Infrastructure Planning Tool (SCRIPT), which is an open-source, scalable, software tool for scenario generation based in real charging data from California. The tool provides an interface for users to change multiple inputs such as aggregation level, number of electric vehicles in the state, electric vehicle battery capacity, charging location (that is, residential, workplace, and public), type of charging control, type of day (weekday or weekend), and daily charging frequency. From these user inputs, the tool generates charging requirement forecasts for millions of electric vehicles, predicts how different charging locations will be affected, shows how electric vehicle load can be reshaped by optimizing vehicle charging, and assesses costs and benefits. SCRIPT uses a novel method, based in machine learning, to model the impact on aggregate load profiles of optimizing vehicle charging for a particular rate schedule.

This report uses workplace charging to demonstrate the method. The report analyzed seven different scenarios targeting California's 2030 electric vehicle goals. The scenarios differ primarily based on the number of vehicles and how much each charging location contributes to the overall load. Across the scenarios analyzed, all resulted in positive net benefits to the state, the county, electric vehicle owners, and ratepayers. Although this report focuses on seven unique scenarios, many other scenarios can be analyzed by changing user inputs.

Keywords: Electric Vehicles, Planning, Smart Charging, Software, Analytics, Machine Learning, Cost-Benefit

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Introduction

Traditionally, electric utilities focused on supplying electricity to customers with predictable loads and located in known and fixed points in the network. The current reality, however, has changed due to: (1) more loads being connected to the electric grid by active converters — that is computers, battery chargers, electric motor drives, and others — presenting different electrical characteristics; (2) renewable generating resources that are typically intermittent and can be located behind the meter and not visible to utilities; and (3) electrification through increasing adoption of electric transportation.

Electric vehicles (EVs) use considerable amounts of energy, and each EV’s electrical load can appear at different points in the network. Electrified transportation is a key part of many plans for deep decarbonization, and many locations around the world are setting aggressive goals to increase EV adoption. California is at the forefront of setting such targets. One of the main goals behind these efforts is to drastically reduce the emissions from the transportation sector, which is currently responsible for approximately 41 percent of California’s greenhouse gas emissions.

A key challenge California faces to reach its transportation electrification goals is understanding how millions of new EVs will manifest as loads in the electricity system. Key inputs affecting estimation of the load from EVs include: the timing of charging sessions; whether charging takes place at a workplace, in public, or at a residence; and how charging control is applied to beneficially shape the load. The utilities and government program planning for the distribution, transmission, and generation systems relies on detailed forecasts of the load. This project developed a flexible modeling tool to generate scenarios, including the impact of charging control, at the necessary scale to plan for future vehicle deployment targets. Furthermore, this tool can assess the costs and benefits from different stakeholders' perspectives.

As with any attempt at modeling the future, there is significant uncertainty, and many assumptions are required. The project approach leveraged statistical models derived from one of the largest data sets to date, with more than 10 million charging events. By designing the approach for speed, the modeling tool will enable a user to interact near real time with the model to compare different scenarios, understand the sensitivity to the modeling assumptions, and add the user’s expert input to the design to better model how EV drivers will charge 10 years in the future. As controlled charging becomes more prevalent and unlocks more flexibility in the load from EVs, it is crucial to include realistic estimates of the future charging load. The tool design included the control rule as an input along with other assumptions, to allow the ability to compare and adjust the control between scenarios. The project team believes these interactive features will communicate the model better than a report with fixed scenarios, and it will enable policy makers to use the model to create specific scenarios.

Project Purpose

The purpose of this project was to develop a tool that helps to understand the effect that increased adoption of electric vehicles will have on the electrical system and ensures that the infrastructure required to support it ultimately supports California's aggressive transportation clean energy goals by accelerating electric vehicle adoption.

The goals of the project were to:

- Develop a predictive smart charging framework for EVs that considers future travel plans of drivers and various power system conditions.
- Perform a cost-benefit analysis for investment in charging infrastructure that considers various future scenarios.
- Develop a comprehensive tool that integrates the two aforementioned elements and can be used by stakeholders to make decisions pertaining to new investments in charging infrastructure.

The result of this effort is the Smart Charging Infrastructure Planning Tool (SCRIPT) — a comprehensive tool that predicts smart charging of EVs and performs a cost-benefit analysis for investment in charging infrastructure from the point of view of different stakeholders under various scenarios.

SCRIPT allows stakeholders to: generate multiple scenarios for future EV charging under different assumptions of adoption; evaluate the potential of smart charging in changing the overall load profile to reduce grid congestion and maximize solar photovoltaic system use; understand the effects that investments in different charging locations — that is, residential, workplace, public — have on the EV load; and perform an assessment of the costs and benefits to the region, EV owners, and ratepayers.

Project Approach

The SCRIPT research and development team consisted of researchers and technology developers from: the Grid Integration System and Mobility Group within SLAC National Accelerator Laboratory; Energy and Environmental Economics, Inc. (E3); the Smart Infrastructure Lab group from University of California, Santa Barbara, led by Professor Mahnoosh Alizadeh; Gridmatic, Inc.; and ChargePoint, Inc.

To achieve the project goals, the team designed a framework for SCRIPT that consists of three main blocks: Data, Analytics, and Interface.

The Data block represents the diverse set of data that was used. A key functionality of this block was to clean and preprocess the data into a structure that the Analytics and Interface blocks could use. The output from this block was the input for the other blocks.

The Analytics block performs all the algorithms and analysis proposed in the tool. Requirements on computational time to ensure a satisfactory user experience were considered and dictated constraints for the algorithms. Four main algorithms and analyses were developed: (1) scenario generation and modeling, (2) smart charging, (3) scenario-based forecasting, and (4) cost-benefit analysis.

An algorithm was developed to generate the load profile for a given scenario, with inputs specified by the user. Examples of these inputs include location, charging level, and time of charging session (that is, weekday or weekend).

The smart charging algorithm focuses on optimizing the charging profile of an EV, or a group of EVs, by controlling the power delivered. A novel data-driven approach drastically decreased the computational cost of applying control within the SCRIPT tool.

The goal of the scenario-based forecasting was to generate future EV loads given different variable inputs. For example, how will the EV load profile change if adoption is higher or lower compared to state and county targets or if more people have access to workplace or public chargers? SCRIPT makes each variable a control knob in the forecasting framework, so a user can change one or more variables at once, given their own assumptions, and quickly generate profiles for new scenarios.

The fourth core functionality of the Analytics block is the cost-benefit analysis. This analysis uses E3's EV Grid model to evaluate the impacts of the EV load profiles generated by the load forecasting algorithm and includes perspectives of three primary stakeholders: EV drivers, the utility customer, and the state or county.

The final block in the proposed framework is the Interface block, which provides the user with an interactive interface through which to execute the algorithms and analysis described in the Analytics block.

Project Results

The SCRIPT project achieved its goals of developing a predictive smart charging and flexible load forecaster capable of conducting a cost-benefit analysis for different scenarios and, ultimately, providing a comprehensive tool that can be used by different stakeholders to perform EV charging infrastructure analysis.

To illustrate the use of the tool, seven scenarios were selected for analysis, with three key variables defining the differences among the scenarios. The tool generated controlled and uncontrolled EV charging profiles for each scenario. Three main conclusions were drawn from the analysis, as follows.

First, drivers in four scenarios rely heavily on residential charging, creating a peak EV load occurring in the evening hours. This could pose a challenge to grid infrastructure since the distribution system at the residential level is not designed with the incremental capacity required to support such growth, and residential upgrades can be costly.

Second, one scenario with more use of public charging provided a better trade-off between residential and non-residential EV loads and more evenly distributed the load throughout the day; however, the scenario has limitations and creates a significant strain on the distribution grid.

Third, two scenarios presented a good trade-off by leveraging workplace charging to support a large fraction of the EV load, shifting a significant portion away from the evening and into the day.

Cost-benefit analyses of the seven scenarios were explored from societal, ratepayer, and EV driver perspectives. Positive results for all California counties and all scenarios suggest that: all entities benefit from EV charging; policy makers should continue efforts to spur EV adoption; utility ratepayers — both those with EVs and those without — benefit from broader EV adoption; EV charging brings additional utility revenue that outweighs electricity supply costs, thus decreasing rates over time; and EV drivers benefit from lower costs compared to conventional vehicles.

The user interface provides an intuitive way for different stakeholders to leverage the capabilities of the tool by: (1) understanding the effects of applying workplace smart charging with the most common rate structures to modify the load shape of workplace charging sites for different counties; (2) generating different scenarios of future EV load demand by selecting assumptions and changing inputs; and (3) performing cost-benefit analyses. The code behind this software tool is open-source and available to the public community on GitHub.

Lessons Learned

Many valuable lessons were learned throughout the project, but two stand out as most important. The first lesson is that there is a trade-off between the optimality of algorithms, computational complexity, and design of an interactive software tool to ensure a satisfactory user experience. Therefore, a clear understanding of the goals and objectives of the analysis is paramount to determining the best trade-off. The second lesson is that large amounts of data from different sources are required to create a realistic, representative picture of the problem being analyzed. Gathering a large volume of data from many sources and connecting the information could benefit the analysis and help to better inform decision makers on the best strategies for investing in a particular charging location, promoting EV adoption, and achieving statewide energy goals in a cost-effective way.

Technology and Knowledge Transfer

The method developed in this project generated, to date, four peer-reviewed conference papers addressing different aspects of SCRIPT with the research community. The project team also presented the work to academia and industry at multiple conferences.

The team identified four main users that can directly leverage the outcomes of this research: electric utilities, industry, federal and state agencies, and academia.

The method developed in SCRIPT has already inspired new research. An extension of the model with a more detailed division of charging locations and drivers into groups is being developed at Stanford University under Professor Ram Rajagopal with PhD student Siobhan Powell. The Clean Transportation Division of the California Energy Commission is collaborating with the team to develop the model and hopes to use its outputs to inform long-term planning scenarios.

The project team is also actively engaging with electrical utilities. Pacific Gas & Electric Company's long-term planning team is interested in using the model to support its scenarios, with particular interest in understanding the control and load flexibility in the SCRIPT model. Conversations with Southern California Edison are ongoing to understand how it can best use SCRIPT.

Finally, SCRIPT is an open-source tool, and the software is available to the general public under the Grid Integration Systems and Mobility (GISMo) group's GitHub: https://github.com/slacgismo/SCRIPT-tool.

Benefits to California

Ratepayers benefit in many ways from this work. By helping utilities anticipate and better plan investments in infrastructure, the flexible EV load forecaster can help to ensure high reliability and minimize the cost of electricity. Because the forecaster provides estimates at the state and county levels for EV load throughout the day, key stakeholders can identify locations to install renewable generation and to optimize the capacity of that generation to support the additional load from charging EVs. For example, our studies showed that more than 80 percent of the uncontrolled EV load could be supplied by local solar, if properly sized, and more than 93 percent if the EV load is properly controlled, while ensuring drivers' energy needs and departure times are satisfied. This reduced load would prevent or delay large infrastructure upgrades, thus minimizing the impact on electricity rates and reducing emissions from bulk generation. Finally, this work supports accelerated adoption of EVs, which significantly reduce emissions relative to combustion engine vehicles: an individual EV saves approximately 33 metric tons of carbon dioxide through its lifetime. Each EV adopted between 2020 and 2030 brings an average benefit of $3,500 (net present value) to its utility beyond the cost of electric service, applying a downward pressure on electricity rates.

CHAPTER 1: Introduction

Many countries around the world are trying to drastically reduce their greenhouse gas (GHG) emissions to combat climate change. In the United States, the main source of GHG comes from transportation (28 percent), followed closely by electricity production (27 percent) (Office of Governor, 2012). Many states are pushing toward electrifying the transportation sector and relying on cleaner generation, such as renewable generation. States such as California are setting aggressive goals to make this transition happen. However, this transition is requiring electrical utilities and system operators to rethink how they plan and operate the system to ensure that generation meets demand.

Traditionally, electric utilities were focused on supplying electricity to customers that had predictable loads and were in known and fixed points in the network. However, the current reality has changed due to: (1) more loads presenting different dynamics due to embedded sensing, power electronics, and active control; (2) renewable resources that are intrinsically intermittent and can be located behind the meter and not visible to utilities; and (3) increasing adoption of electric transportation.

These distributed energy resources (DERs) are fundamentally altering the business of supplying electricity, and their influence will multiply over the coming years with increasing and widespread adoption.

Electric vehicles (EVs) present an interesting challenge for grid operations. They use considerable amounts of energy, and each EV's electrical load can appear at different points in the network. Electrified transportation is a key part of many plans for deep decarbonization, and many locations around the world are setting aggressive goals to increase EV adoption. California is at the forefront of this development. In 2012, then-Governor Jerry Brown issued an executive order establishing a goal of 1.5 million zero-emission vehicles in California by 2025 (EPA, 2018). In 2018, Governor Brown issued another executive order to extend this goal, with a 2030 target of 5 million zero-emission vehicles (Office of Governor, 2018). More recently, in 2020, Governor Gavin Newsom signed an executive order to ban sales of all new gasoline-powered cars and passenger trucks by 2035 (Newsom & Padilla, 2020). One of the main goals behind these efforts is to drastically reduce the emissions related to the transportation sector, which currently accounts for approximately 41 percent of California's GHG emissions (California Air Resources Board staff, 2020).

A key challenge is understanding how these millions of new EVs will manifest as loads in the electricity system. Key inputs affecting estimation of the load include: timing of charging sessions; whether they take place at a workplace, in public, or at a residence; and how charging control is applied to shape the load. Planners with utilities and governments, who are responsible for the distribution, transmission, and generation systems, all depend on detailed forecasts of the load. In this project, a flexible modeling tool is developed to generate scenarios, including the impact of charging control, at the necessary scale to plan for vehicle targets in 2030 and beyond. Furthermore, this tool can assess the costs and benefits from different stakeholders' perspectives.

Existing modeling tools for estimating the load from EV charging fall into two main categories. The first, bottom-up models, uses detailed travel data to simulate an individual driver’s mobility and charging decisions throughout the day. The second, statistical models, focuses on modeling the distributions in charging data or taking a probabilistic approach to driver decisions; it is this category into which the research model falls.

Bottom-up models provide very detailed simulations. In California, the most commonly used tools for simulating EV load are EVI-Pro and EVGrid, which use data from travel surveys, and BEAM, which uses cell phone GPS data (Wood et al., 2018). Each of these models uses the data to recreate individual vehicles’ daily travel to track their batteries’ state of charge, calculate their energy needs, find the set of charging options available to each driver, and model the driver’s decisions to charge.

While these tools can provide very detailed, refined projections, they are often limited by scale and computational expense. Simulating the mobility and decisions of millions of drivers can take hours or days, especially with the inclusion of charging control. It also requires detailed travel data as an input, which is available only for some regions.

Travel data can also be used in statistical models, with approaches including probabilistic models for vehicle state, location, trips, and pattern identification implemented using a variety of algorithms (Ul-Haq, 2018; Wang, 2018; Wang, 2017; Tang, 2015; Li, 2018; Mureddu, 2018; Mu, 2014; Xu, 2018; Crozier, 2019; Sodenkamp, 2019). This project uses statistical modeling of charging data to characterize charging behaviors observed in real data from EV drivers. The data set used is among the largest described in public literature, including more than 10 million charging sessions and nearly 120,000 individual drivers. Other research in this area has depended on smaller data sets, the largest of which has 400,000 sessions (Sadeghianpourhamami, 2018; Flammini, 2018; Morrissey, 2016; Quiros-Tortos, 2018; Neaimeh, 2015; Brady, 2016; Dias, 2018; Nicholas, 2017).

Several of those works focus on statistical models for different parameters of the charging sessions. Summary statistics of the distributions are presented (Morrissey et al., 2016) and mixture model methods are used, both beta and Gaussian (Flammini et al., 2018), to model the distributions for individual charging session parameters. Additionally, other methods have been used to generate new parameters from the data set, which capture the inter-dependence of travel parameters (Brady et al., 2016).

Not all drivers behave in the same, predictable way, and there is often a significant difference between simulated and observed charging choices captured in real data (Dias et al., 2018). Analysis of the data set from *Quantitative Analysis of Electric Vehicle Flexibility: A Data-Driven Approach* found that grouping the drivers according to their choice of charging either near home, near work, or at public charging stations significantly affected their charging session’s statistics (Sadeghianpourhamami et al., 2018).

In addition to the arrival and departure time of the vehicle and the energy required in each session, the load profile for an EV charging session can be altered through controlled charging.

The most common type of control applied to residential charging involves setting timers to delay the start of a charging session until a later time, after the vehicle is plugged in, usually to wait for a less expensive electricity price late at night. Another type of control, commonly applied to workplace charging, involves modulating the power throughout each EV's session to shape the overall load at a workplace site. The load is shaped to optimize an objective of the aggregator, typically the electricity bill faced by the workplace to support the parking lot (Wu, 2018). In that type of control, the individual driver's pay to his/her workplace is not changed, and the drivers usually do not realize their charging has been changed.

Workplace charging offers many benefits to drivers. The availability of workplace charging has been shown to increase adoption by making it possible for more users to switch to EVs, including drivers with high daily mileage (Chakraborty et al., 2019) or those without easy access to charging at their residences (McLaren et al., 2016). Many workplaces in California offer free workplace charging for employees, and investment in installing new workplace charging stations is increasing, driven by this demand. Workplace charging offers many benefits to electricity providers as well, especially in California where shifting charging from the evening peak to mid-day aligns with lower generation costs.

As a flexible load, there is great potential to use workplace charging control to improve the impact of EVs on the grid. Optimizing to better align charging with periods of high solar generation can help reach decarbonization targets (Kara et al., 2015), and optimizing for grid constraints to flatten the load can help reduce EVs' contribution to the system peak (Powell et al., 2020). Flattening the load has also been shown to help extend the lifetime of the transformer supporting each workplace site (Muratori et al., 2020).

It is challenging to model controlled, workplace charging using the tools previously discussed and often very computationally expensive. The bottom-up models are more expensive than the statistical models, but even statistical models that take a probabilistic approach to modeling mobility or charging choices use deterministic approaches for charging control (Quiros-Tortos et al., 2018). The project team has not seen any other model designed to estimate workplace charging control at the scale of millions of vehicles, which is needed for evaluating state and national EV targets. Additionally, no work has integrated a cost-benefit assessment of the impacts of EVs and their load profiles to different stakeholders in such a framework.

This project aims to fill those gaps by making it possible to model EV load faster with different control schemes and cost-benefit analysis at scale. That is an important contribution to the range of tools used for EV planning in California. Scalability was highlighted in a recent review paper on EV modeling tools as an important need to fill (Tucker et al., 2019). As with any attempt at modeling the future, there is significant uncertainty, and many assumptions are required. The project aims to overcome this uncertainty by enabling users to interact near real time with the model to compare different scenarios, understand the sensitivity to the modeling assumptions, and add their own expert input to the design. User input aids in crafting a better model of how EV drivers will charge 10 years in the future. As controlled charging is becoming more prevalent and unlocking more flexibility in the load from EVs, it is crucial to include realistic estimates of the future charging load. The project team's approach includes that as a knob alongside the other modeler assumptions, so the user can compare and adjust the control between scenarios. The project team believes these interactive features will communicate the model better than a report with fixed scenarios, and it will enable policy makers to use the model to create their own scenarios.

CHAPTER 2: Project Approach

The project team was led by the Grid Integration Systems and Mobility (GISMo) group within SLAC National Accelerator Laboratory and the invaluable knowledge, support, and development of project partners, including the team from Energy and Environmental Economics, Inc. (E3); the Smart Infrastructure Lab group from University of California, Santa Barbara led by Professor Mahnoosh Alizadeh; Gridmatic, Inc.; and ChargePoint, Inc. The team also had support from technical advisors from eIQ Mobility and multiple groups within Stanford University that provided valuable insights, direction, and guidance.

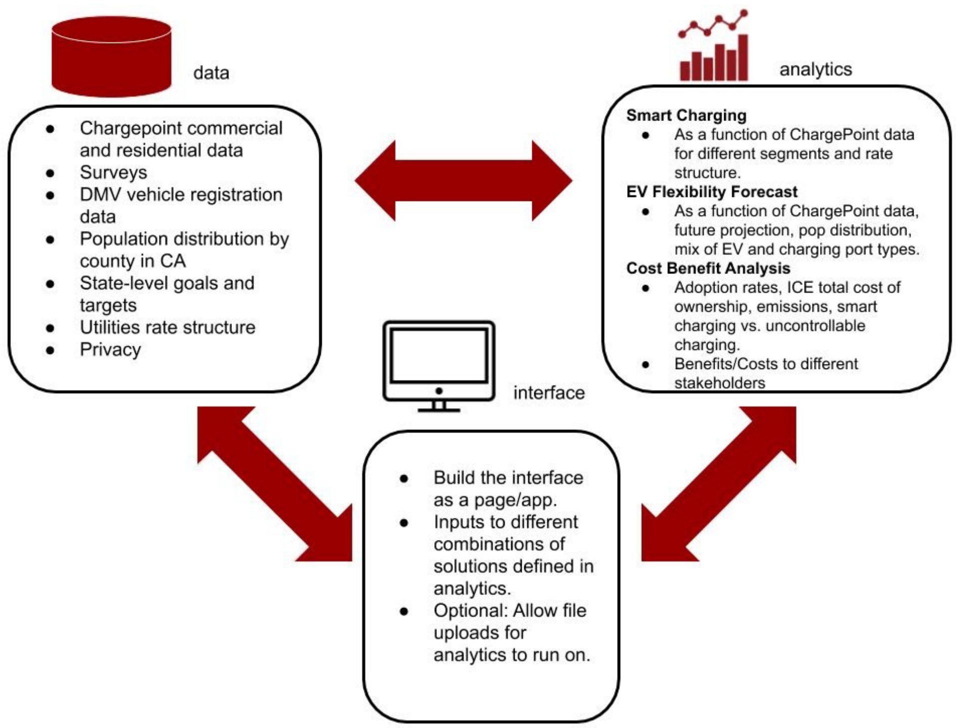
To achieve the project goals, the team applied a variant of the control co-design (CCD) principle described in *Control Co-Design: An Engineering Game Changer* to design the framework used throughout the project (Garcia-Sanz, 2019). The CCD principle follows a concurrent engineering strategy that considers multidisciplinary subsystem interactions from the beginning of the design process. In this project, the diverse set of subsystems that interact with each other are:

- *Scenarios and projections on EV adoption* from accredited institutions, technical advisory committee members, and the project team.
- *Real data from a diverse set of sources*, such as EV charging data from workplace and residential charging locations, surveys, California Department of Motor Vehicle registration information, utility rate structures, and population distribution by county in California.
- *Control algorithms* that, given a scenario defined by existing data, optimize to minimize the electricity cost when given a rate structure.
- *Forecasting algorithms* that generate future load profiles of EVs, given assumptions about future adoption levels, charging infrastructure, availability of controlled charging, EV battery technology, and other factors.
- *Computationally complex algorithms* that need to be performed in a faster way so as not to the affect user experience of the final proposed tool.
- *Privacy protection* for drivers in the data set obtained from ChargePoint so as not to disclose any personal identifiable information.
- *A cost-benefit analysis* that, given different EV load profiles and various external information, performs an assessment of the values and costs from different stakeholder perspectives.

The interaction among each of the aforementioned subsystems during development occurred not sequentially but, rather, concurrently. Figure 1 shows the overall design method used throughout the project. Each subsystem is contained within one of the three major blocks: Data, Analytics, and Interface.

The Data block represents the diverse set of data that was used. A key functionality of this block was to clean and preprocess the data to a structure that the Analytics and Interface blocks could use. One key consideration when defining the structure was efficiency to load and save the data (large files could take multiple hours and were sometimes not able to load or save). To address this issue object serialization and data compression methods were used. The Analytics block performs all the algorithms and analysis proposed by the tool. Requirements on computational time to ensure a satisfactory user experience were considered and dictated how the algorithms were developed. The Interface block provides the user with an interactive interface to perform different analyses of interest. The design of the Interface block affected how the Analytics and Data blocks interacted with each other and within themselves.

Figure 1: Design Method Framework for SCRIPT



Each subsystem is contained within one major block — Data, Analytics and Interface — the three of which interacted with each other throughout the project.

Source: SLAC National Accelerator Laboratory.

Data Block Design

The Data block is the entry point to the SCRIPT tool. This block is responsible for ingesting, cleaning, and preprocessing a variety of data sources with different formats and sizes to be used by the different algorithms in the Analysis block and displayed in the Interface block to the end user. The multiple sources of data included: real workplace and residential charging sessions from the world's largest network of electric vehicle charging stations, ChargePoint, Inc.; most common rate structures in investor-owned utility (IOU) territories; IOU marginal costs of electricity; emissions; vehicle registration data from California's Department of Motor Vehicles; and cost projections and vehicle miles traveled (VMT) for EV and internal combustion engine (ICE) vehicles, among others. Appendix A provides a list of all the data used.

Although each data source is relevant for the successful outcome of the project, the uniqueness of this rich data set is the real charging session data, including sessions from both workplace and residential charging locations. This data set ranges from 2015 until July 2020. The year 2019 was used as the main data source for the analysis presented in this report, while 2018 and 2020 data were used to inform additional metrics.

Specifically, for 2019, the data set consisted of 6.09 million sessions with more than 119,000 individual drivers in nine different counties. Of these sessions, 4.2 million are from workplace charging, 521,000 are from residential charging at single-family homes, 148,000 are from multifamily installations, and the remaining are from other charging stations with categories including retail locations and public parking lots. To the best of the project team's knowledge, this is the largest data set of real-world EV charging data to date. Due to its size, the ingestion, cleaning, and preprocessing steps had to be done carefully.

Data Ingestion

Data is ingested by splitting large files into smaller ones to improve the speed of loading, cleaning, processing, and saving files. This split also facilitates file handling and minimizes potential for software crashes. Once files are in a manageable size, they are fed to the cleaning step.

Data Cleaning

In the data cleaning step, a sequential procedure was developed to remove "bad data." These steps are: (1) eliminate sessions that have 0 kilowatt-hours (kWh) energy; (2) eliminate sessions where total session time is less than 120 seconds; (3) ignore sessions with "Connector Type" — Type 2 Cable and Type 2 Socket; (4) ignore sessions with "Energy (kWh)" greater than 100 kWh for "Session Type" OTHER; (5) ignore sessions not in the Pacific Daylight or Pacific Standard time zone; and (6) discard drivers from out of the country and sessions with "Fees" not in United States dollars.

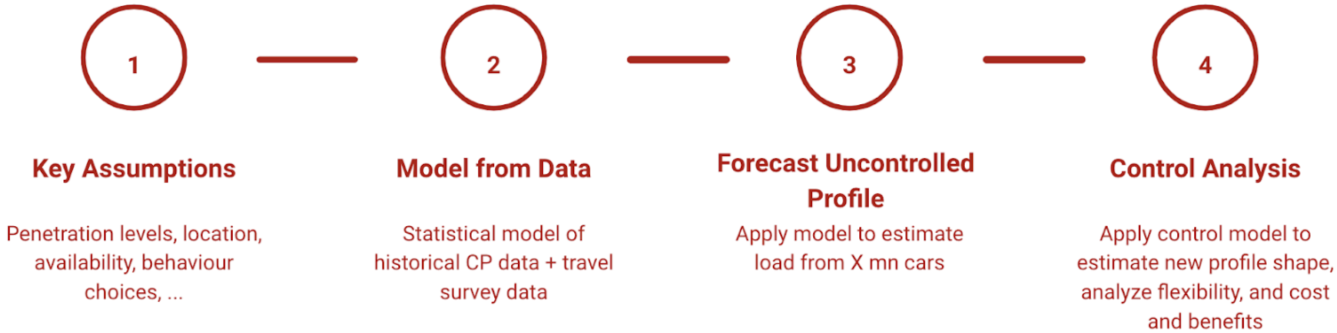
Data Preprocessing

The data preprocessing step generates a multitude of new files that serve different purposes required by other parts of the project. The files were categorized by charging location (that is, residential, workplace, and public). Aggregation at the county level was completed by mapping a session's zip code to its corresponding county, and Gaussian mixture models (GMM) (Powell et al., 2020) were generated for each charging location. In this data preprocessing step, data serialization and compression were implemented, depending on the user's intended usage.

Analytics Block Design

The Analytics block is the brain of the SCRIPT tool. This block is responsible for running the core algorithms and analyses. There are four main algorithms: (1) scenario generation and modeling, (2) smart charging, (3) scenario-based forecasting, and (4) cost-benefit analysis. Figure 2 shows the overall method of the Analytics block.

Figure 2: Analytics Block Methodology



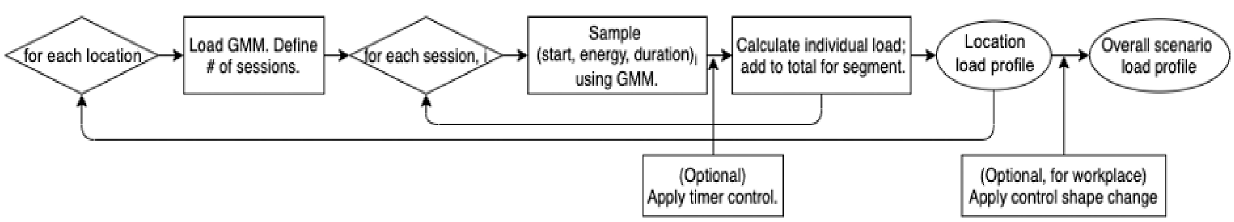
Source: SLAC National Accelerator Laboratory.

The algorithms are exposed to the user through the Interface block. This block provides users with the ability to interact with the inputs, or control knobs, to tailor the analysis to a specific case of interest.

Scenario Generation and Modeling

There are many ways one can go about generating scenarios and new daily EV load profiles from real data. This project's model for generating new scenarios depends on several key input assumptions and exogenous parameters: the number of EV drivers, the distribution of battery capacities, and the number of sessions at each charging location. The segmentation of the model depends on an estimate of the split between drivers who depend on workplace, residential, or public charging, including their preference between different charging levels. The charging levels are level one (L1), level two (L2), and direct current fast charging (DCFC) at rates of 1.4 kW, 6.6 kW, and 150 kW, respectively. Another necessary input is the driver's frequency of charging, or how likely a driver is to charge on a given weekday. The diagram in Figure 3 describes how the scenario load profile can be generated.

Figure 3: SCRIPT Flowchart for Scenario Generation



The pseudo algorithm used to generate the load profile for a given scenario. The number of sessions for each scenario generated is specified by the user. Each load profile modeled with this approach is defined by its location, charging level, and time of use (weekday or weekend). The options for location include single-family residences, multi-unit dwellings, workplaces, or public charging stations. The options for single-family residential charging are L1 and L2. The options for public charging are L2 and DCFC. Workplace and multi-unit dwelling residential charging are assumed to be L2.

Source: Powell. 2020. Large Scale Scenarios for Electric Vehicle Load with Controlled Charging.

The approach depends on fitting models to the raw data, so that sampling from the models when generating new sessions does not rely directly on the raw data. Two main models are used, one to capture the distribution of charging session parameters using mixture models and another for smart charging control.

The dependency on fitted models allows both speed and privacy. Fitting and training the components was time consuming but, once completed, the developed framework allowed the project team to quickly generate new profiles. Adjusting assumptions and applying control rules creates new scenarios, and those can be run on the scale of 5 million drivers in less than one minute. The dependence on fitted models also allowed the project team to separate the tool from the raw data, so that no individual user's data was needed to generate new scenarios. The tool relies on stored versions of the pre-fit mixture models and control model, meaning data can be stored and shared without any individual driver data, to avoid concerns around data privacy.

The approach can be adjusted to capture more specific subsets of the load, for example, including individual regions and zip codes within the data, or including only a subset of drivers with more recent vehicle models with larger battery capacities. That flexibility let the project team generate scenarios for driver behaviors or tune the model toward the infrastructure planning problem of a particular region.

Smart Charging

The goal of smart charging, also referred to as controlled charging, was to optimize the charging of EVs to account for grid conditions. At a residential charging location, this involved setting timers to align charging with the time-of-use (TOU) period with the lowest electricity cost for the homeowner. At a workplace charging location, this optimization was implemented on a per-site or per-parking-lot basis to minimize the electricity bill for the aggregate charging load. That optimization depends on the site's rate structure, often involving peak reduction to respond to demand charges. In both cases, the control must also account for driver's travel (for example, arrival and departure times) and energy needs. Therefore, the input to the smart charging feature of the tool is an EV's or site's uncontrolled load profile, and its output is the optimal controlled profile that minimizes the electricity cost under the rate structure, ensuring the driver's constraints are always satisfied.

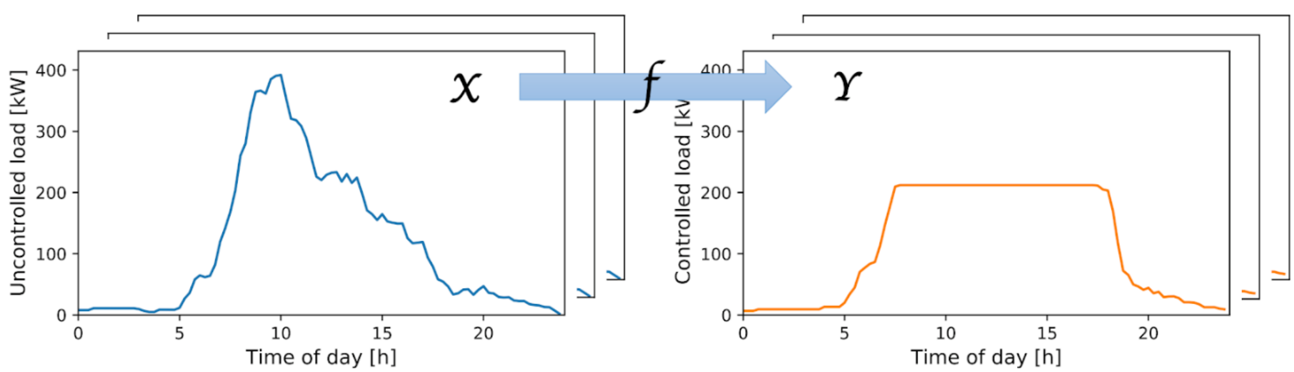
Implementing charging controls is challenging for the workplace charging location due to its high computational costs, since the optimization calculation does not scale well beyond individual parking lots. Because the goal of the proposed tool is to enable users to interact with it, computational times greater than minutes would impact the user experience.

Therefore, a novel data-driven method was proposed, to model workplace charging control to drastically reduce the computational time of generating a controlled profile from an uncontrolled one. The proposed approach was to learn a mapping function, **F**, that, given an uncontrolled profile, generated a controlled profile. Once **F** was defined, a controlled profile was estimated by simply applying it to a given uncontrolled load shape. For example, if one were interested in understanding how different rate structures could affect an existing EV load shape, learning an **F** for each rate and applying it to this profile would give the controlled shape estimations. This approach addressed multiple problems in the existing space of modelling tools in the EV space, most notably: (1) speed in the estimation of controlled EV load profiles by simply applying **F**; and (2) scalability, by being able to estimate charging controls at scale for the millions of vehicles considered by statewide or countywide 10-year plans.

To calculate **F**, multiple uncontrolled daily load profiles, denoted by **X**, were created for representative workplace sites by sampling from the real charging session data. **K** was proposed to denote the number of individual charging sessions comprising each aggregate profile. An optimization problem for the site was formulated and solved for each instance, generating the controlled profiles, denoted by **Y**. Each uncontrolled entry in **X** had a corresponding controlled entry in **Y**. This relation is depicted in Figure 4. Although this process still required performing an optimization for each uncontrolled load profile, this was done only once and offline to build the set of training profiles. Once **F** was learned, no more runs of the optimization were required.

To calculate **F**, best practices for machine learning were followed. The data set was divided into three parts: 70 percent in the training set, 10 percent in the development set, and 20 percent in the testing set. Some parameters, including the parking lot size, were tuned using the development set. The parameters in the mappings were tuned using a grid search with cross-validation in the training set. To model the mapping, **F**, several options were considered, including: linear regression; ridge regression; support vector regression with linear, quadratic, and radial basis function; sigmoid kernels; random forest regression; and neural networks (Powell et al., 2020).

Figure 4: Smart Charging Framework



This depicts the control mapping, F, as it maps from uncontrolled to controlled load profiles. The images used in this example are for parking lot size K = 250, with uncontrolled profiles on the left and controlled profiles on the right. This control was calculated using peak minimization.

Source: Powell. 2020. Large Scale Scenarios for Electric Vehicle Load with Controlled Charging.

Scenario-Based Forecasting

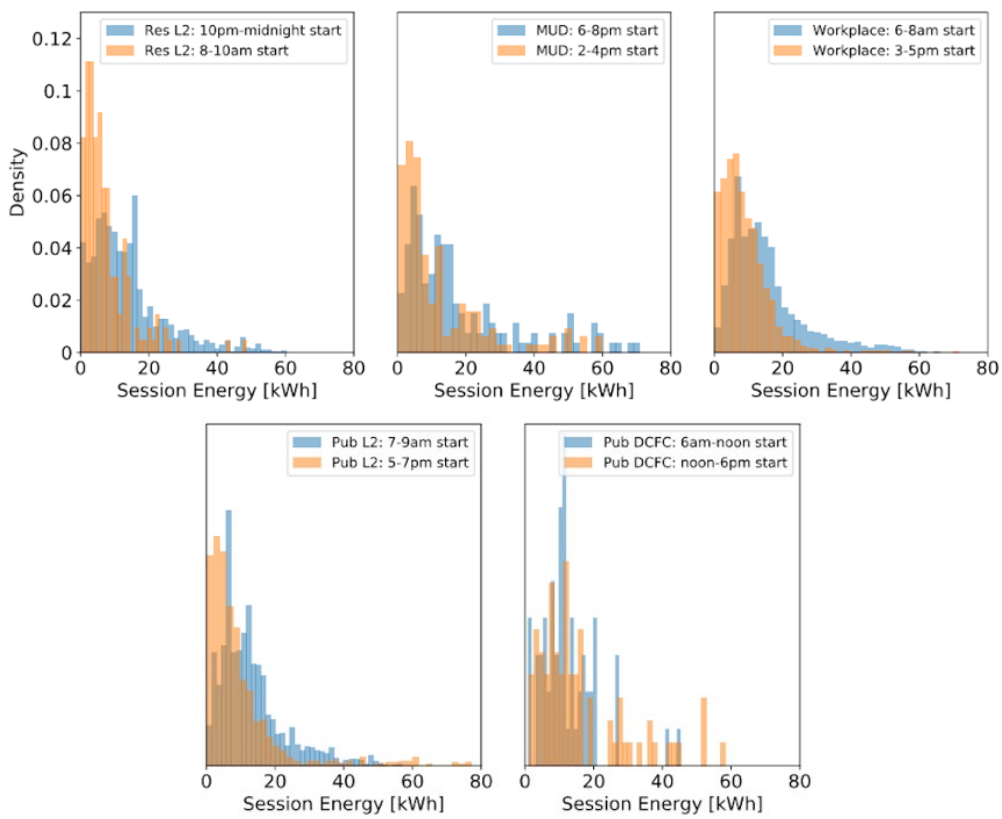
The goal of the forecasting was to generate future EV loads given different variable inputs. For example, how the EV load profile will change if: (1) adoption is higher or lower compared to state and county targets; (2) charging flexibility increases or decreases, if battery technology and thus EV range improves; or (3) more people have access to workplace or DC fast chargers. Many analyses trying to answer these questions fix all variables available in the model but one and generate a profile for several values of that one variable. SCRIPT makes each variable a control knob in the forecasting framework so a user can change one or more variables at once, given their own assumptions, and quickly generate profiles for new scenarios.

As described in the Scenario Generation and Modeling section, above, the approach depended on fitting statistical models to allow the generation of new sample sessions without directly referencing the raw data. SCRIPT used GMMs to achieve this goal.

Separate sessions were fitted for each charging scenario, divided by features such as location and charging level, using the subset of charging session data from that location. Since each location was preconditioned on the charging level, only two additional values were needed to define each uncontrolled charging session: the session start time and energy.

Coupling the start time and energy to model their joint distribution captures important connections between the two and differences in driver behavior for different start times throughout the day. This effect is illustrated in Figure 5. Looking at the workplace charging location, for example, the typical energy for a session starting in the afternoon is lower than for a session starting during the morning peak. Other researchers' analyses of charging data have highlighted the importance of capturing correlations and joint dynamics among different charging parameters (Dias et al., 2018).

Figure 5: Driver Behavior Throughout the Day at Different Charging Locations

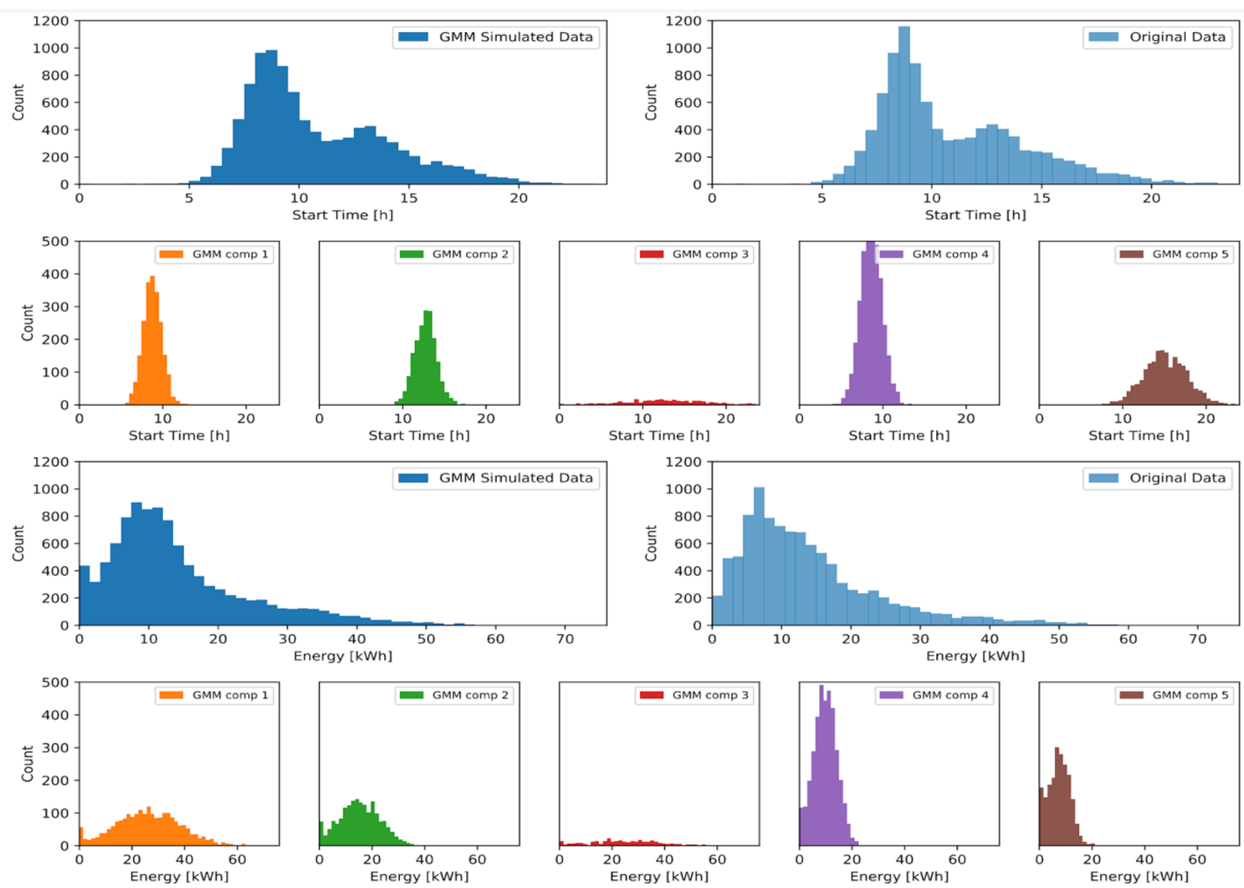


Source: Powell. 2020. Large Scale Scenarios for Electric Vehicle Load with Controlled Charging.

This project found that GMMs captured the distributions of these charging parameters well. An extension on previous work (Quiros-Tortos et al., 2018) was proposed that modeled the joint distribution of the two parameters rather than modeling them each with separate GMMs. A GMM is a weighted sum of G components, each one a multivariate Gaussian (Powell et al., 2020) with mean vector μ_g, covariance matrix Σ_g, and weight in the mixture π_g. The model parameters were fit using maximum likelihood estimation (MLE). In that approach, common to many machine learning applications, an expectation-maximization algorithm is applied to the model likelihood to estimate the parameters μ_g, Σ_g, and π_g. Lastly, to select the number of components in the mixture, G, the Bayesian information criterion (BIC) was used. The GMMs used for different charging locations in the SCRIPT model had values for G ranging between 4 and 8. From the mixture model for Residential L2 charging, components representing the use of timers were removed to create a smooth, uncontrolled residential model. That mixture was used to generate session arrivals and energy requirements for both uncontrolled Residential L2 charging and Residential L1 charging.

Figure 6 shows an example fitting a GMM with five components to weekday workplace L2 charging. The GMM generated 100,000 sessions, and 100,000 sessions were sampled from the raw data to compare and demonstrate the model validation.

Figure 6: Comparison from Simulated Data Using GMM and Original Data



This figure uses the example of weekday L2 workplace charging to illustrate the GMM sessions model. The top two rows of the figure illustrate session start times, taking values between 0 and 24 hours. The bottom two rows illustrate session energies in kWh. The GMM models the two

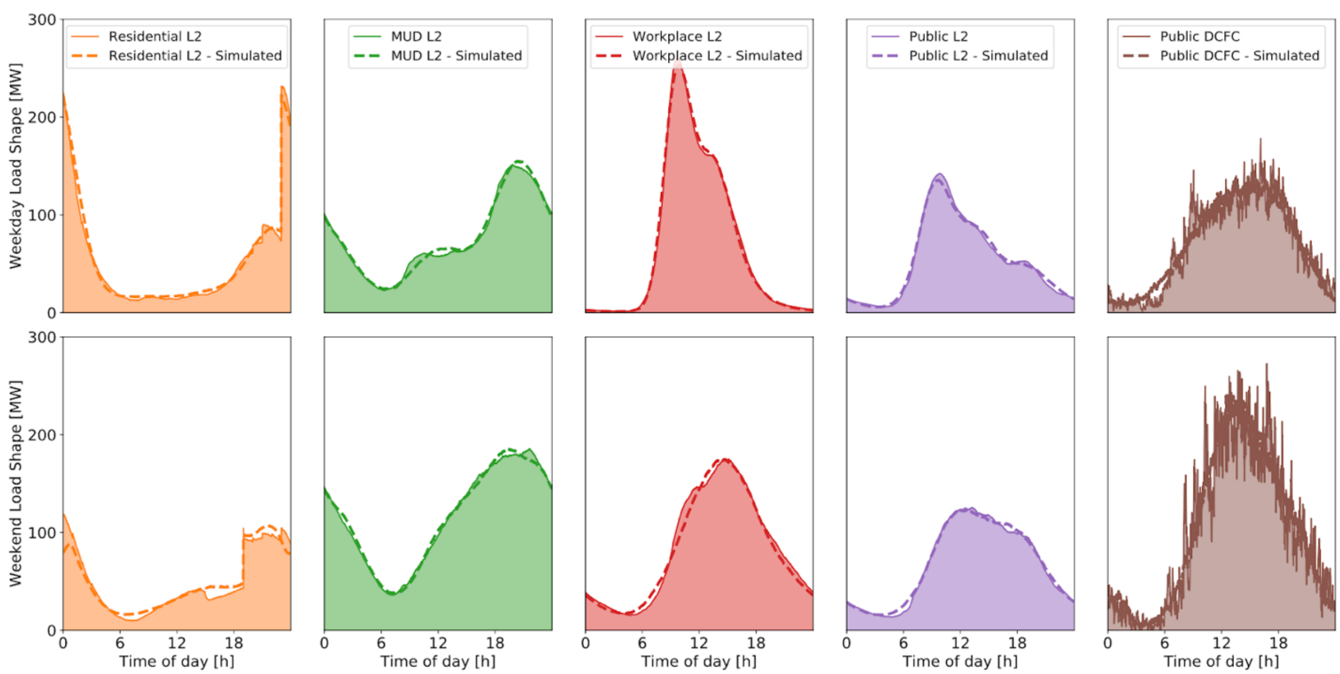
parameters in a joint distribution. Each subsection of the plot includes both the simulated data, showing 100,000 sessions generated using the GMM, and the raw data for 100,000 sessions randomly sampled from the data set. The simulated data is in darker blue on the left, and the raw data is in lighter blue on the right. The simulated energy values are clipped to be non-negative. The GMM used for the simulated data had five components, and each of the 100,000 simulated sessions was generated from one of the component models. The smaller subplots show the samples separated into their five components. According to the weight of each component in the mixture, G, a different number of samples was contributed by each component in the mixture.

Source: Powell. 2020. Large Scale Scenarios for Electric Vehicle Load with Controlled Charging.

There was a good match between the simulated and the raw data, thereby validating this modeling approach. One small difference was introduced by clipping the values for energy, since, with some low probability, the GMMs generate negative values; however, it was found that this had a small impact on the overall model. The distributions in the simulated data were smoother but, overall, the GMMs were a good fit for SCRIPT due to their speed and simplicity.

Figure 7 presents further validation of the model using load profiles for the different charging locations. In each subplot, the dashed line shows the simulated load curve, and the filled line shows a sample of the original data sessions. The project team observed that the simulated load shapes were smoother, especially for the public DCFC location. In each case, increasing the number of components, G, could improve the model fit, but the project found that these simple, cheaper models with 4 to 8 components could represent the load well.

Figure 7: Comparison Between Load Profiles Sampled from GMMs and Original Data at Different Charging Locations



Source: Powell. 2020. Large Scale Scenarios for Electric Vehicle Load with Controlled Charging.

Each load profile in this figure includes 100,000 sessions, on weekdays in the first row and weekends in the second row. To make them comparable on the same axis, the public DCFC scenario included only 50,000 sessions. The project assumed that the rate for L2 charging was

6.6 kW and the rate for DCFC was 150 kW. The high charging level, 150 kW, made the public DCFC location spiky: each session was very short, and only 100 of the 100,000 drivers in the plot need overlap to cause a jump of 10.5 MW. These plots showed 100,000 sessions, not 100,000 drivers, as no adjustments were made for the frequency at which drivers used each charging location. Despite all showing the same number of sessions, differences in session energies seen at each charging location caused the peaks and total energy shown in each plot to be different.

It was possible to observe the impact of timers in the residential charging load, where many drivers have set timers in their chargers or vehicles to delay the start of their session until the lowest price TOU period. The local utility, Pacific Gas & Electric Company (PG&E), has rate schedules for EV drivers to charge at home where the lowest TOU prices begin at 11:00 p.m. or 12:00 a.m. on weekdays and 7:00 p.m. or 12:00 a.m. on weekends. These timers had a significant impact and cause a difficult ramp, especially at 11:00 p.m. on weekdays.

Selected Scenarios

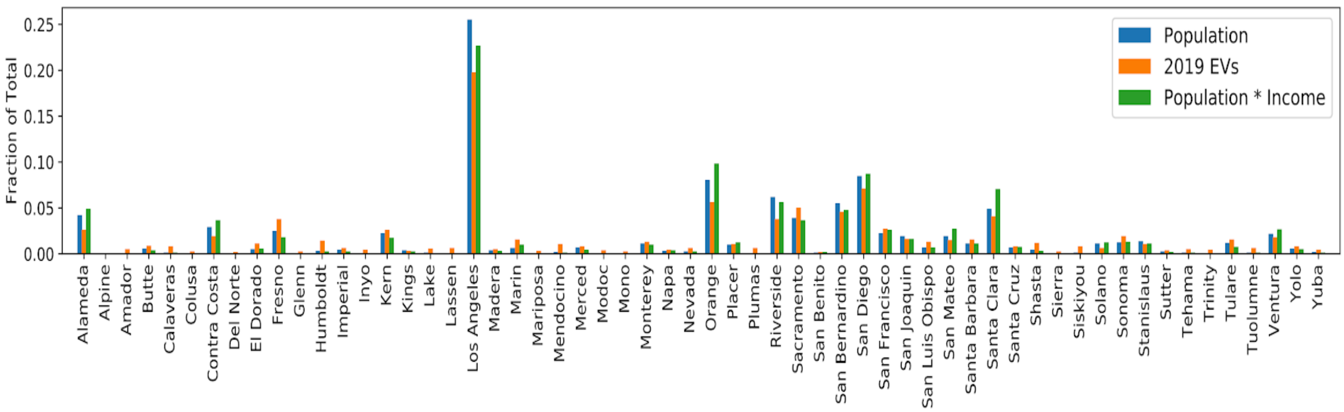
The SCRIPT model was used to study several interesting and important scenarios for California's future EV demand. Each scenario varied the level of EV adoption, the geographic distribution of EVs in California, or the split of drivers between different charging locations. Other assumptions about driver choices were constant across the scenarios.

To select assumptions on the adoption of EVs, several projections and official targets were consulted. As those projections were constantly being revised (usually toward higher levels of EV use), it was decided to include a range of options: (1) Low Adoption, in which there were 1.5 million EV drivers in California by 2030, matching California's previous target before Executive Order B-48-18; (2) the Base Case adoption, in which California met its target of 5 million EVs by 2030 (Office of Governor, 2018); and (3) High Adoption, in which adoption greatly exceeded that level, with 20 million EVs by 2030, passing the 50 percent mark and in closer alignment with the ban on the sale of ICE vehicles starting in 2035 (Newsom & Padilla, 2020).

The vehicle fleet in 2025 and 2030 will be different than that reflected in today's data, both because new technology may enable battery electric vehicles (BEVs) with larger battery capacities and because the large battery capacities observed in some of today's models will become more affordable. In today's data, with a mixture of plug-in hybrid electric vehicles (PHEVs) and BEVs, battery capacities ranged from 10 kWh to 80-plus kWh. Some estimates show that the typical battery capacity for a BEV in 2030 will top 100 kWh (OCDE, 2019). Other estimates suggest that BEVs with battery capacities on the larger end of what is observed today will represent a large fraction of the fleet in 2030 (USDOE, 2020). In the data used, battery capacities greater than or equal to 50 kWh were considered large. The unaltered distribution of battery capacities in the data was labeled as mixed. Conservative estimates were made for the scenarios considered in the analysis. The project assumed that the split of large and mixed battery capacities will be 10:90 in 2025 and 30:70 in 2030.

The decision to purchase an EV is influenced by many factors, including the driver's income, available charging options, travel demand, and the prevalence of EVs in the driver's community (Neubauer et al., 2014). At today's adoption levels, it is assumed that the limited range of models and the high upfront costs of purchasing a BEV have led to concentrations in urban and high-income communities. At the county level in California, this effect is less pronounced. Figure 8 shows the distribution of EVs per county compared with the population distribution.

Figure 8: EV Distributions by County in California



Three distribution cases are shown: first, by population; second, as they were in 2019; and third, a calculation convolving population with income.

Source: SLAC National Accelerator Laboratory.

This effect is expected to diminish toward 2030, as prices decrease and as policies that support equitable adoption continue. To approximate that change, a combination of population and income was used to define the geographic distribution.

One scenario used to study the impact of this assumption was an equitable scenario, where the distribution was purely by population.

The project team observed that many drivers charge less frequently than daily, and the typical frequency depends on which charging location they use most frequently. To account for this effect in the scenarios, the project assumed that residential and workplace drivers — those who depend on charging at home or at work — would charge nearly daily out of habit and assigned on average an 80 percent probability of charging on a given weekday. For workplace drivers, that decreased to just 10 percent on weekends. The project further assumed that public drivers — those who depend on either L2 or DCFC charging at public charging stations — have on average a 50 percent probability of charging on a given weekday.

The final key input was the split between different charging locations. For all scenarios, it was assumed that 10 percent of residential drivers live in multi-unit dwellings (MUDs) and follow the MUD charging pattern. In California, approximately 40 percent of the population lives in a MUD; but there are many barriers to installing and depending on charging at MUDs, so many of those drivers depend on public or workplace charging instead (Chakraborty et al., 2019). Another assumption made was that 55 percent of the drivers charging at single-family residences would use L1 charging and 45 percent would use L2 charging, which could be manipulated using timers.

The Base Case scenario assumed that most drivers would depend on residential charging (80 percent), followed by workplace (10 percent) and public (10 percent, split evenly between L2 and DCFC). This breakdown is similar to charging behavior seen today (Wood et al., 2018).

Many analysts discuss the possibility that more available public charging and rapid, gas station style, fast charging will shift a significant number of drivers away from residential charging (Engel et al., 2018), including many drivers whose adoption is enabled by those public options. The Fast-Public scenario considered that possibility, where public L2 accounted for 20 percent of drivers and public DCFC accounted for 20 percent of drivers. In that scenario, residential charging was reduced to 50 percent of drivers and workplace charging stayed at 10 percent.

There is also significant interest in California in accelerating adoption of workplace charging. Workplace charging has many benefits to the grid: it is more easily controllable than residential or public charging, and its natural timing aligns well with California's surplus of solar energy during the day. As the fraction of solar energy in California's generation mix continues to increase, shifting EVs to those hours presents a significant opportunity.

To capture that possibility, two further scenarios were included: (1) the Work-Public case, a cross between the two where 15 percent of drivers depend on workplace charging; and (2) the Work case, where 40 percent of drivers depend on workplace charging. In the Work-Public case, 20 percent of drivers depend on public charging, split 15 percent and 5 percent between L2 and DCFC, respectively, and the remaining 60 percent continue to use residential charging. In the Work case, only 10 percent of drivers depend on public charging and 50 percent depend on residential.

Altogether, these assumptions and alternatives define the project's seven scenarios: Base Case, Low Adoption, High Adoption, Fast-Public, Work-Public, Work, and Equity. The parameters, which vary between scenarios, are summarized in Table 1.

Table 1: Scenarios Selected for Analysis

	Adoption: Number of Drivers	Geographic Distribution	Charging Location Split as % of Drivers (Res, Work, Pub L2, Pub DCFC)
Base Case	2025: 1.5 million 2030: 5 million	Current distribution x population distribution	(80, 10, 5, 5)
Low Adoption	2025: 1 million 2030: 1.5 million	As in Base Case	As in Base Case
High Adoption	2025: 5 million 2030: 20 million	As in Base Case	As in Base Case
Fast-Public	As in Base Case	As in Base Case	(50, 10, 20, 20)
Work-Public	As in Base Case	As in Base Case	(60, 15, 15, 5)
Work	As in Base Case	As in Base Case	(50, 40, 5, 5)
Equity	As in Base Case	By population	As in Base Case

Source: SLAC National Accelerator Laboratory.

Each assumption was studied separately to highlight its effect on the analysis presented in this report; however, many other scenarios are possible, including combinations of multiple scenarios and elements in this set.

The controlled charging case for each of these scenarios was implemented for the workplace location with PG&E's E19 rate structure. Rather than adjusting or adding new timers to control the residential charging location, these scenarios kept the base level of timer control observed in the data, wherein approximately 30 percent of drivers set timers for 11:00 p.m. or 12:00 a.m. on weekdays and 7:00 p.m. or 12:00 a.m. on weekends.

Cost-Benefit Analysis

To evaluate the impact of SCRIPT's EV charging load shapes, a cost-benefit assessment was conducted. The team leveraged E3's expertise and its EV Grid model to add cost-benefit functionality to the SCRIPT tool and to perform an analysis on the SCRIPT load shapes for several relevant scenarios (see the Selected Scenarios section, above). E3's EV Grid model evaluates the individual costs and benefits incurred across multiple stakeholder perspectives on an annual basis for the lifetime of each EV. Values include the upfront costs and benefits associated with the adoption of an electric vehicle, as well as ongoing lifetime costs and benefits associated with the vehicle's charging behavior and displacement of gasoline. The results show the net present value (NPV) of all costs and benefits as both a total for a given region and on a per-electric-vehicle basis. Results can be presented as total NPV benefits or costs or as a benefit-cost ratio, where total benefits are divided by total costs. A benefit-cost ratio of 1.0 or greater indicates that EVs produce greater benefits than costs from that stakeholder perspective.

Cost-Benefit Perspectives

Because EV adoption and associated charging can affect many different stakeholders, it is important to evaluate costs and benefits incurred from multiple perspectives. E3's cost-benefit assessment evaluates three different stakeholder perspectives: EV drivers (the participant cost test, PCT), utility customers (the ratepayer impact measure, RIM), and the state or county (total resource cost, TRC).

Participant Cost Test

The participant cost test is the most intuitive cost test for EV adoption, as it is used to examine the costs and benefits incurred from the perspective of EV drivers. Costs include the upfront cost premium of an EV over a conventional ICE vehicle, ongoing electricity bills based on the vehicle's charging load shape and utility rate, and the cost of installing charging infrastructure at home. Benefits include any upfront EV incentives (for example, a federal tax credit), the savings from avoided gasoline purchases, and operations and maintenance (O&M) savings from an EV compared to an ICE vehicle.

Ratepayer Impact Measure

The ratepayer impact measure (RIM) test considers the effect of the EV charging load on all electric utility customers. The RIM examines the cost to the utility and its ratepayers to supply electricity for the incremental load from EVs compared to the benefit of additional revenue to the utility in the form of EV customer bills. If the RIM test shows that benefits are greater than costs (a benefit-cost ratio of greater than 1.0), then the test indicates that all utility ratepayers who do not drive EVs still benefit from EV adoption because the additional utility revenue from EV adoption results in downward pressure on rates.

Total Resource Cost

Finally, the total resource cost (TRC) combines all perspectives to look at the costs and benefits of EVs from a regional outlook — in this case, each county in California or the whole state. The costs on a regional perspective include the upfront incremental cost of EVs, the electricity supply cost to serve the EV load, and regional charging infrastructure costs to support the region's level of EV growth. Benefits include the avoided spend on gasoline, reduced O&M costs relative to ICE vehicles, and any upfront vehicle incentives. Utility bills paid by the drivers are not shown in the TRC because these represent a cost to EV drivers but a benefit to the utility and thus net out in the TRC's regional outlook.

Because the TRC combines individual perspectives to showcase costs and benefits incurred by different entities (that is, the driver and the utility), it can be used to show whether a region is better off due to EV adoption. The TRC is often considered to represent policy makers' perspectives to show whether certain policies or programs may benefit their jurisdiction. In this case, the TRC may be used to help inform policy makers as to whether EV adoption will bring overall benefits to their area.

Data Inputs

Vehicle Adoption Forecast

The Base Case scenario was designed to meet the state's transportation electrification goals. In 2012, then-Governor Jerry Brown issued an executive order establishing a goal of 1.5 million zero-emission vehicles in California by 2025 (Office of Governor, 2012). In 2018, Governor Brown issued another executive order to extend this goal, with a 2030 target of 5 million zero-emission vehicles (Office of Governor, 2018). The Base Case assumed that these goals would be met entirely with EVs. E3 interpolated linearly between the current adoption in 2020 and the targets of 1.5 million EVs in 2025 and 5 million EVs in 2030 to produce an annual trajectory of EV adoption in California from 2020 through 2030.

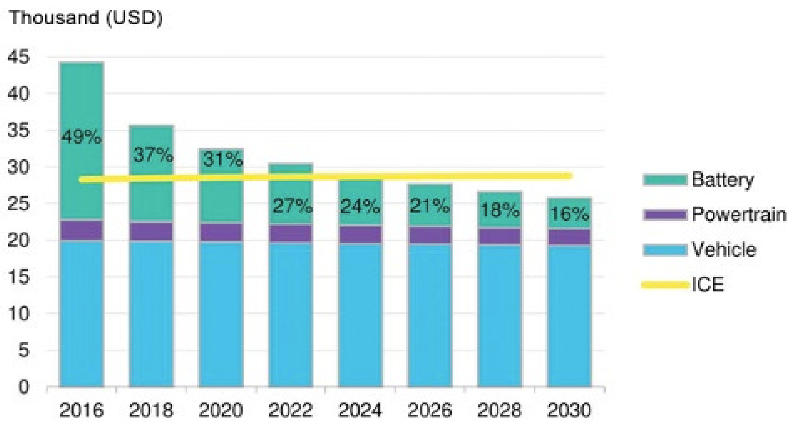
To consider the costs and benefits on a county level, the team allocated the total statewide adoption trajectory to individual counties in California. The allocation to each county is described in the Selected Scenarios section, above.

Incremental Upfront EV Cost

One of the key costs for EVs is the cost premium of an electric vehicle compared to a conventional ICE vehicle. While EV costs are expected to decline over time and eventually reach price parity with ICE vehicles, the near-term incremental costs are an important variable to consider when evaluating the economics of EVs.

E3 generated an annual forecast for cost premiums of EVs based on the cost projections in the Bloomberg New Energy Finance (BNEF) "Electric Vehicle Outlook" report. This forecast through 2030 is shown in Figure 9.

Figure 9: Electric Vehicle Price Forecast Relative to ICE Vehicles



Source: Bloomberg NEF. 2019. "Electric Vehicle Outlook 2019."

The projections used are shown in BNEF's forecast to produce a trajectory of incremental vehicle prices from 2020 to 2024. While the BNEF forecast shows EVs becoming cheaper than ICE vehicles after 2024, E3 took a more conservative approach and assumed that price parity was maintained from 2025 onward. If the analysis had assumed that EVs become cheaper than ICE vehicles after 2024, as shown in the BNEF forecast, the results would have greater net benefits.

Federal Tax Credit

The current United States federal tax credit is up to $7,500 for the purchase of an electric vehicle. This amount varies based on vehicle battery size, and it phases out for each vehicle original equipment manufacturer (OEM) once the OEM reaches sales of 200,000 electric vehicles. E3 assumed that all vehicles in the forecast were full BEVs and thus would be eligible for the entire $7,500 amount as long as it was available. To consider the gradual phase-out by OEMs, E3 considered EV sales data for each OEM and the number of vehicles that could be sold with the full credit amount (EV Adoption, 2020). E3 estimated the average year when each OEM would lose access to the credit and determined that, on average, new vehicles purchased through 2023 would be eligible for federal tax credits.

Other incentives, such as California's Clean Vehicle Rebate Project, utility incentives from the Low Carbon Fuel Standard (LCFS) program, and other local incentives, are not included in this analysis. The TRC represents costs and benefits within a region, and these statewide or local incentives would net out in the TRC since they represent a transfer of funds within the region (that is, a cost to one entity and a benefit to the participant). Additionally, the long-term availability of these incentive programs is unknown. By not including these incentives, the cost-benefit assessment takes a conservative approach to analyzing the impacts of EVs. If these incentives were included, they would further increase the benefits shown in the TRC and participant cost tests and would improve the overall net benefits of EV adoption.

Vehicle Maintenance Savings

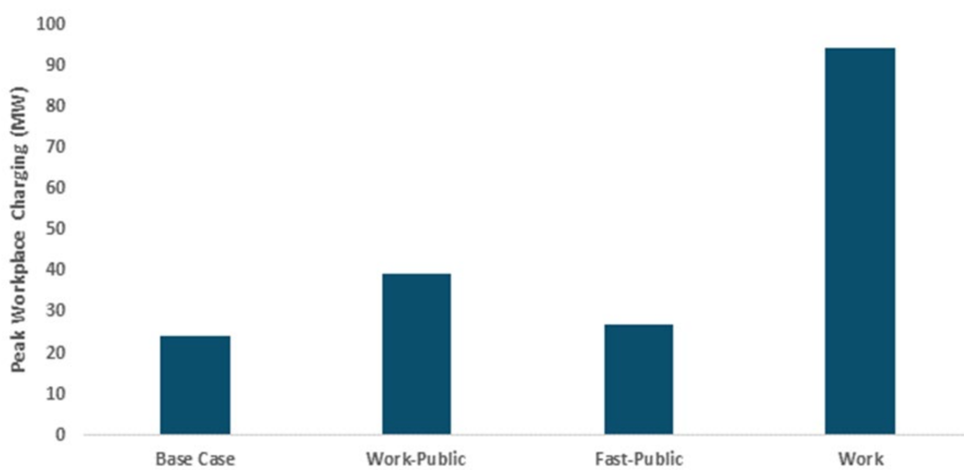
EVs offer O&M savings compared to ICE vehicles. For example, EVs experience less wear and tear on brakes due to their use of regenerative braking, and EVs do not require oil changes because of the electric motor (US DOE, 2020). E3 calculated annual O&M savings for EVs compared to ICE vehicles based on AAA-reported O&M cost data (AAA, 2019) and then adjusted for typical car repair labor costs in California (CarMD, 2017). For the purposes of this analysis, BEVs are estimated to offer $253 per year in O&M savings compared to ICE vehicles.

Charging Infrastructure Need

E3 leveraged the Electric Vehicle Infrastructure Projection Tool Lite (EVI-Pro Lite model) (USDOE, 2021) developed by the National Renewable Energy Laboratory (NREL) to calculate the estimated EV charging infrastructure needed to support the number of vehicles in the adoption forecast. Using the EVI-Pro Lite model, E3 calculated the number of public L2, public DCFC, and workplace L2 charging ports needed to support 1.5 million EVs in California and then converted the number of ports into a ratio of the number of EVs per port. The ratios of the number of EVs per port were used in the cost-benefit model to determine how many charging stations of each type (public L2, public DCFC, and workplace L2) would need to be built in each county in California to support the EV adoption forecast.

For the sensitivities run with higher levels of public or workplace charging access (Fast-Public, Work-Public, and Work scenarios), E3 adjusted the level of charging infrastructure relative to the Base Case in proportion with the new peak loads at a given location. For example, Figure 10 shows the peak workplace charging load for San Francisco County in 2030 for the different charging sensitivities. The number of workplace charging ports was adjusted for each scenario based on the peak load at workplaces in the sensitivity scenario relative to the workplace peak load in the Base Case. Likewise, public L2 and DCFC infrastructure was adjusted based on those peaks in each sensitivity relative to the Base Case.

Figure 10: Workplace Charging Peak Load for Sensitivity Scenarios, San Francisco County 2030



Source: Bloomberg NEF. 2019. "Electric Vehicle Outlook 2019."

Charging Infrastructure Cost

There are two main cost components associated with EV charging stations: first, the electric vehicle supply equipment (EVSE) cost, which is the charging station itself; and second, the "make-ready" costs, which refer to the infrastructure from the utility's service drop to the EVSE. In other words, the make-ready is the infrastructure needed to make a parking spot ready to support an EVSE. Each charging infrastructure type was assigned an EVSE cost and a make-ready cost.

Residential charging infrastructure costs are included as part of EV driver costs in the participant cost test. Public charging infrastructure costs, such as public L2, workplace L2, and public DCFCs, plus residential charging costs, are included in each region's TRC test. Public and workplace charging costs may be incurred by utilities through their charging infrastructure programs, individual site locations, or third-party investors such as EV service providers. The charging infrastructure cost assumptions (HomeAdvisor, 2020) are shown in Table 2.

Table 2: Charging Infrastructure Cost Assumptions

Charging Station Type	EVSE Cost	Make-Ready Cost
Residential L2	$600	$1,600
Public and workplace L2	$4,600	$19,300
DC fast charger (DCFC)	$96,100	$97,400

Source: SLAC National Accelerator Laboratory.

Electricity Supply Costs

To evaluate the cost of electricity from utilities to serve the new EV load, E3 used outputs from the California Public Utilities Commission's (CPUC) Avoided Cost Calculator (ACC). The ACC produces electricity supply cost components as annual hourly costs (annual costs for 8,760 hours per year) for the three large investor-owned utilities (IOUs) in California — PG&E, Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The ACC provides these costs by IOU utility territory and by California building climate zones.

The ACC leverages outputs from the CPUC's Integrated Resource Plan, proceeding to align the ACC output hourly estimated costs for evaluation of distributed energy resources with the state's supply-side planning. The electricity supply costs considered in the cost-benefit assessment include the following four components.

- *Energy Costs:* The utility's cost to procure electricity to serve the system load in each hour of the year
- *Generation Costs:* The utility's cost to procure additional capacity to meet the system peak in each hour
- *Transmission and Distribution Upgrade Costs:* The utility's cost to upgrade the transmission and distribution network to meet local grid peaks

- *Greenhouse Gas Costs:* The utility's cost of cap-and-trade compliance, as well as the cost to procure GHG-free resources to meet the CPUC's Integrated Resource Plan targets

E3 leveraged the ACC's hourly electricity supply cost components for each IOU and building climate zone. It is important to note that the IOUs do not cover all areas of the state — IOUs serve approximately 75 percent of customers in California (US EIA, 2018). Individual counties may include areas that are not served by one of the three IOUs or that may overlap multiple utilities and climate zones. For simplicity in this analysis, each county was assigned one set of electricity supply costs for the closest IOU and climate zone.

Electricity Bills

E3 used current rates from each IOU to calculate the customer bills for EV charging in each county. As with the electricity supply costs, each county was assigned the rates from the closest IOU as a simplification, even though each county may have areas not served by that IOU.

Each type of load profile was assigned an appropriate rate type. For residential charging, E3 leveraged each IOU's EV-specific residential rate. For workplace and public L2 charging, E3 used each IOU's medium-sized commercial rate, and for DCFC charging, E3 used each IOU's large-sized commercial rate or an EV-specific large commercial rate, if applicable, as with SCE. Table 3 shows the rates used for each IOU.

Table 3: Rates Modeled for Each Load Shape Type by Utility

Utility	Residential TOU	Workplace & Public L2	Public DCFC
PG&E	EV2-A	A-10	E-19
SCE	TOU-D-PRIME	TOU-GS-2-Option D	TOU-EV-8
SDG&E	EV-TOU-5	AL-TOU	AL-TOU

Source: SLAC National Accelerator Laboratory.

One important component of customer bills from EV charging is the demand charge. The commercial rates used to model the workplace and public utility bills include demand charges, which are based on the peak demand that the customer's meter reaches each month. If the EV charging is on the same meter as a building's meter, the total peak load used to calculate the demand charge is the peak for the building and the EV charging load combined. To calculate the total demand charge, E3 used building load profiles for workplace and public buildings for Climate Zone 6 (representing Los Angeles) based on Title 24 2016 building standards, with a few minor changes to reflect anticipated 2019 standards updates. For workplace locations, E3 used a sample building load profile for a medium-sized office building with no rooftop solar. For public locations, E3 used the load profile of a strip mall with no rooftop solar. For DCFCs, E3 assumed that the charging stations were on their own meter and thus did not have building load impacts.

It is important to note that these costs represent the bills paid to the utility for the charging. In some cases, such as workplace charging or public charging, the utility rate may not be passed through to the driver (for example, if the charging location chooses its own flat rate for drivers to pay, instead of the utility's TOU rate). In some cases, workplaces or other locations offer free EV charging as an amenity. For simplicity, it was assumed that the utility rates paid by the charging site host are passed through directly to the driver. If the driver-facing rates used by charging station site hosts were significantly different from the utility rates, the PCT results would change accordingly. An EV driver who has access to free workplace charging, for example, would have greater net benefits in the PCT than shown here. The TRC and RIM results would remain the same, since the TRC test does not include utility bills and the RIM test considers the bills paid to the utility by site hosts.

Avoided Vehicle Gasoline

Because electricity costs to charge an EV are included as a cost to EV drivers, it is important to consider gasoline costs avoided as a benefit to EV drivers to fully represent the fuel costs incurred and avoided by driving an EV instead of an ICE vehicle. E3 used gasoline price forecasts from the federal Energy Information Administration's "Annual Energy Outlook 2019."

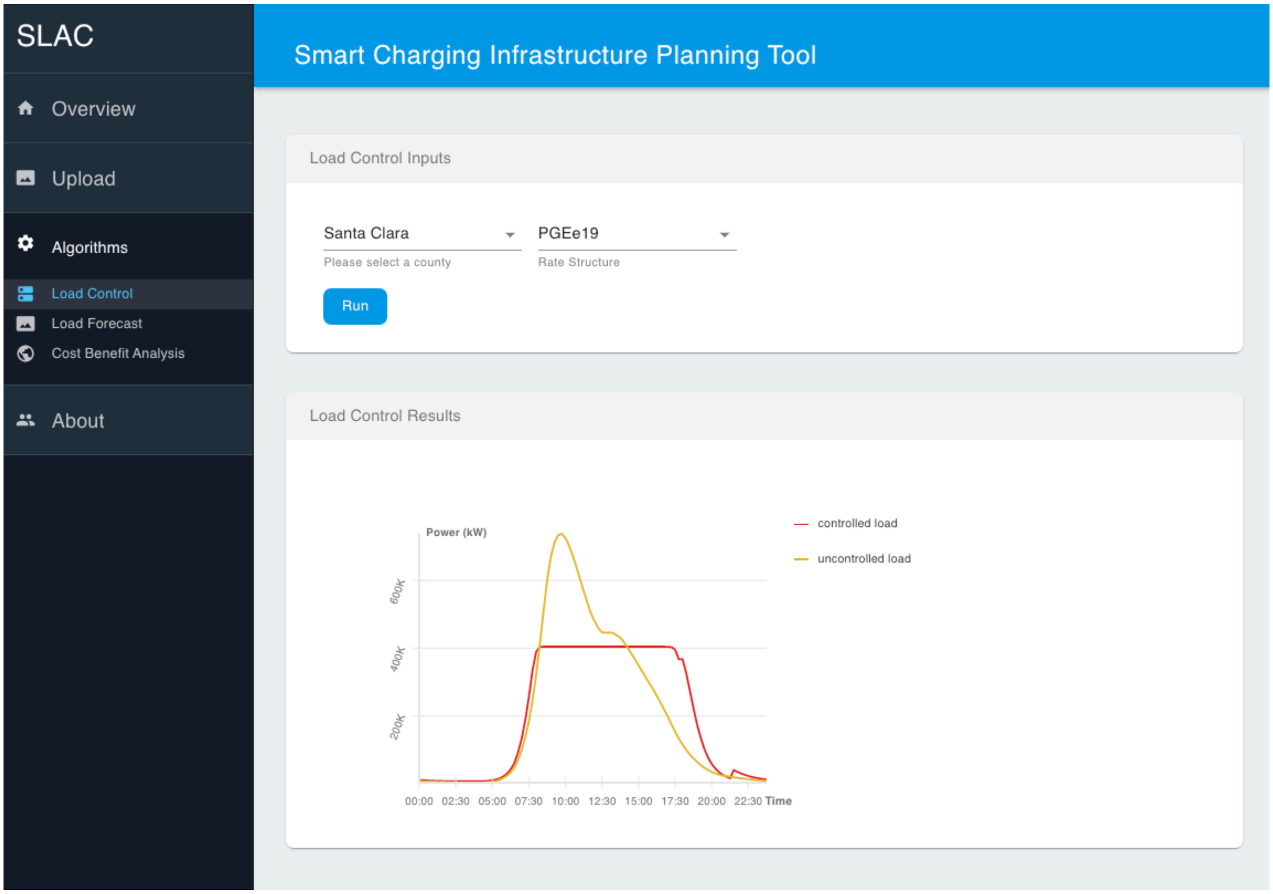
To calculate the avoided gasoline consumption, each EV is compared with a new ICE vehicle procured the same year. For example, an EV procured in 2022 was assumed to have the annual avoided gasoline consumption based on the expected fuel efficiency of a new ICE vehicle in 2022. E3 assumed annual fuel efficiency improvements in new ICE vehicles to account for ICE vehicles becoming more efficient over time.

Interface Block Design

The Interface block design is where users can interact dynamically with the tool and generate their own scenarios and analysis. This is where the different aspects of the project — smart charging, load forecasting, and cost-benefit analysis — come together.

Figure 11 shows the smart charging capabilities of the tool called *Load Control*. This section of the tool enables the user to choose a county and a rate structure and shows how the aggregated workplace load profile can be modified if load is controlled through that smart-charging strategy.

Figure 11: SCRIPT Load Control User Interface



Source: SLAC National Accelerator Laboratory.

Figure 12 shows the *Load Forecast* part of the SCRIPT tool. This section enables multiple user inputs to generate an EV load profile. The user has the following control knobs available.

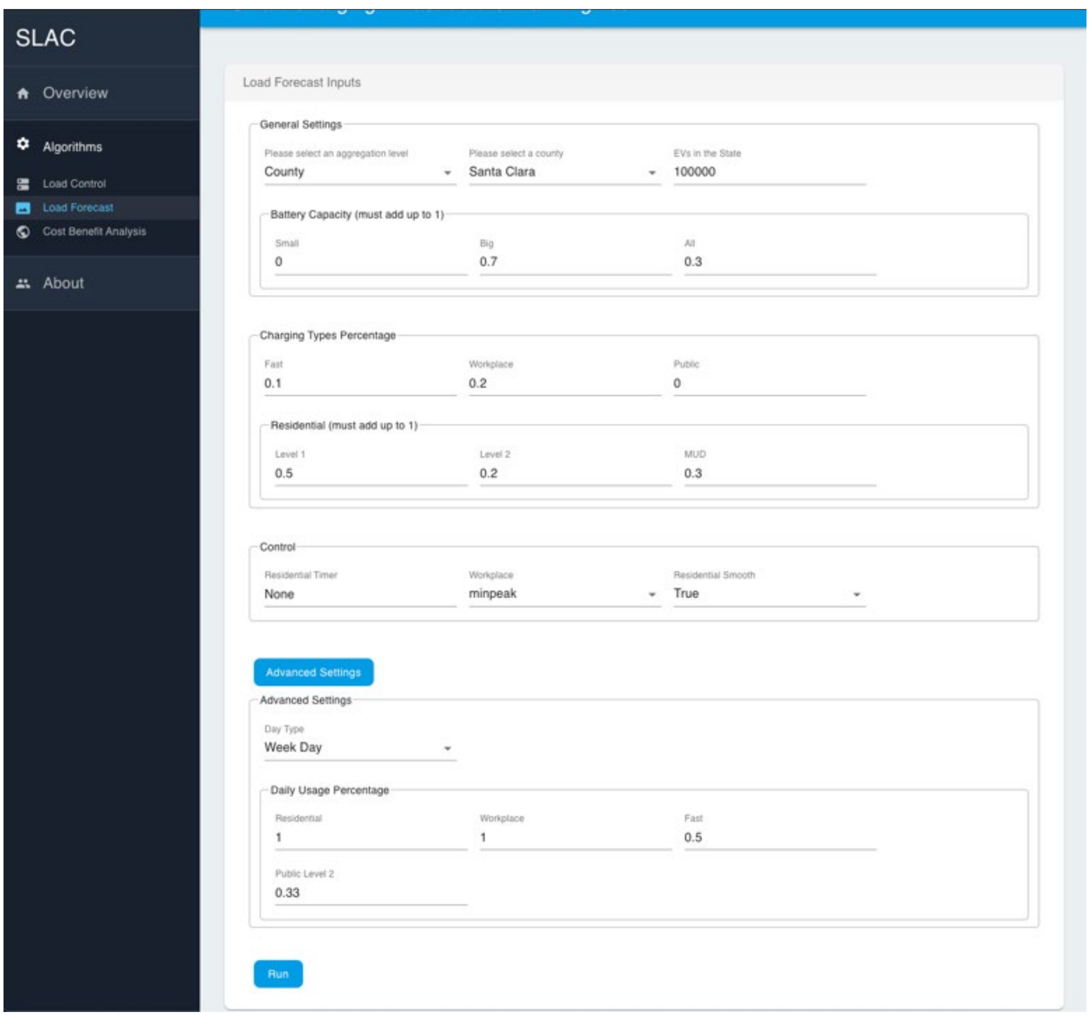
- *Aggregation Level:* This input can be either the entire state or a specific county. If the county option is selected, the user has the alternative to choose the county in which the analysis will be performed.
- *Number of EVs in the State:* This input enables the user to choose how many EVs there will be in the entire state. If a county analysis is chosen, the tool calculates the number of EVs for that county as a percentage of the total number in the state, based on the underlying distribution of EVs per county described in the Selected Scenarios section, above.
- *Battery Capacity:* This input lets the user pick a mixture of vehicle battery sizes for the analysis, as a percentage. Small batteries are those with a capacity less than 50 kWh, and large batteries are those with a capacity greater than or equal to 50 kWh. The model then randomly samples batteries within each category. The All field samples from both Small and Big, according to the base distribution in the data set.
- *Charging Type:* This input lets the user pick how the drivers will be split across the different charging locations and rates, in effect determining which locations and rates

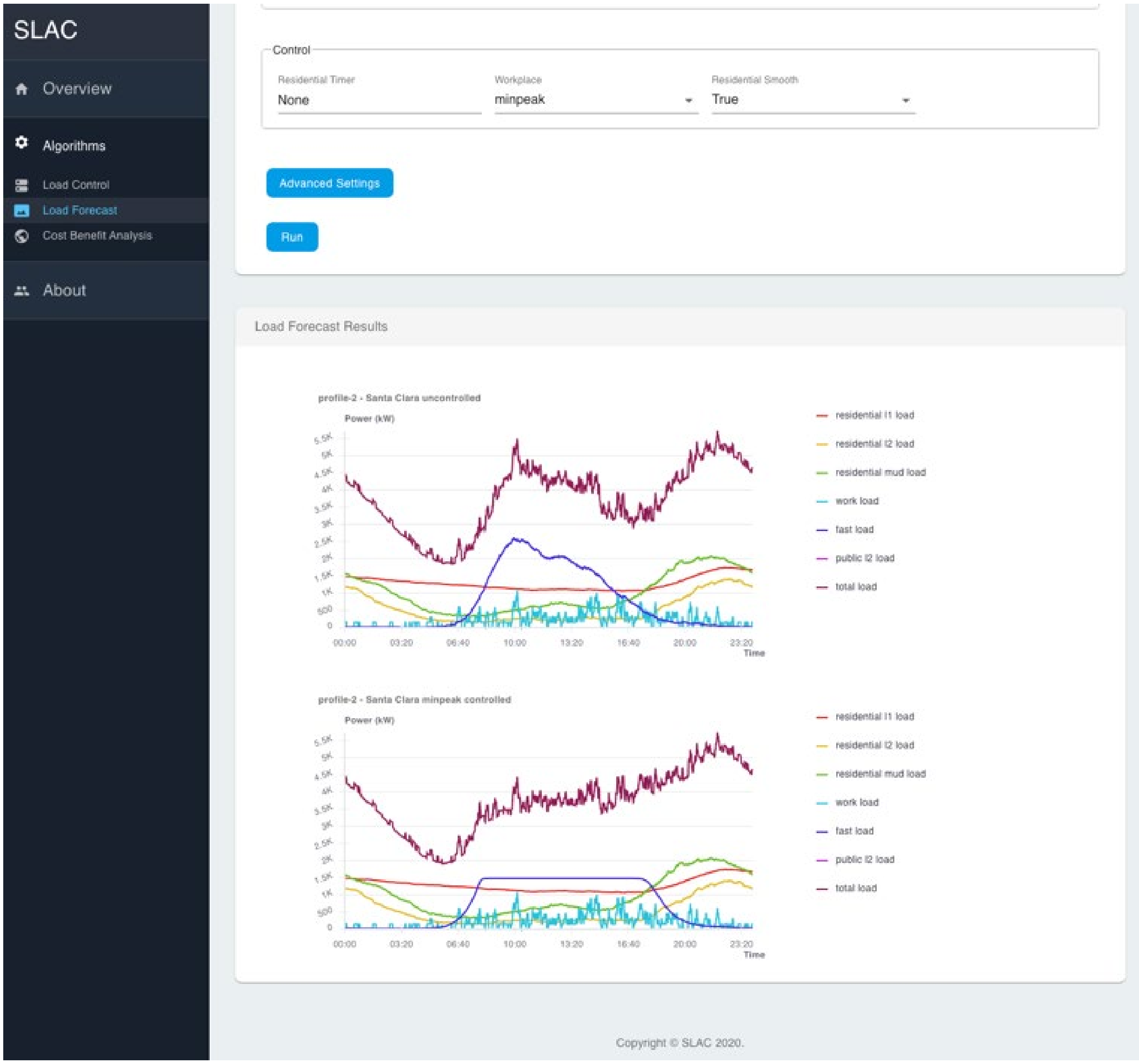
will dominate the load profile for the user's scenario. The locations and charging levels available are fast-public DCFC, public L2, workplace L2, and residential. The residential charging location is divided into three main categories: single L1, single L2, and MUD L2. The combination of these three must add up to 1.

- *Control:* This allows the user to pick the type of control to use for analysis. For the residential location, the available control is to add timers; and for the workplace location, there are multiple options based on the rate structure one is interested in exploring.
- *Day Type:* Within the Advanced Settings tab, the user can choose whether the analysis is targeting weekday or weekend load. Finally, there is the option to tune one parameter of driver behavior through the daily usage percentage, which determines how frequently drivers in each section charge as a percentage probability that they will charge on a given day.

The output of this section shows the profiles, uncontrolled and controlled, generated for each charging location. This section will also let the user save up to four profiles to be used by the Cost-Benefit Analysis section, above.

Figure 12: SCRIPT Load Forecast User Interface

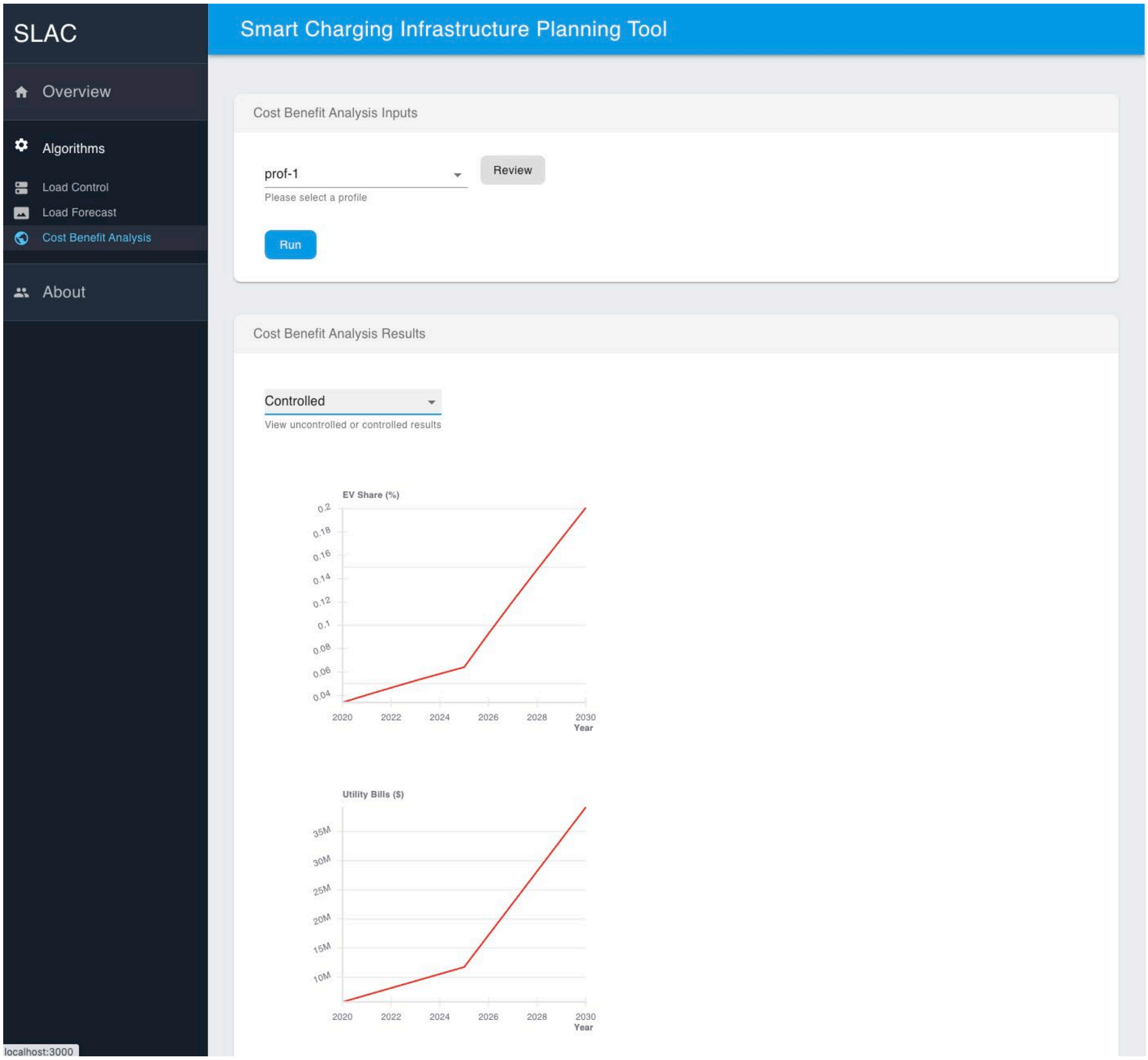




Source: SLAC National Accelerator Laboratory.

Figure 13 shows the last section in the tool, the Cost-Benefit Analysis (CBA). From the profiles generated in the *Load Forecast*, the user can select from the saved profiles to run the analysis. After running the CBA analysis, the user can see the different metrics the tool generates for both uncontrolled and controlled profiles.

Figure 13: SCRIPT Cost-Benefit Analysis User Interface



Source: SLAC National Accelerator Laboratory. All information about the code and how to use it can be found in the GitHub repository: https://github.com/slacgismo/SCRIPT-tool.

CHAPTER 3: Project Results

This chapter provides an analysis of the results obtained from each of the blocks described in Chapter 2: Project Approach. The results demonstrate the successful development of a tool, SCRIPT, that enables stakeholders to: generate multiple scenarios for future EV charging under different assumptions of adoption; evaluate the potential of smart charging in changing the overall load profile to reduce grid congestion and maximize solar photovoltaic system use; understand the effects that investments in different charging locations have on the EV load; and perform an assessment of the costs and benefits to the region, EV owners, and rate-payers. The simple, fast, and intuitive flexibility of this tool fills a gap in the research community.

The organization of this chapter follows the same workflow as the software tool itself. It starts with key insights derived from the data. It then shows the results of the forecasted load profiles generated for each of the selected scenarios. The load profiles are included for both uncontrolled (without smart charging) and controlled charging (with smart charging). Following those results, a cost-benefit assessment of each of the profiles is performed and the benefits to the region, ratepayers, and EV owners are quantified. The chapter ends with comments regarding the key lessons learned throughout the project and future research directions.

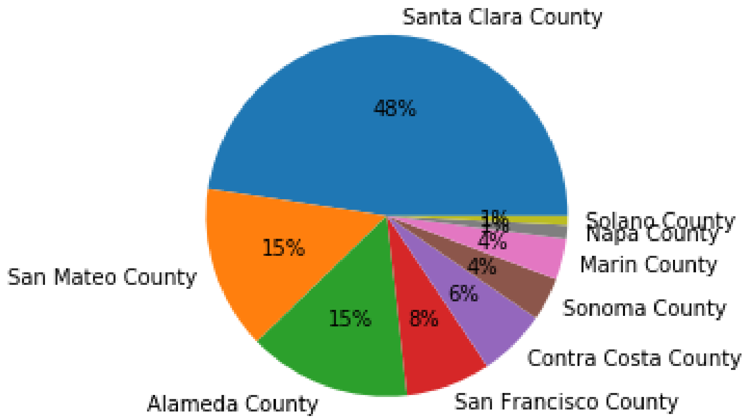
General Statistics of the Available Data Set

From the data set of EV charging obtained for this project, general statistics were calculated to illustrate the data set's distribution in different dimensions. Some of the main data set characteristics are presented here, with the data having been cleaned and preprocessed.

Breakdown by County

Figure 14 shows the breakdown of driver home counties for all drivers in the data set. More than 119,000 drivers are included in this analysis. Santa Clara county has the largest number of EV drivers with 48 percent, followed by San Mateo and Alameda, each with 15 percent.

Figure 14: Percentage of Drivers per Home County



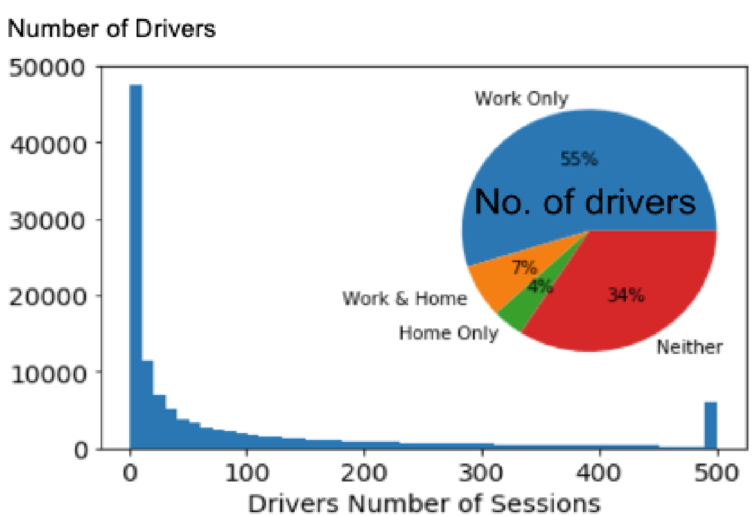
The majority of the drivers (48 percent) are from Santa Clara, followed by San Mateo (15 percent), Alameda (15 percent), and San Francisco (8 percent). The remainder are distributed among other counties in the Bay Area.

Source: SLAC National Accelerator Laboratory.

Breakdown by Different Charging Location and Drivers

The data set provided the charging location where drivers were charging, for example workplace, home, retail, parking, education, and many others. Figure 15 shows the number of sessions for each driver in the data set through a histogram, and it includes a pie chart showing the breakdown of how many drivers use only workplace charging, only home charging, both workplace and home charging, or neither workplace nor home charging. Fifty-five percent of drivers charge only at work, 7 percent charge both at work and at home, 8 percent charge only at home, and 34 percent charge at other charging locations. Many of the drivers have very few sessions in this data set, likely because their main sources for charging are outside the ChargePoint network. There are, however, thousands of drivers who charge frequently in this data set, as depicted in the histogram.

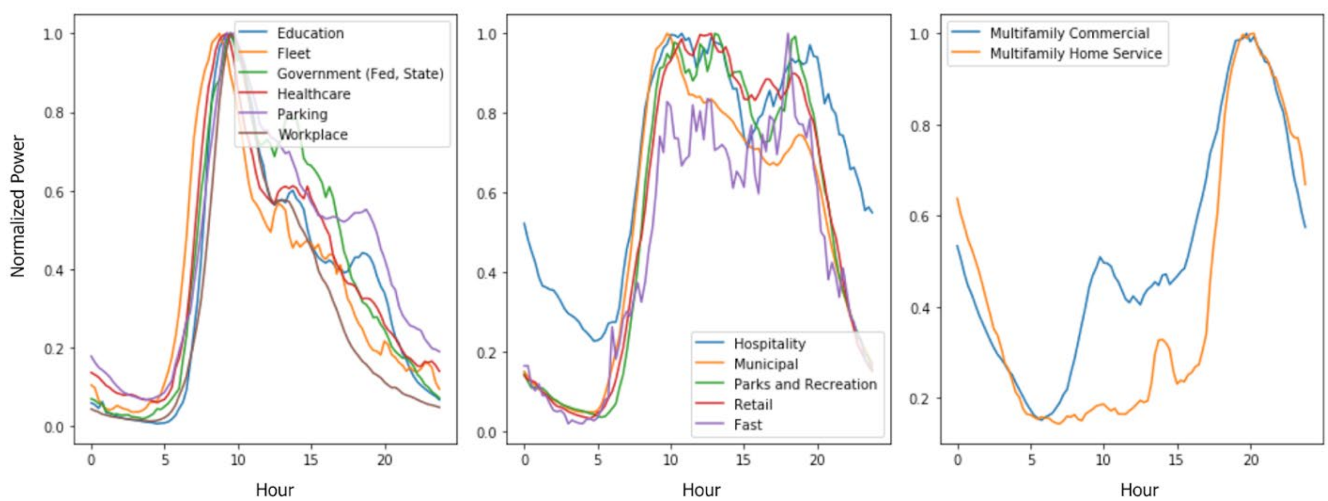
Figure 15: Driver Statistics by Charging Location and Number of Sessions



Source: SLAC National Accelerator Laboratory.

Looking at the different charging locations available in the data set, a typical weekday load shape was calculated for each. Those shapes were clustered together using K-Means clustering, which highlights the charging locations that had the most similar profiles. This method was used to derive fewer charging locations capable of representing the data set. Figure 16 shows the locations that were clustered together for K=3.

Figure 16: Clustered Charging Locations Based on Weekday Normalized Load Profile

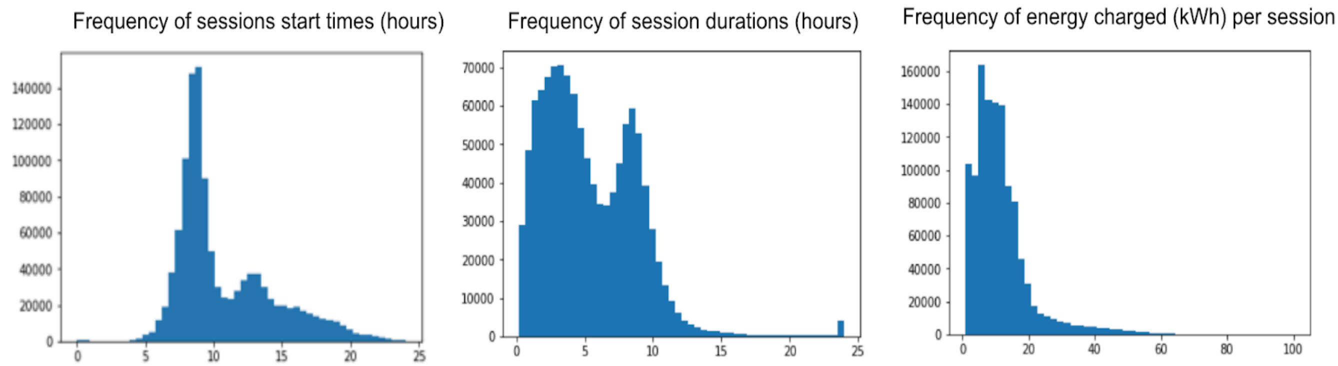


Source: SLAC National Accelerator Laboratory.

The plot on the left in Figure 16 shows load profiles typical of workplace charging, with a peak in the morning and a smaller one early in the afternoon. Several public charging locations fall into this workplace pattern, including charging stations located at government, healthcare, and education sites. This may be because those stations, while open to the public, are most often used by drivers who work at those locations. The middle plot shows load profiles typical of the public category, where load is constant during the day due to frequent use of these stations for short periods of time. The right plot shows load profiles that fall under the residential cluster, where load peaks toward the end of the day. The single-family residential charging location was not included in this clustering analysis of workplace charging data, but it is possible to conclude that the load profiles would be very similar to those of the MUDs.

Looking at the top 1,000 stations by number of sessions, the distributions of session start times, durations, and energies are shown in Figure 17. Session start times have two peaks, one in the morning around 9:00 a.m. and one in the afternoon around 1:00 p.m. This indicates that these stations are mostly located within the general category of workplace. The session duration for the top 1,000 stations is most commonly between 2 and 4 hours, or around 8 hours, as shown by the bimodal distribution observed in the histogram. This behavior supports the assumption of the stations being at workplaces: the first peak reflects drivers who stay only part-time at work (first peak) and then those who stay full-time (second peak). It could also reflect drivers who plug-in during the second peak of arrival times and charge only for the afternoon, or drivers from the morning peak who move their vehicle during lunch once it is fully charged. The energy delivered to these vehicles is typically between 5 kWh and 15 kWh per session.

Figure 17: Distribution of Session Start Times, Durations and Energies (kWh)



The distribution of session start times, durations, and energies (kWh) are from the top 1000 stations. The left figure shows a histogram of the session start times with two peaks, one in the morning around 9:00 a.m. and one in the afternoon around 1:00 p.m. The middle figure shows a histogram of the duration of sessions, with peaks between two and four hours and around eight hours. The right figure shows a histogram of the energy delivered in each session, which most frequently falls between 5kWh and 15kWh.

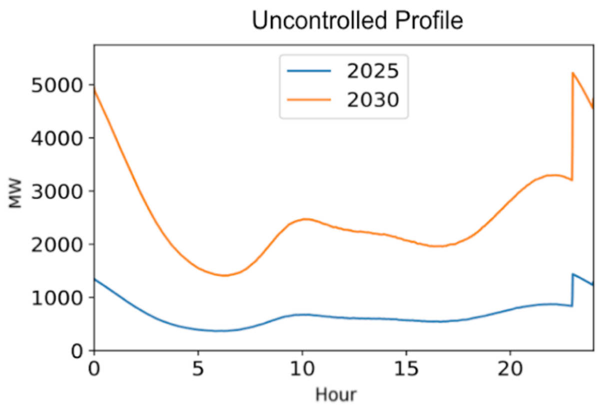
Source: SLAC National Accelerator Laboratory.

Generation of Load Profiles for Each Scenario

Given the scenarios selected for analysis in this report (refer to the Selected Scenarios section in Chapter 2), load profiles were generated for each year (2025 and 2030) with and without smart-charging capabilities. Only two charging locations were affected by smart charging: residential and workplace. In the residential location, control was applied only to L2 stations, and the type of control applied was a simple timer. The timer control acts by scheduling a delayed time to start the charging session, typically aligned with the start of a new price period. The smart charging algorithm used for workplace charging was described in the Smart Charging section of Chapter 2. For the scenarios presented in this section, it was assumed that the workplace charging was under PG&E’s rate structure E-19 (EV Adoption, 2020). Finally, for each scenario, weekday and weekend profiles were generated.

For the Base Case scenario, Figure 18 shows the statewide weekday EV load profile for 2025 and 2030; this is broken down by location and rate in Figure 19 and Figure 20.

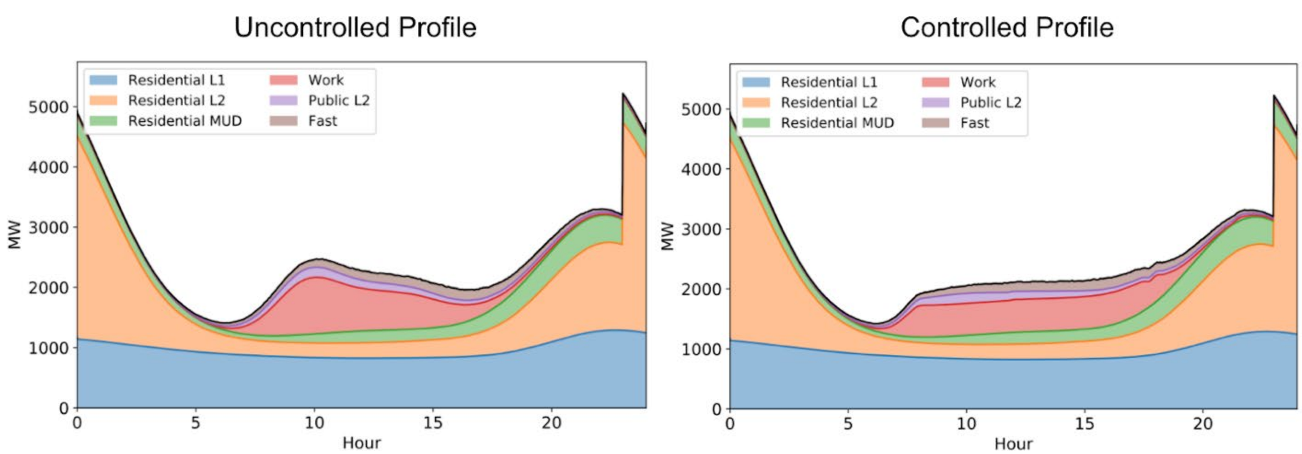
Figure 18: Base Case Weekday — Overall



This figure shows the statewide load profile of EVs in 2025 (blue line) and 2030 (orange line) without smart charging (left) and with smart charging (right). The first thing to note is the increase in load from 2025 to 2030 based on the assumed increase in EV adoption from 1.5 million in 2025 to 5 million in 2030. The second observation is the comparison between the uncontrolled and controlled profiles. When smart charging is adopted at all workplaces, the morning peak, primarily due to workplace charging, flattens out. This phenomenon is more noticeable in 2030, as the number of EVs is more significant.

Source: SLAC National Accelerator Laboratory.

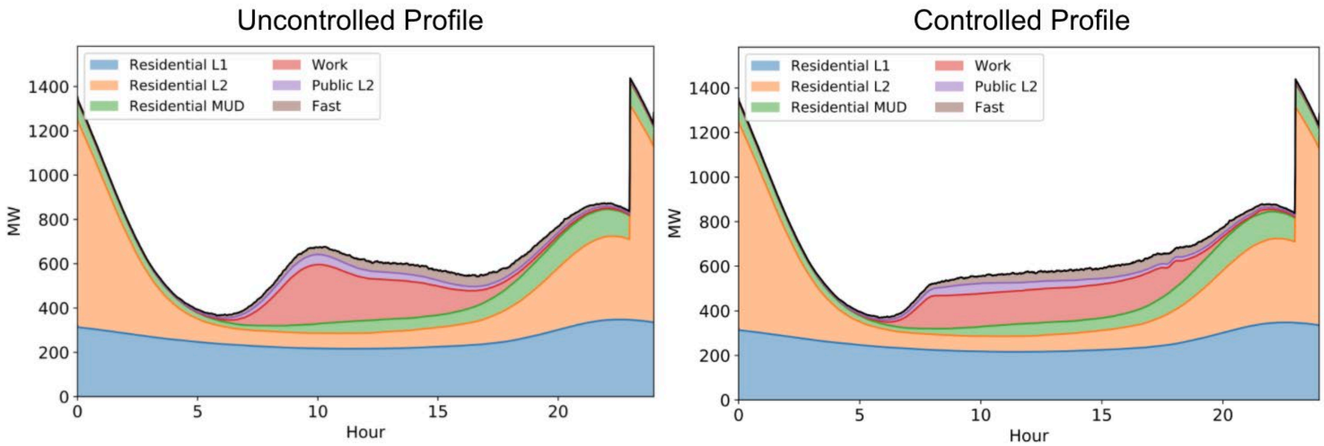
Figure 19: Base Case Weekday — 2030



This figure shows the contribution of each charging location in the overall state EV load profile. Most of the EV load comes from residential charging, as shown by the blue (Residential L1), orange (Residential L2), and green (Residential MUD) areas. From a profile perspective, note how smart charging changes the profile of the workplace location by shaving the early morning peak.

Source: SLAC National Accelerator Laboratory.

Figure 20: Base Case Weekday — 2025

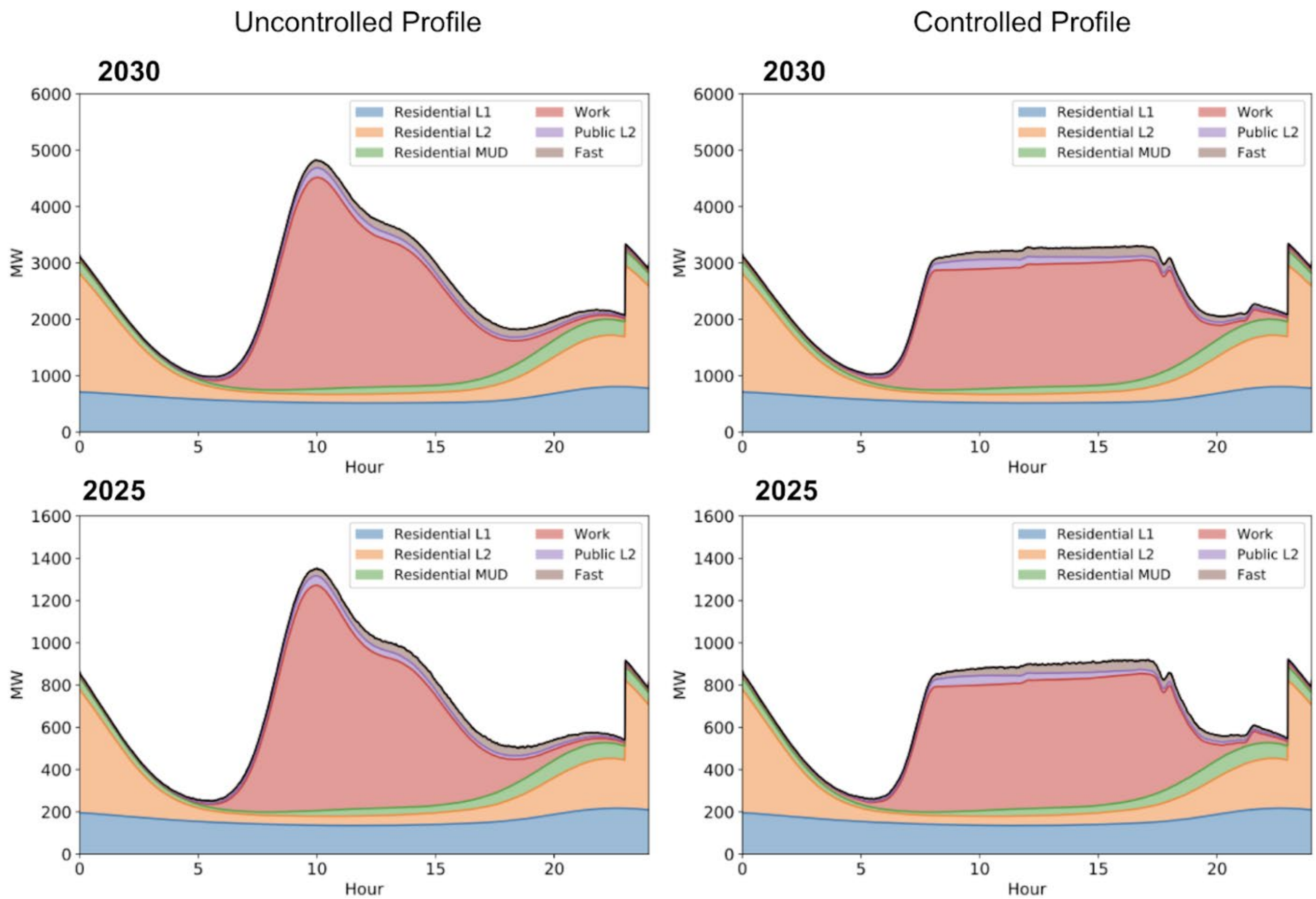


As in Figure 19, most of the EV load comes from the residential charging locations, as seen by the blue (Residential L1), orange (Residential L2), and green (Residential MUD) areas. From a profile perspective, smart charging changes the profile of the workplace location by shaving the early morning peak. Finally, the magnitude difference of the EV load profile is considerable.

Source: SLAC National Accelerator Laboratory.

Figure 21 shows the same graphs as Figure 19 and Figure 20 but for the Work Case scenario. Note how important smart charging is if the adoption of workplace charging continues to grow. Without smart charging, the peaks from the EV load in 2025 and 2030 are significant during the day. This presents a big risk for system operators, as they would need to commit enough capacity to support this excess load while simultaneously supporting other workplace loads, such as buildings, that also peak during the day. This increased load will create considerable stress in the grid infrastructure that, in addition to standard workplace loads, will need to pick up the excess EV load at the same time using the same infrastructure — that is, transformers and lines. Even if solar or other renewable generation sources are installed to support this demand, their intrinsic intermittency has to be supported by grid operators. However, when a smart-charging strategy is applied to the workplace charging location, the excess capacity to support the EV load is drastically reduced. Therefore, it is key that smart-charging strategies in workplace locations are adopted to mitigate impacts of EVs on the electrical grid.

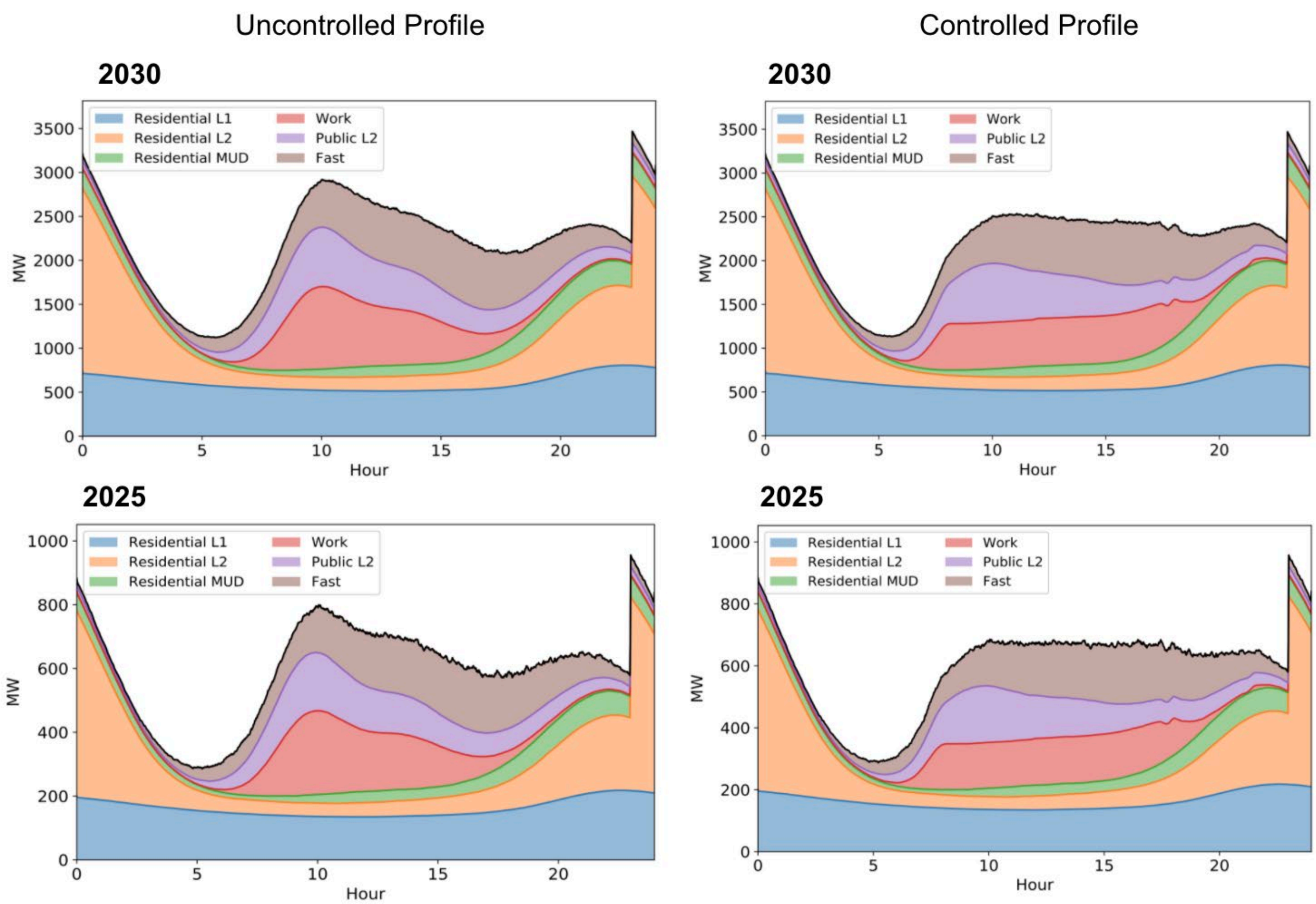
Figure 21: Work Case Scenario Weekday



Source: SLAC National Accelerator Laboratory.

Figure 22 shows the Fast-Public scenario. In this scenario, the percentages of fast and public charging are larger, 20 percent each, compared to the Base Case, where they represent only 5 percent each. Two observations can be made: first, fast charging creates spikes to the load profile — they appear small in the graph, but the scale of the graph is very large; second, the overall load profile is more evenly distributed across the day compared to the other cases.

Figure 22: Fast-Public Case Scenario Weekday



Source: SLAC National Accelerator Laboratory.

The EV load profiles for the other scenarios are shown in Appendix B. From these load profile results it is possible to derive several conclusions.

- The Base Case, High Adoption, Low Adoption, and Equity scenarios all rely heavily on the residential charging location to meet the needs of growing EV adoption. This could pose a challenge to grid infrastructure as the EV load would have to be supported at the distribution/residential level. That means that infrastructure would have to be upgraded at different points in the network to support the excess load. Those upgrades are costly, since they are not centralized but rather distributed at the multiple hot spots in the network. However, it could also present opportunities if smart-charging strategies at the residential level were adopted widely. Simple strategies can be used, such as timers, to spread charging throughout the evening, leveraging the existing flexibility in the residential charging load. One challenge with this approach is coordinating the diverse set of residential charging station manufacturers to achieve a common goal.
- The Fast-Public scenario presents a good trade-off between residential and non-residential charging throughout the day. When workplace smart charging is used, it becomes more evenly spread throughout the day. However, because public and fast

charging are generally not candidates for managed charging, not much could be done to improve those loads. Furthermore, fast charging presents a challenge from a grid operation standpoint. When EVs are connected to these chargers, large amounts of power are demanded from the grid. This means that infrastructure needs to be built or upgraded around these stations to minimize their impacts, and that can ultimately increase the cost of electricity. Finally, with current battery technologies, the frequent utilization of fast charging, like this scenario is proposing, may accelerate battery degradation rates (GEOTAB, 2020).

- The Work scenario significantly increases the EV load during the middle of the day, shifting away from the evening peak observed with more residential charging. This could be beneficial in confronting solar overgeneration and mitigating the duck curve in California. However, as mentioned before, the intrinsic intermittency of renewable generation could become a problem since utilities will need to support this excess load when those resources are not available. If smart-charging strategies are adopted widely at workplace locations, the EV peak during the day can be shaved and the requirements to support this excess load reduced. There are three additional benefits of the Work scenario: (1) workplace stations at a given site are usually from one major manufacturer and thus coordination and load management between stations is easier to implement; (2) co-location with solar and other resources, like batteries and building controls, can be implemented to reduce the requirements of infrastructure upgrades upstream of the charging location; and (3) as with the Fast-Public and Work-Public scenarios, this approach reduces the dependence on residential charging locations and the residential distribution grid to support the load from EVs.

Cost-Benefit Analysis Results

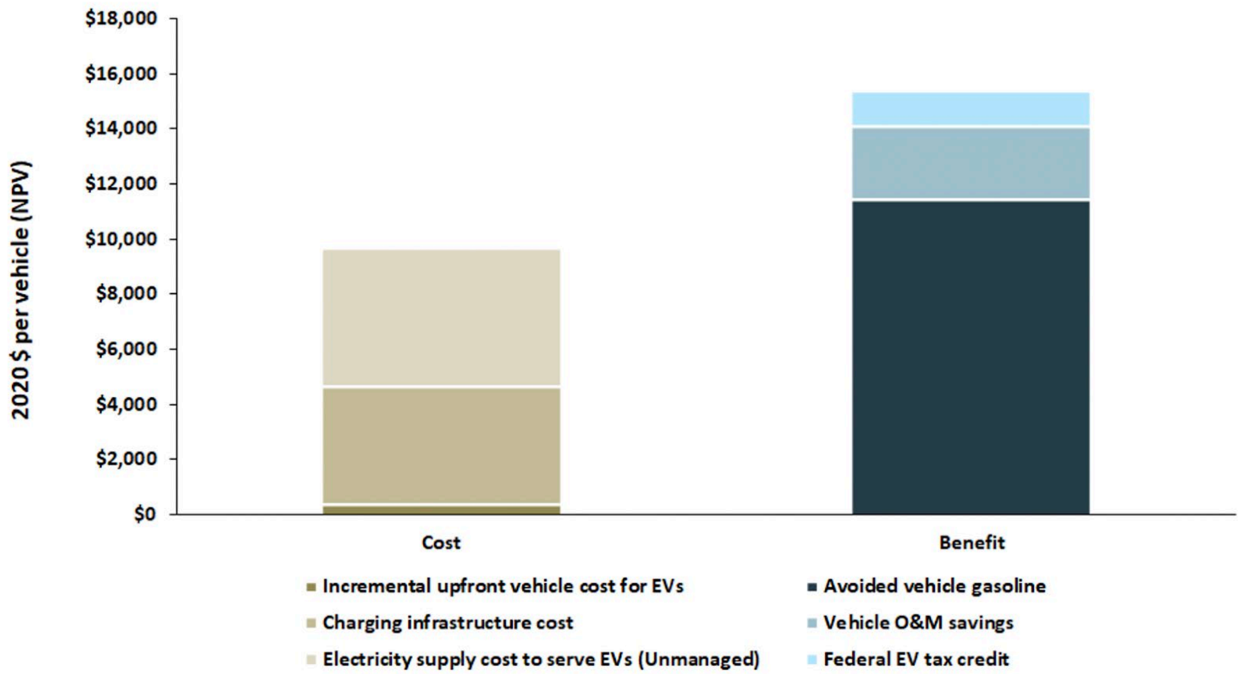
This section presents the cost-benefit assessment for the statewide uncontrolled and controlled shapes in the Base Case. It then performs further analysis at the county level for this scenario. Finally, an analysis is conducted for all seven scenarios for five selected counties to show the sensitivity of the model.

Base Case

A cost-benefit assessment for the Base Case scenario for all counties in the state was performed. Figure 23, Figure 24, and Figure 25 show the TRC, RIM, and PCT results, respectively, for the Base Case statewide. Results are shown with the individual costs and benefits considered in each test on a per vehicle basis for all EVs adopted across California from 2020 through 2030. In all three cost tests, benefits per vehicle exceed the costs, demonstrating that, even under an unmanaged charging scenario, EVs achieve net benefits from the perspectives of an EV driver, all electric utility ratepayers, and society.

Figure 23 shows the TRC results for all EVs adopted in California from 2020 to 2030. Across the state, benefits exceed costs by approximately $5,700 NPT per EV for the lifetime of each vehicle. The TRC costs are driven primarily by the cost of charging infrastructure across the state and the utility’s electricity supply costs to serve the incremental EV load. The incremental upfront vehicle cost represents a small portion of the costs, as the cost premium of EVs is expected to decline over time. The TRC benefits are driven by the gasoline savings, representing the avoided gasoline costs that EV drivers save relative to an ICE vehicle. Vehicle O&M savings and the federal EV tax credit also contribute to the TRC benefits, but to a lesser degree. Because per vehicle benefits exceed costs, the state benefits from EV adoption. The TRC represents a possible viewpoint for a policy maker, demonstrating that EV adoption will, overall, benefit California.

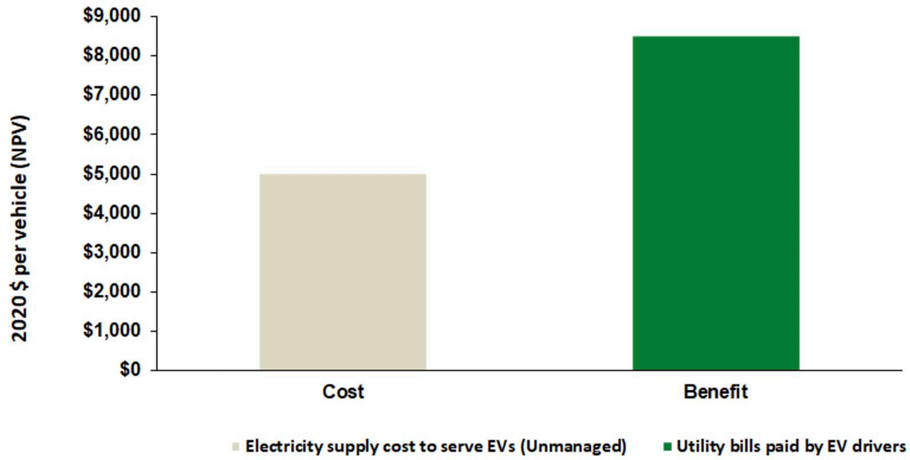
Figure 23: TRC Costs and Benefits Attributable to Personal BEVs Added 2020–2030



Source: SLAC National Accelerator Laboratory.

Figure 24 shows the cost and benefit results for the RIM test in California. The cost side of the RIM test is the electricity supply cost paid by the utility to serve the incremental load from EVs. The benefit side of the RIM test represents the electric bills paid by EV drivers to their utility. Figure 24 shows that benefits exceed costs by approximately $3,500 NPV per EV. This means that each EV adopted in California from 2020 to 2030 brings in an average of $3,500 NPV of benefits to its utility beyond the cost of electric service. Notably, net benefits in the RIM test signify that EVs may ultimately have downward pressure on electric rates, and thus benefit all utility ratepayers.

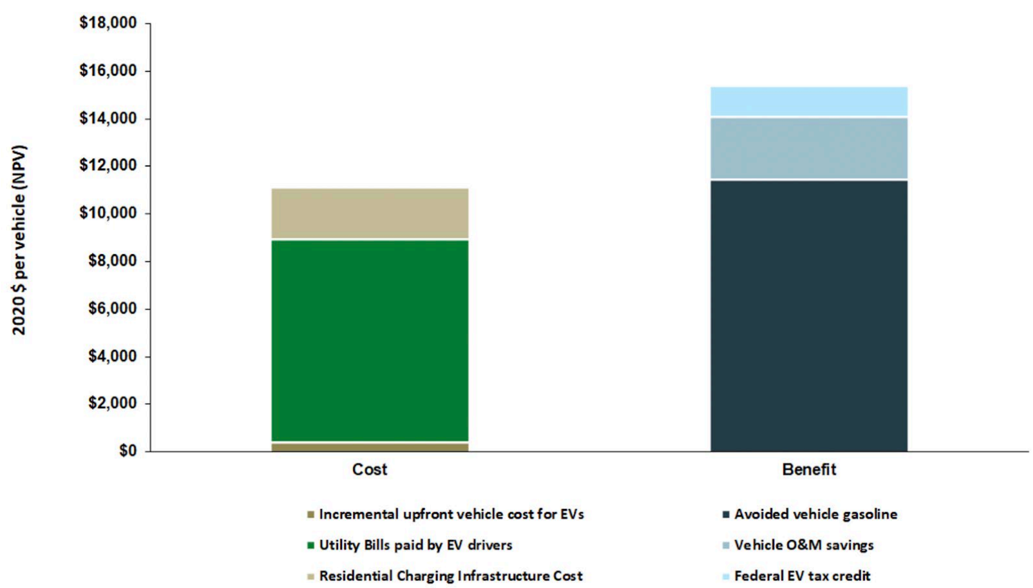
Figure 24: RIM Costs and Benefits Attributable to Personal BEVs Added 2020–2030



Source: SLAC National Accelerator Laboratory.

Figure 25 shows the results of the PCT for California, which represents the perspective of an EV driver. Participant costs are dominated by the electricity bills paid by drivers to charge their EVs. The residential charging infrastructure cost also contributes to PCT costs, and the incremental cost of the EV over an ICE vehicle is a small portion of costs. Participant benefits are led by the avoided gasoline costs that the EV drivers save by driving electric, with additional benefit amounts contributed by the vehicle O&M savings compared to an ICE vehicle and the federal tax credit. As shown in Figure 25, the benefits exceed costs by approximately $4,200 NPV per EV. This means that drivers who adopt an EV from 2020 through 2030 save an average of $4,200 NPV compared to owning an ICE vehicle over the lifetime of their EV. Individual drivers' actual benefits depend on when they purchase their vehicle, as this will affect the federal tax credit amount that the driver receives, among other factors.

Figure 25: PCT Costs and Benefits Attributable to Personal BEVs Added 2020–2030



Source: SLAC National Accelerator Laboratory.

Base Case with Controlled Load Shapes

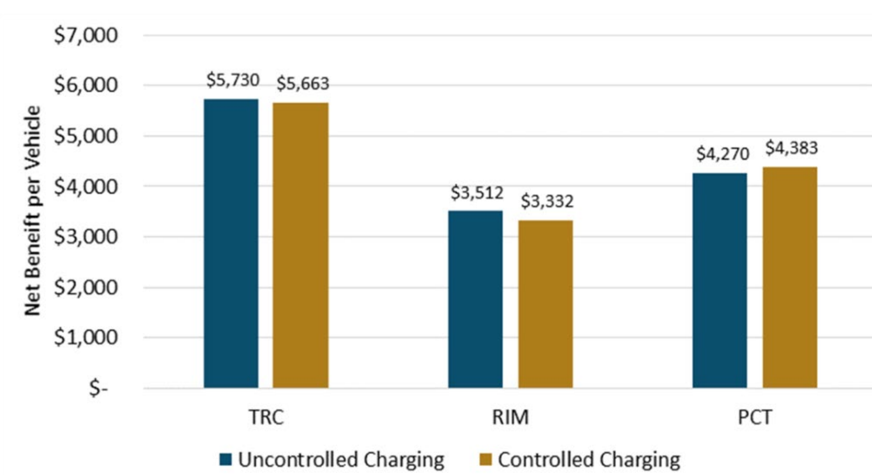
To consider the effect of controlled load, a cost-benefit assessment for the Base Case with controlled load shapes, as described in the Generation of Load Profiles for Each Scenario section, was performed. The net benefits per EV for California for the controlled load shapes compared with the uncontrolled shapes are presented in Figure 26.

Figure 26 shows that, in each of the three cost test perspectives, net benefits per vehicle are similar for both uncontrolled and controlled cases. Because the controlled charging case considered demand charge mitigation, there is an increase in net benefits for the EV driver perspective in the PCT. When the driver responds to the demand charge signal and flattens demand, the driver's electricity bills decrease and thus the overall benefits experienced by the EV driver increase.

However, net benefits decrease slightly in the ratepayer perspective (RIM) for the controlled charging scenario. For the utility perspective, the decrease in customers' utility bills results in a decrease in revenue for the utility, which is a benefit in the RIM test. This is accompanied by a decrease in the electricity supply costs, which are a cost in the RIM test, but the reduction in customers' bills is greater than the corresponding reduction in utility costs. The RIM test still yields positive net benefits but shows a slight decrease in net benefits for the controlled case compared to the uncontrolled case. Better alignment between utility rates paid by customers and the electricity supply costs paid by utilities could help mitigate the decrease in ratepayer net benefits when controlled charging is used.

Net benefits also decrease slightly in the TRC test, due to EVs in the controlled scenario charging during hours with slightly more expensive energy marginal costs, but this decrease in the societal perspective is almost negligible.

Figure 26: Net Benefits Per Vehicle for Uncontrolled Versus Controlled Charging

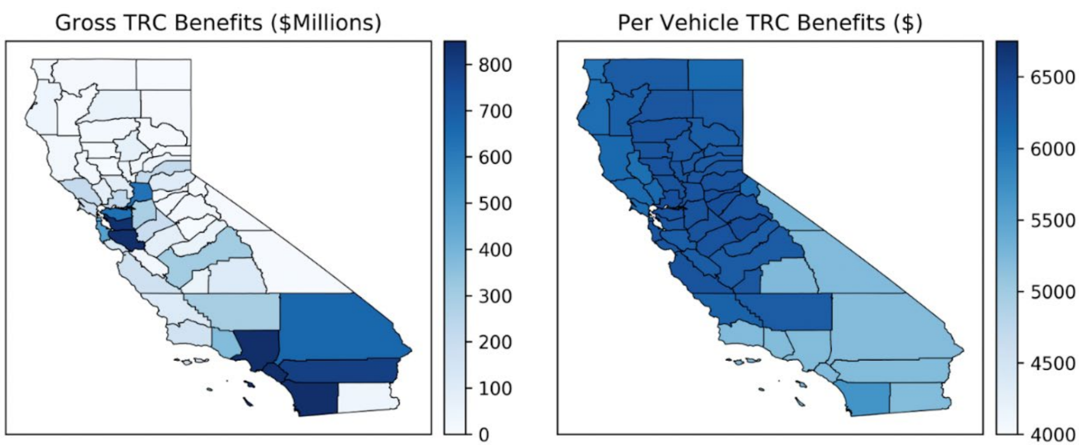


Source: SLAC National Accelerator Laboratory.

County Comparison

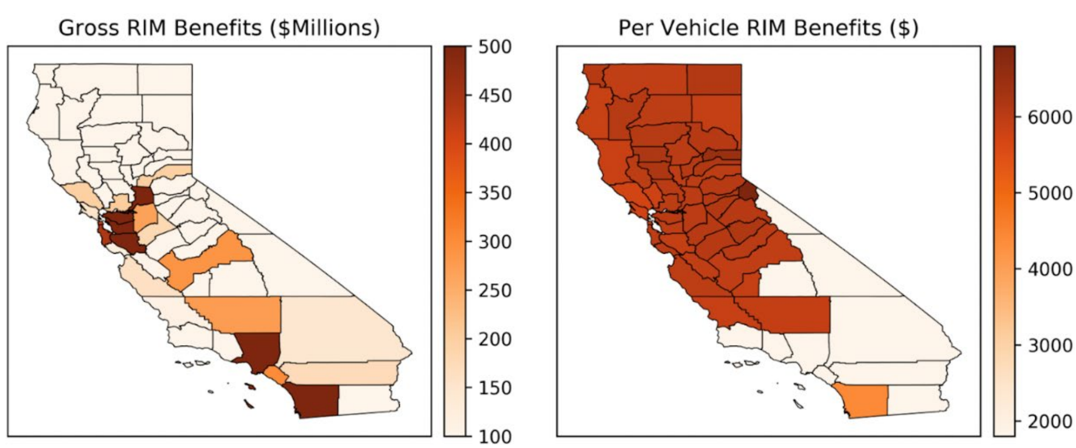
Figure 27, Figure 28, and Figure 29 show how the net benefits for each test in the Base Case vary across all counties in California. In each figure, the total net benefits for the county are shown on the left, and the net benefits on a per vehicle basis are shown on the right. As shown in the left portion of each figure, the total net benefits to each county are largest in population centers where higher EV adoption is projected, namely Los Angeles, San Bernardino, San Diego, and Orange counties in Southern California and Contra Costa, Sacramento, Alameda, and Santa Clara counties in Northern California. Higher EV adoption results in larger net benefits attributed to the county. The right side of each figure shows that, when each county's net benefits are normalized on a per vehicle basis, the benefits are similar from county to county. The main difference among counties results from the utility modeled for each county, causing a general difference between Northern California (PG&E territory) and Southern California (SCE and SDG&E territory). This affects the electric rates experienced by EV drivers to fuel their vehicles and the electricity supply costs paid by the utility to support EV charging. As mentioned in the Cost-Benefit Analysis: Data Inputs section in Chapter 2, each county was assigned one of the IOUs for the purposes of rates and marginal electricity costs for simplicity and data availability. Therefore, the general difference in the per vehicle graphs on the right is representative of the different IOUs (and respective rates and electricity marginal costs) modeled for each county.

Figure 27: TRC Net Benefits on County Level Per Vehicle



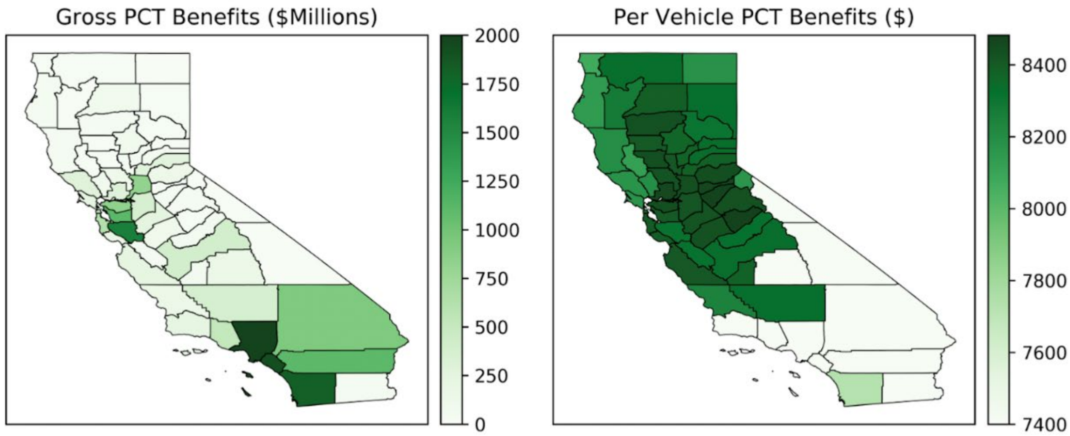
Source: SLAC National Accelerator Laboratory.

Figure 28: RIM Net Benefits on County Level Per Vehicle



Source: SLAC National Accelerator Laboratory.

Figure 29: PCT Net Benefits on County Level Per Vehicle



Source: SLAC National Accelerator Laboratory.

Scenario Comparison

A cost-benefit assessment for all seven scenarios for five counties in California was performed. The five counties were selected to show a range of impacts in geography attributes: more suburban and rural compared to urban areas, Northern California compared to Southern California, and coastal counties compared to the Central Valley. The counties modeled are shown in Table 4.

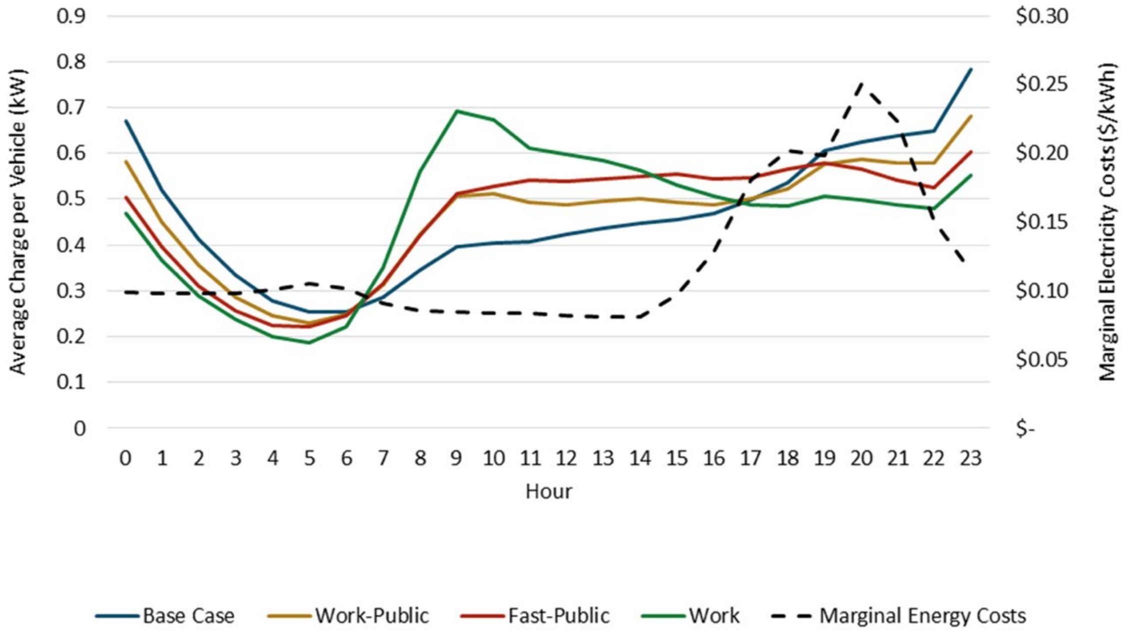
Table 4: Counties Selected for Sensitivity Scenario Comparison

County Selected	Geography	2030 EV Adoption in Base Case
San Francisco	Northern California; coastal	131,355
Los Angeles	Southern California; coastal	1,134,646
San Diego	Southern California; coastal	437,228
Fresno	Northern California; Central Valley	89,885
Kern	Southern California; Central Valley	86,272

Source: SLAC National Accelerator Laboratory.

Figure 30 demonstrates how the load profiles vary by scenario for San Francisco County (with similar variations in load shapes for the scenarios in the other selected counties). The load profiles were normalized to have the same energy per driver, to focus this comparison on their differences in shape. It is possible to see that there is significantly more midday charging in the Work-Public, Fast-Public, and Work sensitivity scenarios relative to the Base Case. When compared with the marginal electricity supply costs, the additional midday charging takes advantage of lower marginal costs when solar is in high supply. The sensitivity scenario load shapes then reduce the amount of charging during the evening peak, when marginal costs are high.

Figure 30: Comparison of Scenario Load Shapes with Utility Electricity Marginal Costs



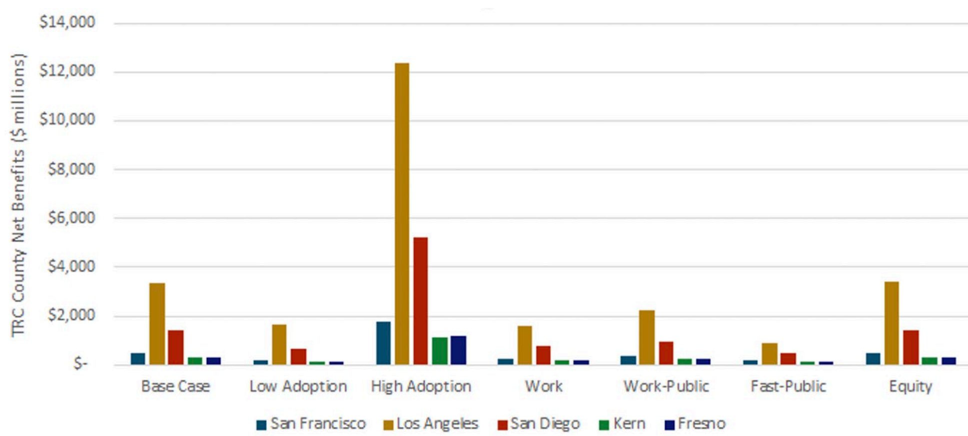
Source: SLAC National Accelerator Laboratory.

The TRC results for all seven scenarios are shown in Figure 31 and Figure 32. Figure 31 shows the total net benefits in each county for each scenario, and Figure 32 shows the per vehicle net benefits in each county. On a total county basis, in Figure 31, the results show how the adoption level impacts overall benefits experienced in each county. Los Angeles County, which has the highest EV adoption in all scenarios, has the largest net benefits. The High Adoption scenario shows larger benefits for all counties compared to their results in the other scenarios. This result makes sense because each EV generates net benefits, and therefore the higher adoption levels scale up total net benefits to the county.

When these results are normalized on a per vehicle basis in Figure 32, it is easier to compare across scenarios and see the factors driving the differences across the various counties and sensitivities. In Figure 32, the Low Adoption scenario has larger per vehicle net benefits than the High Adoption scenario. This is because of the projected EV adoption in each scenario: in the Low Adoption scenario, more EVs are purchased in the earlier years of the forecast and are thus able to take advantage of the federal tax credit; in the High Adoption scenario, the larger adoption occurs later, when the tax credit is assumed to have expired for most vehicle manufacturers. This results in higher average net benefits per vehicle in the Low Adoption case, even though the High Adoption case certainly has larger net benefits in total.

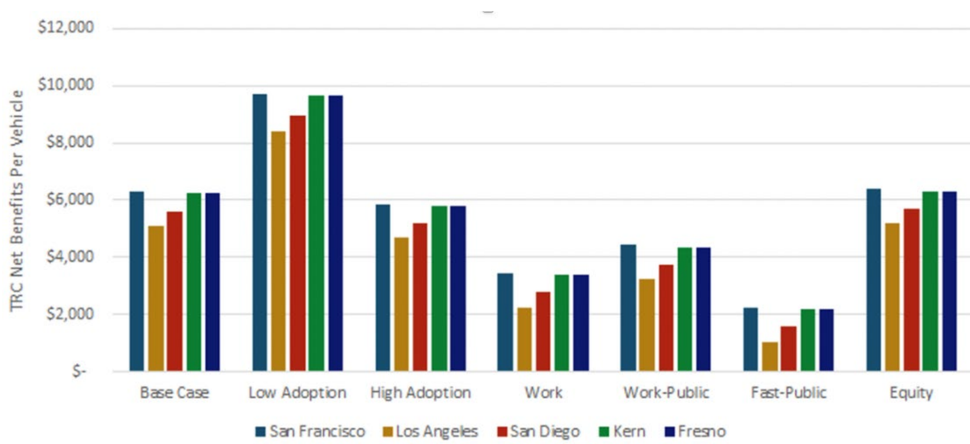
Another trend seen in Figure 32 is the lower per vehicle net benefits in the Work, Work-Public, and Fast-Public scenarios. As previously discussed, compared to the Base Case, these scenarios have load shapes that take advantage of solar overgeneration and low marginal costs during midday hours and reduce charging during the evening peak. This leads to lower electricity supply costs in the TRC. However, more workplace and public charging infrastructure would need to be built to accommodate this increase in midday charging. The increased charging infrastructure costs counteract the decrease in electricity supply costs and therefore lead to lower net benefits. However, it is important to note that increased workplace and public charging will also lead to increased nonmonetary benefits, such as EV driver satisfaction and reduced range anxiety, which are not quantified in this cost-benefit framework. Further, increased charging access may also lead to increased EV adoption, which was not explicitly modeled in the EV forecasts used in the Work, Work-Public, and Fast-Public scenarios. As such, this cost test was limited to the trade-off between charging at lower cost times of day compared with increased public infrastructure to support that charging; it thus did not include other benefits that may occur from this increased infrastructure, which would increase overall net benefits in these scenarios. Appendix C provides additional cost test results for the seven scenarios by each county analyzed.

Figure 31: Total Net Benefits in TRC Per County Per Sensitivity Scenario



Source: SLAC National Accelerator Laboratory.

Figure 32: Per Vehicle Net Benefits in TRC for Each County in Each Scenario



Source: SLAC National Accelerator Laboratory.

Summary of Cost-Benefit Assessment

This cost-benefit assessment explored the societal (TRC), ratepayer (RIM), and EV driver (PCT) perspectives for various EV charging scenarios across California. Notably, all cost test perspectives yielded positive results (net benefits) for all counties in California and in all sensitivity scenarios. The TRC test results show that the state, and each county, benefit overall from EV charging, indicating that policy makers should continue efforts to spur EV adoption and bring benefits to California and its counties. The RIM test shows that all utility ratepayers who do not have EVs may still benefit from broader EV adoption: EV charging brings additional utility revenue that outweighs the electricity supply costs, thus putting downward pressure on rates over time. Finally, the PCT results show that EV drivers benefit from their choice to adopt an EV, with lower lifetime costs compared to conventional vehicles.

As described in the Data Inputs section, above, many of the inputs were selected to err on the conservative side; therefore, the resulting net benefits would be even greater if this input were adjusted. For example, EVs were estimated to have price parity with ICE vehicles in 2025 and beyond. If this analysis considered a scenario where EVs were less expensive than ICE vehicles, such as in the BNEF projection discussed in this study, then the net benefits would increase in both the TRC and PCT results. In addition, the study based the workplace and public charging infrastructure costs on historic values from studies and utility infrastructure programs. Given the early stage in the market, these costs may decline in the future as technology costs decrease and installation efficiencies are developed. Lower infrastructure costs would lead to greater net benefits in the TRC test and the PCT. Finally, this study took a conservative approach to incentives available to EV drivers, since the federal tax credit was assumed to phase out by 2023, and local incentives were not included here. Some EV drivers may experience larger net benefits in the PCT if they are able to take advantage of local EV purchase incentives.

The analysis also did not include the impact of Low Carbon Fuel Standard (LCFS) credits and any potential incentives passed on to drivers through the regulation. LCFS incentives were excluded because of the varying incentive amounts available to drivers. At the time of this analysis, each IOU has its own incentive amount, but all electric utilities in California are transitioning to offer a statewide rebate that will be applied at the point of vehicle purchase. Because of the different incentive amounts and the uncertainty regarding future amounts, this incentive was not included in the analysis. Furthermore, any LCFS credits generated through charging at non-residential charging stations were not included because of the complexity with which the stakeholder generates the credits, the price for which the credits were sold, and the uncertainty regarding if, or how much, of this value is passed on to drivers. If LCFS impacts, such as EV driver incentives provided by the utilities and LCFS credits generated by other entities, were included in this analysis, net benefits in the TRC and PCT results would increase. Future iterations of this analysis could include a calculation to estimate the total value of LCFS credits (under varying LCFS credit price projections) generated by EV charging. However, it would be important to note that this would reflect the overall LCFS value potentially available from EV charging, rather than specific amounts attributed to different stakeholders due to the complexities previously noted. This calculation would be most applicable to the TRC test, showing total potential value in each county or statewide, rather than the PCT, since it is difficult to distinguish how much of this value is passed through to EV drivers for each vehicle each year.

CHAPTER 4: Technology/Knowledge Transfer and Market Adoption

Outreach Activities, Knowledge Gained, and Feedback

The method developed in this project generated, to date, four peer-reviewed conference papers addressing different aspects of SCRIPT with the research community. The project team also presented the work in multiple conferences to academia and industry to understand the needs and better align the outcomes of this project, based on feedback, to provide valuable information to different stakeholders to solve real-world problems (Quiros-Tortos et al., 2018).

The team received multiple rounds of feedback from technical advisory team members, academics, and industry. The most relevant feedback that heavily influenced the design of the project was to: (1) make the data set useful for the community, despite being unable to publish or share the raw data, (2) develop a method that is not limited to the scenarios defined by the project team, and (3) develop technology simple enough to be used by users with different backgrounds. To make the data set useful for the community, the project team developed a novel statistical model that can generate representative EV charging sessions from a fitted model without directly using the data; this model accurately captures relevant metrics and can be used by the research community. To develop a method with fewer limited scenarios, different control knobs are exposed to the user in an intuitive way through a user interface, whereby the user can generate a scenario with any combination of these knobs (such as charging location, battery capacity, and charging level). To simplify the technology, the team developed a user interface to hide all the complexities of the tool, exposing only the key information a user needs to feed the simulator.

Intended Users

The team identified four main users that can directly leverage the outcomes of this research.

- **Electric Utilities:** Utilities can use the technology developed to support planning and infrastructure deployment, given different levels of electric vehicle adoption, different distributions over charging locations (for example, residential, workplace, and public), and different rate structures. Additionally, they can leverage the tool to target specific regions, such as counties and disadvantaged communities with programs to incentivize adoption of EVs.
- **Industry:** As with electric utilities, different industry sectors (for example, consulting, charging station manufacturers, and aggregators) can leverage the technology and method developed to better inform current analysis, target specific charging locations to deploy more technology, quantify potential value from smart charging, and evaluate whether they should invest in developing and deploying smart charging algorithms.

- **Federal and State Agencies:** Government agencies can use the results of this project and the ability to flexibly generate forecasts by changing the control knobs to identify new opportunities for research and to incentivize collaboration between academia and industry. These new opportunities and potential collaborations will allow the development and demonstration of novel algorithms and support sharing of key data sources, which would not be possible otherwise.
- **Academia:** There is a lack of realistic data openly available to researchers. To the best of the project team's knowledge, this project is the largest data set of real-world charging data used for research publications to date. Moreover, this project generated a novel approach to obtaining an accurate statistical representation of this rich and unique data set that can be used by the research community.

Technology Transfer

The method developed in SCRIPT has already inspired new research. An extension of the model with a more detailed division of charging locations and drivers into groups is being developed in a project called SPEECh, Scalable Probabilistic Estimates of EV Charging, at Stanford University under Professor Ram Rajagopal with PhD student Siobhan Powell. Members of the California Energy Commission's Clean Transportation Division are collaborating with the team to develop the model and they hope to use its outputs to inform their scenarios on long-term planning. There has also been interest from the long-term planning team at Pacific Gas & Electric Company in using the model to support its scenarios, with a focus on understanding the control and load flexibility in the SCRIPT model. The project team is confident that this work will continue and pose a valuable contribution to EV planning in California.

CHAPTER 5: Conclusions/Recommendations

SLAC National Accelerator Laboratory, Energy and Environmental Economics (E3), University of California, Santa Barbara, Gridmatic, and ChargePoint teams have successfully developed SCRIPT as a tool to help different stakeholders understand the impact of EV in the electrical grid. SCRIPT developed methods to generate EV load forecasts, for both unmanaged and managed charging, given different user inputs. The inputs available are EV adoption, percentage of charging that happens in different charging locations (residential, workplace, public), EV battery sizes, type of day (weekday or weekend), daily usage percentage within each charging location, type of control in the residential or workplace locations, and different rate structures.

The flexibility presented in this work by exposing the tool's control knobs to the general user is unique and extremely powerful. Modeling the future involves significant uncertainty and requires modeler assumptions. Over time, more assumptions can be informed with observations and the scenarios generated by the tool can be updated.

Finally, by making the tool and algorithms open source, the entire research community working on the electrification of transportation, EV drivers, and many others in fields related to the power sector will significantly benefit.

Project Outcomes

Many outcomes were generated as part of this project in scientific publications (Tucker et al., 2019), as new modeling and control methods, and as software. The major outcomes were:

- A novel data-driven method to drastically reduce the computational time of estimating the impact of controlled charging at scale. It showed that a well-conceived approach could require only a small reduction in optimality to achieve high gains in computational speed.
- A forecaster based on statistical models fitted for each charging location with the raw data, to allow new samples to be generated without exposing drivers' information.
- A cost-benefit analysis framework that provides information about the value to different stakeholders, including utility ratepayers, EV drivers, and regions.
- An open-source tool that the general public can use to understand impacts of EVs, given different assumptions about future scenarios.
- The opportunity for SCRIPT users to explore cost-benefit analysis results beyond the scenarios described here, by varying the different tool parameters. For example, users may explore the cost-benefit impacts of more restrictive charging behavior, such as only residential charging or only DCFC. These types of sensitivities can provide valuable

insights into how the costs and benefits of EV charging can vary for all three stakeholder perspectives.

Lessons Learned

Multiple lessons were learned throughout the duration of the project. The most important were:

- Not to underestimate the time to clean and preprocess large and diverse data sets. All models, analysis, and conclusions are derived from the clean and processed data and thus they are only as good as the data used. Additionally, valuable time can be saved by thinking about the data structure in the early phases of the project: how the different components will use it, what format they are expecting to receive, and how the output should look. Using a method such as CCD in this project is extremely important.
- That, for a tool such as SCRIPT, which depends on many inputs and can be modified at any time, the key to providing the best outcomes is to have a good understanding of which inputs are the most important, provide the best outcomes, and are simple enough for a user. Define these inputs early in the project and ensure that code is designed and implemented in a flexible way that is easy to update later.
- To be strategic about which parts of the code run in the cloud and which parts can run locally. Depending on the complexity of code (algorithms) or size of the data source, running locally can be more efficient, faster, and cheaper, but it may not be ideal if scale is required. Moreover, running in the cloud can take longer if cost is a concern, as higher computational power is more expensive, and this will affect the user experience. Performing a benchmark test of major components of the system on runtimes can help inform the architecture, modeling, and control strategies.

Future Research

This project will take multiple future research directions to advance SCRIPT.

The first direction is exploring the possibility of using other EVSE data rather than only that of ChargePoint. ChargePoint has the largest network of EVSE deployed in the United States and the data obtained for this project is very rich and unique. This new direction would explore if and by how much other EVSE manufacturers’ data would help better explain the current EV loads this project generated for California.

The second direction is looking at the EV landscape from a combination of EV and EVSE data. This project is primarily EVSE-centric and including information from the vehicle side could help explain many factors, such as how often some drivers charge at home or away from home and whether there are any correlations given their home location. For example, would drivers who live in a certain area be more likely to charge at work rather than at home, compared with drivers in a neighboring region? Additionally, having visibility into drivers’ travel information is important from an infrastructure planning perspective.

The third direction will focus on an extension of the model with a more detailed division of charging locations and drivers into groups.

The fourth direction is using this tool to help electric utilities design new rate structures. By modeling how EV load shapes would change under a new rate, utilities could better align the load with times of overgeneration. Rates could also be designed to incentivize more EV adoption and target different communities, such as disadvantaged communities.

The fifth direction is making the tool more flexible to enable users to upload their own data sets. This can be challenging; depending on how large the data set is, performing some of the algorithms can take several hours.

Lastly, from the cost-benefit analysis perspective, additional work for this study could include varying other cost-and-benefit inputs to see how the results change. The TOU rate periods used in this analysis were reflective of 2020 and do not reflect future changes in TOU periods that may be more reflective of grid costs. In addition, future rate structures may provide a stronger signal to incentivize managed charging during hours of solar oversupply. Varying these rate signals would affect the utility bills paid by drivers in the RIM test and PCT. The different TOU periods may also shift EV drivers' charging behavior as they respond to different time-of-day price signals, thus changing the load shapes, utility bills, and utility marginal costs.

Finally, the scenarios described in this study represent only a subset of potential scenarios in the SCRIPT tool. SCRIPT users can explore cost-benefit analysis results beyond the scenarios described here by varying the different tool parameters. For example, users may explore the cost-benefit impacts of more restrictive charging behavior, such as only residential charging or only DCFC. These types of sensitivities can provide valuable insights into how the costs and benefits of EV charging can vary from the perspectives of all three stakeholders — EV drivers, utility customers, and the state and counties.

CHAPTER 6: Benefits to Ratepayers

The penetration of renewable generation in California at both the transmission and the distribution levels continues to grow. With this growth comes many challenges to ensure a reliable and safe supply of power to end customers, due to renewable generation's intrinsic volatility. By leading the nation in aggressively pushing the adoption of EVs, California is also the first to face the challenges of supporting high numbers of EVs on the grid. First, EVs represent a load that can be two to three times as large as a typical house (US EIA, 2020) and, second, to support this increased adoption, electrical infrastructure needs to be either upgraded or added to reinforce the grid. The first challenge tends to grow with the increased adoption of EVs, charging levels, and battery capacity. However, for the second challenge, some action can be taken to minimize or delay the need to build or upgrade grid infrastructure. Taking such action requires planners to better understand the future loads and how much flexibility is in the load from EVs. Therefore, with a flexible way to generate forecasts and assess the potential of smart charging, a more objective decision can be made by grid and utility planners on whether an investment in infrastructure is required.

SCRIPT can help grid and utility planners plan infrastructure upgrades, make smarter investments that drive down electricity costs, design rate structures that benefit Californians, and reduce emissions from better utilization of solar generation.

EV Load Forecaster Helps Utilities Anticipate and Plan Infrastructure Upgrades

Prediction of future EV demand for charging is challenging, since many assumptions must be made with the current limited information available. Predicting 5 to 10 years ahead is even harder when the underlying technology in EVs is developing and improving at a fast pace. Making informed and strategic decisions to minimize impacts on the cost of electricity to end customers requires a forecaster with the ability to account for different and evolving inputs. With the forecaster developed in this project, SCRIPT, utilities can better understand where hot spots and cold spots in EV load will occur, given different sets of inputs. This will also help utilities better plan their investments and anticipate events. With better plans from the utility companies, ratepayers are ultimately the ones to benefit, with lower electricity costs, reliable power, and safer operation of the electricity grid.

Lower Electricity Costs vs. Infrastructure Investments

Smart charging can be used to take advantage of cheaper electricity during certain hours of the day. In California, marginal costs are typically lower during the middle of the day during springtime, when a significant volume of solar energy is produced. However, to take advantage of this lower cost energy during the day, there must be sufficient charging infrastructure available to support EVs at their daytime locations, which are primarily workplaces or public locations.

In the cost-benefit assessment, the Work, Work-Public, and Fast-Public scenarios all tested load shapes with greater amounts of daytime charging compared to the Base Case. To support this increased daytime charging, the cost-benefit assessment assumed that the charging infrastructure at each location would increase proportionally to the peak load relative to that location's peak load in the Base Case. This resulted in higher charging infrastructure costs in each of these scenarios compared to the Base Case, since more charging infrastructure would need to be built to support the higher volume of daytime charging. The cost-benefit assessment found that the Work, Work-Public, and Fast-Public scenarios had lower TRC net benefits than the Base Case because of this trade-off between infrastructure costs and the ability to take advantage of lower energy costs. While the TRC net benefits were still positive in each case, the higher infrastructure costs to build more workplace and public EV charging stations outweighed the benefits of the lower electricity prices.

However, it is important to note that additional charging infrastructure at workplace and public sites will likely lead to other benefits, such as greater EV adoption due to reduced range anxiety (which is an incredibly important benefit and a positive feedback cycle but is not analyzed in this study). Thus, the trade-off between infrastructure investments and increased flexibility is more complicated than studied here and requires additional research. Additional benefits may need to be quantified to truly examine the trade-off.

Informed Rate Design Can Target Specific Customers

Among the many incentives offered to customers by state and federal agencies to increase adoption of EVs, electricity rates are sometimes overlooked. Yet an ill-designed rate structure can become a barrier for increased adoption of EVs (Powell et al., 2020). By enabling utilities to see how different rate structures affect the load profile from EVs, with and without smart charging, SCRIPT can help them make informed decisions on how to design new rates to target specific charging locations or customers, increase grid reliability, enable even higher adoption of EVs, and, ultimately, reduce GHG emissions.

Maximize Electric Vehicle Use of Solar Generation

The additional load created by EVs can be significant and coincide with other adjacent loads. If not properly managed, the load can create more strain on the grid and ultimately affect reliability. To mitigate this potential issue, some approaches use energy storage solutions to offset EV load from the grid (Guidehouse Insights, 2020). However, this solution has the potential to increase the cost of electricity and impact all ratepayers. Another solution is to ensure that EVs can be charged in times when renewable generation like solar energy is available locally or at a higher level in the network. Smart charging, together with weather and solar irradiance forecasts, can minimize the dependency of EV charging to non-zero emissions grid power. It was demonstrated by this project that solar can be used to its fullest potential to charge EVs by prioritizing exclusively solar for a slightly longer period compared to implementing a multi-objective approach that optimizes for cost and solar production. While utilities can be responsible for incurring the upfront cost of solar, its long-term effects in improving the air quality, not contributing to global warming, minimizing O&M costs, and potentially reducing electricity costs outweigh the initial capital cost, and they benefit all ratepayers.

Increased Adoption of Electric Vehicles Reduces GHG Emissions

All ratepayers benefit from the increased number of EVs within their region from a health standpoint, due to reduced emissions and improved air quality. This report demonstrated that each EV saves approximately $12,000 in avoided gasoline costs over the lifetime of the vehicle compared to an ICE vehicle (based on a $3.18 per gallon average gas price in California in 2020) (AAA, 2020). This cost saving translates to a savings of approximately 33 metric tons of carbon dioxide per EV.

Increased EV Adoption Reduces Electricity Costs

The increased adoption of EVs benefits all California ratepayers. The analysis in this report demonstrated that each new EV adopted in California between 2020 and 2030 brings in an average of $3,500 NPV benefits (Base Case analysis) to its utility beyond the cost of electric service. This means a downward pressure on electric rates, which ultimately benefits all ratepayers.

Scalable SCRIPT Technology Limited Only by Available Data

Even though the technology developed in this project provided information at the county and state level, there is no technical limitation that would prevent it from being applied at a lower aggregation level, such as a zip code or a business. The only requirement is to have enough data to generate a statistical model that accurately represents the region being studied. This project initially used data obtained from zip codes where there were a large number of EV charging stations, and thus a large number of sessions. For application to individual businesses, big tech companies and university campuses with large concentrations of EVs and charging stations are examples of locations that would benefit from using SCRIPT to maximize their investments in charging infrastructure.

GLOSSARY AND LIST OF ACRONYMS

Term	Definition
ACC	avoided cost calculator
BEV	battery electric vehicle
BIC	Bayesian information criterion
BNEF	Bloomberg New Energy Finance
CO2	carbon dioxide
CCD	control co-design
CPUC	California Public Utilities Commission
DC	direct current
DCFC	direct current fast charging
DER	distributed energy resources
E3	Energy and Environmental Economics
EV	electric vehicle
EVSE	electric vehicle supply equipment
GHG	greenhouse gas
GISMo	Grid Integration Systems and Mobility
GMM	Gaussian mixture model
GPS	global positioning system
ICE	internal combustion engine
IOU	investor-owned utility
kW	kilowatt
kWh	kilowatt-hour
L1	level one charger
L2	level two charger
LCFS	low carbon fuel standard
MUD	multi-unit dwellings
MW	megawatt
NOX	nitrogen oxide
NPV	net present value
O&M	operation and maintenance
OEM	original equipment manufacturer
PCT	participant cost test

Term	Definition
PG&E	Pacific Gas & Electric Company
PHEV	plug-in hybrid electric vehicle
RIM	ratepayer impact measure
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric Company
TOU	time of use
TRC	total resource cost
VMT	vehicle miles traveled

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Appendix A: Data Sources

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APPENDIX A: Data Sources

Table A-1: Relevant Data Utilized in the SCRIPT Tool to Run the Analysis

EV charging session data	Discount rate
Electricity rate structure	Inflation rate
Vehicle registration data	Annual O&M savings for BEVs
Population distribution	Annual O&M savings for PHEVs
EV load profiles	Vehicle lifetime
Load profile allocation	BEV tax credit amount
Charger assignments	PHEV tax credit amount
Total LDV forecast	Expiration year of tax credit
EV adoption forecast	CO_2 emissions/gallon
EV price differential forecast	NOX emissions/gallon
EV VMT forecast	PM10 emissions/gallon
ICE VMT forecast	SO_2 emissions/gallon
Gas prices	VOCs emissions/gallon
Ports adoption	Annual gallons gasoline/ICE vehicle
Energy marginal cost	Total annual million gallons of gasoline consumed in geography
Generation marginal cost	EVSE make ready cost
Transmission marginal cost	EVSE cost
Distribution marginal cost	EVSE annual price reduction
Annual hourly CO_2 grid emissions	Number of EVSE per meter
Annual hourly NOx grid emissions	Number of plugs per EVSE
Annual hourly PM10 grid emissions	Number of EVs per EVSE
Dollar year for analysis	

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Appendix B: EV Load Profiles for Each Scenario

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APPENDIX B:
EV Load Profiles for Each Scenario

Below are the EV load profile results for the other scenarios, including weekday and weekend.

Figure B-1: Base Case Weekend

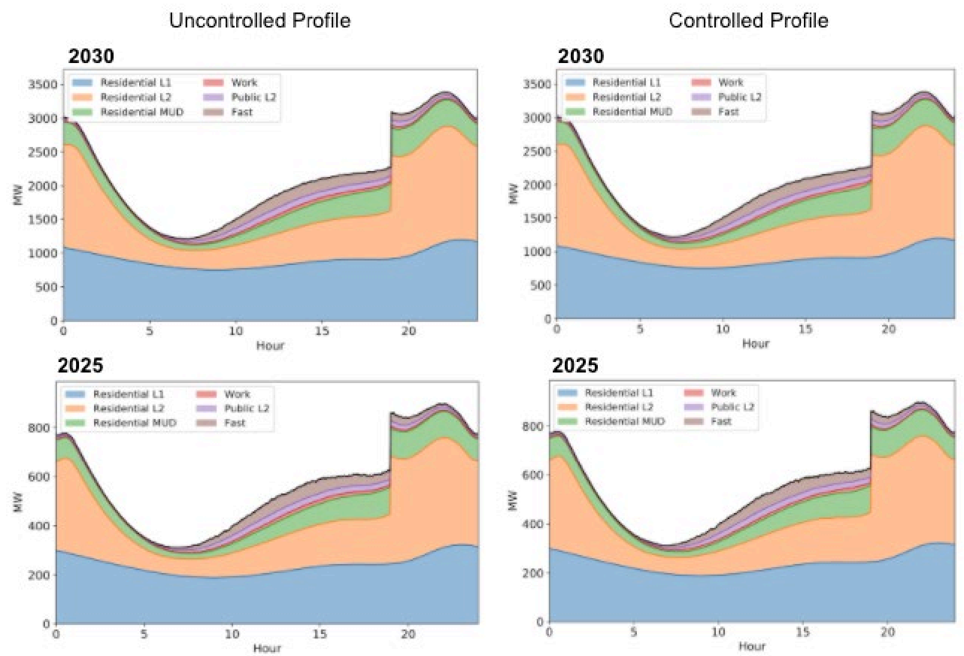


Figure B-2: Work-Public Weekend

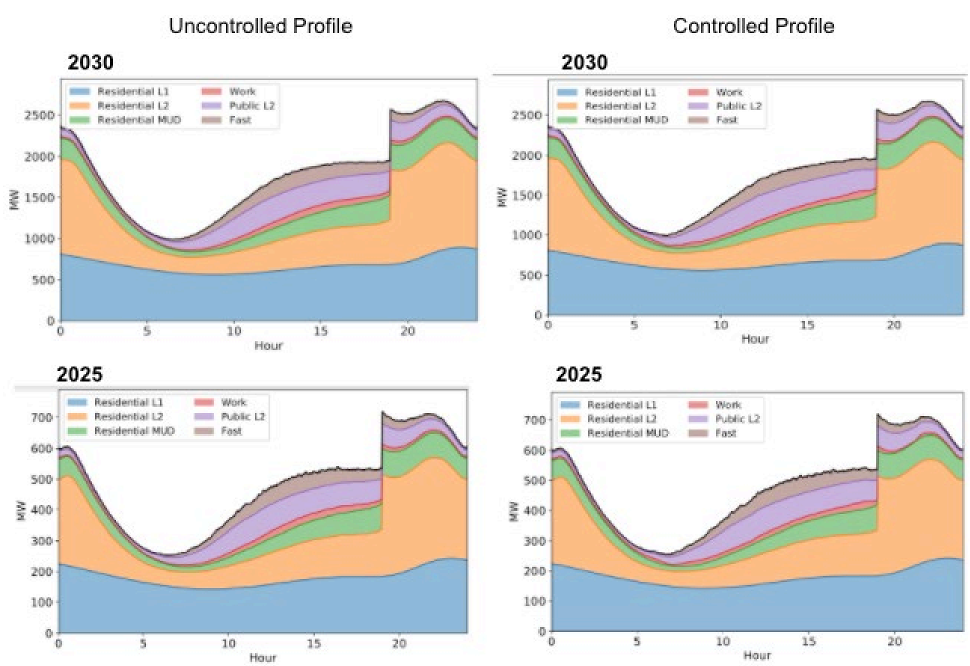


Figure B-3: Work-Public Weekday

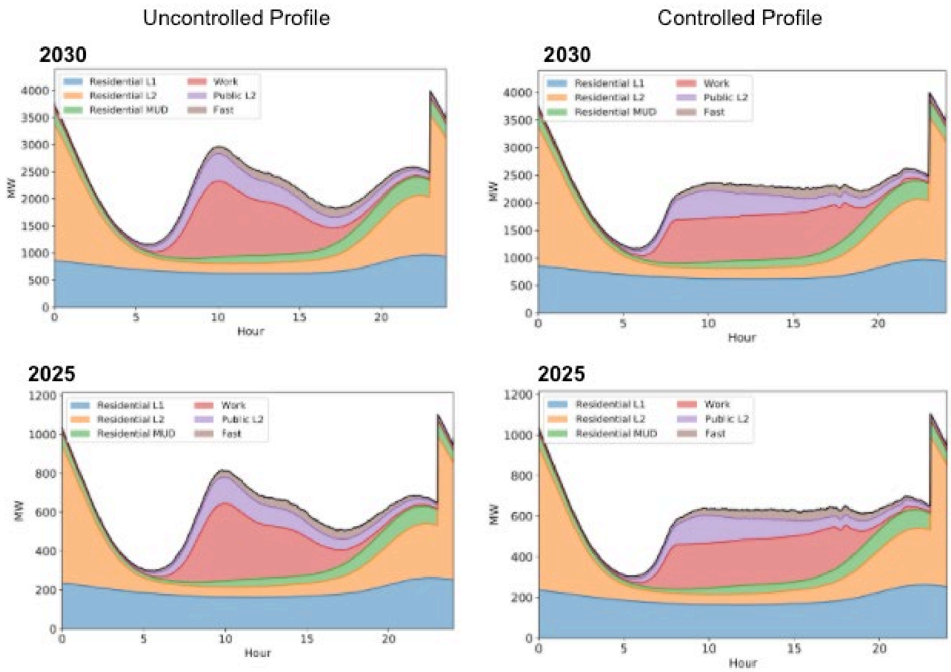


Figure B-4: Work Weekend

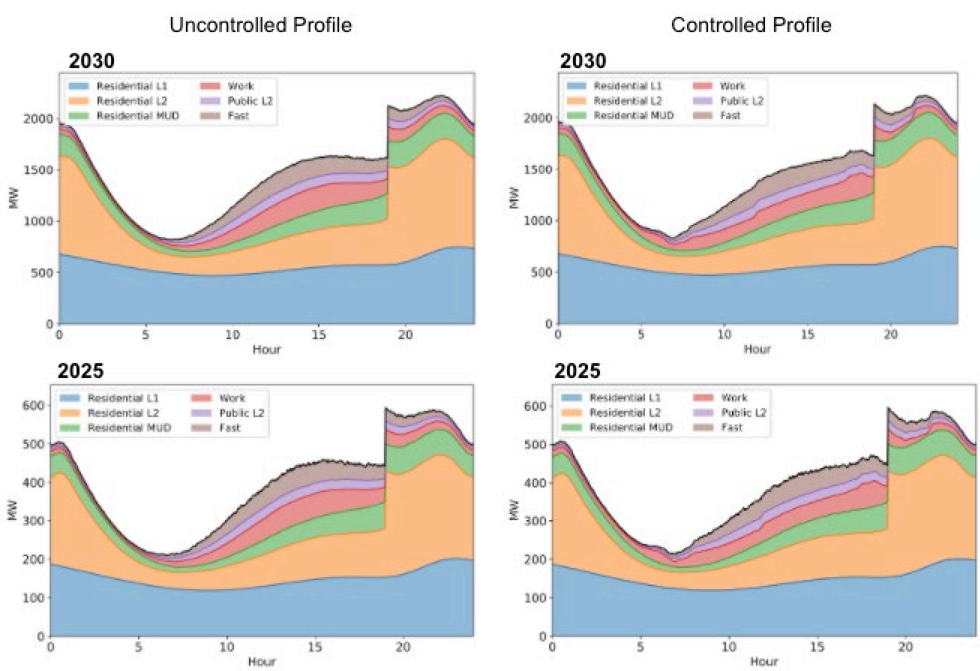


Figure B-5: Low Adoption Weekend

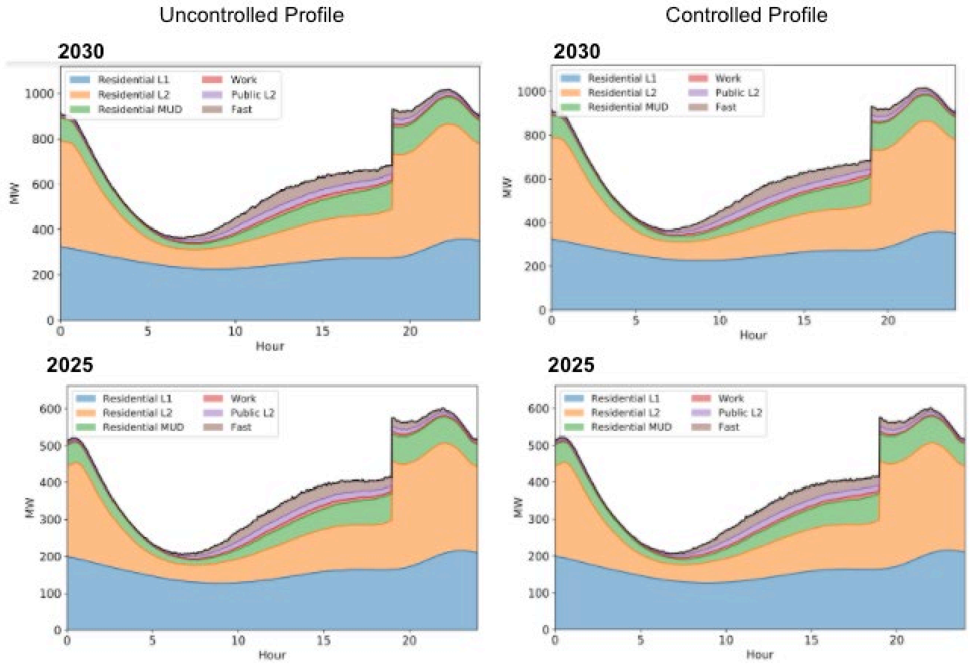


Figure B-6: Low Adoption Weekday

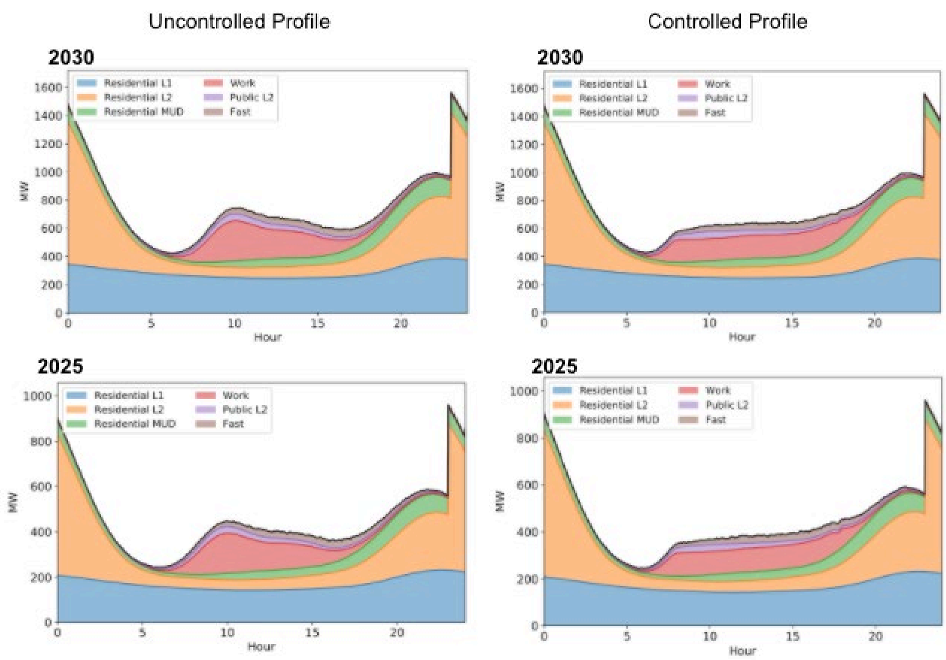


Figure B-7: High Adoption Weekend

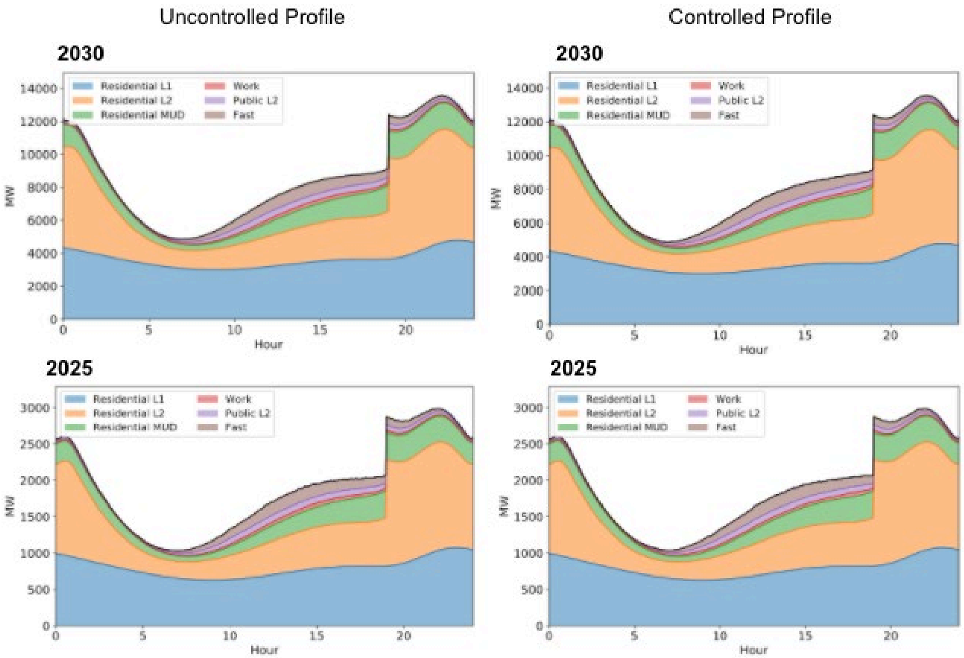


Figure B-8: High Adoption Weekday

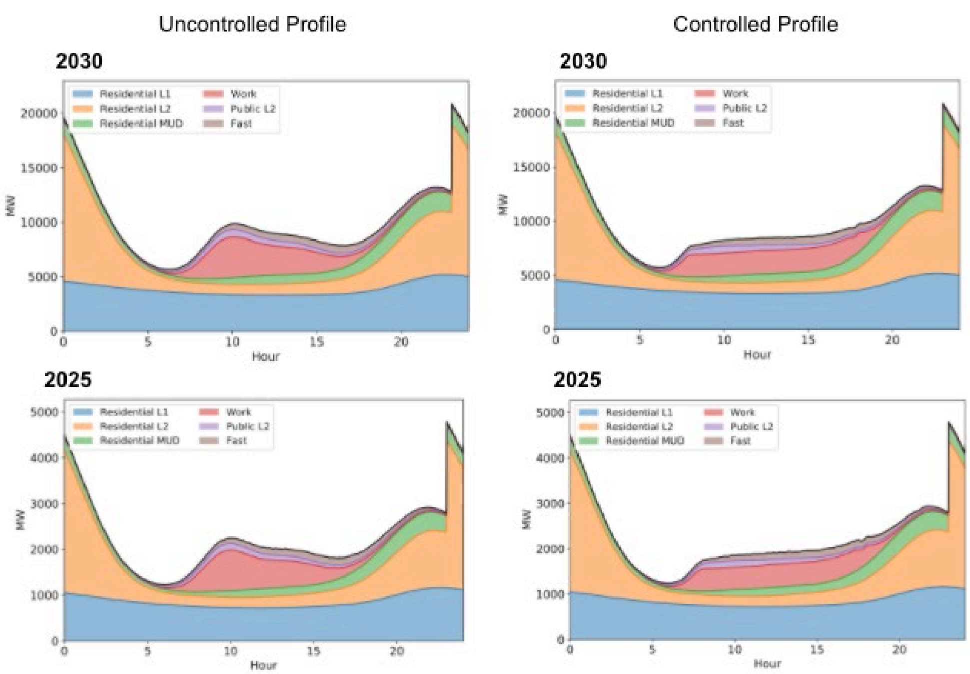


Figure B-9: Fast-Public Weekend

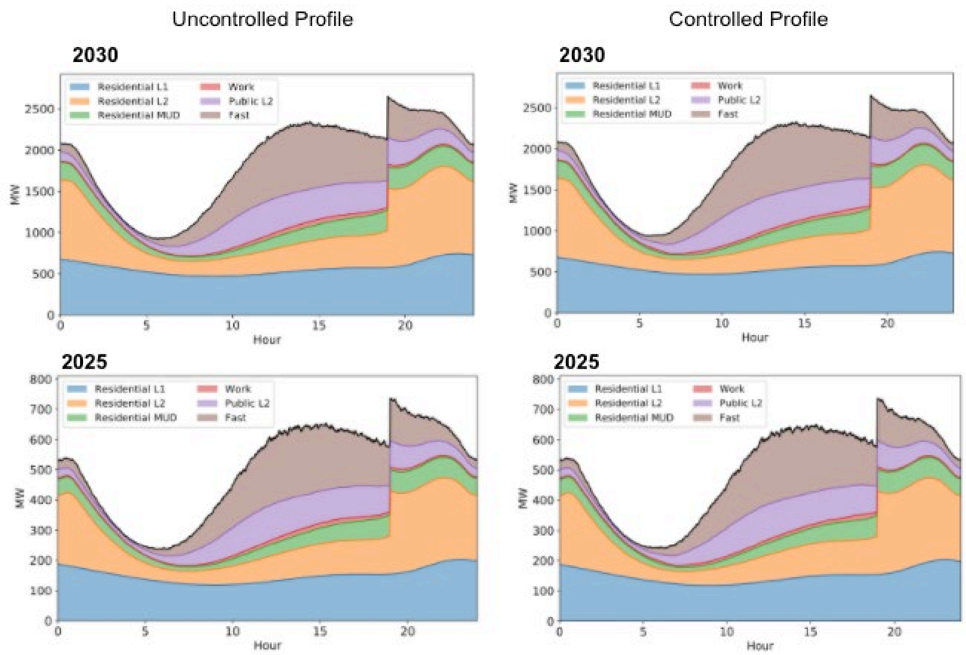


Figure B-10: Fast-Public Weekday

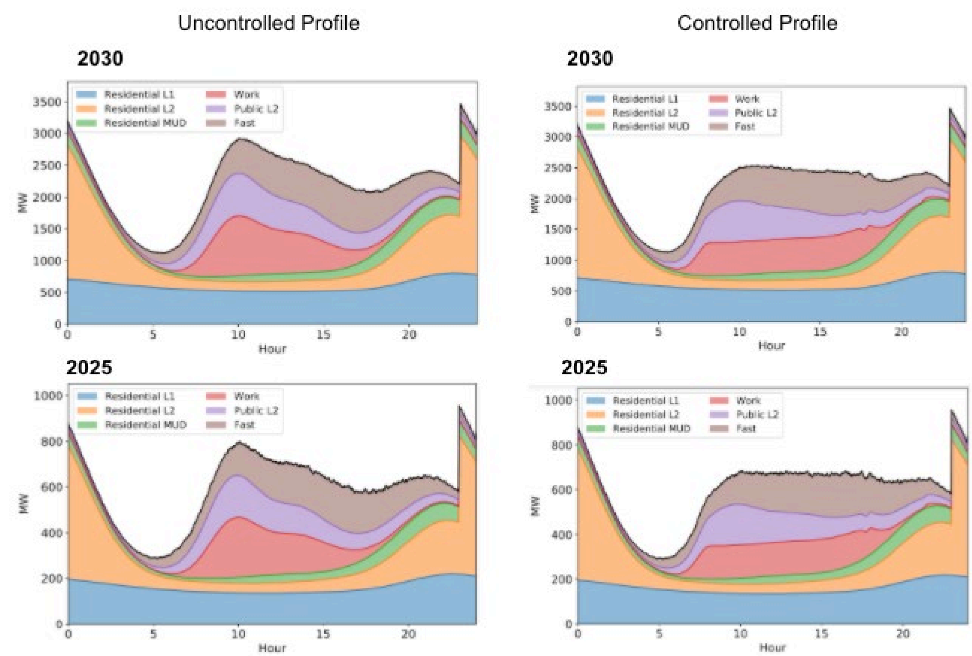


Figure B-11: Equity Weekend

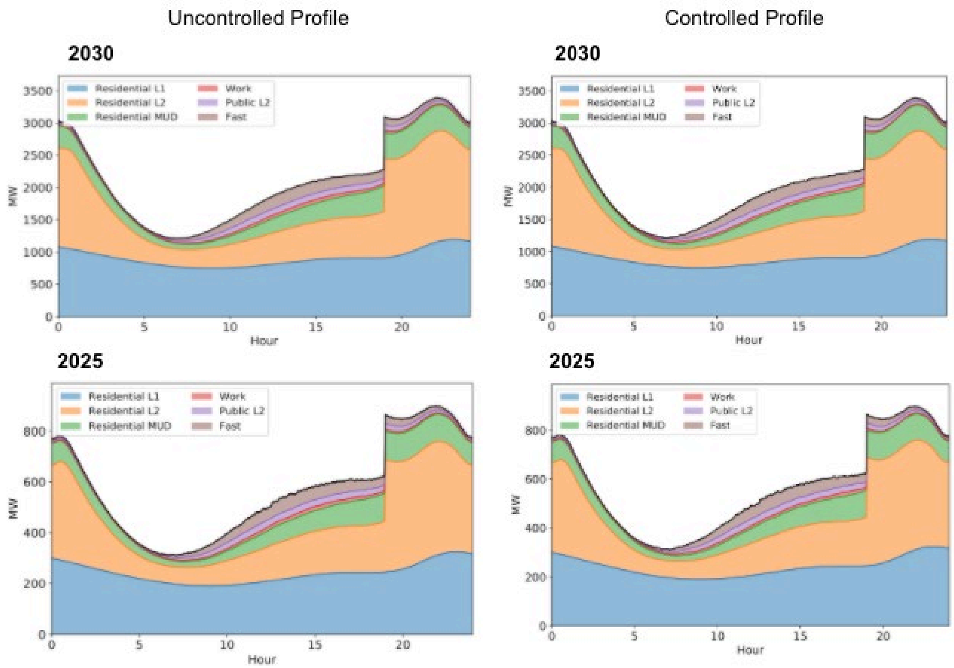
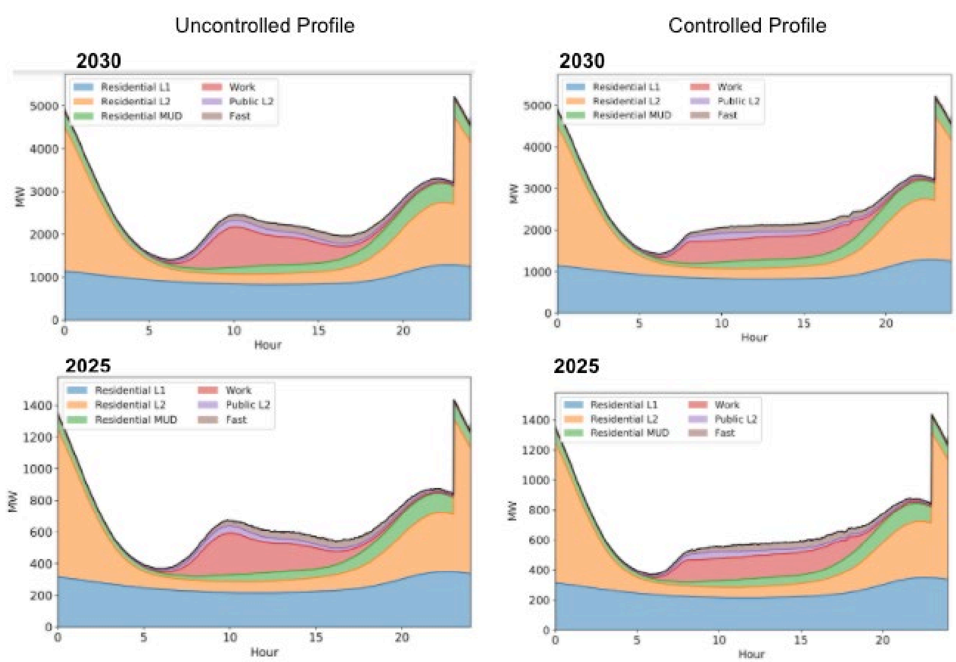


Figure B-12: Equity Weekday



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Appendix C: Cost Test Results

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APPENDIX C:
Cost Test Results

Additional Cost Test Results by County

Below are other results for the cost test performed for each county, analyzed for the seven scenarios.

Figure C-1: San Francisco County Total Resource Cost (TRC) Test

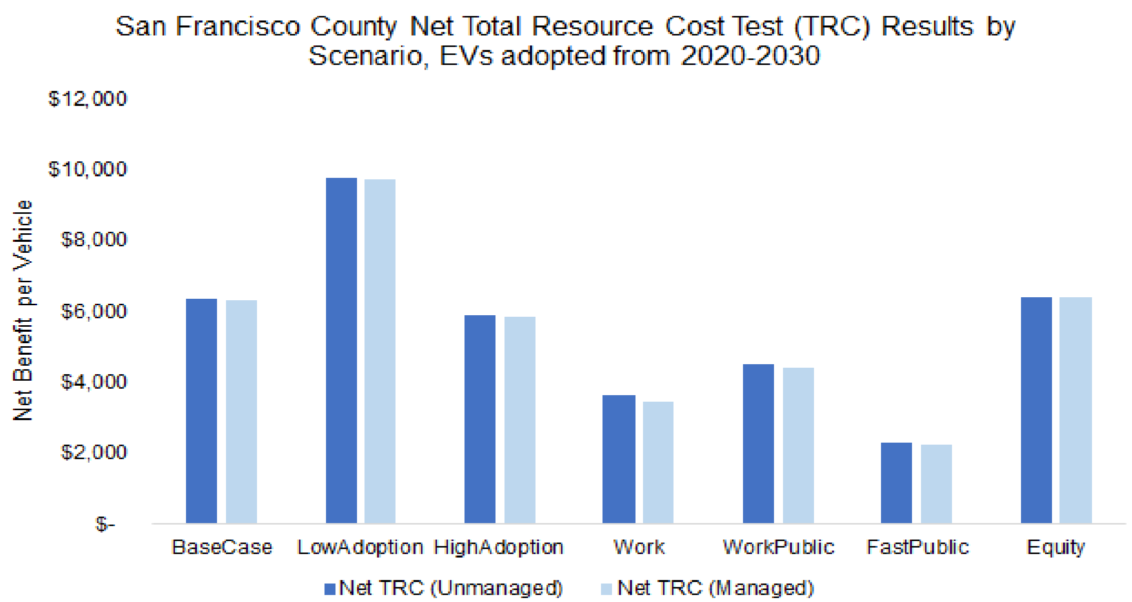

Figure C-2: Los Angeles County Total Resource Cost (TRC) Test

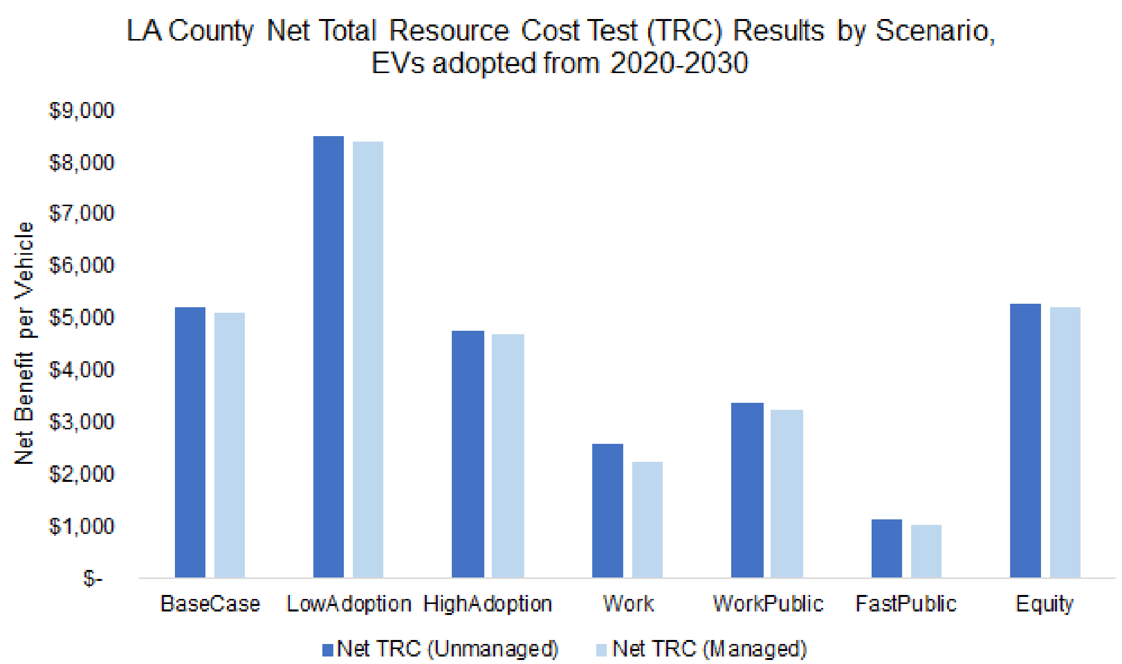

Figure C-3: San Diego County Total Resource Cost (TRC) Test

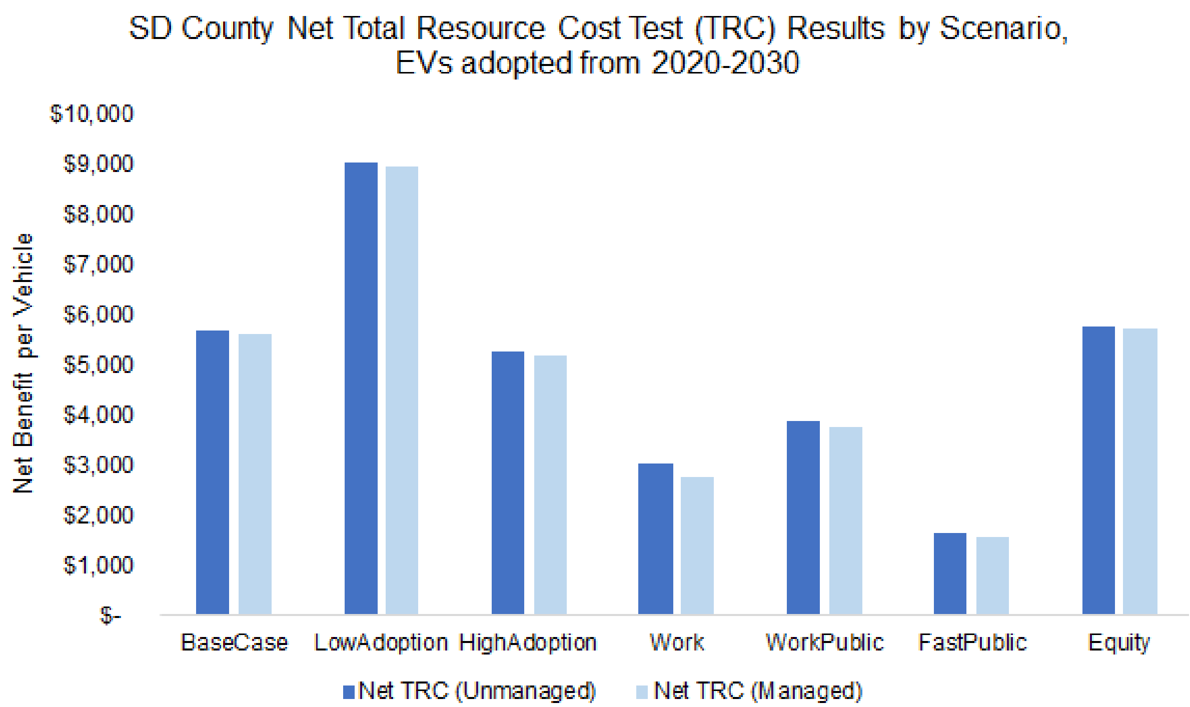

Figure C-4: Fresno County Total Resource Cost (TRC) Test

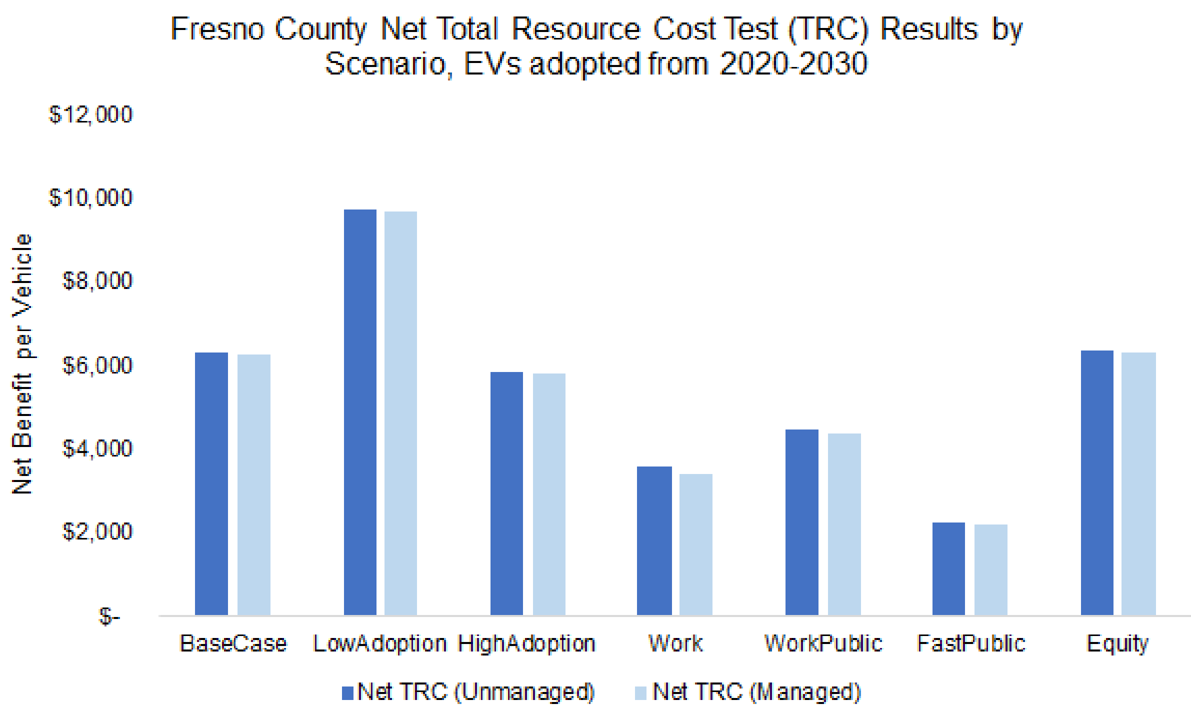

Figure C-5: Kern County Total Resource Cost (TRC) Test

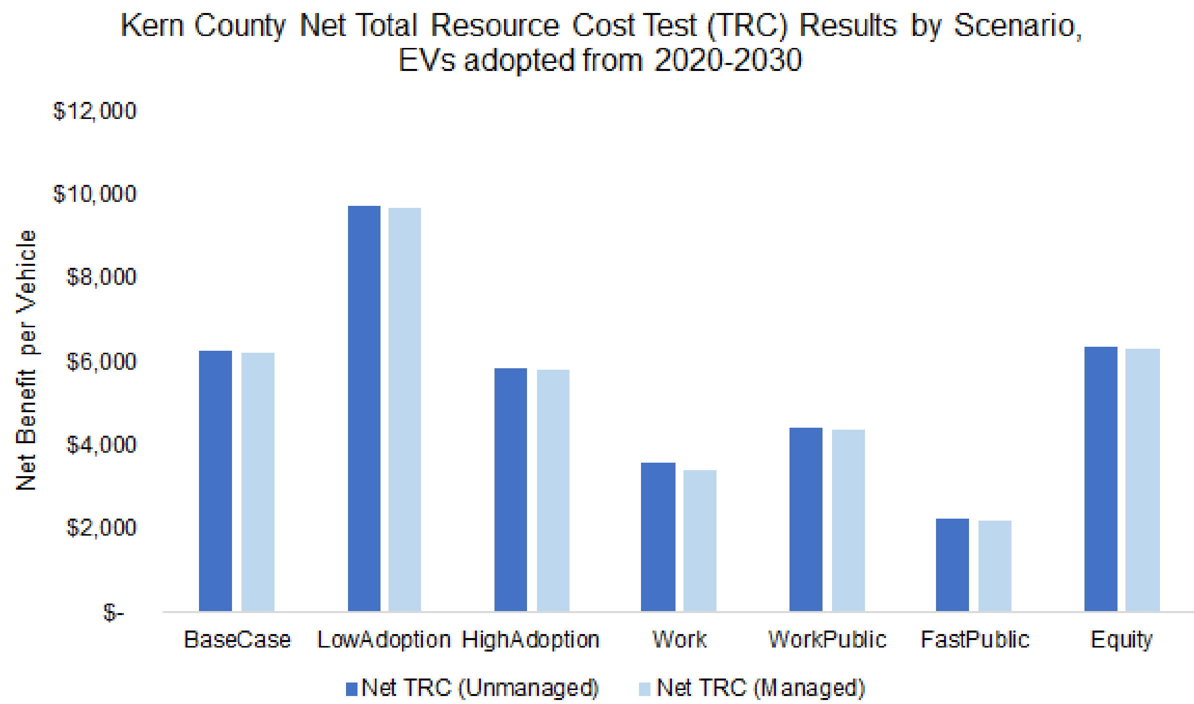

Figure C-6: San Francisco County Ratepayer Impact Measure (RIM) Test

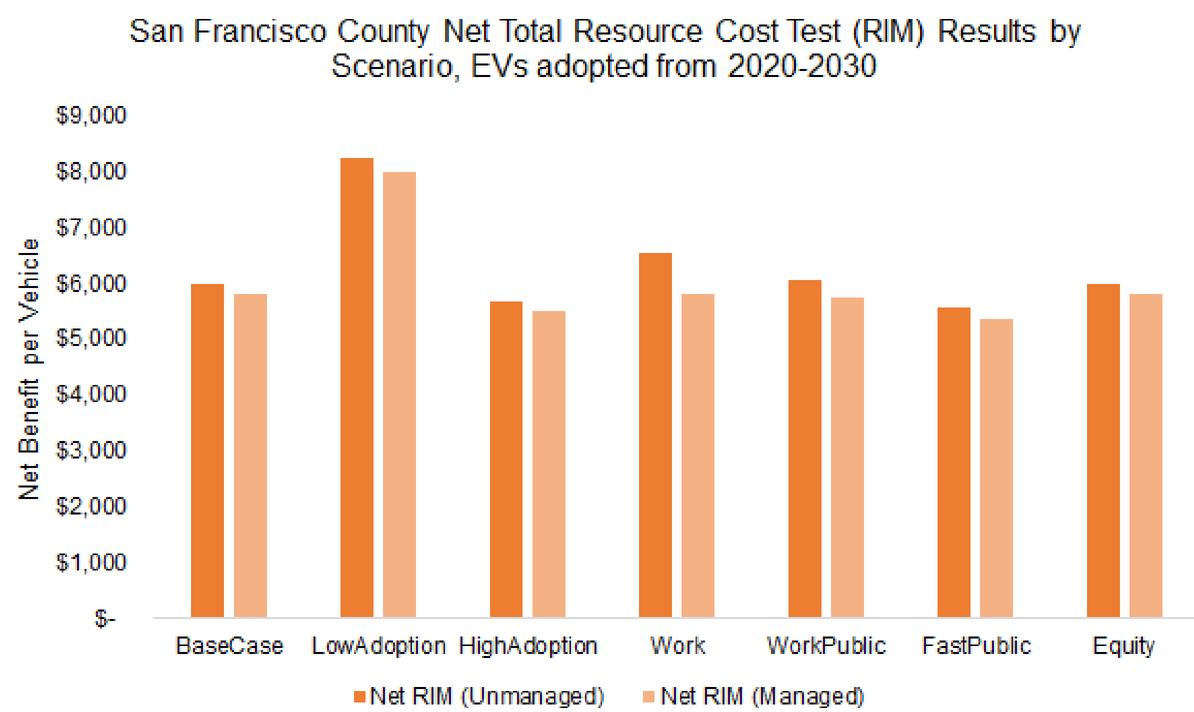

Figure C-7: LA County Ratepayer Impact Measure (RIM)Test

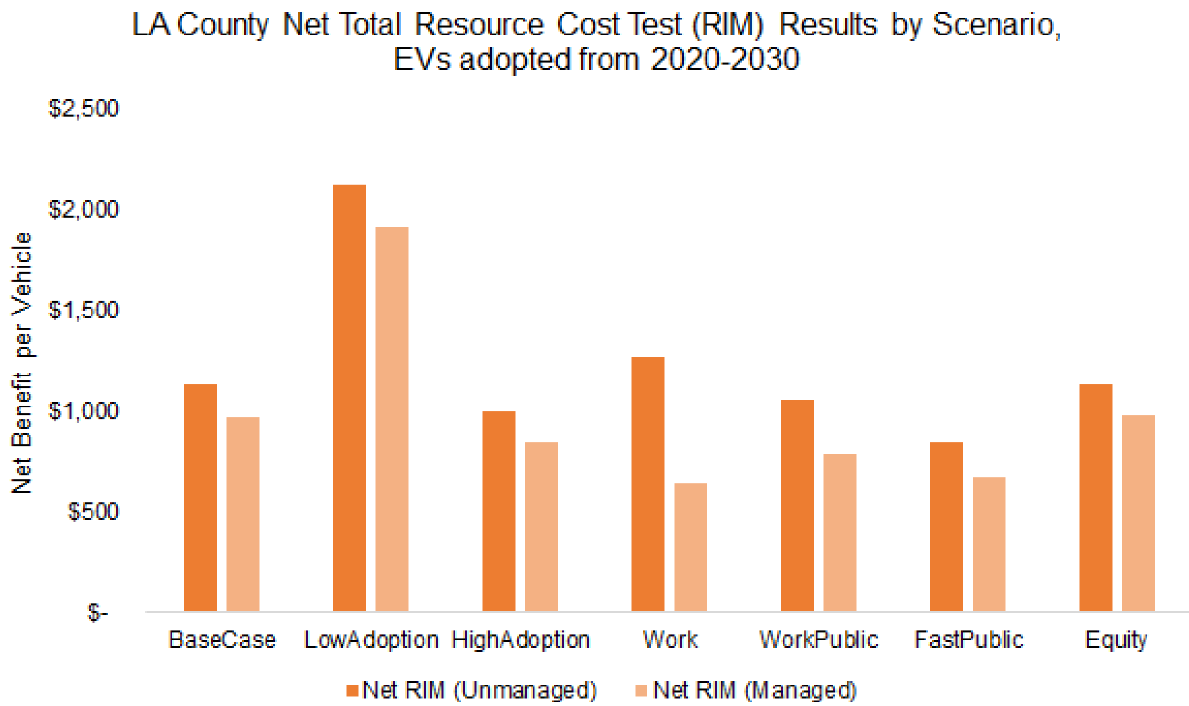

Figure C-8: San Diego County Ratepayer Impact Measure (RIM)Test

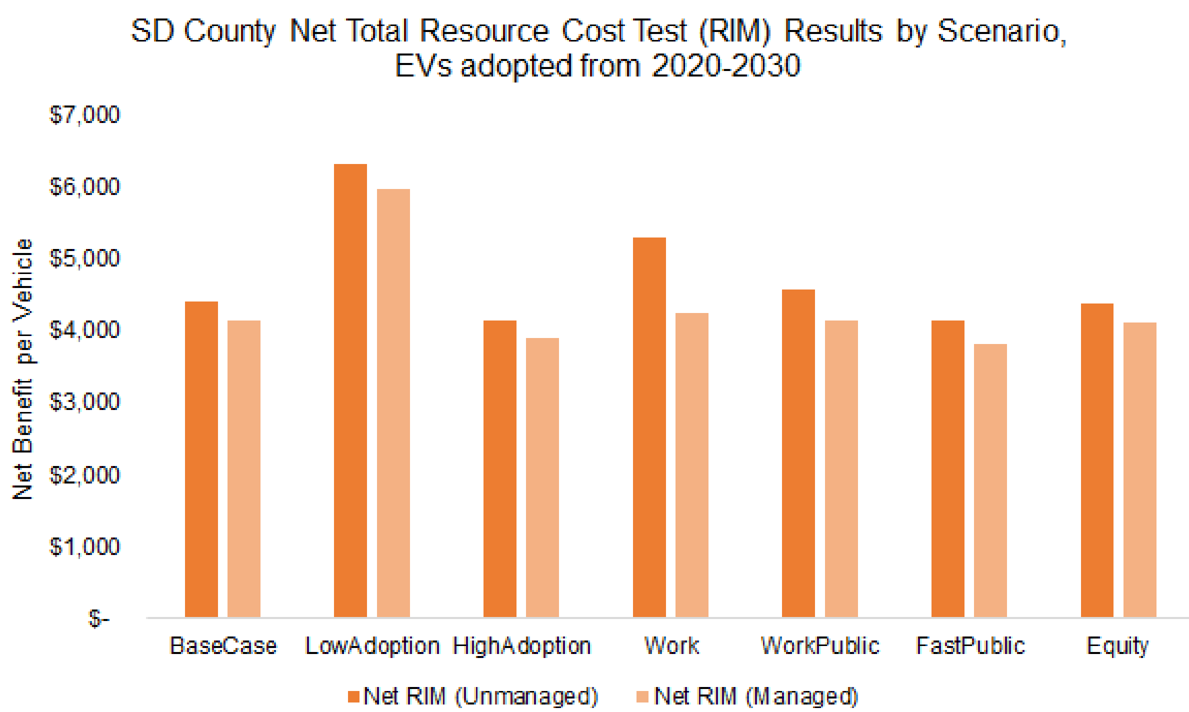

Figure C-9: Fresno County Ratepayer Impact Measure (RIM)Test

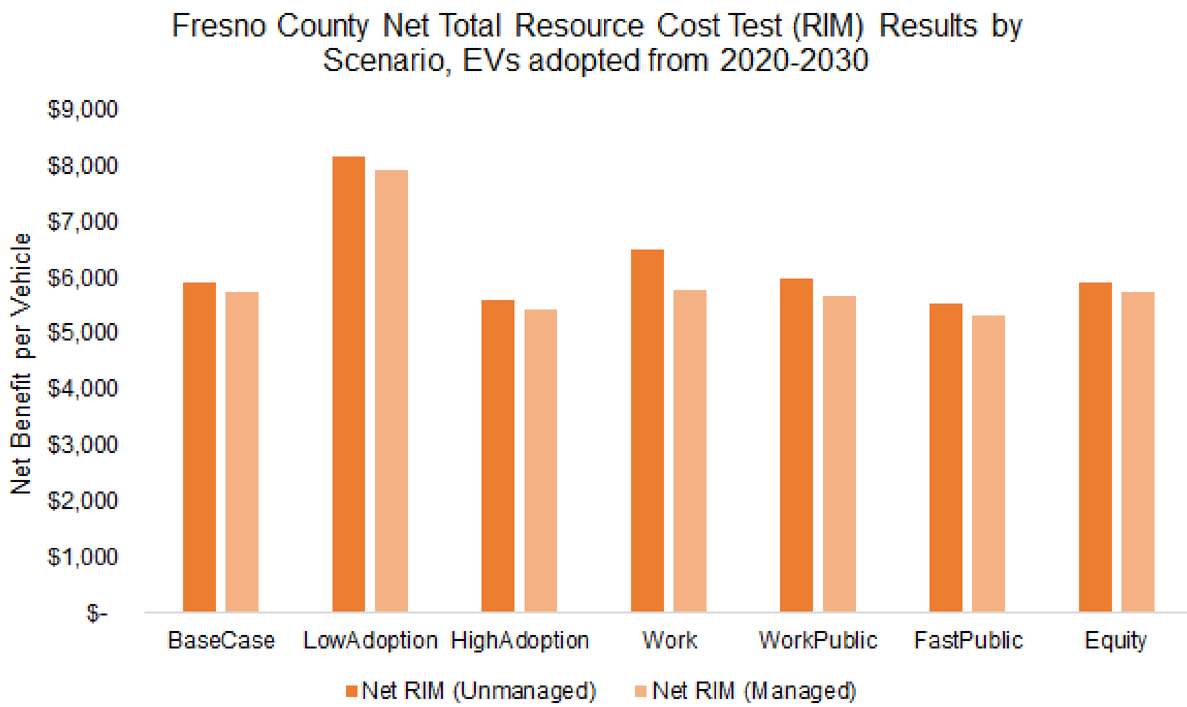

Figure C-10: Kern County Ratepayer Impact Measure (RIM)Test

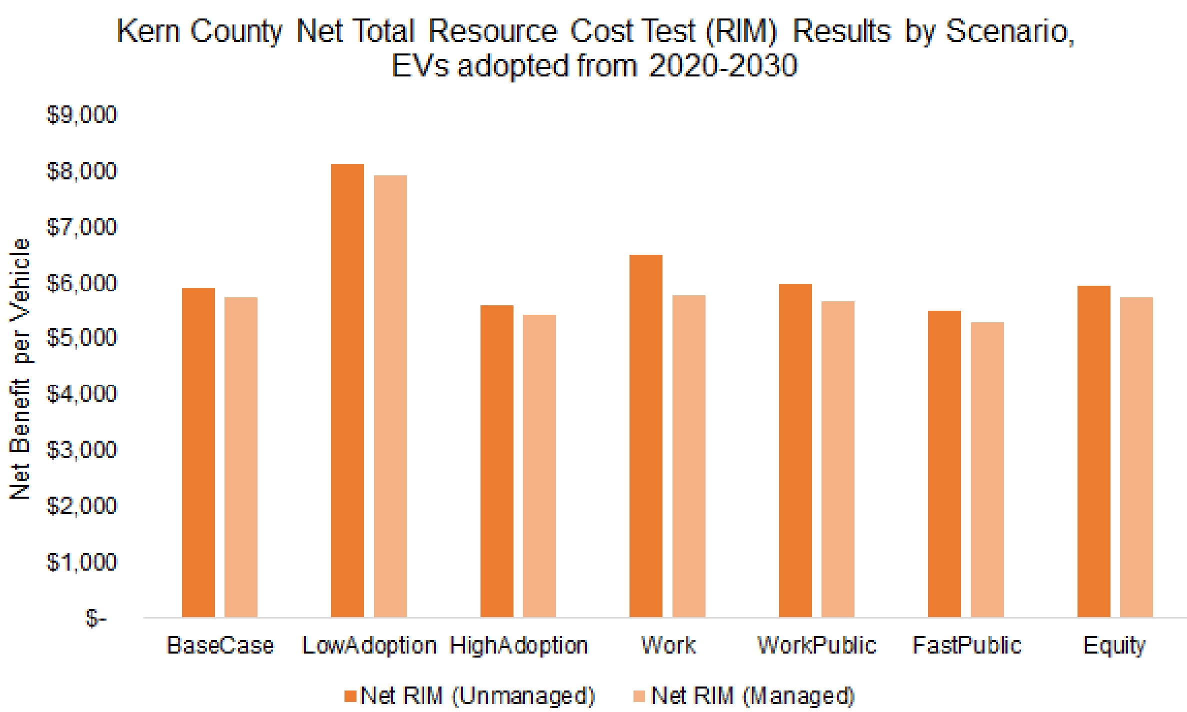

Figure C-11: San Francisco County Net Participant Cost Test (PCT)

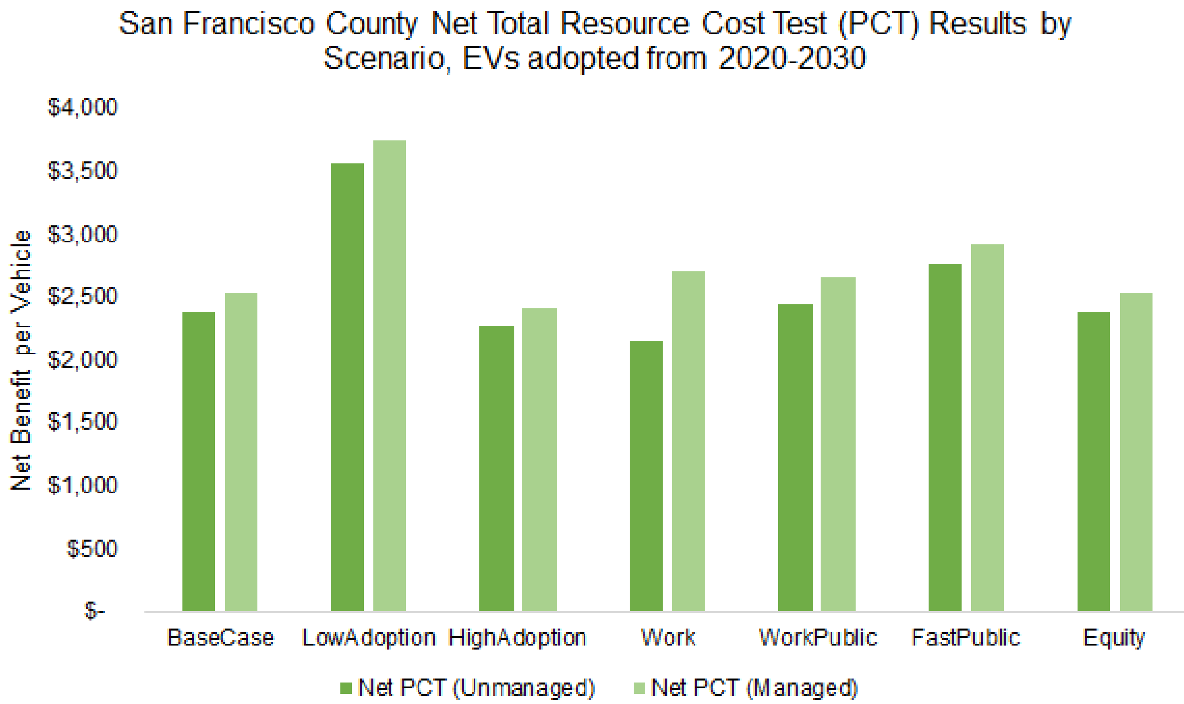

Figure C-12: Los Angeles County Total Resource Cost Test (PCT)

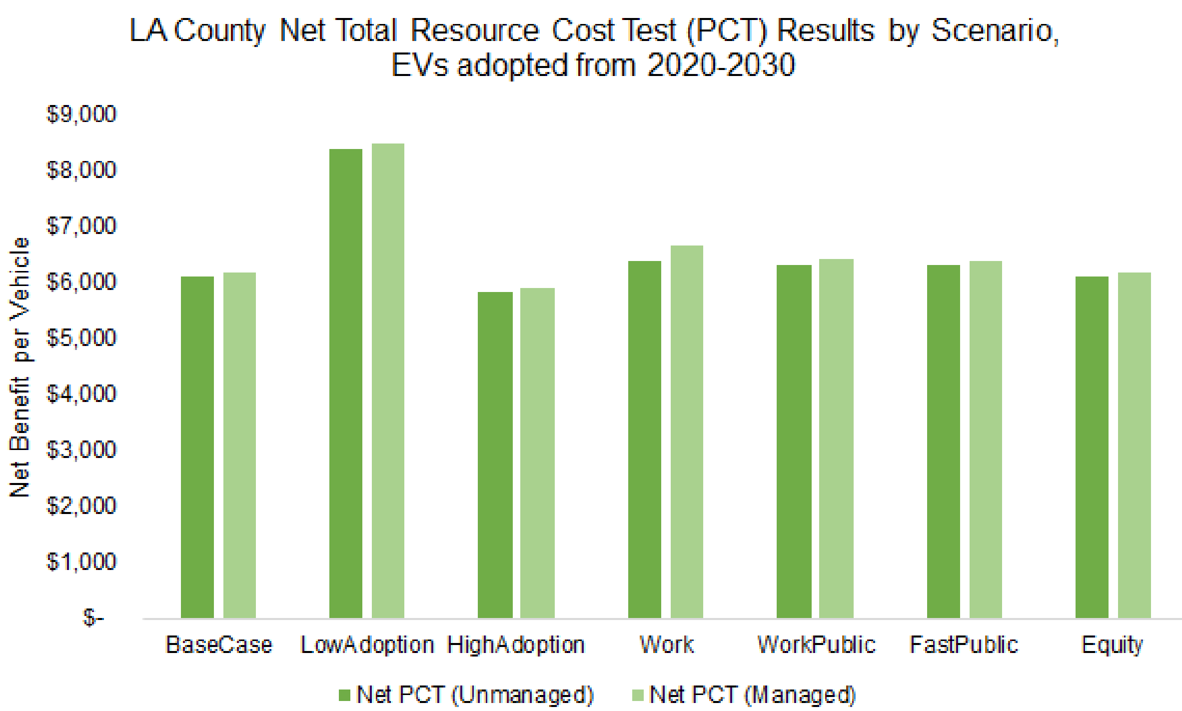

Figure C-13: San Diego County Total Resource Cost Test (PCT)

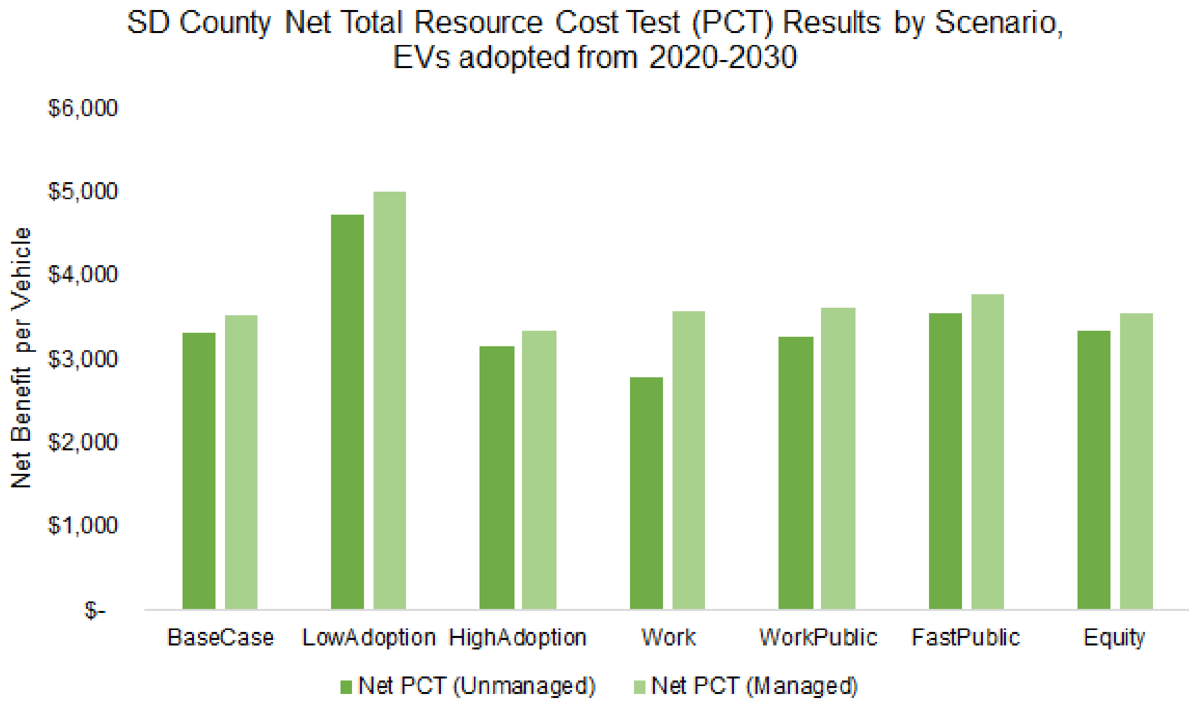

Figure C-14: Fresno County Total Resource Cost Test (PCT)

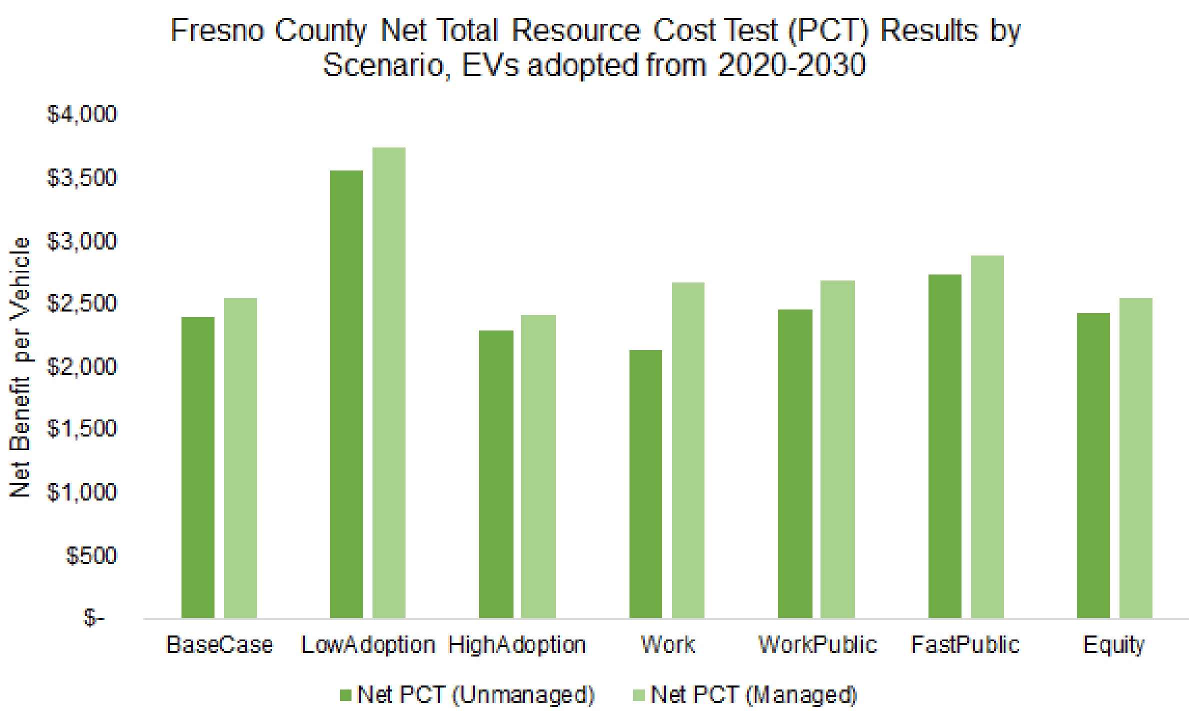

Figure C-15: Kern County Total Resource Cost Test (PCT)