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Electrification Impacts Study Part 1

May 09, 2023

California has some of the most progressive environmental policies and greenhouse gas reduction goals in the world. Senate Bill (SB) 100 established a landmark policy requiring renewable energy and zero-carbon resources supply 100 percent of electric retail sales to end-use customers by 2045.

The California Public Utilities Commission initiated the High Distributed Energy Resources Grid Planning Rulemaking[1] in July 2021 to prepare the electric grid for anticipated high adoptions of Distributed Energy Resources (DERs), including those associated with transportation and building electrification.

The Electrification Impacts Study Part 1 (Part 1 Study) was prepared for review within the High DER Proceeding as a first step towards examining the potential impacts of high adoptions of DERs on the distribution grid, identifying where and when enhancements and investments could be needed, and estimating the potential costs of meeting these needs.

The Part 1 Study presents a granular bottom-up load forecasting methodology that provides locational and temporal information on where and when distribution grid enhancements may be needed. Part 1 study also estimates potential system level costs under an unmitigated scenario.

The preliminary results from the Part 1 Study estimate approximately $50 billion for distribution grid investments by 2035 to accommodate a High DER grid future if measures are not taken to reduce costs and manage load. It is important to consider the system-level cost and load estimates presented in the Part 1 Study to be preliminary.

It should be noted that the Part 1 Study estimates the potential costs of meeting infrastructure needs being exclusively met with distribution assets without considering new real-time dynamic rates and flexible load management strategies. California's aging grid will also require upgrades in certain areas to ensure continuity of service to support current DERs and load, even in the absence of additional DERs.

This study is a learning experience and a starting point to open the discussion on how to reimagine distribution grid planning for the twenty first century and consider the design and implementation of the distribution system needed to accommodate a High DER grid future.

To meet this challenge, it is critical that we receive stakeholder participation in reviewing this study. The Energy Division staff underscore that this is a beginning point in the discussion, and welcome feedback and comments on the Part 1 Study and the proposals for future iterations.

[1] R.21-06-017

kevala

Electrification Impacts Study
Part I: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates

Prepared for: California Public Utilities Commission, Energy Division

Proceeding R.21-06-017 (Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future)

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Acknowledgements

The success of this study depended on multiple voluminous datasets, including advanced metering infrastructure (AMI) data, provided by the three large Investor-Owned Utilities (IOUs)—Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)— under the California Public Utilities Commission (CPUC) *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distribution Energy Resources Future* (Rulemaking 21-06-017) Utility Data Request.

Kevala would like to acknowledge the three IOUs and the California Energy Commission (CEC) for making available to the CPUC and its project consultant the AMI and other necessary data identified in the Research Plan[1] for this Electrification Impacts Study. Kevala has accepted and ingested data provided by the IOUs on behalf of the CPUC deploying all necessary security protocols to ensure the data confidentiality and security of such data.

Kevala would also like to thank the IOUs for their continued cooperation in interpreting the data and responding to additional requests as data issues or limitations were identified. The IOUs' active engagement in this process enabled high-resolution modeling at a scale not achieved before for the State of California.

[1] The *Electrification Impacts Study Research Plan*, dated March 29, 2022, is available at https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/62d8509da2f405169ee10dd0_2022-0329_Electrification%20Impacts%20Study_Final%20Research%20Plan.pdf.

Acronyms and Definitions

Acronyms

AADT: Annual Average Daily Traffic

AAEE: Additional Achievable Energy Efficiency

AAFS: Additional Achievable Fuel Switching

AB: Assembly Bill

AC: Alternating Current

ACC II: Advanced Clean Cars II

ACS: American Community Survey (U.S. Census Bureau)

AMI: Advanced Metering Infrastructure

AUC ROC: Area Under the Receiver Operating Characteristic Curve

BA: Balancing Authority

BE: Building Electrification

BESS: Battery Energy Storage System(s)

BEV: Battery Electric Vehicle

BTM: Behind-the-Meter

C&I: Commercial and Industrial

CARB: California Air Resources Board

CAISO: California Independent System Operator

CARE: California Alternate Rates for Energy

CBECS: Commercial Buildings Energy Consumption Survey

CCA: Community Choice Aggregator

CEC: California Energy Commission

CEDARS: California Energy Data and Reporting System

CPUC: California Public Utilities Commission

D: Decision

DC: Direct Current

DCFC: Direct Current Fast Charging

DDOR: Distribution Deferral Opportunity Report

DER: Distributed Energy Resource

DIDF: Distribution Investment Deferral Framework

DOE: U.S. Department of Energy

DPAG: Distribution Planning Advisory Group

DPP: Distribution Planning Process

EE: Energy Efficiency

EV: Electric Vehicle

EVI-Pro: Electric Vehicle Infrastructure Projection Tool

EVSE: Electric Vehicle Service Equipment

FTP: File Transfer Protocol

GIS: Geographic Information System

GNA: Grid Needs Assessment

GVWR: Gross Vehicle Weight Rating

HD: Heavy Duty

HDV: Heavy-Duty Vehicle

HEIAWG: High Electrification Inter Agency Working Group

ICE: Internal Combustion Engine

IEPR: Integrated Energy Policy Report

IOU: Investor-Owned Utility

IRP: Integrated Resource Plan

JASC: Joint Agency Steering Committee (CPUC, CEC, CAISO, CARB)

kV: Kilovolt

KVA: Kilovolt-Ampere

kW: Kilowatt

kWh: Kilowatt-Hour

L1: Level 1

L2: Level 2

LATCH: Local Area Transportation Characteristics for Households Data

LD: Light Duty

LDV: Light-Duty Vehicle

LOR: Load Offset Ratio

LSE: Load-Serving Entity

MD: Medium Duty

MDV: Medium-Duty Vehicle

MLR: Multilevel Logistic Regression

MSS: Mobile Source Strategy

MUD: Multi-Unit Dwelling

MVA: Megavolt-Ampere

MW: Megawatt

MWh: Megawatt-Hour

NAICS: North American Industry Classification System

NEM: Net Energy Metering

NREL: National Renewable Energy Laboratory

NSRDB: National Solar Radiation Database

NWA: Non-Wires Alternative

OIR: Order Instituting Rulemaking

PCIA: Power Charge Indifference Adjustment

PEV: Plug-in Electric Vehicle

PG&E: Pacific Gas and Electric

PHEV: Plug-in Hybrid Electric Vehicle

PII: Personal Identifiable Information

PR AUC: Precision Recall Area Under the Curve

PV: Photovoltaic Solar Energy System

R: Rulemaking

RASS: Residential Appliance Saturation Study

RCP 8.5: Representative Concentration Pathway 8.5

SB: Senate Bill

SCADA: Supervisory Control and Data Acquisition

SCE: Southern California Edison

SDG&E: San Diego Gas & Electric

SIP: State Implementation Plan

SUD: Single-Unit Swelling

SUV: Sport Utility Vehicle

SSS: State SIP Strategy

T&D: Transmission and Distribution

TAC: Transmission Access Charge

TB: Terabytes

TOU: Time-of-Use

UEC: Unit Energy Consumption

U.S.: United States

VIO: Vehicles in Operation

VIUS: Vehicles in Use Survey

VMT: Vehicle Miles Traveled

ZEV: Zero-Emission Vehicle

Definitions

8760: Generally refers to the number of hours in a typical (non-leap) year.

Adoption model: A model that predicts the consumer's likelihood to adopt a new technology. The model considers multiple variables that can reliably predict the consumer's ability and willingness to adopt a new technology such as the characteristics of early adopters, factors that drive market potential, and historical adoption rates.

Adoption propensity score: The output from the adoption model. It is a measure of the rank of a customer's likelihood to adopt relative to all other customers.

Advanced metering infrastructure (AMI): A time-series energy consumption data measurement and collection system that includes advanced meters/smart meters at the customer site, communication networks between the customer and utility, and data collection and management systems that make the information available to the utility, customer, and authorized third-party vendors.

Area under the receiver operating characteristic curve (AUC ROC): This metric summarizes performance over all adoption thresholds and is designed to quantify how well a model is able to separate adopting premises from non-adopting premises. AUC ROC quantifies how a model performs on the tradeoff between the true positive rate (e.g., predicting adoption at a premise where adoption actually occurred) and the false positive rate (e.g., predicting adoption at a premise where adoption did not actually occur).

Bayesian: An approach to statistical inference that combines prior information about the distribution of an unknown value with posterior evidence from information contained in a sample. In data science, it is a popular technique for building models when labeled ground truth data is relatively limited, but there is subject matter understanding to build upon.

Battery electric vehicle (BEV): Also known as an all-electric vehicle, BEVs use energy that is stored in rechargeable battery packs. BEVs sustain power through the batteries and must be plugged into an external electricity source to recharge.

Behind-the-meter (BTM): BTM refers to customer-sited distributed energy resources (DERs) such as solar PV or battery storage that are connected to the distribution system on the customer's side of the utility's service meter.

Behind-the-meter (BTM) tariff: A set of rate structures (energy based, demand based, or customer charge) and components (costs related to generation, delivery, transmission, and other costs) that apply to customers with DERs.

Building electrification (BE): Refers to the electrification of appliances and equipment in buildings (e.g., electric heat pump replacing gas heating, electric water heaters replacing gas water heaters, electric cooktops replacing gas cooktops).[2]

Bottom-up forecast: A bottom-up method forecasts the generation and load impact from distributed energy resources (DERs) based on adoption models while considering the characteristics of early adopters, factors that drive market potential, and adoption rates applied to the remaining potential customers. The forecast is predicted at a granular level (i.e., at the customer premise level).

California Independent System Operator (CAISO): CAISO is the electric grid operator for California's electrical transmission system.

Coincident peak load: The maximum energy use in an hour compared to all other hours in the year for a collection of loads, such as premises, feeders, or an entire service area. For example, a system coincident peak is the peak of the system for all customers in that system.

Distributed energy resources (DERs): Includes distributed renewable generation resources, energy efficiency measures, energy storage devices, electric vehicles (EVs) and electric vehicle service equipment (EVSE), time-variant and dynamic rates, flexible load management technologies, and demand response technologies. Most DERs are connected to the distribution grid behind the customer's electric meter, and some are connected in front of the customer's electric meter.

Demand modifiers: Refers to the expected hourly behavior from DERs that changes the customer's overall energy use pattern.

Demand response: Refers to any change in net electricity demand made by the customer in response to an economic incentive or grid signal to reduce, increase, or shift net-load relative to what the net-load would have been absent the signal. The change could be temporary or recurring.

Distribution Planning Process: A process, typically done annually, to forecast electric distribution equipment upgrade, improvement, or maintenance needs to maintain safe, reliable, and affordable service while efficiently operating the existing electrical distribution grid.

Electric vehicle service equipment (EVSE): The equipment that interconnects the electricity grid at a site to an EV. Sometimes used more broadly to mean charging station, whether alternating

[2] Electrification of appliances and equipment in buildings is also referred to as fuel switching. Kevala uses building electrification (BE) throughout this Part 1 Study.

current (AC) or direct current (DC) but not including other behind-the-meter (BTM) charging-related infrastructure. EVSE equipment is classified as:

- **Level 1 (L1)**:120 volts AC
- **Level 2 (L2):** 240 volts, AC
- **DC fast charger (DCFC):** 480 volts DC and higher

Energy burden: Percent share of the electricity bill costs with respect to the household income.

Fleet EV: Fleet EVs are zero-emission vehicles owned by or registered to an entity (not an individual) and are used for business-related purposes. Fleet EVs can be LDVs, MDVs or HDVs. Fleet EVs only have BEV powertrains and can be one of 10 vehicle classes.

Grid integration: The practice of developing efficient ways to deliver variable renewable energy to the grid. Robust integration methods look at how to maximize the cost-effectiveness of incorporating variable renewable energy into the power system while maintaining or increasing stability and reliability.

Gross vehicle weight rating (GVWR): The gross vehicle weight rating of a vehicle is the maximum allowable weight of the fully loaded vehicle (including passengers and cargo), as rated by the automobile manufacturer.

Integrated Energy Policy Report (IEPR): California Senate Bill (SB) 1389 requires the California Energy Commission (CEC) to conduct assessments and forecasts of all aspects of energy industry supply, production, transportation, delivery and distribution, demand, and prices. The CEC adopts an IEPR every two years and an update every other year. The energy and DER forecasts produced in the IEPR are used in the California utilities' Distribution Planning Process.

Integrated Resource Plan (IRP): A procurement plan used by utilities that details what resources are to be procured and how they will be procured to comply with California's climate and energy policies, adequately balance safety, reliability, and cost, while meeting the state's environmental goals described in SB 350 and SB 100.

Mean absolute error: Defined as the sum of absolute errors between predicted and actual values, divided by the sample size. A smaller value is better.

Mean absolute percentage error: Average of the absolute percentage errors between the predicted and the actual values. It quantifies the relative versus the absolute typical difference, but it has limited usefulness if the actual values are near zero, where the mean absolute percentage error tends towards infinity.

Multilevel logistic regression (MLR): Logistic regression is a machine learning algorithm, similar to linear regression but designed to predict a binary outcome with a score in [0.0, 1.0] so that it can be applied to classification problems. A multilevel logistic regression separates the population into clusters before applying a logistic regression to the population belonging to each cluster and may be more effective if the differences between those clusters are consistently more substantial than the differences within the clusters.

Net energy metering (NEM): Metering and billing arrangement designed to compensate any generation from DERs that is exported to the utility grid during times when it is not serving onsite load via a bill credit for excess generation.

Net-load: The expected address-level energy use served by the investor-owned utility (IOU) or, in the case of reverse flow, the level of energy the customer is exporting to the grid and the IOU is expected to accept and distribute. It is the sum of actual energy use behind the meter plus or minus the demand-modifying behaviors from DERs.

Node: A transmission node refers to the interface between the distribution and the transmission electric power systems. At transmission nodes, the distribution system is typically represented as an aggregate lumped load in transmission models. Nodes can also be referred as transmission/distribution interfaces or T-D interfaces.

Non-coincident peak load: The maximum energy use of customers, groups of customers, or grid assets; it does not necessarily coincide with the hour of the coincident peak. For example, a customer's peak load is considered non-coincident as it may differ from the system coincident peak. Similarly, a feeder coincident peak, or the peak on that feeder, may be non-coincident with the system peak.

Non-wires alternative (NWA): An electricity grid investment or project that uses non-traditional transmission and distribution (T&D) solutions, such as DERs and load management technologies, to defer or replace the need for specific equipment upgrades, such as transmission lines or transformers.

Order Instituting Rulemaking: Rulemaking proceeding opened by the California Public Utilities Commission (CPUC) to consider the creation or revision of rules, general orders, or guidelines affecting more than one utility or a broad sector of the industry. Comments, proposals, and testimony are submitted by parties to the Order Instituting Rulemaking in written form; oral arguments or presentations are sometimes allowed.

Peak load: The maximum energy use in an hour compared to all other hours in the year. Peak can be used synonymously with coincident peak, which is the maximum energy use in an hour for a collective group of customers. For example, a system coincident peak is the peak of the system for all customers in that system. Similarly, feeder peak is the peak load for all load connected to that feeder. The individual peaks of customers may differ from the coincident peak and are referred to as non-coincident peaks.

Plug-in hybrid electric vehicle (PHEV): Vehicles powered by an internal combustion engine (ICE) and an electric motor that uses energy stored in a battery. The vehicle can be plugged into an electric power source to charge the battery. Some can travel nearly 100 miles on electricity alone, and all can operate solely on gasoline (like a conventional hybrid vehicle).

Power charge indifference adjustment (PCIA): A charge or credit to community choice aggregator (CCA) customers that reflects the difference in the portfolio costs for each IOU and the market value of the portfolio. This mechanism is designed to ensure customers are indifferent to receiving services from a CCA versus the incumbent IOU, consistent with legislative requirements. PCIA rates are based on the year the customer moves to a CCA to ensure the departing customer is not responsible for incremental portfolio costs incurred after joining the CCA. These rates that vary based on year are referred to as the “vintage” of the PCIA rate.

Precision: An evaluation metric that measures the adoption model’s ability to identify relevant data points, such as if a customer adopted. It is calculated by taking the number of true positives (number of times an actual adoption was predicted) divided by the number of true positives plus the number of false positives (the number of times an adoption was predicted that was not seen in the base data).

Precision recall area under the curve: The area under the precision recall curve, which is used to assess the performance over all the adoption thresholds as represented by the precision and recall metrics.

Premise: Contiguous geographic area used by a utility to track billing and usage. It contains service points and meters and should have an address assigned to it.

Recall: An evaluation metric that measures the adoption model’s ability to identify all relevant cases within a dataset. It is calculated by taking the number of true positives divided by the number of true positives plus the number of false negatives.

Root mean squared error: The square root of the average squared difference between the predicted and actual values. It is similar to mean absolute error, but it is more sensitive to outliers where the prediction was far from the actual value.

System-level cost estimate: For the purposes of Part 1 of the Electrification Impacts Study, aggregate system-level costs for each investor-owned utility derived from premise-level load profiles that are applied to known utility infrastructure elements and utility-specific network unit costs (i.e., unit costs of traditional infrastructure). System-level cost estimates are designed to holistically quantify the level of traditional grid investment required to meet the different policy-based outcomes studied in this Part 1 Study in 2025, 2030, and 2035 for Pacific Gas and Electric, Southern California Edison, and San Diego Gas & Electric. With the potential inclusion of mitigation strategies in Part 2[3] of the Electrification Impacts Study, this definition may be updated.

Time-of-use (TOU) rate: A rate plan with rates that vary according to the time of day, season, and day type (weekday or weekend/holiday). TOU rates can encourage the efficient use of the system and can reduce the overall costs for the utility and its customers.

Top-down allocation: A method for providing a transmission system-level aggregate load and DER forecast that disaggregates the load and DER forecast to distribution circuits based on utility data for the circuit (e.g., load, energy, or number of customers) or statistical propensity models.

Vehicle duties: A vehicle duty refers to the three duty types that the U.S. Federal Highway Administration uses to categorize vehicles by gross vehicle weight rating (GVWR). The duty types are:

- **Light-duty vehicle (LDV):** <10,000 GVWR
- **Medium-duty vehicle (MDV):** 10,001-26,000 GVWR
- **Heavy-duty vehicle (HDV):** > 26,001 GVWR

Zero-emission vehicle (ZEV): Vehicles that produce no emissions from the onboard source of power (for example, hydrogen fuel cell vehicles and EVs). Electric vehicles are broken further into two categories: BEVs and PHEVs.

[3] The Research Plan for the Electrification Impacts Study had identified Part 2 as an evaluation of the IOUs' Grid Needs Assessment (GNA)/Distribution Deferral Opportunity Report (DDOR) filings and recommendations for near-term improvements, followed by a Staff Proposal. This step has been renamed as the GNA/DDOR Evaluation and Staff Proposal. As such, the next part of the Electrification Impacts Study will be referred to as Part 2 throughout this report (previously referred to as Part 3).

Executive Summary

The California Public Utilities Commission (CPUC) recognizes that successfully achieving California's electrification and decarbonization goals depends on an electricity grid that can support diverse electrification technologies at scale while maintaining system reliability and ensuring equity and affordability of electricity service for all Californians. This Electrification Impacts Study aims to provide in-depth analysis in support of the policy questions under deliberation at the CPUC.

Specifically, the two-part Electrification Impacts Study series seeks to address the following question: **what is the scope and scale of potential electric grid impacts and the associated costs necessary to support California's ambitious electrification goals?**

This Part 1 Study provides **preliminary** estimates of the scope and scale of potential electric distribution grid impacts for Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E) from widespread transportation electrification and solar photovoltaic (PV) penetration by 2035. This study develops, for the first time, a highly granular load forecast for over 12 million premises across California for baseline load and distributed energy resource (DER) adoption, including PV, battery energy storage systems (BESS), energy efficiency (EE), building electrification (BE), and electric vehicles (EVs).

Kevala, Inc. (Kevala) developed and analyzed a base, or reference case, calibrated to California's Integrated Energy Policy Report (IEPR) and four unmitigated, policy-based alternate planning scenarios; these alternate scenarios focused on modeling transportation electrification loads under differing policy scenarios as transportation electrification is anticipated to be the most significant factor driving increased loads in the near term.[4, 5] The Part 1 Study also considered two different behind-the-meter (BTM) tariffs in the scenarios (described further in Section 1.2.3).

It is important to highlight that this Part 1 analysis was conducted under unmitigated planning scenarios, which assume only traditional utility distribution infrastructure investments. The Part 1 analysis assumed existing time-of-use (TOU) rates and BTM tariffs would be in place throughout

[4] The planning scenarios, assumptions, and data constraints are described in Section 1.2.1 and Appendix 3. These constraints are expected to be addressed in follow-up studies. The follow-up study scenarios may be revised based on stakeholder and agency feedback.

[5] BE loads are also expected to significantly impact the electric grid based on the California Air Resources Board's (CARB's) 2022 State Implementation Plan, which includes zero-emission measures for space and water heating to be implemented by 2030. BE scenarios are proposed to be part of future phases of the analysis planned for the High DER Proceeding (i.e., Part 2 of the Electrification Impacts Study).

the study timeframe. It did not consider alternatives or future potential mitigation strategies such as alternative time-variant rates or dynamic rates and flexible load management strategies.

Follow-up analysis in the study series is proposed include additional statewide electrification scenarios with baseline load and transportation electrification methodologies and scenarios that will be updated with additional data. Kevala also proposes adding BE scenarios aligned to state policy targets and considering potential mitigation strategies in case studies that could inform ways of managing grid impacts and the costs of grid investments.

Background and Study Objectives

This report summarizes Kevala's approach, results, and insights for Part 1 of the Electrification Impacts Study: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates. The CPUC commissioned the Electrification Impacts Study to support Rulemaking (R.) 21-06-017: the *Order Instituting Rulemaking (OIR) to Modernize the Electric Grid for a High Distributed Energy Resources Future*.[6] This OIR is focused on preparing the grid to accommodate a high DER future, capturing as much value as possible from DERs, and mitigating unintended negative grid impacts. This OIR is referred to as the High DER Proceeding throughout this report, while Part 1 of the two-part Electrification Impacts Study is referred to as the Part 1 Study.

The Electrification Impacts Study was designed to inform a number of the scoping questions issued in the November 15, 2021, Scoping Ruling and was guided by the *Electrification Impacts Study Research Plan* (Research Plan),[7] submitted to the CPUC on March 29, 2022. As defined in the Research Plan, the Electrification Impacts Study (split into two parts) will:

- Enable the identification of grid enhancements and changes necessary to support California's stated transportation and building electrification policy goals by 2035.
- Consider alternatives for evaluating distribution capacity expansion and deferral options into the utilities' Distribution Planning Process (DPP).
- Explore increasing the granularity of technology adoption models in high electrification scenarios to inform the development of mitigation strategies which will seek to optimize grid planning, maximize the equity and reliability benefits, and minimize the costs of high electrification.

[6] R.21-06-017, opened with an *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future*, issued on July 2, 2021, https://apps.cpuc.ca.gov/apex/f?p=401:56:0::NO:RP,57,RIR:P5_PROCEEDING_SELECT:R2106017

[7] The full scope of the Electrification Impacts Study is detailed in the Research Plan, dated March 29, 2022, https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/62d8509da2f405169ee10dd0_2022-0329_Electrification%20Impacts%20Study_Final%20Research%20Plan.pdf

- Improve clarity and transparency of electrification scenario inputs, methodologies, and outputs across state energy planning agency processes.

This **Part 1 Study** is a granular customer electricity consumption data analysis designed to support electricity distribution grid planning processes that enable California to meet its state energy goals. This part of the study builds the foundation for a novel framework for distribution planners and policymakers to evaluate grid needs and value grid solutions based on the hyper-granular location of electrification needs. The scope of this Part 1 Study includes the customers and grid infrastructure for the three large California investor-owned utilities (IOUs): PG&E, SCE, SDG&E.

This Part 1 Study is intended to address two main objectives:

1. Estimating system-level unmitigated grid infrastructure costs associated with achieving California electrification policies over longer timeframes than current distribution planning processes (inclusive of distribution grid requirements down to the service transformer level).
2. Demonstrating and assessing new planning and analytic methods, including scenario planning, that enable more granular forecasting accuracy, ability to estimate where and when electrification loads will occur, and the potential impact of DER growth on forecasts.

Part 2[8] of the Electrification Impacts Study proposes to build on the Part 1 results. Leveraging additional data, Part 2 proposes updating the load forecast developed in Part 1 and creating a framework for estimating utility-specific grid investment and assessing programmatic enhancements (e.g., TOU rate structures) and their costs under various scenarios with high DER—namely transportation and BE forecasts, grid integration technologies such as advanced DER controls and flexible load management, and the implications of managed DER growth.

Data Availability and Assumptions

Central to this study was the collection, ingestion, mapping, and analysis of many data sources. Over 100 terabytes of time series data, geospatial and utility grid network data, and socioeconomic data were collected and joined (or linked) to enable Kevala's modeling of each premise. The analysis described in this report relied on these multiple, voluminous datasets and on specific sets of assumptions about each DER type and rate structures and designs that have

[8] The Research Plan for the Electrification Impacts Study had identified Part 2 as an evaluation of the IOUs' Grid Needs Assessment (GNA)/Distribution Deferral Opportunity Report (DDOR) filings and recommendations for near-term improvements, followed by a Staff Proposal. This step has been renamed as the GNA/DDOR Evaluation and Staff Proposal. As such, the next part of the Electrification Impacts Study will be referred to as Part 2 throughout this report (previously referred to as Part 3).

since changed. Updated data beyond the study period used for this report is now available, and certain programmatic assumptions have evolved since the Research Plan parameters of this analysis were finalized in 2022.[8] All of the data elements requested and applied for this study are identified in the Research Plan and further described in Section 1.2.1 and Appendix 2 of this report. The methods and results documented in this report either discuss data types and uses or depict aggregated data in charts and graphics. None of the methods or findings documented in this report are considered confidential.

The Part 1 Study used the following modeling approach applied to the data received:

- Estimate each customer's load over the study period using machine learning based on the actual customer data received to date.
- Develop a premise-specific load profile that reflects adoption of EE, PV, BESS, BE, and EVs.
- Calibrate the results of this modeling to the California Energy Commission's (CEC's) 2021 Integrated Energy Policy Report's (IEPR's) system-level forecasts to ensure consistency with the IOUs' GNAs and the IEPR.[9]
- Aggregate premise-level load profiles that include DER-specific adoption up to the IOU service territory level.
- Identify the magnitude and location of DER adoption and resulting high electrification anticipated for a base case and four alternate scenarios focusing on two DER types, transportation electrification and net energy metering (NEM) BTM tariffs for 2025, 2030, and 2035.[10]
- Identify system-level grid impacts, costs, and affordability of electricity service for customers.

[9] This approach is similar to how the IOUs ensure the forecast used for annual GNA/DDOR preparation does not exceed the IEPR demand forecast. However, the GNA/DDOR process for calibrating to the IEPR is complicated by the known loads issue, as described in Section 3 (pp. 26-34) of the *2022 Independent Professional Engineer Post DPAG Report*.

[10] NEM BTM tariffs refer to a hypothetical alternative compensation structure for BTM PV based on the December 2021 Proposed Decision for R.20-08-020 and incorporate a monthly grid access charge and specific export rate. In December 2022, the CPUC adopted the Net Billing Tariff in proceeding Decision (D.) 22-12-056, which has a different structure than the scenarios included in this study; therefore, the results of these scenarios do not reflect what will happen with the newly adopted Net Billing Tariff. For Part 2 of the Electrification Impacts Study, the 2022 Net Billing Tariff (adopted December 15, 2022 by D.22-12-056) will be used for analytical purposes.

The transportation electrification scenario inputs, drawn from CARB and CEC projections as discussed in Appendix 9, incorporate a range of different zero-emission vehicle (ZEV) adoption levels, including personal vehicles and medium- and heavy-duty freight and port vehicles that were incorporated into the CEC's 2021 Updated IEPR.

For this Part 1 Study, Kevala created different combinations of transportation electrification and NEM BTM tariff outcomes for the scenarios. These two specific DERs were selected for the scenario analysis, in part, to isolate the impact of these two relatively meaningful and dynamic DERs. Further, at the time the Part 1 analysis was finalized, transportation electrification and NEM BTM tariffs had existing or pending state-defined policy goal projections and definitions that served to tie the scenarios studied to actual or proposed state policies. This is not to suggest other DERs such as BE or PV will not be studied or impactful for California's electrification efforts; rather, the goal of Part 1 of the Electrification Impacts Study is to isolate and identify the likely grid impacts from two specific DERs for which there is less program data or for programs that are changing.

Further, this study applied existing BTM tariff assumptions and modified BTM tariff assumptions, as described in Section 1.2.3. The existing BTM assumptions were based on the NEM 2.0 Tariff, and the modified BTM tariff design was based on the December 13, 2021 Proposed Decision for proceeding R.20-08-020.[11] This was the best available information at the time of the Research Plan's completion. For Part 2 of the Electrification Impacts Study, the 2022 Net Billing Tariff (adopted December 15, 2022 by Decision (D.) 22-12-056) will be used for analytical purposes.

Results

California's electricity grid is changing rapidly, driven by significant changes at the premise level. Customer programs and rate designs tailored to elicit individual customer behaviors and responses, changing customer technologies, ambitious statewide energy policy goals, and localized wildfire and climate change impacts all contribute to dynamic electricity grid changes that are unique to each premise. The results of this Part 1 Study build the foundation for an improved framework for distribution planners and policymakers to evaluate grid needs and value grid solutions based on the hyper-granular location of electrification needs.

The results of this Part 1 Study illustrate how consolidating these extensive data sources yields important insights into **where and when distribution grid enhancements are likely to be needed** to support the premise-level impacts of grid electrification, which is critical as California enters a period of capacity expansion and DER proliferation to support state policy goals. These results also help to understand the quality and scope of utility data and to challenge some

[11] Modified BTM tariff assumptions were based on the December 13, 2021, Proposed Decision for proceeding R.20-08-020 (Order Instituting Rulemaking to Revisit Net Energy Metering Tariffs). The Proposed Decision was not adopted by the Commission; it is available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M430/K903/430903088.PDF. Instead, D.22-12-056 adopted the Net Billing Tariff.

traditional DER program assumptions. The following summarizes these and other results of Kevala's Part 1 Study.

Grid Requirements and Associated Costs

Electric distribution grid requirements and their associated costs increase significantly beyond the traditional distribution grid planning cycle, risking stranded investments or missed investment opportunities altogether if datasets are not connected and analyzed holistically.

- **Across these unmitigated load scenarios, Kevala estimates up to $50 billion in traditional electricity distribution grid infrastructure investments by 2035** (see Figure ES-1). This estimate reflects distribution grid needs across the PG&E, SCE, and SDG&E service territories under the policy assumptions used in this report. These costs are estimated with a focus on traditional utility distribution infrastructure investments. Existing TOU rates and BTM tariffs were assumed. The study did not consider alternatives or future mitigation strategies such as alternative time-variant or dynamic rates and flexible load management strategies.
- Kevala examined several scenarios[12] for this Part 1 Study. Both of the High Transportation Electrification scenarios would result in almost doubling the current rate of spend reported by the IOUs in the GNA reports for capacity requirements related to feeders, transformer banks, and substations.[13] These Part 1 Study costs reflect the impact of unmitigated loads.
- Secondary transformer and service upgrades alone are a non-negligible contribution to the total grid capacity upgrade costs, comprising an estimated $15 billion of the $50 billion identified previously and are currently not accounted for in the IOUs' annual GNA reports. PG&E's distribution circuits are projected to reach capacity sooner than SCE and SDG&E. SDG&E is expected to have the least number of feeders reaching full capacity by 2035, with 22% compared to SCE's 36% and PG&E's 48% of feeders.
- The system-level peak load increase from 2025 to 2035 is 56%, on average, across the three IOUs and High Transportation Electrification scenarios[14] (see Figure ES-2); this dramatic

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[12] Kevala generated premise-specific forecasts for five scenarios. The base case represents a premise-level forecast that calibrates the baseline load forecast and the individual demand modifier forecasts to the 2021 IEPR mid-mid case. Each of the four alternate scenarios considers a different combined projection for NEM BTM tariffs and the speed and scope of transportation electrification.

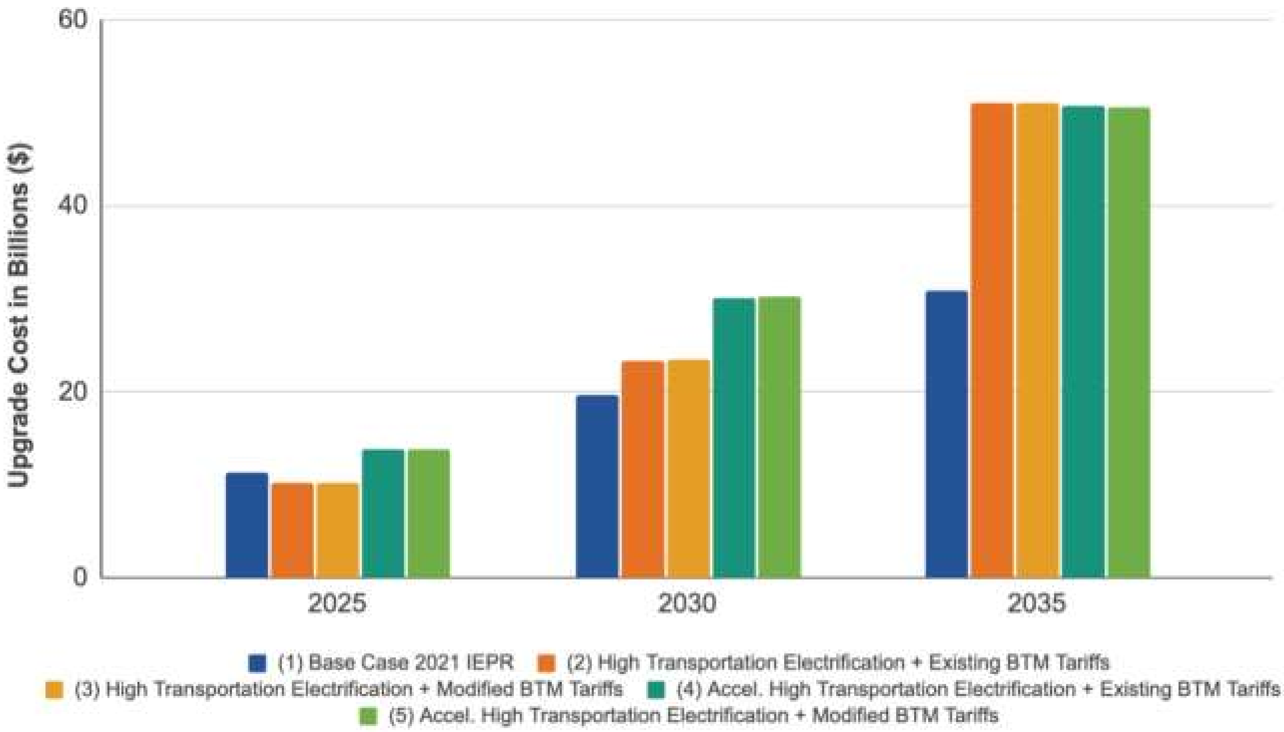
[13] This Part 1 Study evaluates upgrades at the substation, transformer bank, feeder, and service transformer level. It does not include line section upgrades related to the primary lines between the feeder head and the service transformers.

[14] These High Transportation Electrification scenarios are based on the expected level of transportation electrification necessary to meet California's policy goals, such as the transportation electrification goals

increase in peak load for the scenarios considered in Part 1 is primarily due to transportation electrification impacts, with over 60% of this demand coming from light-duty vehicles (LDVs).[15] Peak load is the primary driver of the grid capacity upgrades considered in this Part 1 Study.

- The average percent change in peak load from 2025 to 2035 for the High Transportation Electrification scenarios is more dramatic for PG&E (69%), followed by SDG&E (53%) and SCE (44%).

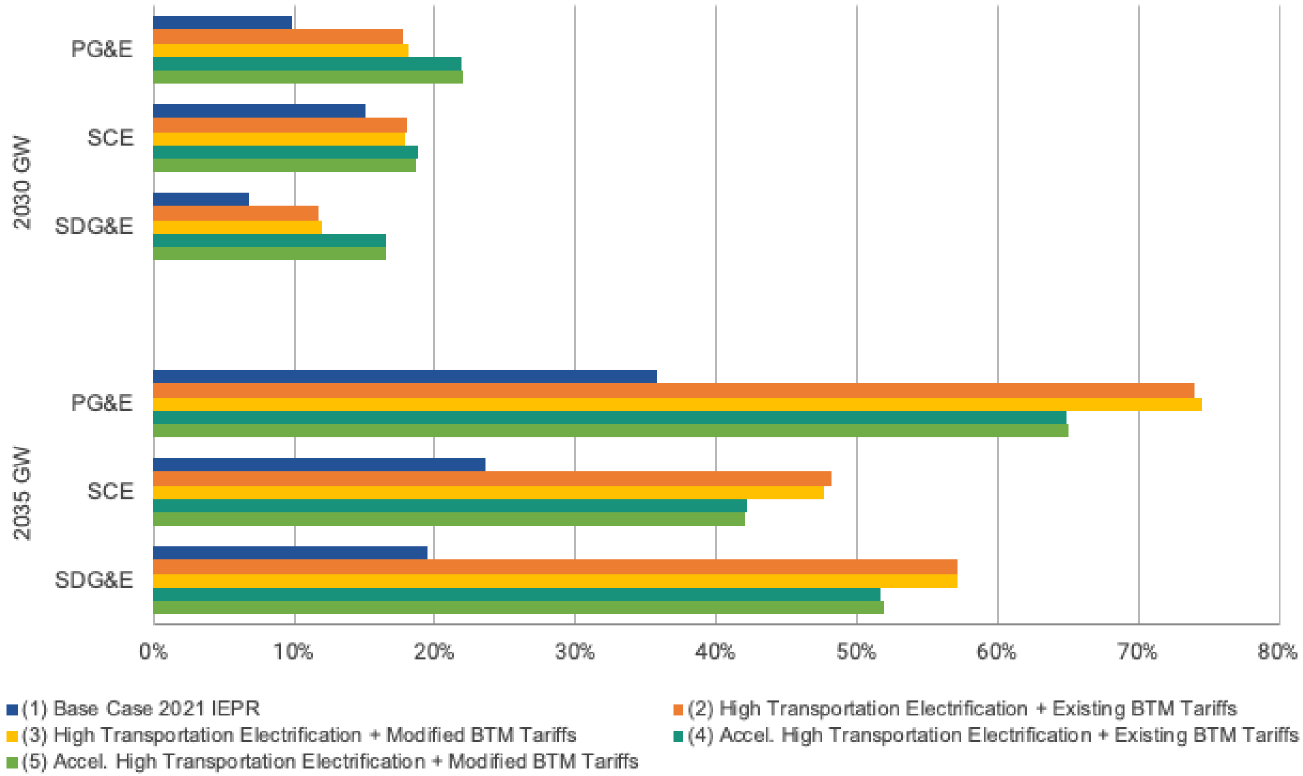
Figure ES-1: Estimated total capacity upgrade costs for the three large California IOUs, including new substations, transformer banks, feeders, and service transformers *(Source: Kevala)*



promulgated in [Executive Order N-79-20] and incorporated into CARB regulation in 2022. The main difference between the High Transportation Electrification and Accelerated High Transportation Electrification scenarios is the speed at which transportation electrification will occur in 2030 and 2035.

[15] Kevala can revisit considering BE targets aligned with state and federal policy goals and incentives in the Part 2 Study.

Figure ES-2: Peak demand percent change by IOU, study year, and scenario (*Source: Kevala*)



Transportation Electrification Grid Impacts

Of the DERs selected in this Part 1 Study for alternate scenario development—transportation electrification and NEM BTM tariffs—**transportation electrification results in significantly greater distribution grid impacts relative to the BTM tariffs assumed in the Part 1 Study.**[16]

- Transportation electrification grid requirements and costs escalate in earnest in 2030 and dramatically increase by 2035 regardless of scenario. The current DPP looks out only five years. This planning framework may not be able to plan for the expected rapid increase in transportation electrification-related infrastructure due to the lead times involved for

[16] To distinguish between the two BTM tariff scenarios, the existing BTM rate design assumed that the NEM 2.0 Tariff structure would persist through the study period. The modified BTM rate design includes a monthly grid access charge of $5/kW and an export rate that offsets the generation rate identified. This structure was consistent with the proposed decision in the proceeding to reform NEM (R.20-08-020) issued on December 13, 2021. Rather than modeling the exact proposal in that proposed decision, Kevala chose this simplified structure as a scenario because it was generally consistent with the proposed decision at the time. Since the study was conducted, the CPUC adopted a final Decision on December 15, 2022 to reform NEM by creating a Net Billing Tariff.

electric distribution grid infrastructure, including mitigation strategies to large capital expenses.

- The NEM BTM tariff scenario used in this Part 1 Study has relatively minimal impact on total electrification grid upgrade costs.

Granular Approach

The **premise-level approach** taken in this Part 1 Study enables a robust assessment of utility distribution grid needs, including:

- **The What:** Identification of a broader scope of infrastructure needs than other studies and an understanding of the relative contribution to net-load of the DERs studied.
- **The When:** A longer planning time horizon than the current DPP.
- **The Where:** The ability to analyze premise-level data and aggregate up provides transparency and opportunities for multiple scenario analysis, including specific locational grid needs and the demographic characteristics of those needs.
- **The How Much:** Differences in unit cost assumptions and grid need calculations between utilities that require further transparency and analysis.

Recommendations for Distribution Planning Process Improvements

This Part 1 report also proposes recommendations for improvements on DPPs. The substantial difference between the estimated capacity expansion costs, in the several tens of billions of dollars, in this study and the recent filings by the IOUs suggest there is a disconnect between the data and the current planning process and framework that, to date, results in minimal-to-no deferral opportunities being implemented.

Also, the significant future grid requirements identified in this study enable the examination of all least-cost options for meeting the reliability, resiliency, and most equitable solutions for those grid requirements on a location-specific basis. Those solutions could include traditional utility distribution upgrades and investments, as well as alternative time-variant rates or dynamic rates, and flexible load management strategies.

In this Part 1 Study, Kevala has demonstrated that it is possible to disaggregate load and DER growth at a premise level:

- Over a 15-year time horizon, which is a longer forecast time horizon (to 2035) than is currently performed for regulatory filings.
- Incorporating multiple scenarios for each of the three IOU service territories in less than one year (the timeframe to conduct the study).

- Identifying significant potential capacity costs previously not identified in current utility distribution planning filings.

As such, Kevala proposes the following key recommendations:

Recommendation 1: PG&E, SCE, and SDG&E should increase the planning horizon for their distribution planning filings. The expected adoption rate of technologies at the grid edge (i.e., at the premise level) in the long term to meet federal and state decarbonization and electrification policies may require the distribution planning horizon to be increased to align with the CEC's IEPR planning horizon (15 years)[17] and the California Independent System Operator's (CAISO's) transmission planning horizons (10 years for annual planning and 20 years for transmission outlook). Increasing the planning horizon for distribution planning filings should help to prepare more efficiently for a distribution grid that can maximize the cost-effectiveness of incorporating DERs and load management technologies to increase system capacity and reliability.

Recommendation 2: PG&E, SCE, and SDG&E should incorporate additional policy-based demand scenarios into their DPPs and annual GNA/DDOR filings. For example, scenarios can consider managed charging assumptions or different rates of EV and BE adoption to better understand the impact of higher or lower electrification loads on planned investments for grid infrastructure. As this Part 1 Study shows, an uncertain load and DER future requires scenario planning that would result in multiple load and DER scenarios being disaggregated in the DPP to better inform the overbuilding and underbuilding risks involved in planning for grid infrastructure needs.

This Part 1 Study, by leveraging advanced metering infrastructure (AMI) consumption data and performing a premise-level modeling of load and DER potential futures, was able to estimate grid upgrades for the scenarios considered at the service transformer level across the PG&E, SCE, and SDG&E territories. Kevala recommends that the DPP consider secondary distribution

[17] As stated in the 2021 IEPR at p. 2, "For the 2021 forecast, these energy demand forecasts are extended out beyond 10 years to 2035 to provide planners with a longer forecasting horizon and support planning for transportation electrification goals." The 2021 and 2022 IEPRs went beyond 10 years to 2035 (15 years), and the 2021 IEPR also included long-term energy demand scenarios to 2050 (30 years) because of increasing policy and planning focus on climate change. See also Public Utilities Code Section 454.57(e)(1), which as of 2022, requires "at least 15 years" to ensure adequate lead time for permitting and construction of approved transmission facilities.

infrastructure grid needs,[18] as described in Recommendation 3, so that such grid upgrades do not become a bottleneck for electrification and are proactively planned for in a cost-effective way.

Recommendation 3: PG&E, SCE, and SDG&E should provide an estimate of secondary distribution infrastructure grid needs to support future state electrification goals in the GNA/DDOR filings, so that secondary infrastructure can be accounted for and proactively planned in a high DER future.

The scope of this Part 1 Study, in terms of understanding the impact on the unmitigated load and DER growth in the scenario considered, stopped at the distribution substation level. However, it is becoming important to also understand the impacts on the sub-transmission and transmission infrastructure. In addition to the recommendations from its evaluation of the IOUs' 2022 GNAs and DDORs,[19] Kevala recommends that the DPP should be able to map the transmission and distribution nodes that are at risk of large capacity grid infrastructure needs, as identified in this Part 1 Study, to enable coordinated and integrated planning of grid infrastructure and mitigation strategies between the distribution and transmission planning processes.

Recommendation 4: PG&E, SCE, and SDG&E should provide information in the GNA regarding distribution planning areas located in transmission- and sub-transmission-constrained nodes,[20] and DDOR planned investment cost estimates should consider associated higher voltage upgrade costs that may be triggered by the distribution investment.

Improving California's understanding of where and when electricity grid enhancements will be needed will likely require additional changes on multiple policy fronts. Data collection and integration across California load-serving entities (LSEs) beyond the three IOUs studied in this Electrification Impacts Study, for example, would enable more complete forecasting for DER

[18] The secondary grid is the part of the electric distribution system between the primary feeder and the customer. The secondary distribution system includes distribution service transformers and secondary main and service conductors to the customer meter. The primary distribution grid is the feeder lines between the substation and the distribution service transformer.

[19] See Kevala's *Distribution Investment Deferral Framework: Evaluation and Recommendations* report, provided to the R.21-06-017 service list on November 14, 2022. The report can be found here: https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/63729a90e35f9cb53c617a14_DIDF%20Evaluation%20and%20Recommendations_Kevala_11.14.22.pdf.

[20] A transmission node refers to the interface between the distribution and transmission electric power systems. At transmission nodes, the distribution system is typically represented as an aggregate lumped load in transmission models.

technologies like EVs that transcend traditional utility boundaries. Specific technology and program policy modifications and regulatory process changes that enable enhanced scenario planning can also be effective tools to increase transparency and manage grid integration risks. Kevala's observations relating to additional policy-related changes related to data, DER forecasting methodologies, and distribution planning processes gleaned in the course of completing this Part 1 Study are outlined in Section 4 of this report.

CPUC Energy Division Staff are conducting a stakeholder review process that will include formal comments to receive input on the current study (Part 1 of the Electrification Impacts Study) and the scope of the future analysis (Part 2 of the Electrification Impacts Study).

Considerations for the Part 2 Study

There are numerous areas of focus to consider in Part 2 of this Electrification Impacts Study. Kevala's options for evolving the premise-based analysis began in this Part 1 Study and will be further refined for inclusion in the Part 2 Study. These options are provided in Section 4.3, and they center on:

- Improvements and updates to certain methodologies developed for Part 1, particularly for transportation electrification and BE.
- Development of scenarios that reflect the most recent policy goals, programs, adopted IEPR demand forecast, and targets adopted by state agencies, in particular those related to BE.[21]
- Potential localized detailed case studies to be identified in Part 2 that would be designed to show the geographic, demographic, and economic impacts on specific customer groups in identified geographic regions.
- Additional and improved data, both from the three IOUs that were the foundation of this Part 1 Study and from other LSEs and regulatory agencies across California.

The Part 2 Study will be designed to support the Phase 1, Track 2 questions identified in the High DER Rulemaking Scoping Memo[22] by building on the framework created in Part 1.

[21] "Appendix F - Building Decarbonization," California Air Resources Board Draft 2022 Scoping Plan, May 2022, and reflected in the CEC IEPR 2022 as described in "Scoping Order for the 2022 Integrated Energy Policy Report Update," California Energy Commission Docket No. 22–IEPR–01.

[22] "Assigned Commissioner's Scoping Memo and Ruling" for R.21-06-017, *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future,* effective November 15, 2021, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M422/K949/422949772.PDF.

1. Introduction

This report summarizes Kevala, Inc.'s (Kevala's) approach, results, and insights for Part 1 of the Electrification Impacts Study: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates.[23] The California Public Utilities Commission (CPUC) commissioned the Electrification Impacts Study to support Rulemaking (R.) 21-06-017: the *Order Instituting Rulemaking (OIR) to Modernize the Electric Grid for a High Distributed Energy Resources Future*.[24] This OIR is focused on preparing the grid to accommodate a high distributed energy resource (DER) future, capturing as much value as possible from DERs and mitigating unintended negative grid impacts. (This OIR is referred to as the High DER Proceeding throughout this report, while Part 1 of the two-part Electrification Impacts Study is referred to as the Part 1 Study.) The Part 1 Study was guided by the *Electrification Impacts Study Research Plan* (Research Plan), submitted to the CPUC on March 29, 2022. The Research Plan stated the following goals:

- Enable the identification of grid enhancements and changes necessary to support California's stated transportation and building electrification policy goals by 2035.
- Consider alternatives for evaluating distribution capacity expansion and deferral options into the utilities' Distribution Planning Process (DPP).
- Explore increasing the granularity of technology adoption models in high electrification scenarios to inform the development of mitigation strategies which will seek to optimize grid planning, maximize the equity and reliability benefits, and minimize the costs of high electrification.
- Improve clarity and transparency of electrification scenario inputs, methodologies, and outputs across state energy planning agency processes.

The Research Plan outlined a multi-part study approach, as shown in Figure 1.[25]

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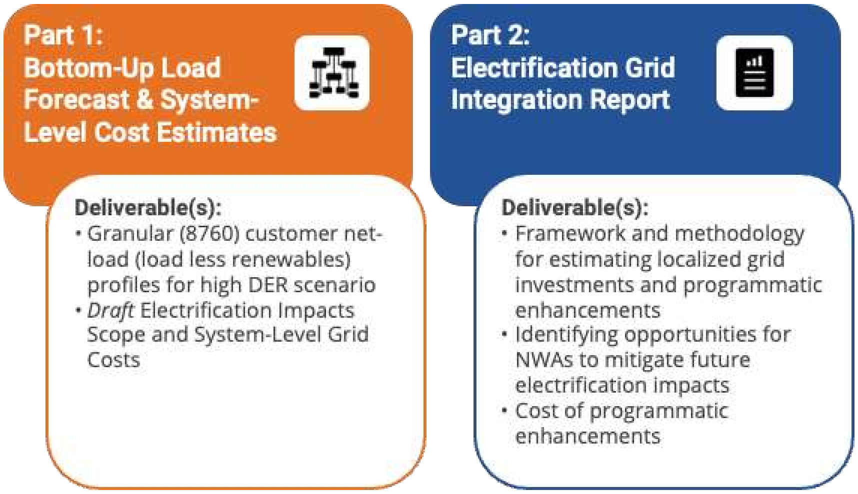
[23] The full scope of the Electrification Impacts Study is detailed in the Research Plan, dated March 29, 2022, https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/62d8509da2f405169ee10dd0_2022-0329_Electrification%20Impacts%20Study_Final%20Research%20Plan.pdf

[24] R.21-06-017, opened with an *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future*, issued on July 2, 2021, https://apps.cpuc.ca.gov/apex/f?p=401:56:0::NO:RP,57,RIR:P5_PROCEEDING_SELECT:R2106017

[25] The Research Plan for the Electrification Impacts Study had identified Part 2 as an evaluation of the IOUs' Grid Needs Assessment (GNA)/Distribution Deferral Opportunity Report (DDOR) filings and recommendations for near-term improvements, followed by a Staff Proposal. This step has been renamed as the GNA/DDOR Evaluation and Staff Proposal. As such, the next part of the Electrification Impacts Study will be referred to as Part 2 throughout this report (previously referred to as Part 3).

Figure 1: The Electrification Impacts Study parts and deliverables *(Source: Kevala)*



This **Part 1 Study** is a granular customer electricity consumption data analysis across all customer classes designed to support electricity distribution grid planning processes that enable California to meet its state energy goals. This part of the study builds the foundation for an improved framework for distribution planners and policymakers to evaluate grid needs and value grid solutions based on the hyper-granular location of electrification needs.

Part 2 of the Electrification Impacts Study is designed to build on these Part 1 results, leveraging additional data to develop an updated framework for estimating localized grid requirements and mitigations that will facilitate the electrification of California's energy system.

The local grid impacts and associated costs developed through this Part 1 Study are ***indicative*** of the scope and scale of potential unmitigated loads and the associated traditional grid buildout to support electrification. These results are not comprehensive. In Part 2, Kevala proposes to update the data used, refine key elements of analysis, and identify potential mitigations for specific locations to build out a localized distribution planning framework.

The scope of this Part 1 Study includes the customers and grid infrastructure for the three large California investor-owned utilities (IOUs): Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric Company (SDG&E). The small multi-jurisdictional utilities located in California (PacifiCorp, Liberty Utilities, and Bear Valley Electric Service) are not included in this study. Figure 2 shows the service territories of the six IOUs in California for reference.

Figure 2: California investor-owned utilities *(Source: ArcGIS)*

This report contains the scope, approach, and Kevala's results from this Part 1 Study. It is organized in the following sections:

- **Section 1** presents an overview of the High DER Proceeding; the data inputs, modeling approach, and DER scenarios developed and used for the Part 1 Study; and the literature review Kevala conducted on load and DER forecasting to inform its work.
- **Section 2** presents the results of Kevala's electrification cost, net-load, and DER adoption and behavior scenarios.
- **Section 3** discusses Kevala's approach, including data ingestion and management, the baseline net-load methodology, and the modeling and calibration methodologies for estimating the hourly demand-side modifiers and electrification grid upgrade costs.
- **Section 4** summarizes Kevala's recommendations for improvements to the DPPs and for planning for Part 2 of the Electrification Impacts Study.

The report also includes several appendices that provide further detail on Kevala's methodology and IOU-specific results.

CPUC Energy Division Staff are conducting a stakeholder review process that will include formal comments to receive input on the current study (Part 1 of the Electrification Impacts Study) and the scope of the future analysis (Part 2 of the Electrification Impacts Study).

1.1. High DER Proceeding Overview

The CPUC recognizes that **successfully achieving California's electrification and decarbonization goals depends on an electricity grid that can support diverse electrification technologies at scale while maintaining grid reliability and the affordability of electricity service** for all Californians. As stated in the July 2021 High DER Proceeding, DER growth is expected to continue to increase in California, especially due to policies and programs driving transportation electrification and its associated DERs (i.e., electric vehicles (EVs) and electric vehicle service equipment (EVSE)). By 2025, EVSE infrastructure in the United States is forecasted to result in more annual DER capacity additions than solar.[26] In California, state-specific transportation electrification and climate goals are expected to result in millions of EV-related DERs by 2030.[27] In addition, state legislation, CPUC proceedings, and local building reach codes are expected to further drive building and mobility electrification. For example, Senate Bill (SB) 1477[28] and Assembly Bill (AB) 3232,[29] designed to reduce greenhouse gas emissions from buildings and support local electrification laws, are likely to further drive DER penetration and electrification.

The High DER Proceeding does not seek to set policy on the overall number of DERs. Rather, it focuses **on preparing the grid to accommodate what is expected to be a high DER future, capture as much value as possible from DERs, and mitigate unintended negative impacts**. As such, **this Electrification Impacts Study is focused on grid preparation, and specifically on estimating the scope and scale of grid impacts from electrification while investigating new methods and tools, consistent with the DER Action Plan 2.0, to "align the CPUC's vision and actions to maximize ratepayer and societal value of an anticipated high DER future.**"[30] The

[26] Ben Kellison and Fei Wang, "What the Coming Wave of Distributed Energy Resources Means for the US Grid," Greentech Media, June 18, 2020, https://www.greentechmedia.com/articles/read/coming-wave-of-der-investments-in-us.

[27] On August 25, 2022, the California Air Resources Board (CARB) codified the light-duty vehicle (LDV) goals set out in Governor Newsom's Executive Order N-79-20 by approving the Advanced Clean Cars II rule (ACC II). ACC II establishes an annual roadmap for achieving 100% of new cars and light trucks sold in California to be zero-emission vehicles (ZEVs), including plug-in hybrid electric vehicles (PHEVs).

[28] SB 1477 was passed on September 13, 2018 and sets new state policy standards for low-emission buildings and sources of heat energy. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1477

[29] AB 3232 was passed on September 13, 2018 and sets new state policy standards for zero-emission buildings and sources of heat energy. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180AB3232

[30] California Public Utilities Commission, "Final CPUC DER Action Plan 2.0," adopted April 21, 2022, https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M467/K470/467470758.PDF.

follow-up parts to this study described previously will refine Part 1 estimates and explore potential methods to mitigate forecast electrification loads.

The Electrification Impacts Study was designed to inform and support several scoping questions for the High DER Proceeding.[31] Specifically, the CPUC's "Assigned Commissioner's Scoping Memo and Ruling" in the High DER Proceeding[32] outlined the key questions to be answered by this study (see sidebar).

These scoping questions indicate a need to review existing electric distribution planning processes—and the data used in each of those disparate processes—to ensure they are sufficient for timely selection and deployment of traditional distribution infrastructure and DER solutions to meet grid needs. Dynamic factors such as new customer and utility technologies, changing customer behaviors, and extreme weather events are likely to require much more precise and timely distribution planning processes to meet California's ambitious electrification requirements while minimizing costs and barriers of equitably distributing the benefits of electrification.

The CPUC's current electric utility annual DPP GNA evaluates necessary grid investments

Scoping Questions from the "Assigned Commissioner's Scoping Memo and Ruling," High DER Proceeding

Track 1, Phase 1

- ***Scoping Question 1:*** Should the Utilities' Distribution Planning Processes (DPPs) be modified to address policy-based issues such as forecasting scenarios for increased electrification, improved data sharing, EV adoption, adoption of real-time rates and related flexible load management technologies, and equity? Should policy forecasting scenarios for higher electrification be used for determining potential grid investments needed to address electrification?
- ***Scoping Question 2:*** How should Utilities' Grid Needs Assessment (GNA) and Distribution Deferral Opportunities Report (DDOR) be coordinated with the draft Transportation Electrification Framework and/or any existing or future Utility transportation electrification planning efforts stemming from the transportation electrification proceeding (R.18-12-006) and any successor proceeding?
- ***Scoping Question 3:*** How can the GNA and DDOR reports better reflect the types of Transportation Electrification investments identified in the draft Transportation Electrification Framework and the legislative directives from AB 841?

Track 1, Phase 2

- ***Scoping Question 1:*** Should Utilities better integrate DERs into their standard annual DPP? If so, in what ways should the Utility DPPs improve with respect to planning for DERs (e.g., capturing additional value from these resources and optimizing resource siting)? How should Utility ownership of DERs be considered in these changes to DPP?
- ***Scoping Question 2:*** Should the DIDF be modified to better capture DER value and optimize DER siting? Improvements may include better aligning the DIDF with Utility DPPs, implementing key insights from the Standard Offer Contract pilot and Participation Pilots adopted in D.21-02-006, and considering additional pilots, as well as evaluating how can DERs provide resource adequacy services when not being used for deferral.
- ***Scoping Question 3:*** Leveraging the analysis identified in Track 1, Phase 1, are there ways in which utility distribution planning representatives could better engage with local and tribal governments, environmental and social justice communities, and local developers to ensure new planned loads and developments are factored into Utility DPPs and local concerns regarding distribution planning are adequately addressed?

[31] Proceeding R.21-06-017, opened with an *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future*, issued on July 2, 2021, https://apps.cpuc.ca.gov/apex/f?p=401:56:0::NO:RP,57,RIR:P5_PROCEEDING_SELECT:R2106017

[32] "Assigned Commissioner's Scoping Memo and Ruling" for R.21-06-017, *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future,* effective November 15, 2021, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M422/K949/422949772.PDF.

based on a single forecast scenario and informs the CPUC of the utilities' plans to invest in grid infrastructure to meet these needs. The forecast used for the GNA is tied to the California Energy Commission's (CEC's) latest adopted Integrated Energy Policy Report (IEPR) forecast,[33] which provides a statewide forecast of energy needs based on an integrated process with multiple California stakeholders. As described in the following section, this Part 1 Study takes a different, premise-based (or bottom-up) approach to forecasting baseline load and anticipating the impacts that meeting the state's ambitious electrification goals could have on the distribution grid if not identified and mitigated. This analysis takes a bottom-up approach, which means the forecast is based off address-specific estimates of energy use. Kevala took this approach to reflect that the implications of electrification start at the address level and must be analyzed at this level to more accurately understand the impacts to the distribution system. Exploring this bottom-up approach compared to current approaches to bottom-up that apply expected load growth and DER adoption at higher aggregation levels allows for an understanding of capacity needs and subsequent capital costs for all asset types in the distribution system (such as secondary transformers, feeders, and feeder banks). In other words, the bottom-up approach enables identification and assessment of grid impacts and costs not commonly identified through existing approaches.

1.2. Part 1 Study Overview and Constraints

This Part 1 Study was designed to anticipate distribution grid impacts due to electrification based on a geographically and temporally granular approach that reflects the unique effects of electrification on each utility circuit for the three large electric IOUs in California. Over 100 terabytes of time series data, geospatial and utility grid network data, and socioeconomic data across all customer classes for each IOU were collected and linked to enable Kevala's modeling of each premise. Data ingestion, identification, and joining comprised the great majority of the Part 1 analysis.

1.2.1. Data Overview and Constraints

Kevala's baseline net-load forecast is based on each IOU's advanced metering infrastructure (AMI) data, which comprised over 60% of the total data ingested and was the most readily joinable with geospatial data. **While AMI data enabled the development of the baseline net-load forecast, ideally it would be linked and validated by supervisory control and data acquisition (SCADA) data to provide the most accurate premise-specific grid requirements.** For this Part 1 Study,

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[33] SB 1389 (Bowen and Sher, Chapter 568, Statutes of 2002) requires the CEC to: "[C]onduct assessments and forecasts of all aspects of energy industry supply, production, transportation, delivery and distribution, demand, and prices. The Energy Commission shall use these assessments and forecasts to develop energy policies that conserve resources, protect the environment, ensure energy reliability, enhance the state's economy, and protect public health and safety." (Pub. Res. Code § 25301(a)).

Kevala was unable to collect and validate all IOU SCADA data and community choice aggregator (CCA) enrollment for SDG&E.[34] Also, key connectivity and cost data was received late in the analysis with minimal processing time in order to be used for Part 1.[35] Kevala is working with the IOUs to complete those datasets for Part 2, which will enable even more accurate 8760 modeling. Other constraints in key datasets available for this Part 1 study include:

- Lack of data for other California utilities outside CPUC jurisdiction (i.e., municipal utilities). Having access to this data would enable projecting requirements that cross traditional utility boundaries, especially for large infrastructure requirements such as airports or ports that host or are likely to host EV fleets.
- Limited data on distributed generation and other historical DER program performance data, constraining the ability to develop data-driven adoption for nascent technologies such as batteries.
- Non-availability of IOU location-specific cost data required the use of generic unit costs that did not take into account terrain, property value, and other location-specific cost drivers.
- Lack of data on address-specific vehicle registrations and granular locational driving patterns required the use of the IOUs' limited EV rate enrollment data as well as Census block group-level vehicle registration data and Census tract-level driving pattern data.
- Kevala did not use future costs of distribution capacity additions, DERs, and future rate designs or levels that were in development and therefore assumed they would remain constant 2022 values over time for the purposes of the Part 1 analysis.[36]

1.2.2. Modeling Overview and Constraints

The modeling approach started with **estimating each customer's load over the study period**, using machine learning based on the actual customer data received to date to develop a **premise-specific load profile that reflects adoption of energy efficiency (EE), photovoltaics (PV), battery energy storage systems (BESS), building electrification (BE), and EVs**.[37] Kevala then **calibrated the results of this modeling to the IEPR's system-level forecasts to ensure**

[34] CCA rates were incorporated into the bill calculations for PV payback and equity for SCE and PG&E; the then-current CCA rates were acquired via the CCA websites. Vintaging for the power charge indifference adjustment (PCIA) was not incorporated due to the lack of vintage data for CCA customers.

[35] PG&E data was generally the most complete and was received first; key datasets required for grid needs and cost analysis for SCE and SDG&E were not received until October 2022.

[36] Rate levels only impacted payback estimates for PV and equity estimates for energy justice. Similarly, DER cost estimates only impacted PV payback.

[37] Baseline load growth (expected load growth due to economic and weather factors) was incorporated into modeled load profiles. Load growth for commercial and industrial customers was assigned to existing premises while load growth for residential assumed new premises with a commensurate load profile proximate to the premise.

consistency with the IOUs' GNAs and the IEPR.[38] Essentially, premise-level load profiles that include DER-specific adoption were then aggregated up to the IOU service territory level; this aggregated load was not allowed to exceed the IEPR demand forecast prepared for each IOU service territory.

Next, **these calibrated premise-level forecasts were used to identify the magnitude and location of DER adoption and resulting high electrification anticipated for a base case and four alternate scenarios** focusing on **two DER types: transportation electrification and net energy metering (NEM) behind-the-meter (BTM) tariffs** for 2025, 2030, and 2035. As detailed in the Research Plan, Kevala selected transportation electrification and NEM BTM tariffs for the Part 1 Study scenarios to isolate the impact of two relatively dynamic DERs for which alternate scenarios tied to then-existing state programs or projections could be defined. NEM BTM tariffs refer to a hypothetical alternative compensation structure for BTM solar PV based on the December 2021 Proposed Decision for proceeding R.20-08-020 and incorporates a monthly grid access charge and specific export rate. This is not to suggest other DERs such as BE or PV will not be studied or impactful for California's electrification efforts; rather, the goal of the Electrification Impacts Study Part 1 is to identify the likely grid impacts from DERs for which there is less program data or for programs that are changing. For example, in December 2022, the CPUC adopted the Net Billing Tariff in Decision (D.) 22-12-056, which has a different structure than the scenarios included in this study; therefore, the results of these scenarios do not reflect what will happen with the newly adopted Net Billing Tariff. The transportation electrification scenario inputs, drawn from California Air Resources Board (CARB) and CEC projections (as discussed in Appendix 9), incorporate a range of different ZEV vehicle adoption levels, including personal vehicles and medium- and heavy-duty freight and port vehicles.

Finally, by **aggregating up to the service transformer**, feeder, transformer bank, and distribution substation levels for the premise-level forecasts, the **magnitude and location of electrification impacts were determined and used to identify system-level grid impacts, costs, and affordability** of electricity service for customers.

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[38] This approach is similar to how the IOUs ensure the forecast used for the annual GNA/DDOR does not exceed the IEPR demand forecast. However, the GNA/DDOR process for calibrating to the IEPR is complicated by the known loads issue, as described in Section 3 (pp. 26-34) of the *2022 Independent Professional Engineer Post DPAG Report*.

Specifically, in this Part 1 Study, Kevala used machine learning of IOU-specific datasets to develop:

- Hourly **baseline net-load[39] estimates** for each customer of the three large electric IOUs for 2025, 2030, and 2035.
- Hourly premise-specific (i.e., customer-level) **net-load forecasts** for the base case and four scenarios (discussed in Section 1.2.3) that incorporate the adoption and behavior profiles of DERs for 2025, 2030, and 2035.
- Initial **distribution capacity expansion** and **system-level cost estimates** for the base case and each scenario in 2025, 2030, and 2035.
- **Aggregated load profiles** and **cost estimates** at the service transformer, feeder, and distribution substation levels for the base case and four scenarios to provide insights into distribution planning capacity upgrades and costs.
- **Net-load** aggregated to each IOU's service territory to provide future insights into transmission planning investments.

The hourly premise-specific net-load forecast serves as the backbone to understanding the impacts of electrification on distribution planning and grid infrastructure needs. While the premise-level forecast was continuous from 2022 through 2035 (i.e., premise-specific hourly load forecasts were generated over the 13-year time period), Kevala selected the forecast years of 2025, 2030, and 2035 for the in-depth cost and equity analyses because:

- 2025 captures the current distribution planning cycle (five years through approximately 2025).
- 2030 (a mid-range year) captures when DERs and the distribution system are likely to be the predominant resources for meeting grid needs.
- 2035 (an outer year) is the timeframe in which transmission solutions could be capable of addressing grid needs.

1.2.3. DER Scenarios

In coordination with the CPUC, CEC staff, and their other consultants, Kevala used the 2021 IEPR for IOU service territory-level load and demand-side modifiers to inform the load and DER targets for the premise-level load and DER calibration to the different scenarios. The 2022 IEPR had not yet been adopted by the time of the Part 1 Research Plan completion in March 2022. Kevala

[39] Net-load references the customer's metered load and is what is expected to be delivered by the IOU or, in the case of reverse flow, the level of energy the customer is exporting to the grid and the IOU is expected to accept and distribute. Because baseline net-load is the customer's metered load, it reflects customer load with the impact of any DERs applicable to that customer, bundled into the metered load amount.

generated the premise-specific forecasts for a base case, based on the 2021 IEPR mid-mid case forecast or likely scenario through 2035,[40] and four additional scenarios:

- Base Case 2021 IEPR (mid-mid case)
- High Transportation Electrification + Existing BTM Tariffs[41]
- High Transportation Electrification + Modified BTM Tariffs[42]
- Accelerated High Transportation Electrification + Existing BTM Tariffs
- Accelerated High Transportation Electrification + Modified BTM Tariffs

The base case represents a premise-level forecast that calibrates the baseline load forecast and the individual demand modifier forecasts to the 2021 IEPR mid-mid case. Each of the four alternate scenarios considers a different combined projection for BTM tariffs and the speed and scope of transportation electrification. These scenarios are based on the expected level of electrification necessary to meet California's policy goals, such as the transportation electrification goals promulgated in Executive Order N-79-20 and incorporated into CARB regulation in 2022.[43]

Although the 2022 IEPR[44] had not been adopted at the time of the Part 1 Research Plan completion in March 2022, ongoing coordination with the CPUC Energy Division and CEC staff enabled the transportation electrification assumptions of the two High Transportation Electrification scenarios to be similar to those applied to the adopted 2022 IEPR demand forecast mid-mid case. The 2022 IEPR demand forecast mid-mid case (i.e., now called the Planning

[40] The IEPR mid-mid scenario includes mid-level adoption scenarios for EE and building and transportation electrification. EE and fuel substitution (BE) aligns to the adopted CPUC goals for proceeding R.13-11-005. Mid-mid refers to Scenario 3 when referring to additional achievable energy efficiency (AAEE) or additional achievable fuel switching (AAFS) load modifiers applied to the mid baseline forecast.
[41] The existing BTM rate design assumptions are based on the NEM 2.0 tariff.
[42] The modified BTM rate design assumptions are based on the December 13, 2021, Proposed Decision for the proceeding titled, *Order Instituting Rulemaking to Revisit Net Energy Metering Tariffs Pursuant to Decision 16-01-044, and to Address Other Issues Related to Net Energy Metering* (R.20-08-020). The Proposed Decision was not adopted by the Commission; it is available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M430/K903/430903088.PDF. Instead, D.22-12-056 adopted the Net Billing Tariff.
[43] Governor Gavin Newsom signed Executive Order N-79-20 on September 23, 2020, establishing the state's goals related to decarbonizing the transportation sector. CARB subsequently adopted its ACC II regulations, which became effective on November 30, 2022. Pursuant to this regulation, all new passenger cars, trucks, and SUVs sold in California will be zero emissions by 2035 (see https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii).
[44] CEC, 2022 Integrated Energy Policy Report Update, February 2023, https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update.

Forecast)[45] reflected transportation electrification levels similar to the Interagency Working Group High Electrification Scenario, which was adopted as a 2021 IEPR demand scenario by the CEC on May 24, 2022 (Resolution No. 22-0524-5).

Transportation electrification and PV are the only demand modifiers that reflect different assumptions for the scenario analyses. Specifically, transportation electrification scenarios assume different levels of EV targets; for PV, the NEM BTM tariff was modified to reflect key components of anticipated NEM reform at the time the study was conducted. This approach was designed to isolate the impact of two factors likely to impact the distribution grid, recognizing there are other factors as well, and to maintain consistency with the 2021 IEPR mid-mid case to the greatest extent possible. Kevala can revisit considering BE targets aligned with state and federal policy goals and incentives in the Part 2 Study.

Table 1 shows the base case and four scenarios in more detail. Section 3.4.7 describes the CEC scenarios and files used to calibrate the different scenarios.

[45] Refer to the 2022 IEPR at p. 46: https://www.energy.ca.gov/sites/default/files/2023-02/Adopted_2022_IEPR_Update_with_errata_ada.pdf.

Table 1: Demand and adoption scenarios used in the Part 1 Study *(Source: Kevala)*

<table>
<tr><th colspan="2">Scenario</th><th>(1) Base Case 2021 IEPR</th><th>(2) High Transportation Electrification + Existing BTM Tariffs*</th><th>(3) High Transportation Electrification + Modified BTM Tariffs*</th><th>(4) Accelerated High Transportation Electrification + Existing BTM Tariffs</th><th>(5) Accelerated High Transportation Electrification + Modified BTM Tariffs</th></tr>
<tr><td colspan="2">Input Name</td><td colspan="5">Demand Forecast/DER Growth Forecast Calibration Target</td></tr>
<tr><td colspan="2">Peak demand</td><td colspan="5">2021 IEPR mid-mid case forecast</td></tr>
<tr><td colspan="2">EE[46]</td><td colspan="5">2021 IEPR mid-mid case forecast</td></tr>
<tr><td colspan="2">BE[47]</td><td colspan="5">2021 IEPR mid-mid case forecast</td></tr>
<tr><td colspan="2">PV [48]</td><td colspan="5">2021 IEPR mid-mid case forecast</td></tr>
<tr><td colspan="2">BESS</td><td colspan="5">2021 IEPR mid-mid case forecast</td></tr>
<tr><td colspan="2">Rates</td><td colspan="5">Held constant through study period at early 2022 levels for each IOU[49]</td></tr>
<tr><td colspan="2">Demand Response[50]</td><td colspan="5">Assumed to be integrated in the peak forecast</td></tr>
<tr><td rowspan="2">ZEV Adoption Forecast Source</td><td>LDV</td><td rowspan="2">CEC 2021 IEPR mid scenario</td><td colspan="2">CARB 2021 Advanced Clean Cars II (ACC II)</td><td colspan="2">CEC 2021 IEPR bookend scenario</td></tr>
<tr><td>MDV/ HDV</td><td colspan="2">CARB 2020 State SIP Strategy (SSS)</td><td colspan="2">CEC 2021 IEPR high scenario</td></tr>
</table>

[46] For EE, the 2021 IEPR mid-mid scenario uses AAEE Scenario 3.

[47] For BE, the 2021 IEPR mid-mid scenario uses AAFS Scenario 3.

[48] While the solar PV and energy storage growth forecasts are listed as using 2021 IEPR mid-mid assumptions, these forecasts will change with any modification in BTM rate design, which is listed as a separate demand modifier. Further, the same adoption propensity score cut-off was used for PV between the two BTM scenarios because the purpose of the Modified BTM scenario was to identify the change in adoption propensity and where PV systems would be adopted given different NEM considerations.

[49] Rates and DER costs were held constant, implying the relationship between rates and the cost of DERs remains constant throughout the study period. Assumptions regarding where IOU rates and costs will go in future years is outside the scope of this study; as a result, rate increase assumptions will mirror cost changes in DERs generally.

[50] The base forecast includes demand response expectations that are already incorporated into IOU forecasts. As a result, Kevala did not complete separate modeling of demand response in Part 1 because it was expected to be negligible in the overall forecast. Kevala can revisit demand response in the Part 2 case studies as a mitigation to alleviate distribution system constraints.

Scenario		(1) Base Case 2021 IEPR	(2) High Transportation Electrification + Existing BTM Tariffs*	(3) High Transportation Electrification + Modified BTM Tariffs*	(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	(5) Accelerated High Transportation Electrification + Modified BTM Tariffs
Input Name		**Demand Forecast/DER Growth Forecast Calibration Target**				
ZEV Adoption Total Vehicle Count (2022-2035, Three IOUs)[51]	**LDV**	3,172,598	10,013,953		9,530,034	
	MDV/ HDV	227,140	218,710		230,876	
BTM Rate Design		Existing BTM rate design[52]	Existing BTM rate design	Modified BTM rate design[53]	Existing BTM rate design	Modified BTM rate design

*The two High Transportation Electrification scenarios incorporate transportation electrification assumptions similar to those applied to the 2022 IEPR demand forecast mid-mid case (i.e., the 2022 IEPR Planning Forecast). At the time the Part 1 Study was developed, the 2022 IEPR had not yet been adopted, so the 2021 IEPR mid-mid case was used for the Part 1 base case.

To distinguish between the two BTM tariff scenarios, the **existing BTM rate design** assumed that the NEM 2.0 Tariff structure would persist through the study period. The time-of-use (TOU) periods, rate differentials among TOU periods, and the cost of BTM PV installations remained unchanged as well. The underlying assumption for this scenario is that the relationship between the cost of PV installations and rates remains unchanged. The **modified BTM rate design** includes a residential monthly grid access charge of $5/kW and an export rate that offsets the generation rate identified. This structure was consistent with the Proposed Decision in the proceeding to reform NEM (R.20-08-020) issued on December 13, 2021. Rather than modeling the exact proposal in that Proposed Decision, Kevala chose this simplified structure as a scenario because it was generally consistent with the Proposed Decision at the time. Since the study was conducted, the

[51] The values in this table represent the forecasted ZEV adoption counts from 2022 to 2035 that the model allocated based on the CARB and CEC ZEV adoption forecasts. These values exclude all ZEV counts prior to 2022, thus they do not represent the total cumulative ZEV counts for all three IOUs.

[52] Existing BTM rate design assumptions based on NEM 2.0 Tariff.

[53] Modified BTM rate design assumptions are based on the December 13, 2021, Proposed Decision for the proceeding titled, *Order Instituting Rulemaking to Revisit Net Energy Metering Tariffs Pursuant to Decision 16-01-044, and to Address Other Issues Related to Net Energy Metering* (R.20-08-020). The Proposed Decision was not adopted by the Commission; it is available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M430/K903/430903088.PDF. Instead, D.22-12-056 adopted the Net Billing Tariff.

CPUC adopted a final Decision on December 15, 2022 to reform NEM by creating a Net Billing Tariff.[54]

1.3. Summary of the Literature Review on Load and DER Forecasting

Kevala conducted a literature review to determine how other technical studies have approached questions regarding the electric grid's readiness to support higher electricity loads. Specifically, Kevala was interested in publicly available studies that have modeled high electrification futures for similar geographic scope and temporal periods as this study. Each study included in the review presented at least two electrification scenarios involving various DERs. The literature review included nine existing studies; these studies focused on individual cities or service areas (Los Angeles, Washington, DC, PG&E's service area in northern California) and on the United States as a whole during similar forecasting periods (approximately 2016-2050).

The literature review presented outcomes on several topics relevant to this study including transmission and distribution (T&D), environmental justice, load flexibility, EE, BE, EVs, and decarbonization. These studies are briefly summarized below:

- The two studies that focused on individual cities—the National Renewable Energy Laboratory's (NREL's) LA100 study,[55] released in March 2021, and the Brattle Group's *Assessment of Electrification Impacts on the Pepco DC System* study,[56] released in August 2021—resulted in annual peak demand growth scenarios within 1% of each other, ranging from 1.0% to 1.7% annually.
- The sole service area study, the Energy Institute at Haas' *Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California?*,[57] released in June 2022, focused on EV and residential electrification through 2050, presenting increased loads and total upgrade costs.

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[54] CPUC's D.22-12-056 can be found at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M500/K043/500043682.PDF.

[55] NREL, *LA100: The Los Angeles 100% Renewable Energy Study*, March 2021, https://maps.nrel.gov/la100/la100-study/report.

[56] Brattle Group, *Assessment of Electrification Impacts on the Pepco DC System*, prepared for Pepco, August 2021, https://www.pepco.com/Documents/1167%20%20Pepco%27s%20Electrification%20Study%20%20082721.pdf

[57] Energy Institute at Haas, *Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California?*, June 2022, https://haas.berkeley.edu/wp-content/uploads/WP327.pdf

- The three studies focused nationally on varying DER scenarios—NREL's *Electrification Futures Study* series,[58] released between 2018 and 2021; Brattle Group's *The Coming Electrification of the North American Economy*,[59] released in March 2019; and Princeton University and Evolved Energy Research's *Net-Zero America: Potential Pathways, Infrastructure, and Impacts*,[60] released in October 2021—ranged greatly in nationwide energy demand forecasts because they did not encompass the same DER scenarios.
- Three studies—CEC's *Electric Vehicle Charging Infrastructure Assessment Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*,[61] released in May 2021; the Institute of Transportation Studies, University of California, Davis, and Cadmus Group's *Distribution grid impacts of electric vehicles: A California case study*,[62] released in December 2021; and Boston Consulting Group's *Revving Up the Grid for Electric Vehicles*,[63] released in December 2019—focused solely on EV growth.

Most relevant to the Part 1 Study is that, of all the studies reviewed, only one used a bottom-up analysis of electrification impacts that included secondary infrastructure: NREL's LA100 study. The remaining studies used a more traditional top-down and holistic approach. This finding further emphasizes the importance of the proof-of-concept in applying a premise-level forecast to improve distribution planning, a key goal of the Part 1 Study. Appendix 1 contains the full literature review. As noted in Section 1.1, this analysis takes a bottom-up approach, which means the forecast is based off address-specific estimates of energy use. Kevala took this approach to reflect that the implications of electrification start at the address level and must be analyzed at this level to more accurately understand the impacts to the distribution system. This approach

[58] NREL, *NREL Electrification Futures Study*, 2018-2021, https://www.nrel.gov/analysis/electrification-futures.html

[59] Brattle Group, *The Coming Electrification of the North American Economy*, prepared for WIRES, March 2019, https://wiresgroup.com/wp-content/uploads/2020/05/2019-03-06-Brattle-Group-The-Coming-Electrification-of-the-NA-Economy.pdf

[60] Princeton University, Evolved Energy Research, *Net-Zero America: Potential Pathways, Infrastructure, and Impacts*, October 2021, https://netzeroamerica.princeton.edu/?explorer=pathway&state=national&table=e-positive&limit=200

[61] CEC, *Electric Vehicle Charging Infrastructure Assessment Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*, May 2021, https://www.ourenergypolicy.org/resources/electric-vehicle-charging-infrastructure-assessment-analyzing-charging-needs-to-support-zero-emission-vehicles-in-2030/

[62] Institute of Transportation Studies, University of California, Davis and Cadmus Group, *Distribution grid impacts of electric vehicles: A California case study*, December 2021, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8749456/

[63] Boston Consulting Group, *Revving Up the Grid for Electric Vehicles*, December 2019, https://www.bcg.com/publications/2019/costs-revving-up-the-grid-for-electric-vehicles

enables the identification and assessment of grid impacts and costs not commonly identified through existing approaches.

2. Results

California's electricity grid is changing rapidly, driven by significant changes at the premise level. Customer programs and rate designs tailored to elicit individual customer behaviors and responses, changing customer technologies, ambitious statewide energy policy goals, and localized wildfire and climate change impacts all contribute to dynamic electricity grid changes that are unique to each premise. The results of this Part 1 Study indicate that these impacts, in the aggregate, could result in tens of billions of dollars in additional necessary investments, across discrete locations, to support California's electrification goals.

California has already invested billions of dollars in infrastructure and technologies to capture, track, and report energy data—from AMI and SCADA technologies to EV registrations and driving patterns. The results of this Part 1 Study illustrate how consolidating these extensive data sources yields important insights into **where and when distribution grid enhancements are likely to be needed** to support the premise-level impacts of grid electrification, which is critical as California enters a period of capacity expansion and DER proliferation to support state policy goals. These results also help to understand the quality and scope of utility data and to challenge some traditional DER program assumptions. This section summarizes the following and other results of Kevala's Part 1 Study:

- **Electric distribution grid requirements and their associated costs increase significantly beyond the traditional distribution grid planning cycle, risking stranded investments or missed investment opportunities altogether** if datasets are not connected and analyzed holistically.
    - **Across these unmitigated load scenarios, Kevala estimates up to $50 billion in traditional electricity distribution grid infrastructure investments by 2035**. This estimate reflects distribution grid needs across the PG&E, SCE, and SDG&E service territories under the policy assumptions used in this report. These costs are estimated with a focus on traditional utility distribution infrastructure investments. Existing TOU rates and BTM tariffs were assumed. The study did not consider alternatives or any of the existing and future mitigation strategies such as alternative time-variant or dynamic rates and flexible load management strategies.
    - Kevala examined several scenarios[64] for this Part 1 Study. Both of the High Transportation Electrification scenarios would result in almost doubling the current

[64] Kevala generated premise-specific forecasts for five scenarios. The base case represents a premise-level forecast that calibrates the baseline load forecast and the individual demand modifier forecasts to the 2021

rate of spend reported by the IOUs in the GNA reports for capacity requirements related to feeders, transformer banks, and substations.[65] These Part 1 Study costs reflect the impact of unmitigated loads.[66]

  - Secondary transformer and service upgrades alone are a non-negligible contribution to the total grid capacity upgrade costs, comprising about $15 billion of the $50 billion identified previously. Such grid upgrades are important to be considered so that they do not become a bottleneck for electrification and are proactively planned for in a cost-effective way.
  - The system-level peak load increase from 2025 to 2035 is 56%, on average, across the three IOUs and High Transportation Electrification scenarios;[67] this dramatic increase in peak load for the scenarios considered in Part 1 is primarily due to transportation electrification impacts, with over 60% of this demand coming from light-duty vehicles (LDVs).[68] Peak load is the primary driver of the grid capacity upgrades considered in this Part 1 Study.
  - The average percent change in peak load from 2025 to 2035 for the High Transportation Electrification scenarios is more dramatic for PG&E (69%), followed by SDG&E (53%) and SCE (44%).
  - Data tracking and reporting gaps across state regulatory agency datasets and load-serving entities (LSEs) should be filled to develop timely forecast scenarios that reflect the dynamic changes to the electricity grid.

- Of the DERs selected in this Part 1 Study for alternate scenario development—transportation electrification and BTM tariffs—**transportation electrification results in significantly greater distribution grid impacts relative to the BTM tariffs assumed in the Part 1 Study.**

IEPR mid-mid case. Each of the four alternate scenarios considers a different combined projection for NEM BTM tariffs and the speed and scope of transportation electrification.

[65] This Part 1 Study evaluates upgrades at the substation, transformer bank, feeder, and service transformer level. It does not include line section upgrades related to the primary lines between the feeder head and the service transformers.

[66] Rates and existing TOU periods were held constant. Assumptions regarding where IOU rates and costs will go in future years is outside the scope of this study.

[67] These High Transportation Electrification scenarios are based on the expected level of transportation electrification necessary to meet California's policy goals, such as the transportation electrification goals promulgated in Executive Order N-79-20 and incorporated into CARB regulation in 2022. The main difference between the High Transportation Electrification and Accelerated High Transportation Electrification scenarios is the speed at which transportation electrification will occur in 2030 and 2035.

[68] Kevala can revisit considering BE targets aligned with state and federal policy goals and incentives in the Part 2 Study.

  - Transportation electrification grid requirements and costs escalate in earnest in 2030 and dramatically increase by 2035 regardless of scenario. The current distribution planning process looks out only five years. This planning framework may not be able to plan for the expected rapid increase in transportation electrification-related infrastructure due to the lead times involved for electric distribution grid infrastructure, including mitigation strategies to large capital expenses.
  - The NEM BTM tariff scenario used in this Part 1 Study has relatively minimal impact on the adoption of PVs and thus on the total electrification grid upgrade costs resulting from the Part 1 analysis.
- **The premise-level approach taken in this Part 1 Study enables a robust assessment of utility distribution grid needs**, including:
  - **The What:** Identification of a broader scope of infrastructure needs than other studies and an understanding of the relative contribution to net-load of the DERs studied.
  - **The When:** A longer planning time horizon than the current DPP.
  - **The Where:** The ability to analyze premise-level data and aggregate up provides transparency and opportunities for multiple scenario analysis, including specific locational grid needs and the demographic characteristics of those needs.
  - **The How Much:** Differences in unit costs and grid need calculations between utilities that require further transparency and analysis.

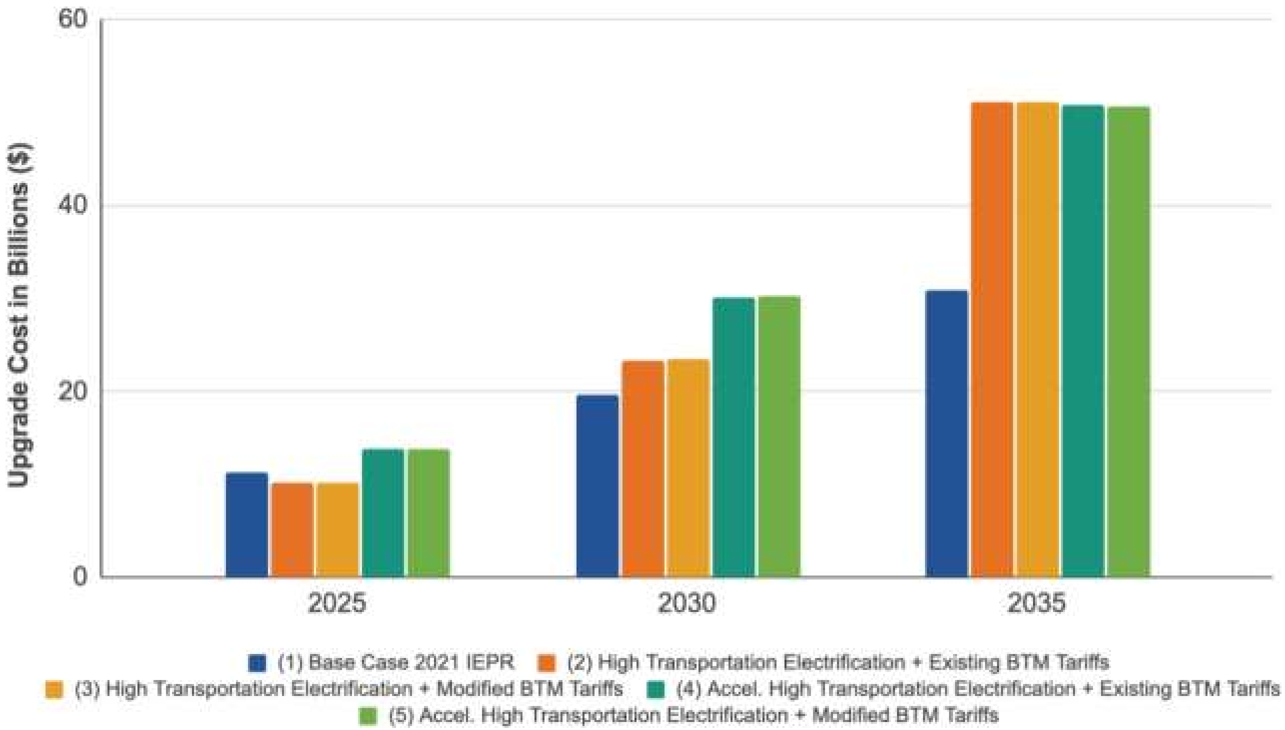
The following sections provide details of the results of Kevala's Part 1 analysis.

- Section 2.1 provides an overview of the indicative costs of the electrification scenarios for 2025, 2030, and 2035.
- Section 2.2 outlines the results of Kevala's net-load modeling.
- Section 2.3 discusses the DER-specific adoption and behavior results for BTM PV, BESS, EE and BE, and EVs and EVSE.
- Section 2.4 provides an overview of the equity and electricity burden implications of Kevala's Part 1 analysis.

2.1. Costs of Electrification Scenarios

Kevala estimates in this Part 1 analysis total potential, unmitigated distribution system investment costs across all three study IOUs of up to $50 billion in 2035 for the High Transportation Electrification and Accelerated High Transportation Electrification scenarios (see Figure 3). As of 2022, the 2021 IEPR base case is no longer a projected state outcome for transportation electrification loads. The adopted 2022 IEPR mid-mid case (i.e., Planning Forecast)[69] reflects transportation electrification assumptions similar to the two High Transportation Electrification scenarios that Kevala modeled. These cost estimates reflect Kevala's distribution grid infrastructure and premise-specific forecast of long-term load and DER growth for the scenarios.

Figure 3: Total capacity upgrade costs for the three large California IOUs, including new substations, transformer banks, feeders, and service transformers *(Source: Kevala)*



For each of the four alternate scenarios (not including the Base Case 2021 IEPR), **total** cost levels by 2035 are approximately the same. The cost differences between the High Transportation Electrification and Accelerated High Transportation Electrification alternate scenarios in 2025 and 2030 are the result of different assumptions for those alternate scenarios about the **pace** of transportation electrification between 2025 and 2030, and 2030 and 2035. The different assumptions about the pace of transportation electrification are key drivers of anticipated distribution upgrade requirements across the 2025-2035 period.

Regardless of the pace of transportation electrification, Figure 3 shows that the **incremental** cost of electrification between 2025 and 2035 is about $40 billion. In other words, the difference between 2025 and 2035 levels for each of the four alternate scenarios is the same regardless of

[69] CEC, *2022 Integrated Energy Policy Report Update*, February 2023, https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update.

alternate scenario. In every alternate scenario, transportation electrification is the key driver of grid impacts. Further, the BTM tariff scenario did not result in a significant impact to distribution system upgrade costs in this analysis.

These cost estimates, derived using distribution system design principles consistent with the design principles used by each of the respective IOUs, are based on circuit-specific analyses of four categories of distribution infrastructure:

- Distribution substations
- Transformer banks
- Feeders
- Service transformers

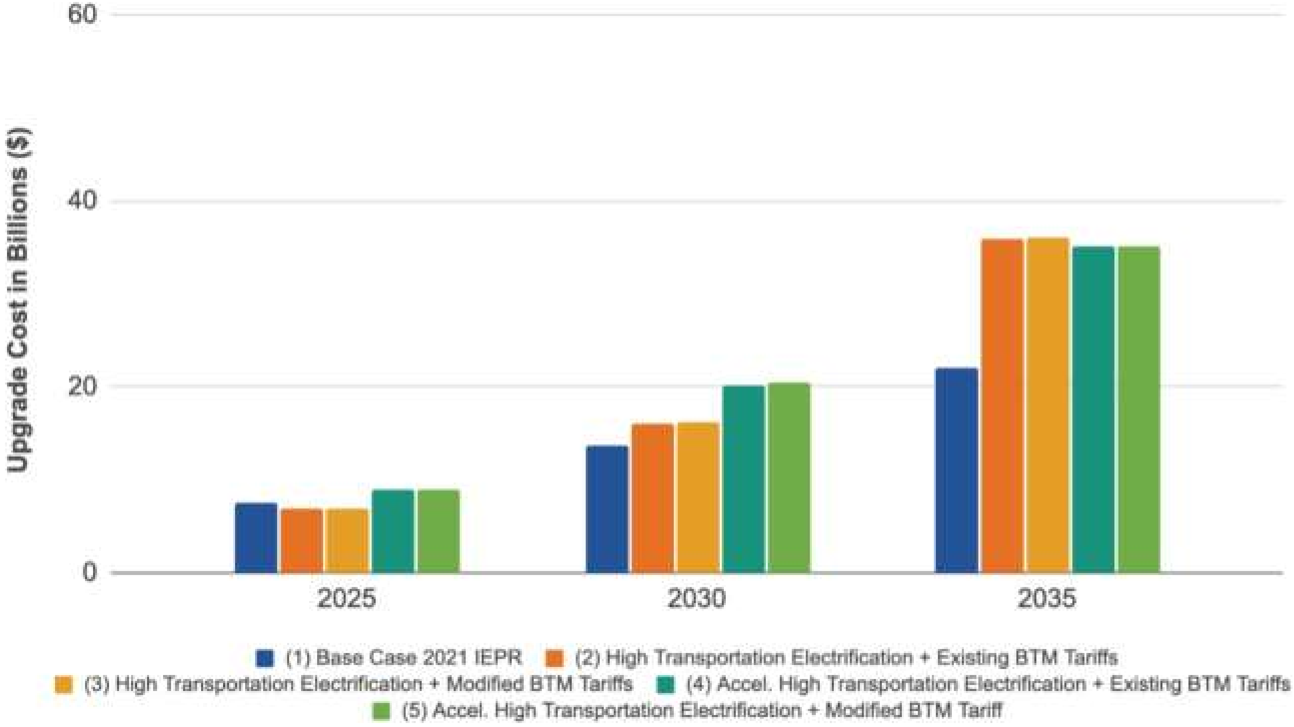
The other electrification impacts studies of which Kevala is aware, including the IOUs' GNA analyses, stop at the feeder level and do not include costs associated with service transformers. For comparison purposes, Figure 4 illustrates the total and incremental costs if the costs of secondary service transformers were excluded from Kevala's estimate to be consistent with other publicly available studies:

- The **total** costs of primary distribution infrastructure capacity upgrades are approximately $35 billion in the High Transportation Electrification and Accelerated High Transportation Electrification scenarios in 2035.[70]
- The **incremental** costs of the transportation electrification scenarios by 2035 are $30 billion in new substations, transformer banks, and feeders.

For more information on the approach, methods, and assumptions to determine capacity infrastructure upgrade costs, refer to Section 3.5.

[70] Although the adopted mid-mid case of the 2022 IEPR (i.e., the Planning Forecast) effectively makes the 2021 IEPR Base Case used for Part 1 Study less relevant as of the time of the Part 1 report issuance in 2023, it is worth footnoting that the total costs of primary distribution infrastructure capacity upgrades in 2035 pursuant to the 2021 IEPR Base Case was estimated to be approximately $22 billion for Part 1. The cost of secondary infrastructure capacity upgrades was estimated to be approximately $9 billion for a combined total of $31 billion under the Base Case.

Figure 4: Capacity upgrade costs for the three large California IOUs, including new substations, transformer banks, and feeders only (excluding service transformers) *(Source: Kevala)*



2.1.1. Benchmarking Part 1 Upgrade Costs to 2022 Distribution Investment Deferral Framework

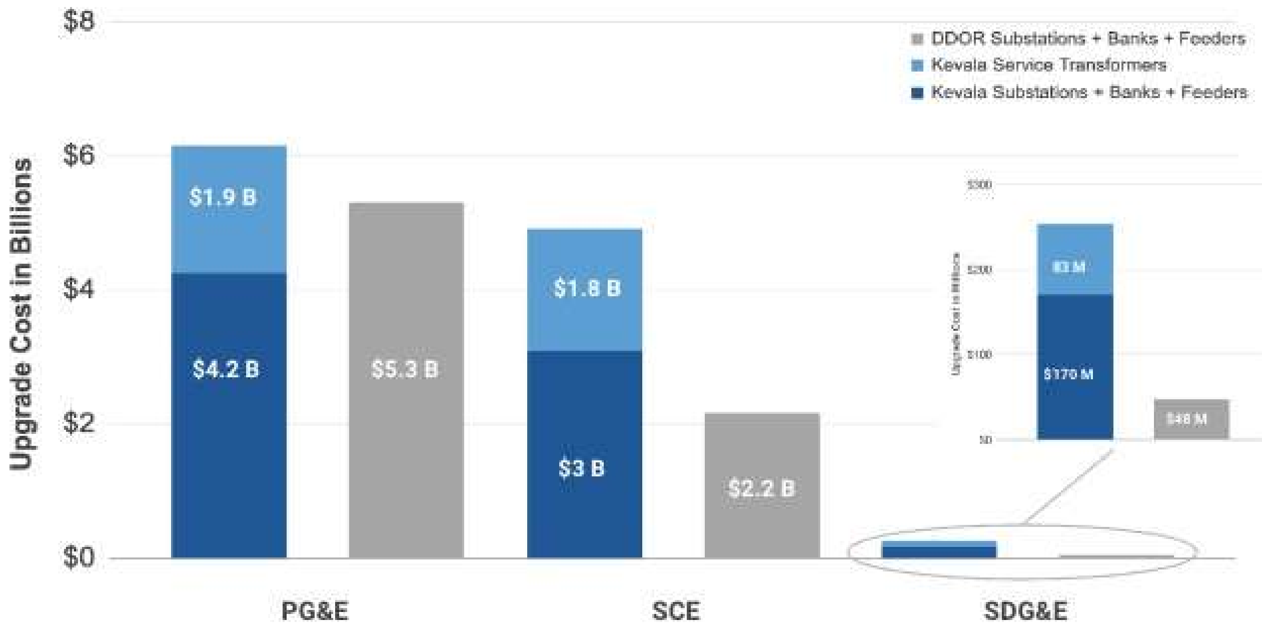
Kevala compared the capacity upgrade costs estimates for the Base Case 2021 IEPR scenario in 2025 to the IOUs' DDOR planned investments required by capacity grid deficiencies identified in the GNA reports (see Figure 5). Kevala's estimated cost for new substations, transformer banks, and feeder values (in dark blue) can be compared to the 2022 estimates from the IOUs in the DDOR capacity planned investments (in gray).

- For PG&E, Kevala's capacity upgrade cost estimate for primary infrastructure is $4.2 billion versus PG&E's estimate of $5.3 billion.
- For SCE, Kevala's primary infrastructure estimate for capacity upgrades is $3 billion versus SCE's reported planned investments of $2.2 billion. For SDG&E, the primary capacity upgrades estimated by Kevala are higher than SDG&E's. Kevala proposes further investigating these differences in Part 2 when looking at mitigation strategies for capacity grid requirements.

On top of the primary infrastructure, Kevala estimated additional upgrades required at the secondary distribution level by estimating the cost of service transformers that would need to be replaced. This non-negligible cost could be included in the Distribution Investment Deferral

Framework (DIDF) in order for DERs to be able to capture the value of deferring or avoiding service transformer costs in the future.

Figure 5: Capacity upgrade costs by IOUs for the Base Case 2021 IEPR scenario in 2025 for new substations, transformer banks, and feeders compared to the DDOR planned investments identified by the IOUs through 2026 in the 2022 DIDF *(Source: Kevala)*



2.1.2. Capacity Upgrade Costs by IOU

Figure 6 shows the total upgrade costs for new substations, transformer banks, feeders, and service transformers by IOU and scenario. The upgrade costs by county for Scenario 2, High Transportation Electrification + Existing BTM Tariffs are included in Figure 7, Figure 8, and Figure 9. These maps illustrate how electrification impacts on grid infrastructure requirements will not be geographically homogeneous, and the importance of beginning to understand where and when the bottlenecks will occur so the grid does not become an impediment to transportation electrification.

Figure 6: Total capacity upgrade costs by IOU and scenario, including new substations, transformer banks, feeders, and service transformers *(Source: Kevala)*

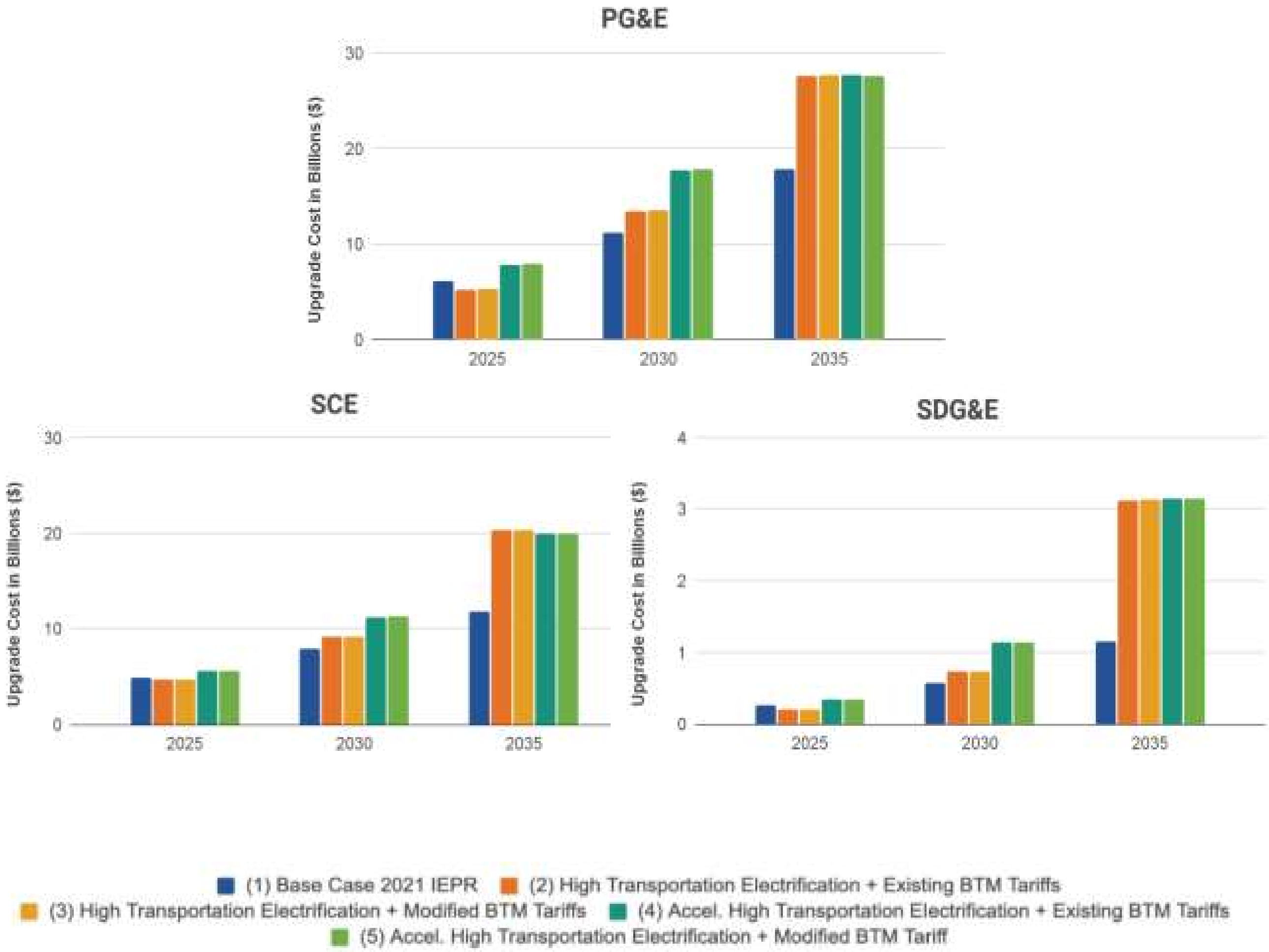


Figure 7: Total capacity upgrade costs for PG&E by county for Scenario 2, High Transportation Electrification + Existing BTM Tariffs (*Source: Kevala*)

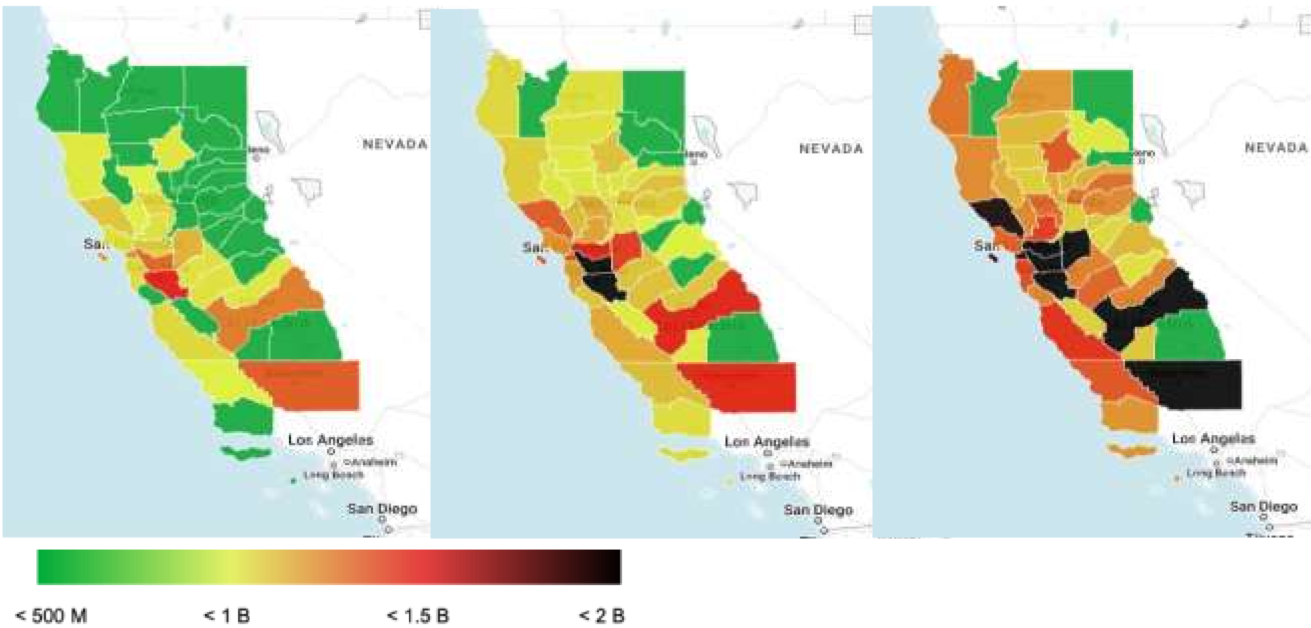


Figure 8: Total capacity upgrade costs for SCE by county for Scenario 2, High Transportation Electrification + Existing BTM Tariffs (*Source: Kevala*)

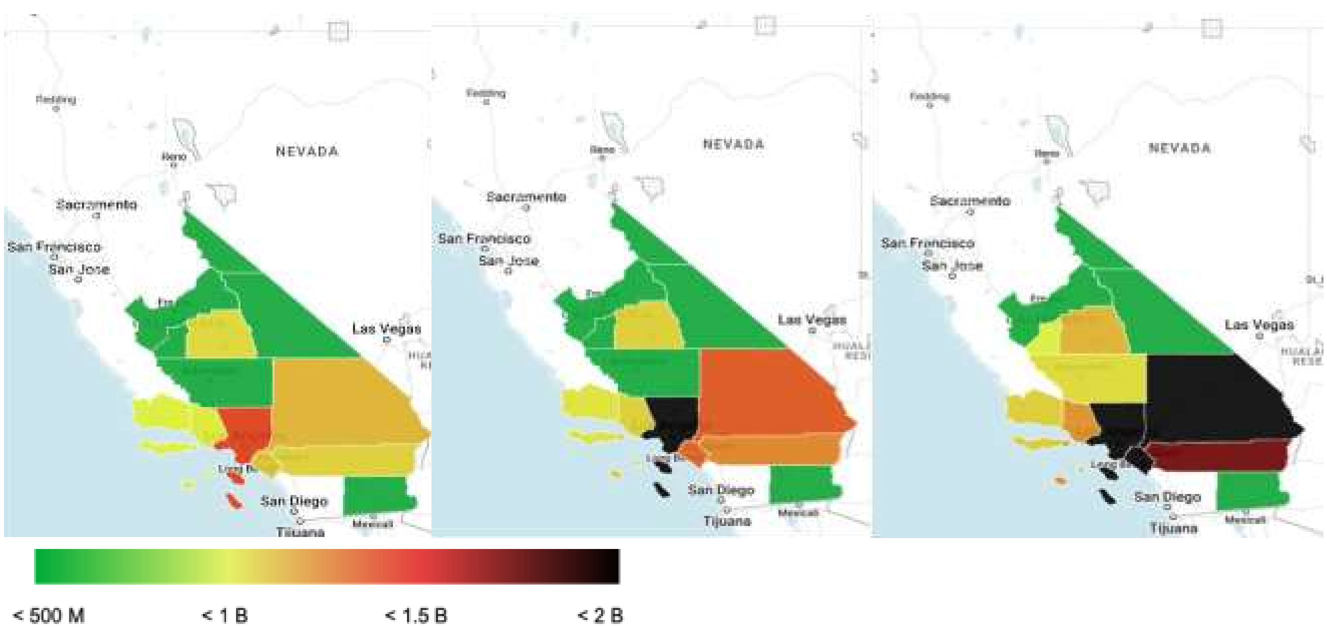
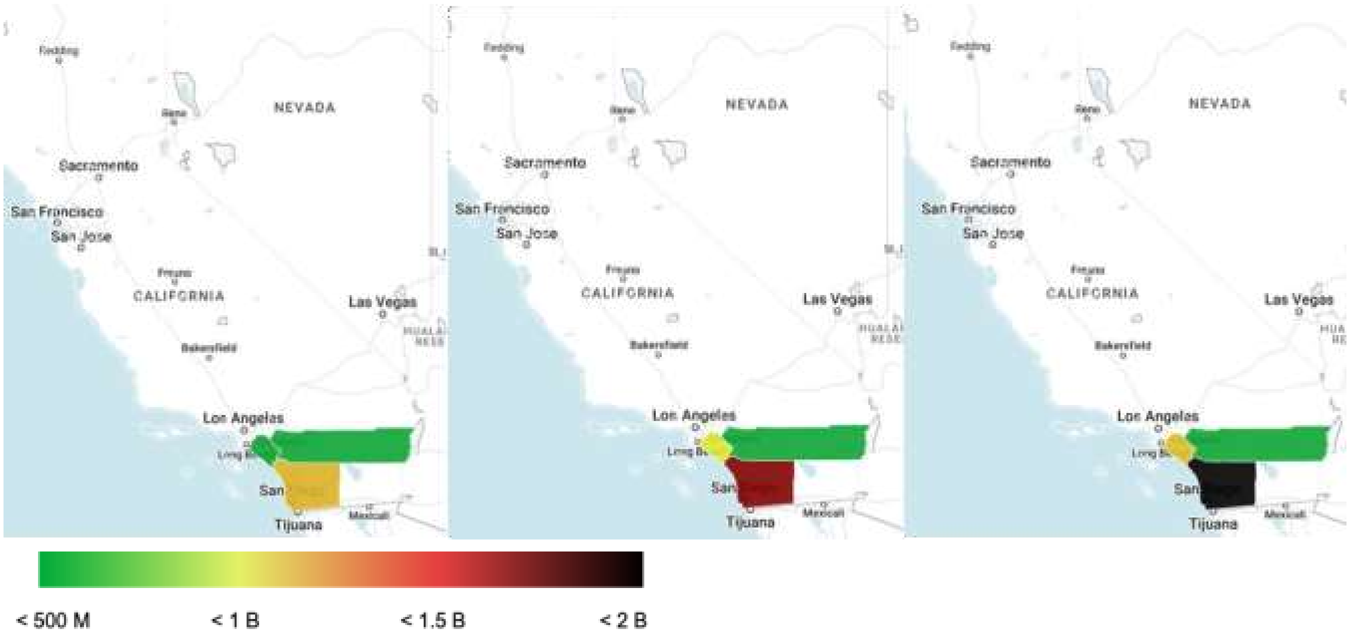


Figure 9: Total capacity upgrade costs for SDG&E by county for Scenario 2, High Transportation Electrification + Existing BTM Tariffs (*Source: Kevala*)



Total grid upgrade costs by IOU for all scenarios are included in Table 2; these costs are further identified by specific grid asset type in Table 3 and Table 4. The difference in costs by IOU are primarily driven by the peak load magnitude served and the number of overloaded assets in the system, and secondarily by the unit cost assumptions of new grid infrastructure.

Table 2: Estimate of total grid upgrade costs, including service transformers *(Source: Kevala)*

Scenario	Total Grid Upgrade Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	$6,155	$4,921	$254	$11,153	$7,964	$572	$17,876	$11,814	$1,152
(2) High Transportation Electrification + Existing BTM Tariffs	$5,255	$4,673	$202	$13,407	$9,206	$738	$27,599	$20,330	$3,123

Scenario	Total Grid Upgrade Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(3) High Transportation Electrification + Modified BTM Tariffs	$5,308	$4,694	$203	$13,546	$9,205	$738	$27,623	$20,380	$3,134
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	$7,801	$5,626	$344	$17,760	$11,147	$1,140	$27,647	$19,914	$3,149
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	$7,886	$5,641	$344	$17,834	$11,321	$1,140	$27,615	$19,936	$3,149

Table 3: Estimate of new substation, transformer bank, and feeder costs *(Source: Kevala)*

Scenario	New Substation + Transformer Bank + Feeder Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	$4,256	$3,086	$171	$7,930	$5,374	$359	$13,010	$8,307	$776
(2) High Transportation Electrification + Existing BTM Tariffs	$3,677	$2,994	$148	$9,315	$6,238	$442	$19,141	$14,662	$2,149
(3) High Transportation Electrification + Modified BTM Tariffs	$3,727	$3,012	$148	$9,451	$6,233	$442	$19,160	$14,709	$2,161

Scenario	New Substation + Transformer Bank + Feeder Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	$5,189	$3,466	$195	$12,104	$7,449	$620	$18,896	$14,133	$2,109
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	$5,272	$3,479	$195	$12,174	$7,620	$620	$18,858	$14,151	$2,109

Table 4: Estimate of service transformer costs *(Source: Kevala)*

Scenario	Service Transformer Upgrade Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	$1,899	$1,835	$83	$3,223	$2,590	$214	$4,866	$3,507	$375
(2) High Transportation Electrification + Existing BTM Tariffs	$1,579	$1,679	$55	$4,092	$2,968	$295	$8,458	$5,668	$974
(3) High Transportation Electrification + Modified BTM Tariffs	$1,581	$1,681	$55	$4,096	$2,972	$296	$8,463	$5,670	$974
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	$2,612	$2,160	$149	$5,656	$3,698	$519	$8,751	$5,781	$1,040

Scenario	Service Transformer Upgrade Costs ($000,000)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	$2,614	$2,162	$149	$5,660	$3,701	$520	$8,758	$5,784	$1,041

Figure 10 shows the aggregated number of grid assets analyzed in this Part 1 Study for the three IOUs, along with the average percentage of overloaded assets by asset category.[71]

Figure 10: Percentage of overloaded assets, averaged across the three IOUs and Scenarios 2-5 *(Source: Kevala)*

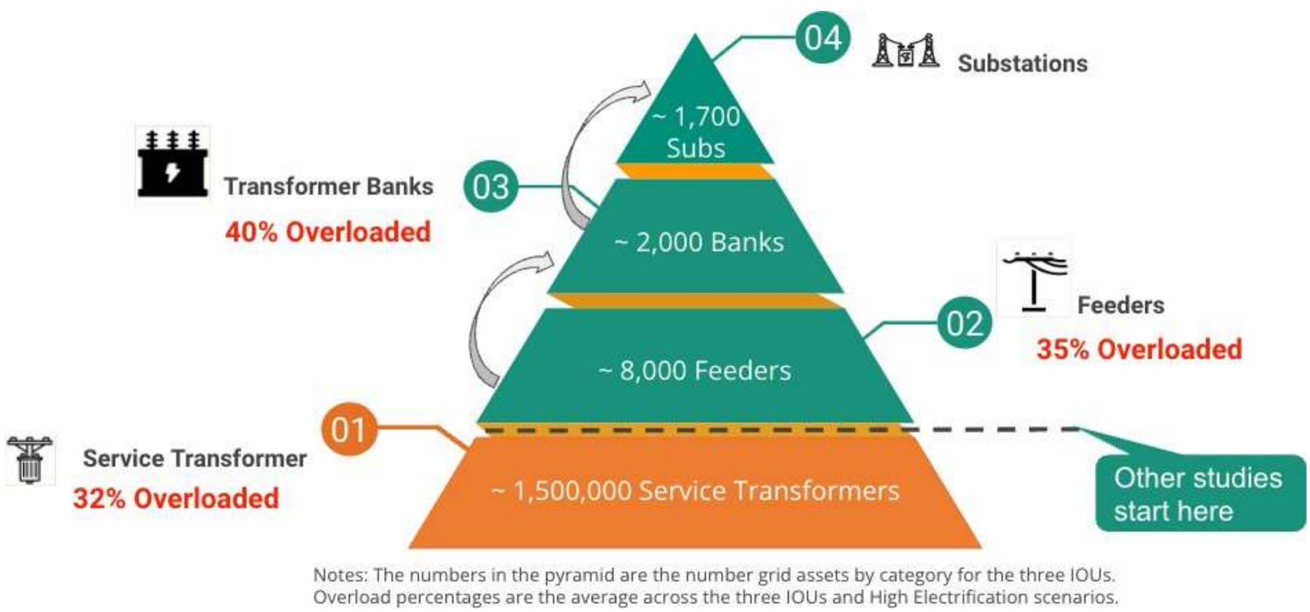
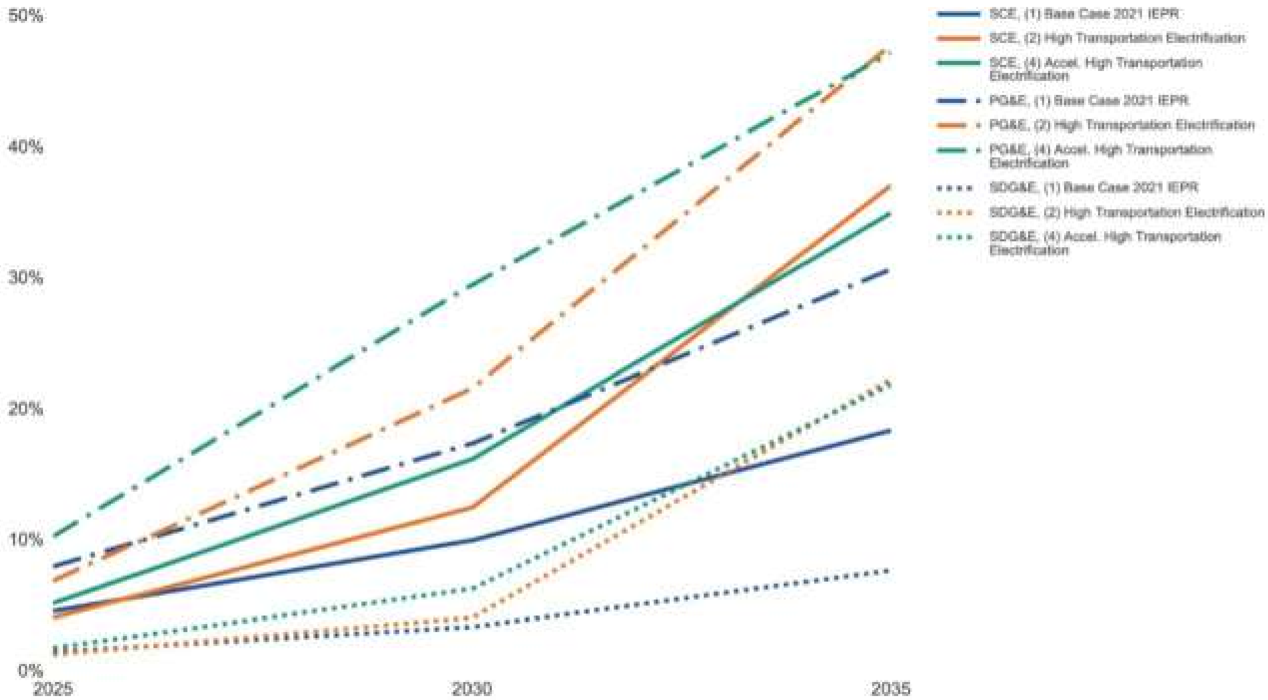


Figure 11 shows the percentage of overloaded feeders over time by scenario and IOU. PG&E has a higher number of feeders that reach the capacity threshold, while SDG&E has the lowest percentage of feeders reaching capacity.

[71] The percentage of overloaded assets in Figure 11 is averaged across the four High Transportation Electrification and Accelerated High Transportation Electrification scenarios (Scenarios 2-5).

Figure 11: Percentage of overloaded feeders by IOU and scenario in 2025, 2030, and 2035 *(Source: Kevala)*



2.2. Net-Load Results

The Part 1 Study enables both:

- An aggregated view of total energy (GWh) and peak load (GW) for each IOU by scenario for each of the three years of the study period.
- A more localized view of specific grid impacts for each IOU by scenario.

Figure 12 and Figure 13 illustrate the aggregate total load growth for each IOU, regardless of scenario, from 2025 to 2035.

Figure 12: Energy by IOU, study year, and scenario *(Source: Kevala)*

Figure 13: Peak demand by IOU, study year, and scenario *(Source: Kevala)*

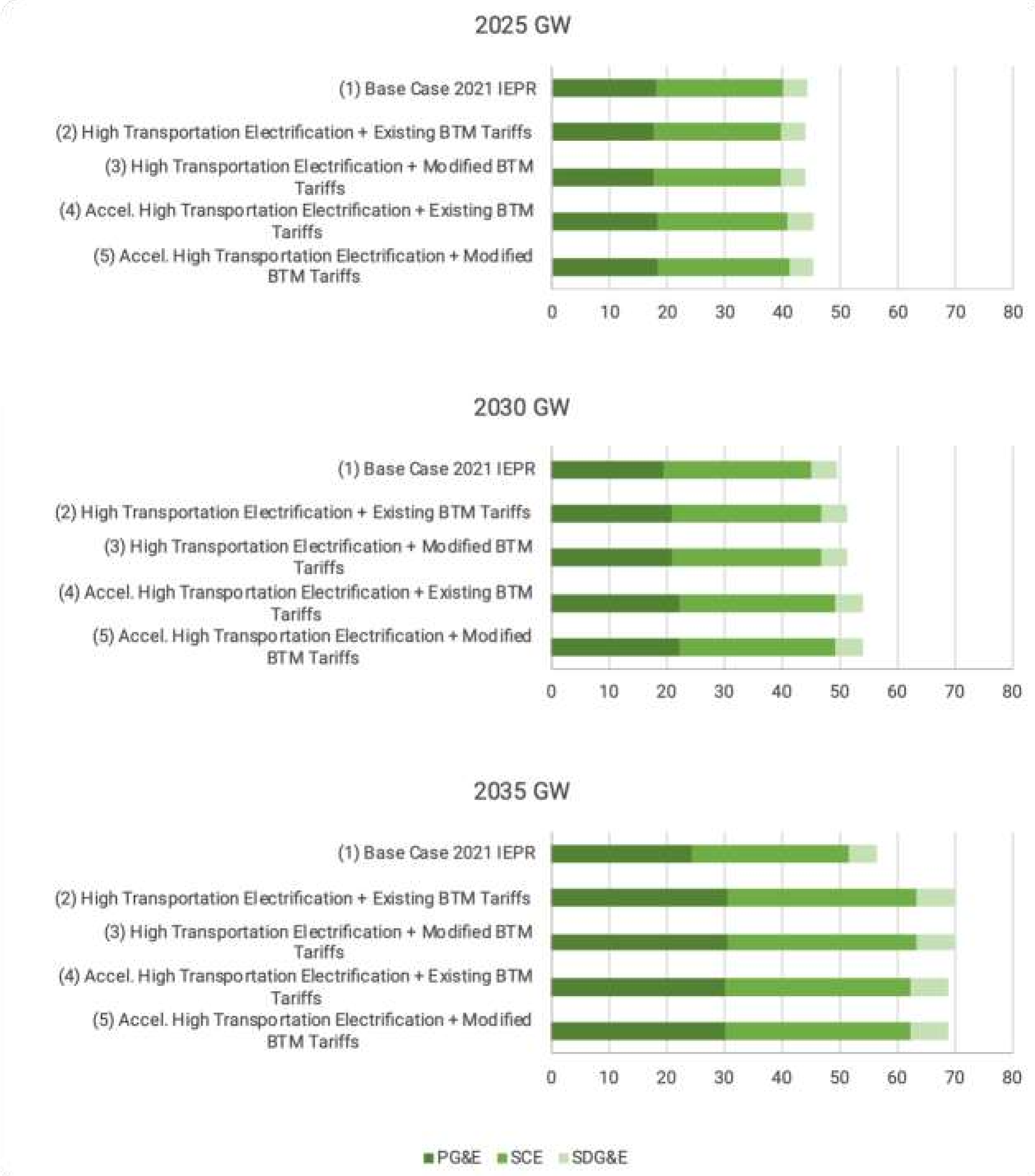


Figure 14 and Figure 15 provide a different lens into total energy and peak load growth by illustrating the dramatic load growth results for each IOU on a percent change basis from 2025 to 2030, and from 2025 to 2035. Peak load is the primary driver of the grid capacity upgrades considered in this Part 1 Study. The detailed data from these figures are shown in Table 5 and Table 6. The peak load increase for the Base Case 2021 IEPR scenario alone by 2035 is between 20% and 30%; for the High Transportation Electrification and Accelerated High Transportation Electrification scenarios, the peak load increase is between 40% and 70% by 2035 depending on the IOU.

Figure 14: Energy percent change by IOU, study year, and scenario (*Source: Kevala*)

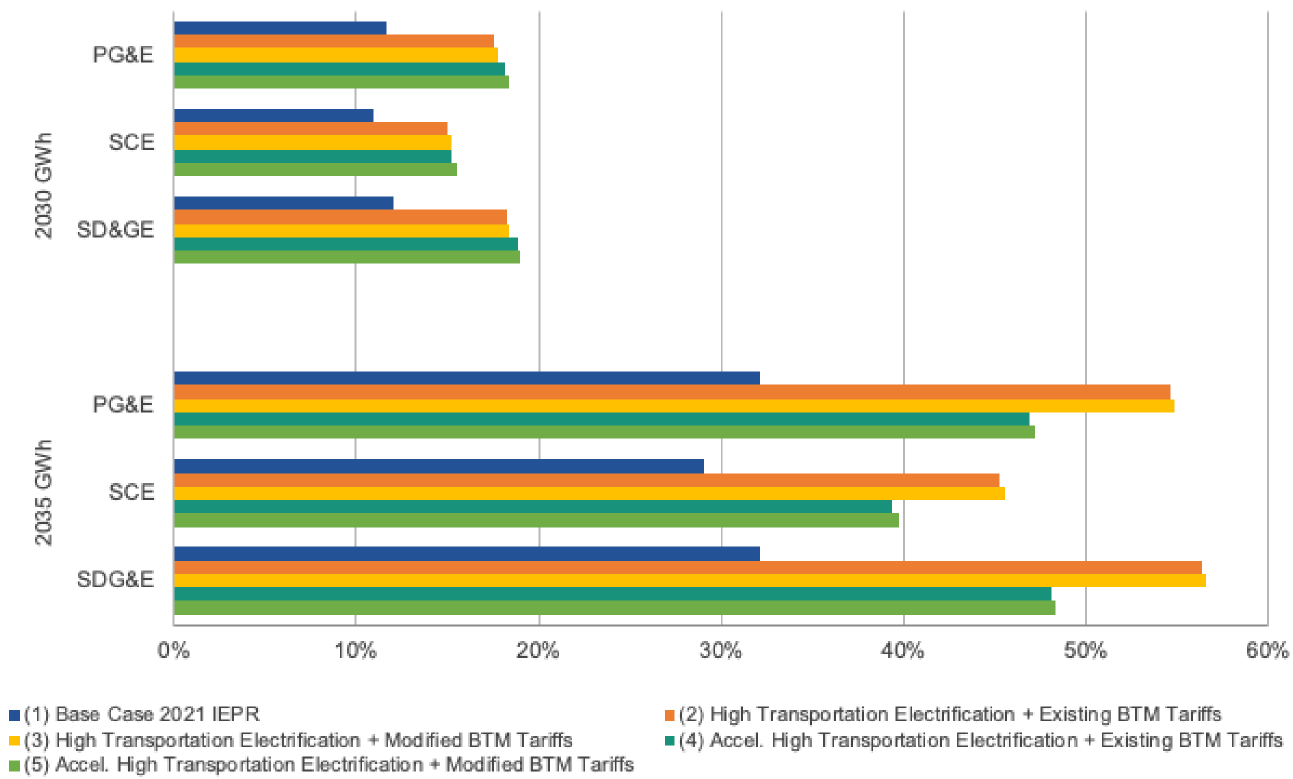
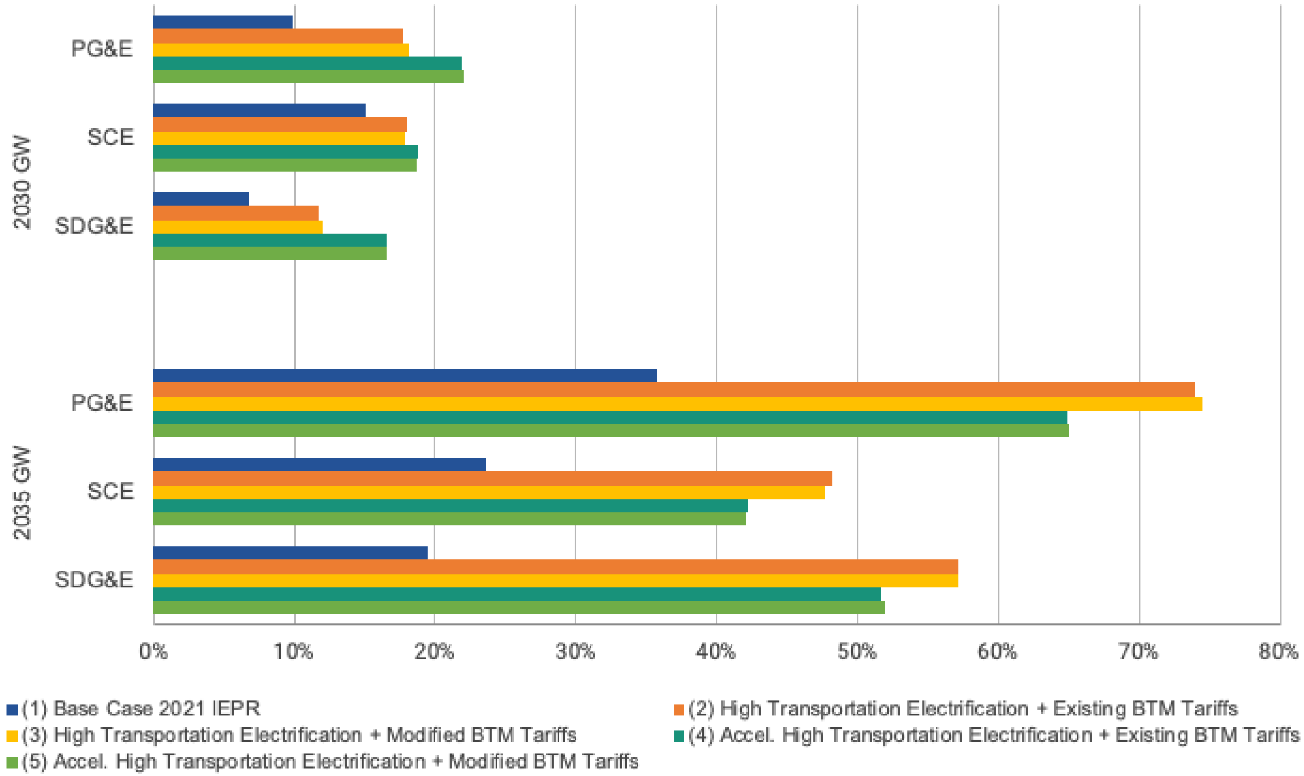


Figure 15: Peak demand percent change by IOU, study year, and scenario *(Source: Kevala)*



This dramatic increase in peak load is due primarily to transportation electrification impacts. Figure 16 and Figure 17 show the hourly net-load profile for PG&E on the peak day in 2035 for the Base Case 2021 IEPR and the High Transportation Electrification + Existing BTM Tariffs scenarios, respectively; these figures illustrate the large contribution to peak load from EVSE charging infrastructure as well as the shift to a nighttime peak load.

Figure 18 and Figure 19 show the personal and fleet EVSE infrastructure charging demand contribution on the peak day for the Base Case 2021 IEPR and the High Transportation Electrification + Existing BTM Tariffs scenarios, respectively, and show the impact of the TOU residential tariffs assumed in the modeling and previously described in Section 1.2; the figures also show the overall large contribution of EVSE charging infrastructure to the system peak load.

Figure 16: PG&E hourly net-load profile by customer sector and by load type for Scenario 1, Base Case 2021 IEPR, for the peak day, August 15, 2035 *(Source: Kevala)*

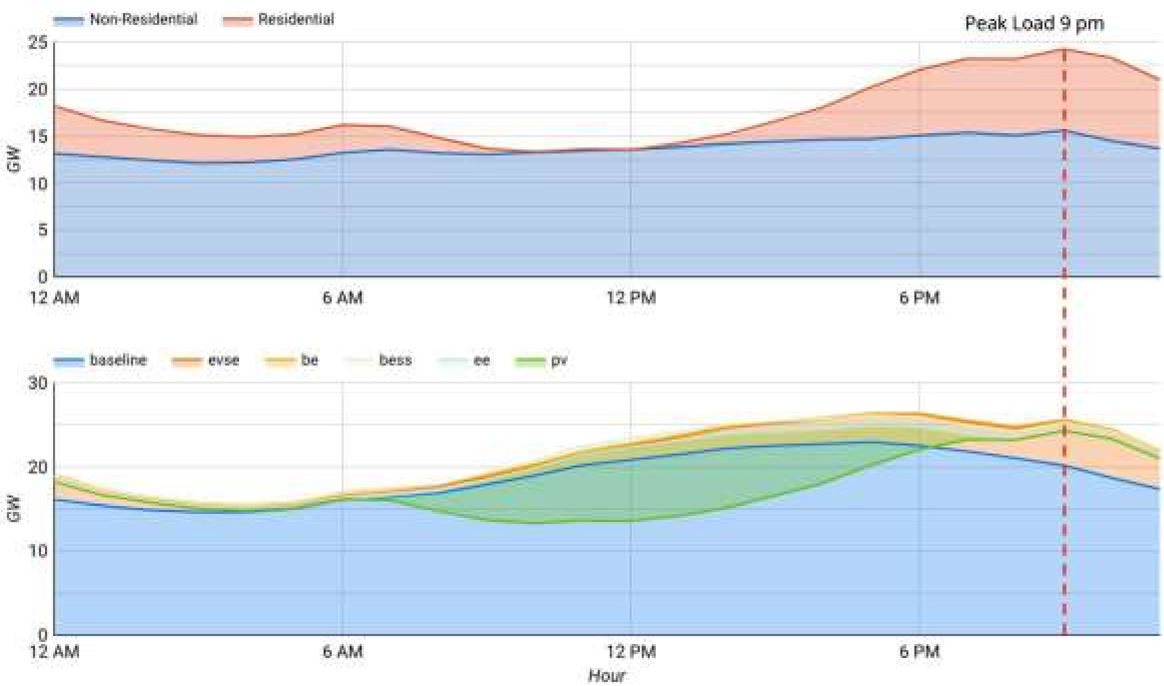


Figure 17: PG&E hourly net-load profile by customer sector and by load type for Scenario 2, High Transportation Electrification + Existing BTM Tariffs, for the peak day, August 15, 2035 *(Source: Kevala)*

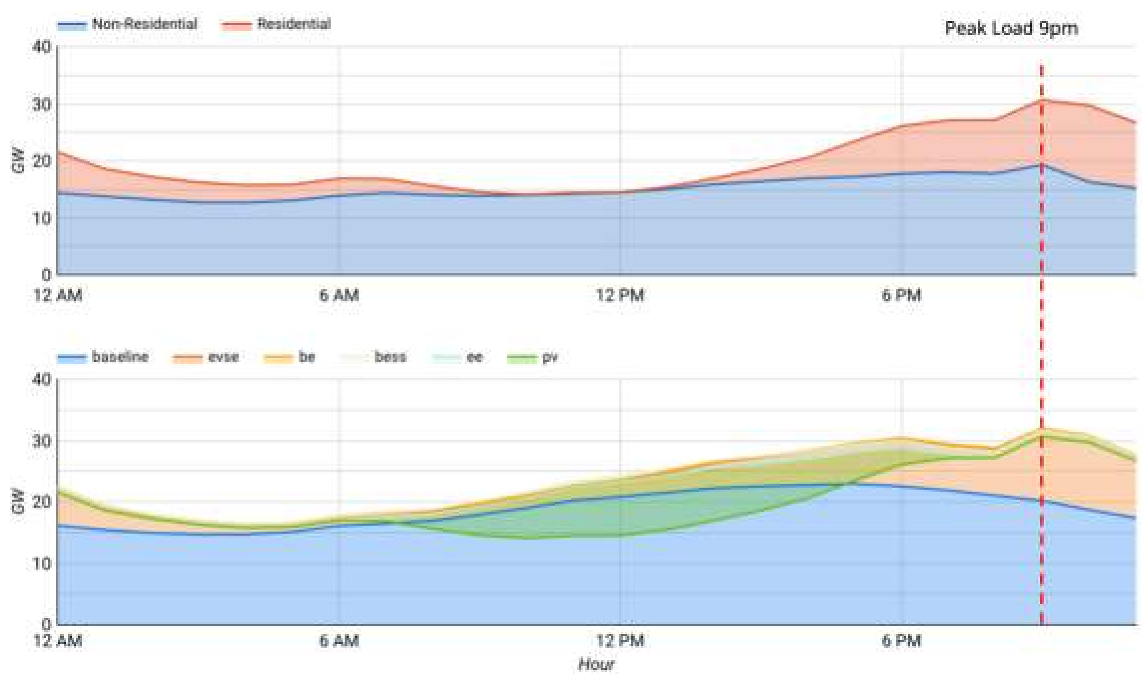


Figure 18: PG&E hourly EVSE profile for Scenario 1, Base Case 2021 IEPR, for the peak day, August 15, 2035 *(Source: Kevala)*

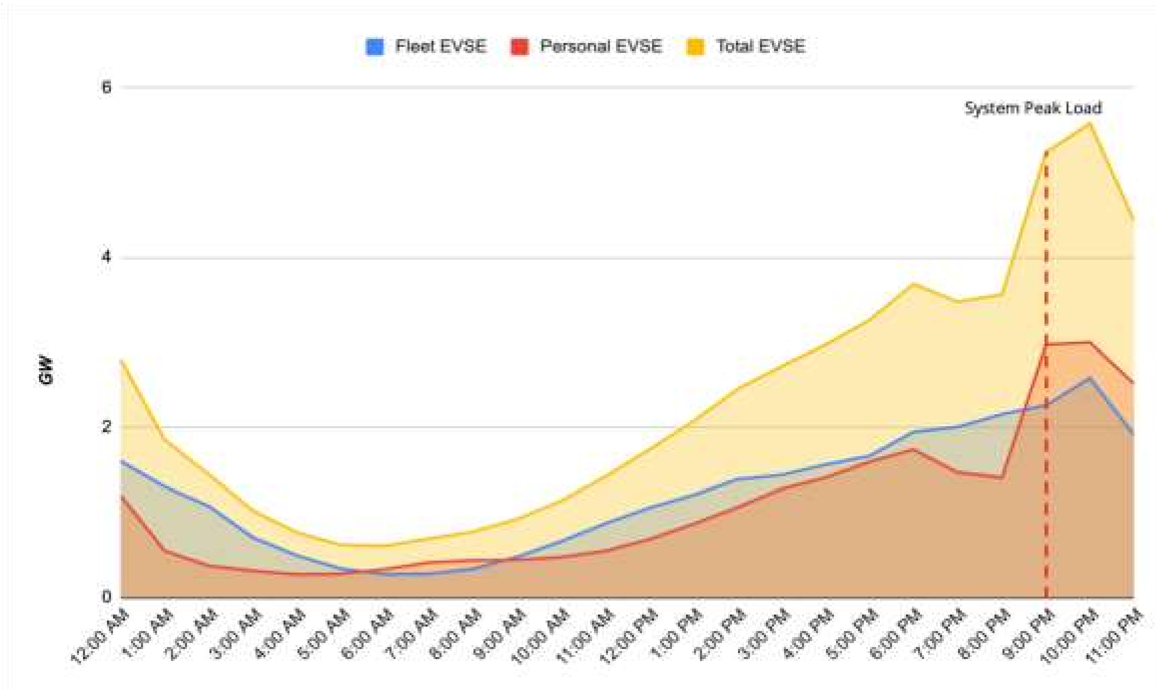


Figure 19: PG&E hourly EVSE profile for Scenario 2, High Transportation Electrification + Existing BTM Tariffs, for the peak day, August 15, 2035 *(Source: Kevala)*

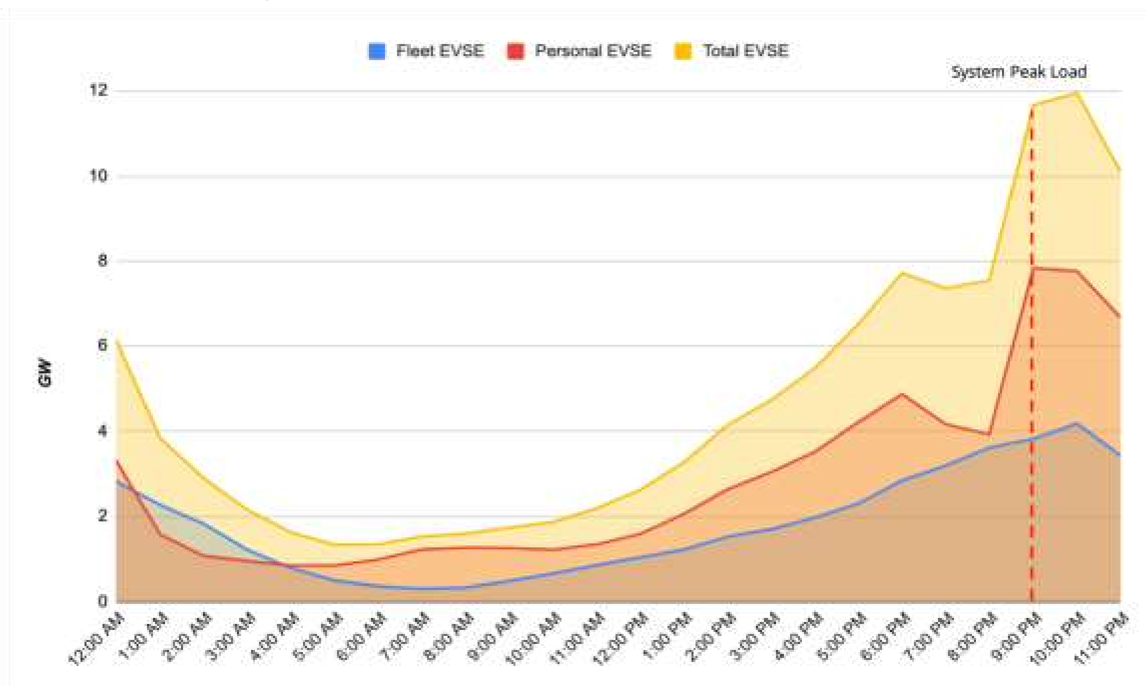


Table 5: Annual energy by study year, IOU, and scenario *(Source: Kevala)*

Scenario	Annual GWh								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	95,963	109,008	20,208	107,137	120,960	22,644	126,778	140,634	26,689
(2) High Transportation Electrification + Existing BTM Tariffs	94,489	107,837	19,910	111,023	123,990	23,547	146,071	156,615	31,127
(3) High Transportation Electrification + Modified BTM Tariffs	95,006	108,149	19,920	111,847	124,601	23,578	147,115	157,424	31,181
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	98,840	111,270	20,863	116,797	128,213	24,792	145,178	155,070	30,898
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	99,357	111,581	20,873	117,621	128,823	24,823	146,222	155,880	30,952

Table 6: Annual peak demand by study year, IOU, and scenario *(Source: Kevala)*

Scenario	Annual Peak Demand (GW)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	17.88	22.14	4.15	19.63	25.46	4.43	24.28	27.37	4.96

Scenario	Annual Peak Demand (GW)								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(2) High Transportation Electrification + Existing BTM Tariffs	17.64	21.98	4.11	20.77	25.95	4.59	30.70	32.57	6.46
(3) High Transportation Electrification + Modified BTM Tariffs	17.66	22.06	4.11	20.78	26.02	4.60	30.72	32.57	6.46
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	18.40	22.49	4.22	22.43	26.72	4.92	30.34	31.99	6.40
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	18.42	22.53	4.22	22.44	26.75	4.92	30.36	31.99	6.41

2.3. Adoption and Behavior DER Results

To convert the baseline net-load forecast to the net-load forecast, Kevala modeled geospatial adoption and behaviors for all of the demand-side modifiers included in this Part 1 Study (BTM, PV, BESS, BE, EE, and EVs/EVSE). The approach ultimately required estimating the load size (i.e., peak demand), behavior of the modifier (i.e., energy use), and adoption of the modifier (did a premise experience the demand modifier size and behavior implications?). The approach used for each demand modifier was slightly modified depending on the calibration target. Specifically:

- The calibration targets for PV, EE, BE, and BESS were a capacity target (MW).
- The calibration target for EVs and EVSE used the number of vehicles (consistent with CARB forecasts to meet state transportation electrification requirements).

Kevala identified premises where economic and demographic characteristics (such as income level) correlated with DER adoption and then the likelihood of adoption based on other factors (e.g., rent versus own, multi-unit dwelling versus single occupant) as well as technology cost curves, program and incentive features, etc.; Kevala then applied a probability distribution for each technology type's adoption. Kevala also simulated the behavior of the demand-side modifiers, resulting in a forecasted net-load that reflects the behavior of EE programs and DERs. The DER-specific results and key insights associated with each DER-specific methodology are summarized in the following subsections.

2.3.1. BTM PV

Using multiple datasets that integrate weather, geospatial, and socioeconomic data enables granular PV adoption and behavior results. Specifically, for PV, consideration of Census block group land area, customer class, maximum baseline load, and median household income, in combination with the traditional method of calculating payback period, enabled Kevala to generate holistic customer PV adoption forecasts. Similarly, using actual weather data to model PV behavior enables consideration of weather correlations between the load and DER forecasts, which are not captured in current forecasts based on typical, averaged load shapes.

A primary question of the PV adoption modeling is the impacts that the existing BTM tariffs or modified BTM tariffs are anticipated to have on long-term BTM PV adoption. The Existing BTM Tariffs scenarios assumed the existing NEM 2.0 rate design would continue through the study horizon and calibrated PV adoption to the 2021 IEPR mid-mid case forecast. In contrast, the Modified BTM Tariffs scenarios assumed a new tariff with a monthly grid access charge of $5/kW and an export rate that offset the generation rate, which was based on but not identical to the proposal in the NEM reform proceeding at the time.[72] The Modified BTM tariffs are anticipated to increase a customer's payback period. The Modified BTM Tariffs scenario was calibrated using the same cutoff adoption propensity score (see Section 3.4.2) that was used to calibrate the Existing BTM Tariffs scenario adoptions to the 2021 IEPR by year and locale. Due to the change in payback period, some customers fall below the adoption threshold and switch from adopters to non-adopters in the Modified BTM Tariffs scenario.

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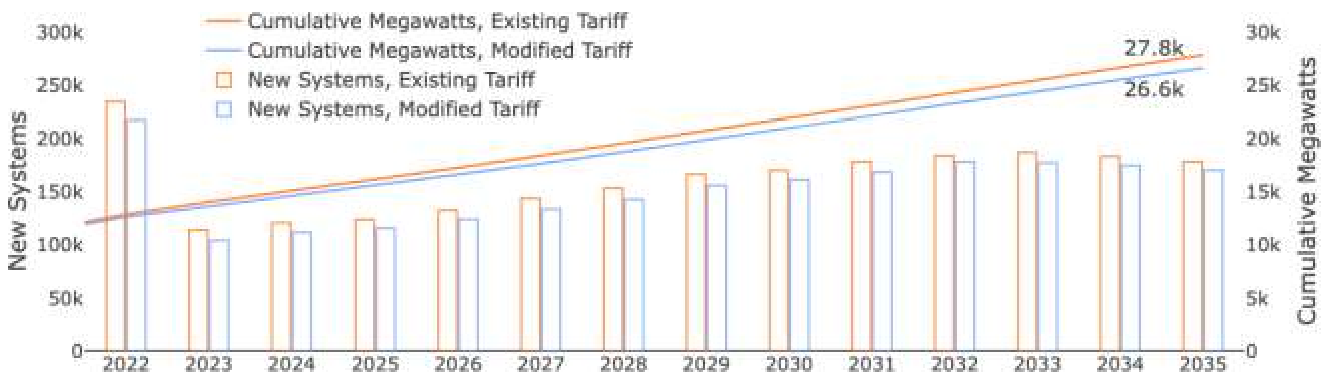
[72] Modified BTM tariff assumptions were based on the December 13, 2021, Proposed Decision for the proceeding titled, *Order Instituting Rulemaking to Revisit Net Energy Metering Tariffs Pursuant to Decision 16-01-044, and to Address Other Issues Related to Net Energy Metering* (R.20-08-020). The Proposed Decision was not adopted by the Commission; it is available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M430/K903/430903088.PDF. Instead, Decision D.22-12-056 adopted the Net Billing Tariff.

By comparing these two scenarios, Kevala can estimate the potential extent of the modified BTM tariff's impact on PV adoptions. Figure 20 shows the outcomes for these two scenarios through 2035, including the number of PV systems and the total installed PV capacity (MW DC) over all three IOUs. By 2035, total installed PV capacity under the modified BTM tariffs (26.6 GW DC) is **only 4.3% lower** than total installations under the existing BTM tariffs (27.8 GW DC). To understand further this relatively small difference between the two scenarios, payback period should be understood in the context of Kevala's premise-specific adoption model. While payback period is one consideration in making an adoption decision, other factors can also play a part, including social trends and barriers to or ease of access.

Figure 20: Total PV installations over all three IOUs by year, comparing the scenarios with existing BTM tariffs or modified BTM tariffs. The left-hand axis shows the incremental number of PV systems added per year, while the right-hand axis shows the cumulative installed capacity (MW).[73] *(Source: Kevala)*



In developing its PV adoption model, Kevala considered not only payback period but also the customer's peak load[74] and demographic information available through the U.S. Census to identify those features most closely correlated with historical PV adoptions in California. Table 7 lists the seven features selected as inputs to the PV adoption model; these were selected based on the available data sources to find the collection of features that together produce the most accurate PV adoption predictions, validated against historical interconnection data.[75] The table ranks these features according to their feature importance, which is a score that indicates how important that feature was when attempting to recreate historical PV adoption decisions.

[73] The modeled jump in PV adoptions in 2022 is due to discrepancies between the interconnection data of historical PV installations, which is current as of April 2021 and also has known data gaps, and the 2022 IEPR PV production estimate. To reconcile those two data sources, Kevala sees 2022 as an adjustment year, after which adoptions proceed much more gradually according to the IEPR forecast.

[74] Peak load might be a motivator particularly for non-residential customers that incur demand charges.

[75] It is important to note that these features can only model *correlation* with PV adoption decisions, but not *causation*.

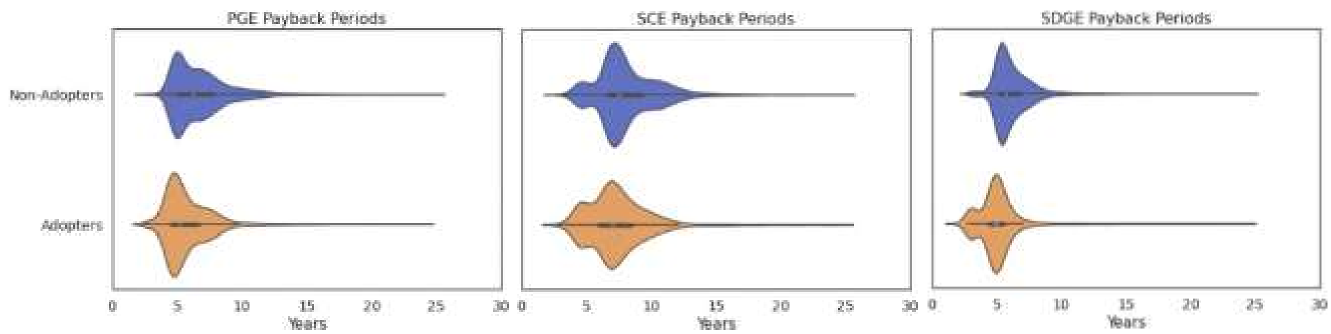
Table 7: Financial, electricity demand, and demographic features used in the PV adoption model, listed in order of their feature importance *(Source: Kevala)*

Feature Importance Order	Feature	Source
1	Census Block Group Land Area[76]	U.S. Census Bureau, American Community Survey (ACS)
2	Residential or Non-residential	Rates / Parcel
3	Maximum baseline (gross) load	AMI
4	Median Household Income	U.S. Census Bureau, ACS
5	Payback period	Rates
6	Population density	U.S. Census Bureau, ACS
7	Percentage owner occupied	U.S. Census Bureau, ACS

Out of the seven features, payback period is not the top predictor—it ranks fifth. When looking at historical adopters in California, the average payback periods of premises that have adopted PV is only a year or two shorter than those that are non-adopters. Figure 21 shows the distributions of historical payback periods calculated by Kevala, comparing adopters and non-adopters for each IOU. While more adopters have shorter payback periods, there are also adopters throughout the range of payback periods, including some relatively longer ones. So while shorter payback period is correlated with adopting PV, it is not the sole or in some cases likely even the main predictor in California.

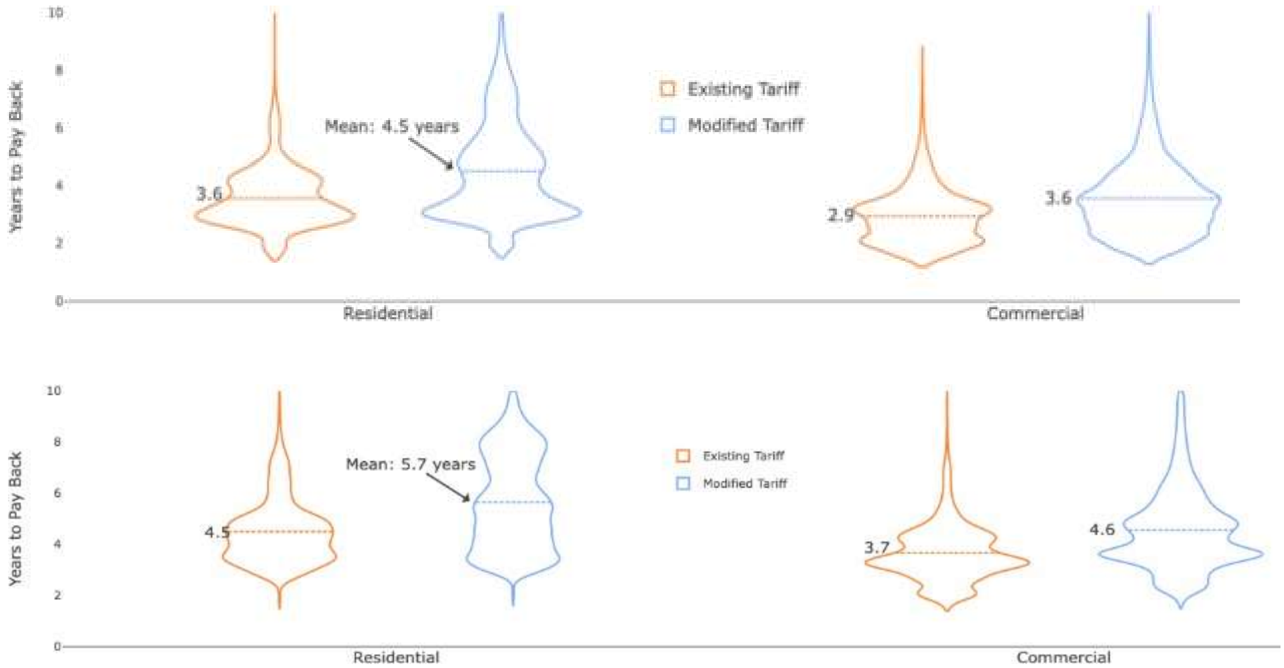
[76] Census Block Group Land Area is a proxy for rural/urban/suburban. Suburban and rural premises have higher historical PV adoptions than urban premises.

Figure 21: Distributions of payback periods in the historical data used to train each IOU's PV adoption model. Historical payback periods are calculated with bill and system costs adjusted to 2016 values. *(Source: Kevala)*



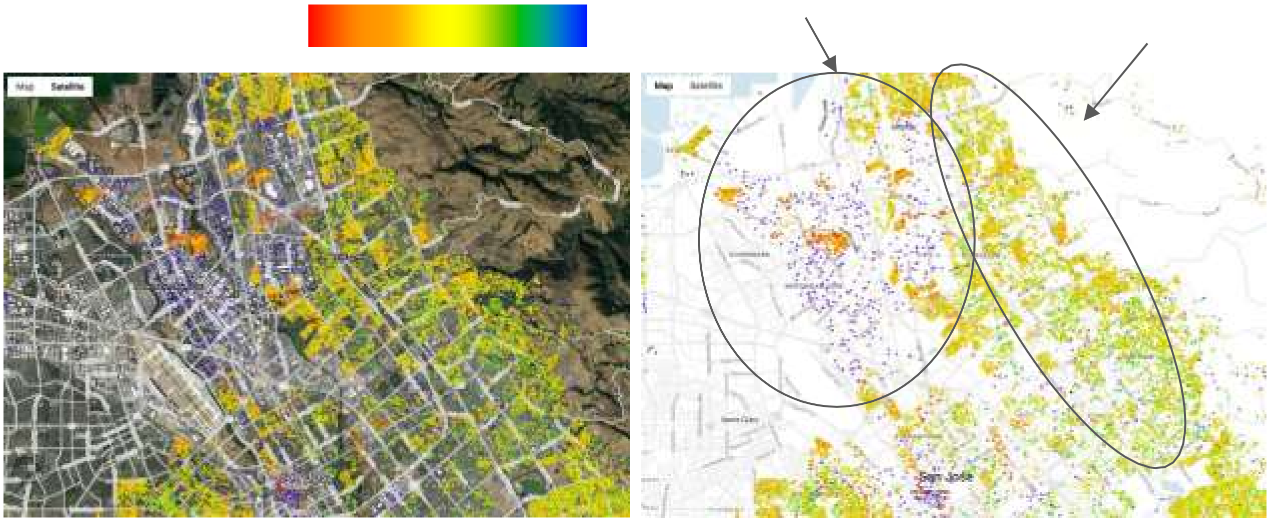
Kevala's PV adoption model then carried these trends in payback period and adoption forward when predicting future adoptions. Figure 22 illustrates the predicted payback periods of future adopters compared to those not predicted to adopt by 2035. As expected, calculated payback periods under the modified BTM tariffs are longer than under the existing BTM tariffs, but the difference is only about a year or less, on average. Therefore, the modified BTM tariffs lead to lower adoption propensity scores—but not dramatically lower. The vast majority of customers still adopt PV even with the higher payback period, leading to the relatively low 4.3% reduction in installed capacity overall.

Figure 22: Distributions of forecasted payback periods of (a) forecasted adopters by 2035 and (b) non-adopters over all three IOUs, showing the residential and commercial sectors. Forecast payback periods are calculated with bill and system costs using 2022 values. *(Source: Kevala)*



To visualize the detailed, premise-level PV size and adoption modeling, Figure 23 illustrates each PV system predicted for adoption in the area shown by 2035 under the existing BTM tariffs. Comparing neighboring residential and commercial and industrial (C&I) areas, differences in PV size and concentration are evident. The residential area is densely packed with small (~3 kW DC-6 kW DC) systems. In contrast, the C&I area, which has higher loads and much larger parcels, is scattered with large (> 12 kW DC) PV systems. This level of geographic fidelity underpins the rest of the feeder and IOU-aggregate results.

Figure 23: PV system adoption in a primarily urban area of PG&E's service territory by 2035, existing BTM tariffs. *(Source: Kevala)*



Zooming out to the state level, the final distribution of systems throughout all three IOUs are mapped in Figure 24 for 2025, 2030, and 2035 for the Existing BTM Tariffs scenario. PV adoption overlaps the population centers as expected, with densely populated areas receiving a higher and higher concentration of PV installations over the course of the forecasting horizon.

A few impacts of the calibration method on the results are important to note. First, as Figure 25 shows, the average size of PV systems adopted *decreases* over the forecasting horizon. This trend is likely caused by the adoption model and calibration method.[77] The adoption model includes premises' peak load as a predictor of adoption—premises with high loads are assigned larger potential PV systems by the sizing algorithm and higher adoption propensity scores by the adoption model. When adoption propensity scores are ranked during calibration, these premises are ranked higher and adopt first. This also contributes to the clustering of late adopters in densely populated areas for premises with low load, where the proposed PV system sized to offset that load is very small.

[77] The Part 1 Study looked at each DER adoption independently and therefore will not capture those premises that install up to 150% of load. Kevala can examine PV sizing in Part 2. Further, Kevala did not make any assumptions about customers expanding their current PV systems.

Figure 24: Concentration of PV adoptions throughout California in (a) 2025, (b) 2030, and (c) 2035 under the Existing BTM Tariffs scenario *(Source: Kevala)*

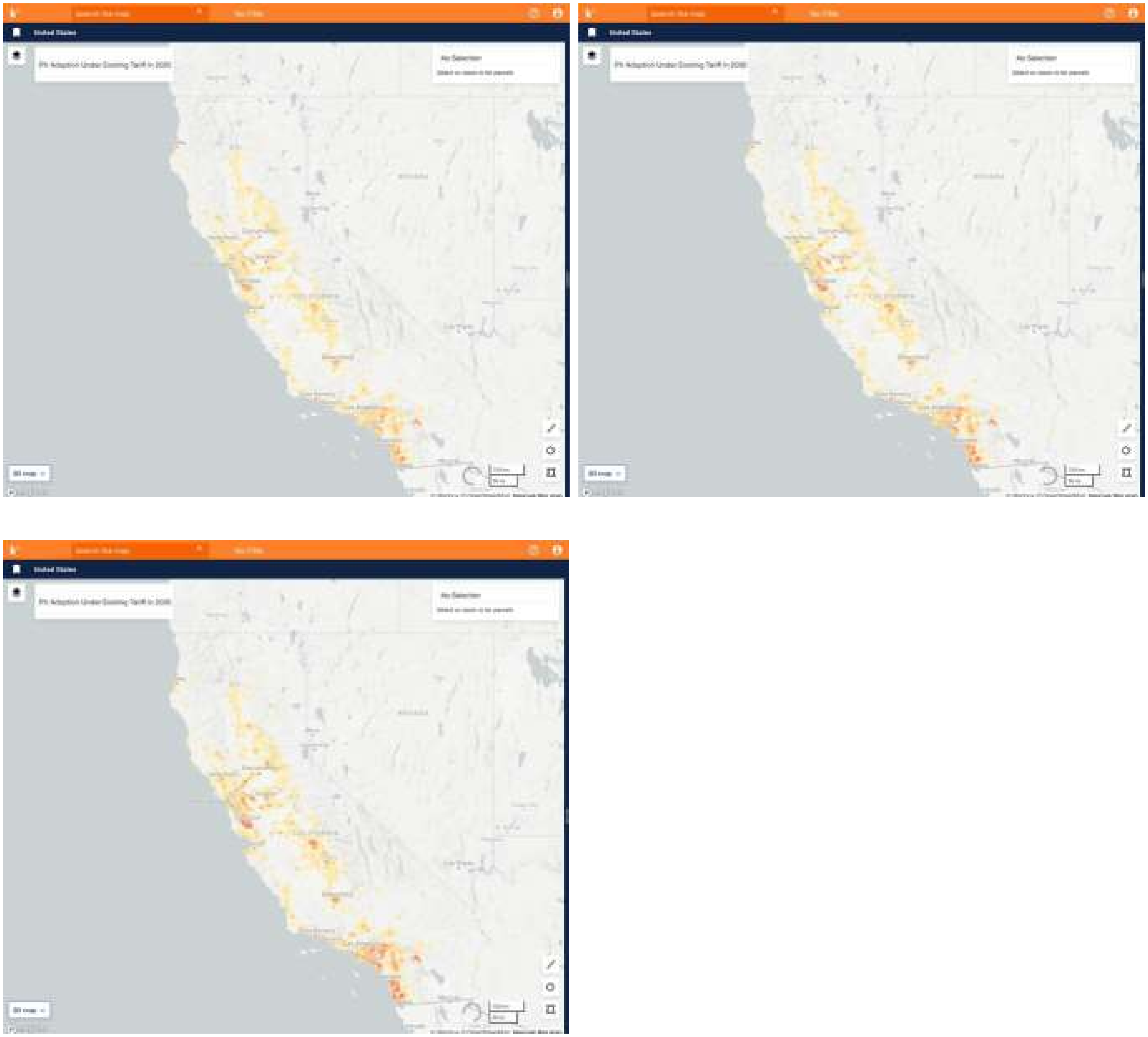
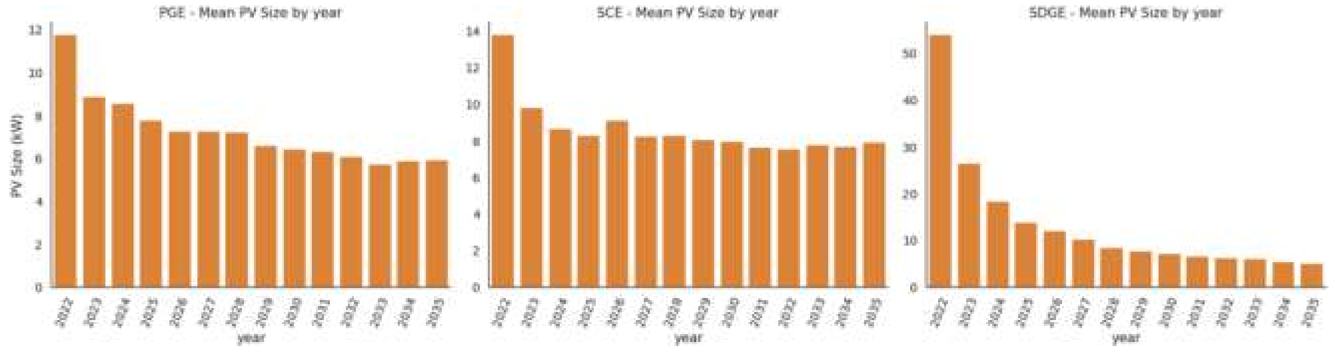


Figure 25: Average size (kW DC) of PV systems adopted by year in the forecasting horizon by IOU *(Source: Kevala)*



Second, Figure 20 shows, there is a significant jump in adoptions in 2022, before the rest of the years smoothly follow the 2021 IEPR targets for the Existing BTM Tariffs scenario. This jump is due to discrepancies between the interconnection data of historical PV installations, which is known to have data gaps, and the 2021 IEPR estimate of PV production for that year. To reconcile those two data sources, Kevala sees 2022 as an adjustment year, after which adoptions proceed much more gradually for 2025, 2030, and 2035.

Kevala also examined the percent contribution of PV to the net-load of the feeder. Figure 26 shows the distribution of the ratio of PV peak load and the net-load in the peak hours. This figure is a box and whiskers chart. The x-axis shows the individual scenarios by study year while the y-axis shows the range of percent contribution of the DER to peak load. Peak load is the estimate of the maximum load on a feeder after the DERs have been adopted. The "x" in each block denotes the median, while the boxes designate the range of the lower and upper quartiles. The wider the range of values, the more diverse the impact. This figure shows the values for 2025, 2030, and 2035. The values for 2025 demonstrate that the distribution of PV contribution to the peak load from the Part 1 Study is narrower, for all scenarios, than the distribution of the same ratio for the GNA. The figure also shows that the contribution to peak load of PV by 2035 is greatly reduced. That is, even though PV peak capacity is increasing over this period, the peak of net-load peak is also moving to hours in the late evening when PV capacity is not able to contribute to reducing that peak load.

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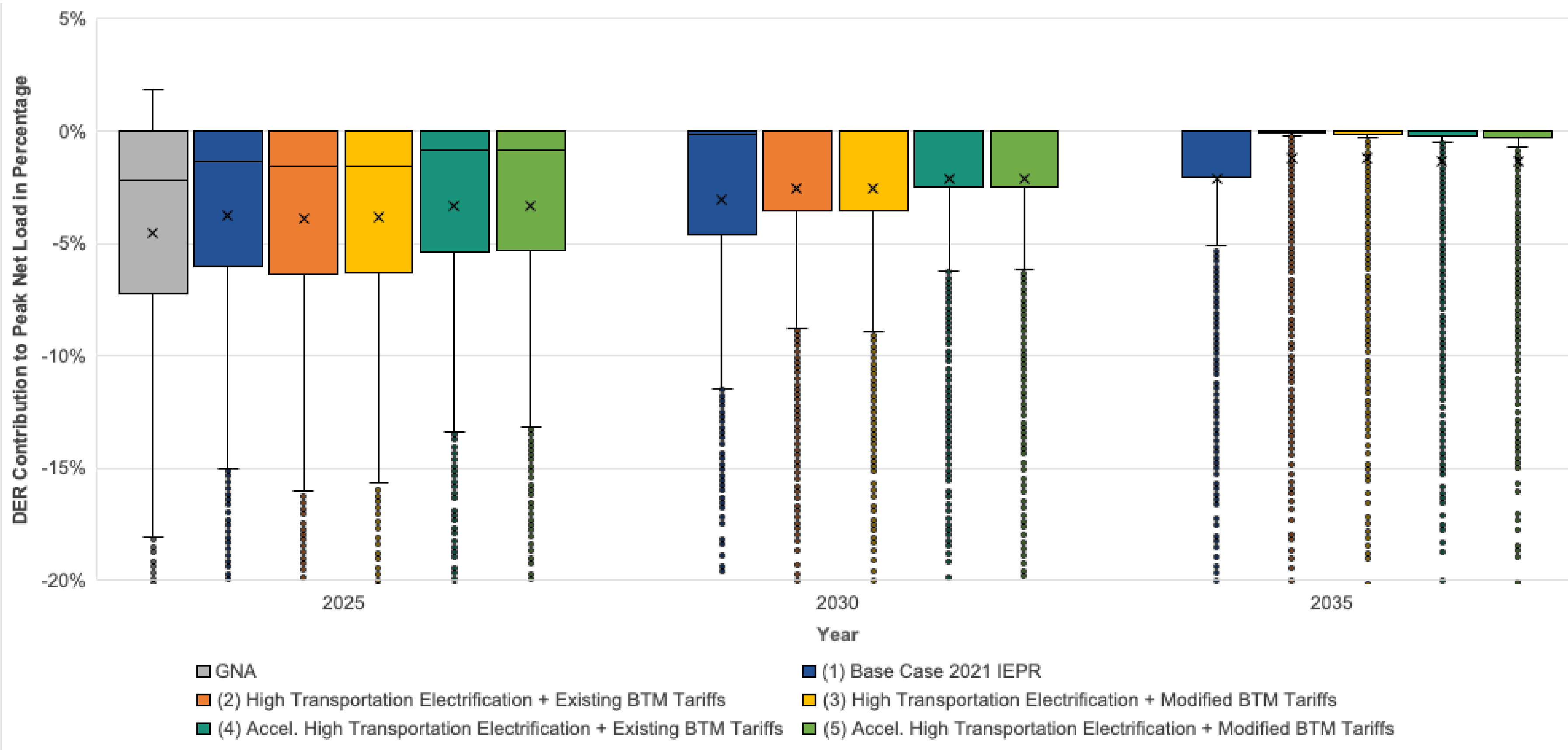
Figure 26: Distribution of PV capacity contribution to peak load (*Source: Kevala*)



Key takeaways from the PV analysis include:

- Changing from the existing BTM tariffs to the modified BTM tariffs is estimated to only reduce installed PV capacity by 4.3% by 2035.
- Shorter payback period is correlated with PV adoptions, but it is not the only or main predictor of adoption in California.
- Due to the current calibration method, the size of PV systems adopted is modeled as decreasing over time, which might overlap with a real-world trend, and a jump in adoptions is modeled in 2022, which is due to data discrepancies.

2.3.2. BTM BESS

To model BTM BESS, Kevala integrated multiple datasets including socioeconomic and geospatial datasets and Kevala's own premise-level PV models. Distributed BESS adoption and operation is tightly tied to PV adoption and usage. By using the outputs of the PV adoption and behavior models as inputs to the BESS models, Kevala was able to directly capture the interactions between these DERs with much higher resolution and granularity than is commonly used.

In developing the BESS adoption model, whether or not a premise has PV was by far the most important feature for predicting BESS adoption. In tandem, for residential customers, Kevala assumed that residential BESS systems are operated to maximize self-consumption of PV. Based on the real-world correlation and this behavior modeling assumption, Kevala further assumed BTM BESS must be adopted with PV for residential premises—that is, BESS must be adopted simultaneously with or after PV. In contrast, the model permits non-residential premises to adopt BESS systems with or without PV, assuming non-residential premises will use BESS to minimize peak demand periods and thus demand charges.

Figure 27 illustrates the BESS adoption results through 2035 for PG&E. The majority of BESS systems are adopted by residential premises. Additionally, almost all BESS adoption includes a PV as well. This is in part due to the high rate of adoption seen in historical data, exacerbated by Kevala's assumption requiring residential BESS to be adopted with PV and that most adopters are residential; this assumption may change due to resiliency-based adoption. While shown here for PG&E, the trends seen in SDG&E and SCE are the same.

Figure 27: (a) MW BESS adopted by customer class and (b) MW BESS adopted with or without PV for PG&E. Trends are similar for the other two IOUs. *(Source: Kevala)*

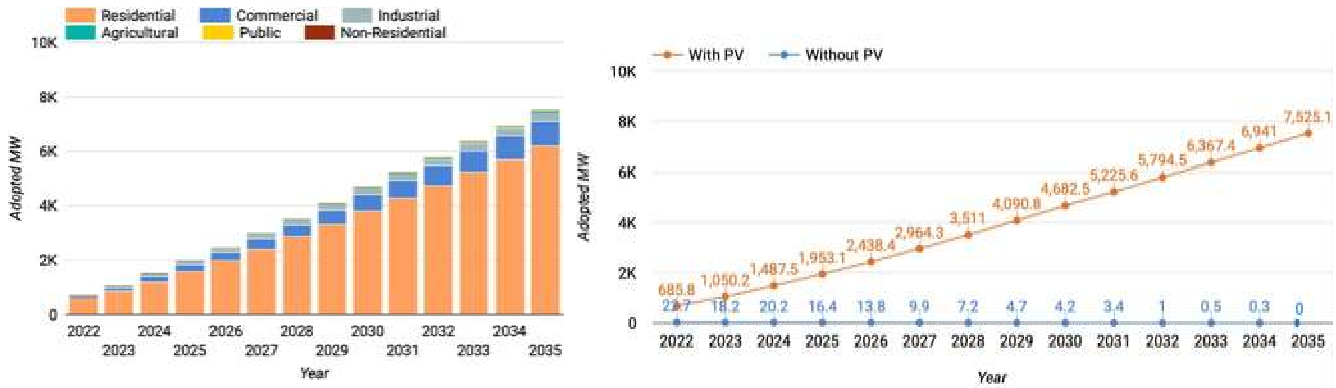
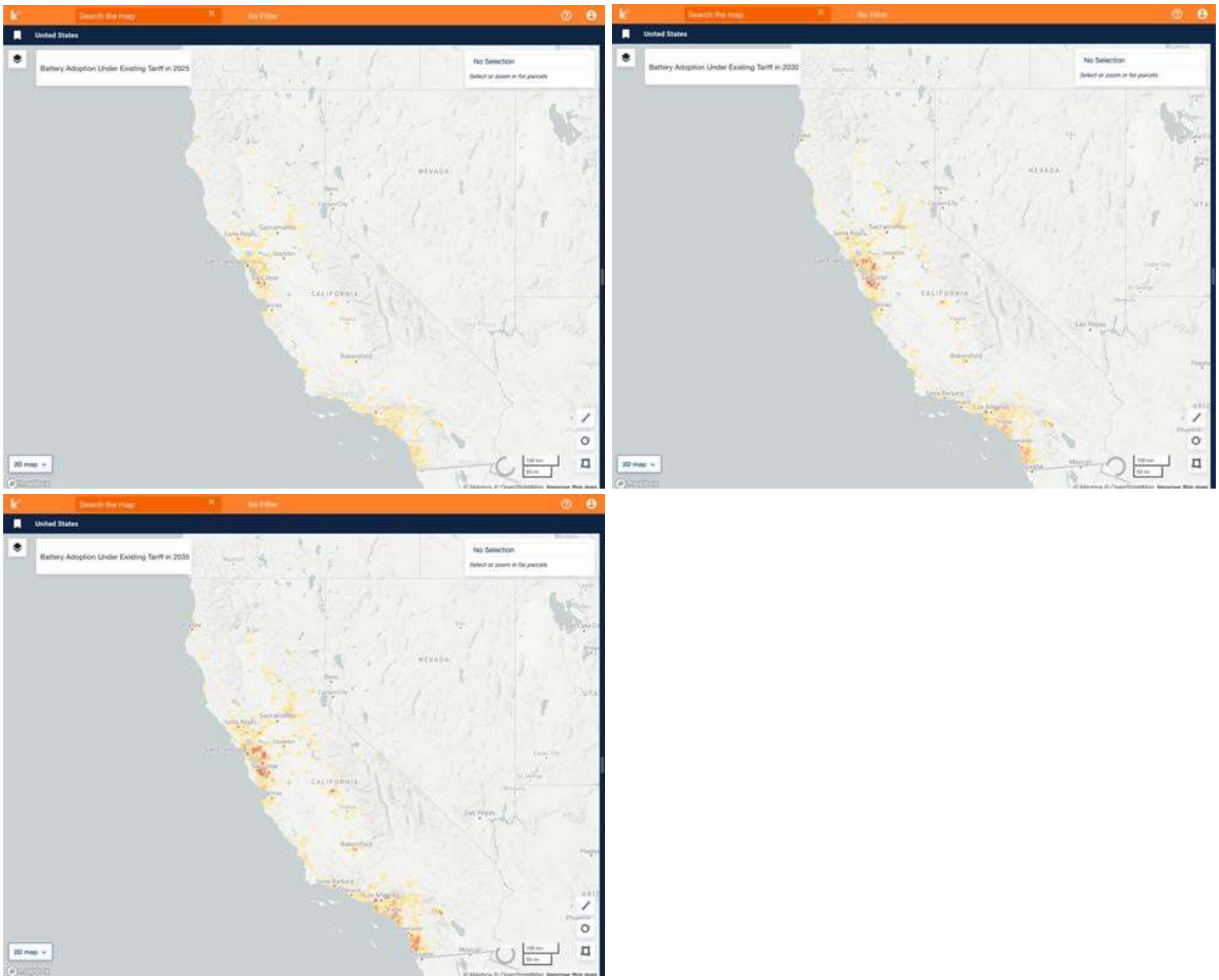


Figure 28 maps these BESS adoptions throughout all three IOUs for 2025, 2030, and 2035. The concentration of BESS systems follows that of PV systems in highly populated areas, with the highest concentrations seen in the Bay and San Diego areas by 2035.

Figure 28: Concentration of BESS adoptions throughout California in (a) 2025, (b) 2030, and (c) 2035 under the Existing BTM Tariffs scenario *(Source: Kevala)*

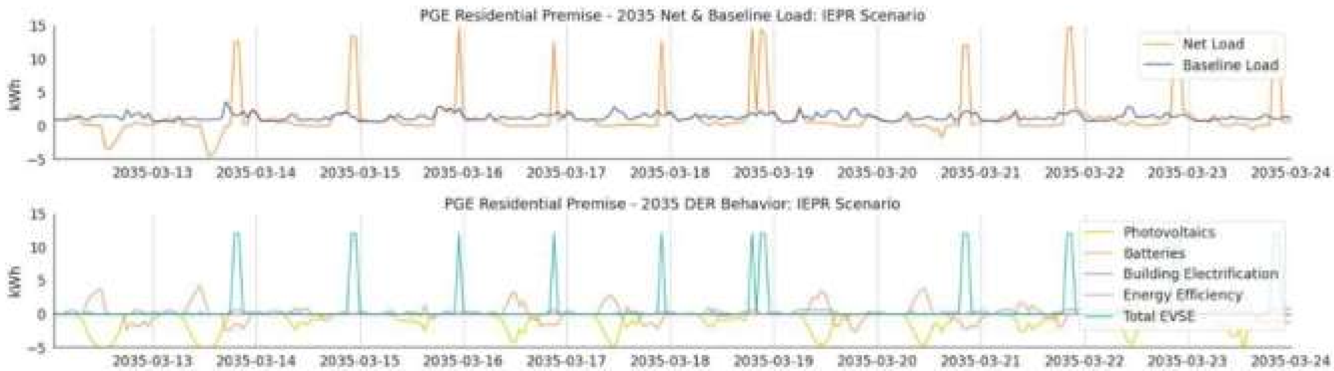


BESS is one of the most versatile DERs in terms of its control algorithms, and while the most popular control algorithms are yet to be determined as the industry matures, its behavior profile depends entirely on the current modeling assumptions. For example, Figure 29 illustrates the baseline load, net-load, and demand modifier profiles for a residential premise with PV, BESS, and two Level 2 (L2) EV chargers.[78] Under current modeling assumptions, the BESS is assumed to optimize self-consumption of PV generation given the baseline load profile. This results in a flat, net-zero net-load profile around midday on many days. However, the BESS control algorithm used for the Part 1 Study did not account for EV charging, thus any evening demand spike caused by EV

[78] Figure 29 is based on modeled data and is illustrative based on the specific assumptions described. Different seasonal, time horizon, or specific DER adoption projections—for example, policy-based building electrification targets adopted by CARB in 2022 and reflected in demand scenarios adopted in the 2022 IEPR—can be explored in the Part 2 Study.

charging was not directly mitigated by the BESS. Specifically, the customer's BESS is not assumed to be used for the customer's EV charging needs; however, the customer is expected to discharge their BESS during the high price evening peak while charging their EV during the lower priced late evening or early morning hours.

Figure 29: Baseline load, net-load, and demand modifier profiles for residential premise that has adopted PV, BESS, two large EVs, and two L2 chargers *(Source: Kevala)*



Kevala also examined the percent contribution of BESS to the net-load of the feeder. A box and whiskers chart, Figure 30 shows the distribution of the ratio of BESS peak load and the net-load in the peak hours. This figure shows the values for 2025, 2030, and 2035. The values for 2025 demonstrate that the distribution of BESS contribution to peak load from the Part 1 Study is slightly narrower, for all scenarios, than the distribution of the same ratio for the GNA. The figure also shows that the contribution to the peak load of BESS by 2035 increases. That is, BESS discharging can be adjusted to offset the peak load if given the right signal to charge at low net-load periods and discharge during high periods.

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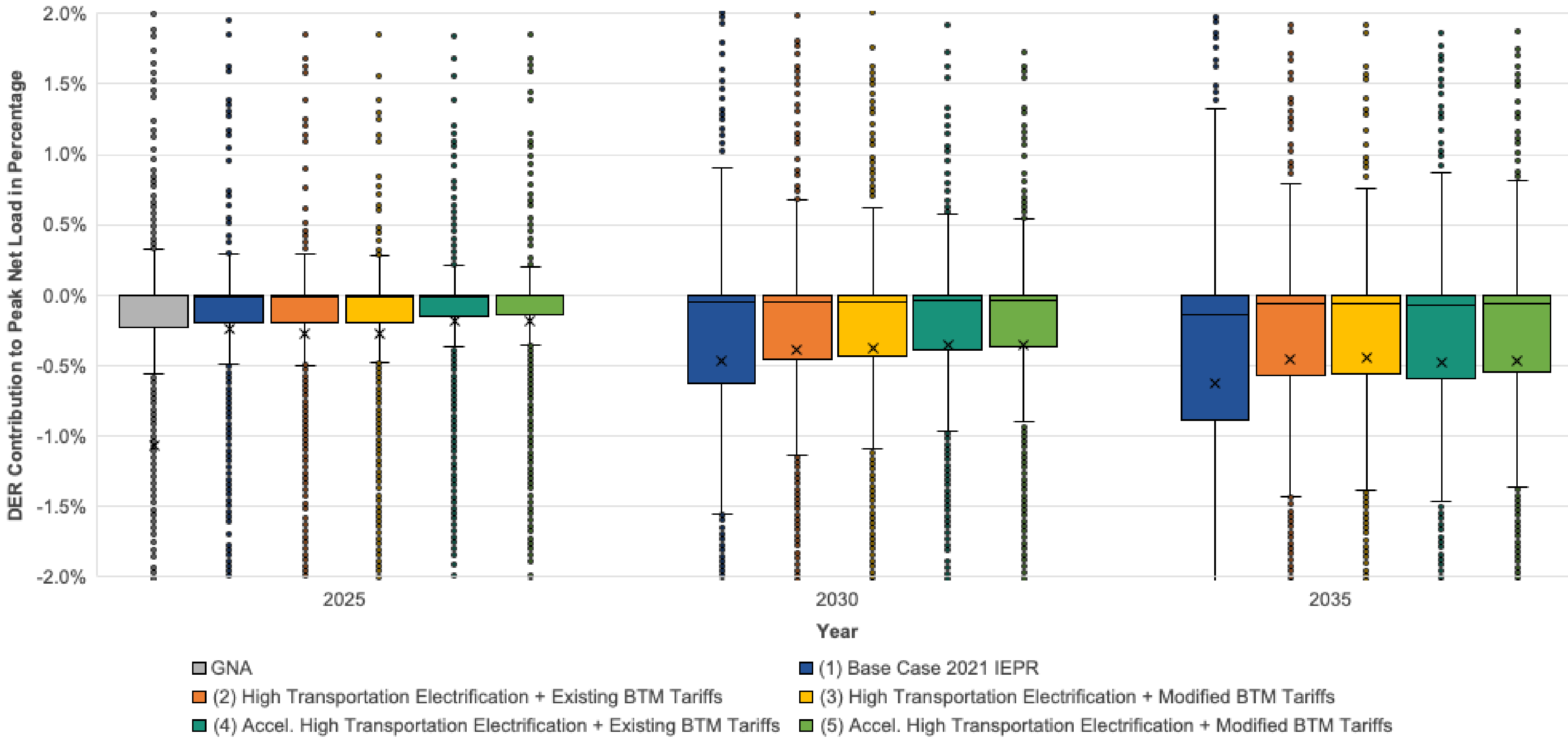
Figure 30: Distribution of BESS capacity contribution to peak load *(Source: Kevala)*



Key takeaways from the BESS analysis include:

- Over 1 million customers have installed PV systems across the three IOUs, providing a wealth of information on adoption propensity, while only a fraction of those customers have installed batteries. This may impact the quality of future adoption predictions based on this data.
- The vast majority of BESS are predicted to be adopted along with PV, which reflects a real-world trend, is consistent with the recent Self-Generation Incentive Program (SGIP) Battery Storage Market Assessment Study, and is reflected in Kevala's assumption in the Part 1 Study that residential premises that adopt storage also adopt PV.
- BESS behavior is assumed to optimize self-consumption of PV (residential) or reduce peak demand periods (non-residential).

2.3.3. EE and BE

To model EE and BE, Kevala integrated multiple datasets including socioeconomic, state studies of BE- and EE-estimated savings, and premise-level AMI data. Distributed EE adoption and energy savings are highly correlated to premise consumption. Due to limited data on BE participation and potential, Kevala assumed BE adoption to be driven by the same factors that drive EE.

The EE and BE adoption calibration follows the 2021 IEPR consumption-level forecast by sector and IOU service territory. EE and BE program delivery and adoption are highly variable by sector due to sector-specific behaviors and the various IOU and state-targeted programs. Furthermore, the 2021 IEPR demand modifiers for EE (additional achievable energy efficiency, or AAEE) and BE (additional achievable fuel switching, or AAFS) are derived from detailed analysis. These analyses, for example, result in zero AAFS impacts over the forecast period for the agricultural sector. Even if Kevala adoption modeling indicates potential for the agricultural sector, the top-down target adoption rate will be zero.

The end result of the EE analysis provides insights into the impact of EE to offset electrification at a feeder level. The electrification comes from BE and EVs (see Section 2.2).

Energy Efficiency

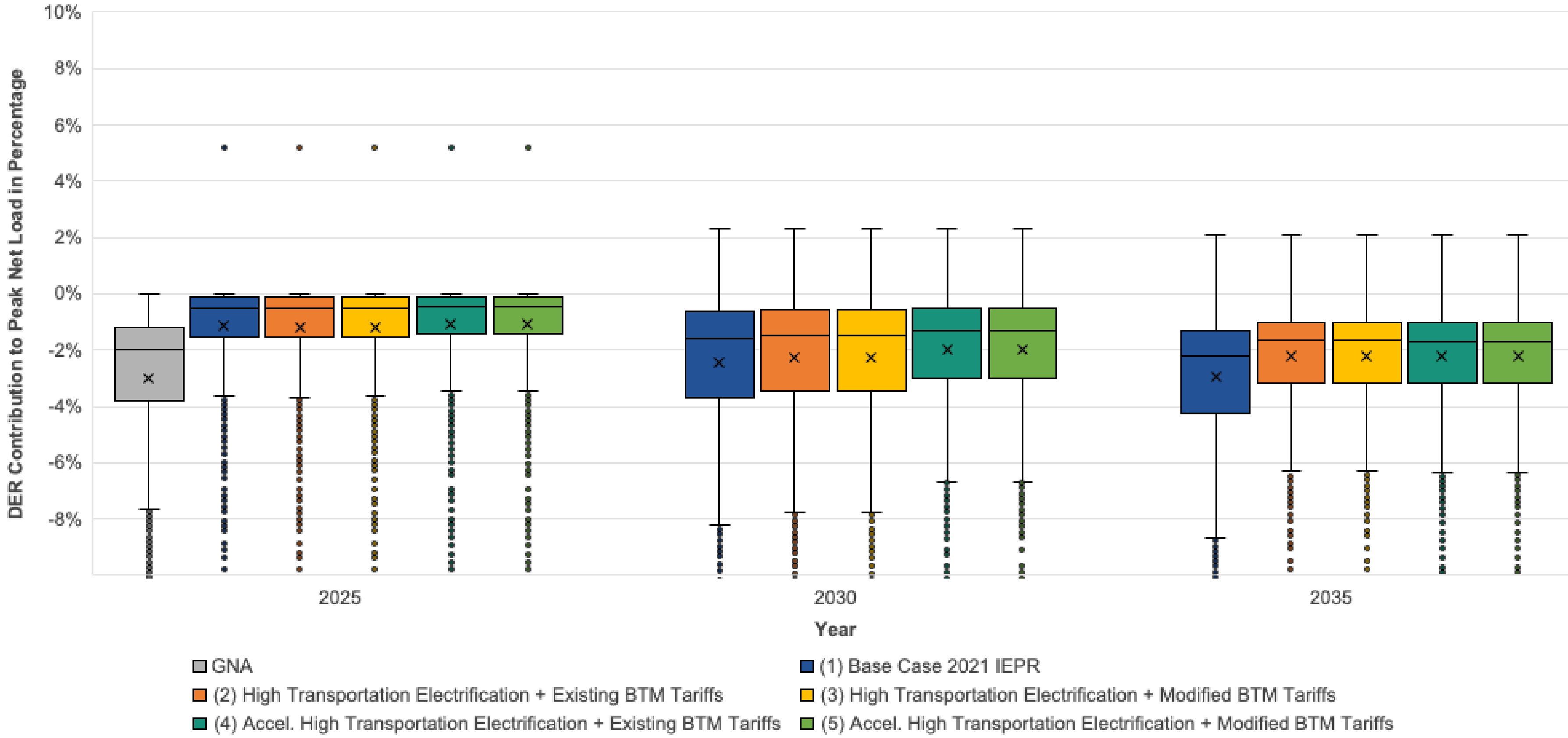
Because EE has been a prevalent demand-side resource for a few decades, the value is embedded in the baseline forecast; therefore, only future, newly adopted EE is included. EE potential is highly variable on a premise-by-premise level, so the current results focus on the feeder-level impacts.

One significant outcome of the analysis is that the current adoption propensity model targets larger energy-consuming premises first based on historical data analytics.[79] Results tend to lean heavily on the larger residential premises.

Kevala also examined the percent contribution of EE to the net-load of the feeder. A box and whiskers chart, Figure 31 shows the distribution of the ratio of EE peak load and the net-load in the peak hours. This figure shows the values for 2025, 2030, and 2035. The values for 2025 demonstrate that the distribution of EE contribution to peak load from the Part 1 Study is much narrower, for all scenarios, than the distribution of the same ratio for the GNA. The figure also shows that the contribution to the peak load of EE in 2030 is greater as EE is forecasted to increase in the 2021 IPER; however, it does not continue to increase through 2035 as net-load increases during that same time due to increased electrification, particularly for the High Transportation Electrification scenarios. That is, because EE savings are highly correlated to energy use at the premise, the contribution of EE toward reducing the net-load remains significant even as the timing of the peak load shifts to later in the day.

[79] See Appendix 7 for adoption evaluation parameters.

Figure 31: Distribution of EE capacity contribution to peak load (*Source: Kevala*)



Key takeaways from the EE analysis include:

- Nearly 100% of PG&E and SDG&E residential premises adopt EE.
- SCE has a lower penetration because residential premise adoption depends on the distribution of residential unit energy consumption.
- The high level of residential adoption reflects the mix of EE—codes and standards programs, behavior, and operations and maintenance.
- Current analysis is less about independent premise-level adoption and more to reflect what happens at a feeder.

Building Electrification

BE potential is highly variable on a premise-by-premise level and depends on existing non-electricity end uses. For residential customers, there is a need to consider existing electric panel service levels, adding barriers that do not exist for EE. For the current study, results focus on the feeder-level impacts.

Because BE uses the same adoption propensity model as EE, the model targets larger energy-consuming premises first based on historical data analytics.[80] Results tend to lean heavily on the larger premises, reducing commercial penetration; however, the patchiness of adoption reflects the cyclical nature of non-residential adoption and the novelty of commercial adoption of BE[81] (industrial adoption is small in the IEPR forecast).

As with EE and other DERs, Kevala examined the percent contribution of BE to the net-load of the feeder. A box and whiskers chart, Figure 32 shows the distribution of the ratio of BE peak load and the net-load in the peak hours. This figure shows the values for 2025, 2030, and 2035. Unlike the BTM PV, BESS, and EE comparisons shown previously, the GNA does not consider increased loads due to BE. Nevertheless, the contribution of BE to peak load over time is clearly demonstrated as the percentages increase over time. However, the impact of other electrification can also be seen in this figure as the percentage of BE contribution declines noticeably for the other four scenarios.

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[80] See Appendix 8 for adoption evaluation parameters.

[81] Commercial end users of natural gas that are targets for electrification include restaurants that are generally hard to reach for EE but have additional barriers to electrification. Similarly, for larger buildings, transitioning gas heating systems to electricity is an emerging technology.

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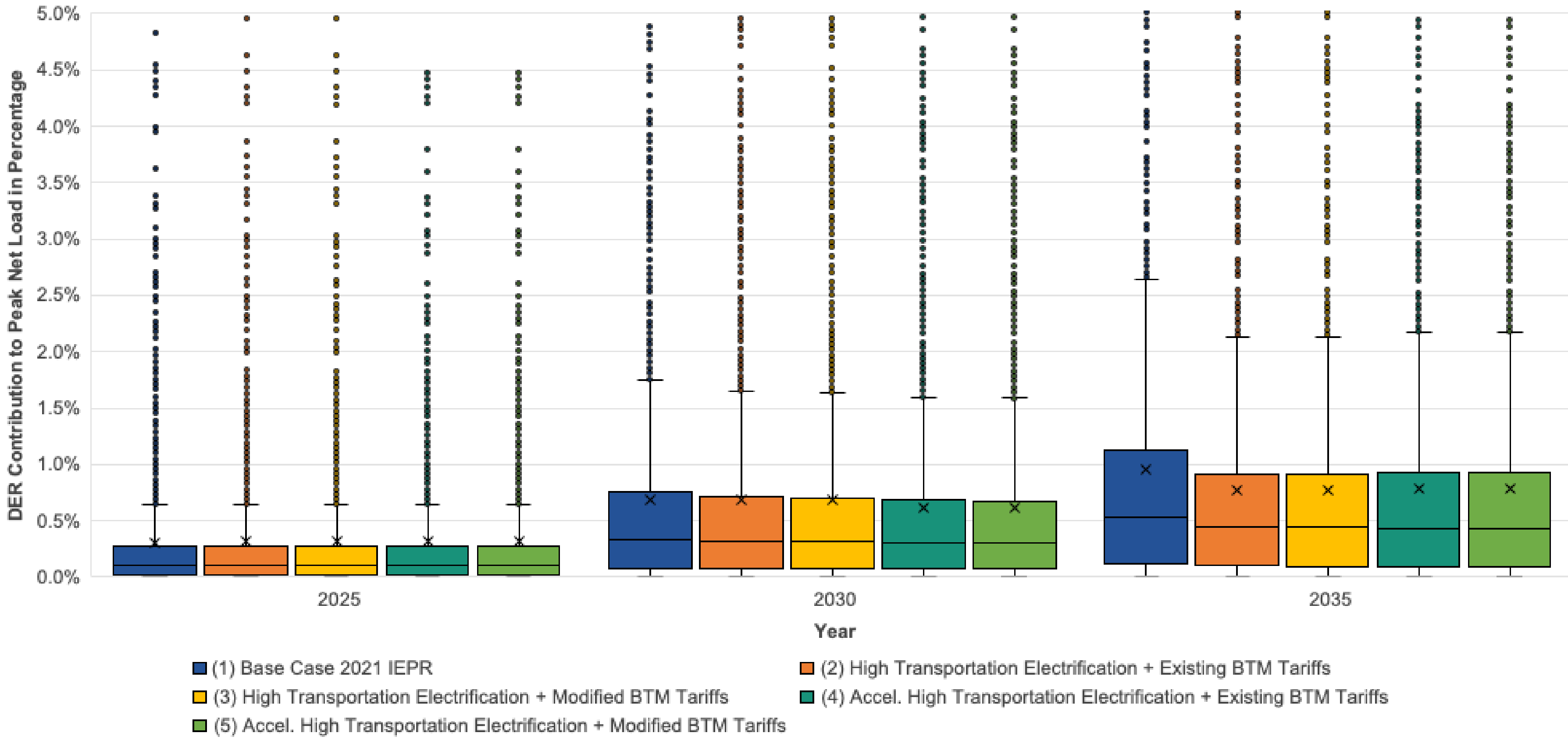
Figure 32: Distribution of BE capacity contribution to peak load *(Source: Kevala)*



Key takeaways from the BE analysis include:

- Modeling BE adoption is highly dependent on the EE algorithms as a proxy because BE adoption has been limited to date.
- Peak load depends on the electrified building load profile, which is typically different than the summer peak.
- Adoption is primarily in residential areas. Commercial adoption varies in magnitude year of year primarily due to impacts achieved in large buildings which meet calibration targets.
- Adoption follows EE feeder distribution but at a lower level of penetration. Feeders that are impacted indicate more adoption in geographically (same feeder level) constrained areas.
- Calibration is at the sector level for 2021 IEPR energy consumption, with minimal-to-no adoption in industrial and agricultural sectors.

2.3.4. EVs and EVSE

Kevala coordinated with the CPUC to identify three CARB and CEC light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) ZEV adoption forecasts to serve as input targets for the base case and four alternate Part 1 Study scenarios. Table 1 (presented in Section 1.2.3) summarizes the CEC and CARB ZEV adoption forecasts and the associated vehicle counts that were used in the study. Kevala selected the three CARB and CEC ZEV adoption forecasts for this Part 1 Study because they represent a meaningful range of ZEV adoption levels that align with California policy goals and market forecasts.

Across the LDV, MDV, and HDV duties, these ZEV adoption targets contained 27 duty, powertrain, and vehicle type combinations, each of which had differing energy usage characteristics and demands. Kevala used an array of premise, demographic, energy, and vehicle registration data to allocate the adoptions down to individual, EV-eligible premises using the adoption methodologies described in Section 3.4.6 and detailed in Appendix 9.

As the ZEV adoption forecast data in Table 1, the total number of 2035 LDVs adopted in the Base Case are roughly one-third the level of the vehicle adoption counts in the High Transportation Electrification and Accelerated High Transportation Electrification scenarios. However, the 2035 MDV and HDV ZEV adoption levels do not follow the same pattern of adoption across the scenarios as the LDV adoption. For MDV and HDV ZEV adoptions, the High Transportation Electrification scenario contains the lowest level of 2035 adoptions, with the level of adoptions between the Base Case and the Accelerated High Transportation Electrification cases being within roughly 1% of each other.[82]

Figure 33, Figure 34, and Figure 35 contain the 2025, 2030, and 2035 adoption counts for LDV and MDV and HDV ZEVs for all three IOUs for the Base Case, High Transportation Electrification, and Accelerated High Transportation Electrification scenarios, respectively.

In the Base Case scenario, the LDV ZEV adoption rate occurs at roughly the same level of acceleration across the forecast horizon, while the LDV adoption rate in the High Transportation Electrification scenario has the steepest rate of increase from 2025-2030 and again from 2030-2035. The High Transportation Electrification scenario also reaches the highest level of total LDV ZEV adoption by 2035. The LDV adoption path of the Accelerated High Transportation Electrification scenario is distinguished from the other two scenarios in that it has the greatest number of adoptions in 2025 and 2030, and then the adoption rate slows slightly compared to the High Transportation Electrification scenario.

The 2035 MDV and HDV ZEV adoptions reach their highest level in the Accelerated High Transportation Electrification scenario and are lowest in the Base Case scenario. Overall, the MDV and HDV ZEV adoption range is between roughly 231,000 and 219,000, or within roughly 6%. The most important differences between the three scenarios' MDV and HDV adoptions are related to the rate of adoption and the composition (i.e., vehicle class breakdowns) across the forecasts. The Base Case and the Accelerated High Transportation Electrification scenarios follow a relatively similar slope of adoption across the forecast horizon, whereas the High Transportation Electrification scenario has a steeper rate of adoption between 2030 and 2035—although this scenario still has the lowest level of overall MDV and HDV ZEV adoption.

[82] The differences in LDV, MDV, and HDV adoption levels between the Part 1 scenarios reflect the different inputs and modeling assumptions used by CARB and the CEC to generate their adoption scenarios and forecasts.

Figure 33: Base Case scenario LDV and MDV/HDV ZEV adoption counts for all IOUs, 2025, 2030, and 2035 *(Sources: CEC, Kevala)*

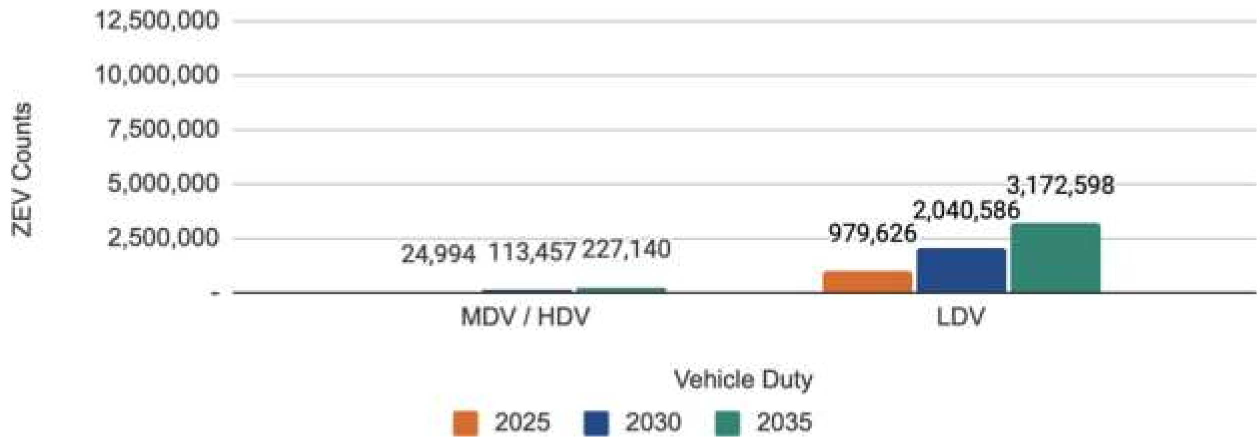


Figure 34: High Transportation Electrification scenario LDV and MDV/HDV ZEV adoption counts for all IOUs, 2025, 2030, and 2035 *(Sources: CARB, Kevala)*

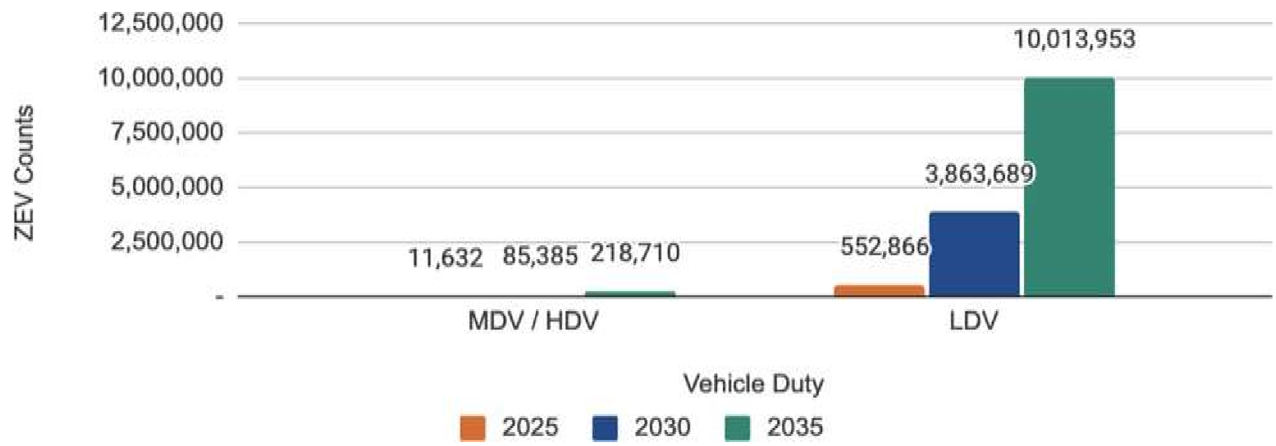


Figure 35: Accelerated High Transportation Electrification scenario LDV and MDV/HDV ZEV adoption counts for all IOUs, 2025, 2030, and 2035 *(Sources: CEC, Kevala)*

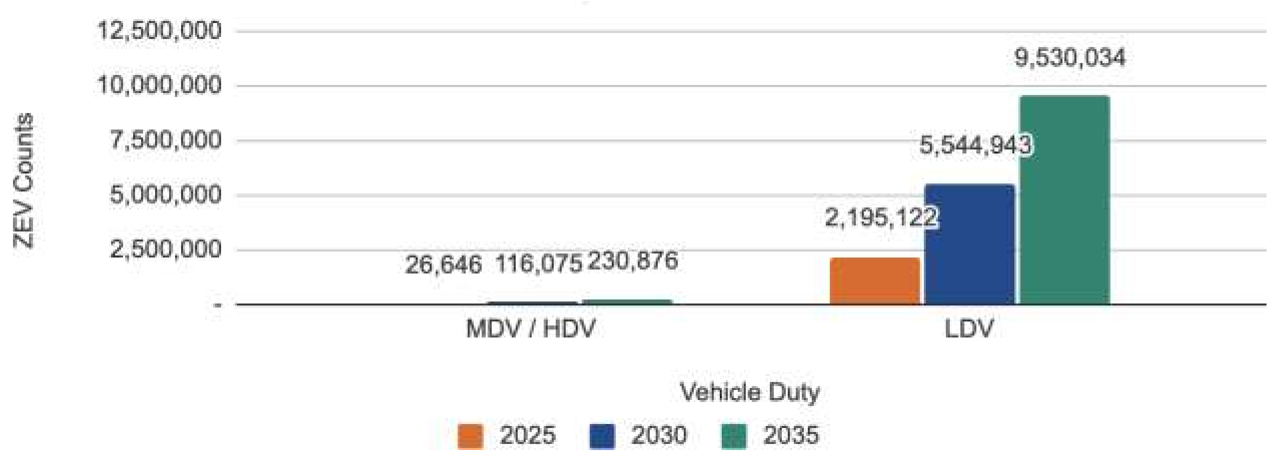


Figure 36, Figure 37, and Figure 38 contain heat maps of geospatial LDV and MDV and HDV ZEV adoptions for PG&E, SCE, and SDG&E. The heat maps represent adoption levels for the Accelerated High Transportation Electrification scenario for 2025, 2030, and 2035, separated by LDV and MDV and HDV ZEV adoptions. The overall trend for adoption is higher uptake in the coastal regions of the three IOUs plus the population and transit-dense inner regions of the state, particularly in the northern Central Valley, plus Fresno, Kern, San Bernardino, and Riverside counties.

Figure 36: PG&E Accelerated High Transportation Electrification scenario ZEV adoption counts, by year and ZEV duty *(Sources: CEC, Kevala)*

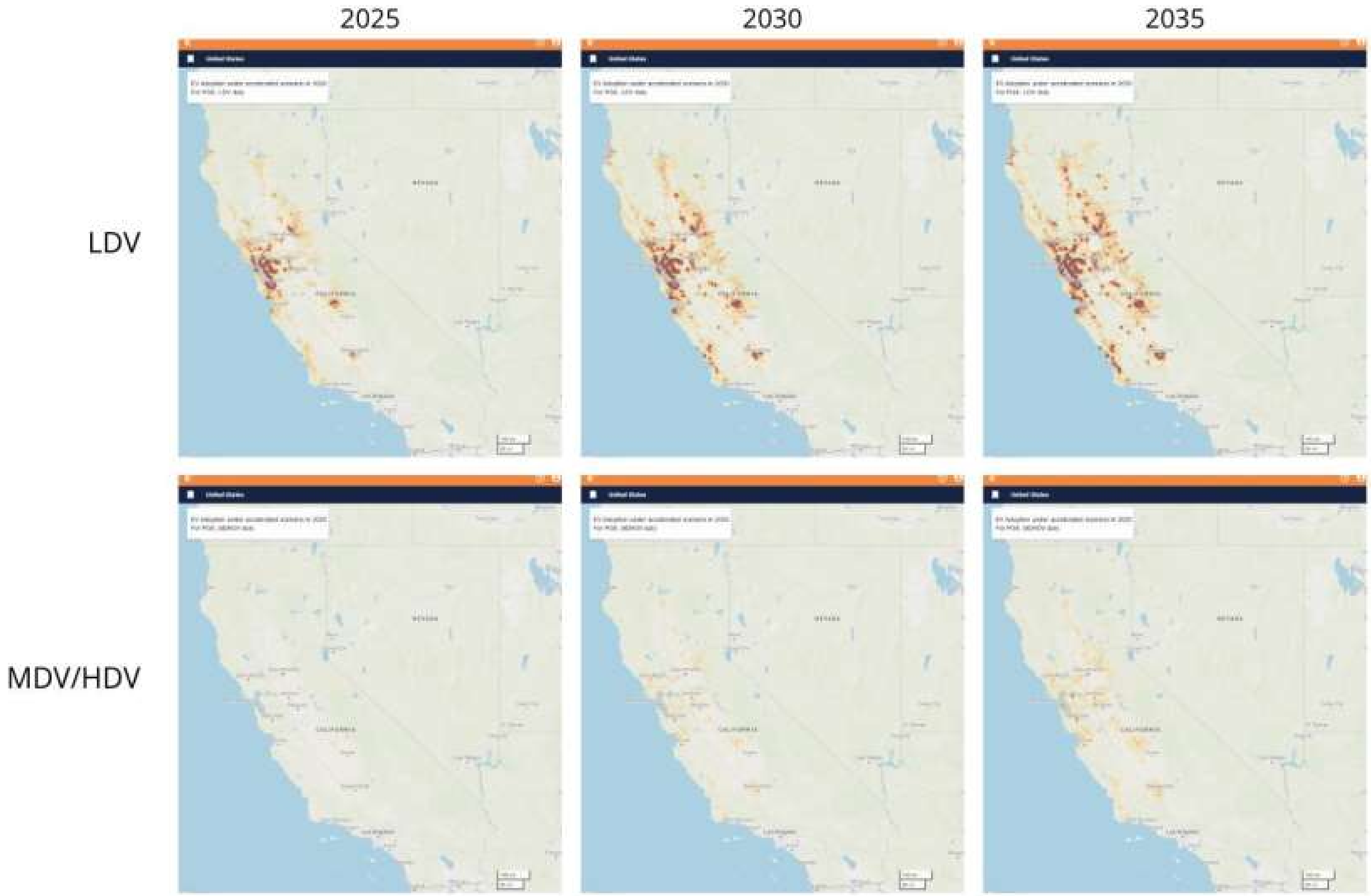


Figure 37: SCE Accelerated High Transportation Electrification scenario ZEV adoption counts by year and ZEV duty *(Sources: CEC, Kevala)*

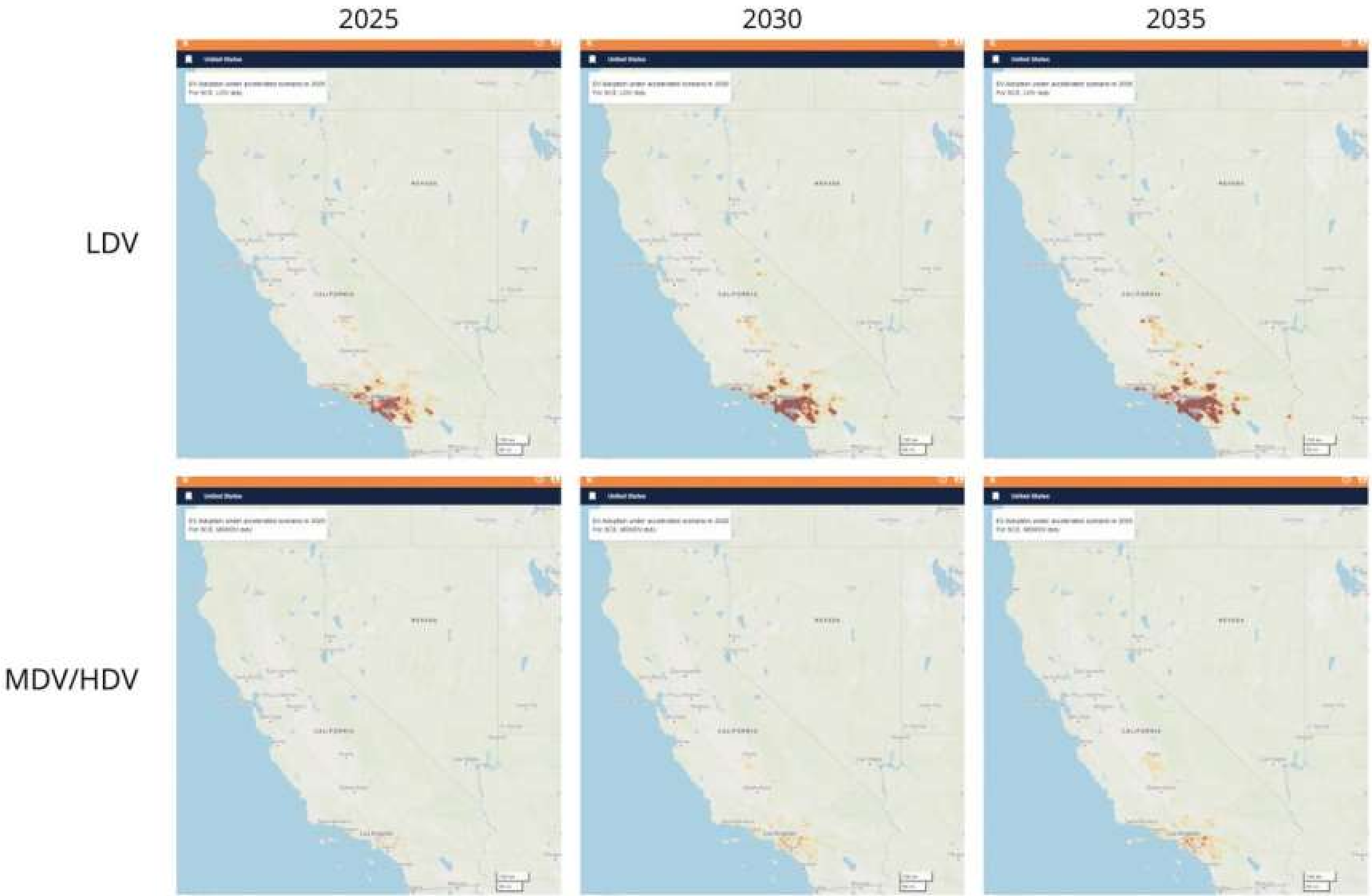


Figure 38: SDG&E Accelerated High Transportation Electrification scenario ZEV adoption counts by year and ZEV duty *(Source: CEC, Kevala)*

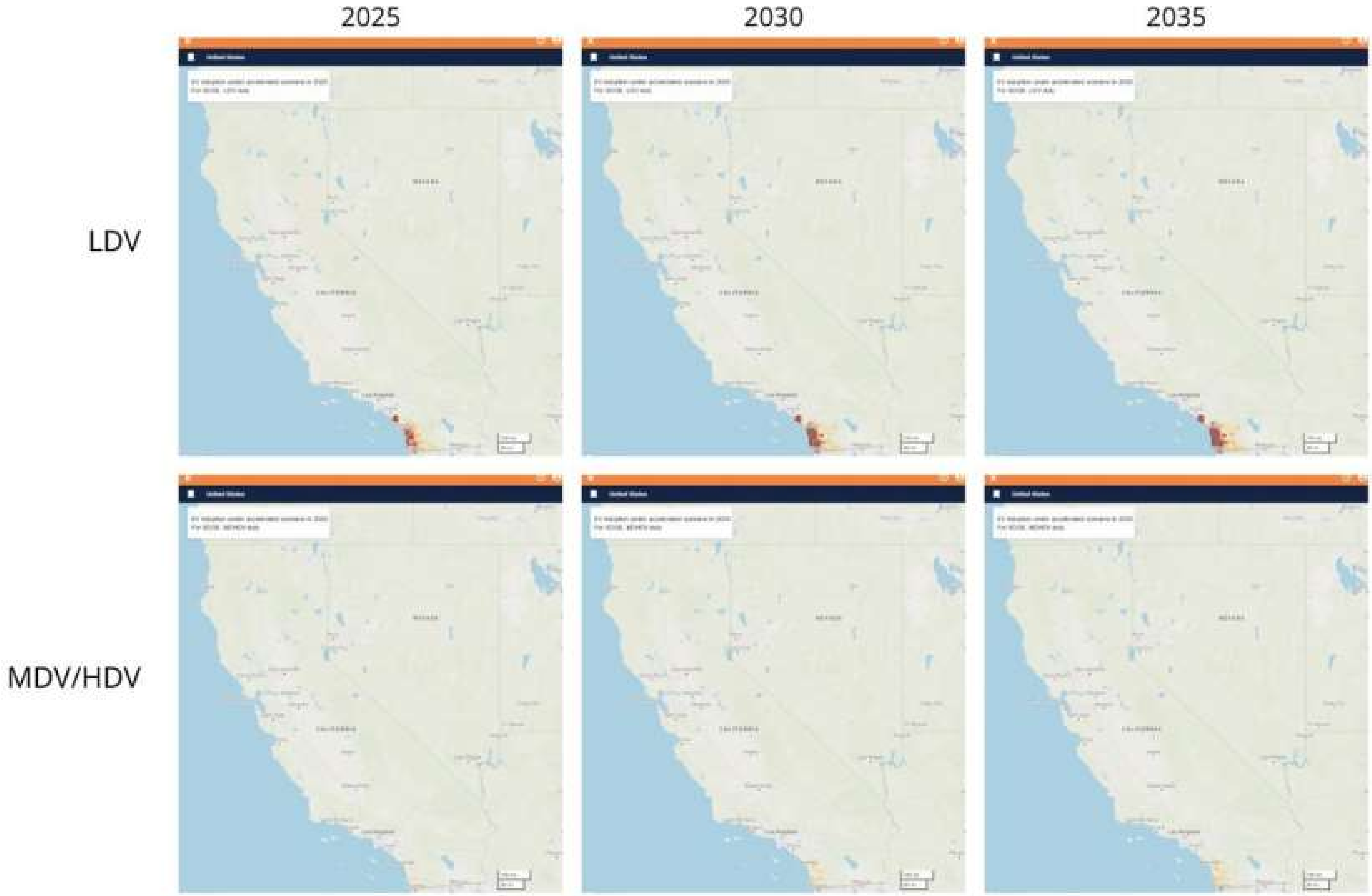


Figure 39, Figure 40, and Figure 41 contain the 2025, 2030, and 2035 EVSE port counts across all charger use cases and demand levels for all three IOUs for the Base Case, High Transportation Electrification, and Accelerated High Transportation Electrification scenarios, respectively.

EVSE ports are separated into three main categories:

- **Primary or secondary charging use cases:**
  - Primary charging use cases are where ZEVs receive the majority of their energy. These include charging at single-unit dwellings (SUDs) and multi-unit dwellings (MUDs) for personal EVs and fleet for fleet EVs. SUD is further classified by TOU and non-TOU, which refers to whether or not the SUD is enrolled on a TOU rate.
  - Secondary charging use cases provide supplemental charging to meet a ZEV's remaining energy needs. These uses cases include public, workplace, and corridor charging, where public and corridor have both LDV and MDV/HDV variations
- **Use case types:** There are six major use cases (SUD, MUD, fleet, public, workplace, and corridor), with several sub-variations based on duty. Use cases are sited based on ZEV adoption levels and premise type.
- **Capacity level:** Each use case has a specified peak demand capacity level (kW) associated with it. For some use cases, this level increases across the forecast horizon. Kevala followed the assumption made in the CEC's AB 2127 Electric Vehicle Charging Infrastructure Assessment – Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030 (Commission Report)" (AB 2127 Report),[83] where L2 capacity remains constant at 6.6 kW, but other use case capacity levels, such as LDV DC fast charging (DCFC) corridor charging, reach 450 kW in 2035.

Kevala calculates the EVSE port counts using the targeted number of ZEV adoptions for each scenario across each year and use case-specific EV-to-EVSE charger ratio contained in the CEC AB 2127 Report's analysis. This approach is described in Section 3.4.6 and detailed in Appendix 9.

As Figure 39, Figure 40, and Figure 41 indicate, the total number of EVSE ports in the three scenarios matches relatively closely to the level of ZEV adoptions across their respective scenarios. Certain factors beyond just the raw number of LDV, MDV, and HDV ZEV counts, such as the powertrain and vehicle class breakdowns, influence the number of ports in each scenario. For instance, although the High Transportation Electrification scenario contains roughly 500,000 more LDV ZEVs in 2035 compared to the Accelerated High Transportation Electrification scenario, the

[83] California Energy Commission, *Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*, July 14, 2021, https://efiling.energy.ca.gov/getdocument.aspx?tn=238853.

share of plug-in hybrid electric vehicles (PHEVs) is much greater in the former compared to the latter. Because PHEVs have lower charging needs, and thus require fewer chargers, the overall port count in the Accelerated High Transportation Electrification scenario is slightly lower than one might have expected without an understanding of these underlying dynamics. It is also noteworthy that fleet chargers are the second most numerous charger use case after SUD-TOU. This is due to the relatively large number of fleet LDV ZEVs that are contained in the CARB and CEC forecasts.

Figure 39: Base Case scenario total EVSE port counts for all IOUs, 2025, 2030, and 2035, with data listed for 2035 values *(Source: Kevala)*

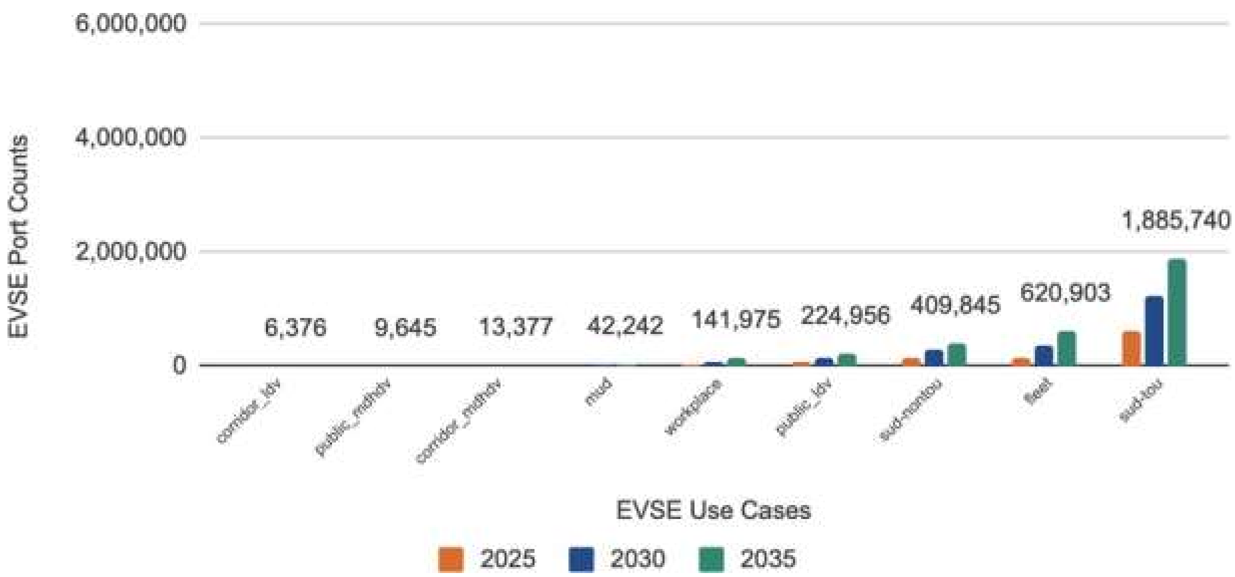


Figure 40: High Transportation Electrification scenario total EVSE port counts for all IOUs, 2025, 2030, and 2035, with data listed for 2035 values *(Source: Kevala)*

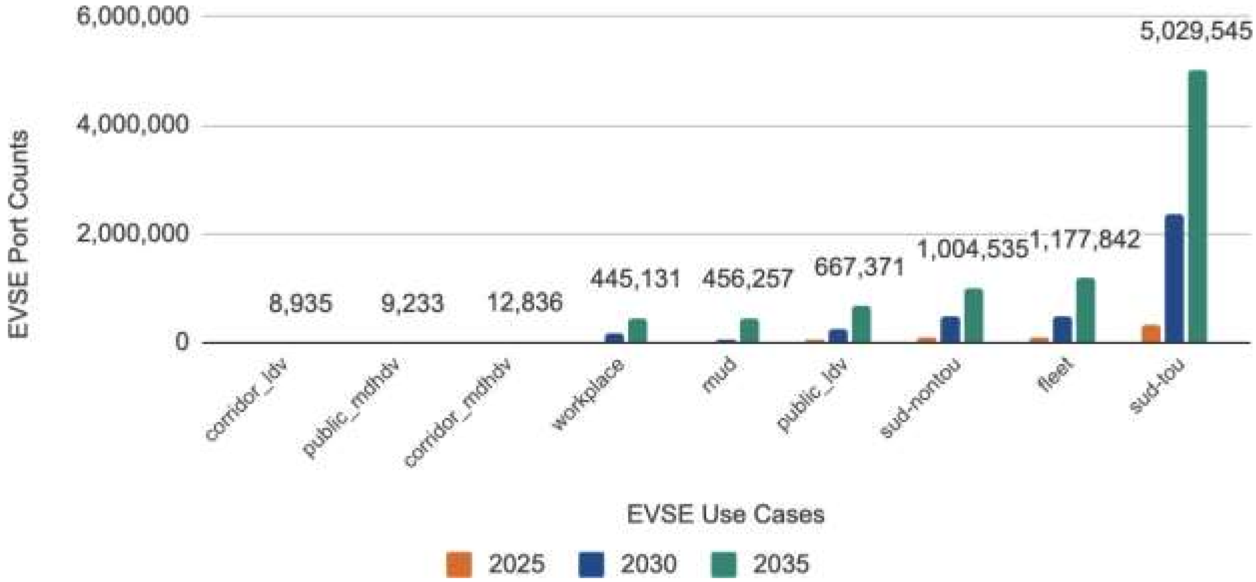


Figure 41: Accelerated High Transportation Electrification scenario total EVSE port counts for all IOUs, 2025, 2030, and 2035, with data listed for 2035 values *(Source: Kevala)*

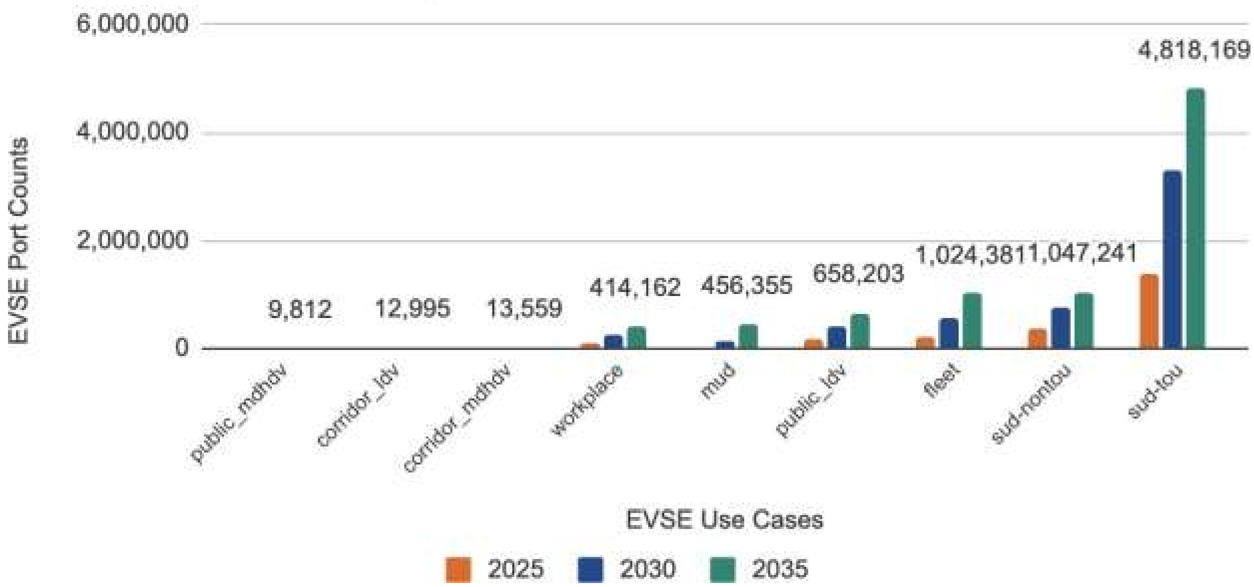


Figure 42, Figure 43, and Figure 44 contain the 2035 EVSE peak day loads across all three IOUs for the Base Case, High Transportation Electrification and Accelerated High Transportation Electrification scenarios, respectively.

Overall, each scenario's all IOU 2035 peak day EVSE loads align with the magnitude of the ZEV adoption forecasts and the accompanying EVSE forecasts that support their respective scenarios' energy requirements. As such, the total EVSE peak load for the Base Case scenario of roughly 10,500,000 kW (10.5 GW) is roughly a third of the peak for the High Transportation Electrification and Accelerated High Transportation Electrification scenarios' peaks, which are 23,800,000 kW (23.8 GW) and 22,800,000 (22.8 GW), respectively.

Across all three scenarios, the timing of the peak hour is the same: 9 p.m. This is the hour when the Part 1 Study assumes the IOUs' TOU rates' off-peak period begins, thus marking the time when the majority of personal and fleet EVs are assumed to begin the bulk of their charging for the next day. The Part 1 Study follows the TOU participation rates assumed in Appendix B of the CEC's AB 2127 Report. The assumption that ZEVs would begin their evening charging at the start of the 9 p.m. off-peak period is a simplifying one that Kevala proposes addressing in the Part 2 analysis to consider more sophisticated ZEV charging management strategies.

Figure 42: Base Case scenario all EVSE loads for all IOUs for 2035 peak day *(Source: Kevala)*

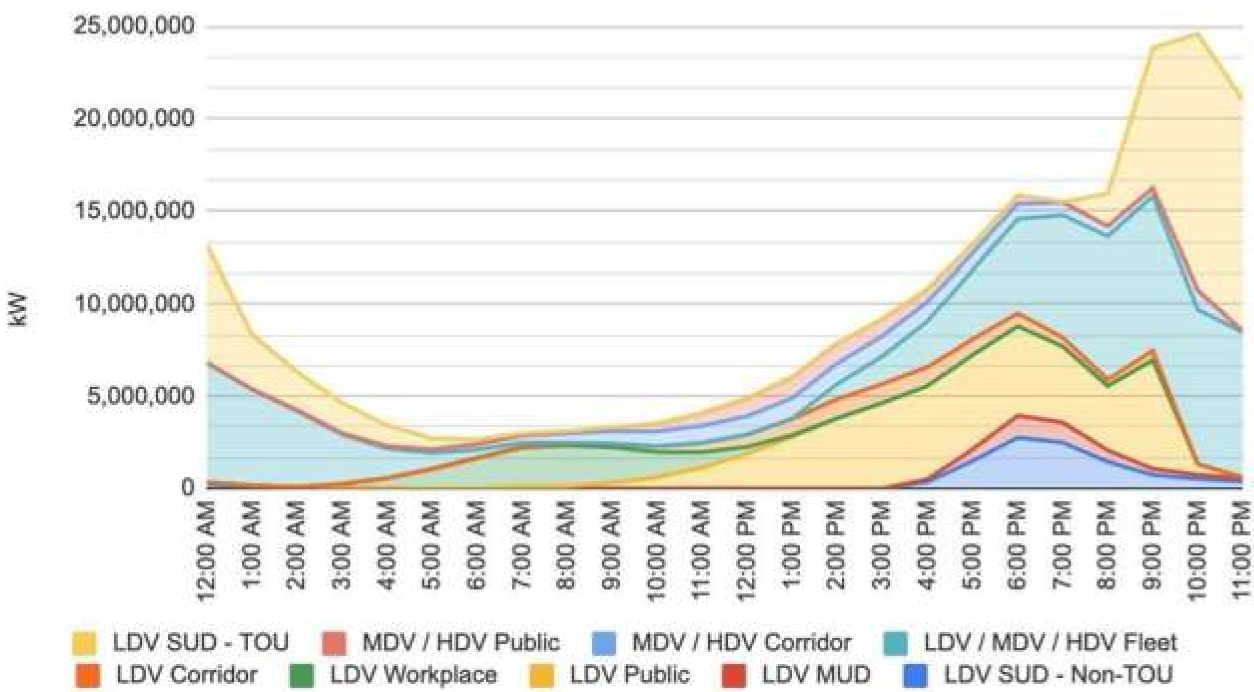


Figure 43: High Transportation Electrification scenario all EVSE loads for all IOUs for 2035 peak day *(Source: Kevala)*

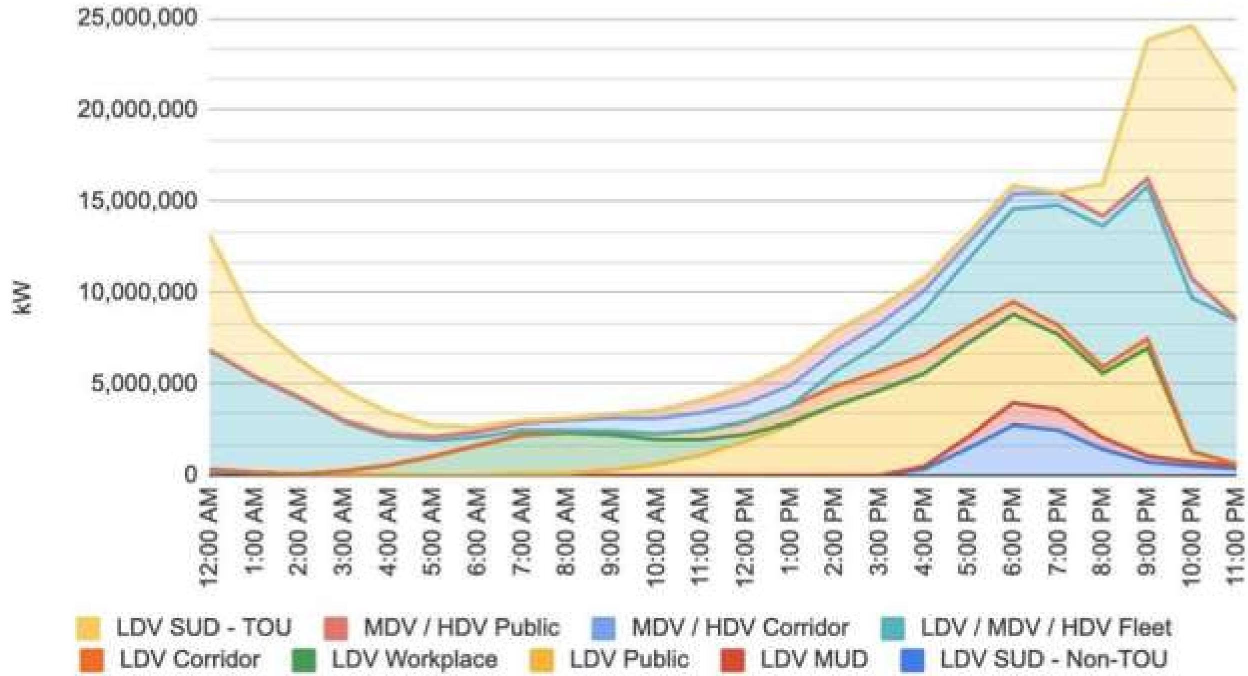
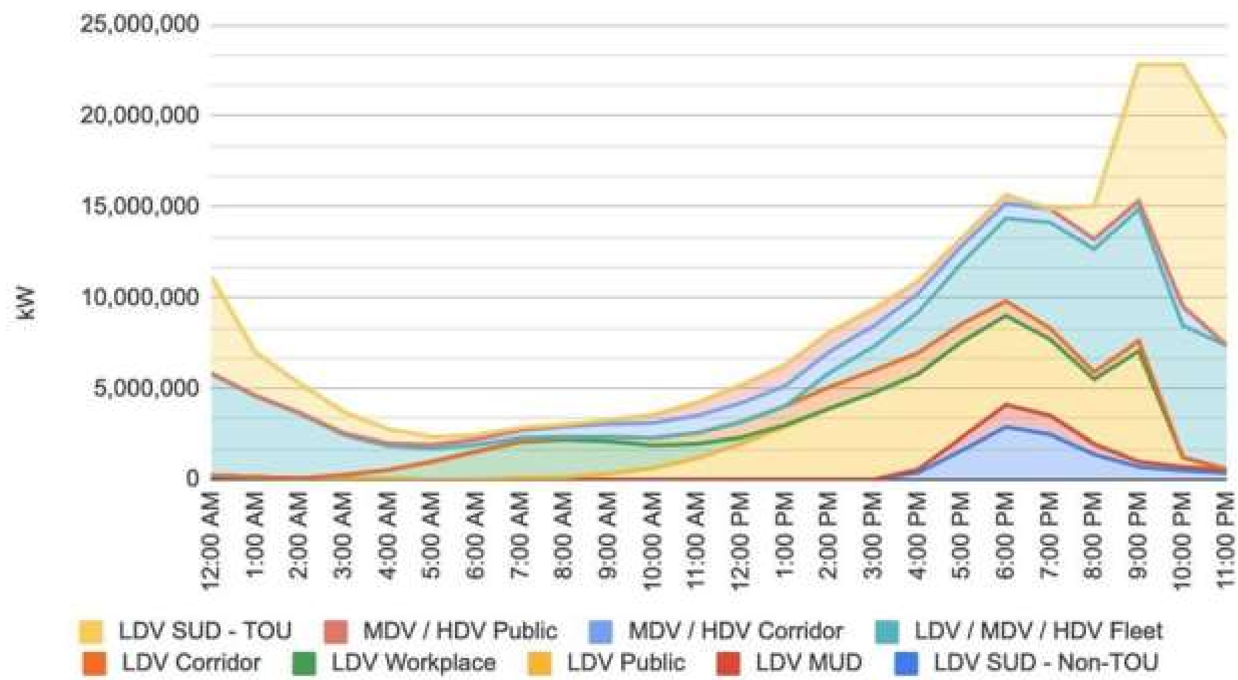
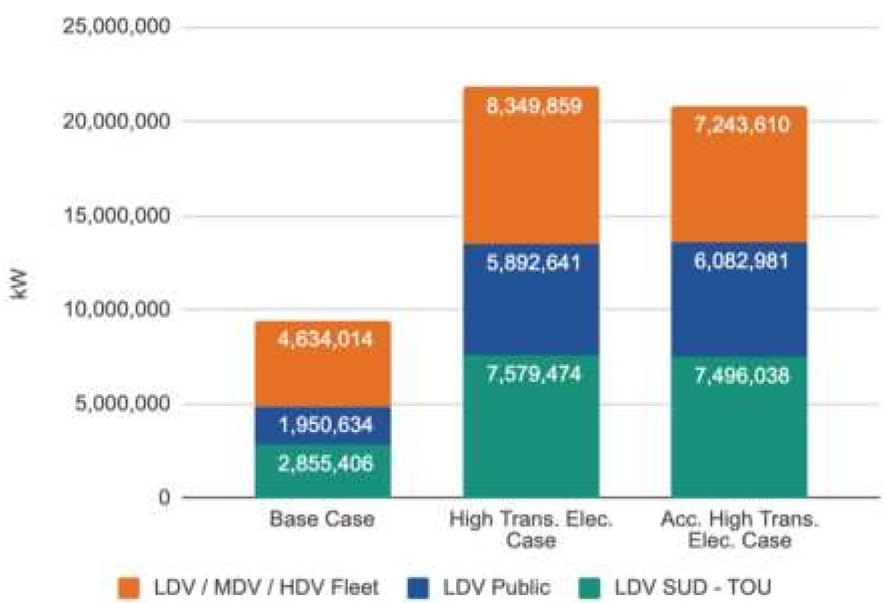


Figure 44: Accelerated High Transportation Electrification scenario all EVSE loads for all IOUs for 2035 peak day *(Source: Kevala)*



The overall composition of the EVSE loads for High Transportation Electrification and Accelerated High Transportation Electrification scenarios' peaks are roughly similar; however, as illustrated in Figure 45, which contains a breakdown of the top three EVSE loads at the peak hour for the 2035 all IOU peak day, fleet EVSE loads for the High Transportation Electrification scenario are roughly 1,100,000 kW (1.1 GW) greater than the fleet EVSE loads for the Accelerated High Transportation Electrification scenario. This is because, despite the High Transportation Electrification scenario having slightly fewer MDV and HDV ZEVs compared to the Accelerated High Transportation Electrification scenario, the vehicle class break of the High Transportation Electrification scenario contains a significantly greater share of HDVs, including urban buses and class 7 and class 8 vehicles, which have greater charging requirements than MDVs. In addition to the proportionally greater charging demands of its class 7 and class 7 HDV ZEVs, the High Transportation Electrification scenario has roughly three times as many LDV PHEV fleet EVs compared to the Accelerated High Transportation Electrification scenario.

Figure 45: All scenarios, three IOU peak day, 2035, peak hour, top 3 EVSE use cases *(Source: Kevala)*

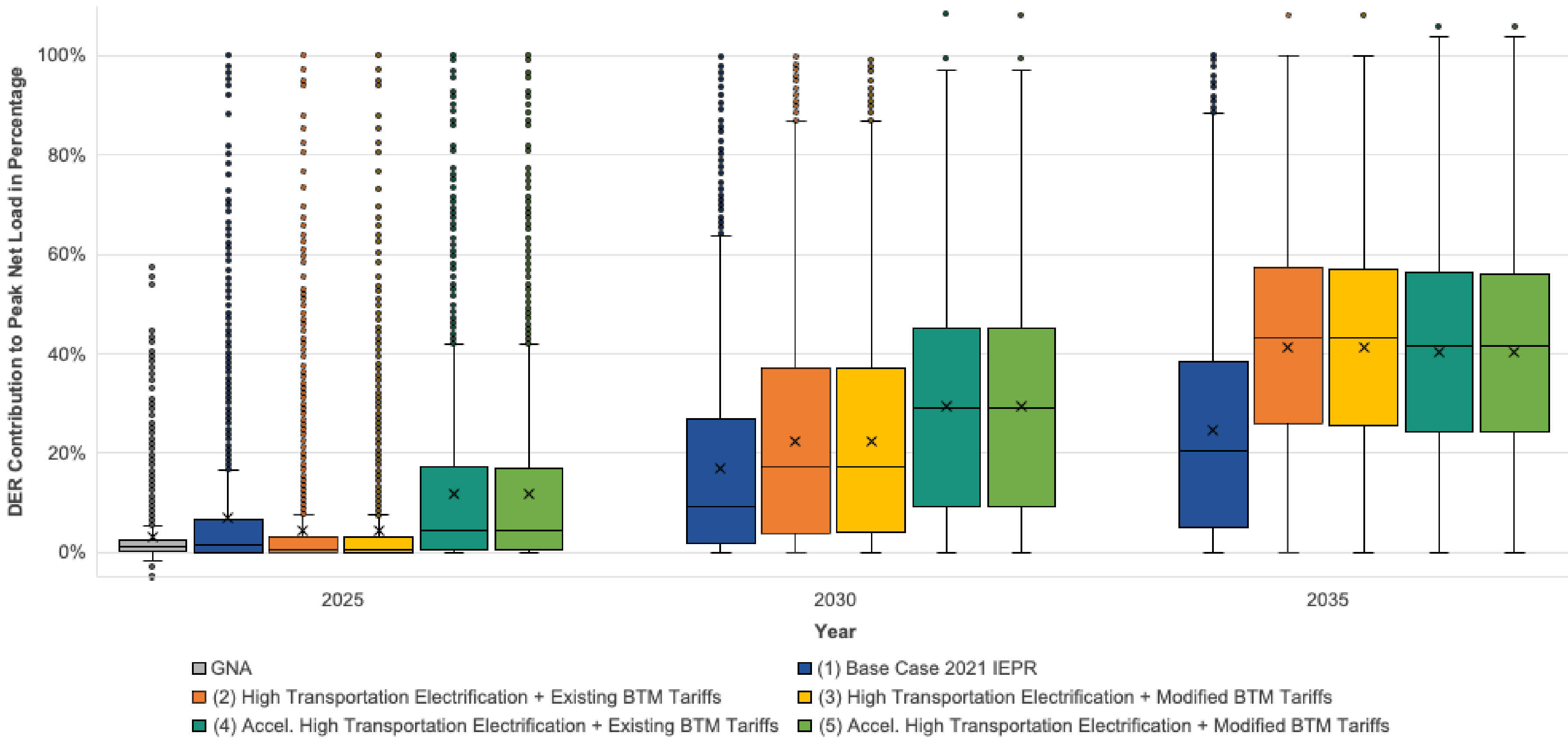


Kevala also examined the percent contribution of EVs to the net-load of the feeder. A box and whiskers chart, Figure 46 shows the distribution of the ratio of EV peak load and the net-load in the peak hours. This figure shows the values for 2025, 2030, and 2035. The values for 2025 show the GNA distribution of EV peak contribution is lower, with a tight center distribution and long tails. The long tails are also evident in the Part 1 Study distributions but vary from scenario to scenario.

The figure also shows the contribution of peak load by EVs is significantly growing over time with an impact of around 5% in 2025 and increases to 30%-50% by 2035. Note that the contribution of PV in 2025 was also about 5%, potentially offsetting the impact from EVs. This is an important finding as the implications of EVs after 2025 are significant, and this figure demonstrates the need to look beyond five years to capture the implications of high electrification in later years.

kevala

Figure 46: Distribution of EV capacity contribution to peak load (*Source: Kevala*)



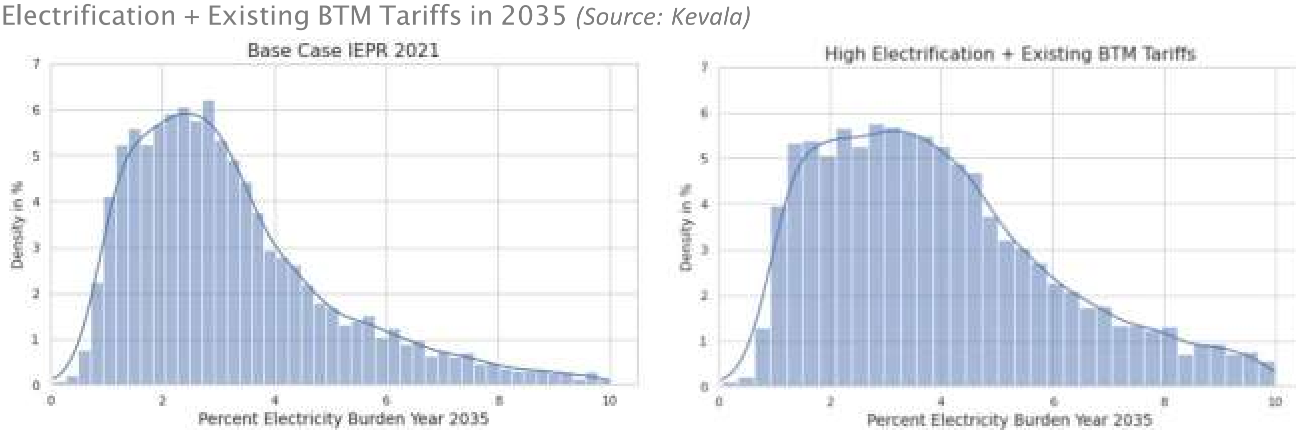
Key takeaways from the EV and EVSE analysis include:

- While overall ZEV adoption forecast counts are the primary driver of forecasted EVSE counts and projected charging loads, the underlying vehicle class breakdowns of ZEV adoption have important impacts on the number and type of chargers required in the future, and the load impacts and profiles of those chargers.
- The projected 2035 all IOU peak hour for EVSE loads is at 9 p.m., which is an assumption-driven outcome based on the assumed start of the IOUs' TOU rates' off-peak period. This is an important assumption that impacts EVSE-driven capacity needs, and therefore upgrade costs, and it is an assumption that will be revisited and adjusted in future analyses.
- While personal EV home charging is an important part of the peak usage, personal EV public charging and fleet charging play a more substantial role in driving the peak hour in 2035. This outcome has important implications for potential mitigations to model in future analysis.

2.4. Equity and Electricity Burden Results

Kevala computed the average electricity burden for residential premises at the Census block level for each of the DER scenarios considered in this study. Electricity burden is defined here as the percent share of electricity bill costs with respect to household income. Figure 47 shows the distribution of the percent electricity burden at the Census block level for the Base Case 2021 IEPR scenario in 2035 (left) versus the High Transportation Electrification + Existing BTM Tariffs scenario in 2035 (right); the figure illustrates how the curve is skewed toward the right for the High Transportation Electrification scenario, which means there are higher electricity burden values, resulting in a higher median value of 3.5% for the High Transportation Electrification scenarios (versus 2.8% for the Base Case 2021 IEPR scenario).

Figure 47: Electricity burden distribution density plot for the Base Case 2021 IEPR and High Transportation Electrification + Existing BTM Tariffs in 2035 *(Source: Kevala)*



The percentage of Census blocks in the high (greater than 5% energy burden), medium (between 3% and 5% energy burden), and low (less than 3%) categories by scenario and IOU are included in Table 8. For all three IOUs, electrification of transportation could result in higher electricity burden under the current study assumptions.[84] As an example, the percent of Census blocks in 2035 with an electricity burden greater than 5% in the Base Case 2021 IEPR scenario is 19.4%, 9.7%, and 2.9% for PG&E, SCE, and SDG&E, respectively. In 2035, in the High Transportation Electrification + Existing BTM Tariffs scenario, the percentage of Census blocks in the high electricity burden category rises to 29.3%, 16.0%, and 5.0% for PG&E, SCE and SDG&E, respectively. Kevala proposes using this information to further inform future High DER Proceeding activities such as staff proposals on how electricity burden can be included in the DPP and DIDF process, as suggested its *Distribution Investment Deferral Framework: Evaluation and Recommendations* report,[85] as well as in the Part 2 analysis to understand how upgrade costs and different mitigation strategies would affect electricity burden for different electrification scenarios.

Table 8: Percentage of Census blocks by electricity burden category low (<3%), medium (between 3% and 5%), and high (>5%) by IOU for all scenarios and years *(Source: Kevala)*

Scenario	Year	Electricity Burden Category	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	2025	Low	48.9%	52.3%	78.5%
		Medium	28.9%	35.4%	17.6%
		High	22.2%	9.3%	3.9%
	2030	Low	51.2%	56.0%	81.1%
		Medium	28.7%	32.2%	15.7%
		High	20.1%	8.7%	3.2%
	2035	Low	52.2%	51.6%	84.9%
		Medium	28.4%	35.6%	12.3%
		High	19.4%	9.7%	2.9%

[84] 2021 Census block household income and rates are kept constant in the Part 1 Study, and potential savings from fossil fuel use are not considered.

[85] Kevala's 2022 *Distribution Investment Deferral Framework: Evaluation and Recommendations* report includes a recommendation (B.7) that proposes to report whether feeders or banks are in a disadvantaged community and report on the percentage of customers with an energy burden greater than 5%; if utilities do not have such data, Kevala recommends identifying feeders/banks serving a significant number of customers on a California Alternate Rates for Energy (CARE) rate.

Scenario	Year	Electricity Burden Category	PG&E	SCE	SDG&E
(2) High Transportation Electrification + Existing BTM Tariffs	2025	Low	49.8%	53.0%	78.8%
		Medium	28.1%	34.8%	17.3%
		High	22.1%	9.2%	3.9%
	2030	Low	45.6%	51.8%	79.3%
		Medium	32.3%	35.9%	17.3%
		High	22.2%	9.3%	3.4%
	2035	Low	35.7%	35.2%	63.0%
		Medium	32.0%	45.8%	32.0%
		High	29.3%	16.0%	5.0%
(3) High Transportation Electrification + Modified BTM Tariffs	2025	Low	46.1%	47.8%	72.9%
		Medium	29.7%	37.8%	22.5%
		High	21.1%	11.3%	2.9%
	2030	Low	40.7%	43.9%	70.3%
		Medium	34.8%	41.6%	25.2%
		High	21.4%	11.4%	2.8%
	2035	Low	31.6%	28.4%	51.0%
		Medium	33.0%	48.7%	42.0%
		High	32.3%	19.9%	5.4%
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	2025	Low	45.3%	49.9%	77.0%
		Medium	31.5%	37.5%	19.1%
		High	23.2%	9.6%	4.0%
	2030	Low	40.0%	47.4%	73.4%
		Medium	33.6%	39.4%	22.8%
		High	26.4%	10.1%	3.7%
	2035	Low	36.6%	37.4%	64.3%
		Medium	32.0%	44.7%	30.7%
		High	28.4%	14.9%	5.0%

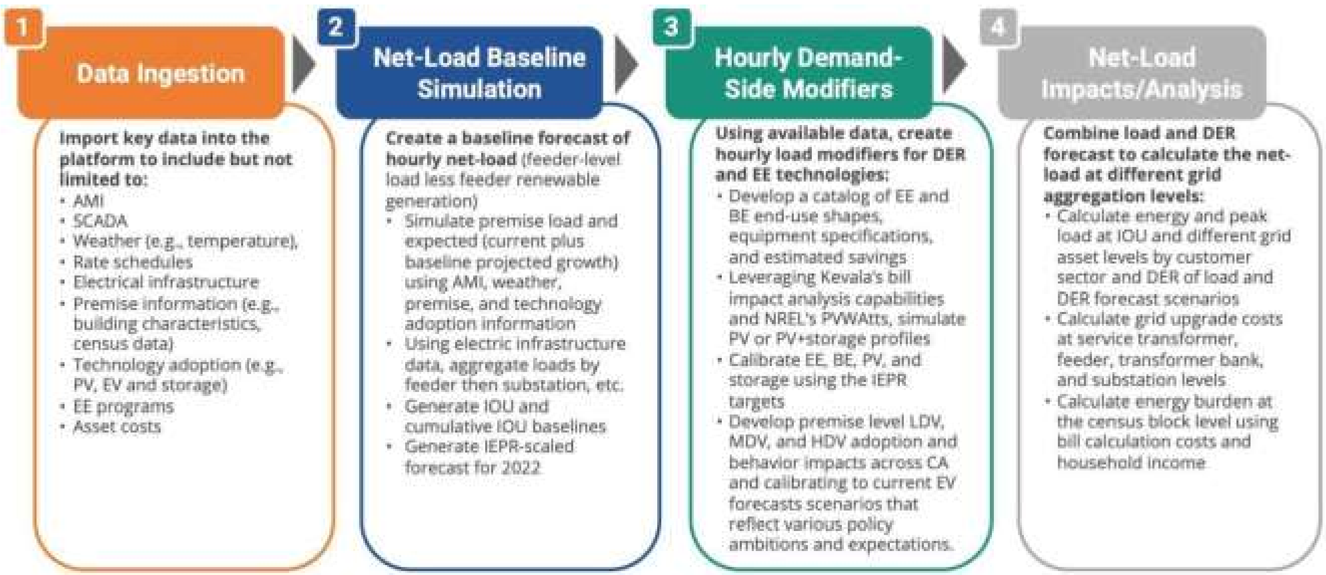
Scenario	Year	Electricity Burden Category	PG&E	SCE	SDG&E
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	2025	Low	41.6%	44.0%	69.6%
		Medium	32.9%	41.3%	25.7%
		High	22.4%	11.7%	3.1%
	2030	Low	35.9%	40.3%	63.6%
		Medium	35.1%	43.9%	31.3%
		High	25.8%	12.7%	3.5%
	2035	Low	32.6%	30.1%	52.3%
		Medium	33.0%	48.0%	40.8%
		High	31.3%	18.8%	5.2%

3. Approach

3.1. Overview

Kevala developed a premise-level (bottom-up) modeling approach to generate hourly (8760) load profiles for 2025, 2030, and 2035 for each customer of three California IOUs. This section describes the approach, including the benefits and limitations, of the steps required to generate the forecast and conduct a cost impact analysis and equity assessment. Figure 48 illustrates this stepwise process.

Figure 48: Premise-specific net-load forecasting, Part 1 Study *(Source: Kevala)*



Step 1: Data Ingestion required collecting and mapping time series data, customer and grid infrastructure, PV and BESS interconnection data, and other metadata into a data schema that allowed for easy access to the collective premise-level dataset. These high-resolution datasets included AMI and SCADA data. Section 3.2 describes this step; Appendix 2 and Appendix 3 provide further detail.

Step 2: Net-Load Baseline Simulation involved determining hourly forecasts of net-load by premise. In this step, Kevala used AMI data from each premise to develop a forecast of hourly energy consumed or delivered by the customer to the IOU and included existing BTM technologies at each premise. This step also included adjusting the net-load to estimate the customer's energy consumption without PV. In this case, Kevala created an hourly PV generation profile for each premise and subtracted from the net-load to create a baseline estimate of the energy use at the premise. Kevala calibrated the net-load baseline forecast to meet the different top-down targets for the scenarios included in this study. Section 3.3 provides the methodology applied in this step and summarizes the results; Appendix 4 provides further detail.

Step 3: Hourly Demand-Side Modifiers forecasted the expected future adoption and related behaviors of DERs. The DERs considered included the following:

- BTM PV systems
- BTM BESS
- BE
- EE
- EVs and EVSE

This Part 1 Study did not include a forecast of future demand response programs because demand response programs are designed to address system peak issues when supply is limited; thus, premise-specific demand response loads cannot be predicted without expected system peak conditions driving the decision to execute the demand response for a specific day. Kevala can revisit demand response in the Part 2 case studies as a mitigation to alleviate distribution system constraints.

Kevala then calibrated the DER adoption and behavior models to meet the different top-down targets for the scenarios included in this study and obtained the final net-load. Kevala then used the final net-load results to calculate the impacts to the grid infrastructure at different aggregation and to calculate other impacts such as energy burden on customers. Section 3.4 describes methodologies for estimating each hourly demand-side modifier, the calibration approach, and the net-load by feeder results.

Step 4: Net-Load Impact Analysis involved aggregating the net-load and demand-side modifier forecasts to feeders to understand the change in loads and peak demand by grid asset over the time horizon. Kevala then used these forecasts to identify grid infrastructure needs to meet these changing load profiles and quantify the costs of these investments.

3.2. Data Ingestion

Central to this study was the collection, ingestion, mapping, and analysis of many data sources. Kevala used a mix of its public records including but not limited to county records or parcel definition and ownership, weather data, and Census data as well as confidential datasets from three California IOUs. This data collection and integration effort was a first for the California IOUs, and perhaps nationwide. While the California IOUs have been leveraging their AMI data for nearly a decade for forecasting and planning, the Part 1 Study was designed to investigate ways of using this hyper-granular data to provide needed and valuable insights to improve distribution planning.

This analysis used several datasets:

- **IOU data**
  - Meter-specific AMI (2018-2021)
  - Grid SCADA measurements
  - Monthly billing information
  - Past DER adoption (type, location, and size) for PV and battery only
  - Customers identified with an EV or EVSE, not including type or size (incomplete dataset)
  - Geospatial information for meters, DERs, and grid infrastructure
  - Electrical infrastructure asset characteristics
  - Rate schedule code by meter ID
  - EE program tracking with meter ID

- **Regulatory data**
  - CEC load and DER forecasts (2021 IEPR) by scenario, forecast zone, and planning area
  - Agency forecasts of EV infrastructure and LDV, MDV, and HDV adoption
  - Historical to 2021 PV interconnections
  - DDOR and GNA studies

- **Publicly available data captured by Kevala**
  - Census
  - Traffic
  - Weather
  - Existing public EVSE infrastructure

- **Purchased data**
  - Experian Vehicles In Operation (VIO)
  - Regrid (parcel data)

To gather much of this data, Kevala submitted several extensive data requests to the IOUs and pursued collecting data from the CPUC and CEC. Through these efforts, Kevala received sufficient data to complete the study. Appendix 2 provides a complete list of all data received, ingested, and processed for the Part 1 Study. Because Kevala needed to finalize all datasets to be used for Part 1 by July 2022, some of the requested data was available but not received in time to process for this publishing. Additionally, some data has not yet been received. Kevala will continue to work with stakeholders to gather additional data for Part 2 and will use data received but not yet applied in that effort as well. Some of this data may include:

- Gas billing and consumption data
- Additional AMI data for before and after the Part 1 Study period
- Additional SCADA data to include system data that enables better matching of AMI and network elements
- Customer program data to include incentives for BE
- Incremental PV and BESS interconnection data for installations after the Part 1 Study period
- Distributed generation and other historical DER program performance data
- IOU location-specific cost data
- Vehicle registrations and driving patterns
- More granular customer billing data (e.g., designation of whether a customer is on an all-electric rate)

Additional data may be required for Part 2; the above list is not meant to be exhaustive of all data needs for that study.

Kevala ingested, mapped, and analyzed the data received and designed and implemented an overall data structure that allows for premise-level analytics that can be aggregated to feeders, substations, and the IOU service territory. Table 9 provides a snapshot of the number of key collection points of distribution AMI data by IOU, which totaled more than 60 terabytes (TB).[86]

Table 9: Data volume statistics *(Source: Kevala analysis of ingested IOU data)*

IOU	AMI Data (TB)	No. of AMI Meters* (Millions)	No. of AMI Data Records (Millions)	No. of Distribution Assets** (Thousands)
PG&E	31	6.1	318,347	916
SCE	25	5.3	251,145	753
SDG&E	7	1.5	75,949	171
Total	**62**	**12.9**	**645,441**	**1,840**

*Combination of 15-minute and hourly meters
**Feeders, (service and bank) transformers, and substations

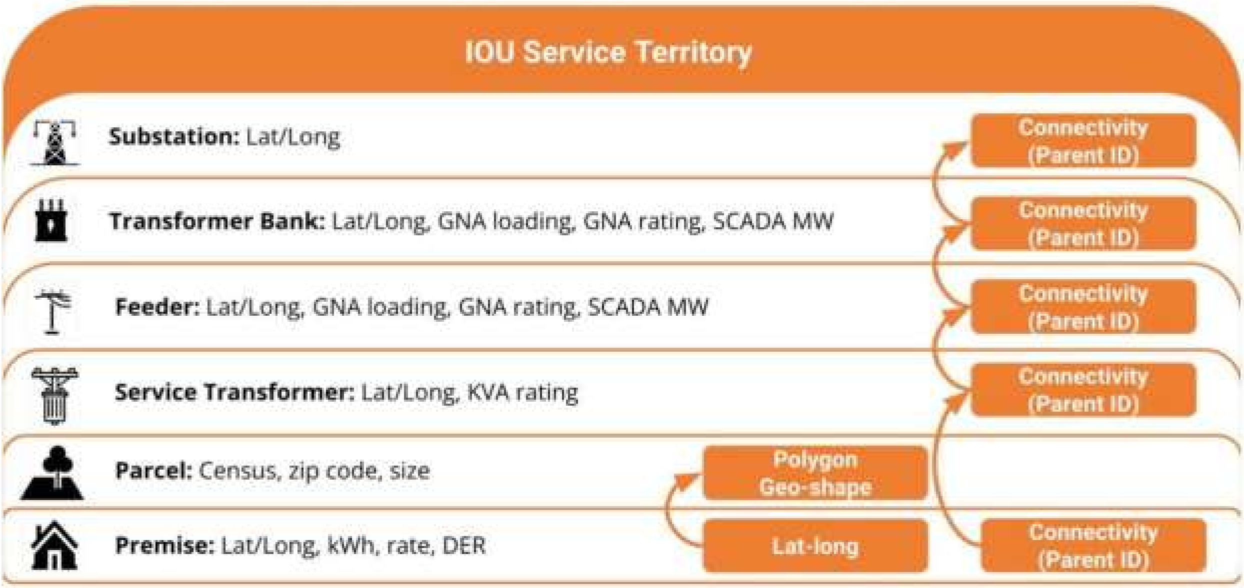
The data collected had to be mapped together to enable proper aggregation of premise-specific data to grid infrastructure and linking known DERs to the grid. The geographic information system

[86] To minimize carbon emissions due to storing and processing large amounts of data, Kevala made an effort to optimize cloud computing at low-to-no carbon intensity servers.

(GIS) geospatial and connectivity information was critical to providing the association between the consumption of a meter to the electrical infrastructure via a one-to-one match to a service point that is connected to a service transformer, then a feeder, and ultimately to a substation transformer bank and a substation.

Other critical datasets for load and DER adoption included the association of a meter to a rate structure and to a parcel and its features such as sector type. Figure 49 outlines the aggregation hierarchy of the different physical layers of the grid considered in the bottom-up analysis.

Figure 49: Grid aggregation hierarchy of the physical layers *(Source: Kevala)*



As Figure 49 indicates, all the grid layers are connected by mapping data among the layers. The premise is associated with an account ID, rate schedule, and service point with GIS mapping to a parcel. The parcel is connected to a service transformer that is connected to a feeder. The feeder connects to a substation bank located in a substation. The individual premise load rolled up to each distribution grid component provides the information needed to assess load and DER growth impacts on different parts of the distribution grid.

To ensure proper data quality, Kevala followed the following process:

- Submitted formal regulatory data requests to the IOUs for specific data, with corresponding receipt of data following regulatory filing discovery processes.
- Inventoried data received with corresponding data dictionary.
- Uploaded data from sources, including:
    - Files attached to emails
    - Data transferred via FTP from the CPUC or each IOU

    - Hard discs received from IOUs (primarily for large datasets such as AMI and SCADA data)
- Framed data to allow for analysis and use by Kevala's proprietary models
- Captured intermediate study results, identified data issues, and tested end-to-end processing.
- Cleaned the data to eliminate outliers and forced parcel mapping.

Kevala's analysis pipeline carried the premise-level analysis up through the distribution grid from service transformer to feeder to substation bank transformer. If there were any broken links in the connection, then the full AMI load did not contribute to quantifying feeder or bank overloading.[87] Table 10 summarizes the findings by IOU as there were a few feeder instances where the premise-to-feeder linkages were not identified in the utility-provided data.

Table 10: Total AMI load compared to load linked with feeders (in AMI net GWh), 2020 *(Source: Kevala analysis)*

Row	Category	PG&E	SCE	SDG&E
1	Total Load Received	72,079	67,123	16,153
2	Load Analyzed*	72,079	60,848	15,073
3	Percentage of Total Load	100%	91%	93%

*Load analyzed is the total load joined from the meter or service point to the linked feeder.

Linking parcels to service transformers to feeders and then to substation transformer banks is critical to the analysis of distribution grid costs due to the adoption of DERs over time. Understanding the grid asset's capacity rating is also necessary and allows for calculating new or upgraded grid needs. Table 11 summarizes the data from the number of feeders where data was received and the number of feeders that could be mapped to a service point and substation bank.

Kevala received critical connectivity data such as feeder linkage to transformer banks very late in the study for SCE and SDG&E;[88] this data has remaining data gaps for PG&E, SDG&E, and SCE. Specifically, from the data provided for the Part 1 Study:

- PG&E is missing connectivity to transformer banks for 13% of the feeders provided in GIS.

[87] The scale of the data and the number of data sources created numerous challenges, especially in matching data across datasets. Appendix 3 lists specific examples of challenges addressed to align datasets and confirm complete datasets.

[88] Feeder connectivity to transformer bank information along with transformer bank sizes were received on September 26, 2022 for SCE and SDG&E.

- SDG&E is missing connectivity to transformer banks for 17% of the feeders provided in GIS.
- SCE is missing connectivity to transformer banks for 14% of the feeders provided in GIS and missing the asset rating for 25% of transformer banks.

Understanding the assigned rating of a feeder is also critical to analyzing distribution grid costs. GNA tables were used to determine the feeder ratings. Because many feeders were not included in the GNA tables, Kevala used default values for ratings when the actual ratings were not available. Utility data completeness and quality issues are described in Appendix 3.

Table 11: Summary of number of substations, transformers, feeders, and related data, missing data highlighted orange *(Source: Kevala)*

	PG&E	SCE	SDG&E
Unique Service Transformers	838,170	562,534	159,686
Service Transformers Missing a Rating	38,506	168	1,594
Service Transformers Missing a Parent Feeder	0	0	0
Service Transformers Missing a Parent Substation	0	3,274	0
Unique Feeders	3,131	4,140	995
Feeders Missing a Rating	**460**	**104**	**216**
Feeders Missing a Parent Substation Transformer	**402**	**580**	**169**
Feeders Missing a Parent Substation	0	72	0
Unique Substation Transformers	1,035	843	176
Substation Transformers Missing a Rating	6	**208**	0
Substation Transformers Missing a Parent Substation	0	15	0
Unique Substations	747	714	282

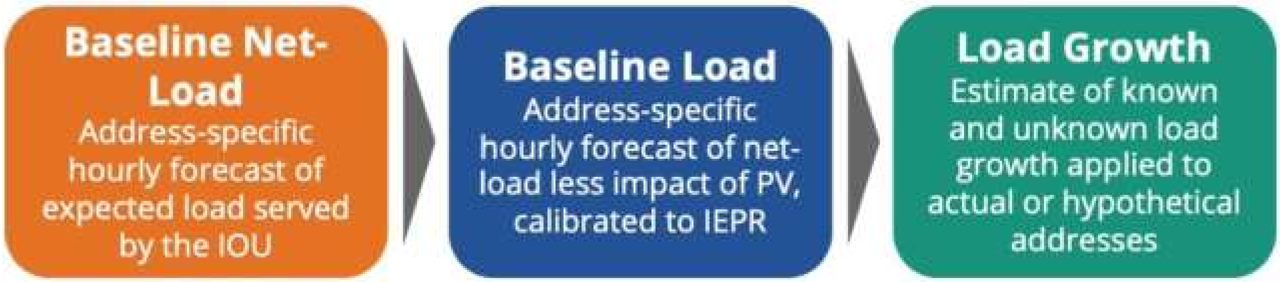
Note: notable data issues related to grid connectivity and ratings are denoted with **bold** text.

3.3. Baseline Net-Load Methodology

The second step of the process involved developing a forecast of premise-level hourly net-loads *before* introducing further demand-side modifiers. It is important to distinguish between the net-load baseline forecast and the forecasts of net-load that include the various scenarios of demand-side modifiers summarized later in this report. For clarity, in this report, the forecast of premise-level loads prior to demand-side modifiers are referred to as **baseline net-load** while the forecasts of net-load with demand-side modifiers are referred to as **net-load forecasts**.

Figure 50 outlines the three states of the baseline net-load methodology.

Figure 50: Baseline net-load methodology *(Source: Kevala)*



3.3.1. Baseline Net-Load Forecast

The **baseline net-load** represents the expected address-level energy use served by the IOU. Historical AMI data provided by the IOUs was considered net-load and included customer-adopted technologies in place during the historical period. For each premise, Kevala used AMI and weather data to train a forecast model for each address. Kevala then used these models to forecast load at the same address over the study period and incorporated any weather changes over that same period. The aggregation of these address forecasts provided the base of the load forecasts for the IOU's service territory.

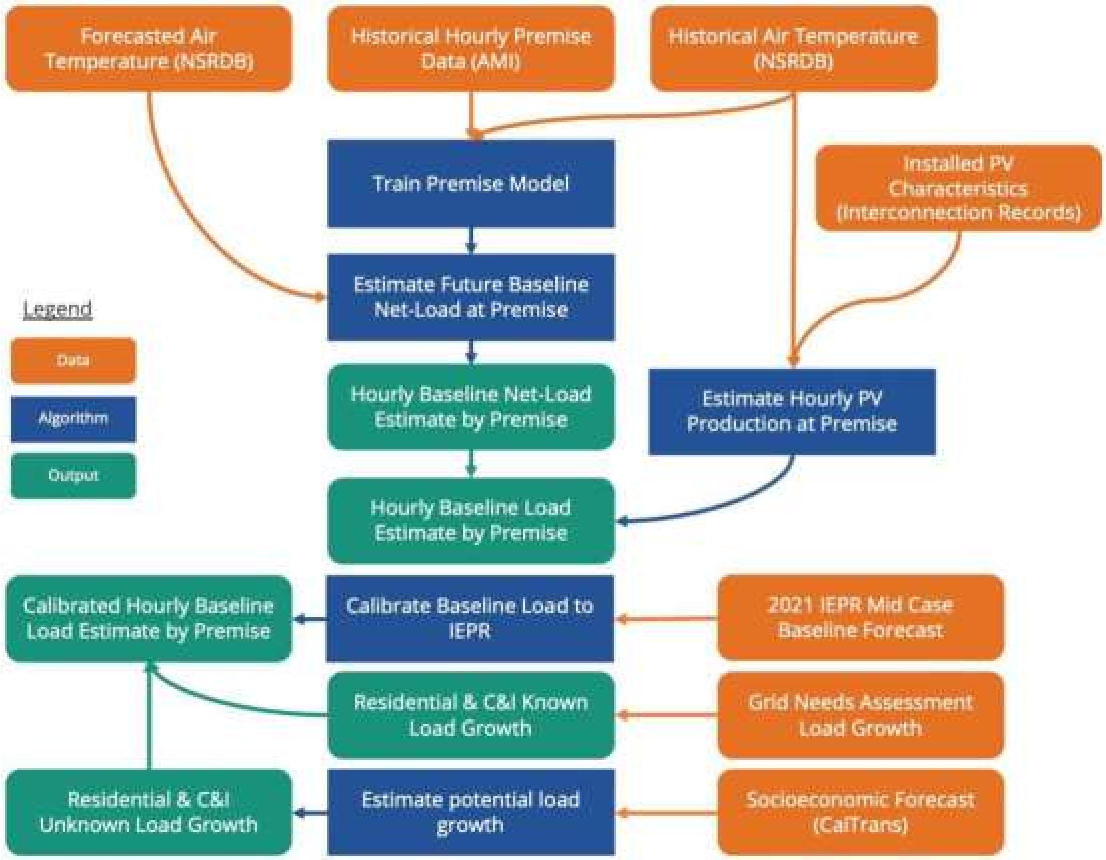
Grounding forward-looking savings on historical data limits the "what-if" in calculating potential. Forecasting is the inherently uncertain process of estimating outcomes by modeling historical and current observations. The historical data provides data points to calibrate modeling efforts and an alignment point to provide some level of confidence to the simulated results. The inherent shortcomings of modeling based on historical observation include the lack of insight into changing market dynamics, which can vary from shifting sentiments to adoption and changes in technology. Changing market behavior, such as corporate sustainability goals, includes shifts in attitudes regarding climate change.

To develop the baseline net-load estimates, Kevala used AMI data from each premise for 2018-2021. The following are the key assumptions associated with baseline net-load modeling:

- Baseline net-load for each premise represents load as measured at the meter and does not include any T&D losses or attributions of unaccounted load.

- Baseline net-load aggregated to the feeder level incorporates estimates of T&D losses based on historical seasonal deviations between SCADA and AMI on that same circuit. Kevala assumes those losses are constant over the forecast horizon.
- Any changes in baseline net-load for an existing premise for which there is AMI data to generate a future net-load estimate will be due to influences from predicted future weather patterns, assuming the Representative Concentration Pathway 8.5 (RCP 8.5) climate change scenario.[89]

Figure 51: Baseline net-load and baseline load estimation process *(Source: Kevala)*



Kevala tested various modeling approaches and algorithms to identify the method that optimized evaluation criteria at the feeder level. The final methodology applied a combination of two machine learning algorithms: decision tree and extremely randomized forest.

- The **decision tree** approach predicts the dependent variable by learning rules that split the training data into successively smaller and more homogenous groups. The decision tree

[89] Hausfather, Zeke, "Explainer: The high-emissions 'RCP8.5' global warming scenario," *Carbon Brief*, August 21, 2019, https://www.carbonbrief.org/explainer-the-high-emissions-rcp8-5-global-warming-scenario/.

approach tends to overfit[90] and performs best in predicting the peak but underperforms on estimating energy levels (e.g., area under the load duration curve).

- The **extremely randomized forest** technique is an extension of the random forest algorithm, which basically generates many decision trees based on different inputs and starting points for the trees. Extremely randomized forest simply applies the same methodology, but cut points or split points (the points at which the decision tree branch splits to other options) are chosen randomly rather than through optimization in a conventional random tree technique. As with the random forest technique, the average outcome of the many trees is used as an estimate. Though the extremely random forest approach generalizes well for out-of-sample forecasts of total energy, it tends to underfit[91] the idiosyncratic observations in the training data and thus is a poor predictor of peaks.

Kevala combined these two techniques to develop two estimates that are averaged to develop one estimate. That is, the strengths of one method offset the weaknesses of the other to provide a reasonable estimate of both peak and total energy. The tree and forest ensemble method stood out above competing approaches on the four evaluation metrics (discussed in Appendix 4), and additional model development efforts focused on optimizing this approach for the net-load prediction task. Specifically, this combined approach proved the most useful for predicting the peak, total energy, and shape of energy consumption across the year (load duration curve) for premises and the aggregated loads at the feeder level.

The benefits of this approach include the following:

- **All AMI data for each premise for all three IOUs was used** in this analysis to generate premise-specific estimates of baseline net-load profiles. This differs from the traditional approach of generating typical load profiles that are then applied based on generic characteristics. That is, the traditional approach assumes that similar customers have

[90] Model overfit implies the model is highly tailored to the input data and does a good job predicting the training data but is less reliable for unseen instances. Overfitting is usually caused by a sample that is too small or does not contain enough data samples that represent the population of outcomes. Overfitting is a problem if the model is designed to predict a wide range of outcomes that are not represented in the sample. For purposes of this study, the overfitting is acceptable, and even desirable, for forecasting peaks but is recognized as underforming for forecasting all hourly loads and thus energy.

[91] Underfitting occurs when a predictive model is unable to fully capture the relationship between the input and output variables, which results in a higher error rate. There are many causes of underfitting, but for purposes of this study, the bias introduced by the extreme random forest functions as a form of regularization. That is, it limits the influence of individual input features, and the corresponding random noise associated with measurement and human behavior, on predictions of energy use, resulting in more accurate generalization for unseen data such as future time points.

identical load profiles. While this approach has proven suitable in the past as generic shapes could be derived from load research exercises that use samples of customers to generate these load forecasts, the use of all AMI data for the three IOUs marks a turning point in the capabilities of load forecasting and demonstrates the value of collecting, processing, and storing hourly data for all customers. Additionally, this approach goes a step further than some advanced data science techniques that train models on a sample of customers. This technique applies the trained model to premise-level inputs to generate premise-level estimates. While these traditional approaches can provide useful information, they fall short of really leveraging all AMI data and developing standalone premise forecasts based on premise models trained with data for that premise.

- **The approach offers premise-level counterfactuals[92] and hypotheticals.** For example, one challenge in DER forecasting is estimating what the customer's load would have been had the DER not been installed, often referred to as counterfactual. This is a common analytical question to evaluate the impact of DERs, particularly the cost-effectiveness of EE and BE programs, the cost and load implication of PV and BESS, and the performance of demand response programs. Offering a premise-level counterfactual based on the customer's actual historical behaviors allows for scenario comparison and an understanding of the implications of DER policy on customer behavior, both before and after DER adoption. This approach also eliminates the need to find a sample of non-participating customers that are representative of the premise's customer to estimate the implications of what the customer would have done had they not adopted a DER. This approach has significant implications for improving the evaluation and measurement of DER and other customer programs and can improve confidence in determining the impacts from these programs.
- **The approach is transparent and easy to verify.** Because Kevala used the premise data to estimate future net-load, a simple visual comparison of the trend of a premise can be analyzed and verified as reasonable for that customer. As part of Kevala's review, the load duration curves of a premise using actual and predicted hourly net-load estimates can show how well the model is estimating the customer's load.
- **The approach allows for estimating the peak load duration curve and total energy consumption** without compromising one forecast point over the other. Most data science techniques focus on getting a current value (e.g., the peak). Being able to forecast a peak accurately, which is technically an outlier or tail event in a customer's energy use distribution, and estimate the area under the distribution curve is a challenging

[92] A counterfactual is an estimate of what would have happened if an action or event had not occurred. In the energy industry it is typically referred to as what the customer's energy use would have been if an action or event had not occurred, such as adoption of an EE technology.

mathematical problem. The ensemble method Kevala developed has overcome this challenge as the results in Appendix 4 demonstrate.

3.3.2. Baseline Load Forecast

The **baseline load forecast** represents the hypothetical demand after removing load impacts due to DERs. To go from baseline net-load estimates to baseline load estimates, the load profile of any adopted DER(s) at a premise needs to be estimated and removed. With the exceptions of PV and BESS interconnection data, there is a lack of information available to identify the actual installation of any BTM DER. As a result, Kevala removed only estimated PV generation (from the System Advisor Model's PVWatts simulator) from hourly net-load forecasts to create baseline load forecasts. Kevala's approach to measuring EE involved training an adoption model based on house characteristics, which included energy consumption at the premise. This approach demonstrated that EE adoption is highly influenced by the level of energy use at the premise. Premises that have implemented EE would have lower premise-level energy use. The EE adoption methodology generally takes into account BTM EE in place, and no further adjustments are planned for EE. The current GNA approach does not allocate BE to the feeder level, and the level of BE has been historically low relative to other DERs; thus, the Part 1 Study indicates no further adjustments are required for BE. Kevala intends to update (i.e., retrain) the baseline models with additional AMI data as part of the Part 2 Study.

To estimate the load impacts due to PV, Kevala used the System Advisor Model's PVWatts simulator[93] and Actual Meteorological Year weather by zip code from 2018 to 2020 to generate an hourly historical PV load profile for premises with known PV systems (see Section 3.4.2). Kevala then estimated baseline load by subtracting the forecasted PV load profile for a premise from the premise-modeled load. Baseline load estimates for each premise represent load as measured at the meter and do not include any T&D losses or attributions of unaccounted load.

The following time series feature inputs were required by the net-load forecast model:

- Hourly net-load (kWh)
- Historical actual hourly air temperature (Celsius) for training models
- Forecasted hourly air temperature (Celsius) for prediction
- Date-time features that can be derived from the timestamp (e.g., hour number, whether the date is an observed U.S. holiday)

The following are the key assumptions associated with baseline load forecast modeling:

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[93] NREL, "PySAM," Version 5, https://sam.nrel.gov/software-development-kit-sdk/pysam.html.

- Baseline load used simulated historical load curves for DER behavior to net out generation attributable to solar panels (PV). The current version does not attempt to disaggregate load due to ZEVs, public EVSE, BESS, EE, BE, or demand response programs.
- Baseline load growth is accounted for using known load growth projections from the utilities and new demand from predicted additions to the stock of residential premises.

Table 12 shows the number of premises by IOU that Kevala needed to adjust due to PV installations.

Table 12: Premises Kevala adjusted due to PV installation by IOU *(Source: Kevala)*

IOU	Number of Premises with PV Interconnection Records
PG&E	522,091
SCE	377,066
SDG&E	190,941

Kevala's final step involved calibrating the baseline load forecast to the 2021 IEPR mid-mid case for system-level loads by planning area. Specifically, the calibration target was the coincident peak forecast for 2022 for each of the three IOUs based on the 2021 IEPR mid-mid case transmission access charge (TAC) area.[94] Kevala calculated this target by subtracting system peak loads of neighboring LSEs included in the TAC area for each IOU. The premise-level hourly baseline load estimates for 2022 were summed up for each IOU to generate an hourly system-level forecast for each IOU. Kevala then identified the peak load for 2022 from this hourly profile for each IOU and compared the result to the 2021 IERP coincident peak calibration target. Kevala then computed the ratio of 2021 peak to the baseline load peak and applied it to every hour of load for each premise to generate a calibrated hourly baseline load.

Known and unknown load growth[95] was then added to this calibrated forecast to generate the baseline load forecast for the study period by premise. While Kevala did not calibrate the unknown load growth (IOUs provided known load growth, so it was already calibrated) in the Part 1 analysis, this growth in load was minimal relative to anticipated load changes from a high DER future and thus unlikely to drive the results of the Part 1 Study. Kevala proposes revisiting the

[94] The TAC level corresponds to the California Independent System Operator (CAISO) transmission aggregate load node; for PG&E and SCE, it also contains load from other municipal and power non-IOUs.
[95] Known load growth refers to load growth that utility planners are aware of from interconnection requests and other coordination with generally large commercial and industrial customers. Unknown load growth cannot be attributed to specific current customers.

overall calibration method by calibrating to the total of baseline load plus load growth in the Part 2 Study.

3.3.3. Load Growth Forecast

This Part 1 Study required the computation of a **net-load forecast**, which incorporates the baseline net-load forecast and a separate process that estimates the expected growth driven by increased loads at existing addresses; these increased loads are driven by economic cycles and new load at new addresses as the number of customers grows, particularly residential customers. This load growth can be categorized as either known load growth or unknown load growth.

For the core problem of forecasting hourly net-load, Kevala designed a modeling approach that could:

- Forecast even with sparse inputs (e.g., missing values for hourly net-load).
- Address complex seasonality, including hourly, weekly, and yearly effects.
- Incorporate extra regressors such as outdoor air temperature.

Though not part of the core forecasting model, Kevala leveraged additional data sources to produce the final results for each IOU:

- For future known load growth: GNA provided by each IOU.
- To estimate unknown load growth: County-level socioeconomic forecasts produced by Caltrans[96]

The following are the key assumptions associated with load growth forecast modeling:

- Caltrans forecast of customer growth provides a reasonable estimate of regional (county-specific) housing starts and other growth metrics to be used to forecast regional unknown load growth estimates.
- Load patterns by current customers are representative of the load profiles for known and unknown load growth.

3.4. Hourly Demand-Side Modifiers

Kevala identified premises where economic and demographic characteristics correlated with DER adoption and then the likelihood of adoption based on other factors (e.g., rent versus own, multi-unit dwelling versus single occupant) as well as technology cost curves, program and incentive

[96] Caltrans, "Long-Term Socio-Economic Forecasts by County, 2020 Data" https://dot.ca.gov/programs/transportation-planning/division-of-transportation-planning/data-analytics-services/transportation-economics/long-term-socio-economic-forecasts-by-county.

features, etc.; Kevala then applied a probability distribution for each technology type's adoption. Kevala also simulated the behavior of the demand-side modifiers, resulting in a forecasted net-load that reflects the behavior of EE programs and DERs.

Kevala used a standardized approach to the non-transportation DER adoption and behavior estimation for the following DERs:

- BTM PV
- BTM BESS
- EE
- BE

3.4.1. Overall Approach to Demand-Side Modifier Estimation

Kevala's approach for estimating each of the five modifiers targeted for this study (BTM PV, BESS, BE, EE, and EVs and EVSE) ultimately required estimating the load size (e.g., peak demand), behavior of the modifier (e.g., energy use), and adoption of the modifier (did a premise experience the demand modifier size and behavior implications?). The approach for each demand modifier was slightly modified depending on the calibration target. Specifically:

- The calibration targets for PV, EE, BE, and BESS were a capacity target (MW).
- The calibration target for EVs and EVSE was the number of units (i.e., ZEV counts).

The calibration target drove the methodology, with PV, BESS, EE, and BE starting with sizing, then estimating behavior, and then developing adoption propensity. This approach is discussed in more detail as follows.

Sizing

The DER sizing method outputs the appropriate capacity or nameplate rating of the DER for a given premise were it to adopt that DER. A size is typically calculated to equal a certain target, defined from some characteristic of the premise's baseline load. For example, residential PV is sized to achieve annual net-zero energy, while BE is sized based on an estimation of the address's load that can be transitioned to electricity (e.g., gas heating to electric heat).

Behavior

The DER's behavior method uses that size or rating to output the hourly resolution (8760 profile) behavior of the DER over the course of a year. Unlike the adoption method described below, which shares a common framework among the DERs, the behavior methods are unique to each DER. For some DERs, including PV and BE, Kevala leveraged existing industry-standard behavior models (ResStock,[97] ComStock,[98] National Solar Radiation Database (NSRDB),[99] PVWatts[100]) as much as possible. In comparison, BESS uses control algorithms to emulate peak shaving, while EE calculates a percent reduction in the baseline load.

Adoption

The adoption method determines the likelihood that a premise will adopt that DER and outputs an adoption propensity score between 0 (definite non-adoption) and 1 (definite adoption). Kevala used a custom machine learning approach to develop its DER adoption propensity models. With this approach, a statistical model uses certain attributes about a premise, called features, to predict a decision about whether or not to adopt a given DER. Kevala built and validated this model using historical adoption data to classify whether or not a premise is likely to adopt a DER, making it a supervised binary classification method. Based on whether the desired features are all numerical or a mix of numerical and categorical (i.e., Yes/No) features, either a Bayesian logistic regression or Bayesian multilevel logistic regression (MLR) model was selected to model the relationships between the features and the likelihood of adoption.

Developing the adoption model for each DER type typically involved the following five stages:

1. **Preliminary data analysis:** Select the most predictive features to include as inputs and to define the final structure of the machine learning model around those features. For each DER, these input features are selected through correlation analysis, reference to existing research,[101,102] and tailored data science methods.
2. **Model training:** Develop model parameters using a portion of the randomly selected premises from the historical dataset.
3. **Model validation:** Run the unused data from the historical dataset through the trained model and then compare it to the actual historical data to validate the model quality. This validation verifies that the model is accurately predicting for the range of actual outcomes (i.e., was not overfit or too tightly tailored to the in-sample data).

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[97] NREL, "ResStock," https://resstock.nrel.gov/.

[98] NREL, "ComStock," https://comstock.nrel.gov/.

[99] NREL, "NSRDB: National Solar Radiation Database," https://nsrdb.nrel.gov/.

[100] NREL, "PySAM," Version 5, https://sam.nrel.gov/software-development-kit-sdk/pysam.html.

[101] Jiafan Yu et al., "DeepSolar: A Machine Learning Framework to Efficiently Construct a Solar Deployment Database in the United States," *Joule* 2, no. 12 (December 19, 2018): 2605-2617, https://doi.org/10.1016/j.joule.2018.11.021.

[102] Icaro Silvestre Freitas Gomes et al., "Coupling small batteries and PV generation: A review," *Renewable and Sustainable Energy Reviews* 126 (July 2020), https://doi.org/10.1016/j.rser.2020.109835.

4. **Model predictions:** Apply the trained model to future input estimates to provide a forecast of the DER adoption propensity.
5. **Calibration:** Rank each premise in order of their adoption propensity scores; based on that ranking, select the premises to adopt up until the top-down calibration target for that DER is met.

As noted previously, the transportation demand-side modifiers (EV and EVSE) were calibrated against a number of units (i.e., ZEV counts) within a forecast rather than an energy value. Because the transportation demand-side modifiers were calibrated to the number of ZEVs contained in the Part 1 Study's selected adoption forecasts, they required a slightly different approach to the sizing, behavior, and adoption stages.

The EV pipeline was executed first, and the outputs from the EV steps then served as inputs to the EVSE pipeline. The EV and EVSE pipeline executed specific calculations for personal (i.e., privately owned) and fleet (i.e., owned by a fleet operator) vehicles and for these vehicles' associated EVSE.

The EV and EVSE modeling pipelines began by identifying the calibration target as the number of total assets (i.e., vehicle counts or charging port counts) to be allocated or sited for a given year. Following this step, the EV and EVSE models conducted the **sizing** step, which determined the type of vehicles or charging ports available (i.e., personal, light duty (LD), battery electric vehicle (BEV), small car, or fleet, depot, DCFC 50 kW) and the total potential count of vehicles or charging ports for a given premise. Importantly, the sizing step only determined what type of asset and how many of those assets could be adopted in the event that premise was selected in the adoption step (actual adoption occurs in the adoption step).

Next, the models ran an **adoption** propensity analysis that calculated the actual type and count of the vehicle(s) or charging port(s) adopted at a given premise for a given year (i.e., one personal, LD, BEV, small car at a residential premise or 10 fleet, depot, DCFC 50 kW at a commercial premise). The adoption step was the last step for the EV model.

For the EVSE pipeline, the **behavior** step was the final step. It involved determining the annual hourly charging profile for a given parcel for a given year based on the energy requirements of the vehicle(s) projected to charge at the given parcel.

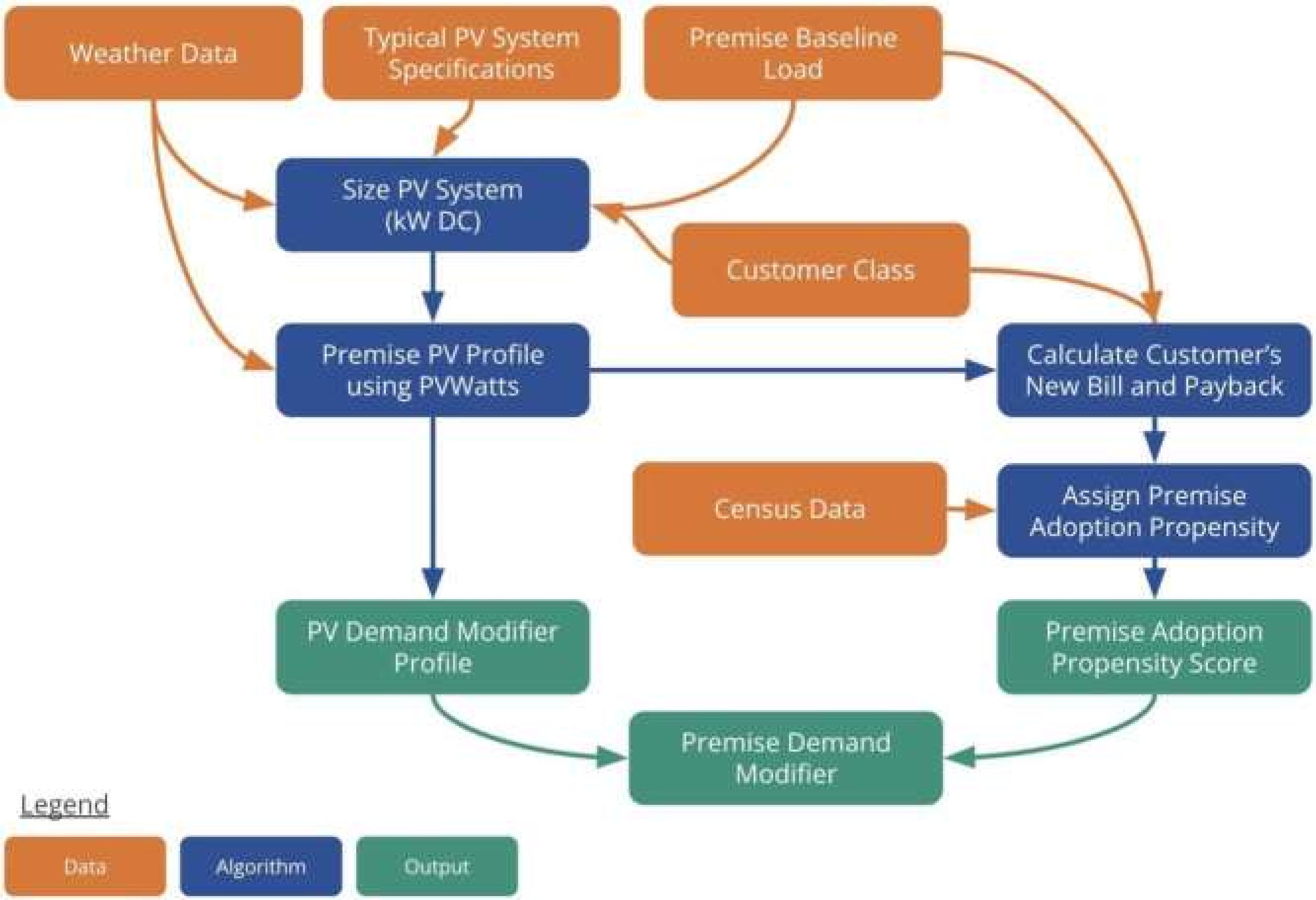
Appendix 9 describes additional details regarding the EV and EVSE modeling methodologies.

3.4.2. BTM PV

As a relatively mature and well-studied DER, modeling BTM PV can utilize well-established datasets and tools available from the U.S. Department of Energy's (DOE's) national laboratories to conduct detailed, site-specific modeling of BTM PV systems. Kevala built its modeling pipeline (see Figure

52) using information about historical BTM PV installations from the IOUs' interconnection data and Lawrence Berkeley National Laboratory's Tracking the Sun dataset,[103] hourly resolution weather data from the NSRDB,[104] and the System Advisor Model's PVWatts[105] simulator. Appendix 5 provides full details of this process.

Figure 52: Flow diagram of BTM PV adoption propensity, sizing, and behavior modeling *(Source: Kevala)*



The modeling process began by sizing a premise's theoretical BTM PV system to offset some portion of its annual gross load. For each Census tract, Kevala calculated the annual energy production of a 1 kW DC, south-facing BTM system by simulating Typical Meteorological Year weather data from the NSRDB through PVWatts. For each premise in that Census tract, Kevala calculated the desired PV system size by linearly scaling the 1 kW DC standard system to meet a defined percentage of the premise's gross annual energy demand. Kevala sized residential

[103] Lawrence Berkeley National Laboratory, Tracking the Sun, 2021 edition, https://emp.lbl.gov/tracking-the-sun.

[104] NREL, "NSRDB: National Solar Radiation Database," 2018-2020 Actual Meteorological Year data, accessed July 2022, https://nsrdb.nrel.gov/.

[105] NREL, "PySAM," Version 5, https://sam.nrel.gov/software-development-kit-sdk/pysam.html.

systems to achieve 100% net-zero energy and non-residential systems based on an empirical evaluation of the ratio of installed PV-to-annual energy usage while also considering rooftop area limits.

To model the hourly behavior of BTM PV, Kevala used residential and non-residential[106] representative profiles for the PV systems in each Census tract.

- First, Kevala derived typical specifications of PV systems historically installed in California from the Tracking the Sun dataset, including average tilt, average inverter loading ratio (or direct current-to-alternating current (DC-to-AC) ratio), and the frequency of the two most common azimuths (south-facing and west-facing) by customer class.
- Next, Kevala used PVWatts to model the hourly resolution behavior of a 1 kW DC system using each Census tract's Actual Meteorological Year weather data from 2020[107] and these typical specifications by customer class. Both south-facing and west-facing systems were modeled, and the final representative curve was a weighted blend of both profiles.
- Finally, Kevala scaled the appropriate representative curve by a given system's installed DC rating to provide its hourly power output.

Kevala developed an adoption model for each of the three IOUs using customer class, peak load, six demographic features, and the estimated payback period on the PV system as predictors. Kevala trained the model against historical PV interconnection records, which is assumed to be the best representation of what PV adoption choices have been for customers in the past. Kevala calculated payback period, which is the estimated period of time it takes for a customer's cumulative savings to equal their upfront costs of adopting PV, from the premise's monthly bills using the baseline load forecast, the PV behavior profile, and NEM rates. As with other DERs, Kevala ranked these adoption propensity scores and compared them to the 2021 IEPR mid-mid case calibration target to select premises to adopt. See Section 3.4.7 for more details on the development of these calibration targets.

The following are the key assumptions associated with PV adoption and behavior modeling:

- **Kevala used common industry default specifications, except where noted.** These default specifications included PVWatts' default assumptions about soiling, shading, and wiring losses (applied equally at every hour in the year), inverter efficiency, and module type (standard crystalline silicon). Additionally, Kevala assumed all rooftops to be south- and west-facing at a given tilt by customer class, because these two orientations are the

[106] Kevala used the Commercial class in the Tracking the Sun dataset for all non-residential systems.
[107] Kevala used 2020 Actual Meteorological Year data to model all years in the 2022-2035 modeling horizon.

most common in the Tracking the Sun dataset.

- Installed PV DC capacity is constrained by the parcel footprint, so parcel footprint was **assumed to be a reasonable estimate of the available space for PV system installations.**
- Historical **PV adoptions as represented by PV interconnections** are a reasonably accurate representation of historical adoption characteristics.
- **Kevala determined PV sizes based on the 2022 baseline load forecast.** A single premise does not typically have significant year-over-year gross load increases, so these changes should be negligible. This approach does not include the impact of the adoption of other demand-side modifiers.
- **Bills and PV system costs used to calculate payback period reflect 2022 values.**
- **PV degradation effects and end-of-life system removal/replacement were ignored.** Kevala ignored year-over-year decreases in PV efficiency due to aging, which resulted in an overestimation of production from older systems as the forecast horizon increases. Similarly, the model did not consider removal or replacement of aging PV systems because the vast majority of systems will still be within their operational lifespan at the end of the forecast horizon.
- **Increases in the annual temperature profile due to climate change were ignored.** While Kevala included climate change-induced temperature increases in the baseline load forecast module, the 2020 air temperature profile was used unchanged as an input to the PV behavior module.
- **The relationship between customer bills and solar costs remained constant.** While Kevala expected rates to increase at the IEPR mid-level escalation rate, the payback period estimates remained constant over time. This is because the estimated cost of PV systems is difficult to predict due to many offsetting factors such as supply chain constraints, government subsidy continuations, and the implications of inflation on PV systems that has not been seen historically.

Kevala believes the results of the BTM PV analytics completed for this Part 1 Study provide accurate and sufficient estimates of the impacts of BTM PV adoption on distribution planning.

3.4.3. BTM BESS

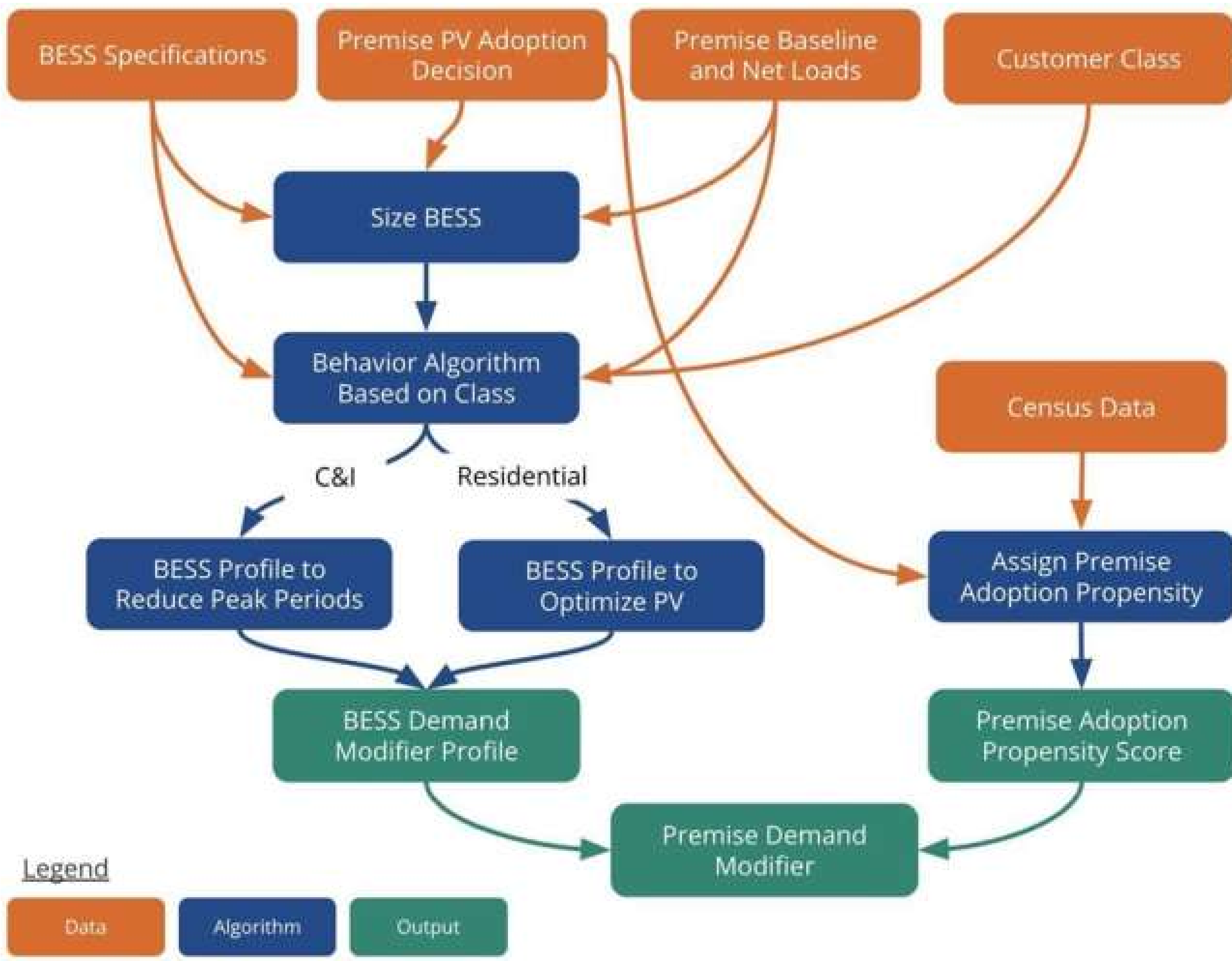
BTM BESS are a rapidly growing DER, though still in the early stages of market adoption. Commonly installed in tandem with a BTM PV system, a BESS is extremely flexible and can be operated to achieve a variety of goals:

- Provide energy backup during emergency conditions
- Reduce peak demand charges for non-residential customers

- Improve utilization of the premise's PV generation to reduce its electricity bills or carbon footprint

While the market penetration of BESS is still very low and the control strategies that will prove to be the most popular and prevalent are still unclear, Kevala has taken the approach of modeling two financially motivated control strategies based on customer class: Kevala's models assume residential customers will try to optimize PV self-consumption while minimizing TOU charges, while non-residential customers will try to use BESS for peak shaving to reduce their demand charges. Figure 53 summarizes the complete BESS modeling process.

Figure 53: Flow diagram of BTM BESS adoption propensity, sizing, and behavior modeling *(Source: Kevala)*



Kevala based its BESS sizing model on the continued adoption of the lithium-ion BESS options commercially available today. For residential premises, Kevala modeled the new BESS as one or more Tesla Powerwalls, where the number of Powerwalls is chosen to provide backup for at least 8% of the premise's gross energy demand on its highest usage day throughout the year. This equates to approximately two hours of backup energy at the BESS peak power output. For commercial premises, Kevala selected one of a range of commercially available BESS options to offer approximately three hours of self-sufficiency per day, up to the ratings offered by the largest BESS available, the Tesla Powerpack. Kevala determined the thresholds for selecting these configurations by analyzing the premises in the historical BESS interconnection data.

The BESS behavior and adoption models depend on the outputs of the PV module based on the understanding that most future BESS will be adopted and operated in conjunction with BTM PV (see Section 3.4.2). Once a BESS model was sized for a premise, Kevala modeled its behavior based on the premise's customer class. Kevala assumed residential premises would charge when PV exceeds gross demand and discharge when gross demand exceeds PV, constrained by its state-of-charge limits. A residential BESS generally charges during the day and discharges in the early evening, which also approximates the desired behavior to minimize TOU charges, which are highest in late afternoon and early evening. In contrast, non-residential customers charge during the lowest net-load hours and discharge during the highest net-load hours in each 24-hour period to emulate demand charge reduction.

Kevala assigned each premise an adoption propensity score using an IOU-specific machine learning adoption model trained on the historical interconnection data. The most important predictor was whether or not the premise had PV. Non-residential premises with PV adopted BESS at much higher rates than non-residential premises without PV, while the adoption model simply did not allow residential premises without PV to adopt BESS due to the assumptions of the behavior algorithm. In addition to PV, the other predictors in the adoption model were customer class, peak load, and three demographic features. Kevala ranked and compared the adoption propensity scores to the 2021 IEPR mid-mid case calibration target to select premises that ultimately adopt BESS. Appendix 6 provides full details of the BESS sizing, behavior, and adoption model development and validation. See Section 3.4.7 for more details on the development of these calibration targets.

The following are the key assumptions associated with Kevala's BESS adoption and behavior modeling:

- **Residential customers must adopt PV in the same year or earlier**. The BESS behavior model for residential customers assumed they are maximizing PV self-consumption; therefore, only residential customers with PV were allowed to adopt BESS. A small number of residential premises in the historical interconnection data had BESS but not PV, but these were ignored.
- **BESS payback period was not used as a predictor in the adoption model** because current payback periods are very long and may not be indicative of the future prices of BESS as the BTM BESS market matures.

- **BESS configurations were based on currently commercially available lithium-ion battery packs** and did not account for projected changes in storage technology or common commercial options.
- **The residential BESS behavior model assumed TOU peak periods would continue to be in the late afternoon and early evening** over the modeling horizon.
- **The non-residential BESS behavior model assumed a perfect forecast of each 24-hour period** to identify the lowest load periods for charging and the highest load periods for discharging.
- **BESS degradation and end-of-life removal/replacement were ignored**. This did result in an overestimation of performance over time. The financial impacts of BESS replacement on a given homeowner were not considered given that the initial payback period was also not included in the adoption model.

Kevala believes the results of the BESS analytics completed for this Part 1 Study provide sufficient and reasonable estimates of the impacts of BESS adoption on distribution planning given the nascent nature of the technology in California.

3.4.4. EE

Kevala's method for modeling EE savings profiles required developing an analytical-based approach for defining the energy savings and adoption probability at the premise level. Typically, EE modeling uses the population level from sampled survey data and the Bass diffusion[108] curve for modeling technology adoption. Using this method, the pattern of savings can be predicted using engineering modeling to estimate the level of savings from a measure and then applying adoption levels that apply to a geographic area, such as service territory or even census tract or zip code.[109]

While estimating energy savings from EE at the premise level could follow the same engineering approach described previously, that would be complicated by the lack of information regarding the premise-specific inventory of electricity and gas end uses behind-the-meter, the overall

[108] The Bass diffusion curve is usually based on a simple differential equation that describes the process of how new products get adopted in a population and provides a perspective on how current adopters and potential adopters of a new product interact. Key inputs are typically related to proximity of potential to current adopters and advertising that promotes awareness of the new product.

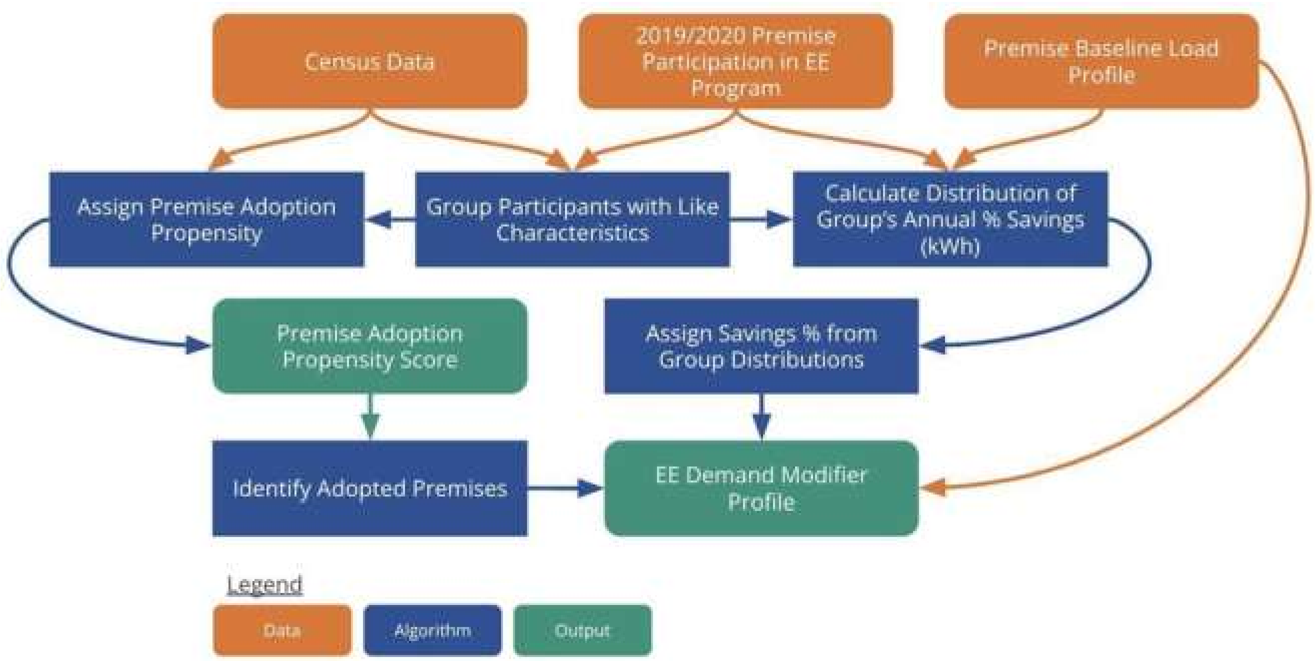
[109] Once measures are installed, the savings are verified by quantifying a counterfactual, which basically requires estimating what customers would have consumed had they not implemented the EE measures and comparing that estimate to their actual use. One shortcoming of this approach is that it is difficult to determine the level of savings from individual measures if more than one measure is installed at the same time or the level of savings from the measure is not systematically greater than the random variation in the customer's load.

condition of the facilities or buildings on the premise, and the level of EE technologies already installed at the premise. Ideally this information would be available for not only a sample of customers used to train premise-level models, but also for all premises in the IOUs' service territories. For the Part 1 Study, this level of data was unavailable.

Kevala's approach seeks to estimate the percent of energy savings potential per premise and the propensity for adopting measures to achieve this level of savings without predicting which and if a particular EE measure is installed at a premise. The underlying assumption for this approach is that the impact of EE adoption is driven less by a specific technology because the level of savings depends highly on diverse premise characteristics and a methodology focused on the level of savings relative to load would be the best predictor of the impact of EE on the grid.

Figure 54 shows the process flow of the EE evaluation method to develop the premise-level EE forecasts. This method is based on an analysis of the California Energy Data and Reporting System (CEDARS),[110] which is a dataset collected by the CPUC of every record of EE program participation from the IOUs. CEDARS tracks the individual premises participating in EE, as well as a measure of cost, incentive, and the total first year energy savings in kilowatt-hours (kWh). A detailed explanation of Kevala's approach and results are shown in Appendix 7.

Figure 54: Flow diagram of EE adoption propensity and demand-side modifier modeling *(Source: Kevala)*



[110] CPUC, "CEDARS: California Energy Data and Reporting System," https://cedars.sound-data.com/. Kevala received 2018-2020 program participation data.

Starting by combining the CEDARS premise participation data with premises' historical hourly load, Kevala identified the potential level of savings by premise.[111] Kevala then ran multiple experiments to identify characteristics that correlate well with the adoption of EE measures based on CEDARS participants to generate adoption propensity scoring for the population.

As a result of the analysis to find commonality of historical participation, the adopted premises leverage three main traits (Appendix 7 provides a more detailed description):

- Average daily delivered energy magnitude
- Ratio of max to mean daily delivered energy, relative to the size of the premise
- Residential versus non-residential

The EE-participating premises were matched directly to the hourly baseline load estimate by customer meter to calculate a percentage of energy savings from EE adoption. That is, these savings calculations were based on the baseline load at the premise, not the baseline net-load estimate, because all premise loads, even those that are offset by PV and storage, may be affected.[112] The algorithm assigned potential energy savings percentages in grouped premises based on the energy savings percent distribution for the EE-participating premises. In simulation, Kevala combined the adoption propensity scores and potential energy savings percentage to select premises that adopt EE until the 2021 IEPR mid-mid case calibration target was reached. See Section 3.4.7 for more details on the development of these calibration targets.

The following are the key assumptions associated with EE adoption and behavior modeling:

- **Premise-level savings percentage was based on EE portfolio program participation.** There are other sources of EE savings such as codes and standards, behavior change from programs and other interventions, energy savings assistance (low-income program participants), and market-driven impacts whose records were not available at the premise level. Leveraging other EE savings tracking efforts (such as the CEC SB 350 analysis or disaggregating group-level data to premise)[113] may lead to more accurate EE savings accruals; however, these were not quantified on a premise-level basis (but were deemed values). For the Kevala model, using the EE program participant-level data was sufficient because Kevala was not forecasting future EE adoption and instead was calculating to the 2021 IEPR mid scenario target for AAEE.

[111] Kevala can examine further leveraging the CEDARS database for EE estimations in Part 2.
[112] Kevala assumed EE and BE to be embedded in the baseline load estimate.
[113] This group-level data includes energy savings assistance programs (low income), home energy reports, upstream or midstream programs, and codes and standards.

- **Savings were assumed to be applied equally on a percentage basis to every hour.** Defining the end-use scale and shape change must be known to a granular level to truly indicate hourly load impacts with EE. The granularity defines the end use and technology type (efficiency, operation, or controls). Each of these dependencies will impact the hourly load.
- **Savings were adopted once in the forecast period**, whereas EE adoption is a continuum and is not a one-and-done activity. Ideally, savings can be accrued in more than one adoption year. There will be cases where the implemented savings percentage value is too high or artificially holding back some premises' potential.

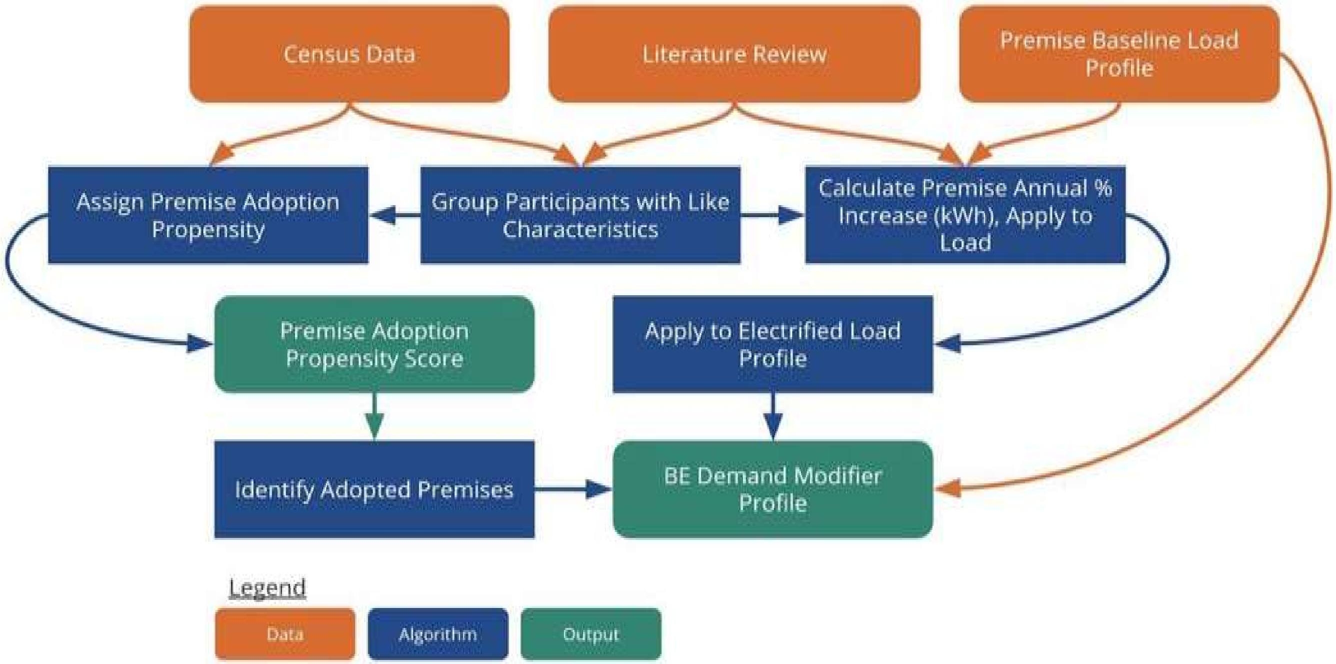
Kevala believes the results of the EE analytics completed for this Part 1 Study provide accurate and sufficient estimates of the impacts of EE adoption on distribution planning.

3.4.5. BE

BE (or fuel substitution) is a relatively new category of DER analysis for the utility industry and is becoming increasingly important in the study of the magnitude and location of future grid needs. This is particularly true in California as policymakers look to reduce carbon by encouraging the replacement of carbon-emitting end uses (such as gas heating) with electric end uses. This increase in BE (as well as transportation electrification, which is discussed later in this report) may result in higher electricity use during peak hours, creating significant strain on the existing distribution infrastructure. However, it also provides opportunities for demand response to offset that increased load during critical peak periods or use of load management to encourage peak shifting to less capacity constrained periods.

Kevala recognizes that the ideal approach to modeling BE is to define the existing loads that may be electrified and the timing of that transition. Unfortunately, Kevala did not have a full set of gas consumption data as of Q1 2022. Therefore, the BE analysis was limited to available data on electricity at the premise level. Figure 55 shows the key steps for the BE analysis, assuming gas loads are unknown. A detailed explanation of Kevala's approach and results are shown in Appendix 8.

Figure 55: Flow diagram of BE adoption propensity and demand-side modifier modeling *(Source: Kevala)*



Kevala's approach leveraged secondary research, publicly available data, and engineering analysis to estimate BE size and behavior. BE size was driven by the customer class (residential versus commercial) and climate zone. Behavior was based on load profiles from established NREL databases. Because appropriate datasets were not yet available to model BE adoption propensity, Kevala used EE adoption propensity values as a proxy. Kevala then ranked the adoption propensity scores from highest to lowest and selected the premises in rank order until the BE calibration target was met.

This analysis defined the available electrification (increase in load) potential on a premise basis. Kevala did review potential adoption analytic sources such as California's 2021 energy efficiency potential study[114] and deemed the method not applicable. See Section 3.4.7 for more details on the development of the calibration targets.

The following are the key assumptions associated with BE adoption and behavior modeling:

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[114] Guidehouse, *2021 Energy Efficiency Potential and Goals Study*, prepared for California Public Utilities Commission, August 20, 2021. https://pda.energydataweb.com/api/view/2531/2021%20PG%20Study%20DRAFT%20Report%202021_Final.pdf

- **Level of BE adoption was set based on customer class, and existing premise-level gas consumption was unknown.** The approach described here assumed an unknown level of gas consumption or even the existence of gas loads. Kevala did not conduct hourly analytics to identify via electric loads if gas loads existed for certain end uses.
- **The existing state of specific end-use electrified load was unknown**. Not knowing if the new consumption was for space heating, water heating, clothes drying, or other, the approach was to apply the new electricity load to a whole building load profile derived from known all-electric building data or models for residential and commercial sectors. Kevala used the NREL ResStock[115] and ComStock[116] libraries for the all-electric default load shapes to apply to the newly electrified loads.
- **There was limited electrification opportunity for certain non-residential premises.** Especially for industrial facilities, there are multiple uses for natural gas. They include high temperature process heating, feedstock input, and all other uses. The first two are considered not feasible for electrification. As a result, a percentage of industrial natural gas will not be electrified.
- **Future, not yet drafted, codes and standards were not included in the baseline load forecast.** The baseline forecast did include application of adopted and pending codes and standards. However, Kevala did not include the application of future codes and standards for existing or new construction in the baseline forecast. Any future BE due to codes and standards was part of the forecast analysis.

Kevala proposes the following for the Part 2 Study:

- Kevala has received and processed the natural gas data from PG&E, SDG&E, and Southern California Gas. The first planned modification is to include gas use or other related metrics in testing a new BE adoption model.
- Kevala plans to request additional data from the IOUs regarding granting incentives to their customers for adopting BE technologies, such as electric water heaters and electric heat pumps.
- Kevala will research other jurisdictions to see if there are any studies that may provide useful in further refining the adoption model and results.

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[115] ResStock is an NREL load profile library using a combination of building models and metered data. Kevala filtered the data to California with the space and water heating fuel set to electricity only.
[116] ComStock is an NREL load profile library. Kevala filtered the data to California with the space and water heating fuel set to electricity only.

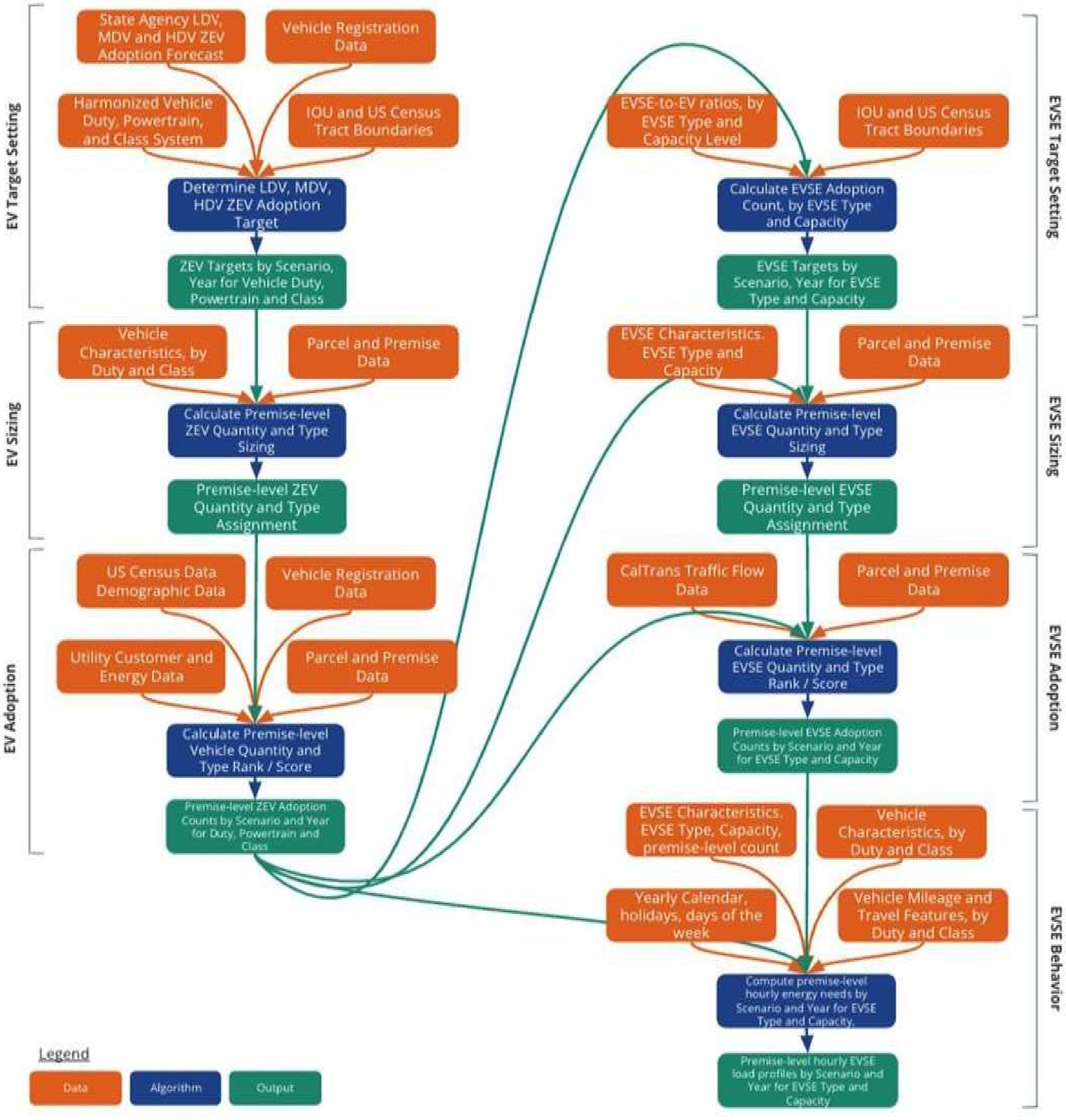
3.4.6. EVs and EVSE

EVs, and the EVSE required to charge them, are a rapidly growing and evolving set of DERs. As the number of ZEVs in California increases from roughly 1.3 million EVs as of October 2022 toward statewide ZEV adoption 2035 levels of roughly 13 million LD EVs and 290,000 MD and HD EVs, this new load will be significant.[117] While California has already achieved a meaningful level of ZEV adoption, the underlying consumer behavior and relevant grid constraints are not yet well-understood given today's level of penetration, particularly for MDVs and HDVs.

Kevala's approach for modeling the energy impact associated with varying levels of ZEV adoption involves seven stages. The first three stages, known as the EV pipeline, involve determining premise-level ZEV adoption by ownership type, duty, powertrain, and vehicle class. The next four stages, known as the EVSE pipeline, calculate premise-level EVSE adoption and hourly energy usage behavior by EVSE type and capacity level. Figure 56 summarizes the complete EV and EVSE modeling process.

[117] California Energy Commission, "New ZEV Sales in California," https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/new-zev-sales.

Figure 56: Flow diagram of EV and EVSE calibration target, propensity, sizing, and behavior modeling *(Source: Kevala)*



Kevala's allocation of forecasted vehicle adoption and charging equipment establishes their existing penetration and location. Allocating new adoptions from one of the three CARB or CEC

ZEV adoption forecasts serve as inputs to the Part 1 Study scenarios. Table 13 summarizes the CARB and CEC LDV, MDV, and HDV ZEV adoption forecasts and the associated vehicle counts that Kevala used in the Part 1 Study.

Table 13: Summary of CEC and CARB LDV, MDV, and HDV ZEV adoption forecasts used for Part 1 Study scenarios *(Sources: CARB, CEC, Kevala)*

		(1) Base Case 2021 IEPR	(2) High Transportation Electrification + Existing BTM Tariffs**	(3) High Transportation Electrification + Modified BTM Tariffs**	(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	(5) Accelerated High Transportation Electrification + Modified BTM Tariffs
ZEV Adoption Forecast Source	**LDV**	CEC 2021 IEPR mid scenario	CARB 2021 ACC II		CEC 2021 IEPR bookend scenario	
	MDV / HDV		CARB 2020 SSS		CEC 2021 IEPR high scenario	
ZEV Adoption Total Vehicle Count (2022-2035, Three IOUs)*	**LDV**	3,172,598	10,013,953		9,530,034	
	MDV / HDV	227,140	218,710		230,876	

*The values in this table represent the forecasted ZEV adoption counts from 2022 to 2035 that the model allocated based on the CARB and CEC ZEV adoption forecasts. These values exclude all ZEV counts prior to 2022, thus they do not represent the total cumulative ZEV counts for all three IOUs.
**The two High Transportation Electrification scenarios incorporate transportation electrification assumptions similar to those applied to the 2022 IEPR demand forecast mid-mid case (i.e., the 2022 IEPR Planning Forecast). At the time the Part 1 Study was developed, the 2022 IEPR had not yet been adopted, so the 2021 IEPR mid-mid case was used for the Part 1 Base Case.

Kevala selected the three CARB and CEC ZEV adoption forecasts for the Part 1 Study because they represent a meaningful range of ZEV adoption levels that align with California policy goals and market forecasts. Kevala identified and selected the Base Case and Accelerated High Transportation Electrification scenarios' ZEV adoption forecasts prior to the High Transportation Electrification scenario's ZEV adoption forecast.[118] At the time Kevala selected these inputs, it was not known that the High Transportation Electrification scenario's LDV ZEV adoption forecast would

[118] The LDV, MDV, and HDV ZEV adoption forecasts were determined by the JASC High Electrification Interagency Working Group and selected in March 2022, after the ZEV adoption forecasts for the Base Case and Accelerated High Transportation Electrification scenarios had been selected. For more information about the Interagency Working Group's high electrification scenario, refer to the May 24, 2022, CEC Resolution (No. 22-0524-5) that adopted it for use in transmission planning and as part of the 2021 IEPR "single forecast set," at https://www.energy.ca.gov/filebrowser/download/4171.

have a greater number of 2035 adoption compared to the Accelerated High Transportation Electrification scenario.

Forecasting the new load associated with these vehicles and chargers is a complex task, given that vehicle charge profiles depend on many variables such as miles traveled, vehicle type (which include 24 duty, powertrain, and vehicle class combinations), charger type (which include 10 use case and capacity combinations), and other variables. As a result, a multifaceted analysis that synthesized multiple datasets was required. The key data sources for the ZEV modeling framework included:

- Forecasted vehicle and charger attributes such as range and battery capacity from the CEC's AB 2127 Report[119]
- Vehicle miles traveled (VMT) by county and vehicle type from the Local Area Transportation Characteristics for Households Data (LATCH) survey[120] and derived from the U.S. Bureau of Transportation Statistics' Vehicles in Use Survey (VIUS), as summarized by M.J. Bradley & Associates[121]
- Vehicle operating schedules from the NREL Fleet DNA dataset[122]
- Existing internal combustion engine (ICE) and ZEVs by census block group from Experian's VIO data[123]

Appendix 9 contains additional details about the modeling steps and datasets used for the EV and EVSE.

Kevala's first step was to harmonize the 2022-2035 ZEV adoption forecasts received from CARB and the CEC. Because the forecasts use different vehicle classification systems and were provided at varying levels of geography, Kevala converted all LDV, MDV, and HDV classes to a standard set

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[119] California Energy Commission, *Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*, July 14, 2021, https://efiling.energy.ca.gov/getdocument.aspx?tn=238853.

[120] Bureau of Transportation Statistics, "Local Area Transportation Characteristics for Households (LATCH Survey), February 2021, https://www.bts.gov/latch.

[121] M.J. Bradley & Associates, *Medium- & Heavy-Duty Vehicles: Market structure, Environmental Impact, and EV Readiness,* July 2021, https://www.edf.org/sites/default/files/documents/EDFMHDVEVFeasibilityReport22jul21.pdf.

[122] National Renewable Energy Laboratory, "Fleet DNA: Commercial Fleet Vehicle Operating Data," https://www.nrel.gov/transportation/fleettest-fleet-dna.html.

[123] Experian, "Vehicles in Operation (VIO)," https://www.experian.com/automotive/vehicles-in-operation-vio-data.

of vehicle classes and disaggregated statewide forecasts into county and IOU-level targets areas to enable comparison.

Kevala also separated the CARB and CEC ZEV adoptions by their ownership type, which are categorizations that are contained in the agencies' forecasts. Kevala refers to ZEVs that are personally owned by an individual and used for personal, non-businesses purposes as personal EVs. For the purposes of the Part 1 Study, personal EVs are exclusively LDVs. Personal EVs can be either BEVs or PHEVs and can be one of seven vehicle classes. The second category of vehicle ownership type is fleet EVs. Fleet EVs are vehicles owned by or registered to an entity (not an individual) and are used for business-related purposes. Fleet EVs can be LDVs, MDVs, or HDVs. Fleet EVs only have BEV powertrains and can be one of 10 vehicle classes.

The next step was to set the potential number of vehicles and type of vehicle at each premise eligible for vehicle adoption. Kevala modeled residential premises to be sized with one or two personal LD BEVs or PHEVs, with the probability of adopting two vehicles increasing with time. Kevala assigned the vehicle class of these vehicles using probabilities derived from projected vehicle class market share from the AB 2127 Report, which references CARB's 2020 Mobile Source Strategy (MSS) LDV ZEV adoption forecast.[124] Non-residential premises were sized with up to 180 LD, MD, or HD fleet BEVs or PHEVs of a specific vehicle class based on the following:

- The existing number of ICE vehicles of the relevant vehicle class in the premise's Census tract.
- The annual electrification rate of existing ICE vehicles derived from the EV adoption targets for each vehicle class.
- The estimated area of the premise, with larger premises receiving more vehicles.

Kevala developed separate models for personal and fleet EV adoption. The personal EV adoption model used the density of existing EVs in the Census block, the urban/suburban/rural classification of the premise's Census tract, whether the premise was a likely MUD, peak load, and eight additional demographic features. Kevala trained a Bayesian MLR model against historical EV adopters identified by PG&E in its territory. Because there was not sufficient data within SCE and SDG&E's service areas to conduct the training analysis, Kevala also used the model trained using PG&E data to predict EV adoptions in SCE and SDG&E.

The fleet EV adoption model used customer class, estimated premise area, and estimated premise building footprint to produce an adoption score for eligible premises. Address-level historical fleet

[124] CARB, *2020 Mobile Source Strategy*, September 2021, https://ww2.arb.ca.gov/sites/default/files/2021-09/Proposed_2020_Mobile_Source_Strategy.pdf

EV adopters were not available, so Kevala selected model features and weighted them for importance based on available data and subject matter expertise. For personal and fleet EV adoption models, Kevala ranked the resulting adoption propensity scores by either vehicle class or powertrain (BEV or PHEV) and selected the highest-scoring premises to adopt until meeting the vehicle count targets of the different EV scenarios.

After predicting EV adoptions, Kevala estimated EVSE adoption. EVSE port count targets for each charger use case (e.g., workplace, public, corridor) were first developed for each county in the IOU service territories.[125] Kevala set these targets using EVSE ports-to-EV count ratios derived from the CARB 2020 MSS forecast values contained in the AB 2127 Report from 2022 to 2035. Kevala applied these ratios to the annual, county-level EV adoption results in the Part 1 Study scenarios to set county-level EVSE port count targets.

After setting EVSE port count targets, Kevala sized premises eligible to adopt EVSE with a theoretical charger use case, level—L1, L2, or DCFC—and port count. Kevala sized EVSE at premises as follows:

- Premises that were flagged as likely SUDs received one L1 or L2 charger per vehicle. Kevala assigned SUDs TOU or non-TOU rates to influence EV charging schedules based on projected annual shares of customers on TOU rates by IOU from the AB 2127 Report.[126]
- Premises flagged as likely MUDs received zero or one L1 or L2 charger per vehicle.
- Premises adopting fleets were assigned approximately one L2 or DCFC charger for every two vehicles based on EVSE-to-EV ratios derived from the AB 2127 HEVI-LOAD model results.
- Premises flagged as non-residential and where no EVs were adopted were eligible for public, workplace, and corridor chargers.[127] Where theoretical EVSE was assigned, Kevala based charging use cases and charger levels on probabilities derived from forecasted market shares of charging technology from the AB 2127 Report.
- Premises located in travel corridors were eligible for DCFC corridor chargers serving either LDVs or MDVs and HDVs, and premises located outside travel corridors were eligible for workplace L2 chargers, public L2 chargers serving LDVs, public DCFC chargers serving LDVs, and public DCFC chargers serving MDVs and HDVs. Kevala assigned the EVSE port count at each premise based on probabilities derived from historical port counts per charging station and projected trends in increased port density at charging stations.

[125] Port counts refer to the unit of charging infrastructure that is able to charge one ZEV at one time.
[126] See Appendix B, Table B-9 in the AB 2127 Report for TOU participation rates by utility territory.
[127] A corridor charger is a charger located in major travel corridors, primarily serving long distance travel.

Kevala developed an EVSE adoption model for public, workplace, and corridor chargers that uses customer class, Caltrans traffic and truck volumes, estimated premise area, and the percentage of commercial premises in a premise's Census tract as its core features. Due to the nascent state of public and shared private EVSE networks and incomplete data on existing EVSE in IOU territories, Kevala chose not to train a model based on historical data and instead developed a set of features and corresponding weights in the adoption algorithm based on projected future trends and subject matter expertise. Kevala then ranked the resulting adoption propensity scores and, starting with the highest-scoring premises, selected to adopt until the EVSE port count target for each scenario, use case, and level was met. In the final stage, Kevala produced hourly EVSE charging demand curves for every premise adopting EVSE. The EVSE behavior model simulated the charging patterns of a typical set of vehicles using the charger(s) at the premise over the course of a year as follows:

- For public, workplace, and corridor chargers, this typical set of vehicles was derived from the annual market share and count of EVs in the county the vehicle is based.
- For home and fleet chargers, the EVs adopted at the premise made up the vehicles using the charger(s).
- Beyond information about the charger(s) and vehicle stock, the model used operational inputs such as the VMT required to be met for each vehicle by the chargers, hourly and weekly vehicle operating schedules, and the battery state-of-charge threshold at which to seek charge.

The following are the key assumptions associated with EV and EVSE adoption and behavior modeling:

- **Kevala based future vehicle and EVSE attributes on AB 2127 modeling assumptions**. Due to the inherent uncertainties in future vehicle, battery, and charger technology trends, Kevala chose to use the AB 2127 Report modeling assumptions for these technologies wherever possible.
- **EVs and EVSE were adopted once over the forecast period**. Personal and fleet EVs are often adopted over time as conventional vehicles come to the end of their useful life and are replaced with EVs. This may understate the fleet size and future fleet depot load at individual premises. In Part 2, Kevala can revisit the ability of a premise to add additional vehicles in later years of the forecast period.
- **There were no limitations on density of public, workplace, and corridor EVSE in an area.** While Kevala calibrated its models to forecast geographically dispersed public, workplace, and corridor chargers, premises with similar characteristics and in the same area may adopt chargers, potentially overstating the EVSE demand in specific areas from

these charger types. Future models could consider existing EVSE density when placing chargers.

- **Temperature impacts on charging curves were ignored**. High and low temperatures can have meaningful impacts on charging demand, driven primarily by impacts on cooling and heating loads in the vehicle cabin. Thus, charging loads are likely to be different in summer and winter months in certain geographies of the state.

3.4.7. Calibration to Top-Down Forecasts

As defined in the Research Plan and discussed in each of the preceding sections, Kevala calibrated its Base Case to the 2021 IEPR. The CEC scenarios and files used to calibrate the different scenarios are listed here:

- CEC hourly demand forecast files:
    - CED 2021 Hourly Forecast – PGE – Mid Baseline – AAEE Scenario 3 – AAFS Scenario 3 (PG&E mid case)
    - CED 2021 Hourly Forecast – SDGE – Mid Baseline – AAEE Scenario 3 – AAFS Scenario 3 (SDG&E mid case)
    - CED 2021 Hourly Forecast – SCE – Mid Baseline – AAEE Scenario 3 – AAFS Scenario 3 (SCE mid case)
    - CED 2021 Load Modifiers – 02.22.2022 (Load modifiers mid case)
- CEC load-serving entity (LSE) and balancing authority (BA) file:
    - CED 2021 Managed Forecast LSE and BA Tables- Mid Demand- AAEE Scenario 3 – AAFS Scenario 3 (LSE mid case)

As noted in Section 3.3.2, Kevala calibrated the baseline load forecast for 2022 with no DERs to the "Unadjusted Consumption" or native load peak provided in the CEC 2021 IEPR mid-mid case at the TAC (or aggregate transmission load node) level by IOU. For SCE and PG&E, the resulting maximum baseline load was adjusted by the IOU service territory to TAC-level peak load ratio derived from the CEC 2021 IEPR LSE and BA files.[128] SDG&E was the sole LSE in its TAC area, so no such adjustments were necessary.

For the demand-side modifiers, Kevala used the maximum combined power output of the DER non-coincident with respect to the TAC-level peak load (i.e., the maximum coincident output of each of the DERs forecasted), provided in the 2021 IEPR mid scenario hourly DER forecast at the TAC level. As with the native load, Kevala adjusted this value with the same ratio of the IOU service territory to TAC-level peak load ratio derived from the 2021 IEPR LSE and BA files as a good proxy

[128] Form 1.5c "1-in-5 Net Electricity Peak Demand by Agency and Balancing Authority (MW)," using the LSE mid-case.

of service territory to TAC ratio for DERs' maximum output. Kevala adjusted the combined output for PV and BESS with the combined DER output to maximum installed capacity ratios derived from Kevala's behavior modeling result curves.

Lastly, Kevala used the adoption counts for LDVs and MDVs/HDVs from the 2021 IEPR mid scenario provided by the CEC as targets of the adoption stage for EVs. Each of these base case assumptions is listed in Table 14, Table 15, and Table 16.

Table 14: Base Case 2022 baseline load calibration targets by IOU *(Source: CEC)*

Forecast	PG&E (MW)	SCE (MW)	SDG&E (MW)
Baseline load	20,410	22,146	4,749

Table 15: Base Case 2021 IEPR forecasted EV targets for 2025, 2030, and 2035 *(Source: CEC)*

Duty	Powertrain	PG&E (Thousands of Vehicles)			SCE (Thousands of Vehicles)			SDG&E (Thousands of Vehicles)		
		2025	2030	2035	2025	2030	2035	2025	2030	2035
LDVs	BEV	613	1,050	1,562	408	693	1,021	128	217	319
	PHEV	252	365	452	258	367	450	59	88	104
MDVs and HDVs	BEV[129]	11	54	109	11	47	94	2	8	16

Table 16: Base Case 2021 IEPR EE, BE, PV, BESS calibration combined DER output targets for 2025, 2030, and 2035 *(Sources: Kevala, CEC)*

IOU	PG&E (MW)			SCE (MW)			SDG&E (MW)		
Year	2025	2030	2035	2025	2030	2035	2025	2030	2035
EE	- 426	-889	-1309	-465	-999	-1477	-103	-210	-307
BE	222	522	855	154	346	562	22	46	73
PV	-7,094	-9,653	-12,090	-4,023	-5,488	-7,197	-1,908	-2,525	-3,139

[129] IEPR mid targets for MDVs/HDVs were provided as combined counts of total BEVs and PHEVs. Given the uncertainty in the share of BEVs and PHEVs, Kevala modeled all MDVs/HDVs as BEVs.

IOU	PG&E (MW)			SCE (MW)			SDG&E (MW)		
Year	2025	2030	2035	2025	2030	2035	2025	2030	2035
Residential Storage	121	274	436	45	105	175	39	81	121
Non-Residential Storage	45	97	144	36	76	112	11	23	34

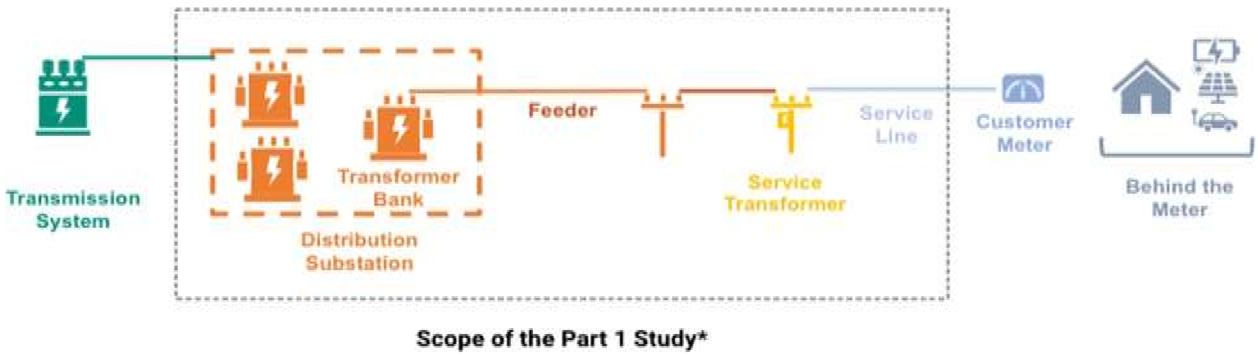
3.5. Estimation of Electrification Grid Upgrade Costs

The approach to streamlining the capacity-driven upgrade requirements can be summarized in three steps:

1. Determining the peak load at different key infrastructure points of the grid to estimate if there is an overload.
2. Determining new infrastructure assets required to mitigate the overload.
3. Using the unit cost for installed new assets provided by the IOUs to determine the costs.

Creating premise-level hourly disaggregated net-load profiles enables Kevala to calculate the coincident peak load at different aggregation levels. For this study, Kevala calculated the distinct coincident peak load for all service transformers, feeders, and substation transformer banks to determine long-term thermal capacity upgrades for the different scenarios and time horizons. A simplified grid diagram depicting the grid infrastructure assets and their connectivity is provided in Figure 57. From left to right, a transmission line feeds a distribution substation that typically has anywhere between two and four transformer banks; each transformer bank serves a number of feeders to distribute power to the neighborhoods. The feeders serve thousands of customers via primary lines or line segments that distribute the power to service transformers on poles or underground pad-mounted transformers. Service transformers step down the voltage for a few customers (up to a dozen) to the customer utilization voltage, and the power is finally delivered to the customer meter via secondary service lines.

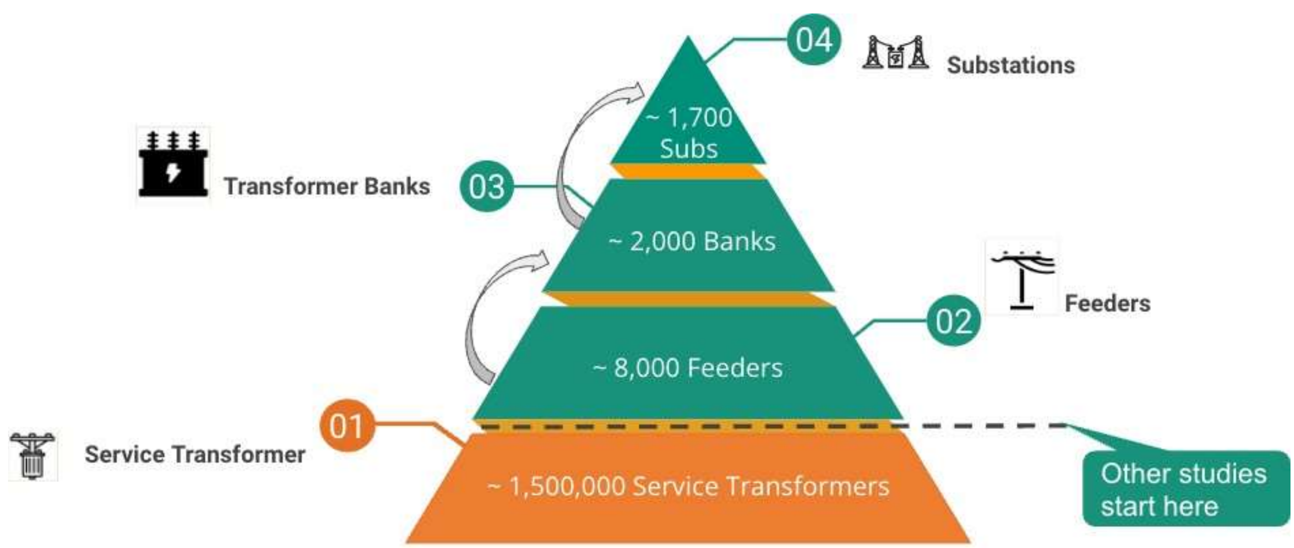
Figure 57: Grid infrastructure connectivity diagram of substations, transformer banks, feeders, and service transformers that distribute electric power to customers via the distribution grid *(Source: Kevala)*



*The scope of the Part 1 Study does not include the transmission (and/or sub-transmission) system feeding the distribution substation or the primary line segments from the feeder head to the service transformers.

For a better sense of the number of assets at which Kevala performed a capacity grid needs assessment, Figure 58 shows the number of service transformers to substations that Kevala analyzed. The unit cost of replacing each of the different assets increases from the bottom of the pyramid to the top—e.g., a new substation has higher unit costs (multiple tens of millions of dollars), and a new service transformer has lower unit-cost (multiple tens of thousands of dollars). The detailed unit-cost assumptions by assets type are presented in the Section 3.5.1.

Figure 58: Number of substations, transformer banks, feeders, and service transformers analyzed by Kevala in the Part 1 Study for the three IOUs *(Source: Kevala)*



Notes: The numbers in the pyramid are the number grid assets by category for the three IOUs.

Kevala calculated the upgrade costs based on the unit costs of grid assets and distribution design principles provided by the each of the IOUs, including:

- Typical number of feeders by substation transformer bank size
- Typical number of transformer banks in a substation
- Overloading criteria for service transformer, feeder, and substation transformer bank

The detailed design assumptions are included in Appendix 10, Appendix 11, and Appendix 12.

3.5.1. Distribution Grid Asset Unit Costs

Table 17 summarizes the unit costs (including overhead and installation costs) provided by the IOUs. New substation costs used in this study and provided by the IOUs do not include transmission line extensions or distribution feeder lines outside the substation.

The differences in the substation unit costs between the IOUs are summarized as follows:

- PG&E substation unit costs are based on Table 17-27 of the 2023 General Rate Case and include land, regulatory, material, and construction costs for assets within the substation fence.
- SDG&E substation unit costs are based on the installation of four 69/12 kV transformers (each rated at 28 MVA) and four quarter section switchgear; they do not include cost estimates for other requirements and factors such as land acquisition, site development, environmental permits, transmission and distribution infrastructure, control shelter, protection equipment, and relays.
- SCE substation unit costs are based on the average cost of five historical substation projects and include distribution substation installed equipment costs and land.

Regarding transformer bank unit costs, the IOUs provided installed transformer costs. PG&E uses 45 MVA for new installs while SCE and SDG&E typically use the 28 MVA size. Feeder costs for PG&E and SDG&E include the costs of a 2-mile primary run. PG&E included the fixed feeder breaker costs of $1.4 million and the primary conductor cost for which Kevala used the average of overhead and underground runs, resulting in $470/foot. SDG&E included the per distance cost of primary trench and conduit and primary cable adding up to $601/foot. SCE provided a typical cost for primary feeder by voltage class, and Kevala used the average cost, resulting in $5,473,094 per feeder, and it includes all equipment and labor to construct the entire circuit, including the primary distribution line.

Table 17: New substation, transformer bank, and feeder unit costs *(Source: Kevala)*

IOU	Substation	Transformer Bank	Feeder
PG&E	$27,000,000	$11,800,000 (45 MVA)	$6,363,200
SCE	$39,663,589	$2,019,011 (28 MVA)	$5,473,094
SDG&E	$20,912,000	$4,685,000 (28 MVA)	$6,689,760

Table 18 includes the service transformer costs by type and size, including equipment (transformer and secondary cable) and installation costs for PG&E, SCE and SDG&E respectively.

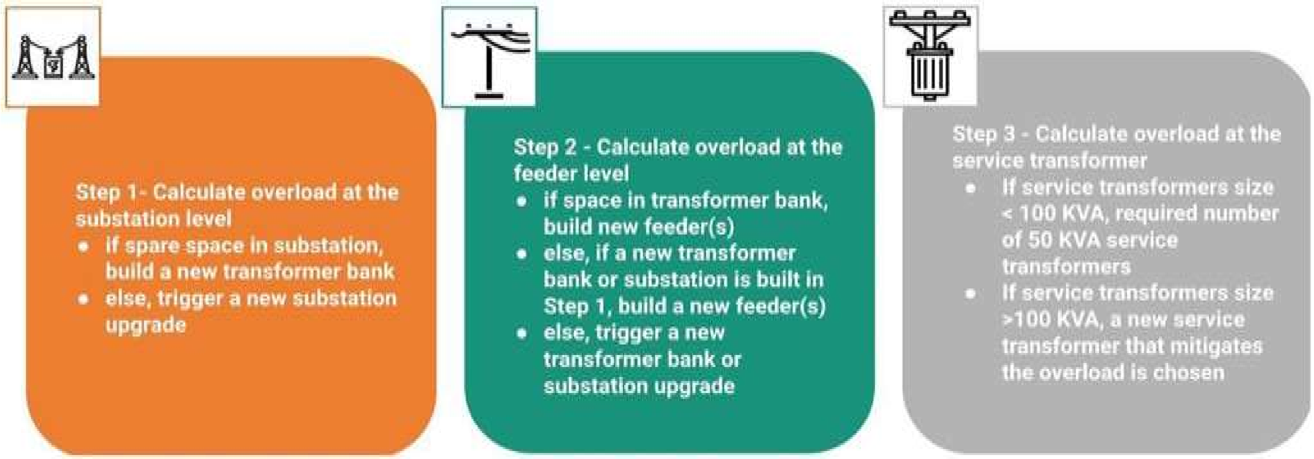
Table 18: New service transformer and secondary cable equipment and labor costs by IOU *(Source: Kevala)*

Service Transformer Size (KVA)	PG&E	SCE	SDG&E
<150	$22,000	$19,000 (Residential)	$22,000
150	$39,000	Not standard size	$59,700
300	$47,000	$39,140 (C&I)	$61,600
500	Not standard size	$50,470 (C&I)	$67,500
750	$58,000	$58,710 (C&I)	$74,000
1,000	$72,000	$74,160 (C&I)	$126,100
1,500	$98,000	$101,970 (C&I)	$133,400
2,500	Not standard size	$193,640 (C&I)	$152,100

3.5.2. Approach to Grid Upgrade Requirements

Figure 59 outlines the grid upgrade costs method.

Figure 59: Thermal capacity upgrade cost calculation method at different grid asset levels *(Source: Kevala)*



The approach is summarized in the following steps:

- **Step 1:** Kevala calculated the coincident peak at the 2,054 transformer banks for the three IOUs. Kevala assumed that load can be transferred between transformer banks at the substation level. As such, the overload was calculated at the substation level by adding ratings of the transformer banks to determine an overload. The sum of the peak load at the transformer banks within a substation was compared to the sum of the transformer bank ratings to determine the overload. If an overload was determined based on the overloading criteria at the transformer bank level provided by the IOUs and the substation has space based on the typical number of transformer banks in a substation, then one or more transformer banks were added and the corresponding costs calculated. However, if there was no more space at the substation to accommodate the required number of new transformer bank(s) to solve the overload, then a new substation was added and upgrade costs calculated.
- **Step 2:** Kevala calculated the coincident peak at each of the 8,256 feeders and compared it to the feeder rating to determine the overload. If an overload occurred based on the overlaying criteria provided by the IOUs for feeders, and there were one or more spare breakers on the transformer bank based on the typical number of feeders by transformer bank size, then one or more feeders to mitigate the overload were built and the corresponding costs calculated. However, if there was no more space on the transformer bank to add the number of feeders required to mitigate the overload, then, if there was a new transformer bank or substation that was built in the previous Step 1, then one or more feeders to mitigate the overload were built and the corresponding costs calculated. If there

was no more space on the transformer bank and no new transformer banks or substations were built in Step 1, then a new transformer bank or substation upgrade was triggered.

- **Step 3:** Kevala calculated the coincident peak at each of the 1,560,390 service transformers for the three IOUs and compared the result to the service transformer rating to determine the overload. For customers connected to service transformers with a rated capacity less than or equal to 100 KVA, based on the magnitude of the overload, Kevala added the required number of 50 KVA service transformers and calculated the corresponding costs to solve the overload. For C&I customers connected to service transformers with rated capacity greater or equal to 150 KVA, a new next size-up service transformer that would mitigate the overload was chosen from the service transformer size tables provided by the IOUs.

Kevala did not include other grid deficiency needs such as thermal line section, voltage, and resilience in the Part 1 Study, but they may be revisited as appropriate in the case studies in Part 2.

4. Recommendations for Improvements on DPP and Part 2 Planning

This Part 1 Study demonstrates that it is possible to connect premise-specific characteristics to develop long-term location-based scenarios. **Scenario planning that reflects localized and dynamic conditions and behaviors is a critical risk identification and mitigation method for distribution planners and policymakers.** Distribution planners, for example, need additional tools to anticipate diversified and location-specific grid requirements; policymakers need additional tools to develop and evaluate the cost-effectiveness and metrics of utility investments, customer programs, and rate designs going forward. **In short, missing the where and when of necessary grid investments risks making stranded investments or missing opportunities to electrify altogether.** Because the grid is changing at the premise level, utility and policy decisions should be informed by a premise-level understanding of where and when electricity grid enhancements will be needed to meet California's ambitious energy policy goals.

This section outlines recommendations for improvements to the DPPs. This section also summarizes Kevala's approach for evolving the premise-based analysis begun in this Part 1 Study into the Part 2 Study. Kevala's proposed Part 2 approach is designed to support the Phase 2, Track 1 questions identified in the High DER Rulemaking Scoping Memo by building on the data collected and analyzed to date in Part 1.

4.1. Recommendations for DPP Improvements

The results of this Part 1 Study suggest that understanding where and when electricity grid enhancements are needed will require changes on multiple distribution planning fronts. Based on these results, Kevala recommends these specific changes relating to the utilities' distribution planning approaches, infrastructure included in the distribution planning processes, and data used in utility distribution planning.

First, using the approach detailed in Section 3 of this of this Part 1 Study report, Kevala has demonstrated that it is possible to disaggregate load and DER growth and predict distribution impacts at a premise-level:

- Over a 15-year time horizon, which is a longer forecast time horizon (to 2035) than is currently performed for regulatory filings.
- Incorporating multiple scenarios for each of the three IOU service territories in less than one year (the timeframe to conduct the study).
- Identifying significant potential capacity costs previously not identified in current utility distribution planning filings.

These results suggest there is a disconnect between the current distribution and DER planning processes that are near-term focused and locational grid requirements that are likely to materialize under different DER adoption scenarios over the longer term. These processes result in minimal-to-no deferral opportunities being implemented.[130] Further, these results suggest that studying how DER and other load management techniques can avoid or mitigate the significant capital costs identified in this study will be a critical component of achieving California's electrification goals.

Recommendation 1: PG&E, SCE, and SDG&E should increase the planning horizon for their distribution planning filings. The expected adoption rate of technologies at the grid edge (i.e., at the premise level) in the long term to meet federal and state decarbonization and electrification policies may require the distribution planning horizon to be increased to align with the CEC's IEPR planning horizon (15 years)[131] and the California Independent System Operator's (CAISO's) transmission planning horizons (10 years for annual planning and 20 years for transmission outlook). Increasing the planning horizon for distribution planning filings should help to prepare more efficiently for a distribution grid that can maximize the cost-effectiveness of incorporating DERs and load management technologies to increase system capacity and reliability.

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[130] See Kevala's *Distribution Investment Deferral Framework: Evaluation and Recommendations* report: https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/63729a90e35f9cb53c617a14_DIDF%20Evaluation%20and%20Recommendations_Kevala_11.14.22.pdf.

[131] As stated in the 2021 IEPR at p. 2, "For the 2021 forecast, these energy demand forecasts are extended out beyond 10 years to 2035 to provide planners with a longer forecasting horizon and support planning for transportation electrification goals." The 2021 and 2022 IEPRs went beyond 10 years to 2035 (15 years), and the 2021 IEPR also included long-term energy demand scenarios to 2050 (30 years) because of increasing policy and planning focus on climate change. See also Public Utilities Code Section 454.57(e)(1), which as of 2022, requires "at least 15 years" to ensure adequate lead time for permitting and construction of approved transmission facilities.

Recommendation 2: PG&E, SCE, and SDG&E should incorporate additional policy-based demand scenarios into their DPPs and annual GNA/DDOR filings. For example, scenarios can consider managed charging assumptions or different rates of EV and BE adoption to better understand the impact of higher or lower electrification loads on planned investments for grid infrastructure. As this Part 1 Study shows, an uncertain load and DER future requires scenario planning that would result in multiple load and DER scenarios being disaggregated in the DPP to better inform the overbuilding and underbuilding risks involved in planning for grid infrastructure needs.

This Part 1 Study, by leveraging AMI consumption data and performing a premise-level modeling of load and DER potential futures, was able to estimate grid upgrades for the scenarios considered at the service transformer level, across the PG&E, SCE, and SDG&E territories. Kevala recommends the distribution planning process should **consider secondary distribution infrastructure grid needs**,[132] as described in Recommendation 3, so that such grid upgrades do not become a bottleneck for electrification and are proactively planned for in a cost-effective way.

Recommendation 3: PG&E, SCE, and SDG&E should provide an estimate of secondary distribution infrastructure grid needs to support future state electrification goals in the GNA/DDOR filings, so that secondary infrastructure can be accounted for and proactively planned in a high DER future.

The scope of this Part 1 Study, in terms of understanding the impact on the unmitigated load and DER growth in the scenario considered, stopped at the distribution substation level. However, it is becoming increasingly important to also understand the impacts on the sub-transmission and transmission infrastructure. There is currently a lack of understanding on the coordination of identified grid constraints and mitigation strategies that may affect all levels of the grid (i.e., transmission, sub-transmission, and distribution). Kevala has already provided specific recommendations in the evaluation of the IOUs' 2022 GNAs and DDORs[133] related to coordination

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[132] The secondary grid is the part of the electric distribution system between the primary feeder and the customer. The secondary distribution system includes distribution service transformers and secondary main and service conductors to the customer meter. The primary distribution grid is the feeder lines between the substation and the distribution service transformer.

[133] See Recommendation 1 on p. 54 in Kevala's *Distribution Investment Deferral Framework: Evaluation and Recommendations* report, provided to the R.21-06-017 service list on November 14, 2022. The link can be

on capacity planning activities between the DIDF and CAISO's transmission planning process. In addition to these recommendations to the DIDF, Kevala recommends that the distribution planning process should be able to map the transmission and distribution nodes that are at risk of large capacity grid infrastructure needs, as identified in this Part 1 Study, to enable a coordinated and integrated planning of grid infrastructure and mitigation strategies between the distribution and transmission planning processes (see Recommendation 4).

Recommendation 4: PG&E, SCE, and SDG&E should provide information in the GNA regarding distribution planning areas located in transmission- and sub-transmission-constrained nodes,[134] and DDOR planned investment cost estimates should consider associated higher voltage upgrade costs that may be triggered by the distribution investment.

Finally, electric distribution grid requirements and their associated costs increase significantly beyond the traditional distribution grid planning cycle and risk being missed if key datasets continue to be applied in data silos (i.e., if datasets are not connected and analyzed holistically). A holistic view of the entire interconnected state electrical grid is needed to ensure sufficient system planning. Existing data is extensive and shows significant potential when linked to better capture local adoption and include equity considerations. Continued data consolidation and review can enable identification of primary and secondary grid requirements and provide transparency and enumerable opportunities for scenario analyses.

Recommendation 5: PG&E, SCE and SDG&E should update the mapping of the connectivity of their respective distribution grid assets and ratings in the 2023 GNA report. Further, the IOUs should update any changes in network connectivity data in subsequent annual filings. As demonstrated in this Part 1 Study, mapping between feeders and transformer banks is critical information that enables identification of opportunities to transfer load as well as points of potential distribution grid overload. In the datasets received for this study, feeder-to-bank connectivity was incomplete for PG&E, SDG&E, and SCE, and the transformer bank ratings were incomplete for SCE (see Section 3.2). This improved and ongoing network data hygiene is critical to accurate and dynamic scenario planning.

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found here: https://uploads-ssl.webflow.com/62a236e9692c48e1d16898b3/63729a90e35f9cb53c617a14_DIDF%20Evaluation%20and%20Recommendations_Kevala_11.14.22.pdf

[134] A transmission node refers to the interface between the distribution and the transmission electric power systems. At transmission nodes, the distribution system is typically represented as an aggregate lumped load in transmission models.

An important input to performing granular load and DER disaggregation is the customer sector designation. In this Part 1 Study, the customer sector was defined first by rate class, then by North American Industry Classification System (NAICS) code (from rates data), and finally by parcel customer class from publicly available census data. Kevala found misaligned NAICS codes, particularly when the rate code was not provided. For example, some premises classified as residential were confirmed by Kevala to be large non-residential. The customer sector designation is a critical consideration in distribution planning. Kevala proposes further investigating the extent of the misclassification errors to inform the IOUs to use for their load and DER disaggregation methods in the DIDF process and to refine the input data for Part 2.

Recommendation 6: Develop a standard for each IOU to provide a consistent customer sector designation, which is a key driver to determining accurate locational load and DER forecasts, in particular expected growth from transportation electrification.

Kevala offers these recommendations for CPUC and stakeholder consideration in the High DER Proceeding. The above recommendations are the most notable reflections on the Part 1 Study process and are not an exhaustive list of potential distribution planning process changes for the CPUC to consider. Additional observations and perspectives will likely be offered in the course of the proceeding and be considered as part of staff proposals anticipated in Tracks 1 and 2 of the proceeding.

4.2. Long-Term Implications

This section offers a longer-term view of the implications of the Part 1 Study to achieve California's electrification goals. The premise-based scenario planning approach applied in Part 1 indicates that traditional distribution planning tools and assumptions and program assumptions may need to be reconsidered. **Distribution grid planning that incorporates DERs throughout the process instead of at the end may help to identify and mitigate planning risks.** Essentially, incorporating distributed resources in the distribution planning process may enable California to capture the uncertainty of both supply and demand in order to plan the grid infrastructure and DERs to meet distribution capacity expansion, reliability, and equity needs. Specifically:

- **Probabilistic-based methods and metrics** similar to those used in CAISO's transmission planning (loss of load probability, loss of load expectation, effective load carrying capability,[135] etc.) can be developed for distribution planning in an iterative process to better inform the uncertainty and risks of different planning scenarios. [136]

- Transmission planning and resource adequacy processes already take into account uncertainties like unexpected generator outages, variable load and generation, and changes in the weather, which are becoming increasingly important. Evaluating these uncertainties statistically, bulk system grid planners project resource needs to reach an acceptably low level of risk of capacity shortages.
- The underlying concept is to use randomness[137] to solve problems that might be deterministic in principle, such as determining capacity requirements to improve decision-making and risk management.
- **EV forecasting methods should evolve to include long-term LDV, MDV, and HDV** and proactively determine future capacity expansion grid needs and deferral opportunities.

- There is a lack of understanding of how mitigation strategies can be stacked to solve capacity expansion constraints. Kevala recommends that **mitigation strategies such as utility customer programs, rates, and third party-provided solutions along with utility-owned solutions all be considered in the distribution infrastructure planning process to meet long-term grid and equity needs**. For example, based on the scope of this Part 1 Study:
  - Rates alone are no longer the silver bullet for where and when generation capacity needs diverge from the where and when of distribution capacity needs.
  - The DIDF planning process does not take into account customer programs and rates and considers short-term deferral values only.
  - Electricity burden should be incorporated as an input to the DIDF.

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[135] Loss of load probability is the probability that load will exceed generation in a given hour.
Loss of load expectation is total number of hours wherein load exceeds generation. This is calculated as the sum of all hourly loss of load probability values during a given time period (e.g., a calendar year).
Effective load carrying capability is the additional load met by an incremental generator while maintaining the same level of system reliability.
These metrics are defined in "Stochastic Modeling Status Report California ISO Workshop," https://www.caiso.com/Documents/Presentation_E3_LOLP_Model_Feb10_2012.pdf.

[136] Jeremy Keen, Julieta Giraldez, et al., *Distribution Capacity Expansion Planning: Current Practice, Opportunities, and Decision Support*, November 2022, https://www.nrel.gov/docs/fy23osti/83892.pdf.

[137] Random variables such as load and DER adoption location and sizes, converge to the deterministic distribution of the random states so that the statistical interaction between the variables vanishes.

- Planning processes should better **reflect the local technology adoption roadmaps** and trends to **proactively plan supply and infrastructure needs and** avoid the grid becoming a barrier to electrification and DER adoption plans.
  - Siloed planning processes risk missing the convergence of generation, transmission, and distribution capacity needs.
  - Actual premise-level behaviors cannot be represented with generic load shapes that can miss the local impacts of load and DER growth, in particular of EVSE infrastructure.

Data collection and integration across California LSEs beyond the three IOUs studied in this Electrification Impacts Study could enable much more complete forecasting for DER technologies like EVs that transcend traditional utility boundaries. Specific technology, program, and regulatory process changes that could enable enhanced scenario planning may be effective tools to increase transparency and help manage grid integration.

- Limited historical data for newer DER technologies requires continued augmentation.
- Utility service territory boundaries do not reflect socioeconomic, carbon emissions, or technological boundaries, and some additional datasets that will be necessary or beneficial to the Part 2 analysis may not originate from PG&E, SCE, or SDG&E. Vehicle registrations and driving pattern-related data, sub-transmission data for PG&E and SDG&E, or publicly owned utility data for areas adjacent to the IOUs in this study, for example, may be sourced through collaboration with other state agencies and publicly owned utilities. Kevala recommends coordination across those public organizations to the extent possible to enable as robust a Part 2 analysis as possible.
  - Kevala suggests the CPUC continue to pursue data sharing agreements with the CEC, CARB, and DMV and leverage existing data sharing agreements across IOUs and CCAs.
  - Kevala suggests the CPUC and CEC pursue data sharing agreements with municipal utilities to ensure complete datasets across the entire geographic forecast area of California.

4.3. Part 2 Study Options and Considerations for Methods, Scenarios, Case Studies, and Updated Data

The Part 1 Study focused on illustrating how it is possible to better prepare for a future with high electrification by disaggregating multiple long-term policy-driven scenarios to the premise level to identify where and when grid infrastructure bottlenecks will occur. **The proposed approach for the Part 2 Study focuses on running additional statewide electrification scenarios with**

baseline load and transportation electrification methodologies and scenarios that will be updated with additional data. Kevala also proposes adding BE scenarios aligned to state policy targets. These proposed scenarios are designed to identify the range of electrification impacts on the distribution grid and to identify potential mitigation measures such as DERs, innovative rate structures, and load management techniques that could help manage those impacts.

Some of the key questions proposed to be explored in Part 2 are:

- How can a **long-term view of 15 or 20 years, in alignment with CEC and transmission planning horizons,** into where and when grid infrastructure bottlenecks or underutilized assets might occur be used to inform the distribution planning process and prioritize and plan for longer-lead grid investments and mitigation strategies?
- What are the elements of the DPP that need to change to better **capture additional value from DERs** to mitigate the risk of grid constraints due to a high electrification future?
- Can defining and quantifying **granular community- and customer-level equity metrics** be incorporated in the decision-making of optimal solutions to prepare and mitigate the risks of grid constraints due to a high electrification future?
- How can the distribution planning process incorporate **scenario planning and sensitivity analysis** around TOU rate structures, carbon impact, and affordability as well as future utility advanced management and control capabilities of DERs?

Throughout this Part 1 report, Kevala identified considerations for additional analytics and applications of this Part 1 Study for the Part 2 Study. There are innumerable combinations of methodological refinements, calibration and mitigation scenarios, and additional data to collect and analyze that could be considered in Part 2. Kevala's proposed scope for the Part 2 Study that is likely to provide the most significant insights and address the scoping questions raised in the High DER Proceeding is summarized in the following sections.

4.3.1. Distribution Planning Process and Mitigation Strategies

In the Part 2 Study, Kevala proposes exploring elements of an improved DPP that integrates DERs based on a weighted decision-making approach that can quantify risks and evaluate traditional wired and non-wires solutions to enable policy-driven future scenarios. The framework is based on:

- Longer-term planning horizon(s)
- Multiple scenario planning for load and DER growth and mitigation strategies
- Premise-level analysis of DER adoption, behavior, and sizing
- Additional planning objectives definitions and quantifications

- Increased access to data
- Specific stakeholder engagement and feedback received to date in the proceeding

The process will explore defining and quantifying new planning objectives for multi-objective distribution planning. The current GNA evaluation framework looks at capacity, reliability, voltage, and resiliency grid needs. In Part 2, Kevala proposes updating the definitions and quantifications of these four grid limitations and exploring additional objectives that can be quantified and prioritized for multi-objective distribution planning, such as:

- Local carbon emissions
- Energy burden
- DER hosting capacity
- Sub-transmission and transmission congestion relief

In Part 2, Kevala proposes to explore incorporating these additional metrics into a weighted decision analysis process to evaluate the potential fan of grid investments and mitigation strategies that can be implemented at the community level and better inform decision-making when planning grid investments.

4.3.2. Methodological Refinements

With additional and updated data (see Section 4.3.5), Kevala anticipates updating key elements of the underlying net-load methodologies. There are likely myriad improvement opportunities to be made in Part 2. Kevala has identified several possible methodological refinements below, focusing on the ability to improve understanding and visualization of electrification impacts on disadvantaged communities and refinements to the baseline load forecast methodology, BE methodologies, and EV methodologies.

- Incorporate disadvantaged community grid impact visualization capabilities into Part 2 results, consistent with CalEnviroScreen definitions.
- Update, or retrain, the baseline models with additional and improved AMI data and revisit the overall calibration method for load by calibrating to the total of the baseline load plus load growth in the Part 2 Study in order to continue to distinguish between baseline load profile versus electrification profile for appropriate DER behaviors.
- Refine the BE sizing, behavior, and adoption methodologies to explore different sizing models for residential versus non-residential premises, reflect specific technologies, and update for relevant metrics.
- Refine various aspects of the personal EV and fleet EV adoption methodologies using additional data sources to support more granular adoption choices and EV sizing and

vehicle type assumptions; revisit the EV adoption and TOU rate enrollment and behavior assumptions.
- Incorporate the load shapes and TOU differentials implicit in rate design alternatives as directed by the CPUC to update or test DER adoption scenarios.

Kevala believes these DER methodological refinements are most likely to have a disproportionate electrification impact on the distribution grid and are most likely to benefit from enhanced or updated datasets. Additional methodological refinements may be required for Part 2; the above list is not meant to be exhaustive. Kevala welcomes stakeholder input into specific additional methodological refinements that may be required to support Part 2 analysis.

4.3.3. Calibration Scenarios

As described in Section 1, Kevala focused its calibration scenarios on a base case scenario consistent with the 2021 IEPR and four alternate scenarios comprising alternate policy-based assumptions for Transportation Electrification and PV adoption resulting from BTM tariffs. This approach was designed in the Research Plan for this Electrification Impacts Study to isolate the impact of initial key factors likely to impact the distribution grid and to maintain consistency with the 2021 IEPR base case to the greatest extent possible.

These alternate scenarios have highlighted the benefits of testing the impact of different policy outcomes on the distribution grid. Kevala suggests identifying additional planning scenarios that could be studied in Part 2. Numerous scenarios may be possible and should be narrowed to focus on scenarios that are most likely to inform recommendations for the High DER Proceeding. As such, Kevala proposes developing scenarios in Part 2 that are:

- Likely to reflect the range of potential impacts on the distribution grid.
- Reflect DER programs or technologies that are more nascent or have relatively less available actual program data.

Potential scenarios to be included in Part 2 include the following:

- Scenario(s) that incorporate IEPR 2022 planning scenario design and possibly IEPR 2023 (depending on availability of IEPR 2023 scenario timing with the High DER Proceeding needs).
- Additional appropriate DER policy-based scenarios as developed and requested by California energy planning and regulatory agencies, with a focus on transportation electrification forecasts.

- BTM tariffs that reflect the Net Billing Tariff adopted by D.22-12-056 in December 2022 and the potential restructuring of rates in the Demand Flexibility R.22-07-005 (i.e., fixed charges).[138]
- Scenario(s) for accelerated BE adoption that are consistent with SB 1477 and AB 3232.
- As appropriate, Kevala also recommends extending the planning horizon up to 2050 as appropriate for each scenario, consistent with select other studies and Kevala's own recommendations to lengthen the distribution grid planning horizon (see below).

While the number of scenarios should be limited for Part 2, each scenario can include probabilistic simulations to accommodate for random variables in load and DER allocation results and provide metrics around uncertainty to inform deterministic outcomes to plan the distribution grid.

4.3.4. Mitigations through Case Studies on a Specific Region's Assets

To further provide value to the High DER Proceeding using a premise-level distribution planning model, the Part 2 Study proposes illustrating the DPP provided in Section 4.3.1 via case studies that will focus on a specific region's assets in the PG&E, SCE, and SDG&E service territories. These case studies will focus the analytical aperture on a specific region's assets (e.g., substation(s), feeder banks, feeder segments, and service transformers) and investigate the short-, medium-, and long-term capacity requirements that the region may face under varying levels of load and DER growth.

One of the primary goals of these case studies is to better understand the uncertainty inherent in distribution planning and proactively mitigate impacts and implement risk management strategies that maximize the value of DERs and load and DER management strategies in distribution planning.

Kevala has identified the following list of potential screening criteria and scenario variables that it could use to generate a robust range of insights from these case studies:

- **Geographic screening**
  - Urban, suburban, rural
  - Coastal, inland
- **Climate/weather**
  - Typical meteorological weather year
  - Severe weather years (i.e., 1-10, 1-100, 1-500 weather years)
- **Demographic screening**
  - Various income deciles/quartiles

[138] Decision 22-12-056, *Decision Revising Net Energy Metering Tariff and Subtariffs*, issued on December 19, 2022, https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M500/K043/500043682.PDF.

- Electricity burden deciles/quartiles
- Various disadvantaged community statuses
- Electricity burden deciles/quartiles

- **DER adoption scenarios**
    - Low, medium, high BE adoption
    - Low, medium, high LDV ZEV adoption
    - Low, medium, high MDV/HDV ZEV adoption
    - Low, medium, high PV + BESS adoption
- **Rate and technology scenarios**
    - Green TOU rates (focused on shifting usage toward the middle of the day when solar generation is highest)
    - Real-time hourly rates
    - Advanced, high-penetration demand response (>75% penetration of air conditioning load control, heat pumps, heat pump water heaters)
    - Vehicle-to-grid adoption for MDV/HDV ZEVs
- **Distribution asset composition**
    - Number of substations
    - Miles of feeder lines
    - Number of service transformers

Over the course of the Part 2 Study, Kevala will narrow down the number of screening criteria and scenario variables it proposes executing to identify the specific geographic regions to investigate and publish. Kevala invites stakeholder comments and recommendations for specific geographic or network areas to be included in the Part 2 case studies.

As part of the mitigation strategies and risk management approach, Kevala proposes focusing on the following aspects in the case studies:

- Exploring and testing NWAs, TOU and dynamic rates assumptions, demand response, and advanced DER management and control techniques as a mitigation to alleviate distribution system constraints.
- Identifying disadvantaged community areas with the most urgent need of load mitigations and proposing potential least-cost, best-fit solutions to understand how upgrade costs and different mitigation strategies would affect electricity burden and other energy justice metrics for different electrification scenarios.
- Understanding the interplay between personal EV home charging contribution to peak load and personal EV public charging and fleet charging that could play a more substantial role in driving the peak hour in 2035 and beyond.

- Identifying other grid needs as applicable to the case study area such as voltage and resiliency.
- Exploring statistical variation and probabilistic simulation to better inform uncertainty via:
    - Single scenario, random draw scenario modeling
    - Monte Carlo-based probabilistic scenario modeling

Energy Division is currently exploring options to enable Part 2 to report case study results through non-confidential visualizations that depict specific geographic areas.

4.3.5. Data

As noted in Section 3.2, Kevala did not receive all datasets in time to be used in the Part 1 analysis or the datasets were incomplete. Similar to the Part 1 approach, Kevala proposes developing a comprehensive data request to support the Part 2 analytic scope. That data request will be informed by stakeholder comments and reactions to this Part 1 analysis and by input on other outstanding data needs. Kevala's initial recommendations for additional or more complete datasets required for Part 2 include the following:

- Latest adopted IEPR demand forecast and scenarios (i.e., 2022 IEPR)
- Gas billing and consumption data to match AMI data time periods received
- Additional AMI data for before and after the Part 1 Study period (e.g., complete 2022 dataset); post-2022 AMI data is not anticipated to be necessary for Part 2 but would add accuracy to the results if it can be collected in time for study inclusion)[139]
- Additional SCADA data to include system data that enables better matching of AMI and network elements, including additional data after the Part 1 Study period
- Updated distribution power flow models
- More complete grid infrastructure mapping data[140]
- Customer program data to include incentives for BE
- Incremental PV and BESS interconnection data for installations after the Part 1 Study period
- Distributed generation and other historical DER program performance data
- IOU location-specific cost data
- Additional data sources to support EV sizing and vehicle type assumptions
- Vehicle registration data from the California Department of Motor Vehicles

[139] For Part 1, PG&E AMI data covered the period 2018 Q1 to 2021 Q3; SCE 2018 Q1 to 2021 Q1; and SDG&E 2018 Q1 to 2021 Q1. For Part 2, the deficiencies in historical PG&E and SDG&E AMI data need to be remedied to meet the Energy Division data request requirements in Data Request 4.0 issued on August 30, 2022; additional years of AMI data will be requested by Energy Division.

[140] For Part 2, PG&E, SCE, and SDG&E feeder to transformer bank mapping data as required by Energy Division Data Request 1.0 issued on December 3, 2021.

- More granular customer billing data (e.g., designation of whether a customer is on an all-electric rate)

Additional data may be required for Part 2; the above list is not meant to be exhaustive of all data needs for that study, and it may not be possible to gather all of the data listed in the timeframe required for the High DER Proceeding. Kevala welcomes stakeholder input into specific additional datasets that may be required to support Part 2 analysis.

Finally, Kevala recommends that a more regular data sharing process be established for certain datasets only (e.g., AMI data, SCADA data, customer interconnection data). Because Part 1's goal was to provide a high-level cost estimate of the infrastructure requirements for different electrification scenarios, the scale of the data gaps experienced in Part 1 did not significantly affect the results. As the CPUC plans for the Part 2 analysis, however, data gaps must be identified and resolved on a much more timely basis. Establishing a regular cadence for receiving updated data (for example, quarterly) will enable faster turnaround times for identifying data gaps, more updated scenario analysis that reflects most recent grid behaviors, and an exploration of location-specific mitigation measures to distribution capacity planning constraints.

Appendix 1. Literature Review on Load and DER Forecasting

Table A1-1: Summary of literature review *(Source: Kevala analysis)*

Study Name, Authors, Organization, Year Released	Scope of Study	Geographic Coverage and Number of Customers (if provided)	Time Coverage	Electrification Scenarios	Relevant Outcomes for Electrification Impacts Study	Results on Increase in Peak Load (kW) or Energy Demand (kWh) and Cost Impacts (if available)
Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California? Elmallah, Brockway, Callaway Energy Institute at Haas 2022	Focuses on the PG&E service area in Northern California, which serves 4.8 million electricity customers and is subject to aggressive targets for both EV adoption and electrification of residential space and water heating. Creates spatio-temporally detailed electricity demand forecasts and compares that demand to distribution infrastructure limits across a range of technology adoption scenarios.	PG&E service area in Northern CA 5.7 million customers	2020-2050	Consistent with California's EV targets, the scenarios assume that PG&E territory reaches 3.1 million EVs by 2030 and 12.5 million by 2050. The following scenarios are studied for 2030, 2040, and 2050 with upgrade needs and costs being assessed for substations and circuits separately: **<u>Vehicle Electrification</u>** **Standard:** 67% of plug-in EVs have home charging **More commercial:** 50% of vehicles have access to overnight charging, more commercial daytime charging **More residential:** 95% have access to overnight charging **Demand Response:** Smoothing residential nighttime charging from 10 pm to 5 am **<u>Residential Electrification</u>** **Reference/"Business-as-usual":** +17.5% in # homes electrified b/w 2021-2050 **Medium:** +33.2% **High:** +43.5% **<u>Combined Scenario</u>** **Scenario A:** Lower demand on residential circuits (medium RE scenario + more commercial EV) **Scenario B:** Higher demand on residential circuits (high RE scenario + more residential EV) **Scenario C:** Higher demand w/ demand response (high RE scenario + DR EV)	<u>Distribution</u>: In PG&E, between 95 and 260 feeder upgrades per year between now and 2030, roughly 3x the pace of projects that PG&E has planned for through 2025. Upgrade requirements in PG&E territory will add up to approximately $1B between 2021 and 2030 (closer to $5B by 2050). Existing excess capacity on commercial circuits means that commercial charging locations will not increase distribution costs. Electrification of residential space and water heating will lead to fewer impacts on distribution feeder capacity than EV charging, but that both transitions will require an acceleration of the current pace of upgrades. Timing and location have a strong influence on total capacity additions in important ways (ex. Scenarios that favor daytime EV charging have similar impacts to those with managed nighttime residential charging, but uncontrolled nighttime residential charging could have significantly larger impacts) Projects that these upgrades will add at least $1 billion and potentially over $10 billion to PG&E's rate base. Assumes that the total charging demand in PG&E's territory will be 39% of the statewide total.	**<u>Combined Scenarios Loads & Costs</u>** **<u>Upgrade Needs: Substation + Circuits (GW)</u>** **<u>Total GW</u>** Scenario A 2030 0.92 2040 3.07 2050 7.99 Scenario B 2030 1.4 2040 4.77 2050 3.18 Scenario C 2030 0.81 2040 3.18 2050 7.05 **Total Costs ($B) – Median Load** Scenario A 2030 $1.45 2040 $3.45 2050 $6.13 Scenario B 2030 $1.96 2040 $4.29 2050 $7.30 Scenario C 2030 $1.33 2040 $7.06 2050 $10.09

Study Name, Authors, Organization, Year Released	Scope of Study	Geographic Coverage and Number of Customers (if provided)	Time Coverage	Electrification Scenarios	Relevant Outcomes for Electrification Impacts Study	Results on Increase in Peak Load (kW) or Energy Demand (kWh) and Cost Impacts (if available)
Electric Vehicle Charging Infrastructure Assessment Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030 CEC Staff CEC 2021	A California statewide assessment of the charging infrastructure needed to achieve the goal of 5 million ZEVs on the road by 2030 and reduce emissions of greenhouse gases to 40 percent below 1990 levels by 2030. Executive Order N-79-20 directed the CEC to expand this assessment to support the levels of electric vehicle adoption required by Executive Order N-79-20 (8 million ZEVs by 2030)	California	2020-2030	**Vehicle Electrification** **AB 2127:** 5 million ZEVs by 2030 **Executive Order N-79-20:** 8 million ZEVs by 2030	Electric Vehicles: **California will need more than 700,000 shared private and public chargers in 2030 to support 5 million ZEVs** as called for in AB 2127 and nearly **1.2 million chargers to support 8 million ZEVs to achieve the goals of the Executive Order N-79-20**. Counts for chargers at workplaces, public destinations, and multi-unit dwellings generally indicate the number of Level 2 chargers needed. In some cases, Level 1 chargers may be sufficient at select multi-unit dwellings. These values do not include chargers at single-family homes.	CEC models project that electricity consumption in 2030 from light-duty vehicle charging will result in: - 5,500 megawatts (MW) around midnight - 4,600 MW around 10 a.m. on a typical weekday - +25% and +20% electricity demand at those times, respectively
LA100: The Los Angeles 100% Renewable Energy Study NREL 2021	True bottoms-up study to determine the impact of powering Los Angeles with 100% renewable power. NREL ran building simulations, customer adoption models, assessed the cost-benefits of different supply resources, and analyzed the potential for overload on the transmission and distribution network.	City of Los Angeles 1.4 million customers	2020-2030 2030-2045	3 scenarios: **Moderate**: Moderate demand growth and improvements to energy efficiency. Least change beyond Business as Usual (BAU) case. **High**: Assumes 100% building electrification, 80% passenger PEV adoption by 2045, and 12% shiftable demand. **Stress**: Full electrification of the High scenario, but lower EE/DR rates.	Transmission and distribution: **90%** of customer-adopted renewables connected to the 4.8-kV distribution network; up to **1,000 MW** utility-scale solar and **700 MW** battery storage connected to 34.5-kV transmission grid. Upgrades required on **90%** of feeders/circuits to address overloads. Environmental justice: Customer rooftop solar in disadvantaged communities increases from **35% of total in 2020** to **37-41% of total in 2045**. Study includes pathways to ESJ inclusion, e.g., targeted distribution upgrades to account for electricity use in low-income areas.	Compound year-over-year demand growth: Moderate: **1.6%** (**38,900 GWh** by 2045) High: **2.2%** (**46,200 GWh** by 2045) Peak demand: Moderate: **7810 MW** (**1%** growth) High: **8660 MW** (**1.5%** growth) Distribution Upgrade Costs:
Assessment of Electrification Impacts on the Pepco DC System Brattle Group; Pepco 2021	Simulate load growth to meet DC's climate goals through electrification and explore the role of load flexibility and energy efficiency to manage growth.	Washington, D.C.	2021-2050	**Baseline forecast**: Based on PJM's projection for Pepco system **Brattle high alternative baseline**: 0.4% peak growth in summer and winter	Load flexibility and energy efficiency: Reduce total 2050 peak demand by **14%**, eliminating roughly **40% of the load growth** that otherwise would occur between 2021 and 2050	Estimated average annual peak demand growth rate of **1.4% to 1.7% between 2021 and 2050.** Electrification shifts D.C. from a summer-peaking system to a winter morning peak

Study Name, Authors, Organization, Year Released	Scope of Study	Geographic Coverage and Number of Customers (if provided)	Time Coverage	Electrification Scenarios	Relevant Outcomes for Electrification Impacts Study	Results on Increase in Peak Load (kW) or Energy Demand (kWh) and Cost Impacts (if available)
Distribution grid impacts of electric vehicles: A California case study Jenn, Highleyman Institute of Transportation Studies, University of California Davis; Cadmus Group 2021	Employs real-world feeder circuit level data in California from PG&E to measure the capacity of local feeders. Models the adoption of electric vehicles down to the census block and take advantage of real-world vehicle charging data to simulate the future loading on circuits throughout Northern California.	California	2020-2035	6 scenarios, each one with 75% BEVs and 25% PHEVs with 84% of BEVs and 58% of PHEVs being long-range, respectively: **1M LD EVs** **2M LD EVs** **3M LD EVs** **4M LD EVs** **5M LD EVs** **6M LD EVs**	Electric Vehicles: Comparing the shape of the charging demand load to baseload electricity demand, the peaks are not coincident. However, peak baseload often occurs in the early evening which coincides with the time that charging load demand begins to increase for the day. Charging demand is lowest during the day, which is nearly the opposite profile of renewable solar generation, residential rooftop and local solar generation can have a mitigating effect on transformers and feeder lines if utilized correctly. This points to opportunities for managed charging, even with smart charging (as opposed to V2G), by load shifting many of the peak events can be reduced or eliminated—thus reducing the need for transformer and other distribution infrastructure upgrades. Distribution: In the **6 million vehicle scenario**, there are a total of **443 feeders (~20% of all feeders) exceeding their capacity threshold**, yet **only 88 of these feeders will have upgrades that will allow them to feasibly operate in the long-term.** If California were to meet its decarbonization goals by 2045, this would probably require upgrades across the entire distribution network.	Reaching the 2030 goal of 5 million electric vehicles could **add on the order of 20 TWh annual electricity demand**, an increase of about 10% of total electricity load in California.
NREL Electrification Futures Study NREL 2018-2021	Potential for electrification and impact to the demand side of all major sectors of U.S. energy system; intended to provide foundational data to assess isolated impacts of electrification – not intended to be predictive. "High" electrification scenario explores 'what-if' scenarios, including disruptive technologies.	Across the United States	2016-2050	3 scenarios: **Reference**: Baseline case, least electrification **Medium**: Widespread electrification among "low-hanging fruit" (EVs, heat pumps, some industrial) **High**: Transformational change with technology advancements and policy support	Building electrification: Residential heat pumps are cost-competitive with gas furnaces in the 2030s and by 2050 in cold climates under Medium scenario. Electric vehicles: **84%** EV stock penetration by 2050 under High Electrification. LDV, HDV, and electric transit accounts for up to **76%** of vehicle miles traveled in 2050.	Total demand (national) increases by **80 TWh/year** on average in High Electrification scenario, and **1.5-1.8%/year** depending on technology advancement scenario.

Study Name, Authors, Organization, Year Released	Scope of Study	Geographic Coverage and Number of Customers (if provided)	Time Coverage	Electrification Scenarios	Relevant Outcomes for Electrification Impacts Study	Results on Increase in Peak Load (kW) or Energy Demand (kWh) and Cost Impacts (if available)
The Coming Electrification of the North American Economy Brattle Group; WIRES 2019	Provide insights into whether the electric grid will be able to support electrification needed for a low-carbon economy, and the extent of future necessary infrastructure development.	Across the United States	2020-2050	2 scenarios: **Base Electrification Case**: Potential for electrification based on current technology and policy drivers. **High Electrification Case**: Assumes 100% transportation, space and water heating electrification by 2050 to significantly reduce nationwide greenhouse gas emissions.	Building electrification: Doubles to 10% in 2030 and fully electrify in 2050 under High Electrification scenario. Electric vehicles: At least **8,100** DCFC stations needed in cities and towns to complement home and workplace charging. **3.4** DCFC plugs needed for every 1,000 battery electric vehicles (BEVs).	By 2030, electrification could increase nationwide annual energy demand by 5% to 15% (**200 to 600 TWh**) and by 25% to 85% (**1,100 to 3,700 TWh**) by 2050 DCFC complexes will likely comprise **5-10 MW** of peak demand.
Net-Zero America: Potential Pathways, Infrastructure, and Impacts Princeton University; Evolved Energy Research 2021	Identify pathways to achieving net-zero carbon in the U.S. by 2050. The study looks at supply side fuels such as oil, coal, nuclear, CO2 storage, solar, wind etc. and how their usage will vary across the different scenarios of electrification, renewable energy capacity etc. It factors in energy demand across all major sectors like buildings, industrial use, transportation etc.	Across the United States; state-specific data available	2020-2050	5 scenarios: **E+**: Aggressive Electrification **E-**: Less aggressive Electrification **E- B+**: Less aggressive Electrification; High biomass **E+ RE-**: Aggressive Electrification; Constrained Renewable **E+ RE+**: Aggressive Electrification; 100% renewable by 2050	Decarbonization: Scenarios range from **$4-6T** to decarbonize in 2018 USD. Electric vehicles: In E+ scenario, light-duty vehicle stock grows from **2% (5.2M) in 2020** to **17% by 2030 (49M) and 96% (328M) by 2050.** Building electrification: Residential heat pumps grow from **10% of stock in 2020 to 80% (119M)**. Transmission and distribution: E+RE+ scenario requires **$25.8B** in cumulative capital investments for electricity distribution in California by 2050.	Total demand (national) increases by **145%** in E+ scenario, **300%** in E+RE+ scenario.
Revving Up the Grid for Electric Vehicles Boston Consulting Group 2019	Examine the EV-related generation, transmission, and distribution costs for a "representative" utility, based on assumptions about EV growth through 2030.	Across the United States	2019-2030	9 scenarios: Levels of EV adoption for light-duty fleet within utility territory: **10%, 15%, 20%** Charging patterns: **Optimized**: 50% of charging occurs in off-peak hours **Moderately optimized**: 33% of charging off-peak; 33% in shoulder, mid-, or partial-peak; 33% during on-peak hours **Non-optimized**: 25% off-peak charging; 25% shoulder, mid-, or partial-peak charging; 25% 50% during on-peak hours	Electric vehicles: For 1.1M EVs in service by 2030, **$2.8 billion through 2030** in cumulative T&D investments are necessary, for an estimated grid capacity upgrade cost of **$2,600 per EV.** Temporally and locationally optimized charging would reduce T&D costs by **70% through 2030**: $5,800 in the non-optimized charging scenario to $1,700 in the optimized scenario	Average EV energy consumption of **2,960 kWh** per year from 2019 to 2030 (for representative utility).

Appendix 2. Data Received, Ingested, and Processed

The Part 1 analysis is based on numerous datasets; this includes data provided by California regulatory agencies and the investor-owned utilities (IOUs), as well as other significant datasets that are publicly or commercially available that were important in developing the baseline load forecasts and distributed energy resource (DER) load modifier forecasts. Kevala collected and ingested over 100 terabytes of data to complete the Part 1 analysis. The specific datasets leveraged by Kevala are identified in the following sections.

A2.1. IOU Data

- **Meter-specific advanced metering infrastructure (AMI), 2018–2020:**[141] Most of the data is in hourly increments. Some meters are in 15-minute data. A small handful of meters are in 5-minute increments. The data streams include meter ID, timestamp, kWh net, kWh delivered, and kWh returned.
- **Grid supervisory control and data acquisition (SCADA):** Measurements at available locations of the electrical infrastructure. Hourly or sub-hourly instantaneous grid asset readings including:
    - Amps by phase
    - Power factor
    - MVA
    - MW
    - Volts
- **Past DER adoption** (type, location and size) for PV and battery only.
- **Geospatial information for meters, DERs, and grid infrastructure:** Coordinates and downstream/upstream relationships between grid assets.
- **Electrical infrastructure asset characteristics:** Data includes ratings of grid assets such as voltage or capacity rating.
- **Rate schedule code by meter ID and monthly billing information:** Monthly consumption, monthly bill, rate code, North American Industry Classification System (NAICS) or customer code, alternative provider, etc.

A2.2. Regulatory Data

- California Energy Commission (CEC) load and DER forecasts (Integrated Energy Policy Report (IEPR)) by scenario, forecast zone, and planning area
- Agency forecasts of electric vehicle (EV) infrastructure and light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) adoption

[141] Some utilities provided months into 2021. All IOUs provided data through March 2021.

- Historical to 2021 photovoltaic (PV) interconnections
- Distribution Deferral Opportunities Report (DDOR) and Grid Needs Assessment (GNA) studies for grid asset ratings (when not provided in IOU datasets)
- Energy efficiency (EE) program tracking with meter ID: CEDARS (EE 2018-2020) program data at a meter level, if applicable

A2.3. Publicly Available Data

- U.S. Census Bureau's American Community Survey (ACS): 5-year 2016, 2017, 2018, 2019, and 2010-2019 Census block group geometries for demographic indicators and forecasts
- Caltrans long-term socio-economic forecasts: Demographic forecasts by county
- Transportation:
    - California road network and expected traffic type:
        - Traffic Volumes Annual Average Daily Traffic (AADT) (Caltrans GIS Data)
        - Truck Volumes AADT (Caltrans GIS Data)
    - Charging station locations: U.S. Department of Energy's (DOE's) Alternative Fuels Data Center: Alternative Fueling Station Locator
    - California LDV/MDV/HDV registration data: California Air Resources Board (CARB) EMFAC Fleet Database
    - Vehicle miles traveled (VMT), urban/rural/suburban label by Census tract: U.S. Department of Transportation, Bureau of Transportation Statistics, Local Area Transportation Characteristics for Households (LATCH) (see Data link)
    - California projections of zero-emission vehicle (ZEV) range and battery technology and EV service equipment (EVSE) power ratings: Assembly Bill (AB) 2127 Commission Report
- Climate and weather data:[142]
    - Statistically down-scaled climate projections, RCP8.5 (Cal-Adapt)
    - National Renewable Energy Laboratory's (NREL's) National Solar Radiation Database (NSRDB)

[142] Kevala sourced historical weather data for each Census tract from the NSRDB for 2018-2020. Data for calendar year 2021 was not published at the time this study was completed. Kevala sourced projections of future climate out until 2035 from the Cal-Adapt LOCA Downscaled CMIP5 climate model data, using the Representative Concentration Pathway 8.5 (RCP 8.5) emissions scenario from the HadGEM2-ES model. Kevala created a dataset that combines historical local weather patterns with the long-term projection of future climate by rescaling measurements of actual 2020 temperatures to the localized projections provided by the climate model. Specifically, Kevala rescaled each month of hourly temperature readings so the monthly minimum and maximum matched those provided by the statistically downscaled long-term climate model outputs.

- NREL's End-Use Load Profiles for the U.S. Building Stock: For defining default load profile for newly electrified loads in residential and commercial buildings
- CEC's Residential Appliance Saturation Study (RASS) survey statistics: Used the public version of the data from the report to analyze BE residential, either for known gas loads or unknown gas loads.
- Lawrence Berkeley National Laboratory's Tracking the Sun dataset: For determining typical technical specifications for behind-the-meter (BTM) PV in California.
- Microsoft Building Footprints dataset: For creating DER model features per premise related to building footprints of associated parcels.

A2.4. Purchased Data

- Experian Vehicles in Operation (VIO) data: For Census block group-level internal combustion engine and ZEV registrations.
- Regrid: For creating DER model features per premise related to parcel acreage and land use.

Appendix 3. Data Challenges and Solutions

Kevala must ensure that the datasets are complete and good enough for analysis. Good enough may mean that data gaps exist, but there are assumptions and workarounds implemented that are sufficient for the study's objectives. Table 10 and Table 11 highlight some of the gaps in analyzing the full investor-owned utility (IOU) load.

A3.1. Mapping Geospatial Grid Infrastructure, AMI, and Rates

Conducting a bottom-up analysis of distribution grid planning requires the ability to rollup load from each individual service point to the various interconnected grid components. Kevala aggregated each of the service points up to the service transformers, from the service transformers to the feeders, and from the feeders to the substation transformer bank at the substations. In Section 3.2, Kevala describes the hierarchical aspects of the distribution grid used in the analysis.

There are many touchpoints where the connections can break down. Each IOU provided multiple datasets with varying degrees of detail. In all cases, Kevala needed a separate table, the ID relations table, to join meters to service points to premises and to service account IDs. This table includes relationship start and end dates. These dates indicate if the account is still active at a specific service point. The service account IDs connect to the rates. Multiple accounts can exist at a service point but not necessarily at overlapping times. The distinct time periods impact the rate code ID. Some challenges occurred in the joining (or linking) of distributed energy resource (DER) interconnection data, service points, premises, and meters; examples include:

- **Single meter identifier being mapped to multiple premises.** Kevala found these meters by the relation start and end dates and by reusing meter and service point IDs.
- **Bad dates for meter IDs where the dates were flipped or mismatched dates to join meter IDs in the ID Relations table.** Kevala dropped these meters from the analysis.
- **DER interconnection data cannot be matched to premises or mapped to multiple premises:** In some instances, photovoltaic (PV) and battery energy storage system (BESS) interconnections could not be mapped to a premise based on the data received. These DERs were not included in the analysis. As part of Kevala's efforts to update interconnection data in Part 2, Kevala proposes working with the IOUs to ensure all interconnected DERs can be included.

Kevala needed the service points to connect them to the upstream distribution grid components. Some meters or service points did not have corresponding distribution (downstream feeders or substations) data. To remedy this, Kevala conducted geospatial matching of premises and feeders to increase the percentage of premises joined (see Table 10). Furthermore, for the three IOUs, on average, 15% of feeders were missing a join to a substation bank (see Table 11).

The end goal of the analysis was to check load growth and DER impacts on the different distribution grid components: the service transformer, feeder, and substation bank transformer. Kevala had to join the geographic information system (GIS) data to equipment rating data, which did not always exist in the GIS data, using the Grid Needs Assessment (GNA) feeder and bank listing to support dataset completion. If the GNA was not enough (did not include each distribution grid asset ratings), Kevala used default capacity rating values.

Because the goal of the Part 1 Study was to provide a high-level cost-estimate of the infrastructure requirements for different electrification scenarios, the scale of the data gaps does not significantly affect the results. However, it will be important to remedy the data incompleteness issues described for the Part 2 Study in order to explore local mitigation measures to distribution capacity planning constraints.

A3.2. Data Quality and Completeness

A3.2.1. AMI Data

Forecasting premise-specific load from advanced metering infrastructure (AMI) data opens up new possibilities for capacity analysis but also presents unique challenges. AMI data provides a detailed picture of energy demand over time for a location, but data collection procedures and the resulting data are not rigorously standardized. Various types of devices, collection parameters, and data cleaning procedures are employed within and across utilities, which adds to the variety of resulting data quality issues to be surmounted.[143]

The first data quality hurdle is invalid meter readings, such as invalid timestamps or inaccurate metadata used to link identifiers. The resulting load observations from these issues cannot be associated with a place and time, so they cannot be used for analysis.

After ingesting all valid AMI data, Kevala's analysis of the aggregated data revealed two types of systematic data quality concerns: measurement anomalies and collection gaps. An example of a systematic measurement anomaly is the physically impossible level of load recorded across most meters in Pacific Gas and Electric's (PG&E's) data on April 7, 2018. Kevala observed a notable collection gap in March 2020 in the AMI data received from Southern California Edison (SCE), with

[143] A general background on AMI data quality considerations can be found in Blakely, Logan, Matthew J. Reno, and Kavya Ashok. "AMI Data Quality and Collection Method Considerations for Improving the Accuracy of Distribution Models." In *2019 IEEE 46th Photovoltaic Specialists Conference (PVSC)*, 2045–52. https://doi.org/10.1109/PVSC40753.2019.8981211.

over 1 million meters missing observations in this timeframe. San Diego Gas & Electric's (SDG&E's) AMI data exhibited a similar gap in readings across most meters for late April 2020.

Individual meters can also contain outliers and missing data that need to be addressed. Kevala attempted to identify and remove unrealistic outliers from individual load time series and imputed net-load for any missing timestamps based on hourly temperature and other measurements from the same meter. All load forecasts were evaluated against heuristics to detect any anomalous forecasted load values that would result from outliers in the input data.

Additional sources of measurement error are embedded in the AMI data that cannot be readily detected or corrected, including biased or noisy measurements, time synchronization issues, and meters that may be completely missing from the data Kevala received.

While AMI data quality issues and data gaps exist, they did not significantly impact results for the Part 1 Study because system-level energy and capacity annual values were validated with California Energy Commission (CEC)-reported consumption values. Kevala proposes incorporating data validation into the Part 2 Study to ensure any issues do not impact the quality of the Part 2 results.

A3.2.2. Rates and Billing Data

Kevala ingested IOU and community choice aggregator (CCA) rates schedules. Rates applied to the Part 1 Study were those in effect as of April 2022, and do not reflect any rate changes adopted after that time. The data for rate schedules was limited and did not include the following:

- The year a premise joined a CCA limited the ability to identify which power charge indifference adjustment (PCIA) rate should apply (PCIA rates are vintaged and vary according to the year joining a CCA)
- Designation of residential baseline by climate zone
- Designation of unique medical and all-electric baselines
- Exempted rates with different time blocks (some customers are able to keep an expired rate after a tariffed rate has been retired)
- Connected load versus peak load rates
- For some IOUs, service level (e.g., primary versus secondary)

Aside from these rate data gaps, an additional challenge was the inability to identify whether a customer moved from one rate schedule to another for the historical data sample studied (i.e., customers shifting from tiered rates to default time-of-use).

Kevala used the customer sector designation for DER adoption model training. The designation was defined first by rate class, then by North American Industry Classification System (NAICS) code (from rates data), and finally by parcel customer class. Kevala found misaligned NAICS codes, particularly when rate code was not provided. For example, some premises classified as residential were confirmed by Kevala to be large non-residential. The customer sector is a critical consideration in distribution planning. Kevala proposes further investigating the extent of the misclassification errors to inform the IOUs to use for their load and DER disaggregation methods in the Distribution Investment Deferral Framework (DIDF) process and to refine the input data for Part 2.

A3.2.3. Interconnection Data

Kevala ingested DER interconnection datasets from each of the IOUs to serve two modeling purposes:

- Model the existing PV and BESS systems
- Train the machine-learning DER adoption models to forecast future adoptions

This data has a few known data quality issues that impact one or both of these uses. Kevala received the interconnection datasets as of April 2021 (data does not contain the DER adoptions from the remainder of 2021 and 2022). This impacts the modeling of existing systems but is not expected to significantly impact the adoption model training for future adoptions. This data issue can be resolved in Part 2 by requesting and receiving updated interconnection datasets from the IOUs.

As noted in the Mapping Geospatial Grid Infrastructure, AMI, and Rates section, joining this interconnection data to the premise-level data also required additional data manipulations, including combining multiple DERs mapped to a single premise or excluding DERs that Kevala could not match.

In particular, the interconnection data for BESS had significant data quality issues. Two rating requirements fully define a BESS:

- Power rating (kW), which is the maximum output of the system.
- Energy rating (kWh), which indicates how long the BESS can sustain its maximum output.

In the interconnection dataset, about 80% of the records were missing the energy rating. Commercially available lithium-ion batteries can typically sustain their maximum output for 2-4 hours, meaning their energy-to-power ratio is 2:1 to 4:1. Kevala resolved this issue by assuming a ratio of 2:1 for BESS in the interconnection data that does not have an energy rating. In Part 2, Kevala proposes requesting additional BESS interconnection data and anticipates this data quality issue will remain unresolved unless the IOUs have supplemental data to address the gaps.

Additionally, there was some clearly erroneous energy rating data, leading to unrealistically high energy ratings. For example, some installers appeared to use constant 4- or 5-digit codes in the energy rating column, implying MWh-scale batteries on residential premises. For Part 1, all non-zero BESS energy ratings from the interconnection data were retained if they could be matched to a premise. The unrealistically large energy ratings do not significantly impact the results for Part 1 because all batteries were assumed to begin each year with 0 kWh of stored energy. Therefore, the available energy in these residential batteries would be dictated by the excess produced by the premises' corresponding PV systems on any given day, which is expected to be much lower than these unrealistic capacities.

Appendix 4. Baseline Net-Load and Baseline Load Modeling Methodology

As outlined in Section 3.3, baseline net-load represents the customer's load at the meter, or what is actually delivered to or received from the customer. Baseline load represents the hypothetical demand of a customer after removing the load impacts of any adopted distributed energy resources (DERs) from net-load. The core components of the baseline load forecast are an initial hourly net-load forecast and estimates for hourly DER impacts for premises where a known DER installation exists. The baseline net-load estimate discussed in this appendix refers to the initial baseline net-load estimates used for predicting baseline load.

A4.1. Model Requirements

To ensure accuracy, robustness, and repeatability, the baseline net-load model had to meet the following task-specific requirements.

- **Inclusive.** Use as much of the advanced metering infrastructure (AMI) data provided by the utilities as possible.
- **Flexible**. Address potential sparsity in the net-load input data, as AMI data sources can contain missing values.
- **Holistic**. Incorporate complex interactions between seasonal components that drive load demand, such as hourly, weekly, and yearly effects.
- **Transparent.** The forecast model should not be a black box—model output should be interpretable with respect to its inputs.

To meet these requirements, Kevala:

- Avoided compressing the data into aggregates or buckets such as daily total load or 576 load profiles before forecasting.
- Incorporated algorithms to adjust for missing or anomalous data.
- Included the influence of extra regressors such as outdoor air temperature.
- Generated hourly forecasts that can be examined and scrutinized.

A4.2. Input Data Preparation

The metered load data Kevala received from the three IOUs was predominantly recorded at an hourly resolution, although some meters had 15-minute or 30-minute interval AMI reads. Though Kevala's load forecasting approach can be applied to more granular data, sub-hourly measurements were summed to full hours for consistent processing across meters. Each AMI record contained a timestamp, meter identifier, and two fields measuring the net kilowatt-hours returned ("kWhReturned") and delivered ("kWhDelivered") to the meter. Removing kWhReturned from kWhDelivered yielded a combined hourly metered net-load ("kWhNet") that Kevala used as the target for prediction.

The baseline net-load estimates aligned with DER adoption and behavior models in taking an individual customer address or premise as the unit of analysis. For each premise, Kevala summed net-load for all associated meters to create a historical dataset of premise-specific hourly net demand. For each resulting premise time-series, any missing timestamps or missing values for net-load were imputed with an ensemble similar to the final forecast models discussed below, using hourly historical temperature and any valid load measurements as inputs. Appendix 2 identifies the historical and future hourly air temperature datasets that comprised the foundational load measurement assumptions; additional date-time features were appended to the input dataset including hour number, day of month, day of week, month number, and a flag representing whether the date was a holiday.

A4.3. Accuracy Metrics and Success Criteria

Predicting premise-level load has three complex and, from an analytical perspective, competing optimization objectives. Specifically, baseline net-load predictions must be accurate in terms of:

1. Total annual load
2. Load duration shape of the annual load (e.g., the shape of hourly loads ranked from highest to lowest)
3. Peak load

Because common machine learning loss functions assess performance, on average, across all samples and penalize big misses, predicting the timing and magnitude of peak load can be a particular challenge for models optimized for forecast error alone. To ensure its load forecasts were optimized for the three metrics, Kevala measured forecast accuracy using multiple metrics that are meaningful indicators of model performance relative to these optimization goals.

Additionally, because the goal of forecasting premise-level load is to identify constraints in the larger distribution system, model performance could not be assessed solely at the level of individual premises. Bottom-up load forecasts must be accurate (in total and peak) when aggregated to the level of a distribution asset such as the service transformer or feeder. Kevala conducted model selection against aggregate metrics to ensure the forecasts were accurate for feeder-level aggregates and not merely for individual premises. This is an example of how the SCADA data for utility infrastructure loads were used in the analysis (i.e., as a check of the aggregated premise-level load totals).

During model selection, Kevala assessed competing models using the following aggregate metrics, which are ordered by their relative importance with (1) being the highest priority. Each metric yielded a distribution of errors, from which the median error was taken as the decision criterion.

1. **Median monthly feeder peak net-load absolute deviation:** The absolute difference between peak of the baseline net-load estimate aggregated to the feeder level and feeder peak net-load, by month. Metric units are in kilowatts (kW).
2. **Median monthly feeder peak hour absolute deviation:** The absolute difference (in number of hours) between the aggregated baseline net-load monthly feeder peak hour and the actual feeder net-load peak hour. Metric units are in hours.
3. **Median monthly feeder total energy absolute deviation:** The difference between the aggregated feeder-level monthly baseline net-load estimate and the actual feeder-level total energy by month. Metric units are in kilowatt-hours (kWh).
4. **Median hourly absolute deviation by premise:** The differences between premise hourly baseline net-load estimates and actual hourly net-load. Metric units are in kW.

A4.4. Selection of the Ensemble Model

Kevala conducted initial model selection using PG&E data spanning January 1, 2018 to September 30, 2021. Once the best modeling approach was refined, Kevala generated forecasts and evaluated them for all three IOUs. PG&E data was used for model selection because Kevala was able to collect, ingest, and process this data relatively quickly given the timeliness and quality of the data provided. This allowed Kevala the necessary time to explore model structures and develop a robust experimentation process to ensure the appropriate selection of a model.

A4.4.1. Experimental Setup

The COVID-19 pandemic affected load demand in complex and far-reaching ways, as commuting, occupancy, and consumption patterns were disrupted and reorganized over time. To guard against net-load forecasts being biased by either this disruptive period or the relatively stable period before, Kevala assessed each model tested using a combination of a one-year backcast (March 1, 2019-February 29, 2020) and a one-year hold-out set spanning the last year of available AMI data (October 1, 2020-September 30, 2021). Kevala trained all models using the same date range for input data: January 1, 2018-September 30, 2020. Notably, during model selection none of the models were provided inputs from the one-year hold-out set, allowing for a fully out-of-sample forecast evaluation that most closely mirrored how forecasts are actually used.

To test and optimize a variety of potential models effectively, Kevala used a stratified sample of 5,000 premises per customer sector to train each competing model, resulting in a total training population of 47,158 premises. Prediction and evaluation used data for a sample of 52 feeders to assess model performance on a subset of complete feeders, which resulted in a total test population of 98,777 premises.

A4.4.2. Results

Kevala tested a variety of relevant modeling approaches including, but not limited to, linear regression,[144] auto-regressive models,[145] and ensemble methods that use bagging[146] or boosting.[147]

The tree and forest ensemble method stood out above competing approaches on all four evaluation metrics, and additional model development efforts focused on optimizing this approach for the net-load prediction task.

Table A4-1: Evaluation metrics for best net-load forecasting method *(Source: Kevala)*

Evaluation Metric	Method: Tree and Forest Ensemble
1. Median monthly feeder peak load deviation, kW	456.17
2. Median monthly feeder peak timing deviation, hours	1
3. Median monthly feeder total energy deviation, MWh	200.22
4. Median hourly premise error, kW	0.17

The ensemble method is an equally weighted combination of a traditional decision tree and a set of extremely randomized trees. The decision tree component splits the input data at the points that minimize squared error, which can overfit the training data. The extremely randomized forest component splits the data at random points, which can result in underfit. By combining these two related methods, Kevala's predictions overcame the limitations of each while training the complex nonlinear interactions between seasonality, temperature, and net-load.

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[144] Linear relationships among variables are used to formulate a predictive model. Key examples used in the utility industry are regression models that predict energy use based on a handful of prescribed exogenous variables such as temperature, size of premise or type of customer.
[145] Autoregressive techniques involve a sequential regression of temporal data and other related inputs such as temperature variability to estimate a forward trend to predict future outcomes.
[146] Bagging, or bootstrap aggregating, methods combine the predictions of many weak models, each trained on fixed-size samples of the training data (with replacement).
[147] Boosting methods train basic models sequentially so that the prediction errors at each iteration are used to improve the predictions of the next round.

A4.5. Baseline Load

For each premise with a known PV installation, Kevala removed estimated PV generation from hourly net-load forecasts to create baseline load forecasts, which represent total hourly demand at the premise. Kevala created estimates of hourly PV production using the same method described in Appendix 5.

Appendix 5. Behind-the-Meter PV Modeling Methodology

This appendix contains detailed information about the behind-the-meter (BTM) photovoltaic (PV) sizing, behavior, and adoption algorithms, including evaluation results used to validate each model on historical data. Kevala believes the results of the BTM PV analytics completed for this Part 1 Study provide accurate and sufficient estimates of the impacts of BTM PV adoption on distribution planning. Figure 52 (see Section 3.4.2) shows Kevala's modeling pipeline, which uses information about historical BTM PV installations from the investor-owned utilities' (IOUs') interconnection data and Lawrence Berkeley National Laboratory's Tracking the Sun dataset, hourly resolution weather data from the National Solar Radiation Database (NSRDB), and the System Advisor Model's PVWatts simulator.

A5.1. BTM PV Sizing

For each premise, Kevala sized a theoretical BTM PV system to offset some portion of the premise's annual gross load. For each Census tract, Kevala calculated the annual energy production (E_{PV}) of a 1 kW direct current (DC), south-facing BTM system by simulating Typical Meteorological Year weather data from the National Renewable Energy Laboratory's (NREL's) NSRDB[148] through PVWatts[149] using the specifications listed in Table A5-1. Kevala calculated the tilt and DC-to-alternating current (AC) ratio values as the average values reported in Lawrence Berkeley National Laboratory's 2021 Tracking the Sun dataset.

Next, for each premise in that Census tract, Kevala linearly scaled the DC rating from 1 kW DC to the level required to meet a defined percentage of total annual premise load; this percentage is called the load offset ratio (LOR). Using this linear scaling resulted in a DC system size of P_{DC}:

$$P_{DC}\ (kW\ DC) = \frac{1\ kW\ DC}{E_{PV}\ (kWh)} \times E_{load}\ (kWh) \times LOR$$

Kevala assumed that residential PV systems are sized to achieve net-zero energy on an annual basis, corresponding to a LOR of 100%. For non-residential parcels, the LOR is 84% based on an internal evaluation of the commercial premises in 10 feeders in PG&E territory.

The possible system size was further constrained by the building footprint of the premise's parcel, where available.[150] This constraint assumed 100 square feet of rooftop area are required to install

[148] The key weather variables from the NSRDB are direct normal irradiance, diffuse horizontal irradiance, air temperature, and wind speed.
[149] NREL, "PySAM," Version 5, https://sam.nrel.gov/software-development-kit-sdk/pysam.html.
[150] Microsoft Building Footprints, https://www.microsoft.com/en-us/maps/building-footprints.

each 1 kW DC of PV capacity.[151] Kevala derated the building footprint by a factor of 75% to account for unusable rooftop area (i.e., 25% of the area is unusable).

Table A5-1: Specifications and assumptions for PV sizing method *(Source: Kevala analysis of Tracking the Sun and historical advanced metering infrastructure (AMI) data)*

Customer Class	Tilt	DC-to-AC Ratio	Load Offset Ratio
Residential	19°	1.13	100%
Non-Residential	12°	1.13	84%

Kevala then evaluated this model by comparing actual versus estimated DC capacity for a subset of existing PV systems in each IOU, where actual installed capacity was obtained from the historical interconnection data. For this historical evaluation, a premise's annual gross demand E_{load} was back-calculated from the premise's 2018-2020 historical AMI (net-load) by adding a historical PV production estimate. Kevala estimated the historical PV production using the PV behavior method (described below) using the NSRDB's Actual Meteorological Year weather data for 2018-2020 and the actual DC capacity from the interconnection data as inputs. This historical gross load estimate then provided the necessary input to the sizing algorithm.

Kevala validated the model on a subset of premises from each IOU:

- 3,358 premises in Pacific Gas and Electric (PG&E) (from a subset of 10 feeders)
- 2,314 premises in Southern California Edison (SCE) (from a subset of 14 feeders)
- 4,615 premises in San Diego Gas & Electric (SDG&E) (from a subset of 11 feeders)

Only the premises on each feeder that installed a PV system as of the April 2021 interconnection dataset were included. Figure A5-1 shows the distributions of the actual versus estimated systems sizes, which are also summarized in Table A5-2.

The estimated system sizes were strongly correlated with the system sizes from the interconnection records (with a Pearson correlation coefficient of 0.78 for PG&E) and followed a similar distribution as the interconnection records, although with a higher standard deviation. There is some bias toward overestimating the actual system size by an average of 0.5 kW DC-1 kW DC.

[151] U.S. Department of Energy, SunShot Initiative, 2018, p. 2, http://bcapcodes.org/wp-content/uploads/2017/03/MODULE-3-Part-2-slides-37-60-Architectural-Integration-into-Building-Design-3-22-2018-w-notes.pdf.

Figure A5-1: Histograms of estimated versus actual PV system size (kW DC) *(Source: Kevala)*

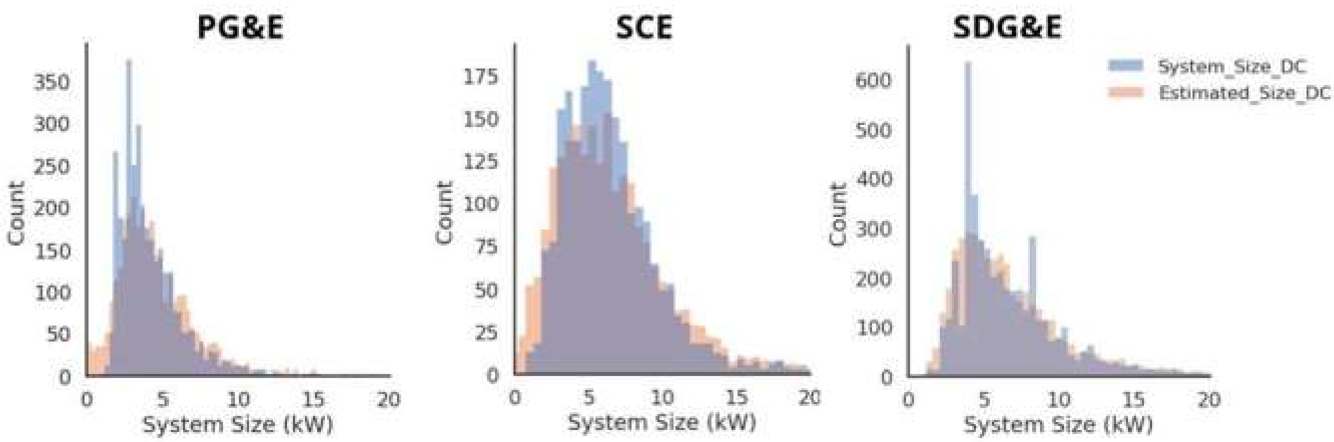


Table A5-2: Descriptive statistics of the distributions of actual versus estimated PV system size (DC) by IOU *(Source: Kevala)*

		Mean (kW DC)	Median (kW DC)	Standard Deviation (kW DC)
PG&E	Actual	6.3	3.6	26.3
	Estimated	8.1	4.0	63.8
SCE	Actual	7.9	6.0	25.9
	Estimated	8.4	6.0	40.9
SDG&E	Actual	8.7	5.9	50.7
	Estimated	8.6	5.9	35.1

Table A5-3 reports point-wise error metrics, including mean and median absolute error and absolute percentage error. The mean error metrics are higher than the median error metrics, indicating some outliers with very high error. Percentage errors are also higher for non-residential premises, but these constitute a very small fraction of the total number of premises with installed PV.

Table A5-3: Point-wise error metrics of actual versus estimated PV system size (DC) by IOU *(Source: Kevala)*

	Customer Class	Count	Mean Absolute Error	Median Absolute Error	Mean Absolute Percentage Error	Median Absolute Percentage Error
PG&E	Residential	3,285	1.6 kW	1.0 kW	39%	27%
	Non-Residential	73	93.9 kW	15.9 kW	83%	34%
SCE	Residential	2,282	3.2 kW	2.3 kW	54%	39%
	Non-Residential	32	75.1 kW	8.6 kW	200%	60%
SDG&E	Residential	4,462	2.1 kW	1.2 kW	29.5%	20.3%
	Non-Residential	153	34.2 kW	4.8 kW	74.0%	32.9%

A5.2. BTM PV Behavior

Kevala simulated hourly resolution (8760) PV production curves using PVWatts, with weather inputs from the NSRDB. To reduce computation, Kevala generated typical production curves of a 1 kW DC system by Census tract and customer class and then scaled these curves by the kW DC rating determined by the PV sizing algorithm to derive the production of a given premise. The inputs to PVWatts for the normalized production curves for each Census tract were as follows:

- **Weather:** NSRDB Actual Meteorological Year 2020.
- **Location:** Latitude and longitude of centroid of Census tract.
- **Tilt and AC-to-DC ratio:** Derived by customer class from the Tracking the Sun dataset and reported in Table A5-1. Kevala used the Commercial customer class in the Tracking the Sun dataset for all non-residential systems.
- PVWatt's default values were used for all other specifications, except azimuth.

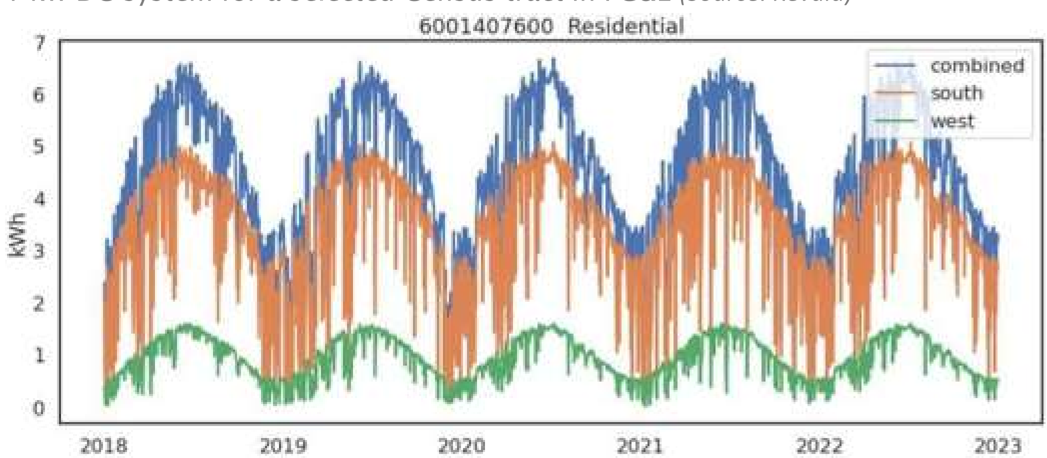
Kevala selected the two most common azimuths from the Tracking the Sun dataset—south-facing (180˚) and west-facing (270˚)—and ran PVWatts twice, once with each azimuth. Kevala then used the distributions of the azimuth by customer class in the Tracking the Sun dataset to produce weights for blending these two curves into one standard curve by customer class and by census tract. Table A5-4 reports the weights.

Table A5-4: Weighting factor for each azimuth by customer class *(Source: Kevala)*

Azimuth	Residential	Non-Residential
180° (South)	0.754	0.876
270° (West)	0.246	0.124

As an example, Figure A5-2 illustrates this blended curve for one Census tract, showing the weighted south-facing, weighted west-facing, and the combined generation time-series for 2018-2020. Note that daily energy output is illustrated here, although the underlying behavior curve is still in units of average power at an hourly resolution. 2018-2020 Actual Meteorological Year weather data was used to model 2018-2020; Typical Meteorological Year weather data was used to model 2021 (due to a delay in the availability of recent weather data in the NSRDB), and Actual Meteorological Year 2020 was used for the forecasts for 2022 onward.

Figure A5-2: Relative contributions of south- and west-facing components to the daily energy production of a 1 kW DC system for a selected Census tract in PG&E *(Source: Kevala)*



A5.3. BTM PV Adoption

Kevala selected and trained a multilevel logistic regression (MLR) model to model PV adoption propensity using the features reported in Table A5-5. The features selected for this model included customer class, payback period, peak load, and demographic features from the U.S. Census Bureau's American Community Survey (ACS). Kevala calculated the payback period based on the sizing estimates. To train and validate the PV adoption model, Kevala calculated bills with Net Energy Metering (NEM) 2.0 rates[152] and adjusted the bill and system cost to 2016 values.[153]

The MLR model first grouped premises by the categorical variable (customer class) and then trained a regression model on the remaining numerical features. The overall regression model was the same for the two customer classes, but because the customer classes had unique training data, the regression resulted in unique parameters for each group. Each numerical feature was represented by a normal distribution in the MLR model; to better fit a normal distribution, some features with long tails were log-transformed.[154]

Table A5-5: Categorical and numerical features used to train the PV adoption model *(Source: Kevala)*

Categorical or Numerical	Feature	Granularity	Data Source	Log-Transformed?
Categorical	Customer class: residential or non-residential	Premise level	Rates	N/A
Numerical	Payback period	Premise level	Rates and PV sizing outputs	No
	Percentage of owner-occupied premises	Census block group	Census-ACS	No
	Maximum daytime baseline load	Premise level	Baseline (gross) load[155]	Yes
	Percentage of college or higher education degree holders	Census block group	Census-ACS	No

[152] Kevala made a simplifying assumption during the PV adoption model training that all historical PV adopters were on NEM 2.0 rates rather than a mix of NEM 1.0 and NEM 2.0 rates. During the bill calculations for future years, Kevala assigned historical adopters either the NEM 1.0 or NEM 2.0 rate they were assigned upon installation.

[153] During the prediction stage when determining future PV adopters, Kevala assigned future adopters NEM 2.0 in the Existing BTM Tariffs Scenario or the December 2021 Proposed Decision for proceeding R.20.08-020-inspired rate in the Modified Tariffs scenario. The bill and PV system cost reflected 2022 values.

[154] For datasets with far outliers, also referred to as distributions with long tails, a logarithmic transformation can pull the outliers closer in so that a normal distribution better represents the underlying data.

[155] During model training, Kevala calculated the baseline load input from customer AMI data plus a PV production estimate using PVWatts for those customers with known PV systems from historical interconnection data. During model forecasting, the baseline load input was the output from the baseline load forecast model (see Section 3.3.2).

Categorical or Numerical	Feature	Granularity	Data Source	Log-Transformed?
	Median household income	Census block group	Census-ACS	No
	Median age	Census block group	Census-ACS	No
	Census block group land area	Census block group	Census-ACS	Yes
	Population density	Census block group	Census-ACS	No

For each IOU, Kevala selected a subset of feeders to train and validate an IOU-specific PV adoption model. Table A5-6 summarizes this data. Kevala randomly split the premises in each IOU's subset into a training (in-sample) set (67%) and a validation (out-of-sample) set (33%). The MLR model was trained on the 67% of in-sample data and then the training and validation data were run through the trained model to generate adoption propensity scores for all premises. Kevala calculated the evaluation metrics precision[156] and recall[157] using an adoption threshold (see Table A5-6), which was based on the historical adoption rate in each IOU's training and validation dataset. Kevala used the interconnection data to identify the historical adoptions.

Table A5-6: Summary of the subset of IOU data used to train and validate each IOU-specific adoption model; each IOU's subset was further split into training (67%) and validation (33%) datasets *(Source: Kevala)*

IOU	No. of Feeders Included	True Adoption Rate	Adoption Threshold
PG&E	10	11%	Prob >= 0.775
SCE	14	15%	Prob >= 0.66
SDG&E	11	27%	Prob >= 0.637

[156] Precision is an evaluation metric that measures the adoption model's ability to identify relevant data points, such as if a customer adopted. It is calculated by taking the number of true positives (number of times an actual adoption was predicted) divided by the number of true positives plus the number of false positives (the number of times an adoption was predicted that was not seen in the base data). Kevala calculated this metric at the IOU-specific adoption threshold reported in Table A5-6.

[157] Recall is an evaluation metric that measures the adoption model's ability to identify all relevant cases within a dataset. It is calculated by taking the number of true positives divided by the number of true positives plus the number of false negatives. Kevala calculated this metric at the IOU-specific adoption threshold reported in Table A5-6.

Table A5-7 reports the evaluation results for each IOU's adoption model using three different metrics that describe the adoption model's quality from different perspectives. Precision is the frequency at which a predicted PV adoption actually happened in the interconnection data. Recall is the percentage of all actual adoptions that were predicted by the model. Either of these metrics can be manipulated by selecting either a very high or very low adoption propensity score as the threshold of adoption; therefore, machine learning models of this type are often evaluated under all possible thresholds using area under the curve metrics. For highly unbalanced datasets, such as PV adoption where the likelihood of adoption is relatively low, the preferred metric is the precision recall area under the curve (PR AUC).[158]

A few results attest to the quality of the models:

- First, there is consistency in the evaluation metrics between the training and validation dataset, which indicates the model is not overfit and did a good job of generalizing to the out-of-sample data.
- Second, the precision and recall values being greater than the historical adoption rate in this unbalanced dataset indicates a better-than-random adoption selection (e.g., values of ~0.5 for PG&E are greater than the adoption rate of ~0.1).

Across IOUs, the models for PG&E and SDG&E perform more strongly than the model for SCE. One possibility for this discrepancy is that historical adoptions in SCE territory have been correlated with different demographic features than those in the other two IOUs.

Table A5-7: Adoption evaluation metrics for each IOU's adoption model *(Source: Kevala)*

	Data Subset	**Precision**	**Recall**	**PR AUC**
PG&E	Training	0.48	0.51	0.46
	Validation	0.49	0.49	0.47

[158] PR AUC is the area under the precision recall curve; it is used to assess the performance over all the adoption thresholds as represented by the precision and recall metrics. There are a few areas under the curve metrics, and PR AUC is the most appropriate AUC metric for PV adoption, where the incidence of historical adoption is relatively low. This is referred to as a highly unbalanced dataset. For more information, see: Daniel Rosenberg, "Unbalanced Data? Stop Using ROC-AUC and Use AUPRC Instead," *Towards Data Science,* June 6, 2022, https://towardsdatascience.com/imbalanced-data-stop-using-roc-auc-and-use-auprc-instead-46af4910a494.

	Data Subset	Precision	Recall	PR AUC
SCE	Training	0.32	0.33	0.30
	Validation	0.32	0.32	0.31
SDG&E	Training	0.61	0.62	0.67
	Validation	0.62	0.62	0.69

A5.4. BTM PV Base Case Results and Scenarios

In addition to the base case scenario run for BTM PV that was calibrated to PV capacity forecasts in the 2021 Integrated Energy Policy Report (IEPR), Kevala ran scenarios for PV adoption to explore the change in adoption propensity resulting from an alternative rate design for NEM. The base case NEM pricing scenario assumed the NEM 2.0 structure to persist through the study period. The time-of-use (TOU) periods and rate differentials remained unchanged, and the cost of BTM PV installations was held constant. Therefore, the underlying assumption for this study is that the relationship between the cost of PV installations and rates remains unchanged. The second scenario involved adopting a new rate structure for residential NEM that included a monthly grid access charge of $5/kW and an export rate that offset the generation rate. This structure was consistent with the Proposed Decision in the proceeding to reform NEM (R.20-08-020) issued on December 13, 2021. Rather than modeling the exact proposal in that Proposed Decision, Kevala chose this simplified structure as a scenario because it was generally consistent with the Proposed Decision at the time. Since the study was conducted, the CPUC adopted a final Decision on December 15, 2022 to reform NEM by creating a Net Billing Tariff.

The BTM PV forecast shows that PV's percentage contribution to the system peaks is between 0% and approximately 23% across the three IOUs. The results at the feeder level are far more diverse. For example, for the base case for PG&E in 2025, PV's percentage contribution to each feeder's peak range from 0% to -75%, while the percentage contribution at the IOU level is -1.81%. Table A5-8 shows the PV percentage contribution to the system-level peak by IOU and forecast year. Due to PV production's dependence on the sun, the relative impact of PV on the peak load depends not only on the capacity of PV installed but also the hour of day that the peak load occurs. For all scenarios and IOUs, the peak-load hour migrates from late afternoon (4 p.m. PT for SDG&E and SCE) or early evening (7 p.m. PT for PG&E) in 2025 to 9 p.m. PT by 2035; this is due to the deployment of electric vehicles (EVs) and evening EV charging. Therefore, even as the installed capacity of PV increases over the study horizon, its impact on the peak load decreases to a 0% percentage contribution for all IOUs and scenarios by 2035, except for the SCE base case.[159]

As reported previously, the Modified BTM Tariffs scenario results in a 4.3% reduction in installed PV capacity by 2035. When looking at impacts on the net-load hour, the relative difference between these two scenarios is smaller.[160] In 2025, the Modified BTM Tariffs scenario reduces the magnitude of PV's percentage contribution by less than 0.4% across the IOUs. By 2035 under any high transportation electrification scenario, there is no difference in PV's impact on system-level peak load between the two BTM Tariff scenarios because the peak load hour occurs after the sun has set.

Table A5-8: PV percentage contribution to the net-load peak by IOU, forecast year, and scenario (Source: Kevala)

Scenario	PV Percentage Contribution to Peak Net-Load								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	-1.81%	-8.70%	-23.22%	-2.30%	-4.92%	-3.75%	0%	-4.39%	0%
(2) High Transportation Electrification + Existing BTM Tariffs	-1.84%	-8.76%	-23.42%	0%	-4.83%	-3.62%	0%	0%	0%
(3) High Transportation Electrification + Modified BTM Tariffs	-1.77%	-8.37%	-23.35%	0%	-4.55%	-3.59%	0%	0%	0%
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	-1.76%	-4.46%	-22.82%	0%	-1.18%	0%	0%	0%	0%

[159] This scenario is an exception, at which the 2035 peak hour occurs at 6 p.m. PT instead of 9 p.m. PT.

[160] The two BTM rate design scenarios can be compared for a given transportation electrification scenario (e.g., Scenario 2 versus 3 or 4 versus 5).

Scenario	PV Percentage Contribution to Peak Net-Load								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	-1.69%	-4.26%	-22.75%	0%	-4.43%	0%	0%	0%	0%

For the Part 2 Study, other rate design scenarios may be considered as part of the mitigations in the case studies. Such scenarios may include changing DER behavior patterns to reflect reactions to new TOU periods to address high electrification scenario challenges. Kevala understands that rate design is a highly complex process that involves a deep understanding of each IOU's avoided costs in the future as well as policy objectives and customer acceptance and response. Kevala will work in close collaboration with the CPUC on any rate design changes assumed to test PV adoption or other DER adoptions and will most likely rely on load shapes rather than expected marginal costs and maintain the same price differentials currently in TOU rates.

Appendix 6. Behind-the-Meter Battery Energy Storage System Modeling Methodology Details

This appendix contains detailed information about the behind-the-meter (BTM) battery energy storage system (BESS) sizing, behavior, and adoption algorithms, including evaluation results used to validate each model on historical data. Kevala believes the results of the BESS analytics completed for this Part 1 Study provide reasonable and sufficient estimates of the impacts of BESS adoption on distribution planning given the nascent nature of this technology in California. Figure 53 (see Section 3.4.3) summarizes the complete BESS modeling process.

A6.1. BTM BESS Sizing

The BESS sizing model analyzed a premise's net (baseline) load (demand plus photovoltaic (PV)) to select the number of commercially available battery modules to potentially install. Kevala adjusted the battery features for capacity (kWh) and power (kW) to a set of standard commercially available batteries (see Table A6-1). For residential systems, the power rating of a BESS system was sized to meet a defined percentage of maximum daily energy consumption.[161] The model then selected a corresponding number of Tesla Powerwalls to exceed this threshold.

Table A6-1: Ratings of commercially available BESS systems considered by the BESS sizing model162 *(Source: Kevala)*

Options by Customer Class	Power rating (kW)	Energy rating (kWh)	Energy-to-Power Ratio	Manufacturer
Residential	5	14	2.8	Tesla
Non-Residential	5	13.5	2.7	Tesla
	13.5	10	1.3	Solaredge
	7.6	17	1.9	Pika/Generac
	9	11	2.2	Energport
	5	64.5	2.2	Energport
	29	45	1.6	Energport

[161] Kevala defined this percentage by calculating daily energy consumption on a 24-hour basis and selecting the maximum consumption over the year; it was not calculated from the peak demand hour.
[162] Kevala assumed a standard 90% round-trip efficiency for all models.

Options by Customer Class	Power rating (kW)	Energy rating (kWh)	Energy-to-Power Ratio	Manufacturer
	29	129	2.2	Energport
	60	129	2.2	Energport
	55	110	2.0	Delta
	125	268	2.1	CPY
	125	250	2.0	Dynapower
	130	232	1.8	Tesla

For non-residential premises, Kevala assumed the BESS systems to charge from the grid, so the size was optimized to reduce demand charges over a given duration. (The battery attempts to charge during the daily intervals in which load is lowest and discharges during the daily intervals in which load is highest.) If the model did not find a commercially available battery that provided the desired autonomy duration, then the model returned the largest battery system available (Tesla Powerpack with power rating of 130 kW and energy rating of 232 kWh).

The sizing model included two important configuration options:

- Duration (the maximum number of hours of a battery autonomy) for non-residential premises
- Percentage of maximum daily energy consumption the BESS can serve for residential premises

To find the best parameters, Kevala used a grid search approach, considering duration from a range of 2-4 hours and the percentage of maximum daily load from 0.05 to 0.8. Kevala compared predicted sizes to actual interconnection records for the premises in each IOU territory that had BESS installed:

- 18,500+ premises in Pacific Gas and Electric (PG&E)
- 11,000+ premises in Southern California Edison (SCE)
- 8,000+ premises in San Diego Gas & Electric (SDG&E)

As discussed further in the Interconnection Data section, these counts were based on April 2021 interconnection data, after BESS mapped to the same premise were combined together and BESS that could not be mapped to a unique premise were excluded. Also, as noted, approximately 80%

of interconnection records were missing energy ratings and only provided power ratings, so Kevala imputed energy ratings using a 2-to-1 energy-to-power ratio. Because of this missing data,[163] Kevala emphasized the power rating estimation over the energy rating in conducting this evaluation. Using this historical data, Kevala found the thresholds that resulted in the lowest mean absolute error,[164] root mean squared error,[165] and mean absolute percentage error[166] to be 3 hours' duration for non-residential systems and 8% of maximum daily energy consumption for residential premises. The 8% threshold corresponds to about 2 hours of energy backup over a 24-hour period.

Table A6-2 shows the results of the evaluations. The mean absolute percentage error on the power ratings is about 30%. The vast majority of residential premises were allocated a single Tesla Powerwall, which reflects current market availability and limited historical data. The results are also skewed by some very high commercial outliers.

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[163] This issue is expected to persist for Part 2 even if Kevala receives a more up-to-date interconnection dataset unless the IOUs have updated their data gathering practices.

[164] Mean absolute error is defined as the sum of absolute errors between predicted and actual values, divided by the sample size. It quantifies the typical difference between the predicted BESS rating and the actual rating in the interconnection data, and a smaller value is better.

[165] Root mean squared error is the square root of the average squared difference between the predicted and actual values. It is similar to mean absolute error, but it is more sensitive to outliers where the prediction was far from the actual value.

[166] Mean absolute percentage error is the average of the absolute percentage errors between the predicted and the actual values. It quantifies the relative vs. the absolute typical difference, but it has limited usefulness if the actual values are near zero, where the mean absolute percentage error tends toward infinity.

Table A6-2: Ratings of commercially available BESS systems considered by the BESS sizing model
(Source: Kevala)

IOU	Power Rating			Energy Rating		
	MAE (kW)	RMSE (kW)	MAPE (%)	MAE (kWh)	RMSE (kWh)	MAPE (%)
PG&E	3.45	25.4	31%	60.6	590	60%
SCE	3.60	20.7	26%	10.3	42.6	53%
SDG&E	8.0	69.6	29%	17.1	140	48%

MAE: mean absolute error; RMSE: root mean squared error; MAPE: mean absolute percentage error

A6.2. BTM BESS Behavior

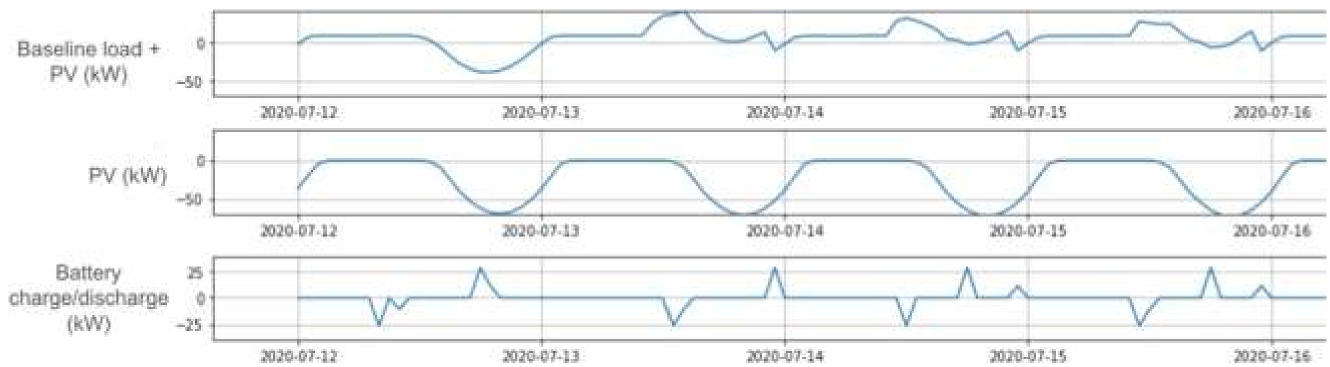
The BESS behavior model implemented different sets of logic for residential versus non-residential premises using the outputs of the sizing model, the premises' net-load (baseline plus PV) time series, a 90% depth-of-discharge limit, and a 90% round-trip efficiency estimate.

For **residential premises**, Kevala assumed the premise is attempting to maximize its self-consumption of PV. The algorithm took in a time series (8760) of net-load data and tracked battery state-of-charge at the same temporal resolution (e.g., hourly). Charging occurred when net-load was negative, limited by that hour's net-load value, the battery power rating, and the available state-of-charge headroom. Discharging occurred when net-load was positive, limited by that hour's net-load value, the battery power rating, and the available stored energy. The algorithm took round-trip efficiency losses into account in the discharging stage, assuming a standard 90% round-trip efficiency for all BESS models. The discharge will typically happen in the early evening hours as the sun goes down, which coincides with current time-of-use (TOU) peak periods, although TOU optimization was not explicitly built into the algorithm.

For **non-residential premises**, Kevala assumed the premise is attempting to reduce demand charges by reducing its peak periods. The battery charges at the times of day when demand is lowest and discharged when demand is highest. The algorithm took in a time series (8760) of net-load data but did not track state-of-charge on an hourly basis. Instead, the algorithm used the battery's energy-to-power ratio to identify how many time series intervals (e.g., 1-hour intervals) it would take for the battery to discharge from full capacity to empty at the battery's maximum discharge rate. For example, a 29 kW battery with 45 kWh energy rating could operate during two (n=2) 1-hour intervals (one at maximum power output, one at less-than-maximum output).

Then, for each 24-hour period (in this case, in the UTC time zone), the algorithm selected the n-lowest hourly intervals in the net-load data to charge and the n-highest hourly intervals to discharge. This assumed a perfect forecast of each 24-hour period. The charge/discharge power was limited by the maximum power rating and the state-of-charge but not by the net-load value; that is, the battery was allowed to discharge more than the simultaneous net-load, potentially resulting in net-exports during discharging rather than a zeroing out of the net-load. Figure A6-1 illustrates this behavior for a premise with PV and BESS. For this n=2 battery, there are two intervals of charging or discharging a day, where the magnitude of the first interval is at the maximum power rating, and the second interval is at a less than maximum power rating due to state-of-charge limits.

Figure A6-1: Example of a non-residential premise's baseline load plus PV, PV, and BESS profiles for July 2020. Battery is sized to 29 kW and 45 kWh; time stamps shown are in UTC as opposed to local time in California. *(Source: Kevala)*



A6.3. BTM BESS Adoption

Kevala selected and trained a multilevel logistic regression (MLR) model to model BESS adoption propensity using the features reported in Table A6-3. The features selected for this model included customer class, whether or not the premise had PV, maximum load, and demographic features from the U.S. Census Bureau's American Community Survey (ACS). The MLR model first grouped premises into four groups by the categorical variables (customer class, has/does not have PV), then trained a regression model on the remaining numerical features. The overall regression model was the same for the four groups, but because each group had unique training data, the regression resulted in unique parameters for each group. Each numerical feature was represented by a normal distribution in the MLR model; to better fit a normal distribution, some features with long tails were log-transformed.[167]

[167] For datasets with far outliers, also referred to as distributions with long tails, a logarithmic transformation can pull the outliers closer in so that a normal distribution better represents the underlying data.

Table A6-3: Categorical and numerical features used to train the BESS adoption model *(Source: Kevala)*

Categorical or Numerical	Feature	Granularity	Data Source	Log-Transformed?
Categorical	Customer class: residential or non-residential	Premise level	Rates	N/A
	Has PV: Yes or no	Premise level	PV adoption model	N/A
Numerical	Percentage of owner-occupied premises	Census block group	Census-ACS	No
	Maximum daytime baseline load	Premise level	Baseline (gross) load[168]	Yes
	Percentage of college or higher education degree holders	Census block group	Census-ACS	No
	Median household income	Census block group	Census-ACS	No

Compared with other distributed energy resources (DERs) such as PV, very few BESS systems have been installed in California, which complicates training the MLR model. Less than 0.5% of premises have BESS installed, which means the historical data available to train the BESS adoption model is considered a highly unbalanced dataset. Unless a method is added to account for this, data science models based on unbalanced datasets tend to predict only one outcome. In this case, a I model would always predict non-adoption because it is so much more prevalent in the training set. To address this issue, Kevala added a step during the BESS adoption model training called

[168] During model training, Kevala calculated the baseline load input from customer advanced metering infrastructure (AMI) data plus a PV production estimate using PVWatts for those customers with known PV systems from historical interconnection data. During model forecasting, the baseline load input was the output from the baseline load forecast model (see Section 3.3.2).

undersampling,[169] which is a data science technique that mitigates the impacts of unbalanced training data.

To train each investor-owned utility's (IOU's) BESS model, Kevala randomly split all premises[170] in that IOU into two subsets: a training (in-sample) set (67%) and a validation (out-of-sample) set (33%). Kevala conducted undersampling on the training set only to address the issue of the unbalanced dataset before training the MLR model. Then, both the training and validation data were run through the trained model to generate adoption propensity scores for all premises. Kevala calculated the evaluation metrics of precision and recall using an adoption threshold, which was based on the historical adoption rate in each IOU's training and validation dataset. Kevala used the interconnection data to identify the historical adoptions.

Table A6-4 reports the results for all three IOUs. The evaluation metrics are consistent between the training and validation dataset for each IOU, which indicates the models are not overfit and did a good job of generalizing to the out-of-sample data. While the precision and recall values are low, they are greater than the historical adoption rate in this highly unbalanced dataset, which indicates a better-than-random adoption selection (e.g., values are greater than the historical adoption rate of <0.005). The PR AUC metric is considered the most pertinent metric for highly unbalanced datasets, and while there is strong consistency in the PR AUC results, the values are considered low; this speaks to the challenges of modeling future adoption predictions on such a limited historical dataset.[171]

Table A6-4: BESS adoption evaluation metrics for each IOU's adoption model *(Source: Kevala)*

	Data Subset	**Precision**	**Recall**	**PR AUC**
PG&E	Training	0.127	0.134	0.083
	Validation	0.126	0.133	0.082

[169] Undersampling randomly removes samples from the majority class (e.g., premises that have not yet adopted BESS in the historical data) to resolve the challenges from unbalanced training data. For more information on undersampling, see: The imbalanced-learn developers, "3. Under-sampling — Version 0.9.1.," https://imbalanced-learn.org/stable/under_sampling.html.

[170] Premises must have all the data features listed in Table A6-3 to be eligible, and residential premises with BESS installed but no PV are ignored based on the behavior assumptions described previously. For example, the eligible dataset for PG&E comprises 4.8 million premises, after removing 252,000 premises for missing data and 169 residential records that have installed BESS but not PV.

[171] See Appendix 5 for detailed definitions of precision, recall, and PR AUC.

	Data Subset	Precision	Recall	PR AUC
SCE	Training	0.090	0.093	0.059
	Validation	0.094	0.098	0.060
SDG&E	Training	0.094	0.095	0.071
	Validation	0.098	0.100	0.072

A6.4. BTM BESS Base Case Results and Scenarios

The Modified BTM rate design scenario results in slight differences in BESS outcomes compared to the Base Case scenario (calibrated to the 2021 Integrated Energy Policy Report, or IEPR) because of the linkage between BTM PV and BESS. Similar to PV, the adoption propensity score used to calibrate the Existing BTM Tariffs BESS scenario was used to calibrate the Modified BTM Tariffs BESS scenario. Kevala did not directly include payback period in BESS adoption modeling, but there are indirect follow-on effects for premises that switch from PV adopters to non-adopters. If a premise does not adopt PV, its adoption propensity for adopting BESS falls dramatically.

Table A6-5 shows the BESS percentage contribution to system peak by IOU, year, and scenario. In all cases, the percentage contribution is negative (around -1% or less). A negative percentage contribution implies that BESS are discharging in aggregate during the peak load hour. As the system peak load hours are modeled to occur in the late afternoon, shifting to evening as the adoption of electric vehicles (EVs) progresses, this overlaps with the time when residential BESS are discharging following as or after the sun sets.[172] The results at the feeder level are far more diverse, including some feeders that peak while BESS are charging in aggregate instead of discharging. For example, for the base case IEPR scenario for PG&E in 2025, BESS's percentage contribution to each feeder's peak ranges from -13% to 20%, while the percentage contribution at the IOU level is -0.77%.

[172] This behavior is based on the current assumptions that TOU mid-peak and peak period will continue to be in the late afternoon and evening in the future. TOU periods are implicitly rather than explicitly included in the current residential BESS behavior algorithm.

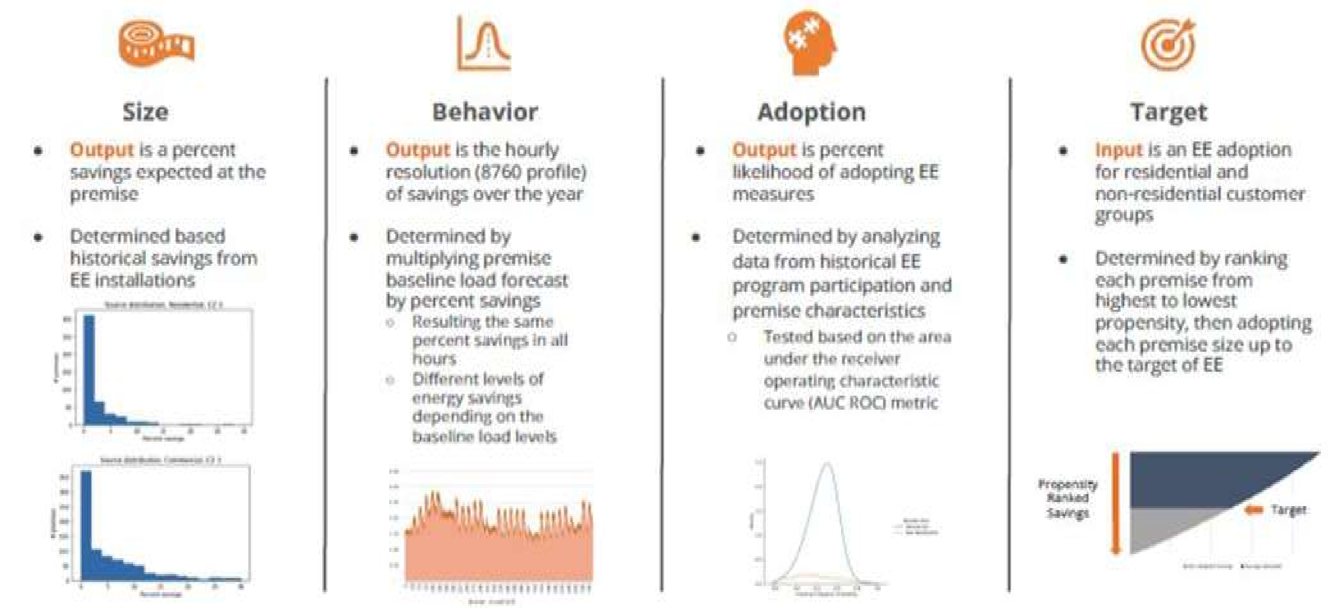
Table A6-5: BESS percentage contribution to the net-load peak by IOU, forecast year, and scenario *(Source: Kevala)*

Scenario	BESS Percentage Contribution to Peak Net-Load								
	2025			2030			2035		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
(1) Base Case 2021 IEPR	-0.77%	-0.04%	-0.58%	-1.80%	-0.07%	-1.73%	-1.32%	-0.06%	-0.92%
(2) High Transportation Electrification + Existing BTM Tariffs	-0.78%	-0.04%	-0.59%	-0.91%	-0.07%	-1.67%	-1.04%	-0.06%	-1.17%
(3) High Transportation Electrification + Modified BTM Tariffs	-0.75%	-0.03%	-0.58%	-0.87%	-0.07%	-1.64%	-1.00%	-0.05%	-1.14%
(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	-0.75%	-0.04%	-0.57%	-0.84%	-0.12%	-0.44%	-1.06%	-0.06%	-1.18%
(5) Accelerated High Transportation Electrification + Modified BTM Tariffs	-0.72%	-0.03%	-0.57%	-0.80%	-0.07%	-0.43%	-1.01%	-0.06%	-1.15%

Appendix 7. Energy Efficiency Modeling Methodology Details

This appendix contains detailed information about the energy efficiency (EE) sizing, behavior, and adoption algorithms, including evaluation results used to validate each model on historical data. Kevala believes the results of the EE analytics completed for this Part 1 Study provide accurate and sufficient estimates of the impacts of EE adoption on distribution planning. Figure 54 (see Section 3.4.4) shows the process flow of the EE evaluation method to develop the premise-level EE forecasts. Figure A7-1 summarizes EE modeling.

Figure A7-1: EE modeling summary *(Source: Kevala)*



A7.1. EE Sizing

Kevala employed a stepwise approach to quantifying the estimated total annual energy savings from EE technologies for each premise. The key steps for sizing EE include the following:

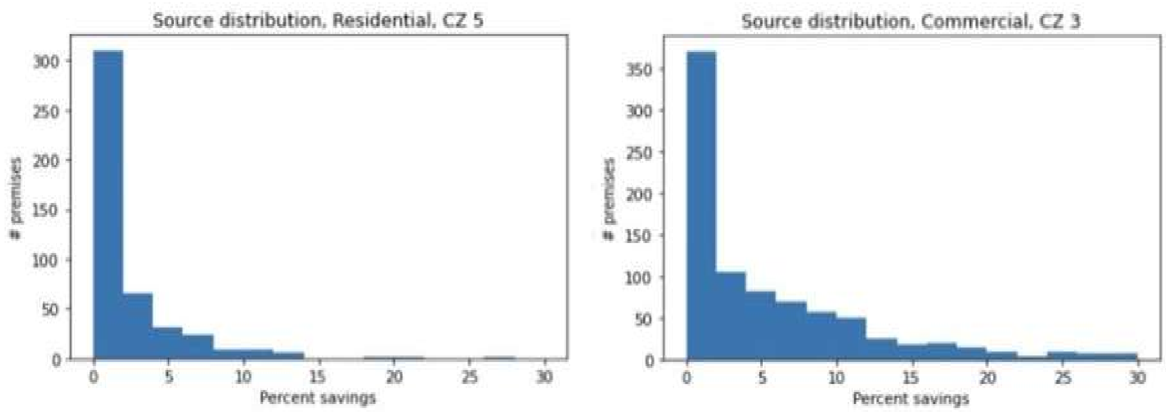
1. **Identify historical EE program participants (i.e., participating premises).** Using the California Energy Data and Reporting System (CEDARS) database,[173] Kevala first identified which customers participated in EE programs between 2018 and 2020, and the estimated energy savings resulting from each participating premise. Next, Kevala matched those participating premises to the historical premise-level advanced metering infrastructure

[173] California Public Utilities Commission (CPUC), "CEDARS: California Energy Data and Reporting System," https://cedars.sound-data.com/.

(AMI) data received from the utilities to quantify the participant's annual baseline load energy consumption prior to EE program participation.

2. **Calculate percent savings.** Using only participating premises for which baseline load energy consumption prior to EE program participation could be calculated, Kevala calculated the ratio of the first year of gross annual energy (kWh) savings[174] to the sum of the participating premise's energy consumption the year prior to participating.
3. **Develop distribution of percent savings by customer group.** First, Kevala classified each participating premise in the sample by customer class and California Energy Commission (CEC) climate zone. Next, Kevala calculated the distribution of percent savings for each classification. Figure A7-2 provides an example of these residential and commercial sector percent savings distributions. Table A7-1 shows the customer class and CEC climate zones for which Kevala computed the distribution of savings.

Figure A7-2: Example distribution of percent savings by grouped premises using EE program portfolio participation data *(Source: Kevala analysis)*



Note: CZ = climate zone

Table A7-1: Customer classes and CEC climate zones *(Sources: Kevala, CEC)*

Customer Classes	CEC Climate Zones
Residential Commercial Agricultural Industrial Public	1-16

[174] Estimate of gross annual savings was based on data from the CEDARS database.

4. **Estimate potential annual savings by premise.** Based on a premise's class and CEC climate zone, Kevala randomly selected the percent annual savings for each premise from the relevant sample distribution. Kevala multiplied the baseline load forecast for 2025, 2030, and 2035 for each premise by the percent annual savings to estimate the annual energy savings from EE participation for each premise.

A7.2. EE Behavior

Kevala assumed the hourly shape of savings to be the same as the baseline load forecast for the premise. That is, Kevala calculated the premise EE load profile by multiplying an identified premise's annual percent savings by the forecasted hourly baseline load for that premise. Kevala recognizes that the profile of energy savings depends on the EE technologies employed by the participating premise. Ideally, a profile of savings by measure would be applied to the premise. Kevala was not able to identify which EE measures were installed at each premise.

A7.3. EE Adoption

To forecast which premises will adopt EE, Kevala applied the following process based on historical EE program participation. Kevala understands that many more premises implement EE without participating in an EE program. Additionally, some EE is implemented via changes in codes and standards that impact all new construction and influence what is available in the market (e.g., a customer can only choose from available equipment to replace an air conditioner, light bulbs, etc.).

1. **Estimate EE adoption propensity.** Kevala analyzed data from historical EE program participation to understand those premise-level characteristics that drive EE adoption. Using a Bayesian modeling approach, Kevala trained a model that related premise attributes (features) to actual EE adoption (target) to estimate EE adoption propensity scores.

   Some key assumptions go into this adoption modeling approach:

   - The adoption of EE in the sample of adoptions from 2018 through 2020 is representative of adoption in the population for 2025, 2030, and 2035.
   - There is a statistically robust relationship between the features and target.

   To evaluate the performance of the adoption model, Kevala chose the area under the receiver operating characteristic curve (AUC ROC) metric. This metric summarizes performance over all adoption thresholds.[175] Kevala chose this metric because it is designed to quantify how well the model is able to separate the adopting premises from the non-adopting premises. Specifically, AUC ROC quantifies how the model performs on the tradeoff between the true positive rate (e.g., predicting adoption at a premise where adoption actually occurred) and the false positive rate (e.g., predicting adoption at a premise where adoption did not actually occur). The AUC ROC is bounded between 0.0 and 1.0, with higher scores indicating better performance and 0.5 indicating that the model performs at the same level as random chance.

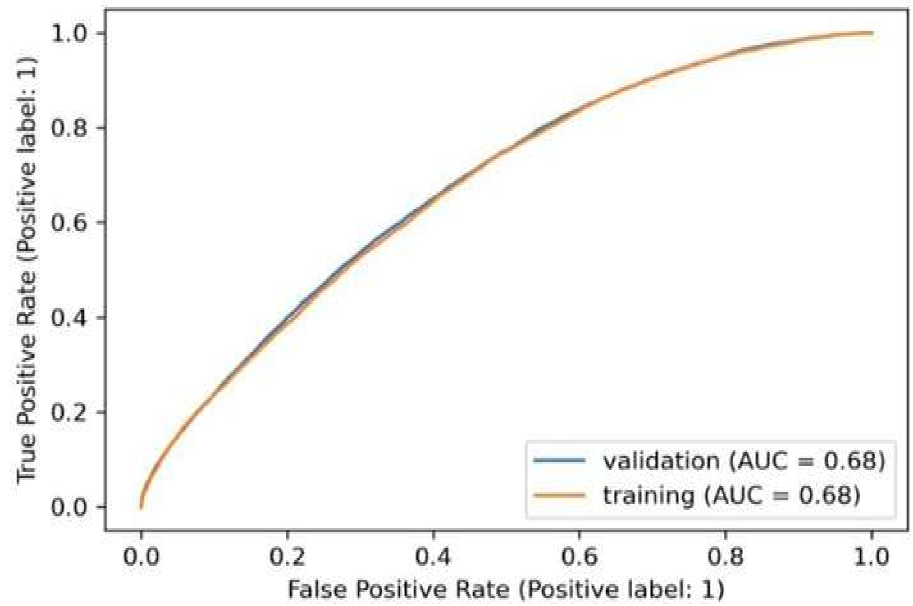
This metric is appropriate for this study because adoption levels are based on targets that vary for different scenarios or time horizons, and the best choice of model is one that performs well regardless of the threshold value selected. The best performing and conceptually reasonable feature set based on the AUC ROC score of 0.68 (see Figure A7-3)[176] included the following features:

- **Log-scaled mean daily delivered energy:** An indicator of the magnitude of load at the premise. The prominence of this metric in driving adoption could be caused by the limited data available, which may be biased to measures with larger savings driven by high energy use and misses smaller, behavior-related actions such as home energy reports.
- **Log-scaled ratio of max to mean daily delivered energy:** An indicator of the peakiness of load at the premise.
- **Log-scaled parcel building footprint square feet:** An indicator of the size of the buildings at the premise.
- **Residential or non-residential premise indicator variable:** Used to create the multilevel split in the model such that residential premises are modeled with different parameters from non-residential premises.

[175] Wikipedia provides a helpful overview of this model at: https://en.wikipedia.org/wiki/Receiver_operating_characteristic.

[176] Kevala had a better performing model with a score of 0.75 on the validation data and 0.76 on the training data, but it was deemed to be overfit and had lower validation set scores.

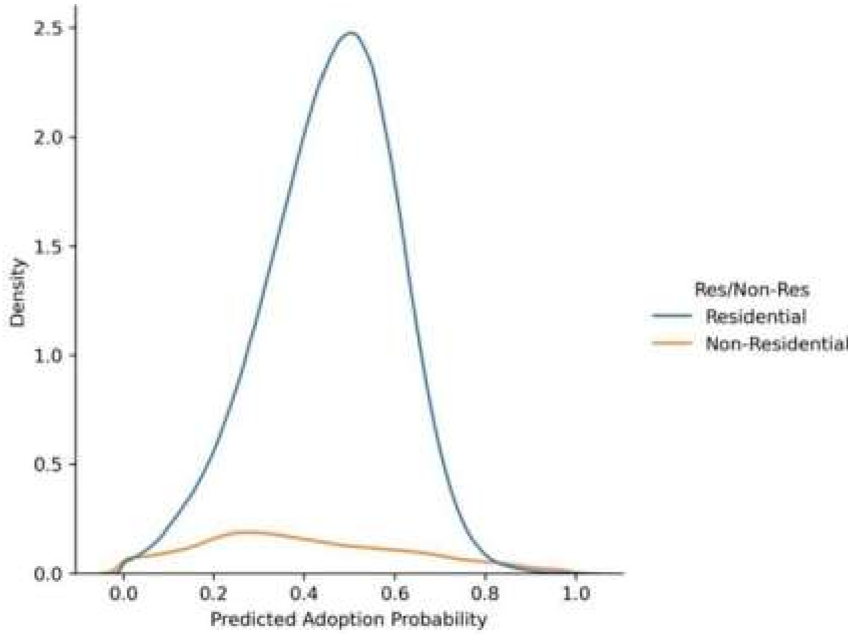
Figure A7-3: AUC ROC score for EE adoption modeling *(Source: Kevala analysis)*



To follow up on the analysis, Kevala examined the distribution of predicted probabilities produced by the model to understand any patterns the model is capturing.

Figure A7-4 shows the distribution of predicted probabilities for residential versus non-residential premises. The predicted probabilities for residential premises appear to follow a skewed normal distribution, while the non-residential premises have a flatter distribution with a higher mean probability.

Figure A7-4: Distribution of predicted probabilities for residential versus non-residential premises *(Source: Kevala analysis)*



Note: The y-axis (Density) is normalizing the data so the area under the histogram integrates to 1.

Kevala reviewed whether climate zones or percent of savings features were statistically significant drivers of adoption. Neither were found to be strong drivers of adoption.

After experimenting with including payback (calculated as average measure costs per first year kWh saved basis per sector), Kevala found that feature also did not prove to be a significant contributor. This may be due to the lack of data available to determine which EE measures participating premises implemented. That is, these payback estimates ignored the potential distribution of costs (on a per kWh of savings basis) based on the varying costs of measures adopted (e.g., the cost per kWh of savings for efficient lighting could be very different for weatherization measures, which may be influenced by premise-specific characteristics). Further, actual costs and associated incentives of measures installed through programs are highly dependent on the savings delivery mechanism, be it codes and standards, a rebate program, a behavioral program, or market forces.

The Part 1 Study findings related to the lack of statistically significant drivers of adoption are further supported by the CPUC's 2021 *California Energy Efficiency Market Adoption Characteristics Study*.[177] This study identified that true customer purchase decision behavior

[177] Guidehouse and Opinion Dynamics, *California Energy Efficiency Market Adoption Characteristics Study Methodology and Results,* April 2021, https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-

is not solely based on financial indicators and the complexities of the decision for each unique measure or customer cannot be simply captured via a survey or objective characteristics. The study attempted to inform willingness-to-adopt algorithms with financial and non-financial indicators in customer decision-making using behavioral science research. The non-financial indicators included the customer's perception of a technology's environmental impacts, social status/statement signaling, ease of installation, and aesthetics or features unrelated to energy use as key data points.

2. **Rank premises by adoption propensity.** Kevala used the adoption propensity scores for each premise to rank premises with the highest level of propensity for each customer class listed first.

With the sizing, behavior, and adoption propensity results, Kevala then calibrated adoption to the 2021 Integrated Energy Policy Report's (IEPR's) mid-mid case scenario.

1. **Develop EE adoption targets by class.** To ensure the level of EE adoption is calibrated to the IEPR mid-mid case scenario, Kevala used the EE forecast from the IEPR estimated for each transmission access charge (TAC). This forecast was then further divided by customer class to generate a target for each class by IOU. These targets were annual non-coincident peak energy savings from EE by class by year.

2. **Select premises for adoption by forecast year.** For each class, Kevala selected premises for adoption by selecting premises in their ranked order until the annual target savings for the forecast year for the class was reached. Once a premise was selected for adoption, Kevala assumed the EE savings would persist for the remaining forecast years. For example, if a premise was chosen to provide savings in 2025, those savings remained in place through 2035, effectively lowering the incremental targets of EE adoption in subsequent years.

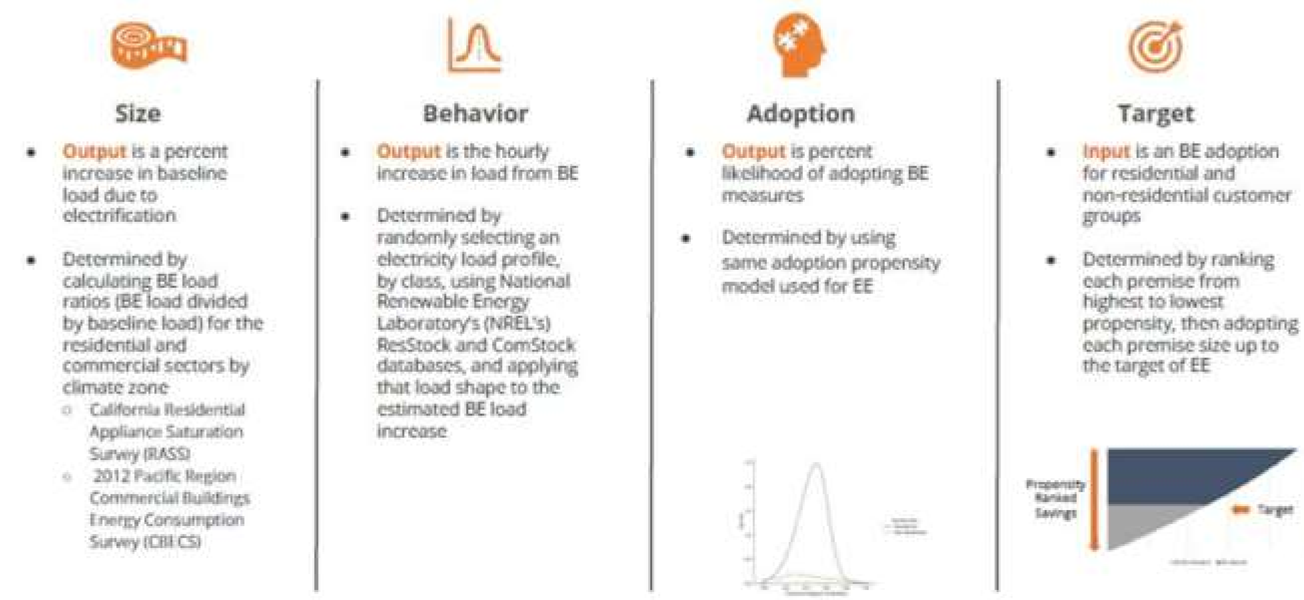
   Because the total portfolio EE adoption was based on the 2021 IEPR mid-mid case scenario, when the adopted premises reached maximum non-coincident demand savings, the data pipeline stopped the adoption calculation. Based on the 2021 IEPR analysis, a range of percent savings were achieved across the sectors. As a result, the EE adoption aligns to the IEPR mid-mid case energy forecast allocation by sector.

division/documents/energy-efficiency/2021-potential-goals-study/market-adoption-report-final.pdf?sc_lang=en&hash=131848F75C4A50EB35D9247F45FB4257

Appendix 8. Building Electrification Modeling Methodology Details

This appendix contains detailed information about the building electrification (BE) sizing, behavior, and adoption algorithms, including evaluation results used to validate each model on historical data. Figure 55 (see Section 3.4.5) shows the key steps for the BE analysis. Figure A8-1 summarizes BE modeling.

Figure A8-1: BE modeling summary *(Source: Kevala)*



A8.1. BE Sizing

Typically BE (also known as fuel substitution) sizing would be a function of the amount of fuel that electricity would replace, such as replacing a natural gas heater with an electric heater. Kevala originally planned to base BE sizing on annual gas consumption at the premise; however, that data was not available for this study.[178] As a result, Kevala's approach involved sizing BE at the premise using the premise's existing baseline consumption. Kevala used the following steps to calculate the size of BE potential at each premise.

1. **Calculate annual kWh baseline load.** Using the baseline forecast (net-load less photovoltaic (PV) behavior), Kevala estimated the baseline load at each premise for each of the forecast years (see Section 3.3).[179]

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[178] Kevala requested gas usage data from the investor-owned utilities (IOUs) but only Southern California Gas' data was available at the time of this study.

[179] Kevala assumes energy efficiency (EE) and BE to be embedded in the baseline load.

2. **Develop BE load ratios.** Kevala calculated BE load ratios for the residential and commercial sectors by climate zone. Kevala did not develop BE load ratios for the agricultural or industrial sectors because there is limited application of BE to agriculture and fuel substitution at industrial sites is highly diverse.

   The methodology to generate these load ratios varied by the residential and commercial sectors:

   a. For the residential sector, Kevala used the California Residential Appliance Saturation Survey (RASS)[180] by climate zone unit energy consumption (UEC) for:
      i. Heat pump and furnace fan unit
      ii. Whole home
      iii. Electric water heating
      iv. Space cooling
   b. For the commercial sector, Kevala used 2012 Pacific Region Commercial Buildings Energy Consumption Survey (CBECS) data [181], The specific end uses for potential electrification in commercial buildings included space heating, water heating, and cooking. The percent increase in kWh of the baseline whole premise consumption was the multiplication of the following three values by end use.
      i. Percentage of the population of buildings with natural gas consumption
      ii. Percentage of buildings with the end use of interest
      iii. Percentage of the whole building consumption attributed to that end use

3. **Apply BE load ratios.** After developing the BE load ratios and matching them to a premise based on the premise's class and climate zone, these ratios were applied to the premise baseline load forecast calculated in the first step.

Kevala had planned a more detailed sizing approach using natural gas data but did not receive it in time for this study. Kevala has since received and processed the natural gas data from the IOUs for the Part 1 Study sample period (2018-2021). Kevala proposes requesting additional natural gas data for Part 2 to match the additional advanced metering infrastructure (AMI) data being requested (post-2021 and potentially before 2018).

Further, some of the data Kevala used in the existing method was dated. Specifically, Kevala used the 2012 Pacific Region CBECS data because the 2018 end use-related tables had not yet been

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[180] California Energy Commission, *2019 California Residential Appliance Saturation Study, Volume 2: Results*, Tables 37-39, July 2021, https://www.energy.ca.gov/sites/default/files/2021-08/CEC-200-2021-005-RSLTS.pdf.

[181] U.S. Energy Information Administration, *2012 CBECS Survey Data*, Tables E1, E2, and E5, https://www.eia.gov/consumption/commercial/data/2012/index.php?view=consumption.

published. Kevala has confirmed that the U.S. Energy Information Administration released the 2018 CBECS data on September 28, 2022, so it is available for use in the Part 2 Study.

Kevala also proposes to explore creating different sizing models for residential versus non-residential to further refine its approach in Part 2.

A8.2. BE Behavior

Typically, new consumption from BE would be based on the end use converted to electricity, such as space heating, water heating, or clothes drying. Unfortunately, this data was not available at the premise level for the Part 1 Study. As a result, Kevala defined a load profile appropriate for the new electricity consumption using the National Renewable Energy Laboratory's (NREL's) ResStock[182] and ComStock[183] databases. Specifically, Kevala randomly chose a load shape from the used distribution of the all-electric default load shapes from those two NREL databases for each premise. Kevala then applied these randomly chosen load shapes to the electrification size for the premise.

While the NREL databases are a good choice for the load shapes and should continue to be used for the Part 2 Study, Kevala proposes improving on these profiles by pursuing two options:

- First, Kevala will look at refining BE to specific technologies, such as heat pumps, for sizing and load shapes. In this case, Kevala will use the same process for BE for other technologies that are less prevalent but could emerge as more dominant during the study period (e.g., natural gas-intensive industrial processes).
- Second, Kevala will look to estimate the change in load profile versus the electrification profile. That is, in using NREL's electric-only load profiles as the load shape, the results may not be reflecting the change in use. For example, using the load profile for an all-electric home for the incremental BE load that is layered on a baseline load forecast that does not include electric load could underestimate the peak use of the home that results from electric heat as the peak use is muted by a shape that includes other less weather sensitive loads.

A8.3. BE Adoption

Historical data on adoption of BE technologies is needed to train a model that predicts future adoptions. Further, BE only occurs if there are other fuels that can be substituted with electricity,

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[182] ResStock is an NREL load profile library using a combination of building models and metered data. Kevala filtered the data to California with the space and water heating fuel set to electricity only.
[183] ComStock is an NREL load profile library. Kevala filtered the data to California with the space and water heating fuel set to electricity only.

such as natural gas. Therefore, BE adoption is uniquely dependent on the level of natural gas use at the premise. For this study, Kevala was not able to develop a robust BE adoption model due to the lack of historical adoption data and natural gas data for all IOUs. Kevala requested data regarding gas use from each IOU, but it was not received in time to incorporate into this study. As a result, Kevala used the same adoption propensity scores from EE for BE to rank order the BE adoption by premise. Appendix 7 provides the EE adoption and adoption evaluation results used to validate each model on historical data before its use in the prediction pipeline.

Kevala proposes several efforts to address this gap in Part 2:

- Kevala has received and processed the natural gas data from Pacific Gas and Electric (PG&E), San Diego Gas & Electric (SDG&E), and Southern California Gas. The first planned modification is to include gas use or other related metrics in testing a new BE adoption model.
- Kevala plans to request additional data from the IOUs regarding granting incentives to their customers for adopting BE technologies, such as electric water heaters and electric heat pumps.
- Kevala will research other jurisdictions to see if there are any studies that may provide useful in further refining the adoption model and results.

For the Part 1 Study, Kevala held the BE forecasts constant across all scenarios. For the Part 2 Study, Kevala proposes to explore potential scenarios for accelerated BE adoption that are consistent with Senate Bill (SB) 1477[184] and Assembly Bill (AB) 3232.[185] Kevala will work with the California Public Utilities Commission (CPUC) in developing these high BE scenarios.

The Part 2 Study proposes exploring mitigation options to reduce the implications of high DER adoption.

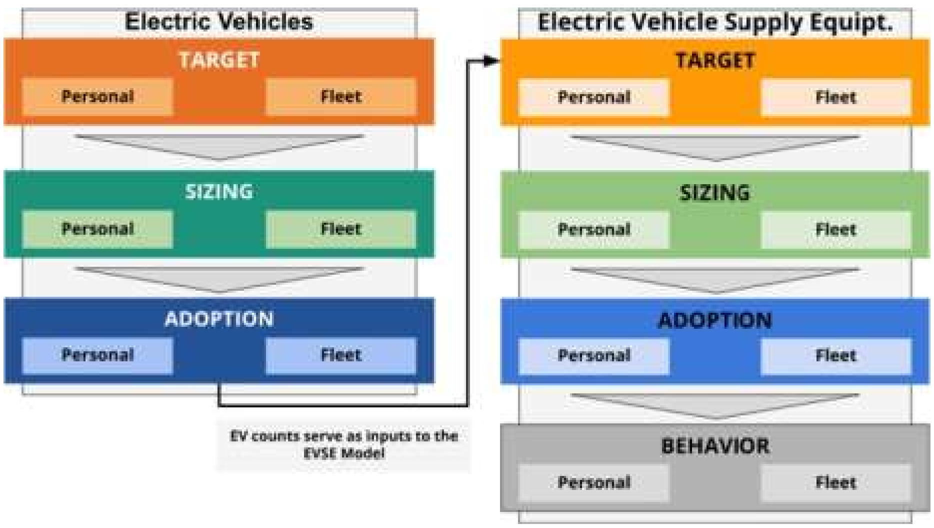
[184] SB 1477 was passed on September 13, 2018 and sets new state policy standards for low-emission buildings and sources of heat energy. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1477.

[185] AB 3232 was passed on September 13, 2018 and sets new state policy standards for zero-emission buildings and sources of heat energy. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180AB3232.

Appendix 9. EV and EVSE Modeling Methodology Details

This appendix contains additional details regarding the data sources and methods Kevala used to generate the premise-level electric vehicle (EV) adoption allocations and EV service equipment (EVSE) siting forecasts that animate the EVSE charging behavior and their subsequent grid impacts. EV counts serve as inputs to the EVSE model (see Figure A9-1).

Figure A9-1: EV and EVSE pipeline modeling overview *(Source: Kevala)*



A9.1. EV and EVSE Modeling Overview

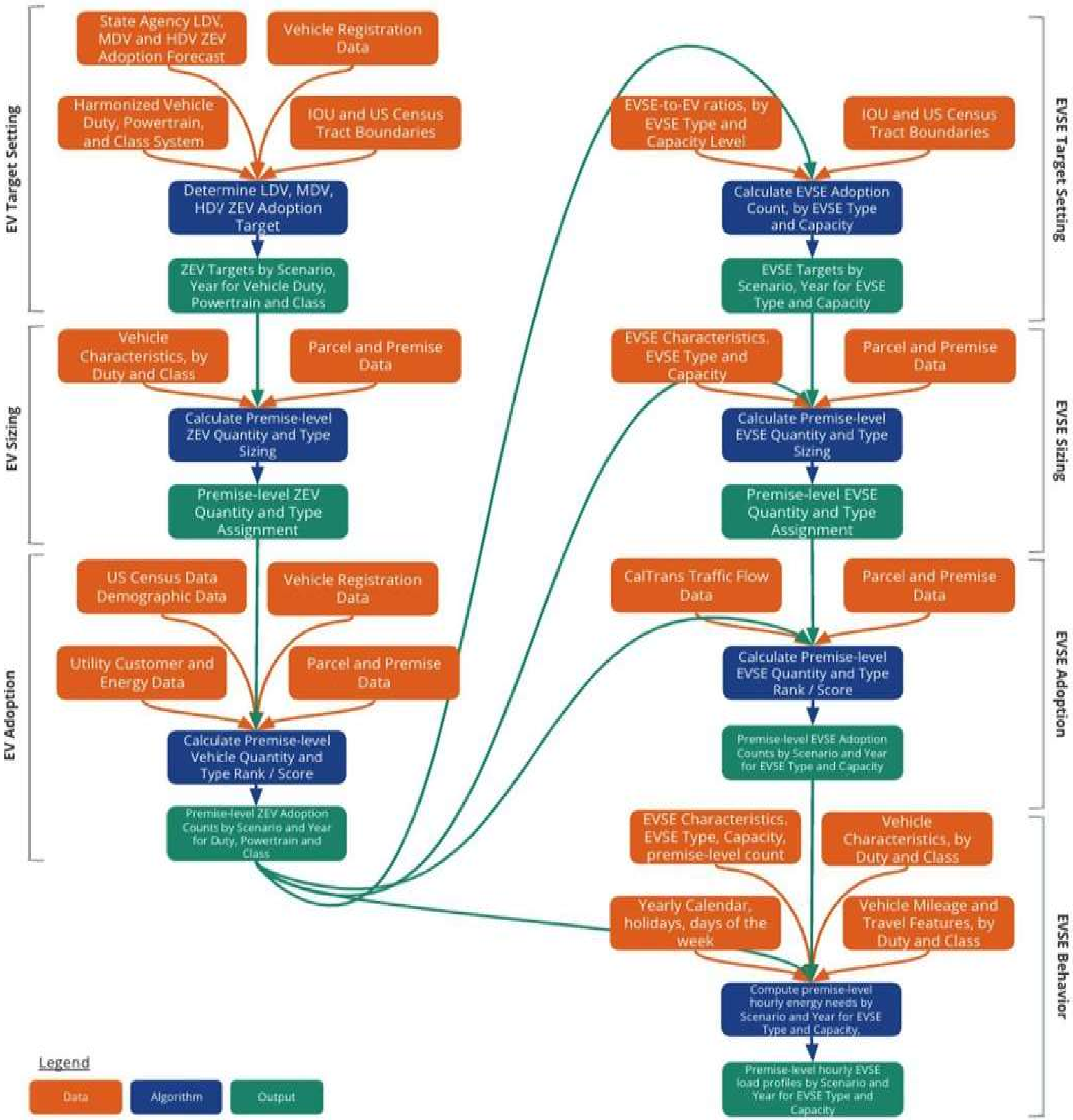
Figure A9-2 summarizes the high-level, interconnected computational steps that Kevala executed for the EV and EVSE modeling pipelines. As the figure indicates, the EV pipeline was executed first, and the outputs from the EV steps then served as inputs to the EVSE pipeline. The EV and EVSE pipeline executed specific calculations for personal (i.e., privately owned) and fleet (i.e., owned by a fleet operator) vehicles and for these vehicles' associated EVSE.

The EV and EVSE modeling pipelines began by identifying the target number of total assets (i.e., vehicle counts or charging port counts) to be allocated or sited for a given year. Following this step, the EV and EVSE models conducted the **sizing** step, which determined the type of vehicles or charging ports available—i.e., personal, light-duty (LD), battery electric vehicle (BEV), small car, or fleet, depot, direct current fast charging (DCFC) 50 kW—and the total potential count of vehicles or charging ports for a given premise. Importantly, the sizing step only determined what type of asset and how many of those assets could be adopted in the event that premise is selected in the adoption step; the step of actual adoption occurred in the adoption step.

Next, the models ran an **adoption** propensity analysis that calculated the actual type and count of the vehicle(s) or charging port(s) adopted at a given premise for a given year (i.e., one personal, LD, BEV, small car at a residential premise or 10 fleet, depot, DCFC 50 kW at a commercial premise). The adoption step was the last step for the EV model.

For the EVSE pipeline, the **behavior** step was the final step. It involved determining the annual hourly charging profile for a given parcel for a given year based on the energy requirements of the vehicle(s) projected to charge at the given parcel.

Figure A9-2: Summary of the high-level EV and EVSE pipeline modeling steps *(Source: Kevala)*



The EV and EVSE modeling methodologies differed from the Part 1 Study's other DER modeling approach in several important ways.

- **Forecasted EVs were taken as an input into the EV model:** For each scenario, the EV model used one of three California state agency zero-emission vehicle (ZEV) adoption forecasts as direct modeling inputs. These forecasts represented the most reasonable and robust reflection of California's ambitious ZEV adoption policies at the time of their selection in the second quarter of 2022. To reflect the grid impacts associated with the achievement of the state's ZEV adoption policies, the Part 1 Study used state forecasts that are already serving as inputs to inform other statewide modeling and planning decisions. For the other DER models, Kevala calculated or estimated the forecasted number of DER counts for given technology (i.e., PV or BESS) based on an analysis of the data. Further details about these adoption forecasts are provided in the following sections.

- **Target setting—not sizing—was done as the first step of the EV and EVSE modeling process:** Whereas the Part 1 Study's other DER modeling pipelines began with a sizing step, the EV and EVSE modeling pipelines began with a target step. As described previously, this is because Kevala designed the EV analysis to reflect the obtainment of the state's ambitious 2035 ZEV adoption targets, which are contained in the state agency ZEV adoption forecasts that set the targets the EV model seeks to achieve for each year in each scenario.
- **The EV and EVSE modeling steps followed a different sequence than other DERs:** The other DERs modeled in the Part 1 Study follow a sizing-behavior-adoption sequence. The EV and EVSE models did not follow this sequence. Instead, the EV model followed a target-sizing-adoption approach, and the EVSE model followed a target-sizing-adoption-behavior approach.
- **The EVSE model contained four steps: target, size, adoption, behavior:** The EVSE model was the only DER model with four steps. As described previously, this is because it contained a target step in addition to the three other core steps (size-adoption-behavior).

The following sections contain further details on the target, sizing, adoption, and behavior steps illustrated in Figure A9-1.

A9.2. EV Adoption Targets

In consultation with the California Public Utilities Commission (CPUC), Kevala selected publicly available light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) ZEV adoption forecasts produced by the California Air Resources Board (CARB) and California Energy Commission (CEC) to serve as the ZEV adoption forecast inputs for the Part 1 Study's five electrification scenarios. Table A9-1 summarizes the CEC and CARB LDV, MDV, and HDV ZEV adoption forecasts and the associated vehicle counts that Kevala used in the Part 1 Study.

Table A9-1: Summary of CEC and CARB LDV, MDV, and HDV ZEV adoption forecasts used for the Part 1 Study scenarios *(Sources: CARB, CEC, Kevala)*

		(1) Base Case 2021 IEPR	(2) High Transportation Electrification + Existing BTM Tariffs**	(3) High Transportation Electrification + Modified BTM Tariffs**	(4) Accelerated High Transportation Electrification + Existing BTM Tariffs	(5) Accelerated High Transportation Electrification + Modified BTM Tariffs
ZEV Adoption Forecast Source	**LDV**	CEC 2021 IEPR mid scenario	CARB 2021 Advanced Clean Cars II (ACC II)		CEC 2021 IEPR bookend scenario	
	MDV / HDV		CARB 2020 State SIP Strategy (SSS)		CEC 2021 IEPR high scenario	
ZEV Adoption Total Vehicle Count (2022-2035, Three IOUs)*	**LDV**	3,172,598	10,013,953		9,530,034	
	MDV / HDV	227,140	218,710		230,876	

*The values in this table represent the forecasted ZEV adoption counts from 2022 to 2035 that the model allocated based on the CARB and CEC ZEV adoption forecasts. These values exclude all ZEV counts prior to 2022, thus they do not represent the total cumulative ZEV counts for all three investor-owned utilities (IOUs).

**The two High Transportation Electrification scenarios incorporate transportation electrification assumptions similar to those applied to the 2022 IEPR demand forecast mid-mid case (i.e., the 2022 IEPR Planning Forecast). At the time the Part 1 Study was developed, the 2022 IEPR had not yet been adopted, so the 2021 IEPR mid-mid case was used for the Part 1 Base Case.

Kevala selected the three CARB and CEC ZEV adoption forecasts for the Part 1 Study because they represent a meaningful range of ZEV adoption levels that align with California policy goals and market forecasts. The CPUC project team facilitated the acquisition of these adoption forecasts, which CARB and CEC provided directly to CPUC.

As Table A9-2 shows, the number of LDV ZEVs in the High Transportation Electrification scenario (10,013,953) are greater than the number of LDV ZEVs in the Accelerated High Transportation Electrification scenario (9,530,034), which is counterintuitive because the scenario names indicate that the Accelerated High Transportation scenario should have higher adoption than the High Transportation Electrification scenario. This difference occurred because Kevala identified and selected the Base Case and Accelerated High Transportation Electrification scenarios' ZEV adoption forecasts prior to the High Transportation Electrification scenario's ZEV adoption forecast.[186] At the time Kevala selected these inputs, it was not known that the High Transportation Electrification scenario's LDV ZEV adoption forecast would have a greater number of 2035 adoptions compared to the Accelerated High Transportation Electrification scenario. As such, it was the timing—not a deliberate modeling choice—that drove this counterintuitive outcome.

Because the CARB and CEC ZEV adoption forecasts use different vehicle classification systems, Kevala needed to harmonize the forecasts' classification systems into a common set of vehicle classes based on the CEC's vehicle classification system. Table A9-2 summarizes Kevala's harmonized CARB and CEC vehicle classes. Importantly, the LDV, MDV, and HDV harmonized classification system also aligns to the Experian Vehicles in Operation (VIO) data, which was Kevala's source of vehicle registration data.

The VIO data is a purchased dataset that provides vehicle registration information at the Census block group level for the year, make, model, duty, powertrain, and vehicle class for the vehicles registered in a given Census block group. Kevala used this data to develop detailed insights into where current vehicle types (i.e., duty, powertrain, vehicle class) are registered so that it could appropriately allocate vehicles from the CARB and CEC ZEV adoption forecasts in a manner that corresponded to their historic geographic registration location.

Table A9-2: Summary of Kevala's harmonized CARB and CEC vehicle classes *(Sources: CARB, CEC, Kevala)*

Duty	**Powertrains**	**Vehicle Classes**
LDV	BEV, Plug-in Hybrid Electric Vehicle (PHEV)	Small Car, Large Car, Small Sport Utility Vehicle (SUV), Large SUV, Pickup, Van, Sport Car
MDV	BEV	Gross Vehicle Weight Rating (GVWR) 3, GVWR 4-5, GVWR 6, GVWR6 - Delivery

[186] The LDV, MDV, and HDV ZEV adoption forecasts were determined by the Joint Agency Steering Committee (JASC) High Electrification Interagency Working Group and selected in March 2022, after the ZEV adoption forecasts for the Base Case and Accelerated High Transportation Electrification scenarios had been selected. For more information about the Interagency Working Group's high electrification scenario, refer to the May 24, 2022, CEC Resolution (No. 22-0524-5) that adopted it for use in transmission planning and as part of the 2021 IEPR "single forecast set," at https://www.energy.ca.gov/filebrowser/download/4171.

Duty	Powertrains	Vehicle Classes
HDV	BEV	GVWR7, GVWR8*, GVWR8 - Box Truck, GVWR8 - Long Haul Tractor, School Bus, Urban Bus

*GVWR8 - Box Truck and GVWR8 - Long Haul Tractor were differentiated from GVWR8 to model their distinctly long daily average vehicle miles traveled (VMT).

A9.2.1. Personal EV Targets

Personal EVs are vehicles that are owned—or expected to be owned—by an individual user and are not registered or used as an asset by a fleet operator. Kevala undertook the following steps to generate scenario-specific personal EV targets (i.e., vehicle counts by duty, powertrain, and vehicle class) from the three CARB and CEC ZEV adoption forecasts and scenarios:

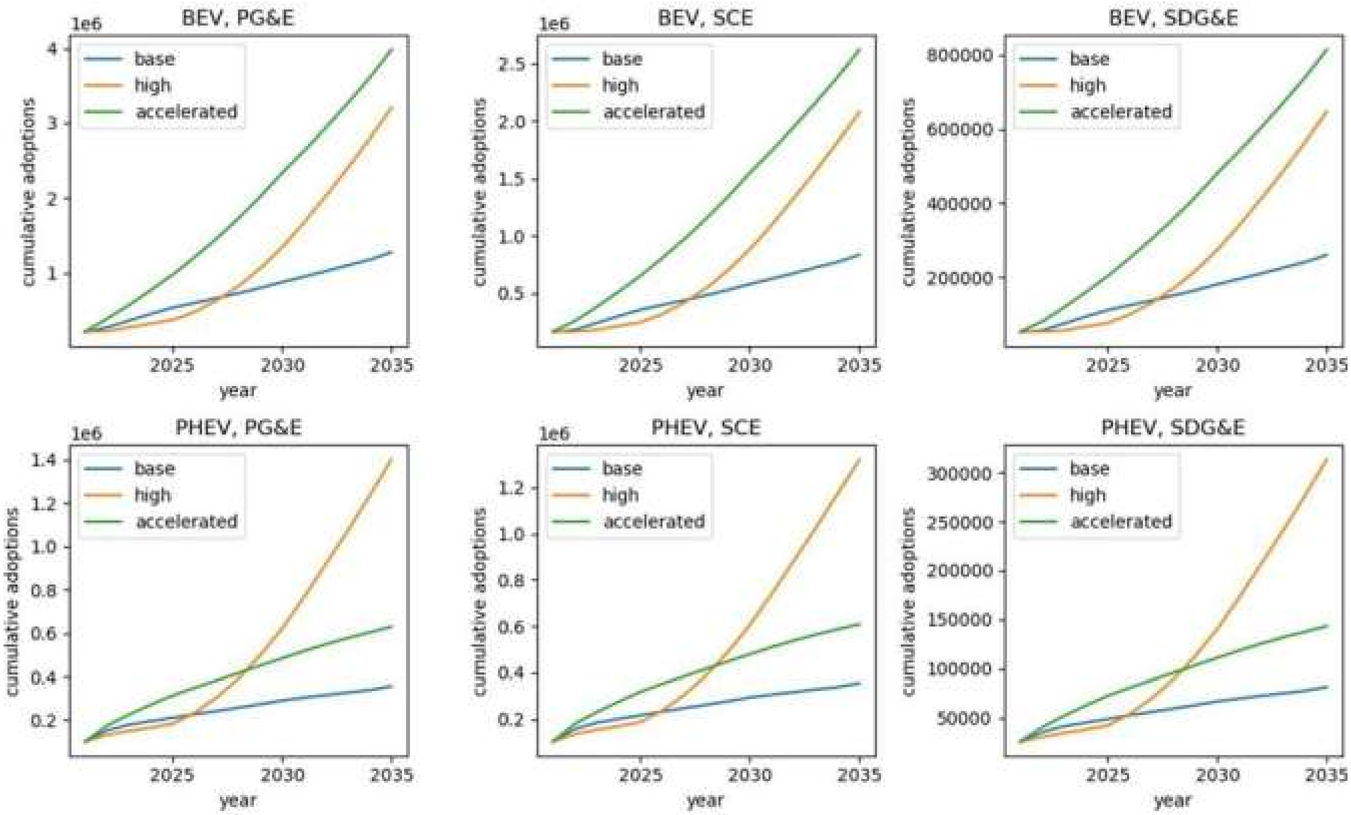
- For each year of each forecast or scenario, isolated the LDV adoptions and then separated these ZEV adoptions into personal LDVs from the fleet LDVs. Set targets using only personal LD ZEV counts.
- Harmonized the associated vehicle counts by duty, powertrain, and vehicle class to the common Kevala vehicle class system (see Table A9-2).
- Allocated the state- and forecast zone-level associated vehicle counts to the IOU service area level.

As Figure A9-3 illustrates, there were important differences between the personal EV adoption rates across the three IOUs and vehicle powertrains for the Base Case, High Transportation Electrification, and Accelerated High Transportation Electrification scenarios.

- For all three IOUs and across powertrains, the Base Case scenario ZEV adoption forecast (CEC 2021 IEPR forecast mid case) had the lowest level of overall personal EV adoptions.
- For the PHEV powertrain type, the High Transportation Electrification scenario (which used an early version of CARB's ACC I vehicle populations to 2025 and ACC II vehicle populations after 2026) had the highest adoption level.
- For the BEV powertrain type, the Accelerated High Transportation Electrification scenario (CEC 2021 IEPR Bookend Forecast Case) had the highest level of adoption.

The differing rates of personal EV adoption by powertrain types, which vary significantly in their energy requirements, and across the various forecasts and scenarios created differing energy and demand requirements that influence the grid impacts associated with the vehicles.

Figure A9-3: Personal EV targets by scenario, utility, powertrain, and year. Y-axis is the number of vehicles. *(Sources: CARB, CEC, Kevala)*



While the personal EV target did contain a small number of MDVs (such as motor homes, RVs, or MD trucks), these counts were sufficiently small and the uncertainty associated with them was sufficiently small that Kevala excluded them from the Part 1 analysis.

A9.2.2. Fleet EV Targets

Fleet EVs are vehicles registered—or expected to be registered—by an entity or operator that will not be using the vehicle for personal use. While these EV targets are described as fleet targets, Kevala designed them to represent the total population of non-personally owned or registered vehicles; they were not organized or grouped in a manner that enables adoption forecasting for an individual *fleet operator's* specific fleet vehicle. As such, identifying the fleet EV targets does not constitute the development of individual, fleet entity-level EV targets.

For the fleet EV targets, Kevala followed steps similar to those it executed to develop the personal EV targets to develop scenario-specific fleet EV targets (i.e., vehicle counts by duty, powertrain, and vehicle classes) from the three CARB and CEC ZEV adoption forecasts:

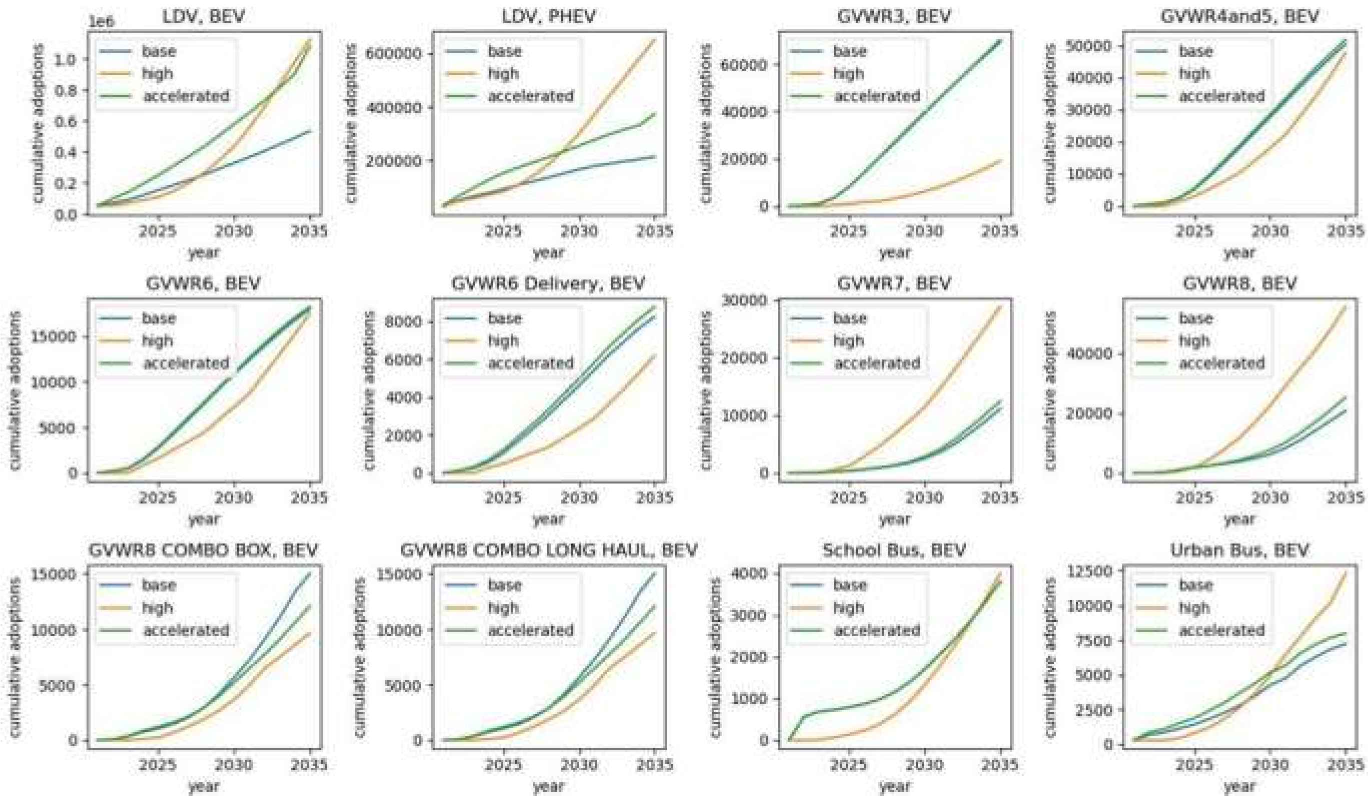
- For each year of each forecast, isolated the LDV adoptions and then separated these ZEV adoptions into personal LDVs from the fleet LDVs. Set targets using only fleet LD ZEV counts.
- Identified all MD and HD ZEV counts and added these vehicles to the fleet target.
- Harmonized the CARB and CEC forecasted vehicle counts by duty, powertrain, and vehicle classes to the common Kevala vehicle class system (see Table A9-2).
- Allocated the state- and forecast zone-level CARB and CEC forecasted vehicle counts to the Census tract level using Experian VIO data for each year of each forecast.

After completing these steps, Kevala had the flexibility to aggregate each adoption forecast's annual Census tract-level fleet EV target counts across a variety of geographic levels, including counties and the IOUs' service areas.

The series of charts contained in Figure A9-4 present the cumulative fleet EV adoption counts, broken out by vehicle class, powertrain, and year. Some noteworthy trends emerge across the three scenarios from the detailed comparison of these vehicle class adoption rates.

- GVWR3 BEV counts for the High Transportation Electrification scenario, the inputs for which are sourced from CARB's 2020 SSS MDV/HDV ZEV adoption forecast, were low compared to the adoption rates of this vehicle class compared to the other two scenarios. This difference is because for the harmonized vehicle class mapping Kevala developed to align the disparate vehicle classes contained in the CARB and CEC forecasts, the GVWR3 vehicle class only maps to CARB's LHD2 vehicle class, and CARB's 2020 SSS MDV/HDV adoption forecast contains relatively few of these vehicles.
- For the GVWR8 Combo Box and GVWR8 Combo Long Haul vehicle classes, the Base Case scenario had greater vehicle counts compared to the High Transportation Electrification and Accelerated High Transportation Electrification scenarios. This difference is a reflection of the underlying vehicle class breakdowns contained in the CEC ZEV adoption forecasts used to set these scenarios. Similarly, the High Transportation Electrification scenario's relatively large number of GVWR7 and GVWR8 counts compared to the Base Case and Accelerated High Transportation Electrification scenarios are also a reflection of the underlying vehicle class breakdown contained in each respective scenario's ZEV adoption forecast targets.

Figure A9-4: Fleet EV targets by scenario, statewide, vehicle class powertrain, and year. Y-axis is the number of vehicles. *(Sources: CARB, CEC, Kevala)*



Unlike the personal EV targets, which excluded MDV (and HDV) vehicles, the fleet EV targets contained all MDV and HDV vehicles the state agency forecasts identified as non-personally owned vehicles.

A9.3. EV Sizing

The EV sizing stage involved determining the vehicle *type* and the *quantity* of EVs that could potentially be adopted at a given EV-eligible premise in a given year.

A9.3.1. Vehicle Type – Personal and Fleet

For personal and fleet EVs, Kevala specified each vehicle type by duty, powertrain, and vehicle class. The vehicle type combinations for LDV, MDV, and HDV are presented in Table A9-3 and align with the harmonized CARB and CEC vehicle classes contained in Table A9-2. The MDV and HDV duty, powertrain, and classes apply exclusively to fleet EVs whereas the LDV duty, powertrain, and classes may apply to fleet and personal EVs.

Table A9-3: Summary of vehicle type duty, powertrain, and vehicle class used for sizing personal and fleet EVs *(Sources: CARB, CEC, Kevala)*

Duty	Powertrain	Vehicle Class
LDV	BEV	Small Car
		Large Car
		Sport Car
		Small SUV
		Large SUV
		Van
		Pickup
	PHEV	Small Car
		Large Car
		Sport Car
		Small SUV
		Large SUV
		Van
		Pickup
MDV	BEV	GVWR3
		GVWR 4 and 5
		GVWR6
		GVWR6 Delivery
HDV	BEV	GVWR7
		GVWR8
		GVWR8 Combo Long Haul
		GVWR8 Combo Box
		Urban Bus
		School Bus

Each premise was eligible to adopt only one vehicle type at a premise. If more than one vehicle were adopted at a premise, say for a fleet, they would all be of the same vehicle type. This is a simplifying assumption Kevala made in the absence of sufficient empirical evidence regarding the exact composition of premise- or address-level vehicle registration data. Kevala proposes exploring additional data sources to support this analysis in the Part 2 Study.

After determining the possible vehicle type combinations by duty, powertrain, and vehicle class, Kevala assigned each of the vehicle types a forecast of the vehicle battery capacity (in kWh) and range (in miles). Kevala sourced LDV battery capacity and range forecast data from the CEC's Assembly Bill (AB) 2127 Report. For MDV and HDV battery capacity and range information, Kevala sourced current model year data from the U.S. Department of Energy's (DOE's) Alternative Fuels Data Center.[187] Because the MDV and HDV data did not contain a forecast of the necessary vehicle attributes, Kevala applied the rate of change observed in the CEC's AB 2127 Report for the LDV BEV Pickup vehicle class forecast data to develop the necessary forecast for the MDV and HDV attributes.

Taken together, these two values provided a vehicle type's fuel economy in kWh per mile, which was the amount of energy (kWh) a given vehicle type requires to travel the number of miles it is expected to cover in a given year. Each vehicle type combination (i.e., duty ***x*** powertrain ***x*** vehicle class) had its own fuel economy (kWh/mile) forecast, and each vehicle class had its own annual VMT.

Kevala sourced LDV VMT values from the U.S. Bureau of Transportation Statistics' Local Area Transportation Characteristics for Households (LATCH) data, which provides personal vehicle mileage by county.[188] Kevala sourced MDV and HDV VMT values from the U.S. Bureau of Transportation Statistics' Vehicles in Use Survey (VIUS), as summarized by M.J. Bradley & Associates.[189]

A9.3.2. Vehicle Quantity – Personal and Fleet

Similar to vehicle type, Kevala assigned a vehicle count to each premise eligible to adopt an EV. In the sizing step, the vehicle quantity being assigned to a given premise is determining the number of vehicles that would be adopted in the adoption stage *should the given premise be selected by the adoption propensity algorithm*. Thus, although each EV-eligible premise was assigned a vehicle quantity for each year, not all premises were selected for a given scenario in a given year. Details on the adoption stage are provided in the EV Adoption section.

For premises eligible to adopt personal EVs, which include single-unit dwellings (SUDs) and multi-unit dwellings (MUDs), the vehicle count was randomly assigned to each premise based on

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[187] U.S. Department of Energy, Alternative Fuels Data Center, Alternative Fuel and Advanced Vehicle Search, https://afdc.energy.gov/vehicles/search/results.csv?current=true.

[188] Bureau of Transportation Statistics, "Local Area Transportation Characteristics for Households (LATCH Survey), February 2021, https://www.bts.gov/latch.

[189] M.J. Bradley & Associates, *Medium- & Heavy-Duty Vehicles: Market structure, Environmental Impact, and EV Readiness,* July 2021, https://www.edf.org/sites/default/files/documents/EDFMHDVEVFeasibilityReport22jul21.pdf.

probabilities Kevala assumed for SUDs and MUDs. The probabilities of vehicle quantity at each premise varied based on the year and whether the premise was a SUD or MUD. For SUD premises, the quantity of vehicles that could be adopted was either one or two, with the probability of adopting two vehicles increasing slightly in each year. For MUD premises, Kevala assumed just one vehicle could be adopted. Kevala made these simplified assumptions because there is a lack of data to determine exactly the number of vehicles that are appropriate to assume for SUD and MUD premises, and these assumptions were assumed to be conservative. Importantly, these assumptions did not limit the total number of vehicles that could be adopted; they simply restricted the number of vehicles that could be adopted at a single premise.

For fleet EV-eligible premises, Kevala used the following procedure to assign a count of fleet EVs:

1. Identify the total number of adoptions expected to occur for the combination of scenario, year, Census tract, and vehicle type that applied to the premise.
2. Based on the year, assume no more than 50% of the total adoptions in a Census tract could occur at any one premise.
3. Calculate the maximum number of adoptions that could occur at a premise by multiplying the results of steps 1 and 2.
4. Gather the percentile ranking of the premise within its Census tract in terms of area. Premise area was estimated by dividing each parcel's area by the number of premises on the parcel. Normalized the rank to the range [0,1], so the lowest-ranked premise had a score of 0 and the top-ranked premise had a score of 1.
5. Multiply that score by the maximum number of adoptions that could occur at a premise to obtain the number of EVs adopted at the premise.

To give an example of the entire process: if a Census tract will adopt 300 fleet BEV LDVs in 2025, and the maximum percentage of adoptions that could be assigned to a premise in this tract is 50%, then the maximum number of fleet BEV LDVs in the premise is 300 * 0.50 = 150 for that year. If a premise is ranked in the 33rd percentile for the area, it will be sized with 0.33 * 150 = 50 vehicles.

Kevala also set an upper limit on the number of fleet vehicles that could be adopted at one premise. This value, 180, was based on the 99.9th percentile of the Federal Motor Carrier Safety Administration's Motor Carrier Census data.[190]

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[190] Federal Motor Carrier Safety Administration, Motor Carrier Census data, https://ai.fmcsa.dot.gov/SMS/Tools/Downloads.aspx.

A9.4. EV Adoption

The EV adoption model incorporated a variety of inputs to calculate a premise-level score that was used to rank a premise's likelihood to adopt either personal EVs or fleet EVs based on the eligibility criteria of the premise itself.

After each EV-eligible premise within a geographic area was scored, the adoption model then selected the number of premises based on their score (starting from the highest ranking premises, then moving down the ranking) until the number of vehicles—by duty, powertrain, and vehicle class—achieved the personal EV and fleet EV targets for the given scenario and year. (The number and type of personal EVs and fleet EVs assigned to a given premise were determined in the EV sizing stage, described previously.)

Importantly, while the overall number of ZEVs is still very low across the three IOUs service areas, the number of personal EVs was sufficient to enable more sophisticated premise-level adoption modeling compared to the modeling that is possible with fleet EVs. This is because the number of fleet (i.e., non-personally owned) EV adoptions, particularly of MDVs and HDVs is, at this point in time, too low to enable the type of more complex adoption modeling that is possible with personal EVs.

A9.4.1. Personal EV Adoption

The personal EV adoption model provided a premise-level score for the adoption of vehicles categorized for personal use on a subset of residential premises.

The underlying personal EV adoption model framework was based on Bayesian multilevel logistic regression (MLR), which provides an adoption propensity score for a given premise in a year. Kevala used the urban group feature (i.e., urban, suburban, and rural) provided in the U.S. Bureau of Transportation Statistic's dataset as the grouping level of the multilevel model with the assumption that different urban groups have different drivers of EV adoption.

In addition to the urban group features, the personal EV adoption MLR model considered the following categories of features to score a premise's likelihood of adopting the vehicle type and the quantities determined in the sizing stage.

1. **Parcel-level features** (Source: Regrid third-party parcel data)
    a. Average premise area and footprint
2. **Utility customer data** (Source: utility's customer information)
    a. Residential customer sector
    b. SUD or MUD residences (determined using utility data and parcel data)

3. **Demographic features** (Source: U.S. Census data)
    a. Home ownership
    b. Education
    c. Race
    d. Age
    e. Income
    f. Population density
4. **Hourly energy usage features** (Source: utility's advanced metering infrastructure (AMI) data)
    a. Max daytime hourly netload aggregated by premise (net kWh)
5. **Vehicle population features** (Source: Experian VIO data)
    a. EV density (number of ZEV vehicles per population in a Census block group)

To score premises for personal EV adoption, Kevala conducted a rigorous, multiple-step process to evaluate and identify the categories and features contained in the above list, along with the decision to use the urban group feature as the level in the MLR. This process involved the following five steps:

1. **Data exploration:** Kevala conducted a detailed data exploration exercise involving the cleaning and merging of multiple utility and third-party datasets to identify a group of premises with sufficiently complete features and EV adoption data to support the EV adoption model development. Ultimately, because only Pacific Gas and Electric (PG&E) had enough premises with utility-provided EV identification data, Kevala selected its data for the model development process. Kevala then applied this model to the other IOUs' service areas because there was not sufficient data to develop IOU-specific models based on Southern California Edison (SCE) and San Diego Gas & Electric's (SDG&E's) current data.

    PG&E's service area contained 4.3 million usable residential premises in its service area, where 116,000 premises were labeled by PG&E as being EV adopters. The number of labeled EV adopters is fewer than the 331,000 LD EVs that PG&E reported residing in its service area in its 2021 Annual EV Report.[191] The discrepancy between the number of EVs that can be positively identified at a premise compared to the total number of registered vehicles in a service area occurs because not all EV owners enroll on utility EV rates or EV programs. As such, the number of premises where EV adoption could be positively

[191] "Compliance Filing of Southern California Edison Company (U 338-E), San Diego Gas & Electric Company (U 902 E), and Pacific Gas and Electric Company (U 93 E) Pursuant to Ordering Paragraph 2 of Decision 16-06-011," R.18-12-006, Excel Files to Joint IOU's Compliance Filing on OP 2 to D.16-06-011, March 31, 2022.

confirmed was low: only 2.5% of 4.3 million premises. This type of highly unbalanced dataset, with relatively thin data on which Kevala could conduct its analysis, created challenges in identifying features that were consistently highly predictive of EV adoption. Despite this challenge, Kevala was able to develop a strong, defensible personal EV adoption model.

2. **Feature selection:** The 4.3 million PG&E premises that passed the screening process had 164 potential features, from which Kevala selected 20 for initial inclusion for rigorous feature selection. The feature selection process included two steps. First, Kevala conducted an initial correlation analysis to measure the strength of the association between two variables, which supports the identification of features with stronger statistical correlations with the target variable (EV adopted) and helps identify features that should be removed from the analysis because they are cross-correlated and duplicative. Second, Kevala applied the two features' selection methods to identify the optimal number of model features. Table A9-4 presents the final parameters selected for the MLR.

Table A9-4: Personal EV adoption model features *(Sources listed in the second column)*

Order	Source	Feature
1	AMI	Log of max hourly daytime load
2	Vehicle Registration	Log of density of existing EVs in census block
3	Parcel	Normalized number of premises on parcel
4	U.S. Census Bureau-American Community Survey (ACS)	Log of census block group population density
5	Parcel	Multi-Unit Dwelling Label
6	Parcel	Normalized estimated premise building footprint
7	Census-ACS	Median household income
8	Census-ACS	Percent of white householders
9	Census-ACS	Median age
10	Census-ACS	Percent education level of college or more
11	Census-ACS	Percent of households owner occupied
12	Parcel	Rank of estimated premise area in census tract

Order	Source	Feature
13	Census-ACS	Urban group (rural, suburban, urban)
14	Parcel	Normalized estimated premise area

3. **Model structure:** Determining the model structure, namely the levels in the MLR, was an important step that occurred roughly in parallel to the feature selection step. After conducting a variety of different tests, Kevala determined that adding urban group (urban, suburban, rural) levels to the MLR improved modeling performance compared to models without the urban group levels. Based on this observation, Kevala decided to use the urban group levels in its final model.
4. **Train model with in-sample data:** After determining the model's structure and features, Kevala iteratively trained the personal EV adoption model on a randomly selected subset of the data to refine the feature coefficients and determine their correlation with the target variable, EV adoption.
5. **Evaluate model's performance with out-of-sample data:** Once a version of the model was trained, Kevala tested its predictive performance against a subset of the data that was excluded from the model training step. Because the model had not been exposed to this out-of-sample data, this data could serve as a test of how well the model could predict the actual adoption of personal EVs. Steps 4 and 5 were conducted iteratively until the very best model coefficients were determined and the highest level of correct recall could be achieved.

A9.4.2. Fleet EV Adoption

Kevala assigned a score between 0 and 1 to each fleet EV-eligible premise; this score represents its propensity to adopt fleet EVs. After all premises were scored, Kevala ranked the premises and applied a threshold so that only the highest-scoring premises adopted ZEVs.

For each non-agricultural premise, Kevala used the premise's estimated area (i.e., the square footage of all building and non-building property associated with the premise) and the ratio of the premise's estimated area to the premise's estimated building footprint to rank the premise. This calculation essentially ranked a commercial, industrial, or other non-agricultural, non-residential premise by the amount of non-building area available at the premise. Because far too few adopted fleet EVs are currently registered, Kevala assumed this value to be the best proxy for a premise's likelihood of adopting a fleet EV. This is an approach that Kevala can revisit in the Part 2 Study.

Kevala used a similar method for agricultural premises, again using the premise's estimated area as the first feature, but the second feature was only the premise's estimated building footprint—not the ratio of the premise's area to its building footprint. Kevala made this choice to reduce higher scores on agricultural premises with large amounts of cropland (non-building area that is not available for fleets) and increase scores on agricultural premises with higher building footprints more likely to have non-EV fleet vehicles domiciled.

A9.5. EVSE Adoption Targets

Kevala determined the EVSE adoption targets using the ZEV adoption targets contained in each scenarios' ZEV adoption forecasts and a ratio of how many EVSE charging ports are assumed to be required to support a given population of ZEVs. The concept of an EVSE-to-EV ratio is well-established; this approach is used for the U.S. DOE's Alternative Fuels Data Center's Electric Vehicle Infrastructure Projection Tool (EVI-Pro) Lite tool, which also underpins the EVSE forecasting model for the CEC's AB 2127 Report.[192]

EVSE-to-EV ratios are specific to the type EVSE charging port and its charging capacity, as well as the duty and powertrain of the ZEV. For the Part 1 Study, Kevala drew upon the EVSE use cases and demand levels contained in the AB 2127 Report, along with its own assumptions when they were not contained in the AB 2127 Report. Table A9-5 summarizes the EVSE use cases and charging level included in this Part 1 Study. Additional details regarding the combination of EVSE use cases and charging levels used for this study are contained in the EVSE Sizing section.

Table A9-5: Summary of EVSE use cases and charging level by ZEV ownership type and duty *(Sources: CEC, Kevala)*

Ownership	Duty	Use Case	Primary / Secondary Use Case	Demand Level
Personal EV	LDV	SUD (Time-of-use (TOU), non-TOU)	Primary	Level 1 (L1), Level 2 (L2)
		MUD	Primary	L2
		Public	Secondary	L2, DCFC
		Workplace	Secondary	L2
		Corridor	Secondary	DCFC

[192] U.S. Department of Energy, Alternative Fuels Data Center, EVI-Pro Lite tool, https://afdc.energy.gov/evi-pro-lite/load-profile/assumptions.

Ownership	Duty	Use Case	Primary / Secondary Use Case	Demand Level
Fleet EV	LDV	Fleet	Primary	L2
	MDV / HDV	Fleet	Primary	DCFC
		Public	Secondary	DCFC
		Corridor	Secondary	DCFC

Kevala categorized EVSE ports into two groups and generated EVSE adoption targets for these groups using slightly different approaches. The EVSE categories are as follows:

- **Primary charging use cases:** EVSE use case where a ZEV sources its primary energy from, usually during nighttime charging. These can be conceptualized as home charging.
    - SUD (enrolled on a TOU rate)
    - SUD (not enrolled on a TOU rate)
    - MUD
    - Fleet depot
- **Secondary charging use cases:** EVSE use cases that provide supplemental charging to meet the ZEV's remaining energy needs. These can be thought of as daytime chargers that are used by personal EVs while at work, shopping, or on long distance trips and by fleet EVs when they are conducting long-haul routes or otherwise requiring charging away from their home base.
    - Public (LDV and MDV/HDV)
    - Workplace
    - Corridor (LDV and MDV/HDV)

For the SUD primary charging use cases, Kevala assumed that all adopted BEV and PHEV personal EVs received either an L1 or L2 charger, with 39% adopting an L1 and 61% adopting an L2. For MUDs, one L2 charger was allocated for every five personal EVs that were adopted.

For the fleet depot primary charging use case, Kevala used the EVSE-to-EV ratio from the AB 2127 Report, which is roughly 0.5, or one charger for every two vehicles. Kevala applied this ratio for LDV and MDV/HDV fleet EVs, where LDVs were assigned L2 chargers and MDV/HDVs were assigned DCFC chargers.

To find the number of EVSE counts for the secondary charging use cases of public, workplace, and corridor for a given scenario, year, county, and type of charger, Kevala found an appropriate ratio of EVSE ports to EVs and multiplied it by the number of relevant EVs that were adopted. Kevala calculated the EVSE-to-EV ratios as described below.

Corridor LDV DCFC Ratio

For the denominator of the EVSE-to-EV ratio, Kevala used the total number of BEVs from the AB 2127 Report's 2020 CARB Mobile Source Strategy (MSS) values for 2020, 2025, 2030, and 2035. For the numerator, the EVSE port count, Kevala took the predictions from AB 2127 Report, Tables E-1 through E-4; for each charger level 150 kW and higher, Kevala took the median of the upper and lower bounds, then summed across charger levels for the total EVSE count. Kevala used linear interpolation to obtain values for intermediate years.

Corridor and Public MD/HDV DCFC Ratio

Kevala used a similar approach for these two use cases. The ratio of 350 kW chargers to MDV/HDVs in 2030 in the AB 2127 Report (roughly 0.08) was used for all scenarios and years. Kevala assumed these EVSE ports would be split 60/40 between the corridor and public use cases, so the ratio was multiplied by 0.6 or 0.4 depending on the use case.

Public LDV L2 and DCFC, and Workplace L2 Ratios

Kevala derived these EVSE port to EV count ratios from the annual forecasted statewide EVSE port and EV counts from the AB 2127 2020 CARB Mobile Source Strategy results. These statewide ratios were applied evenly to each county in the study area.

EV Counts

Kevala counted the relevant EVs (in a given scenario, year, county) for each EVSE type:

- Corridor LDV DCFC: LDV BEV
- Corridor MDV/HDV DCFC: MDHDV BEV
- Public MDV/HDV DCFC: MDHDV BEV
- Public LDV L2: LDV BEV plus PHEV
- Public LDV DCFC: LDV BEV
- Workplace L2: LDV BEV plus PHEV

Kevala then multiplied these vehicle counts by the matching EVSE-to-EV ratio to obtain annual EVSE port targets by charging use case, county, and scenario. As described in the EVSE Adoption section, these county-level EVSE targets were ready for allocation to individual premises.

A9.6. EVSE Sizing

EVSE sizing models determine the type and quantity of chargers to be adopted at a given premise, for a given year and a given scenario. In the EVSE sizing step, charger type and quantity are highly interrelated. As such, determining the type and quantity of EVSE that a premise is sized for effectively occurs simultaneously. This is particularly true for the primary charging use cases, where type and quantity are determined at the same time and are a direct function of whether the premise adopts an EV in the EV adoption stage.

The EVSE sizing stage first determined an eligible premise's charger type, such as SUD, MUD, and fleet or public, workplace, and corridor. After this, Kevala used the premise's charger type as an input to the algorithm that determined the quantity of chargers the given premise could adopt in the EVSE adoption stage.

Table A9-5 summarizes the EVSE use cases, primary and secondary use case categorization, and charging level included in the Part 1 Study.

Primary Charging Use Cases

Kevala determined the premise-level EVSE type and quantity for the primary charging use cases, including SUD, MUD, and fleet, using the following process:

- **SUD EVSE type:** Premises marked as having the "Residential" customer sector based on the utility-provided rate code and the utility-assigned North American Industry Classification System (NAICS) code and determined by Kevala likely to be a SUD were eligible for any LDV and primary charging use case "Single-Unit Dwelling: TOU Rate" and "Single-Unit Dwelling: non-TOU" rate.
    - *SUD EVSE count:* Every personal EV adopted at a SUD premise, regardless of TOU status, received either an L1 or L2 EVSE charger. Each personal EV was assumed to receive its own charger.
- **MUD EVSE type:** Premises marked as having the "Residential" customer sector based on the utility-provided rate type and utility-assigned NAICS code and determined by Kevala likely to be a single unit at a MUD, or a premise with one master meter representing a whole MUD were eligible for any LDV and primary charging use case "Multi-Unit Dwelling."
    - *MUD EVSE count:* For MUDs, the EVSE-to-EV ratio was 0.2, meaning 1 L2 MUD charger was provided for every five personal EVs adopted.
- **Fleet EVSE types:** Premises marked with "Commercial," "Industrial," "Agricultural," "Public," or "Non-Residential" customer sector based on their utility-provided rate type and utility-assigned NAICS code were eligible for any LDV or MDV/HDV with the primary charging use case "Fleet Depot."

- *Fleet EVSE count:* For fleet depot charging use cases, Kevala used a fixed EVSE-to-EV ratio from the HEVI-LOAD model in the AB 2127 Report, which was roughly one DCFC charger to every two MDV/HDV fleet EVs adopted at a given premise. LDV fleet EVs were allocated EVSE at the same ratio, but they were allocated L2 chargers, not DCFC ones.

Kevala determined the execution of EVSE sizing for a given premise by whether the premise was selected to adopt one or more EVs in the EV adoption stage described previously. If a premise's adoption score met a given scenario and year's threshold for EV adoption, then that premise would automatically be sized in the EVSE sizing stage with the type and number of chargers its EVs require.

Secondary Charging Use Cases

Kevala determined the premise-level EVSE type for the secondary charging use cases, including public, workplace, and corridor, through the following process described. Unlike the primary charging use cases where the first step was a function of the premise type (i.e., residential, commercial, industrial, etc.), the secondary charging use case process began with calculating the quantity of chargers by EVSE type using the EVSE-to-EV ratios described in the EVSE Adoption Targets section.

- **Public and workplace EVSE types:** There were three combinations of public EVSE chargers based on the vehicle duty that they support and their capacity level: Public LDV L2, Public LDV DCFC, and Public MDV/HDV DCFC. There was only one type of workplace charger: Workplace LDV L2. The probability of a given public or workplace EVSE type being assigned to an eligible premise was a function of the given EVSE type's market share. For example, if the EVSE adoption target for public and workplace EVSE types for a given scenario and year was 10,000, if 2,500 of those chargers were Public LDV L2 charger, then the likelihood that an eligible premise would be assigned a Public LDV L2 charger was 25%.
    - *Public and workplace EVSE counts:* Kevala determined the total quantity of public and workplace EVSE types for a given scenario and year in the EVSE adoption target step using the appropriate EVSE-to-EV ratios. The number of public or workplace EVSE chargers adopted at a given eligible premise was based on an analysis of the U.S. Department of Energy's Alternative Fuels Data Center Alternative Fueling Stations Locations dataset, which contains the number of ports, by type, a given address has installed historically.[193]

[193] Department of Energy, Alternative Fuels Data Center, "Alternative Fueling Stations Locations," https://afdc.energy.gov/stations/.

- **Corridor EVSE types:** There were two combinations of corridor EVSE chargers based on the vehicle duty they support: Corridor LDV DCFC and Corridor MDV/HDV DCFC. The probability of a corridor-eligible premise being assigned either an LDV or MDV/HDV charger was a function of that charger type's market share. For example, if the total corridor EVSE target for a given scenario and year was 1,000, if 750 of those chargers were MDV/HDV chargers, then the probability of a given corridor-eligible premise adopting an MDV/HDV charger was 75%.
    - *Corridor EVSE counts:* Kevala determined the number of corridor-EVSE types for a given scenario and year in the EVSE adoption target step using the appropriate EVSE-to-EV ratios. As with the public and workplace EVSE types, the number of corridor-EVSE chargers adopted at a given eligible premise was based on an analysis of the U.S. Department of Energy's Alternative Fuels Data Center Alternative Fueling Stations Locations dataset. Because this dataset contains limited information on corridor chargers, Kevala used the address-level public DCFC port counts as a proxy.

Once the EVSE sizing state determined the EVSE type, it then assigned each charger its kW power rating based on its specific EVSE type and capacity level, as well as the year of adoption. Kevala used the following values, which are sourced from the AB 2127 Report. These values were derated from their nameplate capacity levels to reflect real-world operating performance.

- **SUD L1:** 1.9 kW (assumed to be fixed across all forecast years and vehicle classes)
- **SUD L2:**
    - BEV: 7.7 kW-12.0 kW (depending on forecast year and vehicle class)
    - PHEV: 3.9 kW-6.2 kW (depending on forecast year and vehicle class)
- **MUD L2:**
    - BEV: 7.7 kW-12.0 kW (depending on forecast year and vehicle class)
    - PHEV: 3.9 kW-6.2 kW (depending on forecast year and vehicle class)
- **Fleet LDV L2:**
    - BEV: 7.7 kW-12.0 kW (depending on forecast year and vehicle class)
    - PHEV: 3.9 kW-6.2 kW (depending on forecast year and vehicle class)
- **Fleet MDV/HDV DCFC:** 45 kW (assumed to be fixed across all forecast years and vehicle classes)
- **Public LDV L2:** 6.6 kW (assumed to be fixed across all forecast years and vehicle classes)
- **Public LDV DCFC:** Varies by year according to the charging power and market share of BEV LDV vehicle types. For each year, Kevala took a weighted average of the charging power values in Table B-7 of the AB 2127 Report, with the weights given by the market share of each vehicle type.
    - 116 kW-277 kW (depending on forecast year)

- **Public MDV/HDV DCFC:** 345 kW (assumed to be fixed across all forecast years and vehicle classes)
- **Workplace L2:** 6.6 kW (assumed to be fixed across all forecast years and vehicle classes)
- **Corridor LDV:** Varies by year according to AB 2127 Figure B-3:
  - 2020: 145 kW
  - 2025: 245 kW
  - 2030: 345 kW
  - 2035: 445 kW
- **Corridor MDV/HDV DCFC:** 345 kW (assumed to be fixed across all forecast years and vehicle classes)

A9.7. EVSE Adoption

Kevala determined a premise's EVSE adoption propensity by whether the EVSE was a primary charging use case or a secondary charging use case.

Primary Charging Use Cases

For primary charging use cases (SUD, MUD, and fleet), a premise's EVSE adoption propensity was entirely dependent on whether the premise adopted one or more personal EVs or fleet EVs in the EV adoption stage. For example, if a residential SUD premise was sized with two BEVs in the EV sizing stage and the premise's score ranked above the necessary threshold in the EV adoption stage, then the premise would automatically receive two SUD chargers. The probability associated with the type of SUD chargers it adopts (i.e., L1 or L2) were determined for the premise in the EVSE adoption target stage.

Secondary Charging Use Cases

Because secondary charger use cases were adopted at premises that do not domicile personal EVs or fleet EVs, their adoption propensities were based on premise-level features, not whether they have adopted an EV.

Workplace and public adoption propensity scores were the average of two features:

- The premise's percentile rank, based on area, in its county expressed as a value between 0 and 1
- The fraction of commercial premises in the premise's Census tract.

The two features were given weights of 0.7 and 0.3, respectively, and Kevala added a degree of randomness to incorporate real-world uncertainty.

For corridor charger adoption propensity, Kevala assigned each premise a score based on the volume of traffic nearby. Kevala used the Caltrans traffic and truck volumes Annual Average Daily Traffic (AADT) datasets, which contain data for traffic markers throughout California. For 50 kW chargers, Kevala used the total traffic volume; for 350 kW chargers, the volume of trucks was used. Traffic volume was expressed as a rank between 0 and 1—that is, the traffic marker with the highest total traffic volume had a total traffic volume score of 1, and the marker with the median truck volume had a truck volume score of 0.5. To obtain the adoption score for a premise, Kevala found the five closest traffic markers and randomly chose one based on a range of different probabilities. Kevala added a degree of randomness to incorporate real-world uncertainty.

A9.8. EVSE Behavior

Across all EVSE charger types, Kevala generated the hourly EVSE behavior load curves on an hourly basis using a model that simulates hourly charging usage based on the input variables contained in Table A9-6.

Table A9-6: EV and EVSE input variables for hourly EVSE load curves *(Sources: U.S. Census Bureau, U.S. Bureau of Transportation Statistics, NREL, Kevala)*

Input Variable	Description
EVSE Vehicle Inputs	List of vehicle attributes from EV sizing stage that contain the following attributes: • Vehicle class: Class of vehicle (e.g., Large SUV, GVWR3) • Vehicle quantity: Number of vehicles at the location • Capacity: Maximum range/capacity of EV • Efficiency: EV efficiency (miles/kWh)
Mean Departure Time / Mean Return Time	The average hour a vehicle departs/arrives at the charging location/ depot on an operational day
Depart Time Standard Deviation / Return Time Standard Deviation	Departure/return time standard deviation
Mean Route Mileage / VMT Standard Deviation	The average/standard deviation miles an EV travels during an operational day between departure and return time
Active Days of Week	Day of operations for a fleet EV
Holidays	Whether the fleet is operational on Federal U.S. holidays

Input Variable	Description
Charge Threshold	The state of charge at which EV starts seeking a charge
Simulation Start / Simulation End	Start and end dates of the charging simulation
Charger Type	The type of charger (L1, L2, DCFC) that makes up the charger or group of chargers supporting the EVs at a given premise
Charger Quantity	The number of chargers sited at a given premise
Power	Charger power (kW) from EVSE sizing stage
EVSE Use Case	EVSE use case for which charging behavior simulation is run; it can be SUD, MUD, fleet, public, corridor, etc.

Given a range of input variables provided for a given simulation, an EVSE behavior curve was generated such that the vehicles meet their charging requirements in the shortest time available given the charging quantity/power. Kevala ran these simulations millions of times across each year of each forecast and then aggregated them at scale for all of the appropriate vehicle and charger combinations.

Primary versus Secondary Charging Use Cases

There are important differences between the primary charging use cases (SUD, MUD, and fleet use cases) and the secondary charging use cases (public, workplace, and corridor use cases) for EVSE load modeling.

For primary charging use cases, Kevala sized a premise for some vehicle(s) and then sized for EVSE to accommodate them. These vehicles were assumed to be consistently associated with their respective primary chargers. Therefore, it was possible to reasonably determine when these vehicles use their primary charger (e.g., in the evenings) and how much charge they need (daily VMT). For example, if a town had seven premises, and each premise had one small car, each premise would also have its own primary L1 or L2 charger (seven primary chargers in total).

For secondary charging use cases, Kevala sized premises first for EVSE. Because these are secondary charge points, the number of assumed charging events (rather than the exact, unique vehicle expected to charge at the EVSE) was used to simulate the charger's behavior curve. Kevala used changing behavior analysis described in the AB 2127 Report,[194] and the latest version of the U.S. DOE's EVI-Pro 2 tool to develop its assumptions.[195] The EVSE vehicle inputs (see Table A9-6) drawn from geospatially proximate vehicles that have been adopted served as inputs to the EVSE behavior curve simulation. Continuing the example from above, the modeling assumption would be that each of these small cars uses a public DCFC charger once per week. Table A9-7 provides the events-per-day assumptions Kevala made for the secondary charging use cases.

Table A9-7: Secondary charging use cases: number of charging events per day, by year, EVSE use case, and EVSE type *(Sources: CEC, Kevala, NREL)*

EVSE Use Case and Type	Year	Events Per Day
Workplace, L2	2025	2
	2030	2
	2035	2
Public LDV, L2	2025	2
	2030	3
	2035	3
Public LDV, DCFC	2025	4
	2030	5
	2035	6
Public MDV / HDV, DCFC	2025	4
	2030	4
	2035	4
Corridor LDV, DCFC	2025	5
	2030	7
	2035	8
Corridor MDV / HDV, DCFC	2025	6
	2030	6
	2035	6

[194] California Energy Commission, *Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*, July 14, 2021, p. B-6, https://efiling.energy.ca.gov/getdocument.aspx?tn=238853.

[195] National Renewable Energy Laboratory, "Electric Vehicle Infrastructure Projection Tool (EVI-Pro): California Energy Commission (CEC) Integrated Energy Policy Report (IEPR) Workshop," August 6, 2020, p. 10, https://www.nrel.gov/docs/fy21osti/77651.pdf.

Appendix 10. PG&E Distribution Planning Assumptions

Pacific Gas and Electric Company (PG&E) provided the capacity planning criteria and typical design parameters that are summarized in Figure A10-1. Kevala used these in determining the infrastructure requirements in this study.

Figure A10-1: Assumed design parameters and capacity planning criteria for PG&E (subject to change)

Pacific Gas & Electric

Standard Power Transformer Sizes
- 230/21 kV : 75 MVA
- 230/12 kV : 45 MVA
- 115/12 kV : 45 MVA
- 70/12 kV : 30 MVA
- 60/12 kV : 30 MVA

Max Loading Criteria
- <= 3 Dist Transformers per Substation
- Nameplate Rating @ 100%

Typical Number Circuits per Transformer
- 75 MVA = 3 Circuits
- 45 MVA = 4 Circuits
- 30 MVA = 3 Circuits

Service Transformer Loading Criteria (Utility did not provide)
- Residential ~ 150%
- Commercial & Industrial ~ 125%

Appendix 11. SCE Distribution Planning Assumptions

Southern California Edison (SCE) provided capacity planning criteria and typical design parameters that are summarized in Figure A11-1. Kevala used these in determining the infrastructure requirements in this study.

Figure A11-1: Design parameters and capacity planning criteria provided by SCE

Southern California Edison

Standard Power Transformer Sizes
115/33 kV : 28 MVA
115/16 kV : 28 MVA
115/12 kV : 28 MVA
66/16 kV : 28 MVA
66/12 kV : 28 MVA

Max Loading Criteria
<= 4 Dist Transformers per Substation

Typical Number Circuits per Transformer
28 MVA = 3 Circuits

Service Transformer Loading Criteria
Residential ~ 150%
Commercial & Industrial ~ 125%

Appendix 12. SDG&E Distribution Planning Assumptions

San Diego Gas & Electric Company (SDG&E) provided the capacity planning criteria and typical design parameters that are summarized in Figure A12-1. Kevala used these in determining the infrastructure requirements in this study.

Figure A12-1: Design parameters and capacity planning criteria provided by SDG&E

San Diego Gas & Electric

Standard Power Transformer Sizes
138/12 kV : 28 MVA
69/12 kV : 28 MVA

Max Loading Criteria
<= 4 Dist Transformers per Substation
Nameplate Rating @ 100%

Typical Number Circuits per Transformer
28 MVA = 4 Circuits

Service Transformer Loading Criteria
Residential ~ 150%
Commercial & Industrial ~ 125%

(End of Attachment 1)