GRID MODERNIZATION LABORATORY CONSORTIUM
U.S. Department of Energy

Electric Vehicles at Scale – Phase II DISTRIBUTION SYSTEM ANALYSIS

PNNL Report

March 2022

PNNL-32460

PACIFIC NORTHWEST NATIONAL LABORATORY
operated by
BATTELLE
for the
UNITED STATES DEPARTMENT OF ENERGY
under Contract DE-AC05-76RL01830

Printed in the United States of America

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March 2022

Prepared for
the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Executive Summary

The use of electric vehicles (EVs) in the United States has grown significantly during the last decade, posing benefits to the environment but also potential load delivery challenges to our grid. To better understand the growth in EVs, the Department of Energy (DOE) asked Pacific Northwest National Laboratory (PNNL) to perform an authoritative study of the impacts of EVs at scale on the electric grid.

The Phase I study focused on the bulk power electricity impacts. This EV-at-scale Phase II work addresses key questions of interest to DOE related to the impacts of EV in the distribution systems:

1. When (which year), where, and how many EVs will be adopted and how will they be charged?
2. Given some prospective answers to the above question, what would be the EV hosting capability of a distribution system circuit?
3. How could the hosting capability be expanded to accommodate more EVs and what would be the potential measures and cost?

This report documents the methodologies developed as part of this project and provides EV adoption modeling examples using distribution system circuit data provided by industry partner Southern California Edison (SCE).

Key Outcomes

1. **High-spatial Resolution EV Adoption Modeling**

   This project established a new EV adoption modeling (EVAM) methodology for estimating the likelihood of EV adoption at the household level (unique street addresses). The model is fitted with California's Department of Licensing registration data and socio-economic inputs such as household income, assessed home value, and access to EV charging infrastructure. This model estimates the likelihood of EVs to be charged within neighborhoods. The spatial results of projected EVs are then passed on to a power flow simulation capability to estimate potential condition-specific power flow violation problems of the distribution system at the circuit/feeder level.

2. **Development of Tools for Estimating EV Hosting Capabilities**

   We developed a methodology and programming scripts for estimating EV hosting capabilities for distribution system planning. These scripts utilized PNNL's GridLAB-D simulation platform and feature preprocessing routines that sampled the EV adoption results, launched thousands of simulations, and post-processed the results to identify potential power flow issues that would violate American National Standards Institute standards for nominal operating conditions.

3. **Testing Development Tools for an SCE Distribution Feeder**

   In collaboration with SCE, we tested these methodologies and tools on a single distribution system circuit selected by SCE engineers. The distribution circuit provided electric services to 2,381 customers. The report concludes with a brief outline of next steps to implement the methodology into a user-friendly tool for distribution system planners.

It should be noted that the EV adoption assumptions for light-duty vehicles in this Phase II study are consistent with those used in the Phase I study.

Major Findings

1. The EVAM estimated probability of EV adoption by addresses within neighborhoods associated with the selected SCE test feeder. We identified high sensitivity to vehicle price and income. The model was formulated for three EV categories that varied by driving range capability. We estimated EV adoption with and without specific incentives, such as federal versus additional utility incentives. The model was calibrated to SCE's target of EV making up 76% of the light-duty vehicle stock by 2040. For the calibration, all state and federal incentives were applied throughout the forecasting horizon.
2. Given projections of EV adoption, the GridLAB-D results for the selected SCE distribution feeder (Mallet) indicated no operational challenges until 2025. After 2025, because of the cumulative EV load growth, we identified some overloading of secondary transformers. Overloading conditions will increase with continuing EV growth unless mitigation strategies were applied. The modeling results allowed the distribution system planner to identify the specific secondary transformers that need to be upgraded to avoid voltage violations and exceedance of rated capacities. Given the specific distribution circuit topology, we identified specific locations highly prone to overloading.
3. We explored two mitigation strategies: (1) infrastructure upgrading and (2) smart charge management as a demand management strategy.
    a. Infrastructure upgrading: Two investment strategies were explored: aggressive and conservative. Adopting an aggressive strategy would result in upgrading more distribution circuits sooner in the EV growth period, followed by a period with no additional upgrade requirements. Following a conservative strategy for circuit upgrades would result in a just-in-time measure, which would require a more gradual and ongoing need for upgrade investments over a longer timeframe.
    b. Smart charge management: Smart charge management can defer upgrading. For the selected SCE feeder, the deferment potential of smart charge management could be between 5 and 15 years over the 2021–2050 period. The value for this deferment of a secondary transformer would be a cumulative benefit of over $300,000 for the Mallet distribution feeder analyzed. Expressed in $/EV per year, the SCM benefit is approximately 77.
4. Proposed are next steps to enhance the modeling capabilities to include EV market adoption projections for mid- and heavy-duty vehicles as well as automating the developed capabilities for broad access by community leaders and distribution planning engineers.

Acknowledgments

The study authors express their appreciation and gratitude to the Department of Energy for funding for this study. The authors appreciate the guidance by Department of Energy project managers Dr. Jake Ward and Mr. Lee Slezak for their leadership and direction.

The authors also thank Southern California Edison for providing distribution system data. We would like to give special appreciation to the following contributors to this study:

- Southern California Edison staff members Anthony James, Jordan Smith, and Muhammad Dayhim for their guidance on electric vehicle demands and overall guidance on which questions and tools would be of highest value to utility companies in California and the greater United States.
- Both legal councils from Pacific Northwest National Laboratory and Southern California Edison for coordinating the details for the Pacific Northwest National Laboratory technical team to receive proprietary infrastructure data and load profiles.
- The California Department of Motor Vehicles for their assistance with large quantities of data.
- Pacific Northwest National Laboratory's data scientists who set up data repositories that meet the data security requirements for highly personal vehicle registration data, as well as cleaning up the data for the technical team to use for the electric vehicle adoption model.

Acronyms and Abbreviations

ANSI	American National Standards Institute
DER	distributed energy resource
DOE	Department of Energy
EV	electric vehicle
EVAM	EV adoption model
HEV	hybrid vehicle
ICE	internal combustion engine
kV	kilovolt
kVA	kilovolt-ampere (rating for alternate current assets)
kWh	kilowatt hour(s)
LDV	light-duty vehicle
NHTS	national household travel survey
NREL	National Renewable Energy Laboratory
PHEV	plug-in hybrid electric vehicle
PNNL	Pacific Northwest National Laboratory
pu	per unit (dimensionless unit often used in engineering)
SCE	Southern California Edison
SCM	smart charge management
WECC	Western Electricity Coordinating Council

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1.0 Introduction

A combination of state and federal incentives, decarbonization directives, increasingly affordable electrical vehicles (EVs), and increasing fast-charging options are accelerating the transition to electrified on-road transportation (Gohlke and Zhou 2021). The resulting increase in electrical load from charging activity is expected to challenge the operational limits of power distribution networks, forcing a rethink of current utility planning practices in preparation for the future. To better understand this emerging scenario, the Department of Energy (DOE) asked Pacific Northwest National Laboratory (PNNL) to perform an authoritative study of the impacts of EVs at scale on the electric grid in two phases. Phase I focused on impacts of EVs to the bulk power system. Phase II addresses the impacts of EVs on the distribution system.

1.1 Background

In Phase I, PNNL assessed bulk power system impacts in the Western U.S. grid that are expected to derive from high-growth EV adoption across all vehicle segments (i.e., light-duty, medium-duty, and heavy-duty) (Kintner-Meyer et al., 2020). The bulk power system comprises power plants and the high-voltage transmission network.

The key outcomes of that study were: (1) resource adequacy in the Western Electricity Coordinating Council (WECC) may be adequate for high EV growth under normal operating conditions in 2028; (2) EV resource adequacy could be doubled when managed charging strategies are applied; (3) additional generation for EV charging could be provided with natural gas combined cycle plants; and (4) EV charging could reduce renewable energy curtailments by 25 to 75%.

As an extension of the Phase I bulk power analysis, Phase II focused on EV charging impacts on a mid- to low-voltage distribution system that deliver electric power from the transmission system (substation) to EV chargers and individual residential and commercial customers.

Whereas Phase 1 comprehensively analyzed high-growth EV impacts to the WECC bulk power system, Phase II developed methodologies to enable distribution system planning engineers to perform EV impact analyses on their systems (in lieu of performing an authoritative analysis of EV impacts on distribution systems overall). This decision to focus the development of a generalizable, broadly applicable methodology reflects the recognition of the broad diversity of distribution system configurations, design guidelines, and localized customer compositions within a utility service territory, not to mention across the WECC. Capturing this large diversity presented a computational challenge beyond the scope of the study. Furthermore, a reduction of this large parameter space of distribution system configurations to a few archetypical distribution configurations representing the WECC was not likely to reveal any meaningful information for the planning engineering community. Therefore, Phase II activities were directed to develop a methodology for distribution system planning engineers to assess the future adoption of EVs for the local feeders/circuits within their network with respect to grid assets overloading and voltage deviations and to manage the distribution system to accommodate the additional EV load. The goal was to establish methods that will be easily emulated and adopted by distribution engineers.

1.2 Overview

This Phase II report describes the methodology for the EV load-demand assessment of distribution systems and applies it to a single distribution Southern California Edison (SCE) feeder circuit. Ultimately, this study contributes two distinct new analysis modules to the EV mission space:

1. A high-granularity EV light-duty vehicle (LDV) market adoption model that addresses how many, when, and where EVs are forecast to be adopted within the distribution system.
2. Use of the EV adoption forecast to analytically determine the hosting capability of a given distribution system feeder using GridLAB-D. Hosting capability represents the maximum new load emerging from EV adoption that can be accommodated in a distribution system with no violations against American National Standard Institute (ANSI) code.

Within this study, we determine a single SCE circuit's EV hosting capability and evaluate measures to expand the hosting capabilities using common measures such as distribution system upgrades. We also explore how smart charge management (SCM) can move EV-generated load to less stressful (off-peak) times, thus avoiding exceedances of thermal or voltage range limits.

This report includes a detailed description of the methodology, including the EV adoption model (EVAM) and EV hosting capability estimation, and its application to a SCE distribution system circuit scenario that illustrate what new results can be generated and how to interpret modeling results. Appendices contain supplementary information about adoption models, data, and incentive and charging data scenarios used in this study.

2.0 Methodology

The Phase II methodology includes: (1) an LDV market adoption model and (2) a power flow analysis to determine the impact of EV adoption on individual distribution feeders. Each method is described in this report using SCE's Mallet feeder[1] as the example use case.

2.1 Need for New Planning Tools

Currently, predictive tools to forecast likely EV market adoption at a distribution feeder level do not exist. However, planning engineers need to understand when, where, and how anticipated EV load-demand will affect capacity ceilings of existing distribution circuits. Therefore, a highly granular model is needed to estimate where on the circuit and when in the future EV load-demand may be anticipated. Existing tools focus on projecting EV charging loads across larger geographic regions (e.g., national, state, county, or utility footprint-level). This project addressed this methodological gap and developed an address-specific adoption model to enable distribution system planners to understand localized demand-conditions that will inform utility distribution network investment decisions.

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[1] More information about the SCE Mallet feeder is provided in Figure 3 below.

2.1.1 Current Practice

California leads the nation in considering EV load impacts on the power grid and is the source of currently accepted best practices related to EV load projections. The California Energy Commission provides investor-owned utilities with utility-specific EV demand forecast in its annual *Integrated Energy Policy Report*.[1] SCE planning engineers receive this utility-specific forecast and then disaggregate it, first to a zip code-level forecast using propensity scores obtained from zip code-level customer income data. The zip code-level forecast is further distributed to underlying circuits using "circuit mileage" as a weight. Unfortunately, this top-down approach generalizes regional adoption characteristics to circuit level, potentially misrepresenting customer-specific adoption tendencies that can lead to inaccurate circuit planning. Other states have even less data available to estimate location-specific impacts of EV on the grid.

Furthermore, distribution system planners require analysis tools to perform extensive scenario analyses for guiding utility investment decisions; a tool considers all possible future adoption scenarios before deciding on likely constrained system components and applicable mitigation strategies. The systematic analysis of a large scenario space would be computationally intensive, requiring efficient power flow analysis software and hardware that produce desired outcomes in reasonable time.

The following sections present a methodology for circuit-level EV adoption forecasting and impact estimation in support of utility planning. The methodology, shown in Figure 1, is a two-step, bottom-up process. In the first step, an EVAM outputs future year-specific, household-level EV adoption probability using socio-economic data such as vehicle registration, household-level income estimates, and home price assessments as inputs. In the second step, the household-level adoption probabilities are used to perform impact analysis using a Monte Carlo approach and to identify constrained grid components to be considered in future investment planning decisions.

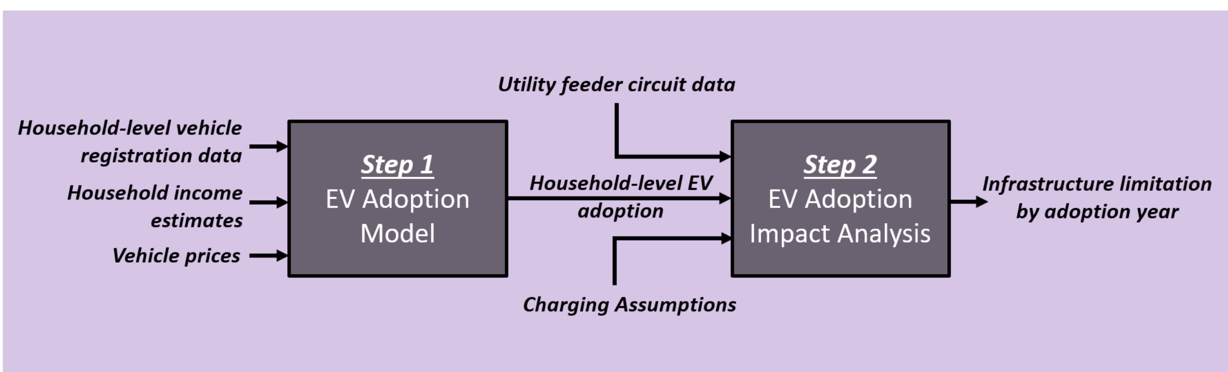

Figure 1. Overall methodology for EV adoption forecast modeling and impact estimation

2.2 High-Resolution EV Market Adoption Model

The EV forecasting model estimates future demand in the form of electricity load associated with increased EV adoption numbers and the type of EV batteries. Presently, batteries with longer ranges

[1] See https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report

(i.e., higher charging capacities and higher charging rates) tend to correspond with more expensive vehicles. Thus, the rate and magnitude of specific EV adoption is driven by numerous factors such as available EV model choices, financial capacity (ability to purchase a vehicle), philanthropic beliefs (environmental championship), social considerations (status-signaling through EV ownership), more practical concerns such as availability and access to charging infrastructure, and routine maintenance and operating costs.

The decision to purchase an EV is multifaceted. Published research has established that variables such as income, incentives, car price, and charging infrastructure play significantly into purchase decisions (Al-Alawi and Bradley 2013), from which inferences may be made. Since socio-economic characteristics (i.e., income), along with housing types (i.e., single-family versus multi-family), vary widely across states, counties, and zip codes, we parameterized our model with household data from homes located within the Mallet feeder's geographic area. Also, the model formulation inherently considers peer influence effects on EV adoption, which is the essence of diffusion models and is discussed in greater detail in Appendix B. The EV forecasting model for this study was informed by historic sales that are the basis for peer influence. Given the desire to forecast EV load impacts at the feeder level, our bottom-up approach only uses data from the feeder of interest to inform the forecast and adoption behaviors.

The remainder of this section explains our model selection by reviewing pertinent EV adoption literature, describing our market (EV sales) adoption model, and sharing how our consumer choice model helps define consumer preferences to refine EV allocation to specific households.

2.2.1 Justification for Selection of EVAM

Many utilities use diffusion models at the zip code or county level, then drill down to the feeder using methods such as population weighting (Dwyer 2018). However, this is problematic because the adoption characteristics within a specific feeder may differ substantially from adoption characteristics averaged across a zip code or county, leading to inaccurate feeder-level forecasts. The Electric Power Research Institute produces an EV forecast at the county, state, and national levels using a meta data approach, analyzing and drawing upon several EV forecasts from reliable sources, such as universities (Alexander 2017). The National Renewable Energy Laboratory (NREL) produces EV loads at the feeder for charging and grid research (Neuman et al. 2017). This NREL study produces several EV adoption scenarios as percentages of the market (e.g., the percentage of EVs as part of the national stock or the percentage of sedan EVs of total EV stock, etc.). NREL lists several secondary data sources for the EV projections, such as the Electric Power Research Institute, NREL's Automotive Deployment Options Projection Tool, and the Energy Information Administration's *Annual Energy Outlook*. Regarding discrete choice models, both Argonne National Laboratory and NREL developed multinomial logit models (LVACFlex and ADOPT, respectively), which predict factors that influence vehicle purchase decisions; however, these models do not produce specific EV forecasts but create market share projections by powertrain technology (Stevens et al. 2017, Brooker et al. 2015).

Our literature review did not uncover any EV forecasts developed from the feeder level up, or what we refer to as the "bottom-up" approach. By capturing the socio-economic and housing characteristics specific to the customer, a bottom-up approach will enable utility planners to develop more accurate EV adoption forecasts. Our bottom-up approach uses a Bass diffusion model to forecast sales within the feeder. To refine the distribution of the forecasted vehicles to individual households even further, we use a binary choice model to develop relationships with variables not represented in the Bass model, such as housing type and charging infrastructure. A more complete review of adoption models is provided in Appendix A.

2.3 Generalized Bass Model

In the original Bass (1969) model, the instantaneous rate of adoption *f* at time *t* is given by the differential equation

$$f(t) = [p + qF(t)][1 - (t)], \tag{1}$$

where *p* is the coefficient of innovation, q is the coefficient of imitation, *F(t)* is the portion of the market who have adopted by time *t*, and *f(t)* is the time derivation of *F(t)* or the portion (fraction) of the potential market that adopts at time *t.* The coefficient of innovation gives the probability of purchase when *t* is zero and captures the innovativeness of potential adopters. The coefficient of imitation "…reflects the pressure operating on imitators as the number of previous buyers increases" (Bass 1969, p. 216). In other words, increased adoption results in a higher chance of social influence, until the point saturation is reached, and the number of new adopters start to decline.

Extensions of the original Bass model allow for the inclusion of explanatory variables to provide better insights into factors influencing either the rate of adoption or market potential (Jain and Rao 1990; Fernandez 1999).

The specific model formulation for the SCE feeder becomes:

$$A_{t,j} = M_j\left(\frac{1 - e^{-(p_j+q_j)(t+B_{1,j}\ln(P_{t,j}))}}{1 + \left(\frac{p_j}{q_j}\right)e^{-(p_j+q_j)(t+B_{1,j}\ln(P_{t,j}))}}\right) \tag{2}$$

Here $P_{t,j}$ is average price of EVs at year *t* for car group *j*.[1] M_j is exogenous in this model to better align with SCE targets, defined below. P, q, and B_j, the coefficient for EV price, are solved by the model using non-linear least squares. The explanatory variable is vehicle price. Limited data (only eight time series observations from eight years of EV sales) resulted in limited explanatory variables. Income was initially tested as an explanatory variable but proved insignificant. Vehicle prices were found to be statistically significant. Section 2.3.1 provides high level information about the data used in the model. More detailed data information can be found in Appendix B. Section 3.0 describes how the general Bass model was applied for a specific distribution circuit.

2.3.1 Data

Our model included vehicle registration data for each household in the Mallet feeder, EV vehicle price data, and household income data. Vehicle registration data was obtained from California's Department of Motor Vehicles for every home in the Mallet feeder from 2013 through 2020. Price data was obtained

[1] Car groups are categorized according to battery specifications explained in Section 2.3.2.

from Kelly Blue Book and CarMax.com. Household income was estimated based on home values and income distribution data from the Census Bureau.

Vehicle registrations and vehicle price were used directly in the model as dependent and independent variables. Income data was used to define the market size for each adopting group. EVs were aggregated into three groups according to their battery characteristics. The reason for that is not all consumers can afford a high-end EV (such as a Tesla) and may choose a more affordable EV with less driving range. The three groups are defined according to their battery characteristics, with Group 1 having the longest range of batteries, Group 2 with mid-range batteries, and Group 3 with hybrids and the shortest-range batteries.

Table 1. Summary data for Groups 1, 2, and 3: Car facts, average price, average income for purchasers

	Group 1	Group 2	Group 3
EV Range (Miles)	140–300	60–170	17–81
Examples of Vehicles	Tesla, Audi E-Tron	Nissan Leaf, Chevy Bolt	Prius Prime, Chevy Volt
No. of EVs Adopted by 2020	77	19	79
Average EV Price	\$66,821	\$31,828	\$32,199
Average Income	\$150,603	\$94,439	\$116,519

The number and average prices for each group are derived from California Department of Motor Vehicles vehicle registrations between 2013 and 2020. They are shown in Table 2.

Table 2. Number of EVs registered by group and average group price for Mallet feeder[a]

	Group 1		Group 2		Group 3	
Year	Sales	Average Price	Sales	Average Price	Sales	Average Price
2013	1	\$81,413	2	\$31,979	2	\$36,654
2014	2	\$71,941	1	\$31,946	8	\$36,477
2015	2	\$67,744	1	\$29,642	5	\$36,300
2016	3	\$77,250	2	\$26,540	4	\$34,264
2017	4	\$75,959	2	\$34,787	15	\$24,880
2018	22	\$53,835	5	\$35,757	21	\$28,128
2019	18	\$56,635	5	\$31,409	17	\$29,800
2020	25	\$49,788	2	\$32,566	7	\$34,127

a. Vehicle registration data comes from the California Department of Motor Vehicles (2013–2020). Vehicle prices come from Kelly Blue Book and CarMax.com.

Market size is one of the most important model parameters as it drives the overall magnitude of EV adoption. The model assumes the market potential by 2050 is approximately 4,700 EVs. This assumption is based on the number of households in the Mallet feeder (2,381) multiplied by two vehicles per household. Also, the feeder household population is assumed to grow 0.5% per year. Lastly, the model assumes the vehicle market caps at 85% of total market sales, allowing 15% of consumers to adopt alternatively fueled vehicles, such as hydrogen, biofuels, or other burgeoning drivetrain technologies. The market cap of 85% is based on SCE's target adoption rate of 76% of the total LDV market by 2040. Further, the model includes limits on the ability of each group to ultimately adopt based on income.

2.3.1.1 Logit Model to Determine the Probability of EV Adoption by Addresses

After developing the sales forecast for Groups 1, 2, and 3 in the SCE feeder, the next step is to distribute them to households in order to estimate the probability that a particular household purchases an EV. A binary logit model, also known as logistic or binomial regression, computes the probability of an EV adoption. As the name "binary" implies, the dependent variable only has two outcomes: 1) a consumer purchases an EV or 2) a consumer purchases some other vehicle. The model may help determine which variables are instrumental in EV adoption, such as access to home charging and income.

2.3.2 Model Definition

It is a special case of linear regression where the target variable is categorical in nature. It uses a log of odds as the dependent variable. Logistic regression predicts the probability of occurrence of a binary event utilizing a logit function. The functional form for the probabilities in the model is a logistic curve to bound the outcome to be between 0 and 1.

Linear Regression Equation:

$$P(Y = 1|X_1, X_2, \dots, X_n) = F(\beta_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n) \quad (3)$$

where, F is the cumulative logistic distribution function:

$$F(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

So, equation (3) becomes:

$$y_{fitted} = F(x) = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}},$$

Where,

y is either an EV or non-EV,
x_1 is vehicle price,
x_2 is income,

x_3 is access to charging infrastructure,
and β_0 through β_n are the coefficients for intercept term and the explanatory variables, x_n.

2.3.3 Data

The data for the logistic regression is cross sectional and not a time series. Therefore, a different dataset was created for the logistic regression. For this study, the dependent variable, y, took on the value of 1 for EV ownership and 0 for non-EV ownership. Most non-EV vehicles were gasoline-fueled ICE; however, a small percentage were diesel-fueled vehicles. The independent variables were income, vehicle price, and access to charging. More details on the model variables are described below.

2.3.3.1 Vehicle Prices

A binary choice model requires data for both outcomes, i.e., the same set of explanatory variables for events in which ICE and EVs are owned. Due to time constraints, we could not enter prices for all vehicles and randomly selected ICE vehicles. We adjusted the subset by adding additional vehicles so that the average age of the sample equaled the average overall age in the feeder. Again, we used Kelly Blue Book or Carmax.com for current vehicle value. The purchase price of the vehicle would be ideal, but we did not know if and when vehicles changed ownership.

2.3.3.2 Income

Income was the same as with the Bass model, using actual estimated income per household for the EVs and ICE vehicles used in the subset of data instead of averaged data.

2.3.3.3 Charging Access

The model features three types of chargers: public, work, and private. Everyone in the feeder had the same proximity to public charging, resulting in no differentiation in the dataset and limited usefulness in the analysis. We did not have access to work charging; we approximated private charging by using house type. While we did not have access to data that specified whether there was a garage, we had the number of units. A unit of 1 indicates a single-family dwelling. A unit value of 2 indicates a duplex, etc. For this particular feeder, multi-family homes were limited, and the highest unit value was 4.

2.4 Bass Model Scenario Analyses

We performed two scenario analyses for the Bass model: one for the impact of incentives and one for the impact of public charging.

2.4.1 Incentives Scenarios

Although we did not explicitly model incentives as a separate variable, changes in EV price can imply the effect of incentives. We used the relationship between the car price variable and EV adoption from the Bass model to perform scenarios. Current federal incentives are $7,500 per EV for qualifying manufacturers and models. We assumed that the incentives would continue over the forecasting horizon. In addition, we assumed additional $1,000, $3,000, and $5,000 incentives.

2.4.2 Public Charging

Given the limited number of observations for the Bass model, we reduced the multi-variant model to only one independent variable: household income. However, to provide an idea of the impact of public charging, we replaced household income with the annual number of public chargers in zip codes near Mallet (91748, 91750, 91767, 91768, 91769, 91766, 91722) and kept the same dependent variable, the annual number of EV adoptions. Table 3 shows the annual number of public chargers in the vicinity of Mallet households. For our scenario we increased the charger growth by 33% over its current linear projection.

Table 3. Cumulative number of public chargers by year near Mallet (DOE Energy Efficiency and Renewable Energy 2021)

Year	Cumulative No. of Chargers
2011	2
2012	3
2013	4
2014	5
2015	6
2016	6
2017	7
2018	7
2019	8
2020	15

2.5 EVAM Summary

Figure 2 shows the inputs and outputs of the individual submodules that estimate the probability of EV adoption by addresses within an electric feeder.

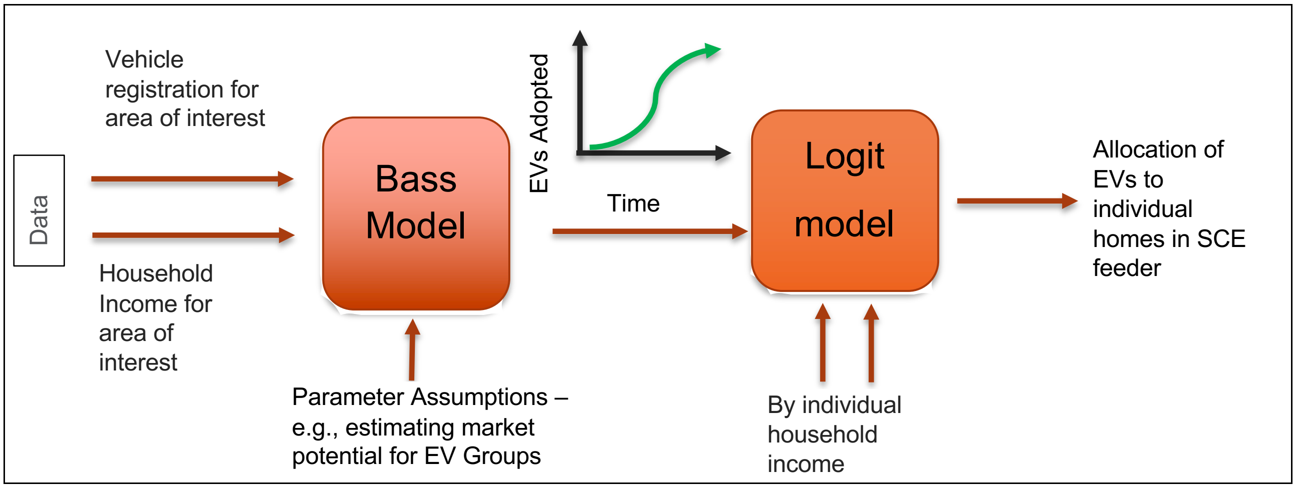

Figure 2. Summary of inputs and outputs of EVAM

2.6 EV Adoption Impact Analysis

The impact analysis identified likely constrained grid components from the additional electrical load introduced by EV charging. Understanding future grid constraints is an essential input to the utility planning process, enabling timely and cost-effective investment decisions for necessary system upgrades.

2.6.1 Integration of EVAM with Power Flow Modeling

The EVAM provided two critical pieces of information: (1) the adoption model provided a forecast of annual group-specific EV adoption numbers for the area of interest (which in this case was the area supplied by a selected SCE feeder circuit); (2) the model provided probabilities of EV purchases by income groups that can be related to addresses. Making use of the probabilities in a deterministic power flow model requires random samples that correspond to the probability distributions. Table 4 shows an example of the forecast for a particular study year.

Table 4. Example of adoption probability for SCE circuit at a given year

Groups	EV Number	Household Income		
		<$75k	$75k–$150k	$150k+
1	40	2%	40%	58%
2	60	15%	50%	35%
3	70	35%	45%	20%

Typical residential circuits service anywhere between a few hundred to a few thousand houses. This equates to numerous ways of sampling and distributing the projected number of EVs across the homes in the circuit, resulting in several possible future realizations. We applied a reduced sampling approach wherein 500 future realizations of EV distributions were randomly selected from a Monte Carlo enumeration of all possible outcomes. This approach helped limit the number of future EV placement scenarios and thus power flow simulations.

The next step in the impact analysis was to perform power flow analysis on the cases generated by the Monte Carlo enumeration. Power flow analysis determined the impact from EV charging load on grid operation, identifying limitations of existing infrastructure to support the demand. From a modeling perspective, two requirements must be met: (1) a detailed representation of the grid model, including the secondary circuit consisting of residential loads, and (2) EV load profiles that was added to the residential loads at locations determined by the Monte Carlo enumeration.

We used PNNL's GridLAB-D to perform the modeling for power flow analysis. The software has a broad array of capabilities to support distribution systems analytics, but most importantly, in the context of this research, the software can run time series power flow simulations with detailed representation of secondary circuits. GridLAB-D's EV objects also produce EV charging load profiles using user-provided charge rates, time of departure/arrival, driving distance, mileage efficiency, and other parameters as input. This allows for the addition of one or more "EV objects" to existing residential loads to capture the impact of charging activity not just at the feeder level but also at the secondary circuit level, which is the transformer supplying electricity at 240V/120V level to a few individual homes. The impact from EV charging was measured using the metrics shown in Table 5. These are standard distribution system operation metrics that were applied to both the primary and secondary sides of the circuit. To exclude rare occurrences, we registered a violation only if it occurred for more than two cumulative hours (two timesteps in the hourly simulation) during the simulation duration. Tracking system performance using these metrics helped determine suitable mitigation strategies.

Table 5. Grid impact metrics

Metric	Acceptable Range
Transformer Thermal	200% of rating
Line Thermal	100% of rating
Continuous Voltage (ANSI-A)	< 0.95 pu OR >1.05 pu (5 minutes)
Instantaneous Voltage (ANSI-B)	< 0.90 pu OR >1.10 pu (instantaneous)

Note: "pu" means per unit, which normalizes a measurement and makes it dimensionless.

2.7 Mitigation Using Infrastructure Upgrades or SCM

Typically, transformer thermal violations and voltage violations tend to limit the EV hosting capacity. To enhance EV hosting capacity, we considered two mitigation strategies to reduce the risk of violations: (1) infrastructure upgrade and (2) SCM, as described below.

2.7.1 Transformer Upgrade Plan

In this mitigation strategy, an existing transformer that is expected to be thermally overloaded with increased EV loads is slated to be replaced with a higher rated transformer. Transformer upgrades are estimated to cost around $87/kilovolt-ampere (kVA) on average. A secondary transformer at a rated capacity of 75kVA would cost $6,525. Transformers are the second most expensive asset upgrade after substation upgrades (Balducci et al. 2004). Therefore, a transformer upgrade plan needs an exhaustive study and careful assessment. As mentioned earlier, a transformer is considered thermally overloaded if its loading exceeds 200% of its rating for more than cumulative 2 hours in a 3-month simulation period. However, for a given EV penetration level, each transformer will have a different probability of getting overloaded. For example, a particular transformer may get overloaded in 5% of all possible EV deployment scenarios (simulated using Monte Carlo approach as described in Section 2.7.1), whereas another transformer may get overloaded in 90% of the scenarios. The percentage of scenarios in which a transformer gets thermally overloaded can be interpreted as the overloading probability of a transformer. To identify the transformers for upgrade, we used a "repeated offender" methodology. In this method, all transformers with an overloading probability more than a certain threshold number were considered for upgrade. The threshold can be chosen by the utility based on engineering judgment and cost-benefit analysis. The selection of 0% threshold represents the most aggressive strategy and most expensive mitigation in which all transformers with a non-zero overloading probability are upgraded. This can also be interpreted as a strategy with no risk of violations with EV adoption. On the other extreme, a selection of 100% threshold represents a minimally expensive strategy where a transformer is not upgraded unless it is 100% guaranteed to be overloaded. This means that every hour of the year, a transformer will be overloaded. In this strategy, the risk of the system going under stress with EV adoption is quite high. In practice, a middle ground can be chosen to minimize risk within a particular utility's budget constraint. In this study, we used 20% as the threshold to identify transformers for upgrade.

2.7.2 Transformer Upgrade Deferral via SCM

Adverse impacts from increased load associated with EV adoption can be mitigated by exploiting available flexibility in charging scheduling. According to the national household travel survey (NHTS) 2017 data, the average person in the United States drives 25.9 miles per day. Assuming an average EV mileage of 3.85 miles/kilowatt hour (kWh) and a typical level-2 charger of 6 kW in residential buildings, an EV only needs a little more than an hour to fully charge daily (NHTS 2017). According to NHTS 2017 data, an average parking time of an EV at home is around 7 hours.

This leaves significant room for EVs to have charging time flexibility.

Coordinated EV scheduling to mitigate peak demand is commonly referred to as SCM. The different SCM methods available can be broadly classified into two categories: active and passive. In active SCM methods, an aggregator or utility collects data from the EV owners and directly sets the charging schedule to meet grid objectives based on a financial arrangement a priori. An EV owner's preference of fully charging the EV before a particular time (typically home departure) is honored in these control strategies. In passive SCM methods, utilities establish time-varying electricity tariffs (Time of Use prices) to incentivize customers to charge EVs during low price periods, thus shifting the EV demand from evening to midnight when the load is minimal. SCM can have different objectives such as peak load shaving, congestion management, voltage regulation, and infrastructure upgrade deferral.

In this study, we analyzed the impact of SCM on the deferral of transformer upgrades. Using SCM strategies, EV demand can be shifted from evening to midnight, thereby delaying EV demand and relieving demand pressures on the transformer during peak hours, potentially enabling utilities to defer upgrades by a few more years, providing significant economic benefits to the utility companies.

This study considered a base case charging behavior in which all EVs start charging as soon as they arrive home and plug in. To compare, we implemented an SCM strategy by randomizing the start time of all EVs between 10 p.m. to 6 a.m. such that all EVs get fully charged before their home departure time. Notably, each vehicle will take different time to fully charge based on its daily travel miles, mileage efficiency, and charger rating. This implementation also mimics a Time of Use price-based SCM strategy in which the off-peak period starts at 10 p.m.

3.0 Application of Methodology on SCE's Mallet Feeder

This section discusses a practical example of the methodology described in Section 2.0. The example illustrates the methodology's capability and value and how it could be applied practically by community leaders and distribution planning engineers.

3.1 Description of SCE Mallet Feeder

The EVAM and impact estimation methodology were applied to a circuit in the SCE service territory to demonstrate their value. This SCE feeder is a 12 kilovolt (kV) circuit servicing primarily residential customers: 2,381 homes through 174 secondary transformers in Rowland Heights, California (see Figure 3). Vehicle registration data from the Department of Licensing indicate a total current adoption of approximately 425,300 EVs for California and 176 for the Mallet feeder neighborhood. The circuit, as expected, is summer peaking, with a peak load exceeding 4 MW as shown in Figure 4. The figure represents a typical summer weekday, wherein the peak load is anticipated at around 5 p.m., coinciding with increasing residential loads as residents return to their homes. Widespread EV adoption is expected to further increase this evening peak as returning residents may plug in their EVs for charging, adding to the existing demand.

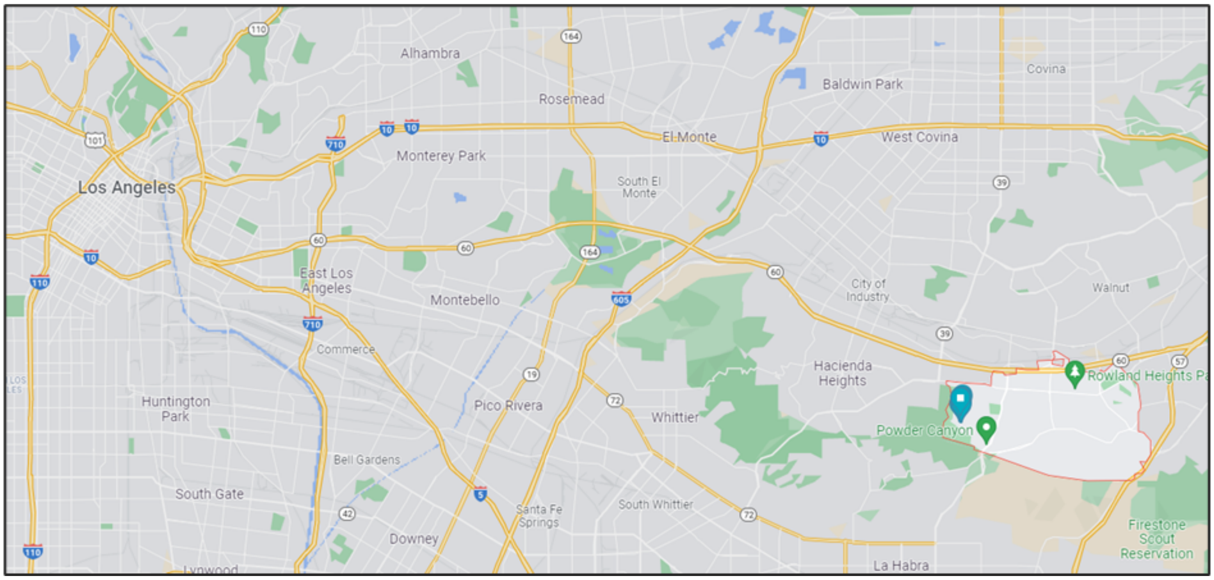

Figure 3. Highlighted area represents Rowland Heights, CA

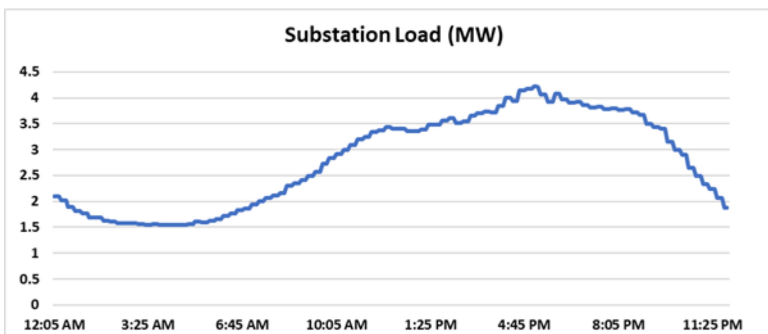

Figure 4. SCE feeder daily load curve for typical summer weekday with about 176 EVs

3.2 EV Adoption Results

It is well established in diffusion of innovation science that earlier groups of adopters have higher disposable incomes. The market in Mallet has been established for 8–9 years and confirms higher income individuals are purchasing EVs, e.g., the average household incomes for Groups 1, 2, and 3 were $150,603, $94,439, and $116,519, respectively. Further, the lowest household income of EV purchasers was in the $80Ks, exempting the more than 1,000 households earning less than $75,000 from that purchase decision. Additionally, the most cited reason for market adoption failure is inadequate price decline (Golder and Tellis 2004). Indeed, a recent Car and Driver article confirmed that some middle-class families are getting priced out of the new car market as growth in new vehicle prices exceeds income growth (Blanco 2019). Therefore, it stands to reason that a key driver for EV adoption projections is household income. Figure 5 shows an estimated household income distribution of 2,381 homes for 2019.

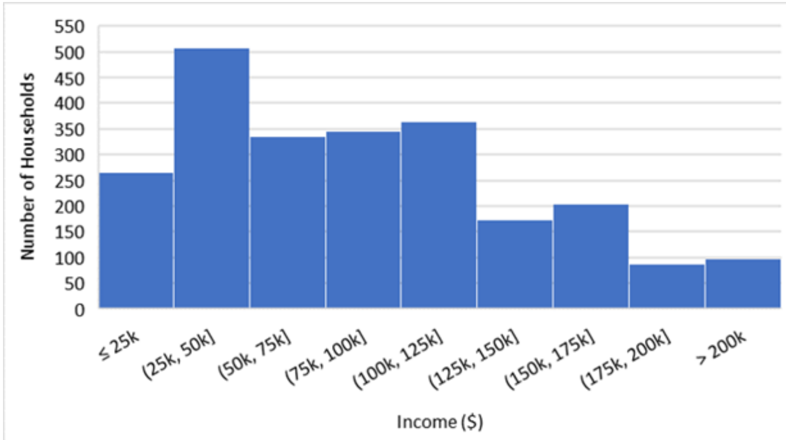

Figure 5. Income distribution for residents in selected SCE feeder in year 2019

Additionally, the Bass results are based on the following data and input assumptions:

- California Department of Motor Vehicle registration data (2013–2020)
- Household income estimates based on Census Bureau American Community Survey (2018)
- Housing prices from Los Angeles County Tax Assessor (2019)
- Market potential assumptions of two EVs per household by 2050, based on personal correspondence with Anthony James, SCE (2021).

Estimated EV adoption for each group and all three groups combined is presented in Figure 6. EV market adoption rates for the three vehicle groups (see Sections 2.3.1 and B.1) can be estimated using EV registration and vehicle price data combined with household income, housing value estimates, and the expected total market potential in the outyears (beyond 2050). Figure 6 shows the annual EV estimates from EVAM for the Mallet feeder through 2050. Aggregate EV adoption in Mallet becomes approximately 85% of the total potential vehicle market size by 2050, as dictated by deterministic assumptions. The Bass model determines the rate and magnitude of the three different groups of vehicles.

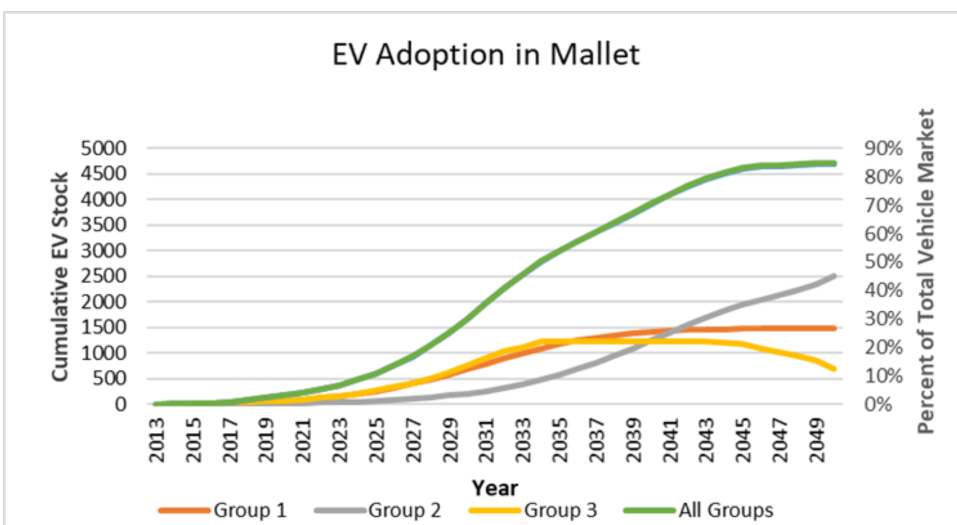

Figure 6. Cumulative EV adoption in SCE feeder by group and year

Table 6. **Tabular results of cumulative EV adoption for SCE feeder**

	2020	2025	2030	2035	2040	2045	2050
Group 1	77	266	690	1,181	1,419	1,480	1,693
Group 2	20	71	215	577	1,249	1,951	2,500
Group 3	79	271	762	1,235	1,235	1,175	700
Aggregate	176	609	1,667	2,994	3,903	4,606	4,692

Of note, EVs within Group 2 (the lower-priced vehicles), ultimately make up the majority of the market, corresponding with the greater number of average and lower income groups, which have yet to adopt any EVs. Also, Group 3 will flatten and begin to taper in 2035 due to the elimination of ICE vehicles, including the hybrid EV/ICE vehicles.

We demonstrate in Appendix C that either increasing the amount of the incentives or increasing the number of public charging stations will result in increased adoption rates. For more information, see details in Appendix C.

3.3 Locational Placements of EVs in Mallet Distribution System

The household income for the Mallet feeder was placed onto a map as seen in Figure 7. With this locational relation of income to addresses, we estimated the probability of an EV from the cumulative pool as shown in Figure 6 to be placed (from the logit model) at any address within the Mallet neighborhood. While the placements are probabilistically distributed, we show a random sample in Figure 8. The progression of increased EV density as a function of time can be seen in the figure in 5-year steps.

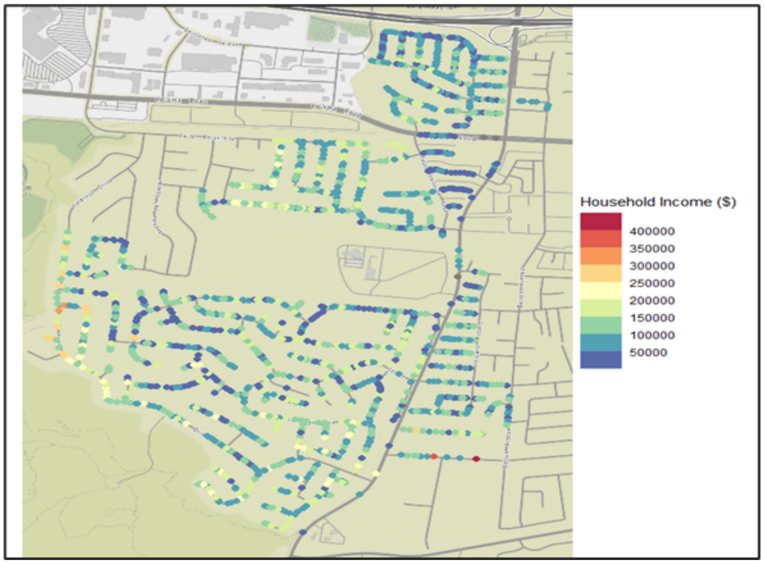

Figure 7. Income by household for SCE feeder

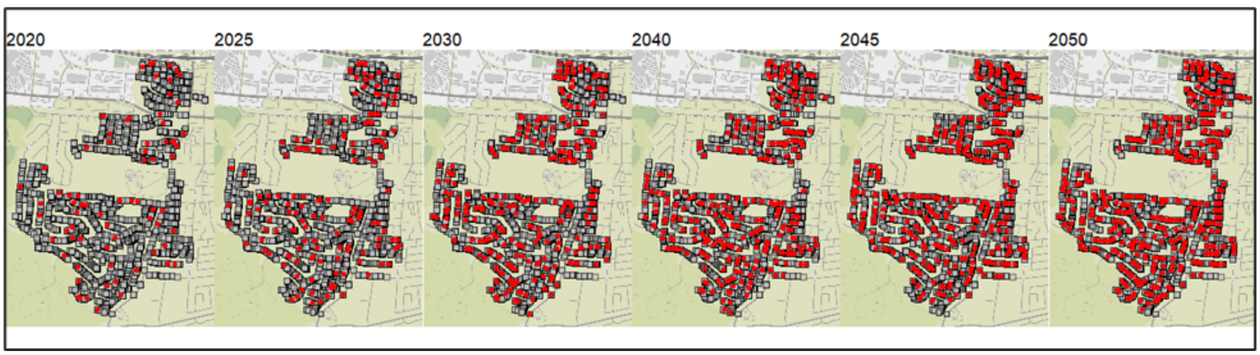

Figure 8. Probabilistic distribution of EVs in 5-year steps, based on sampling

3.3.1 EV Driving Pattern

We used NHTS 2017 data to extract EV driving patterns in terms of home arrival time, home departure time, and daily travel miles. Figure 9 shows a histogram of home arrival and departure time of cars. It can be seen that most cars arrive home in the evening around 5–6 p.m. (17:00 to 18:00). Figure 10 shows the histogram of the daily travel miles showing that most cars travel less than 50 miles daily.

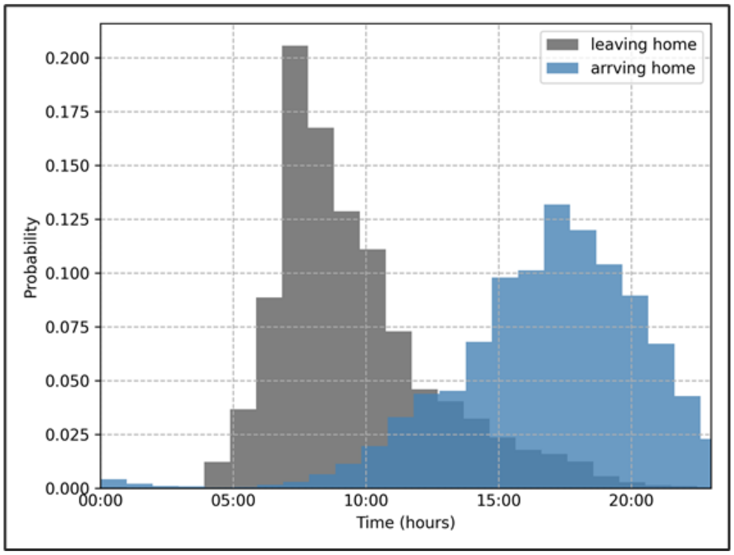

Figure 9. Distribution of home arrival and departure time of cars based on NHTS 2017 data

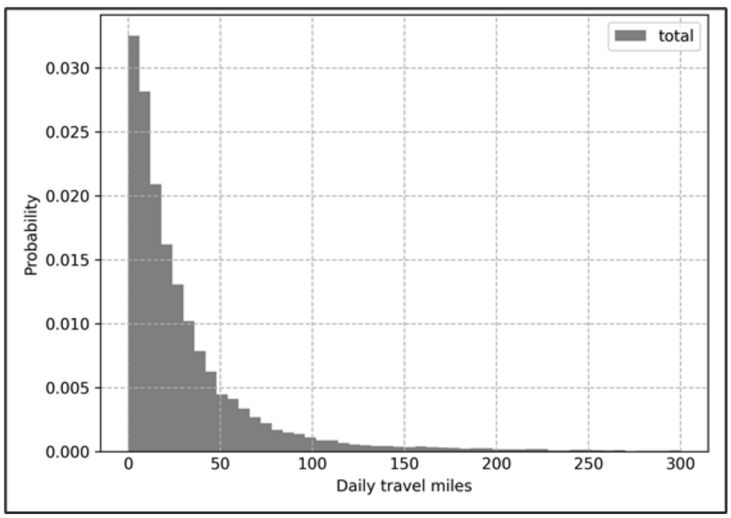

Figure 10. Distribution of daily travel miles of cars based on NHTS 2017 data

3.4 EV Impact Analysis

Figure 11 shows the resulting impact from EV adoption on the SCE feeder, as measured by voltage and transformer exceedance violations (metrics in Table 5). The primary y-axis (left-hand side) is the scale for the colored bar plots, which represent the average count of violating assets across all Monte Carlo scenarios for each study year as a percentage of the total number of assets. The blue colored number on top of each bar denotes the absolute number of violating assets. The green curve, with its scale represented on the secondary y-axis (right-hand side), represents the growth in EV adoption on the circuit with each study year. From this plot, the circuit is primarily affected by exceedance of secondary transformer thermal violations. The number of impacted transformers range from two in 2025 to 32 in 2050. As more residential customers adopt EVs at a neighborhood level, the transformer servicing their homes experiences a collective load beyond its original design limits and is counted as a violating transformer. This does not mean that the transformer will necessarily "blow up," but rather it will be affected in terms of longevity. Long-term voltage violations (ANSI-A) begin to appear in 2040. This is expected due to the additional loading from EV charging resulting in increased voltage drops, particularly near the end of the circuit.

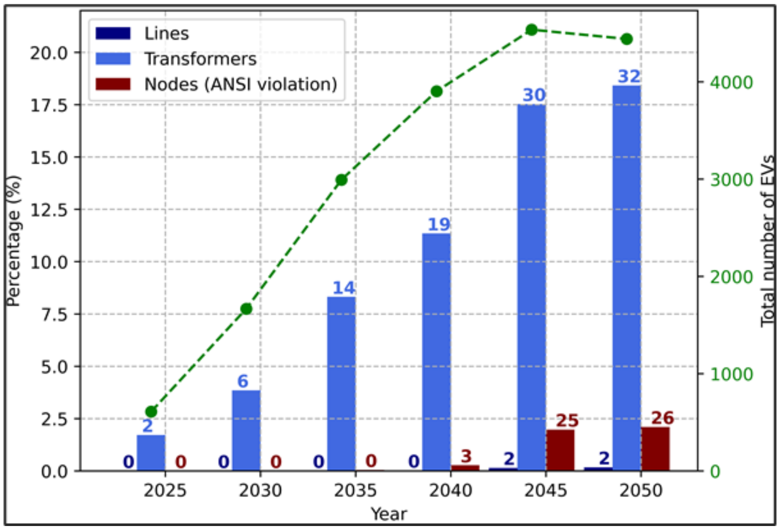

Figure 11. The count of violating assets from EV adoption for SCE feeder

The Monte Carlo process aimed to consider all possible future realizations of EV adoption to make an informed decision on grid components that need to be upgraded. Figure 12 shows the range of transformer violations across the Monte Carlo scenarios for every study year. Each scenario in the Monte Carlo enumeration would result in a different impact due to adoption model-based randomization in EV assignment to residential customers. In other words, transformers' operating limits that are violated in one scenario might not be affected in another scenario for the same study year. Figure 12 shows the range of transformer violations across all the Monte Carlo scenarios for every study year. The "best case," represented by the green circle, denotes the EV distribution scenario that results in the fewest violations. This could, for instance, be the placement of vehicles on secondary circuits being serviced by transformers with enough head room to accommodate the additional load from EV charging. In contrast, the red circle represents the "worst case," denoting the EV distribution that results in the most transformer violations across the circuit. These results might be associated with placements of EVs to homes whose secondary transformers are already heavily loaded without the additional load of EVs

The box represents the scenarios within the customary 10–90% confidence range. It should be noted that public charging and fast-charging options aren't considered in this effort. These charging activities may introduce additional violations, including higher intensity voltage sags during charging, and limitations on the primary circuit components from coincident loads. Using the GridLAB-D simulation tool, it would be relatively simple to simulate scenarios representing additional public charging hubs.

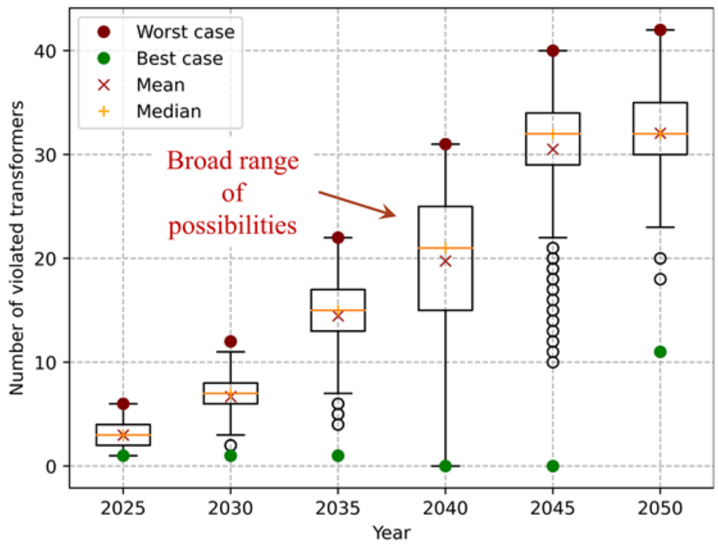

Figure 12. Range of transformer violations across Monte Carlo cases

3.5 Infrastructure Updates to Accommodate Projected EV Fleet

Two primary types of impacts were discovered from the EV adoption scenarios studied through Monte Carlo analysis: thermal violations and voltage violations. Thermal violations result when the power flow through grid components exceeds their operating limits. This could apply to components both on the primary side (e.g., substation transformer, primary conductors) or the secondary side (e.g., service transformers, secondary conductors). Voltage violations result from increased voltage drops across the circuit due to additional demand from EV charging. Two possible mitigation approaches exist: infrastructure upgrades and SCM. In the infrastructure upgrade approach, the limiting transformers are either replaced or reinforced with additional parallel transformers to maintain continuity of service with the increased demand. To mitigate voltage violations, infrastructure upgrades could entail the installation of voltage support devices, such as capacitors, near the impacted circuit area. In the SCM case, customers' charging activity is strategically controlled to mitigate thermal or voltage violations.

The Monte Carlo analysis revealed that the SCE circuit under study was largely limited by thermal violations associated with the secondary service transformers. Both infrastructure upgrade and SCM options were studied for mitigation. The results from this analysis are presented in the following sections.

3.5.1 Conventional Infrastructure Upgrade

In addition to demand increases from EV charging, a thorough infrastructure upgrade plan should also consider projected demand changes from other factors, such as building electrification. For this study, the demand changes from non-EV sources were not considered; the system demand from non-EV sources was held static for all study years up to 2050.

The typical service transformer sizes in the SCE circuit under study were 25 kVA, 37.5 kVA, 50 kVA, 75 kVA, and 100 kVA. Transformer upgrades included upgrading the constraining transformers using the following sequence: 25 kVA, 37.5 kVA, 50 kVA, 75 kVA, and 100 kVA. For example, if a constraining transformer was rated for 25 kVA, it would be replaced with one that was next in sequence, the one rated for 37.5 kVA. This approach was applied to all transformers in need of upgrades.

Transformer upgrades are expensive. The cost per circuit to a utility can quickly stack up if every transformer is upgraded to accommodate all possible future outcomes revealed by the Monte Carlo analysis. A systematic methodology to identify the most-impacted transformers is necessary to prioritize utility investment. Toward this end, we developed the "repeat offender" methodology. Figure 13 plots in descending order the number of Monte Carlo cases with violations counts for each service transformers in the SCE circuit in study year 2035.The repeat offender methodology uses a simple threshold to identify transformers that need to be upgraded. In this case, the red line represents a 20% threshold where all transformers above the line need to be upgraded; all transformers that cause violations in 20% or less scenarios are excluded from the upgrade list. The 20% threshold choice represents an engineering judgment by the authors. In real-world distribution systems planning practices, the repeat offender methodology may be used with the threshold determined by multiple factors, including investment budget and operational experience.

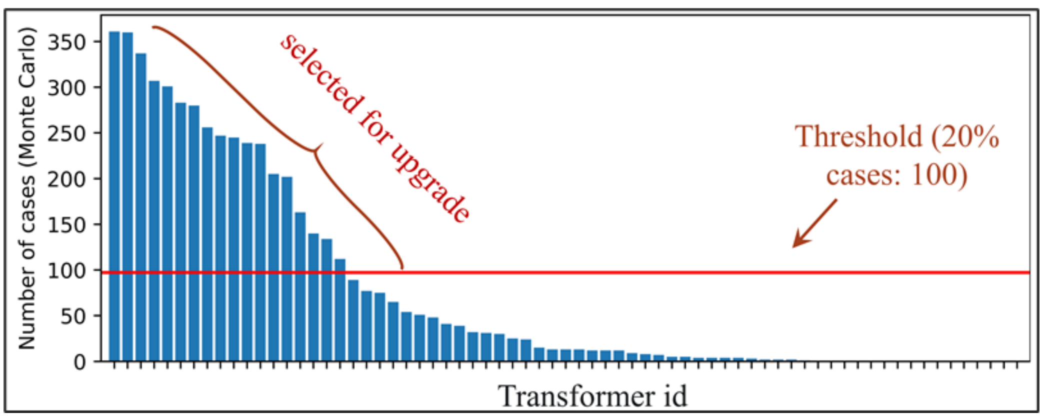

Figure 13. Monte Carlo cases with violations for each transformer for year 2035

Figure 14 shows three upgrade approaches with different risk tolerances to mitigate the impact from EV adoption: most aggressive, middle, and least expensive. The most aggressive strategy uses a 0% threshold, wherein any transformers that violate any of the 500 scenarios are flagged for upgrade to avoid any future risk. The least expensive strategy suggests only upgrading transformers that are violating in all 500 cases, a strategy that would introduce significant risk to utilities. The middle strategy uses the threshold limit set by the repeat offender methodology to balance risk and investment for transformer upgrades. Figure 14 shows the number of transformers that need to be upgraded every five years for each of the three strategies. The most aggressive strategy front loads the upgrades, whereas the minimal expensive strategy defers the upgrade for later years. The middle strategy provides a transformer upgrade plan with the 20% threshold that could balance investment and risk.

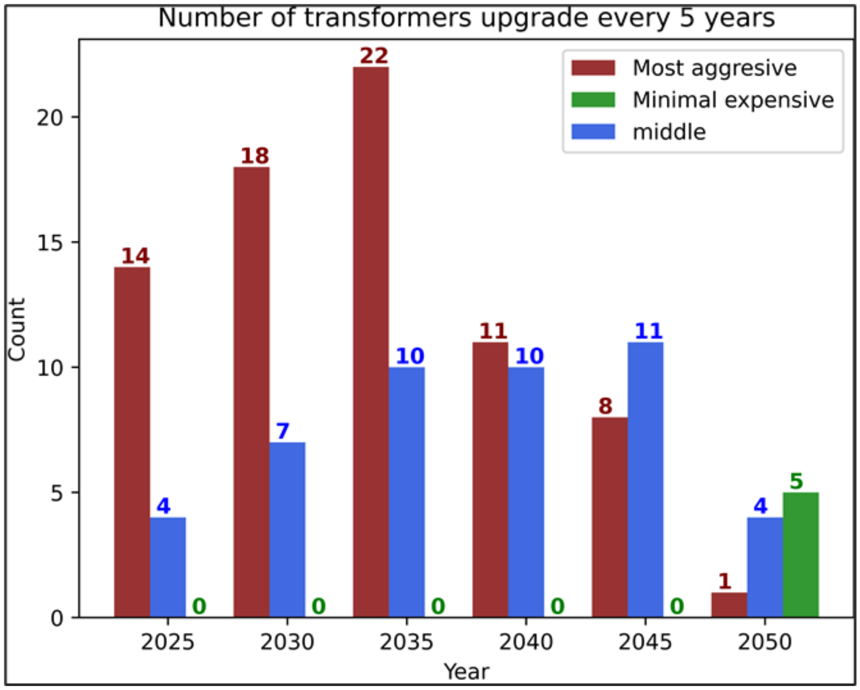

Figure 14. Number of transformer upgrades every 5 years

3.5.2 Upgrade Avoidance by SCM

The aggregate EV demand profile under SCM strategy (as explained in Section 2.7.2) is compared with the base case strategy in Figure 15. The aggregated loads of all EVs for the study year 2035 are shown in Figure 15. In the base case, EV demand starts building from late morning (10:00) as some cars start arriving home at this time per the NHTS dataset (Figure 9), and peaks at around 7 p.m. (19:00). In the SCM case, the EV demand is shifted to midnight. This shift directly supports peak shaving at the substation level, alleviating circuit overloading concerns during peak load hours.

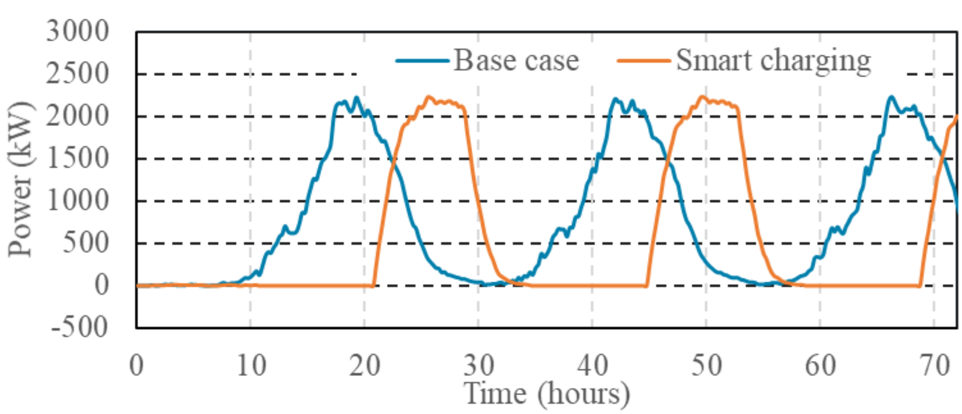

Figure 15. Comparison of the aggregate EV demand profile in base case and smart charging case

Figure 16 shows violation impacts for both the base case and the SCM case for study year 2035. Each bar on the x-axis represents an individual transformer that experienced a violation. Each bar's height denotes the number of scenarios in which a particular transformer exceeded thermal capacity. The orange portion of a bar is always equal or less than the blue, verifying that SCM reduces the possibility of a transformer overloading compared to the base case. As shown, SCM was able to push the overloading probability for most of the transformers (orange height of a bar) below the threshold line, demonstrating that SCM successfully defers transformer upgrades from 2035 to a later year. The probability of five transformers overloading was still more than the threshold; thus, their upgrade could not be deferred. Notably, SCM could avoid upgrading of transformers (left most three transformers) since they had been operating very close to their thermal limit even without EVs. The same procedure can be repeated for each adoption year and an updated transformer upgrade plan in case of SCM can be compared with the base case. The number of transformer upgrades required are significantly reduced for each adoption year due to SCM.

Figure 17 shows the improvements in the number of transformer upgrades between the two cases for each study year. Table 7 illustrates the results slightly differently. Rather than enumerating the avoided upgrades, the deferral duration is shown in five-year steps. All transformers are shown due for upgrades in 2030, 2035, and 2040 and deferred by at least five years due to SCM showing its economic potential. For study year 2040, two transformers can be deferred upgrading by 10 years and for 2045, one unit can be deferred as far out as 15 years.

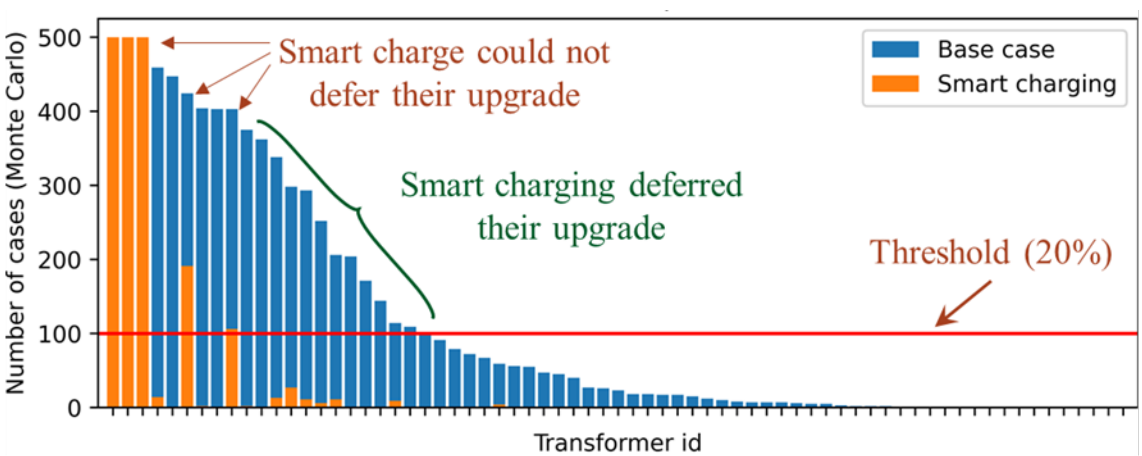

Figure 16. Monte Carlo cases in which a particular transformer is violated with and without SCM, reflecting SCM's impact on transformer upgrade deferral (results generated for study year 2035)

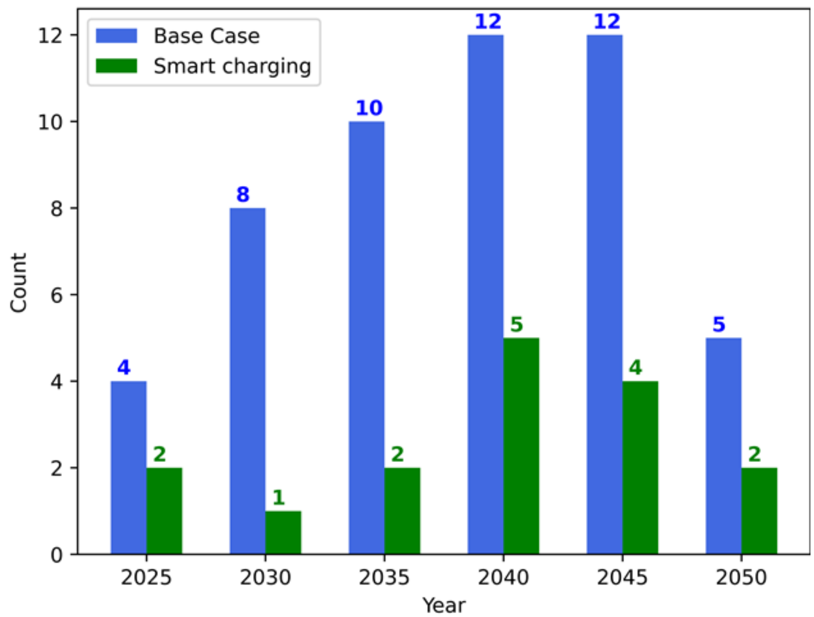

Figure 17. Transformer upgrade plan for every 5 years with and without SCM

Table 7. Summary of SCM's impact on transformer upgrade deferral

Upgrade year – base case	Upgrade year – smart charging					
	2025	2030	2035	2040	2045	2050+
2025	2	1	0	0	0	1
2030		0	2	2	1	3
2035			0	3	2	5
2040				0	0	12
2045					1	11
2050						5

No deferral
5 years deferral
10 years deferral
15 years deferral
20 years deferral
20+ years deferral

3.5.3 Costs of Distribution System Expansions to Accommodate EV Growth

The technical distribution system expansion assessment revealed upgrade requirements predicated on two major assumptions: (1) an EV adoption assumption and (2) two EV charging strategies (with and without

SCM). Other assumptions regarding the natural evolution of the customer base within the Mallet feeder area are likely to occur, including electrification of heating (natural gas furnaces replaced by electric heat pumps) due to legislative requirements and customer choices of investing in distributed energy resources (DER), such as photovoltaic rooftop units and behind-the-meter battery storage. Scenarios with DER and electrification of the building sector assumptions can be readily implemented into the power flow model (GridLAB-D) for the Mallet feeder but were not considered in this analysis.

We can express the upgrade requirements in terms of cost requirements for the two charging assumptions. This reveals SCM's value by simply evaluating the benefits of deferring the upgrade cost for secondary transformers. This raises the question: how do you upgrade and to which next rated capacity can you upgrade a secondary transformer? Achieving an optimal upgrade strategy requires a complex optimization that minimizes the cost for capital investments over the planning horizon. In this study, we provided a simplified approach that assumed an upgrade of the secondary transformer to the next incremental size. Most of the Mallet feeder secondary transformers are rated at 50 kVA; thus, we chose an upgrade to 75 kVA. Table 8 shows the results of such an upgrade.

Table 8. Upgrade requirements and the value of SCM (cost expressed in 2021 dollars[1] and rounded to the nearest thousands)

		2025	2030	2035	2040	2045	2050	Totals
Number of secondary transformer	Without SCM	4	8	10	12	12	5	51
	With SCM	2	1	2	5	4	2	16
Cost requirements	Without SCM	$29,000	$68,000	$100,000	$137,000	$159,000	$77,000	$570,000
	With SCM	$15,000	$9,000	$20,000	$57,000	$53,000	$31,000	$185,000
Benefits of SCM		$14,000	$59,000	$80,000	$80,000	$106,000	$46,000	$385,000

1. Assumes a 3 % inflation rate.

Benefit estimations of SCM are illustrative for two reasons. First, between today and 2050, other evolutions such as consumer-based deployments of DER might significantly affect demand. Second, costs associated with SCM on the utility side to actively manage the EV charging loads have not been considered due to uncertainties regarding what technology may prevail in the future. For example, third-party EV charging management organizations may offer EV charging controls via cell phone infrastructures and telemetrics to the vehicle such that no or minimal cost on the utility are incurred.

Figure 18 shows the marginal impact of upgrades divided by the incremental number of EVs in each five-year period. Costs are escalated to reflect the time value of money. In real term, the relatively static growth in cost per vehicle (years 2025, 2030, and 2035) is driven by the increase in adoption of Group 2 and Group 3 vehicles, relative to Group1 vehicles, whereby producing less load per vehicle. After Group 3 vehicles (hybrids using very little electricity) retire in 2035, the feeder starts to experience higher load per average EV. A large jump in Group 2 adoption at the end of 2050 drives the larger EV load per transformer upgrade (see Figure 6). We further note, that for this study, we assume that battery technologies for the three groups of vehicles remain static over time. In future analysis, we will incorporate evolving battery characteristics as suggested in Appendix B.

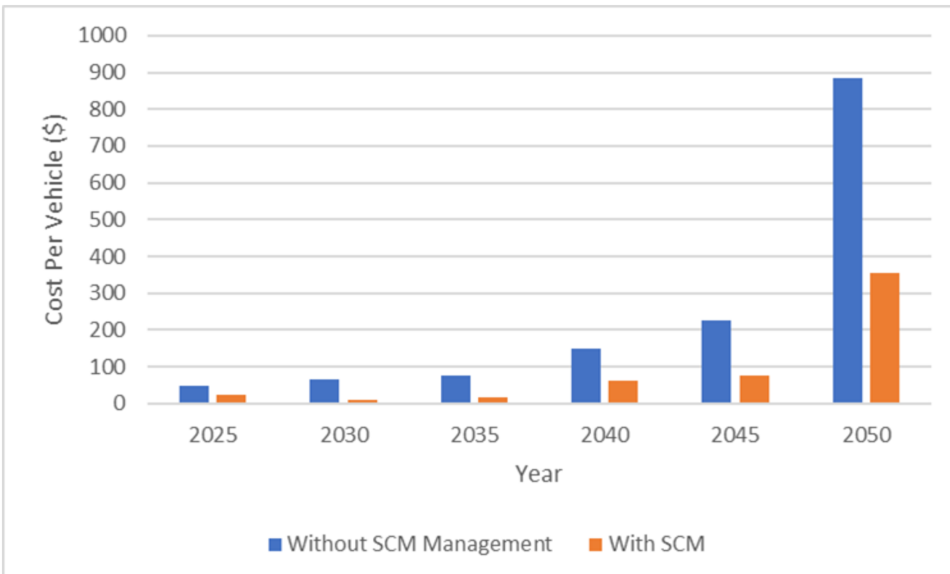

Figure 18. Average cost per vehicle for every incremental upgrade (cost expressed in 2021 dollars).

The benefits of SCM per vehicle per year were evaluated given the values in Figure 18. The average value of SCM for the period of 2020 to 2045 was approximately $77/EV per year.

4.0 Summary and Next Steps

4.1 Summary

Key outcomes of the Phase II study were independent capabilities that (1) provide projections for future years of LDV EV market adoption (EVAM) at various levels of geographic aggregation down to the address level and (2) a set of scripts and routines to perform distribution system power flow studies to estimate the hosting capability of a feeder circuit under a set of EV adoption assumptions. While the audience for this new analytics capability was originally assumed to be distribution system planning engineers, the EVAM generated interest among community energy leaders and transportation planners who are interested in assessing the needs of public charging infrastructure to meet communities' future transportation needs (at the city and county levels). Particularly, the socio-economic characterization and transparency of the adoption model has drawn attention from community leaders who want to use the model to analyze how future investment in public charging infrastructure can benefit underserved populations and to target placement of public infrastructure to support certain populations.

EVAM: The adoption model estimated annual sales figures of three groups of EVs in a certain geographic footprint. The groups of EVs were defined as: (1) long-distance range, (2) short-distance range, and (3) PHEV. The footprint can be as large as a state and as small as the geographic boundary of a distribution system feeder circuit. The inputs to the model were (1) vehicle registration data by years, (2)household income by census blocks, and (3) housing assessed value and characteristics in single versus multi-family homes by addresses. Given these input data, EVAM estimated the annual adoptions of EVs by groups within the given footprint and the propensity of adoption each year by addresses.

This new capability can be used in the following ways:

1. To study the locational aspects of how natural EV adoption may occur in a community and how different socio-economic groups might be affected.
2. To design incentives, such as free electricity for charging, buy-downs through rebate programs, or providing access such as public charging stations to target certain populations.

Hosting capability estimations: This estimation utilizes a sequence of power flow simulations to model the operations of the electric distribution system under the new (forecast) EV load conditions. We demonstrated the power flow simulations using PNNL's GridLAB-D. The model was fed with new EV loads as provided statistically by EVAM (propensity of EV adoption by address). The estimation results allowed a planning engineer to set a risk threshold that characterizes the risk exposure of future EV loads exceeding any operating conditions. The output of hosting capability estimations are (1) an estimation of the maximum number of EVs that can be accommodated in a particular footprint and in which future year that limit is expected to be reached given an adoption rate, and (2) the specific asset/component in the distribution circuit that needs to be updated to meet the adoption rate. The estimation identifies specific component(s) inadequate or deficient for safe operations. The engineer can then explore upgrade strategies to address the limiting set of assets or control strategies of EV load to remediate the limiting condition.

Demonstration of the new capabilities: We demonstrated the capabilities on a single feeder in an SCE service area as an illustrative example. We used California vehicle registration data, home value assessments, house characterization, and household income data. With these inputs, projections of personally owned light-duty EV market adoption was performed by addresses. The results were fed into a power flow model to simulate potential violations against ANSI standards and engineering guidelines. The power modeling identified the location of the violation and the time and frequency of occurrence. With that outcome, the distribution planner was enabled to determine EV hosting capabilities and distribution upgrade strategies if more EVs are expected in the future. The combinations of EV forecasting and the power flow modeling tools provide the analytical instruments that distribution system engineers will need to analyze impacts for a growing EV fleet in the distribution system. We also demonstrated how SCM could be applied to estimate the upgrade deferral and what potential benefits may be realized. For a specific SCE feeder (Mallet) the deferred upgrade using SCM strategies was about 5 years over the planning horizon to 2050, with a total benefit of over $300,000. Expressed in $/EV per year, the SCM benefit is approximately 77.

4.2 Next Steps

During the execution of this project, we briefed community leaders and distribution planning engineers on the capability development and goals of this project. The audience was very interested in availability of capabilities developed in this project, with many inquiring “When would such methodology and/or tool be available for public use?”

Following this positive response, the next step could be developing tools to take our methodology to the next level of automation and software encapsulation so that it can be more widely disseminated or deployed on the Web for more common use. The following next steps are proposed to address the interest encountered by community leaders and utility planning staff:

1) Develop a market adoption model for privately owned LDVs.

2) Develop a market adoption model for medium and heavy-duty vehicles, including commercial fleets and buses.

3) Automate a process and modeling environment for estimating hosting capability.

4) Test the above tools with two to three entities for practicality. Perform analyses that include different SCM approaches and valuation of SCM strategies, as well as co-benefits of SCM with other DER investments before or behind the meter.

5) Commercialize the resulting tool set to the private engineering and consulting communities.

5.0 References

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Appendix A– Literature Review of Adoption Models

Two categories of adoption models relevant to EV adoption are (1) the consumer preference models and (2) diffusion models (Becker 2009, Reitman et al. 2020).

Consumer preference models describe behavior and provide information regarding consumer choices based on existing consumer preference and include discrete choice and agent-based models. Discrete choice models predict choices between two or more discrete alternatives, such as deciding to purchase an EV or ICE car. A common discrete choice model associated with EV adoption is the logit model with example models by Gil et al.(2018); Javid and Nejat (2016); Sierzchula, Bakker, and van Wee (2016); and Soltani-Sobh (2017). Both Javid and Nejat and Soltani-Sobh found fuel price (gas price for the former and electricity price for the latter) to be the most influential factor in EV adoption. Both models identified income as a significant factor. Sierzchula, Bakker, and van Wee found the number of charging stations to be the most influential factor in EV adoption and identified EV price as important to purchase decisions.

The second type of consumer preference model, agent-based models, uses computer simulations to study the interactions between people, things, places, and time, stochastically modeled from the bottom up where individual agents make decisions based on a set of rules based on recognized preferences, such as desired vehicle range, or other purchasing logic, such as operating costs driven by fuel prices (Hoekstra and Hogeveen 2017; Adepetu, Keshav, and Arya 2015; Shafiei et al. 2012). Shafiei et al. found the combination of high gasoline price, decreasing EV price, reducing import tax on EVs, and elimination of charging concerns resulted in the greatest EV adoption. Adepetu, Keshav, and Arya found that, of the variables considered, making EVs more affordable had the highest impact on adoption. Hoekstra and Hogeveen built a complex model with buying and charging modules. The buying module includes cost of ownership plus socio-economic characteristics. The charging module includes a public and private charging network. Although the authors say it will take years to fully finish the model, they have preliminary results. One interesting result is the scenario in which people sold their cars after four years, resulting in adoption increases due to lower total cost of ownership for the resold EVs. Similarly, Adepetu, Keshav, and Arya found, out of all the variables considered, making EVs more affordable had the highest impact on adoption. In comparison, Shafiei et al. found the combination of high gasoline price, decreasing EV price, reducing import tax on EVs, and elimination of charging concerns resulted in the greatest EV adoption. Although agent-based models are good for simulating behavioral feedback and determining potential causal relationships, they are generally very complex and time-intensive to create.

The other category of adoption models are diffusion models, which are conventionally used to forecast market sales. The most common diffusion models are the Bass, Gompertz, and Logistic, which produce a sigmoid-shaped adoption curve of cumulative sales (an S curve), a common growth pattern for diffusion of innovations (Al-Alawi and Bradley 2013). Numerous diffusion models exist for the alternative vehicle market. Reitmann et al.(2020) used a simple logistic growth function to model EV inventory in China. Yini (2005) used a Gompertz model to analyze future EV ownership hybrid vehicle growth. Muraleedharakurup et al.(2010), comparing both Logistic and Gompertz for hybrid vehicle growth in the United Kingdom, found a good fit for both but no significant difference between the models. Most researchers used Bass models for their forecasts, including Brdulak, Chaberek, and Jagodzinski (2021); Yingqi et al.(2016); and Massiani and Gohs (2015), to name a few. These papers used a simple Bass model that reduces consumers into two groups: Innovators, people who purchase first and are influenced only by external influences such as mass media or technical journals, and Imitators, people who purchase later and after internal influences such as word of mouth and observation of others (Bass 1969, Mahajan et al. 1990).

The expression of the Bass diffusion model is

(A.1) $$n_t = \frac{dN_t}{d_t} = p[M - N_{t]} + \frac{q}{M} N_t[M - N_t]$$

where,

n_t is the number of noncumulative adopters at t,

N_t is the number of cumulative adopters at t,

M is cumulative market potential over the whole life,

p is the coefficient of innovation, and

q is the coefficient of imitation.

The three parameters driving the model are p, q, and M. Bass model authors used exogenous values for market size, M, and let the model solve for p and q. The modelers use a combination of ordinary least squares and non-linear least squares for parameter estimation. Massiani and Gohs warn of choosing a plausible M value due to the sensitivity of the outcome to this parameter.

The basis for all Bass models is the differential equation

(A.2) $$f(t) = [p + qF(t)][1 - F(t)],$$

again, where p and q are the coefficients of innovation and imitation, and F_t is the portion of the market who have adopted by time t. Extensions of Bass' basic model allow for the inclusion of explanatory variables to provide better insights into factors influencing either the rate of adoption or market potential. Jain and Rao (1990) and Fernandez (1999) allowed the adoption curve to be refined by a vector of exogenous variables. Extensions of Bass (1969) by Jain and Rao (1990) and Fernandez (1999) were the basis for the adoption model. Solving the differential equation in equation (2) gives

(A.3) $$F(t) = \frac{1 - exp[-(p+q)t]}{1 + (\frac{q}{p})\, exp[-(p+q)t]}.$$

The proportion of the market potential that adopts in the interval (t-1, t) is

(A.4) $$F(t) - F(t-1).$$

Assume an individual's probability of adoption is π. The expected proportion of the total market that adopts between (t-1) and t is

(A.5) $$\pi(F(t) - F(t-1)).$$

The conditional probability of adoption in the same interval given the consumer has not yet adopted is

(A.6) $$\frac{\pi(F(t)-F(t-1))}{1-\pi F(t-1)}.$$

If A_t represents the total number of adoptions by time t and M is the market potential representing the upper limit on the potential number of adoptions or sales, S, in the interval (t – 1, t) are

(A.7) $$S_t = (M - A_{t-1})\frac{\pi(F(t)-F(t-1))}{1-\pi F(t-1)}.$$

Let the probability of adoption vary over time according to a logistic function of a vector of covariates

(A.8) $$\pi_t(\boldsymbol{x}_t) = \frac{exp[\boldsymbol{\gamma} \cdot ln\, \boldsymbol{x}_t]}{1+exp[\boldsymbol{\gamma} \cdot ln\, \boldsymbol{x}_t]} \in (0,1),$$

where $\mathbf{x}_t$ is a k-element vector of variables and $\boldsymbol{\gamma}$ is a k-element vector of coefficients interpreted as the elasticity of adoption with respect to the variable. While Jain and Rao (1990) used only the price of the good, Fernandez (1999) included a vector of exogenous variables in addition to the good's price. Both studies interpreted the coefficients on the natural logarithm of each variable as the elasticity of demand with respect to the given variable.

Such an extension was applied to the EV market by Li, Chen, and Zhang (2017). These authors used a generalized Bass model with 21 monthly observations to test short-term EV forecast accuracy and found "good predictive accuracy." Building on the original Bass model, their generalized Bass model had the following form:

(A.9) $$\frac{dN_t}{d_t} = p[M - N_{t]} + \frac{q}{M}N_t[M - N_t] * x_t$$

where,

(A.10) $$x_t = 1 + \left[\frac{\Delta Pv_t}{Pv_{t-1}} - \frac{\Delta Pg_t}{Pg_{t-1}}\right]\beta_1 + max\left\{0, [\frac{\Delta Cs_t}{Cs_{t-1}}]\right\}\beta_2$$

where, Pv_t is a ratio of electric vehicle price to traditional price, Pg_t is gas price, Cs_t is the amount of charging stations, β_1 is the price impact coefficient, while β_2 is the infrastructure coefficient.

Researchers often lack the luxury of routine data feeds or highly granular data and must create their models based on a limited number of observations. This was the case for Xu and Cheng (2016) who used a generalized Bass model to better understand the adoption of natural gas and compressed gas vehicles using only nine observations. The additional explanatory variables used were 1) the relative price of natural gas compared to conventional fuels, and 2) the number of fueling stations. Xu and Cheng had difficulty converging their models. Original non-linear optimization in Stata failed, but a second attempt using MATLAB's Statistics and Machine Learning Toolbox solved for globally optimal estimates. They found the coefficient of imitation to be significant in all their models. However, the coefficient of innovation, and the coefficients for fuel price and charging stations were not statistically significant in any model specification.

To provide more context, the Bass model is well known for estimating adoption of new products. Starting with its founder, Frank Bass discovered that most new products follow a cumulative adoption path shaped like an S curve, based on Everett Roger's diffusion of innovation. Diffusion is the process by which an innovation is communicated to consumers through various pathways over time, such as word of mouth. In brief, Roger's theory espouses that the adoption process is successively made up of groups (Figure A.1). The adoption groups typically have similar socio-economic characteristics and behavioral/risk characteristics within the group but are heterogeneous between groups. The earlier groups of adopters, such as the Innovators, need very little provocation to adopt and typically have higher disposable incomes, higher education, and higher risk tolerance than later adopter groups. The last adopters groups are unlikely to adopt unless given no other alternative. As a result, an innovation may never reach full market saturation if the benefits do not outweigh the risks for the later groups. The most cited reason for failure of market adoption progress is inadequate price decline (Golder and Tellis 2004).

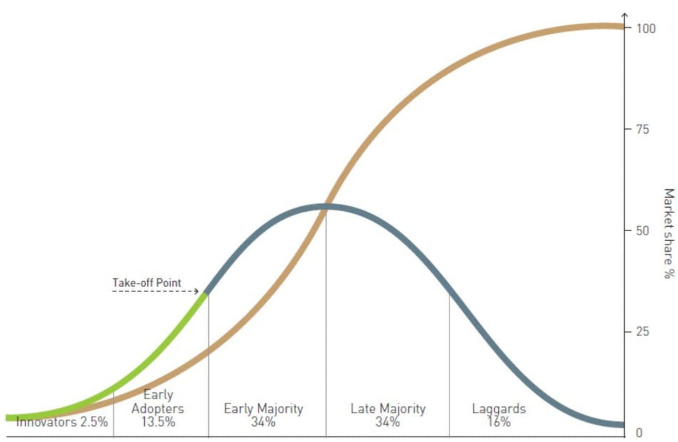


Figure A.1. Adoption life cycle and market diffusion for new technologies (Source: Daly, 2013)

Example adoption curves clearly demonstrate the resulting cumulative adoption S curve and why diffusion models are so prevalent (Figure A.2). As mentioned earlier, Bass models are commonly used to forecast innovations.

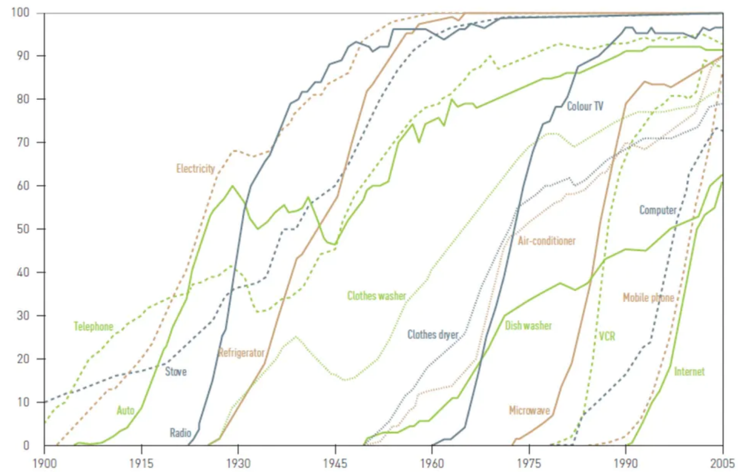


Figure A.2. Technology adoption curves for consumer durables and services (Source: Daly, 2013)

Appendix B – Data

The data focuses on vehicle, socio-economic, and housing characteristics relevant to the SCE feeder, located in Rowland Heights, CA. Since this study uses data sources that enable the research team to characterize individual households of the SCE feeder, the first step in synthesizing the various sources into a time series was to normalize the data into a consistent format. This was critical for normalizing addresses within the feeder's geography so that individual households were consistently referenced/labeled across all the data sources. For example, 123 Smith St. and 123 Smith Street would be treated as separate households if data normalization routines were not applied.

Four of the data sources used in this study followed different address formats:

1. Vehicle registration data from the California Department of Motor Vehicles
2. Tax assessor data from Los Angeles County
3. Census Bureau income distribution by census block
4. Definition of home addresses contained within the feeder provided by SCE.

The data normalization approach included geocoding all the addresses then matching the geocodes. The vehicle registration database was the least refined because registrants' inputs were manually entered, with many non-conforming entries. For example, a city or address could be entered in various ways or with various spellings or even different sequences, i.e., some registrants putting house or apt number last and some starting with those values. Through normalization, approximately 95% of the houses were matched with actual addresses. All homes with EVs were confirmed to have a legitimate address and were not excluded from the dataset. If registration addresses did not match the tax assessor data, the next closest house was used as a proxy for housing price and type. Approximately 90% of the addresses required proxy addresses in the tax assessor database.

B.1 Vehicle Registration Data

The Department of Motor Vehicles data included make, model, and year for every vehicle registered to an address in Los Angeles County from 2010 through 2020. Unfortunately, registration data was only available at a yearly granularity, which limits the number of observations for the time series. However, this approach can easily scale to the monthly or quarterly granularity levels, which are more highly desired to provide more observation and flexibility in the number of parameter estimates. In addition to address normalization, the small number of vehicles registered with the year 2021 was combined with 2020 registered vehicles.

We aggregated EVs into three groups based on their battery range (Table B.1). Battery range infers battery capacity and the corresponding charging load. Groups 1 and 2 are Battery EVs, while Group 3 consists of PHEVs. Group 1 has the longest battery range, followed by Groups 2 and 3. Not surprisingly, since batteries account for nearly a third of EV cost, the longer battery ranged vehicles were also more expensive (The Economist 2021). Group 1 and 3 vehicle sales began in 2013, while Group 2 sales began in 2012. As of 2020, 176 EVs were registered in the SCE feeder, accounting for 2.7% of the total vehicle market of 6,412 vehicles. Also, households with a registered vehicle averaged 2.7 registered vehicles per household. Of EV registrations only, Tesla accounted for the largest market share of EV registrations at 42%, followed by the Prius Prime plug-in hybrid at 22% of EV market share within the feeder.

Table B.1. Summary data for Groups 1, 2, and 3: Car facts, average price, average income for purchasers

	Group 1	Group 2	Group 3
EV Range (Miles)	140–300	60–170	17–81
Examples of Vehicles	Tesla, Audi E-Tron	Nissan Leaf, Chevy Bolt	Prius Prime, Chevy Volt
No. of EVs Adopted by 2020	77	19	79
Average EV Price	$66,821	$31,828	$32,199
Average Income	$150,603	$94,439	$116,519

B.2 Income Estimation Based on Housing Values

Income is an important variable as it influences the vehicle type a household is more likely to buy. Household income is not publicly available, so it must be estimated. Estimation occurs by cross referencing two different data sources: 1) Los Angeles County tax assessor data provides home values and 2) Census Bureau data provides neighborhood income distributions. For identified Census Bureau data blocks, housing values were ranked low to high then matched to the Census Bureau incomes, ranked accordingly. As a result, the SCE feeder containing 2,381 households with vehicles have the income distribution shown in Figure B.1. The average and median incomes for the SCE feeder were $90,513 and $87,499, respectively. The SCE feeder represents approximately 16% of the total population of Rowland Heights. The totality of Rowland Heights has average and median incomes of $96,276 and $75,587, so the feeder incomes are reasonable. Given the household income for each registered vehicle (multiple vehicles can be registered to one home), the income distribution in Figure B.2 shows the majority of vehicle owners falling in the $75,000 to $100,000 income bracket.

Notably, closer to 2,574 total homes appear in the feeder to which income distributions were applied. However, approximately 193 households, or 7.4%, did not have vehicles. This is slightly lower than the national average of 8.7% of households not owning vehicles (U.S. Census Bureau 2018).

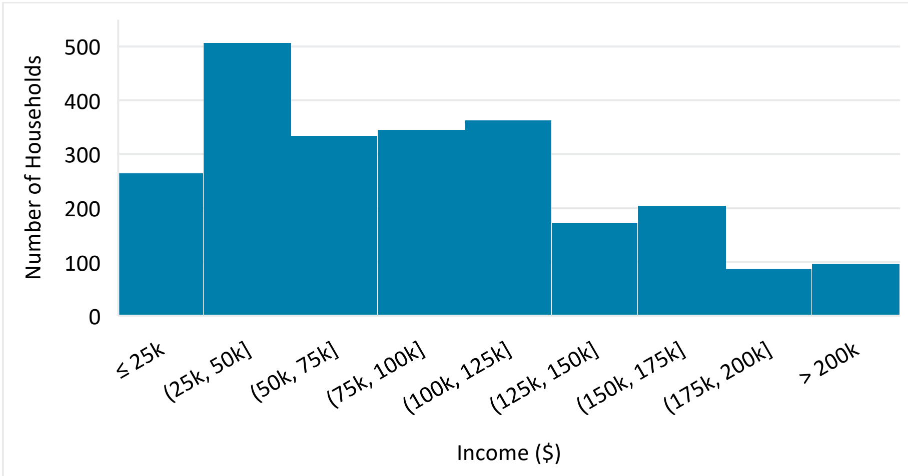


Figure B.1. Income distribution within SCE feeder

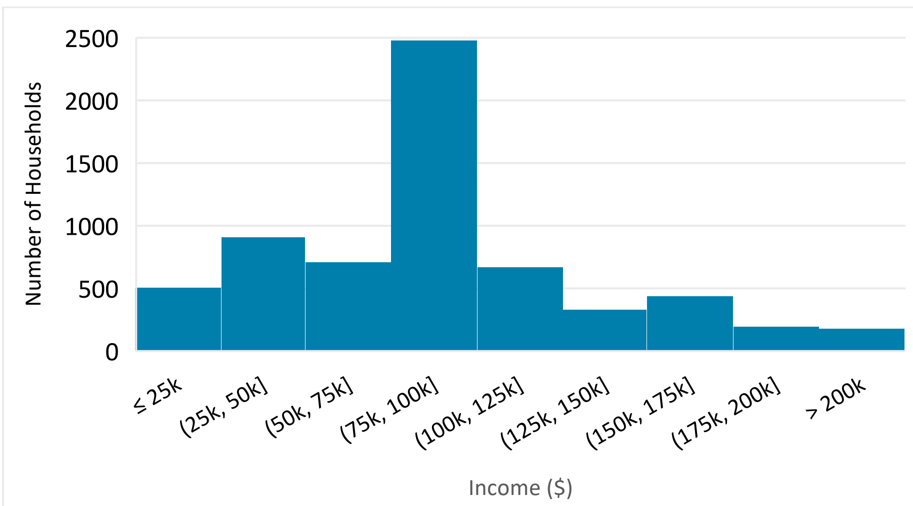


Figure B.2. Income distribution attached to each vehicle in SCE feeder

B.3 EV Prices

EV prices are the original EV price less any incentives. Original manufacturer suggested resale price data was obtained from the Kelly Blue Book website and Carmax websites. All prices were converted to 2020 dollars using the Customer Price Index Inflation Index from the Bureau of Labor Statistics. For the time series, car prices were averaged by group and by year (Table B.2).

Table B.2. Sales and average price for EVs registered in SCE feeder

	Group 1		Group 2		Group 3	
Year	Sales	Average Price	Sales	Average Price	Sales	Average Price
2013	1	$81,413	2	$31,979	2	$36,654
2014	2	$71,941	1	$31,946	8	$36,477
2015	2	$67,744	1	$29,642	5	$36,300
2016	3	$77,250	2	$26,540	4	$34,264
2017	4	$75,959	2	$34,787	15	$24,880
2018	22	$53,835	5	$35,757	21	$28,128
2019	18	$56,635	5	$31,409	17	$29,800
2020	25	$49,788	2	$32,566	7	$ 34,127

Groups 1 and 3 showed downward trending prices while Group 2 remained more static over time. Looking ahead, evidence about the future price of EVs is conflicting. Goreham (2019) reports supply-side limitations and that "[t]he cost and availability of the lithium-ion batteries is still the bottleneck, just as it has always been for a decade now." Goreham adds, "[d]emand isn't limiting the EV market, production is. More specifically, sales trends are dictated by production limitations due to the high cost and limited availability of lithium-ion batteries." According to Scheyder (2019), these statements are corroborated by a Tesla global supply manager for battery metals, who told a closed-door Washington conference of miners, regulators, and lawmakers "the automaker sees a shortage of key EV minerals coming in the near future." For this reason, the impact of incentives on EV adoption must be adequately captured.

Car prices are also affected by federal, state, or local incentives. The current federal credit is equal to $2,500-plus for a vehicle that draws propulsion energy from a battery with at least 5 kWh of capacity, $417, plus an additional $417 for each kilowatt hour of battery capacity in excess of 5 kWh but capped at $7,500 (DOE Office of Energy Efficiency and Renewable Energy, 2021). The credit begins to phase out for a manufacturer's vehicles when at least 200,000 qualifying vehicles have been sold for use in the United States (determined on a cumulative basis for sales after December 31, 2009).

In addition to federal incentives, SCE also offers incentives. Due to privacy concerns, SCE was not able to provide incentives at the household level, so in this study, the incentives were applied to all vehicles. Table B.3 provides the average incentive per year applied to each vehicle.

Table B.3. SCE average EV incentive by year

Year	Average Incentive ($)
2017	450
2018	450
2019	800
2020	1000

B.4 Market Potential

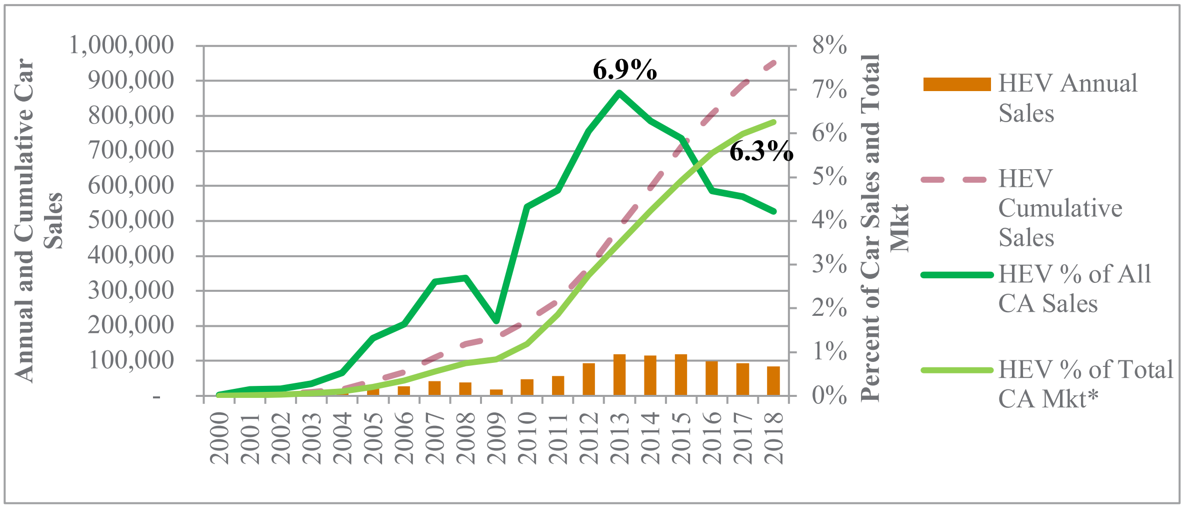
As mentioned in the literature review, the M, or market potential, has the biggest impact on the magnitude of the forecast. Market potential, if left to adopt without a concerted market transformation effort, may not reach the levels intended by governing bodies who are striving for the electrification of the transportation industry. A Bass model would most likely underestimate M if it were an endogenous variable. When allowing the simple Bass model to solve for M, the value was less than the SCE EV targets by an order of magnitude. SCE electrification targets are listed in Table B.4 (SCE, 2019).

Table B.4. SCE electrification goals for light-, medium-, and heavy-duty vehicles by 2030 and 2040

	2030 % of stock	2040 % of stock
Light-Duty EV	25%	76%
Medium-Duty EV	23%	67%
Heavy-Duty EV	6%	38%

Research has shown some indication of alternative vehicle adoption by observing non-plug-in hybrid EV (HEV) adoption. Figure B.3 demonstrates how state-wide HEV adoption occurred over an 18-year period. HEV commercialization began in California in 2000, approximately 10 years prior to PHEVs and EVs. Sales dipped in 2009 after the housing bust and in response to the recession in 2008. Maximum annual sales and annual market share occurred within the 12- to 14-year range. Maximum market penetration was 6.3%, while maximum annual market share of all cars sold in California was 6.9% and has been declining since 2013. One reason that HEVs are declining is that "[h]ybrid cars are now available from multiple makers and even the Prius is no longer considered cutting-edge advanced technology" and that the "role has been taken over by plug-in electric cars" (Voelcker 2018). Further, Ford, General Motors, and Mercedes-Benz, among other auto manufacturers, signed a pledge to stop sales of new gas and diesel-fueled vehicles by 2040 (Miller 2020). These low HEV adoption values may bring awareness to utility planners regarding the challenges of EV adoption, including replacement technologies. Lastly, the 2009 sales dip indicated strong sensitivity to economic conditions, which should be considered in future adoption analyses.[1]

[1] Reuters reported a bankruptcy study showing the auto industry was hardest hit in the United States by the economic downturn. (U.S. News and World Report, 2008).



a. Annual and cumulative HEV sales for the state of California are in blue color and use the left axis.

Data Sources for HEV Sales: 2000–2010 Polk Data (2015). 2011–2012 https://evadoption.com/stats-of-the-week-us-calif-ev-sales-vs-hybrids/. 2013–2018 IHS, Dec 31, 2018.

b. HEV% of all car sales and % of all CA registered automobiles as of the year are graphed in green and use the right axis.

Data Sources: LDV Sales in California – California New Car Dealers Association, https://www.cncda.org/wp-content/uploads/Cal-Covering-4Q-18.pdf. Registered LDVs in California – Federal Highway Association https://www.fhwa.dot.gov/policyinformation/statistics/.

Figure B.3. Non-plug-in HEV in California: Annual and cumulative sales[a] and percent of new sales and percent of total market (operated vehicles)[b]

The model used in this study assumed the market potential by 2050 is approximately 4,700 EVs. This assumption is based on the number of households (2,381) multiplied by two vehicles per household. Also, the feeder household population is assumed to grow at 0.5% per year. Lastly, the model assumed the vehicle market caps at 85% of total market sales. Just as HEVs are being displaced by PEVs, 15% of consumers are assumed to adopt alternatively fueled vehicles, such as hydrogen, biofuels, or other burgeoning drivetrain technologies. (If extrapolated based on SCE's EV targets, the 2050 market saturation would exceed 100%.) Further, the model placed limits on the ability of each group to ultimately adopt based on income. The model assumed Group 1 vehicles would be adopted by households earning over $100,000 while Groups 2 and 3 would more likely be adopted by households with incomes under $100,000. Additionally, the combination of Groups 2 and 3 could not exceed the number of households with income under $100,000. Lastly, auto manufacturers are anticipated to discontinue production of ICEs by 2035. After 2035, PHEVs will start to retire, assuming a battery life and thus total life of 11 years.

Auto manufacturers are likely to produce a wider array of more moderately priced EVs, and like most technologies, prices will continue to decline in general. However, product segmentation will persist; more expensive groups of cars will debut with correspondingly longer-ranging batteries with faster charging capabilities, etc. This study based the evolution of battery specifications on a joint laboratory project from NREL and Idaho National Laboratory showing battery technology progression and potential adoption over time (Pennington 2020). Based on this study, Table B.5 and Table B.6 show simplified estimates of improvements in battery technology. Pennington did not show a corresponding progression for batteries as small as those found in Group 3. For this reason, combined with the anticipated ICE discontinuation, battery specifications remained the same for Group 3 through 2050. In closing, continued EV diversity will likely continue and will create product segmentation that will appeal to differing groups of adopters. Thus, this study maintained three vehicle adoption groups throughout and attributed future battery characteristics to the three groups. Adding battery characteristics over time will help refine EV load as well.

Table B.5. Battery specifications for Group 1 in 5-year increments

	Group 1	Group 1A	Group 1B	Group 1C	Group 1D	Group 1E
Average Range (miles)	220	275	300	300	300	250
Charging Power (kW)	150	150	300	400	575	400

	Group 1 Battery Specification Over Time					
Year	1	1A	1B	1C	1D	1E
2020	100%					
2025	75%	25%				
2030	39%	50%	11%			
2035	35%	32%	23%	6%	4%	
2040	30%	20%	26%	15%	8%	1%
2045	19%	18%	22%	25%	14%	2%
2050	19%	18%	22%	25%	14%	2%

Table B.6. Battery specifications for Group 2 in 5-year increments

	Group 2	Group 2A	Group 2B	Group 2C
Average Range (miles)	115	150	150	275
Charging Power (kW)	50	50	150	150

	Group 2 Battery Specification Over Time			
Year	2	2A	2B	2C
2020	100%			
2025	87%	13%		
2030	61%	7%	5%	27%
2035	48%	12%	8%	32%
2040	30%	20%	10%	40%
2045	0%	10%	10%	80%
2050	0%	10%	10%	80%

Appendix C – Incentive and Charging Data Scenarios

Figure C.1 shows the impact of the incentives based on the Bass model relationship between EV sales and car price. The lower vehicle prices increase both the rate of adoption and the overall magnitude of adoption by making more vehicles affordable or cost competitive.

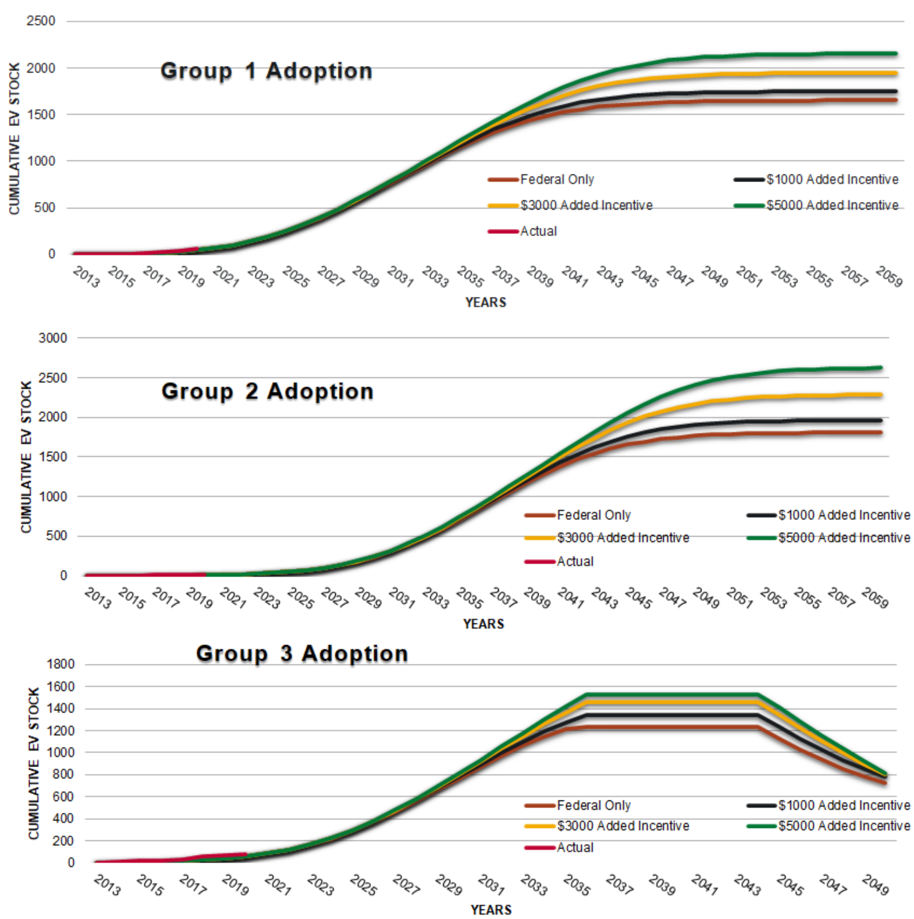


Figure C.1. Impact of incentives on EVs

Figure C.2 shows the increase in adoption if additional public chargers are added to a feeder, based on the current relationship between EV adoption and the number of charging stations. Intuitively, adding public charging stations provides consumers without home chargers, or even those with home chargers, increased user confidence.

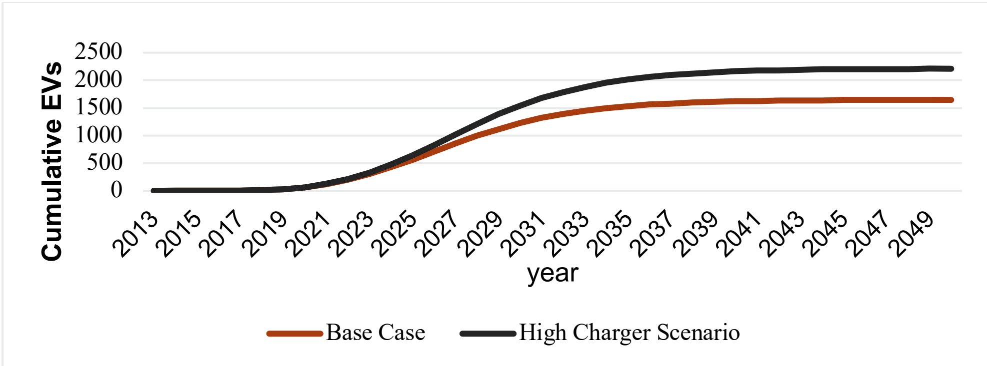


Figure C.2. Group 1 adoption with 33% increase in number of chargers