Distribution Grid Electrification Model

Study and Report

Our mission is to advocate for the lowest possible bills for customers of California's regulated utilities consistent with safety, reliability, and the state's climate goals.

August 2023

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- The California Energy Commission's Advanced Electrification Analysis Branch for providing electric vehicle population, efficiency, and travel data.
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Glossary

Acronyms and initialisms

A.	Application
AATE	Additional Achievable Transportation Electrification
AB	Assembly Bill
ACS	American Community Survey
ACC	Avoided Cost Calculator
AEU	Annual Energy Usage
AMI	Advanced Metering Infrastructure
BE	Building Electrification
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
BTM	Behind-the-Meter
CARB	California Air Resources Board
CEC	California Energy Commission
CED	California Energy Demand (Forecast)
CGR	Cumulative Growth Rate
CPUC	California Public Utilities Commission
D.	Decision
DCFC	Direct Current Fast Charger
DER	Distributed Energy Resource
DDOR	Distribution Deferral Opportunity Report
DGEM	Distribution Grid Electrification Model
DIDF	Distribution Investment Deferral Framework
DMV	Department of Motor Vehicles
EE	Energy Efficiency
EIS	Electrification Impacts Study
EPA	Environmental Protection Agency
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FIP	Freight Infrastructure Planning
GHG	Greenhouse Gas
GNA	Grid Needs Assessment
GVWR	Gross Vehicle Weight Rating
GWh	Gigawatt Hour
HD	Heavy Duty
ICA	Integration Capacity Analysis
IOU	Investor-Owned Utility

IEPR	Integrated Energy Policy Report
IRP	Integrated Resource Plan
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt Hour
LD	Light Duty
MD	Medium Duty
MPGe	Miles per Gallon Equivalent
MW	Megawatt
MWh	Megawatt Hour
NEM	Net Energy Metering
NREL	National Renewable Energy Laboratory
O&M	Operations and Maintenance
OEHHA	Office of Environmental Health Hazard Assessment
OIR	Order Instituting Rulemaking
PG&E	Pacific Gas and Electric Company
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaics
R.	Rulemaking
RE	Renewable Energy
SB	Senate Bill
SCADA	Supervisory Control and Data Acquisition
SCE	Southern California Energy Company
SDG&E	San Diego Gas & Electric Company
SUV	Sport Utility Vehicle
TAC	Transmission Access Charge
TOU	Time-of-Use (Rate)
VMT	Vehicle Miles Travelled

Definitions

Battery Electric Vehicle (BEV): A vehicle powered only by an electric motor and battery. PHEVs are not considered BEVs in this report. BEVs are one of the two types of EVs.

Behind-the-Meter (BTM): Refers to resources located behind a service meter, such that a customer's load and generation from BTM resources are combined with the customer's total load. Typically, rooftop solar and home EV chargers are BTM. Large-scale generators are located in front of the meter (i.e., they are separately metered and not BTM).

Distribution Grid Electrification Model (DGEM): DGEM is our model of the distribution grid. In this document, DGEM refers to not just the model but the study and this report.

Distributed Energy Resource (DER): A DER is an object connected to the distribution system that can serve as a resource for grid operators and planners. DERs include generators such as rooftop PV, shiftable loads such as heat pumps and electric vehicle chargers, home batteries, and energy efficiency.

Feeder: A feeder is an entire distribution circuit, including all branching conductors between a distribution substation and all service transformers.

Category: We use the term "category" to differentiate between personal vehicles and fleet vehicles. Personal vehicles are light-duty vehicles classified as personally owned in the DMV's database. Fleet vehicles include all others, including all MD and HD vehicles, all government vehicles, rental vehicles, and commercial vehicles.

Class: Light Duty, Medium Duty, or Heavy Duty. See Gross Vehicle Weight Rating.

Gross Vehicle Weight Rating (GVWR): Defines the safe, fully loaded weight of a vehicle (including passengers, freight, and the weight of the vehicle itself). This classification is used to categorize vehicles into light duty, medium duty, and heavy duty. We use the CEC's definitions:[1]

- Light duty: GVWR ≤ 10,000 lbs.
- Medium duty: 10,000 lbs < GVWR ≤ 26,000 lbs
- Heavy duty: GVWR > 26,000 lbs

Investor-Owned Utilities (IOUs): Monopolies that provide utility services and are regulated by a government body. For this study, an IOU includes Pacific Gas and Electric Company, San Diego Gas & Electric Company, and Southern California Edison Company.

Mitigation: In this report, mitigations refer to strategies that can solve equipment overloads before they occur. Such strategies include increasing the capacity of physical grid assets, changes to TOU rates to reduce load, and DERs that can reduce net load. Beyond the effects of TOU rates already in place, the mitigations applied by the DGEM include only increasing the capacity of physical grid assets.

Plug-In Hybrid Electric Vehicle (PHEV): Plug-in hybrid electric vehicles are vehicles with a combustion engine and a battery plus electric motor system. Unlike traditional hybrid vehicles, PHEVs can be plugged in. PHEVs are one of the two types of EV.

[1] California Energy Commission, *Medium- and Heavy-Duty Zero-Emission Vehicles in California*, n.d. (CEC, *Medium- and Heavy-Duty Zero-Emission Vehicles in California*). Available at: https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/medium-and-heavy. See section "Understanding Vehicle Weight Class" on the webpage.

Primary Distribution: Consists of feeders and distribution substations. Primary distribution systems typically include three symmetrical power phases and operate between 4 kV and 33 kV in California.[2]

Ratepayer: A customer of a public utility. In this study, a ratepayer refers to the customers who pay electric bills to Pacific Gas and Electric Company, San Diego Gas & Electric Company, or Southern California Edison Company.

Secondary Distribution: Secondary distribution assets include any equipment needed between primary distribution systems and the customer, including, but not limited to, distribution transformers, service drops, and secondary lines. Secondary distribution equipment typically operates between 120 and 480 volts.[3]

Section: A portion of a feeder separated by sectionalization devices, which can connect the section to adjacent sections or break those connections as operational and safety considerations warrant.

Subclass: Vehicle chassis information for LD vehicles, which are split into body types and sizes. Examples include subcompact cars, heavy vans, and compact pickups.

Substation: Substations are large electromechanical infrastructure that use transformers to raise or lower the voltage of electricity. Substations include protection equipment such as circuit breakers. For the purposes of this study, substations refer to distribution substations unless otherwise specified. Distribution substations typically lower voltage from transmission level voltages such as 115 kV or 60 kV to primary distribution voltage, which is most commonly 12 kV.

Transportation Electrification (TE): In the context of this report, TE refers specifically to electric cars and trucks unless otherwise noted. However, TE generally includes conversions of all types of transportation to electric sources of power, including cars and trucks, boats, airplanes, trains, etc.

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[2] Richard E. Brown, *Electric Power Distribution Reliability*, 2017 (Brown) at 4. Available at: https://books.google.com/books?id=CVNW8qW3ggwC.

[3] Brown at 4.

Executive Summary

The Public Advocates Office at the California Public Utilities Commission has undertaken a study of the costs of upgrading the distribution grids of the three largest investor-owned electric utilities (IOUs) to meet California's transportation electrification goals. Our results indicate that the total cost of upgrading the IOUs' distribution grids by 2035 will be approximately $26 billion.[4] This is about half of the cost identified by a similar recent study, the *Electrification Impacts Study Part 1* (EIS),[5] conducted by Kevala, a consultant engaged by the California Public Utilities Commission (CPUC).

California's goal that all new light-duty (LD) vehicles sold be electric by 2035 drives the need to plan for distribution system upgrades and their attendant costs in a manner that is thoughtful, careful, and comprehensive. Building electrification and medium-duty (MD) and heavy-duty (HD) fleet electrification amplify this need. The need for careful distribution system planning is the basis for our Distribution Grid Electrification Model (DGEM). In addition to providing climate and other environmental benefits, electrification could put downward pressure on electric rates by increasing electricity sales. As the cost of providing electric service – including the costs to upgrade the system – are recovered across more units of electricity sold, electrification may cause downward pressure on electricity rates across California. However, this scenario is contingent upon myriad factors, including planning and forecasting to avoid overbuilding grid infrastructure and whether ratepayers pay for costs beyond their traditional responsibilities.

We look forward to the continuing public discourse on how to best plan for and implement the state's transportation electrification goal. In particular, we view all feedback on the DGEM as a crucial part in ensuring that our study helps to advance the state's goals.

Background

As purchases of electric vehicles (EV) in California increase, electricity distribution grids will need to be upgraded to support additional EV charging infrastructure. Forecasting the costs of these upgrades is critical to understanding the drivers of potential future cost impacts to electric ratepayers and the magnitude of these costs. Infrastructure needs and cost forecasts should also inform grid planning and help to assess the necessary timing of building new distribution grid assets. Finally, quantifying the total cost of upgrades allows us to better understand the potential

[4] This figure and all other cost figures in this report are in constant, present-day dollars.

[5] The EIS was issued as an attachment to *Administrative Law Judges' Ruling Setting a Workshop, Admitting Into the Record Part 1 of the Electrification Impacts Study and Research Plan, and Seeking Comments,* May 9, 2023; issued in Rulemaking (R). 21-06-017. Available at: https://docs.cpuc.ca.gov/SearchRes.aspx?DocFormat=ALL&DocID=508423139.

benefits of incentives designed to encourage EV owners to charge at off-peak times when electricity prices should reflect lower system costs.

Our study

The focus of our study is to estimate the cost of upgrading California's three large electric IOUs' distribution grids to meet California's electrification goals. Our methodology involves using the registered address of every vehicle in California to estimate where EV uptake is likely to occur through 2035. We used these locations to model where additional charging load on the three IOUs' distribution grids is likely to appear. We then used this additional load data, combined with forecasted non-EV load growth, as the basis for determining where grid capacity will be exceeded and the cost to upgrade the distribution systems to provide sufficient capacity. We used the estimated cost to upgrade the IOUs' distribution grids to determine the rate impacts on ratepayers.

Based on our analysis and modeling, we estimate that through 2035, the costs to upgrade electric distribution grids will be approximately $26 billion. Using this cost estimate, we find that electrification applies an *overall downward pressure* on rates across all three of the large electric utilities, as shown in Figure ES-1. This is because, all other costs being equal, upward pressure on rates due to increased infrastructure costs due to electrification is more than offset by downward pressure on rates due to the increased consumption of electricity resulting from electrification. All ratepayers, even those who cannot (or choose not to) electrify, could financially benefit from electrification.

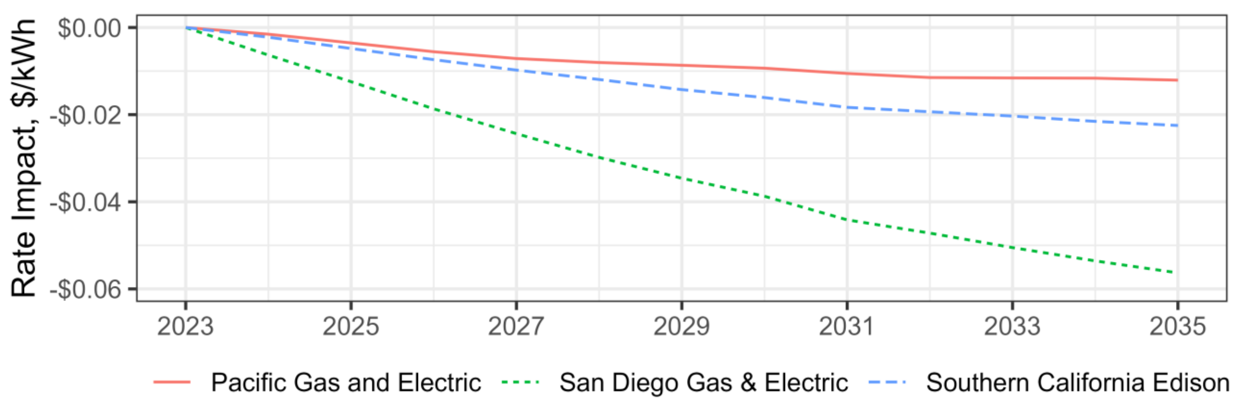

Figure ES-1. Projected rate impacts of electrification. (kWh = kilowatt-hour.)

Our estimate of the costs to upgrade the electric distribution grids has increased since our preliminary results in May 2023, which showed a range of $15 to $20 billion. Our preliminary results were based on the EIS's assumption that two miles of feeder, on average, would have to be upgraded for each feeder overload. Since then, we have analyzed additional data from the three utilities that led us to conclude that, on average, six miles of feeder will have to be upgraded to overcome each overload. This change has a significant impact on the total estimated cost.

Differences between the DGEM and the EIS

The EIS preliminarily estimates the total upgrade costs to be incurred through 2035 by the three utilities is $51 billion. There are two main reasons for the difference between our estimate ($26 billion) and the EIS's estimate. First, as described above, our estimate of average feeder length that is upgraded per overload is three times the EIS's estimate. If we were to use an average length of two miles of feeder to align with the EIS, our cost estimate would decrease, to $16 billion.

Second, the EIS assumes a larger growth in peak load. Our peak load forecast is drawn from and aligns with the California Energy Commission's Integrated Energy Policy Report (IEPR), whereas the EIS's peak load is the result of its unique model and assumptions. Figure ES-2 compares the 2021 and 2022 IEPR forecasts to the DGEM's forecast and the EIS's forecast of peak load growth.

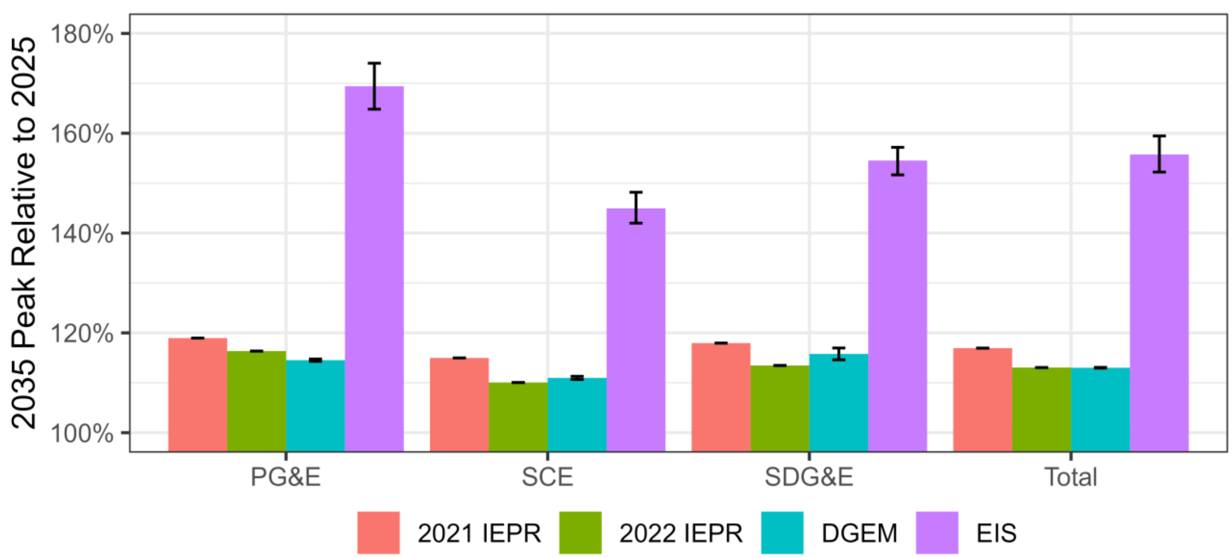

Figure ES-2. Comparison of peak load growth between two IEPRs, the EIS and the DGEM.

The EIS's higher estimated growth in peak load appears to be caused by the times at which the EIS predicts EVs will be charged relative to our load forecast source, the 2022 IEPR. Figure ES-3 shows that the EIS predicts a significant peak in EV charging at 9 p.m., driven by non-EV time-of-use rates which decrease at 9 p.m. Figure ES-3 also shows that the IEPR, which we use, forecasts that EV charging will occur much more evenly throughout the day. As peak load is a key driver of the need to upgrade distribution grids, the EIS's higher peak load growth forecast drives the EIS's higher estimated costs.

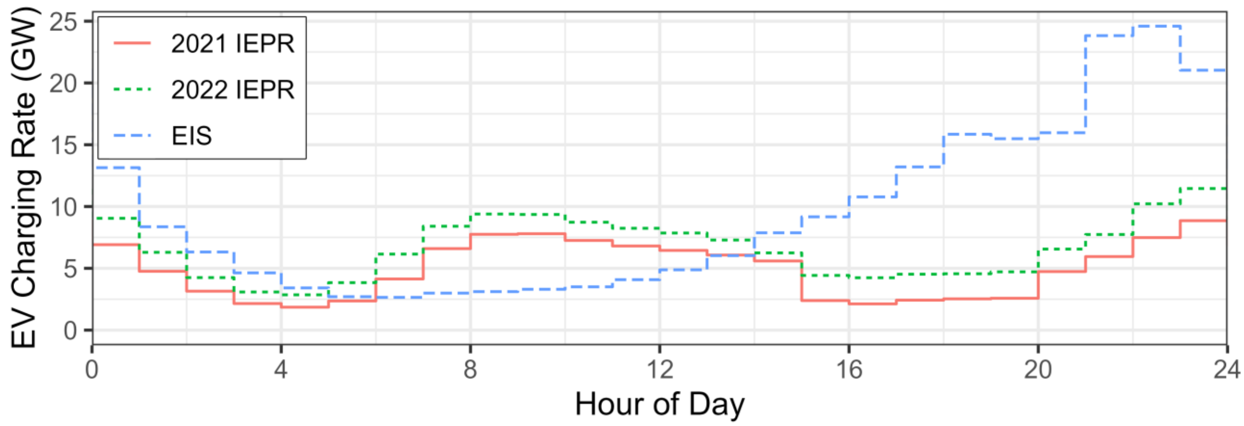

Figure ES-3. Hourly peak-day charging demand in 2035 from the 2021 and 2022 IEPRs and the EIS.

Our conclusions

We estimate that electrification will cost $26 billion in required upgrades to the utilities' distribution grids through 2035. However, this number has significant uncertainty, and the total cost could be as much as $18 billion lower or $31 billion higher. The main factors driving this range are the unit costs of new feeders and substations, particularly the former. In addition, we have found that the increase in electricity sales from electrification may outweigh the costs of distribution investments, causing a downward pressure[6] on residential electricity rates compared to present rates.

However, achieving this downward pressure on residential electricity rates is contingent upon five key model assumptions. Downward pressure on residential rates might not be achieved if:

1. EVs mostly charge in the evening, near peak hours (i.e., 6 p.m. to 10 p.m.), which would drive a higher peak load and, therefore, higher upgrade costs.
2. Electric rates rise to cover additional electrification programs, such as deploying EV chargers.[7]
3. New feeders and substations are more expensive than the DGEM estimates.
4. Expected load growth due to electrification does not occur.
5. Utilities build more infrastructure than is needed or build infrastructure in the wrong locations because upgrade costs will be higher.

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[6] Downward pressure on residential rates means that forecasted rates with electrification are lower than present rates, all other things being equal. Rates may still increase overall due to other factors such as wildfire mitigation or clean energy procurement.

[7] Ratepayers do not typically fund BTM infrastructure such as EVSE because "the primary role of ratepayers [is] to fund utility-side infrastructure upgrades." See Decision (D.) 22-11-040, *Decision on Transportation Electrification Policy and Investment*, November 17, 2022 at 89-90, issued in R.18-12-006. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M499/K005/499005805.PDF.

Good forecasting and planning are key parts of achieving this downward pressure on rates. Utility forecasts must be accurate and not lead to overbuilding of infrastructure. If overbuilding occurs, electrification could cause *upward pressure* on rates. Utility distribution planning processes, therefore, should be based upon realistic forecasts. Planning processes should be flexible and adaptable to provide for incremental infrastructure build and include offramps so that investment plans can be reshaped if it becomes clear that load will not appear when or where it was expected.

Even if electrification leads to downward pressure on rates, we cannot conclude that electric rates will fall. Other utility costs, such as wildfire mitigation or other climate change mitigations, could cause rates to rise in total. Moreover, effective policies, particularly around rate design, are needed to ensure that potential rate decreases are realized. For example, if EV owners are allowed to select a rate that does not recover the marginal cost to provide electricity, electricity rates for other customers could still rise.

The peak load on the distribution grid is a key driver of the upgrades needed, and the time at which EV owners charge is a key contributor to peak load. Approximately 70 percent of the costs identified in the EIS – $35 billion – vanish if EV charging is shifted away from hours of peak demand. Further work should be undertaken to understand in more detail the benefits and costs of mitigations, such as how to effectively incent EV owners to charge at times that could reduce the impact on the IOUs' distribution grids.

We have found that the present planned pace of primary distribution upgrades to the IOUs' distribution grids is approximately equal to what will be needed to meet the state's electrification goal. Prior research found that the pace of primary distribution upgrades needed in the future may far outpace historic upgrade rates for PG&E, and thus, upgrades may pose a bottleneck to electrification.[8] Our study does not corroborate this result.

Finally, our study was a data-intensive exercise, with much of the data coming from the three IOUs. While some datasets were excellent, some, particularly the cost data, lacked robustness. Additional types of data, such as the locations of vehicle fleets, were not available. Improvement in datasets would help achieve convergence in study results toward a consensus on the future cost of grid upgrades to meet electrification needs.

Further work and next steps

We welcome broad input and will engage with a wide range of stakeholders on the results of our study. Our results will also be available to Kevala as Kevala refines its analysis for the

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[8] Salma Elmallah et al., *Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California?*, Environmental Research: Infrastructure and Sustainability, November 9, 2022 at 1. Available at: https://doi.org/10.1088/2634-4505/ac949c.

Electrification Impacts Study Part 2. No single study or pair of studies, particularly at this point in the electrification process, can definitively answer such a complex question as what the 2035 costs of distribution grid upgrades will be. This study aids the continuous discourse on electrification planning and the identification of associated costs and benefits rather than establishing a final cost projection.

Further work should deepen analysis of the impacts of electrification on the grid. Future studies should focus on improving estimates of EV charging profiles and charging locations, the cost of upgrades to overcome each grid overload, MD and HD deployment, and the potential impacts of managed charging. In addition, we did not analyze the impacts of electrification on total home energy costs, including reduced purchases of natural gas and gasoline. Total home energy cost would provide a fuller picture of how electric consumers' energy costs will change as electrification impacts transportation and other sectors.

1 Introduction

California faces unprecedented challenges due to climate change, including increased wildfire risk, more intense droughts and floods, and more extreme weather events such as sweltering heat waves.[9] California has become a national leader in addressing climate change, passing policies aimed at reducing the emissions contributions of the state's economy. In 2006, the California State Legislature passed Assembly Bill (AB) 32, which mandated that California sharply reduce its greenhouse gas (GHG) emissions and identified the California Air Resources Board (CARB) as the state agency responsible for generating GHG reduction implementation strategies and a roadmap.[10] CARB has set forth plans to reduce emissions to at least 40 percent below 1990 emissions levels by 2030 and achieve carbon neutrality by 2045.[11] Various state agencies, depending on their jurisdictions, have outlined regulations to achieve these targets. The regulations principally focus on the high-polluting sectors of the economy, including industry, energy consumption, buildings, transportation, and agriculture.[12] The state is promoting electrification as a large-scale strategy for reducing emissions within several of those sectors.

1.1 Decarbonization through electrification and DERs

Electric vehicles will contribute the most to rising electricity consumption.[13] Electrification of building space and water heating will also play a significant role. In aggregate, the projected electrification to decarbonize California will necessitate some degree of infrastructure upgrades. Key questions facing electric utilities and decision-makers, including the California Energy Commission (CEC) and the California Public Utilities Commission (CPUC), include *where* new electrification load from electric vehicles and other sources will appear on the grid, *when* the load will appear, *how much* load to expect, and *how costly* the resulting infrastructure upgrades will be.

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[9] See Louise Bedsworth et al., *California's Fourth Climate Change Assessment,* 2018. Available at: https://www.energy.ca.gov/sites/default/files/2019-11/Statewide_Reports-SUM-CCCA4-2018-013_Statewide_Summary_Report_ADA.pdf.

[10] California Air Resources Board (CARB), *AB 32 Global Warming Solutions Act of 2006*, September 18, 2018. Available at: https://ww2.arb.ca.gov/resources/fact-sheets/ab-32-global-warming-solutions-act-2006.

[11] CARB, *2022 Scoping Plan for Achieving Carbon Neutrality*, November 16, 2022 (CARB Scoping Plan). Available at: https://ww2.arb.ca.gov/resources/documents/2022-scoping-plan-documents.

[12] CARB Scoping Plan at 1-3.

[13] Salma Elmallah et al., *Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California?*, Environmental Research: Infrastructure and Sustainability, November 9, 2022 (Elmallah et al.) at 18. Available at: https://doi.org/10.1088/2634-4505/ac949c; and Kevala, *Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates,* May 9, 2023 (EIS) at ES-5 to ES-7. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M508/K423/508423247.PDF.

1.1.1 Transportation

The California State Legislature has targeted the transportation sector for decarbonization on the basis that the sector accounts for more than 40 percent of the state's total GHG emissions.[14] Specifically, regulations require that most types of currently fossil fuel-powered vehicles become zero-emission within the next two decades.[15]

State policies are targeting the electrification of vehicles because of the sector's environmental and public health impacts. Combustion engine vehicles emit pollutants such as particulate matter and ozone, which cause major public health problems, including respiratory diseases, fatigue, and, in extreme cases, premature mortality.[16] In light of these pressing problems, CARB in 2022 issued the Advanced Clean Cars II Regulations in support of Executive Order N-79-20.[17] The regulations require that all light-duty (LD) vehicle sales are zero-emission by 2035.[18]

The medium- and heavy-duty (MD and HD) vehicle sector, despite amounting to only six percent of all vehicles in California, has an outsized contribution to the state's emissions and air quality issues.[19] The MD and HD vehicle sector produces 25 percent of the state's on-road GHG emissions and much higher percentages of toxic particulates, such as nitrous oxide and volatile organic compounds.[20] The emissions from the transportation sector cause morbidity and mortality, especially for communities located in industrial regions, truck depots, and highly trafficked transit corridors.[21] In order to tackle these acute public health concerns and achieve the state's climate goals, the California State Legislature and state agencies have passed regulations mandating the decarbonization of most components of the MD and HD sector. CARB, in April 2023, promulgated the Advanced Clean Fleets regulations, which include

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[14] California State Transportation Agency, *Climate Action Plan for Transportation Infrastructure*, July 2021 at 6. Available at: https://calsta.ca.gov/-/media/calsta-media/documents/capti-july-2021-a11y.pdf.

[15] CARB, *California Moves to Accelerate to 100% New Zero-Emission Vehicle Sales by 2035*, Release Number 22-30, August 25, 2022. Available at: https://ww2.arb.ca.gov/news/california-moves-accelerate-100-new-zero-emission-vehicle-sales-2035; and CARB, *California Approves Groundbreaking Regulation That Accelerates the Deployment of Heavy-Duty ZEVs to Protect Public Health*, Release Number 23-13, April 28, 2023 (CARB April 28, 2023 Press Release). Available at: https://ww2.arb.ca.gov/news/california-approves-groundbreaking-regulation-accelerates-deployment-heavy-duty-zevs-protect.

[16] Richard E. Brown, *Electric Power Distribution Reliability*, 2017 (Brown) at 104-111. Available at: https://books.google.com/books?id=CVNW8qW3ggwC.

[17] CARB, *Advanced Clean Cars II*, n.d. (CARB, *Advanced Clean Cars II*). Available at: https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii.

[18] CARB, *Advanced Clean Cars II*.

[19] CARB April 28, 2023 Press Release.

[20] CARB April 28, 2023 Press Release; and Brown at 106.

[21] See Austin L. Brown et al., *Driving California's Transportation Emissions to Zero*, The University of California Institute of Transportation Studies, April 1, 2021 at 104-111. Available at: https://doi.org/10.7922/G2MC8X9X; also see Laura August et al., *CalEnviroScreen 4.0*, California Office of Environmental Health Hazard Assessment (OEHHA), October 2021. Available at: https://oehha.ca.gov/media/downloads/calenviroscreen/report/calenviroscreen40reportf2021.pdf.

requirements that all state and local government vehicle fleet purchases must be zero-emission by 2027, all drayage trucks, and last-mile delivery and yard trucks in California must be zero-emission by 2035, all manufacturers must sell only zero-emission MD and HD vehicles by 2036, and all refuse trucks and local buses must be replaced with clean vehicles by 2040.[22]

Figure 1-1 shows the expected on-road population of electric vehicles (EVs), split into battery-electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Replacing LD, MD, and HD vehicles with EVs will require the transmittal of more energy across California's transmission and distribution grids.

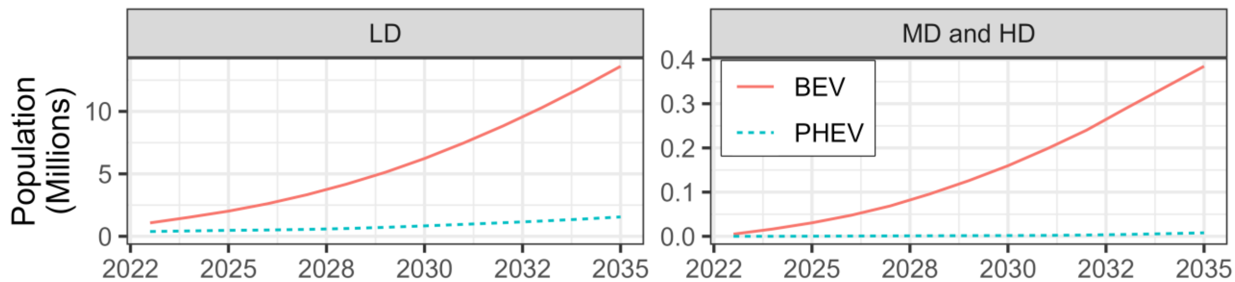

Figure 1-1. Vehicle deployment forecast from the 2022 Integrated Energy Policy Report (IEPR).[23]

1.1.2 Other sources of load growth

Our analysis focuses on the impacts of EV charging on the distribution grid because EVs will be the largest contributor to load growth in the state.[24] However, the electrification of other sectors, as well as economic and demographic growth, will also impact distribution grids. The increasing deployment of customer-sited solar photovoltaics (PV) will also impact load. These additional impacts are included in our analysis.

Residential and commercial buildings are responsible for roughly 25 percent of statewide emissions due to onsite fossil fuel consumption and electricity usage.[25] Meanwhile, the industrial sector generated about 20 percent of statewide GHG emissions in 2020.[26] California building code requires most new homes to be equipped with solar PV (rooftop solar) or to be

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[22] CARB, *Advanced Clean Fleets Regulation Summary*, May 17, 2023 (CARB, *Advanced Clean Fleets Regulation Summary*). Available at: https://ww2.arb.ca.gov/resources/fact-sheets/advanced-clean-fleets-regulation-summary.

[23] From data provided in an email correspondence by the CEC's Advanced Electrification Analysis Branch on April 20, 2023 (data provided by CEC on April 20, 2023).

[24] Elmallah et al. at 18; and EIS at ES-5 to ES-7.

[25] CARB, *Building Decarbonization*, n.d. Available at: https://ww2.arb.ca.gov/our-work/programs/building-decarbonization.

[26] CARB, *California Greenhouse Gas Emissions for 2000 to 2020: Trends of Emissions and Other Indicators*, October 26, 2022 at 20. Available at: https://ww2.arb.ca.gov/sites/default/files/classic/cc/inventory/2000-2020_ghg_inventory_trends.pdf.

powered by a nearby solar array.[27] Beginning in 2023, the CEC commenced requiring that several new commercial buildings have both solar generation and battery storage to capture excess solar production.[28] Commercial, industrial, and residential rooftop solar supplied about seven percent of the state's total electricity generation in 2021.[29] Furthermore, CARB has set targets that all new residential buildings constructed after 2026 and all new commercial buildings after 2029 contain all-electric appliances.[30] The CARB 2022 Scoping Plan also articulates an action to increase the number of electric appliance sales to be installed in existing residential and commercial buildings incrementally to 100 percent by 2035 and 2045, respectively. The state's electrification policies will increase the load on the grid over the next several decades and may contribute to the need to invest in distribution system upgrades.

Figure 1-2 shows projected growth in building electrification demand, which accelerates in the latter half of the decade, reaching 75,000 gigawatt hours (GWh) in 2035. Meanwhile, rooftop solar demand is projected to grow from 27,000 GWh to 56,000 GWh from 2023 to 2035.[31]

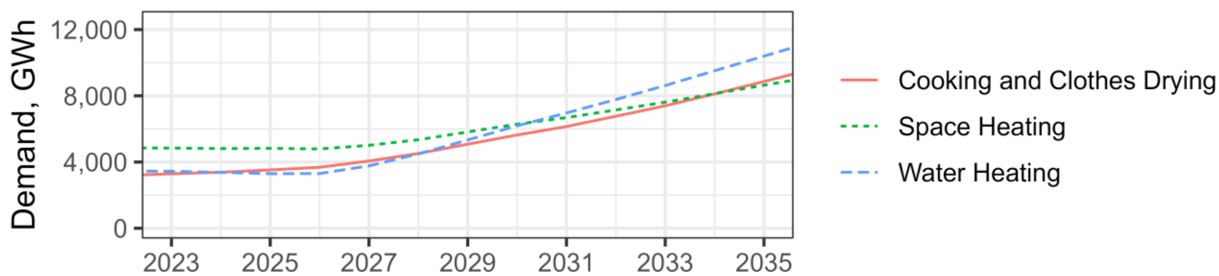

Figure 1-2. Forecasted demand from building electrification sectors.[32]

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[27] CEC, *2019 Building Energy Efficiency Standards for Residential and Nonresidential Buildings for the 2019 Building Efficiency Standards*, December 12, 2018 at Section 110.10. Available at: https://www.energy.ca.gov/sites/default/files/2021-06/CEC-400-2018-020-CMF_0.pdf.; also see CEC, 2019 Energy Code – Solar Ready Requirements, October 2020. Available at: https://www.energy.ca.gov/sites/default/files/2021-04/2019_Energy_Code_Solar_Ready_Requirements_ADA.pdf.

[28] California Building Standards Commission, *Section 140.10 Prescriptive Requirements for Photovoltaic and Battery Storage Systems*, January 2023. Available at: https://codes.iccsafe.org/content/CAEC2022P2/subchapter-5-nonresidential-and-hotel-motel-occupancies-performance-and-prescriptive-compliance-approaches-for-achieving-energy-efficiency#CAEC2022P2_Ch05_Sec140.10.

[29] CEC, *CEDU 2022 Baseline Forecast – State,* 2022 (CEC, *CEDU 2022 Baseline Forecast – State*). Available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update-2.

[30] CARB Scoping Plan at 75.

[31] CEC, *CEDU 2022 Baseline Forecast – State*.

[32] CARB, *Draft 2022 Scoping Plan AB 32 GHG Inventory Sectors Modeling Data Spreadsheet*, May 2, 2022 (CARB, *AB 32 GHG Inventory Sectors Modeling Data Spreadsheet*). Available at: https://ww2.arb.ca.gov/sites/default/files/2022-05/2022-draft-sp-PATHWAYS-data-E3.xlsx.

1.2 DER policy at the CPUC

In July 2021, the CPUC commenced Rulemaking (R.) 21-06-017, *Order Instituting Rulemaking (OIR) to Modernize the Electric Grid for a High Distributed Energy Resources Future*. R.21-06-017 focuses on preparing the electric grid for a high penetration of distributed energy resources (DERs),[33] including electric vehicles and related infrastructure.[34] Furthermore, R.21-06-017 considers the planning and forecasting strategies that are necessary to determine the timing and scope of system investments needed to facilitate the integration of DERs into the grid.[35] If planners do not properly forecast where and when load growth, especially from EVs, will appear on the grid, electric investor-owned utilities (IOUs) could build billions of dollars of under-utilized assets, or be unable to satisfy increasing energy demand.[36] Studies using the most up-to-date methods and data are integral to effectively planning for load growth and informing future grid investments.

1.3 The Electrification Impacts Study

In May 2023, the CPUC published the *Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates* (EIS), a CPUC-initiated study completed by the data analytics company Kevala. The EIS is a preliminary study that analyzed the cost of distribution infrastructure upgrades resulting from load growth, including transportation electrification (TE), in the service territories of Pacific Gas and Electric Company (PG&E), San Diego Gas & Electric Company (SDG&E) and Southern California Edison Company (SCE). Kevala plans to conduct a Part 2 of the EIS, which will update the load forecast from Part 1 and assess how the integration of grid technologies (e.g., flexible load management) and programmatic strategies (e.g., rate designs targeted at load management) affect load growth under a variety of electrification scenarios.[37] The EIS forecasts load growth for more than 12 million premises across California, including from building electrification (BE), energy efficiency (EE), and from forecasted DER adoption such as EVs, rooftop solar, and battery energy storage systems (BESS).[38] The EIS specifically varied the levels of EV adoption

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[33] A DER is an object connected to the distribution system that can serve as a resource for grid operators and planners. DERs include generators such as rooftop PV, shiftable loads such as heat pumps and electric vehicle chargers, home batteries, and energy efficiency.

[34] *Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future*, July 2, 2021 at 2, and 8; issued in R.21-06-017. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M390/K664/390664433.PDF.

[35] *Assigned Commissioner's Scoping Memo and Ruling*, November 15, 2021 at 2; issued in R.21-06-017. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M422/K949/422949772.PDF.

[36] EIS at 120.

[37] EIS at E-3.

[38] EIS at E-1, and 1.

and net energy metering (NEM)[39] behind-the-meter (BTM) tariffs in order to assess the likely grid impacts of these two dynamic DER types that are undergoing policy-driven expansion.[40] The EIS scrutinized the effects of load growth at the primary and secondary distribution levels and preliminarily estimated that up to $51 billion in distribution grid upgrades could be needed by 2035.[41] This $51 billion is composed of $27.6 billion in investment by PG&E, $21.1 billion by SCE, and $3.1 billion by SDG&E.[42] The EIS also finds that the rising demand of a high electrification future could necessitate longer-term distribution planning by the IOUs.[43]

1.4 Grid impacts studies in general

The EIS is not the only study of its kind. Several studies have examined the impacts of load growth due to increased EV adoption and electrification and the concomitant grid infrastructure upgrades at a large-scale within California. The studies used a variety of methods, considered varying geographical areas, and scrutinized different types of DERs.[44] Table 1-1 juxtaposes our Distribution Grid Electrification Model (DGEM) study and several of these studies.

Table 1-1. Comparison of large-scale EV grid impacts studies.[45]

Study	Distribution Assets Modeled	Cost Inputs	Baseline Load / Overload Calculation	Objective and DERs Modeled	Central Costs Estimate
DGEM	Substations, banks, feeders	IOU unit costs	SCADA	Electrification: Baseline, electrification,[46] EV	$26 billion by 2035 (3-IOUs)
EIS Part 1	Substations, banks, feeders, service transformers	IOU unit costs	AMI	Electrification: Baseline plus PV, BESS, EV, EE, BE	$51 billion by 2035 (3-IOUs)
Elmallah et al.	Substations, feeders	DIDF ($/kW)	ICA	Electrification: Heat pumps, LD EV	$5 billion by 2050 (PG&E)

[39] The NEM program is the state's main financial incentive program designed to support the installation of rooftop solar at customers' residences and other sites by allowing customers to significantly reduce their energy bills based on the solar energy their systems generate. See CPUC, *Net Energy Metering*, n.d. Available at: https://www.cpuc.ca.gov/NEM/.

[40] EIS at 7.

[41] EIS at ES-4 to ES-5.

[42] EIS at 27.

[43] EIS at ES-6.

[44] The EIS Part 1 is the most comparable to this study; it applies to the same geographic area.

[45] We used modified data from the CPUC and Kevala, *Electrification Impacts Study (EIS) Part 1*, May 17, 2023 at slide 26. Available at: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/infrastructure/distribution-planning/2023-0517-eis-part-1-workshop_combined-slides.pdf. 3-IOU means the combined service territories of PG&E, SCE, and SDG&E. NREL is the National Renewable Energy Laboratory; LA is Los Angeles; DIDF is the distribution investment deferral framework; kW is kilowatt; SCADA is supervisory control and data acquisition; AMI is advanced metering infrastructure; ICA is integration capacity analysis; LADWP is the LA Department of Water and Power.

[46] Derived from IEPR growth rates of non-TE loads.

Study	Distribution Assets Modeled	Cost Inputs	Baseline Load / Overload Calculation	Objective and DERs Modeled	Central Costs Estimate
NREL LA 100[47]	Banks, feeders, service transformers	IOU unit costs	SCADA	100% RE: Baseline plus PV, BESS, EV, EE, BE	$1.5 billion by 2045 (LADWP)

Elmallah et al. evaluated the distribution system upgrade needs in PG&E's service territory and found that vehicle electrification will contribute the most to load growth.[48] This load growth will require PG&E to annually upgrade 95 to 260 feeders and two to five substations through 2030, depending on the EV charging scenario.[49] These annual figures equate to between 1,267 and 1,679 feeders and between 12 and 17 substations requiring upgrades through 2030.[50] Elmallah et al. concluded that between 2021 and 2050, PG&E may need to invest $1 billion to potentially over $10 billion (with a central estimate of around $5 billion) to upgrade the feeders and substations in its service territory to accommodate electrification.[51]

1.5 DGEM scope and objective

The DGEM study offers an independent estimate of the cost and impacts of integrating EV and non-EV load growth into the distribution grid. Our research entails:

A. Predicting the location of EV adoption through 2035.

B. Calculating the load placed on primary distribution infrastructure due to EV uptake and other load growth.

C. Estimating the primary and secondary distribution grid upgrades necessary to meet the rise in electricity demand and their costs.

D. Forecasting the electric rate impacts of increased load and grid investment. For electric grid impacts only, we considered generation, transmission, and distribution grid investments.

We have four main objectives:

[47] National Renewable Energy Laboratory, *LA100: The Los Angeles 100% Renewable Energy Study and Equity Strategies*, March 2021. Available at: https://maps.nrel.gov/la100/la100-study/report.

[48] Elmallah et al. at 18.

[49] Elmallah et al. at 13-14.

[50] Elmallah et al. at 16; Elmallah et al., *Supplementary Information - Can distribution grid infrastructure accommodate residential electrification and electric vehicle adoption in Northern California?*, November 9, 2022 (Elmallah et al., *Supplementary Information*) at 25-28. Available at: https://cfn-live-content-bucket-iop-org.s3.amazonaws.com/journals/2634-4505/2/4/045005/revision2/ERISac949csupp1.pdf?AWSAccessKeyId=AKIAYDKQL6LTV7YY2HIK&Expires=1689975309&Signature=ueZ7b%2Fn35zPbsq%2B0Bctni1dRGNY%3D. For the feeder and substation upgrade needs, we referenced the EV scenario and the combined EV and residential electrification scenarios.

[51] Elmallah et al. at 1.

1. Determine the potential upcoming costs to customers and concomitant rate impacts.[52] Will electrification drive customer rates up or down?
2. Establish the urgency of necessary expenditures on grid assets. Do we need to plan further ahead to meet the state's electrification goals?
3. Describe how sensitive the outcomes are to changing inputs. What are the drivers of the costs to ratepayers?
4. Begin to understand how mitigation strategies, such as managed EV charging through rate design, can reduce infrastructure costs. How much investment can managed charging avoid?

Through this publication we aim to continue the discourses on distribution planning, the future of the distribution grid, and electrification. We center our work on the best available data, a sound and transparent methodology, and clear, implementable recommendations. With these foci, we aim to help decision makers understand the impacts of electrification, make sound policy choices, and determine where future research is needed. Moreover, understanding the degree of uncertainty in this and other studies can help decision makers to develop planning methods appropriate for an unpredictable future.

2 Methods

This section provides an overview of the methods and key datasets used in the DGEM. Figure 2-1 depicts the methodological flow. Appendix A provides additional details.[53]

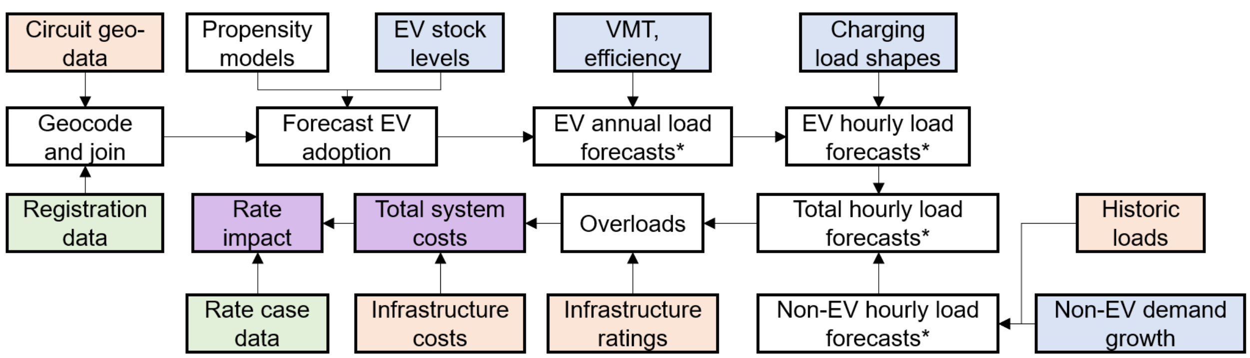

Figure 2-1. Study process schematic. Blue cells represent input data from the IEPR (Planning Scenario), orange cells represent IOU datasets, and green represents data from other sources. The purple cells show the primary study results. *= by infrastructure (i.e., for each feeder and substation).

[52] To our knowledge, this is the first large-scale distribution grid study to evaluate rate impact.

[53] Due to confidentiality of data used in several steps of this study, underlying data and code will not be made publicly available.

As Figure 2-1 shows, we relied on the IEPR Planning Scenario for much of the DGEM data. Table 2-1 details the nature of the relationship between parameters within the IEPR and the DGEM.

Table 2-1. Relationship between the DGEM assumptions and the 2022 IEPR Planning Scenario.

Parameter	DGEM Relationship to 2022 IEPR Planning Scenario
Peak load	Unconstrained but aligned with the IEPR[54]
State EV population	Constrained to the IEPR
EV population within each IOU's service territory	Not constrained to the IEPR[55]
Granular EV locations	Not considered in the IEPR
Annual EV charging energy	Constrained to the IEPR per vehicle
Hourly EV charging power	Constrained to the IEPR per vehicle
Growth in non-EV demand	Constrained to the IEPR at the IOU level

The DGEM analysis consisted of four primary phases:

1) We developed propensity models and forecasted EV adoption through 2035.
2) We calculated the peak demand placed on distribution grid infrastructure due to EV uptake combined with projected non-EV load growth and existing loads.
3) We estimated where distribution grid upgrades would be needed across most of California (the combined territories of the three large IOUs) and the cost of these upgrades.
4) We calculated the impact of generation, transmission, and distribution costs on rates.

The DGEM studies the combined service territories of PG&E, SCE, and SDG&E, as depicted in Figure 2-2.[56] The DGEM Study Area (S), as described below, is a subset of the portion of the IOU service territories for which distribution grid asset data for the three IOUs were available.

[54] See Section 3.3 for an analysis of how closely peak load aligns between the DGEM and the IEPR.

[55] See Appendix B for an analysis of how closely EV demand (a good but imperfect indicator of population) aligns between the DGEM and the IEPR.

[56] CEC, *Electric Load Serving Entities (IOU & POU)*, December 16, 2021 (CEC, *Electric Load Serving Entities*). Available at: https://cecgis-caenergy.opendata.arcgis.com/datasets/b662fc6de88c415fb232ed3dcf9d5d4e/explore. The IOUs' service territories came from publicly available CEC data.

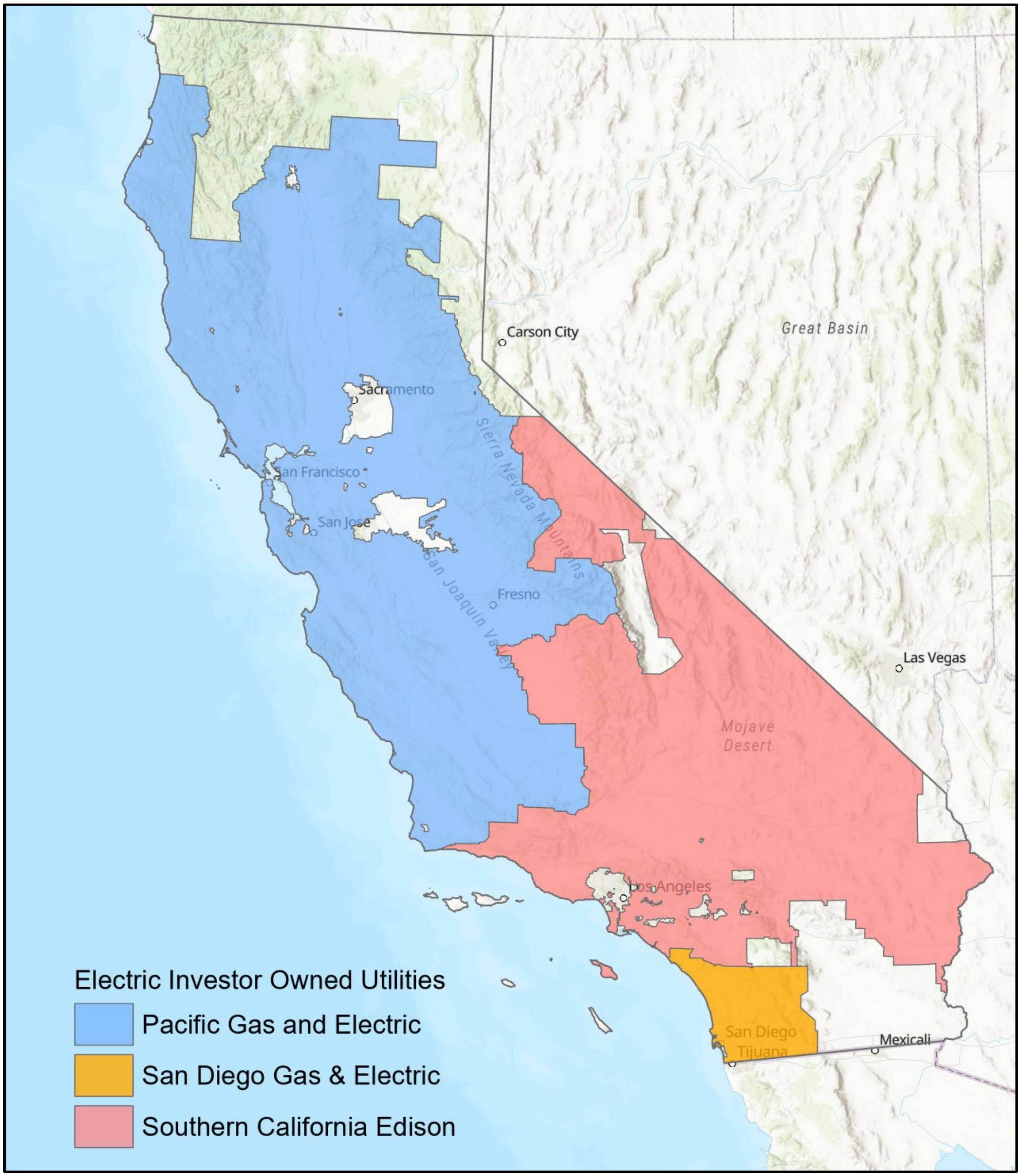

Figure 2-2. IOU service territory areas considered by the DGEM.

2.1 Predicting EV adoption through 2035

The California Department of Motor Vehicles (DMV) provided us and the CEC with a dataset containing all registered motor vehicles in California (excluding motorcycles), current to the end of 2021. The data included registration addresses, vehicle makes and models, and fuel types (e.g., electric, diesel, gasoline). The CEC processed the data, adding vehicle class from the make and model of the registered vehicles. We geocoded[57] the dataset using the registration address to derive the latitude and longitude for each vehicle registration. We then eliminated records that were unable to be geocoded or that fell outside of the IOUs' service areas[58] and spatially joined each record to the nearest utility feeder.[59] Finally, we eliminated records associated with feeders with incomplete data, resulting in a subset of the IOUs' service territory that we call the Study Area (S). Table 2-2 shows the number of registration records retained at each stage of the process.

Table 2-2. Number of vehicle records retained from DMV data into the DGEM Study Area.

Class	IOU	Total (T)	Matched (M)	3-IOU (I)	Study Area (S)	S/I	S/M	M/T
LD	All	30,013,130	29,185,643	22,498,935	21,906,860	-	75.1%	-
MD	All	661,923	611,871	460,185	450,353	-	73.6%	-
HD	All	360,546	323,050	243,557	238,574	-	73.9%	-
All	PG&E	-	-	9,896,459	9,765,311	98.7%	-	-
All	SCE	-	-	10,469,094	10,208,696	97.5%	-	-
All	SDG&E	-	-	2,837,124	2,621,780	92.4%	-	-
All	All	31,035,599	30,120,564	23,202,677	22,040,146	97.4%	75.0%	97.1%

Table 2-2 also displays three calculated parameters that were used later in the analysis:

1. S/I indicates the share of vehicles in the combined service territories of the three IOUs (3-IOU) (i.e., 97.4 percent) considered in the DGEM.
2. S/M approximates the share of vehicle sales in California that occur within the DGEM's Study Area (e.g., 75.1 percent for LD vehicles).
3. M/T is the share of present vehicles that are accounted for in the DGEM (i.e., 97.1 percent of records matched with an address. We expect this trend to hold within the Study Area, which would lead to 2.9 percent of present EVs not being located).

Next, we scored conventional-fueled vehicles (i.e., neither BEV nor PHEV) using several propensity models. We used one set of models for personal LD vehicles (herein referred to as

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[57] Geocoding is the process of transforming a description of a location, such as an address, to geographic coordinates that can be mapped to a location on the Earth's surface. See Environmental Systems Research Institute, *What Is Geocoding?,* n.d. Available at: https://desktop.arcgis.com/en/arcmap/latest/manage-data/geocoding/what-is-geocoding.htm.

[58] CEC, *Electric Load Serving Entities*.

[59] The primary distribution feeder data came from the confidential versions of the Wildfire Mitigation Plans of PG&E, SCE, and SDG&E. We only included feeders for which we also had load and rating data. The publicly available versions are available: PG&E, 2022 Quarterly Reports. Available at: https://www.pge.com/en_US/safety/emergency-preparedness/natural-disaster/wildfires/wildfire-mitigation-plan.page; SCE, Wildfire Mitigation Plan Update & Related Documents. Available at: https://www.sce.com/safety/wild-fire-mitigation; and SDG&E, *2022 Wildfire Mitigation Plan*, February 11, 2022. Available at: https://www.sdge.com/2022-wildfire-mitigation-plan.

personal vehicles) and another set for all MD and HD vehicles, as well as non-personal (e.g., government, commercial) vehicles (herein referred to as fleet vehicles).[60] Each model result was used in parallel with the others to create a set of scenarios that captured the range of possibilities for needed distribution system upgrades and total infrastructure upgrade costs.

For personal vehicles, we applied the following two models:

1. Each vehicle received a random score.
2. Each vehicle's score was calculated from a logistic regression on the current DMV dataset. We used income, education, building information, commute length, and family size as independent variables and whether a vehicle was an EV as the dependent variable. All these factors are supported by the literature[61] and were significant, with varying effect sizes;[62] higher education had the largest effect size.[63]

For fleet vehicles,[64] we used the following four models:

1. Each vehicle was assigned a random score.
2. Each feeder was assigned a random score. All the vehicles on that feeder then received the same random score.
3. Each vehicle received a score equal to the ratio of EV (PHEV + BEV) to total vehicles <u>on its feeder</u> in its class (LD/MD/HD). All vehicles with a score of zero received a random score between zero and negative one (so that they were randomly selected after vehicles on feeders with some EV adoption in their class).
4. Each vehicle received a score equal to the ratio of EV to total vehicles <u>with the same body type</u> in its class (LD/MD/HD). All vehicles with a score of zero received a random score between zero and negative one (so that the vehicles with no EV adoption in their body class were randomly selected after those with some EV adoption in their class and body type).

The parallel models helped to compensate for the uncertainty in the future spatial dispersion of vehicles. Some of the uncertainty derives from the fact that current trends in EV adoption may not hold as EVs become cheaper. The uncertainty in future EV adoption trends makes

[60] We elected not to consider personal MD and HD vehicles within the personal model for the following reasons: 1) it is likely that many of these vehicles are personally owned but used for commercial purposes, and 2) the share of these vehicles registered as non-personal, and the relative impact of MD and HD compared to LD are both small.

[61] See Appendix A.3.3.1 for elaboration.

[62] Effect size measures the strength of the relationship between two variables.

[63] See Appendix A.3.3.1 for further details.

[64] MD, HD, and non-personal LD vehicles.

forecasting EV deployment a challenge. This is particularly true for the nascent MD and HD sector, which has virtually no trends from which to extrapolate.[65]

Finally, we ranked vehicles based upon their propensity score (keeping each propensity score set as a separate scenario) and assigned non-EVs to become EVs in each year until the population established by the IEPR Planning Scenario[66] was reached.[67] The IEPR Planning Scenario includes the impacts of policy, including the Advanced Clean Cars II and Advanced Clean Fleets regulations established by CARB.[68] To reassign vehicles, we first reduced the populations in the IEPR to correspond to the DGEM Study Area, by vehicle class (S/M in Table 2-2) and split the LD forecast into personal and non-personal vehicles, based upon the share in the 2021 DMV vehicle registration dataset.[69] For each class, we first converted the highest-ranked conventional vehicles to EVs, and the next highest-ranked set to PHEV.[70]

These methods generated one table per propensity model, showing EVs based on their year of adoption, subclass, drivetrain, and associated feeder. The tables also included all current EVs. See Appendix A.3 for more information.

2.2 Calculating peak demand

We separated peak demand into two components: 1) EV demand growth, and 2) historic demand plus non-EV demand growth.

2.2.1 EV demand growth

For each vehicle subclass, we calculated annual energy consumption by multiplying the expected miles of travel per year by the vehicle efficiency (kilowatt hours [kWh] of charging energy

[65] See Dana Lowell et al., *Medium- & Heavy-Duty Vehicles: Market Structure, Environmental Impact, and EV Readiness*, M.J. Bradley & Associates (MJB&A), July 2021 (MJB&A). Available at: https://www.erm.com/globalassets/documents/mjba-archive/reports/2021/edfmhdvevfeasibilityreport22jul21.pdf.; also see National Grid and Hitachi Energy, *The Road to Transportation Decarbonization: Understanding Grid Impacts of Electric Fleets*, September 2021 (National Grid & Hitachi Energy). Available at: https://www.nationalgridus.com/media/pdfs/microsites/ev-fleet-program/understandinggridimpactsofelectricfleets.pdf.

[66] Data provided by CEC on April 20, 2023. These are internal model data that are not published. The DGEM uses only the IEPR's Planning Scenario.

[67] An important assumption of this analysis is that vehicle owners want to maintain their current vehicle type and, when it is their turn, they swap their current conventional vehicle to an equivalent EV. The data provided by the IEPR were broken down into forecasts by sub-category (e.g., car-subcompact), but we did not enforce that our population changes matched the IEPR's at this level of granularity.

[68] CEC, *2022 Integrated Energy Policy Report Update*, May 10, 2023 (CEC, 2022 IEPR) at 46, and 49. Available at: https://efiling.energy.ca.gov/GetDocument.aspx?tn=250084.

[69] 92.7 percent of LDs are personally registered. See Table A-4 in Appendix A.2.

[70] For example, in the LD-personal model, if the IEPR populations indicate that 200,000 more EVs and 50,000 PHEVs should be deployed, the 200,000 highest-scored conventional vehicles would be converted to EVs, and the following 50,000 highest-ranked conventional vehicles would be converted to PHEVs.

needed to drive one mile).[71] The CEC provided the vehicle efficiency and expected vehicle miles traveled (VMT) that it calculated for the models used in the 2022 IEPR.[72] The vehicle efficiency varied across time (i.e., EVs generally become more efficient and drive further in the future). The annual energy consumption results are depicted in Figure 2-3.

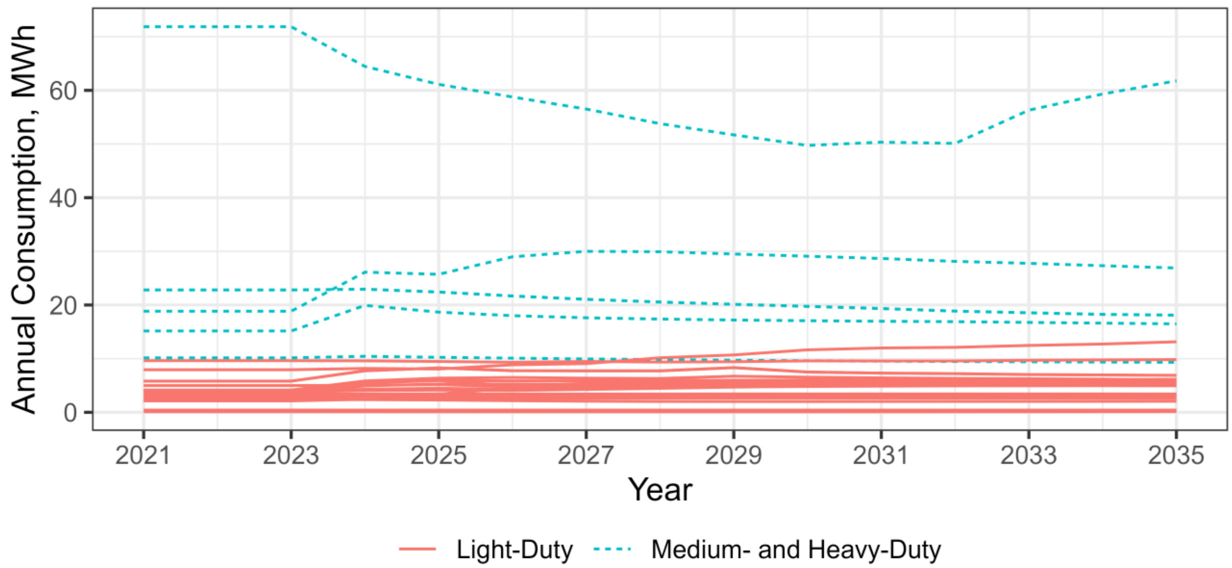

Figure 2-3. Annual consumption from IEPR data for BEVs. PHEVs consume 60 percent of the electricity of an equivalent EV in our model. The outlier at the top is class 8 trucks.

We then applied the annual consumption to each EV and tallied up the results across each feeder, keeping LD separate from MD and HD because these classes have different charging load shapes. This achieved the annual energy consumption on each feeder by each vehicle class (LD or MD and HD).

We derived charging load shapes from IEPR data, as described fully in Appendix A.5. In short, variation in EV charging across hours of the day is significant, and the load shapes are projected to evolve over time. However, the day-to-day variations were not significant.[73] The lack of day-to-day variation allowed us to use a single daily load shape for each vehicle class for each year. Figure 2-4 sets out two examples.

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[71] According to our April 21, 2023 email correspondence with the CEC's Advanced Electrification Analysis Branch, efficiency includes drivetrain efficiency, battery and charging losses. See Department of Energy Office of Energy Efficiency & Renewable Energy, *Where the Energy Goes: Electric Cars*, n.d. Available at: https://www.fueleconomy.gov/feg/atv-ev.shtml.

[72] Data provided by CEC on April 20, 2023. See Appendix A.4 (especially Table A-8) for additional details.

[73] Except that weekday charging is significantly greater than weekend charging in many hours. For that reason, we used weekday charging shapes.

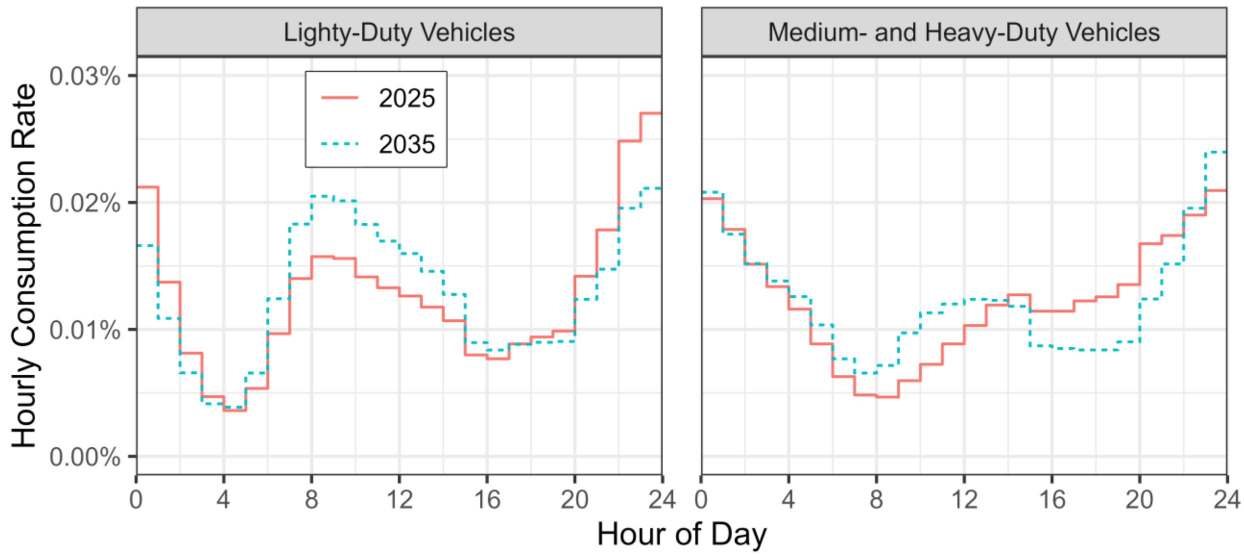

Figure 2-4. Selected load shapes for two example years – 2025 and 2035. The hourly consumption rate is the energy consumption in a given hour divided by the total annual consumption in that year.

The DGEM multiplied the hourly consumption rate by the annual energy consumption by vehicle class to yield the hourly energy consumption on each feeder. The DGEM carried out these calculations for each year of the study and each propensity scenario. Then, for each substation, we summed up the hourly load on each of the feeders connected to that substation to calculate the total hourly load per substation.

2.2.2 Historic demand and non-EV growth

Historic demand was used to establish the capacity available on distribution equipment and the baseline load to which future non-EV increases were applied. To establish the historic demand, we used a set of feeder loading data provided by the three IOUs for 2021 or 2022 (depending upon utility). These data provided 576 observations per year (24 hours per day times 12 months per year times two day-types: weekend and weekday) or more (depending upon the IOU). Because we used 24-hour charging load profiles, we captured 24-hour profiles of historical load composed of the highest loading in each hour of the year (e.g., the maximum loading from 1-2 p.m. on any day of the year).

Then, we subtracted our calculated 2021 charging demand to estimate a base-year non-EV demand. We turned this base-year estimate into a forecast by multiplying each observed peak by the cumulative intra-hour non-EV growth rate[74] between the base year and the forecast year, as

[74] For example, if demand at 5 p.m. were 10 megawatts (MW) and peak demand at 5 p.m. grew 2 percent from 2021 to 2022 and 3 percent from 2022 to 2023, our forecasted 2023 peak demand would be: 10 MW · (1.00+0.02) · (1.00+0.03) = 10.506 MW.

established in the 2021 and 2022 IEPRs.[75] In effect, this copied the growth rate of all non-EV loads and resources, which include rooftop solar, home battery storage, energy efficiency, and fuel switching (e.g., from natural gas to electricity), effects of population growth, cultivation, and other factors.

Penultimately, we summed non-EV load at each substation. Finally, we summed EV and non-EV load and extracted the maximum value for each year. This value represents the peak load on each piece of infrastructure, in each year, for each set of propensity scenarios.

2.3 Estimating upgrades and upgrade cost

The next methodological steps consisted of forecasting upgrades and their associated costs. We directly analyzed feeders and substations in the primary distribution system and estimated secondary distribution infrastructure costs as a percentage of primary distribution system costs.[76] We did not assess non-wires mitigations, which include changes to TOU rates that might obviate the need for upgrades, infrastructure such as DERs that may provide mitigations at a lower cost, and load transfers between feeders or substations.

Each IOU provided a set of infrastructure ratings for feeders and transformer banks. For PG&E and SDG&E, these ratings account only for thermal limits – they do not consider voltage stability, resiliency, operational flexibility, or other constraints. For SCE, the limits entailed planned loading limits, which include operational flexibility considerations. We combined the transformer bank ratings within each substation to calculate a total substation rating.[77]

To calculate overloads, we subtracted the power rating of each substation or feeder from its calculated peak load. Then, we calculated the number of units necessary to cure each overload. Each mitigation – a new feeder or a new substation bank – has a fixed capacity which was generally but not always sufficient to cure an overload. Multiple feeders or transformer banks were applied to cure overloads if a single unit was insufficient.

Finally, we calculated the cost of addressing overloads in each year. As with the propensity model, we used scenario analysis where there was uncertainty. For feeders, we modeled low-,

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[75] We used the 2021 IEPR for 2021 and 2022 data and the 2022 IEPR for data from 2023 forward. 2021 CED hourly mid-baseline scenario forecast for each IOU is available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2021-integrated-energy-policy-report/2021-1. (2021 CED). See also 2022 Hourly Forecast Planning Scenario forecast for each IOU (i.e., PG&E, SCE, and SDG&E). Available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update-2. (2022 CED).

[76] See Table A-12 in Appendix A.8. Our analysis does not account for the impacts of EVs and other load growth in BTM infrastructure.

[77] This is an optimistic simplification since load cannot necessarily be trivially transferred from one bank to another or split up across multiple banks as can be implied by this method. However, the opposite approach would be overly conservative since load can sometimes be cheaply transferred. The EIS took the same approach (see EIS at 118).

medium-, and high-cost scenarios based on three different feeder length and unit cost assumptions. For substations, we also modeled low-, medium- and high-cost scenarios with different transformer bank and substation costs and substation upgrade frequencies. For both feeders and substations, we included an additional Replicate scenario that used the cost estimates and assumptions from the EIS.[78] Furthermore, we used the contribution of secondary infrastructure costs to total costs in the Replicate scenario to forecast secondary costs in each scenario.[79] The highest and lowest costs used in the DGEM are shown in Table 2-3. Some factors were varied by IOU, which is not reflected in Table 2-3. For a more detailed breakdown of the cost estimate methods and scenarios, see Appendix A.8.

Table 2-3. Highest and lowest upgrade cost estimates. All costs in millions of dollars.

Scenario	Feeder length (miles)	Feeder cost	Transformer bank cost	Substation marginal cost	New substation frequency
Lowest cost	1.35	$2.9	$2.0	$15	6.4%
Highest cost	10.9	$32	$12	$38	42%

2.4 Rate Impact

For each IOU in each year of the analysis, we calculated the average residential rates with the increased load and costs associated with electrification and compared them to 2023 average residential rates. We accounted for the calculated increase in revenue requirements for the IOUs associated with distribution capital and maintenance expenses, plus forecasted transmission and generation costs, and weighed them against the forecasted increase in electricity volume. Then, we compared rates with this additional electrification to rates without it to determine the potential rate impact of electrification.

We assumed a marginal operations and maintenance (O&M) cost of 3.5 percent per year on the un-depreciated value of new capital. This was informed by data from the most recent general rate case applications of PG&E, SCE, and SDG&E.[80] Transmission costs are accounted for through the transmission access charge (TAC), which we projected rising to $20 per megawatt hour (MWh) in 2029 and exceeding $25/MWh in 2035.[81] Generation costs were derived from

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[78] EIS at 117.

[79] 45 percent, 40 percent, and 47 percent of the primary distribution costs in the Replicate scenario were used as secondary infrastructure costs for all scenarios for PG&E, SCE, and SDG&E, respectively. We used 2035 data and excluded the Baseline scenario. See EIS at 26-29.

[80] See Appendix A.9 for details and data sources.

[81] See The Public Advocates Office, C*omments on Draft Transmission Plan of the California Independent System Operator*, April 25, 2023 at Section 9, Table 1. Available at: https://stakeholdercenter.caiso.com/Comments/AllComments/3b5eb926-9bce-4c7f-806c-9ae156a4f9f3#org-b4bc96db-9bb3-478b-a339-41f5d6e8413c.

the 2022 avoided cost calculator (ACC),[82] including costs associated with generation energy, generation capacity, ancillary services, greenhouse gases, and high global warming potential gases.

Appendix A.9 elaborates on the methods for the rate impact study.

3 Results and Discussion

We estimated the costs to upgrade the distribution grids of the three largest electric IOUs in California to meet the state's forecasted EV deployment and other load growth through 2035 to be $26 billion.[83] Based upon the uncertainties quantified (see Section 4.2) we believe that the cost estimate could be as much as $18 billion lower or $31 billion higher. Sections 3.1 through 3.6 explore these results. We calculated this cost estimate based on forecasted EV deployment (Section 3.1) to growing energy demand (Section 3.2) and peak load growth (Section 3.3). Sections 3.4 and 3.5 describe the increasing utilization of utility assets and the quantity and rates of upgrades, respectively. Section 3.6 evaluates the total cost of upgrades.

The EIS preliminarily forecasted that $51 billion will be required to upgrade the IOUs' distribution grids through 2035.[84] The EIS and the DGEM differ in part because of disparate load shape assumptions, unit costs, and other inputs. Section 3.7 compares the two studies in detail.

Section 3.8 explores the rate impact of electrification, considering both the infrastructure investment and the increased volume of energy sales.

The number of upgrades and associated costs identified in the DGEM do not include non-wires mitigations. Non-wires mitigations include programmatic mitigations, such as changes to current time-of-use (TOU) rates that might obviate the need for upgrades entirely, and infrastructure such as DERs that may be able to provide mitigations at a lower cost than wires solutions. The inclusion of these types of mitigations may substantially reduce the cost of grid upgrades compared to what our model predicts.

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[82] See CPUC, *2022 Distributed Energy Resources Avoided Cost Calculator Documentation*, June 22, 2022 (*2022 Distributed Energy Resources Avoided Cost Calculator Documentation*). Available at: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/demand-side-management/acc-models-latest-version/2022-acc-documentation-v1a.pdf.

[83] This figure and all other cost figures in this report are in constant, present-day dollars.

[84] EIS at ES-26 to EIS-27. This value is the average total grid upgrade costs in Table 2 excluding Scenario 1.

3.1 Spatial distribution of EV adoption

We used a series of propensity models to predict the conversion of conventional vehicles to EVs up to the total annual EV population predicted by the 2022 IEPR.[85] For personal vehicles, our propensity regression model considers commonly used EV adoption predictors such as education level and income (see Appendix A.3.3.1). Figure 3-1 shows the predicted density of EV adoption.

[85] See 2022 CED, Hourly Demand Forecast Files, Planning Scenario.

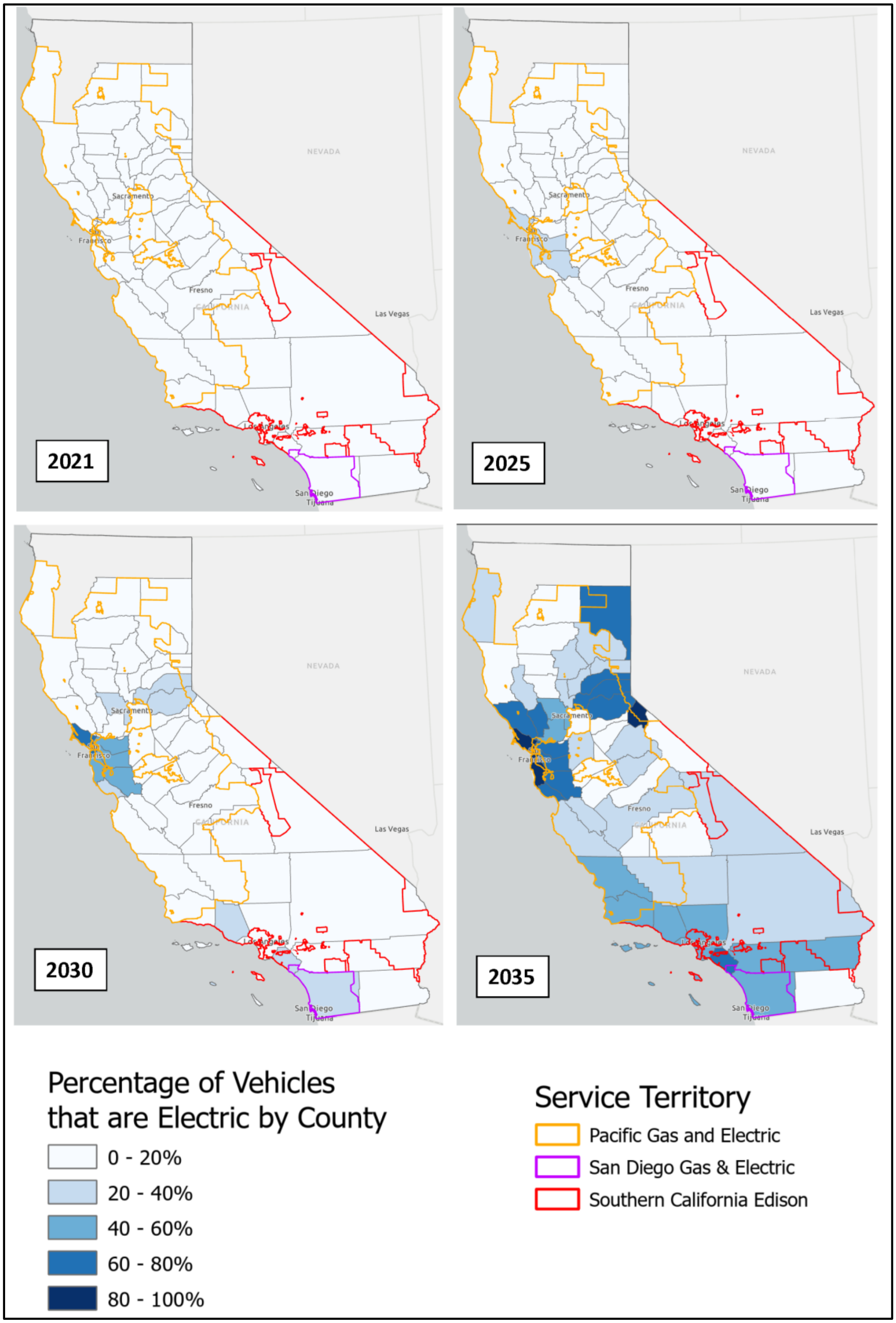

Figure 3-1. Predicted county-level density of personal EV adoption through 2035.

The propensity regression model for personal vehicles, as shown in Figure 3-1, results in a clustered distribution of EV uptake. At the county level, the share of EVs is heterogenous in all time periods. The highest levels of EV uptake are in San Francisco and the surrounding Bay Area, counties near El Dorado and Sacramento, and most of Southern California's coastal regions, notably Orange County. This is due to the higher education and income (the factors most predictive of EV adoption, see Appendix A.3.3.1) in these areas.

We note that some counties are largely served by other utilities, which can lead to inaccurate concentrations. For example, our model only considers 56 vehicles in Alpine County (north-east elbow in Figure 3-1, 80-100 percent EV adoption by 2035) and 606 in Lassen County (north-east corner in Figure 3-1, 60-80 percent EV adoption by 2035), so the high levels of EV adoption in these counties have little significance.[86]

The spatial distribution of EV adoption is important for several reasons. The rising EV sales increases the electric load on the local grid; therefore, counties with a high EV uptake are more likely to require grid upgrades. This is even more prevalent in higher density areas where EVs may be more common and infrastructure upgrades are more costly (e.g., San Francisco and the surrounding Bay Area).

In urban areas like San Francisco, our propensity regression model for personal vehicles predicts a high concentration of EVs in 2035. Figure 3-2 shows the concentration of EVs through 2035 in San Francisco census tracts. Across the county (which has the same border as the city), 80-100 percent of vehicles are expected to be electric by 2035.

[86] Lassen County is largely served by Lassen Municipal Utility District and Alpine County is largely served by Liberty Utilities.

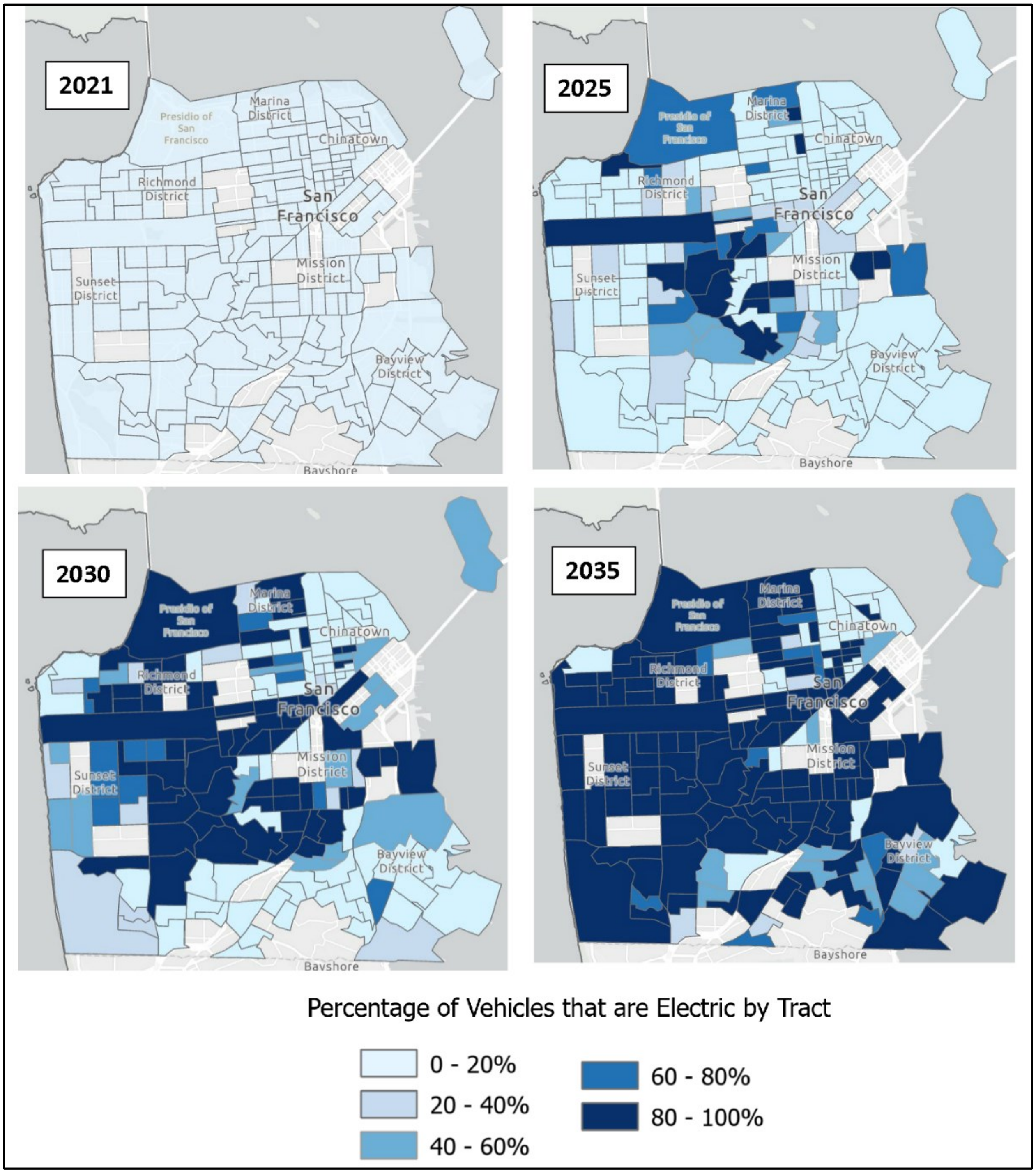

Figure 3-2. Predicted density of personal EV uptake within San Francisco County census tracts. Empty areas were omitted due to incomplete utility asset data.

The DGEM predicts that San Francisco will experience heterogeneous adoption in the early years – with the highest levels of heterogeneity in 2025 and tapering but continuing heterogeneity in 2030. By 2035, nearly all census tracts within SF are forecasted to experience high levels of EV adoption. According to PG&E, San Francisco is the highest cost area for grid infrastructure development.[87] Therefore, San Francisco could be responsible for a significant portion of the total cost of upgrades despite its famously small footprint (seven miles by seven miles).

We do not provide graphs of EV concentrations from other vehicle adoption models for two reasons. First, fleet vehicles are much fewer in number than LD vehicles and have a significantly lower impact on distribution grids than LD EVs. Second, the second propensity model for personal vehicles concentrates personal vehicles evenly across the DGEM Study Area, so this model's map would be uniform.

3.2 Annual energy demand due to EV adoption

Figure 3-3 depicts the demand on the electric grid due to LD (left) and MD and HD (right) charging, as predicted by the DGEM and the 2022 IEPR Planning Scenario. Since the DGEM draws from the IEPR Planning Scenario, the two demand forecasts closely align. Alignment with the IEPR is important because the IEPR is the basis for the State of California's energy planning.[88] All state government agencies and IOUs are required to consider the IEPR in their future asset and climate change response planning.

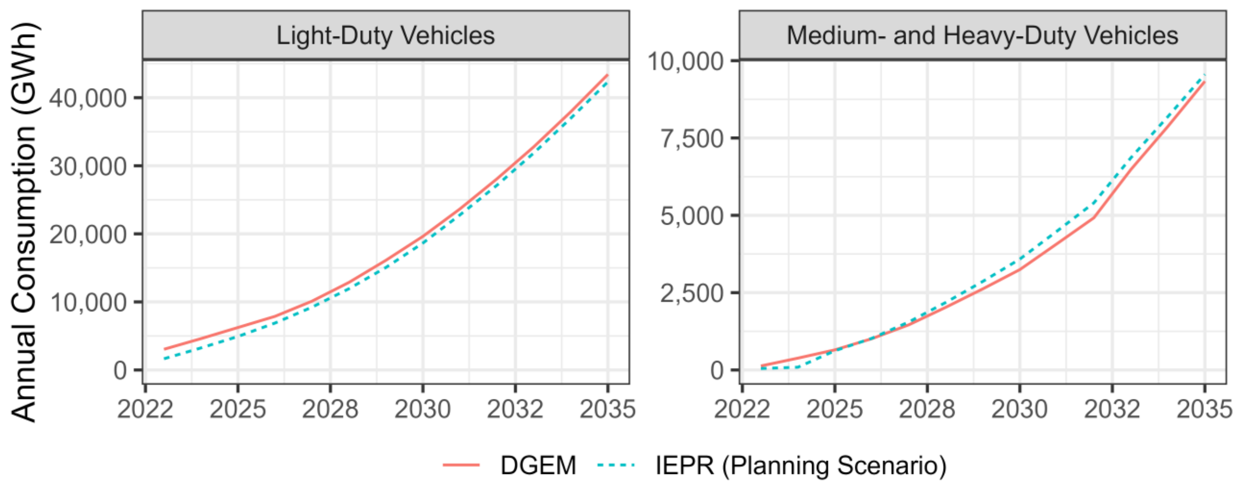

Figure 3-3. Comparison of demand forecasts between the DGEM and the IEPR.

[87] See *Pacific Gas and Electric Company 2023 General Rate Case Exhibit (PG&E-4) Electric Distribution Workpapers Supporting Prepared Testimony Chapters 14-23 Volume 2 of 2* (PG&E TY 2023 GRC Exhibit PG&E-4), June 30, 2021 at 165; issued in Application (A.) 21-06-021.

[88] It is California policy to use the IEPR as a "single forecast set" for all electric resource planning. See Pub. Res. Code § 25301(e). Specifically, the Integrated Resource Plan (IRP) uses hourly load profiles for demand-side modifiers, which include electric vehicle demand. See CPUC, *Draft Inputs & Assumptions – 2022-2023 Integrated Resource Planning (IRP)*, June 6, 2023 at 13. Accessed at: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2023-irp-cycle-events-and-materials/draft_2023_i_and_a.pdf.

The difference in consumption between the DGEM and the IEPR Planning Scenario may come from the percentage of statewide sales allocated to the three IOUs. Additional differences likely come from different quantities of vehicles in particular subclasses (e.g., the DGEM may deploy more LD sport utility vehicles [SUVs] and fewer LD sedans than the IEPR, or vice versa) and different average MD and HD EV energy consumption. The IEPR assesses energy demand by vehicle make and model, which is a more granular level than the DGEM. The DGEM assesses energy demand by vehicle subclass.

3.3 Peak demand growth

Our data show a nearly identical growth in combined peak demand to the IEPR. Table 3-1 shows that the rate of peak load growth across the IOUs' territories remains within three percent between the IEPR and the DGEM. The DGEM predicts two percent slower growth for PG&E, three percent faster growth for SCE, and two percent faster growth for SDG&E. The growth rate differences are caused by the modestly higher deployments of EVs in SCE's and SDG&E's territories in the average case and correspondingly lower deployments in PG&E's service territory (see Appendix B).

Table 3-1. 2021 to 2035 peak demand growth rate comparison.

Model	PG&E	SCE	SDG&E	Total
DGEM	17%	14%	23%	16%
IEPR[89]	19%	11%	21%	15%

3.4 Increased infrastructure utilization and overloads

Systemwide increases in peak load will lead to increasing peak loads on individual infrastructure, such as feeders and substations. Distribution grid infrastructure as it exists today may require upgrades due to the increasing electrification of transportation and buildings and growth in other sectors of the economy.

The peak utilization factor, which is the ratio of the peak loading of a piece of infrastructure to its capacity, describes how close a piece of infrastructure (i.e., a feeder or a substation) is to overload. For example, a feeder with a rating of 10 MW and a peak load of 8.7 MW would have an 87 percent peak utilization factor. We expand this concept to the entire set of assets within

[89] Demand for 2021 was drawn from the CEC, *California Energy Demand Forecast, 2021-2035*, high-baseline scenario files for the three IOUs under the Hourly Demand Forecast Files. Available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2021-integrated-energy-policy-report/2021-1. The demand for 2035 was drawn from the CEC, *California Energy Demand Update, 2022-2035,* the Planning Scenario files for each of the three IOUs under the Hourly Demand Forecast Files. Available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update-2.

each IOUs' service territory. To do so, we sum up non-coincident peak loads and divide by the sum of ratings:

$$Peak\ Utilization\ Factor = \frac{Peak\ Load_1 + Peak\ Load_2 + Peak\ Load_3 + \ldots + Peak\ Load_n}{Rating_1 + Rating_2 + Rating_3 + \ldots + Rating_n}$$

Figure 3-4 shows the resulting forecasted peak utilization factors for the IOUs, without any further upgrades or mitigations.

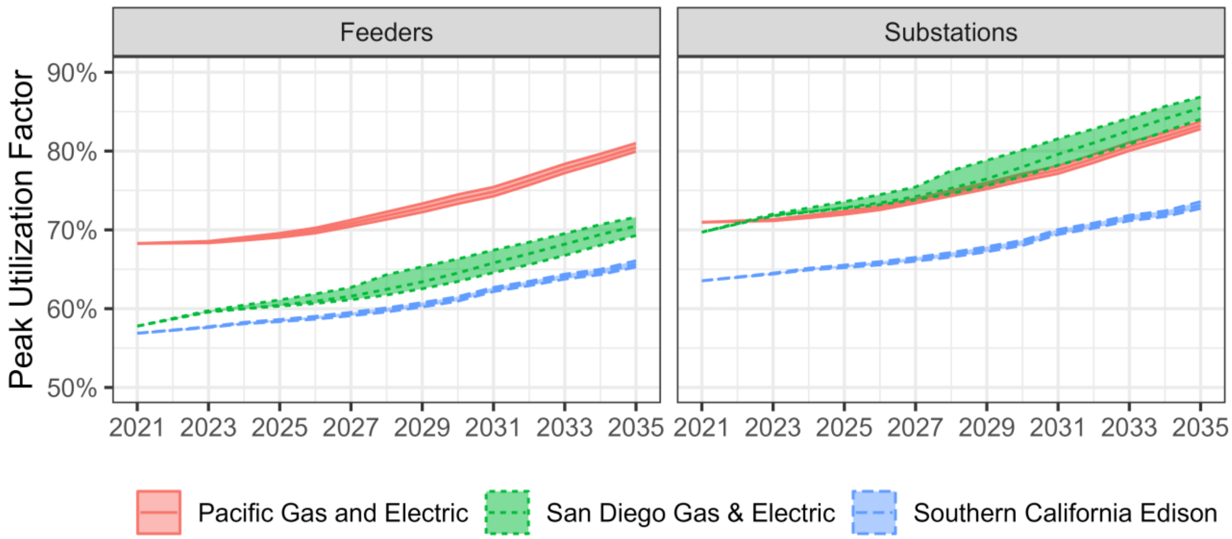

Figure 3-4. The peak utilization factor increases at nearly the same rate for three IOUs. Lines show median, maximum, and minimum peak utilization factors across scenarios.

Peak utilization factors grow at approximately the same rate across the three IOUs. SCE has an approximately ten percent lower utilization than PG&E across the study period for both feeders and substations. SDG&E has a similar feeder utilization factor to SCE and a similar substation utilization factor to PG&E.

Increasing peak utilization drives infrastructure exceedances. While the average piece of infrastructure in each IOU's service territory does not require an upgrade, differences in utilization lead to the overutilization of some assets. Overutilization necessitates infrastructure upgrades (in our model, but other mitigations can be applied in practice). Figure 3-5 projects the share of infrastructure that will experience overutilization, without upgrades or other mitigations, in each IOU's service territory in future years.

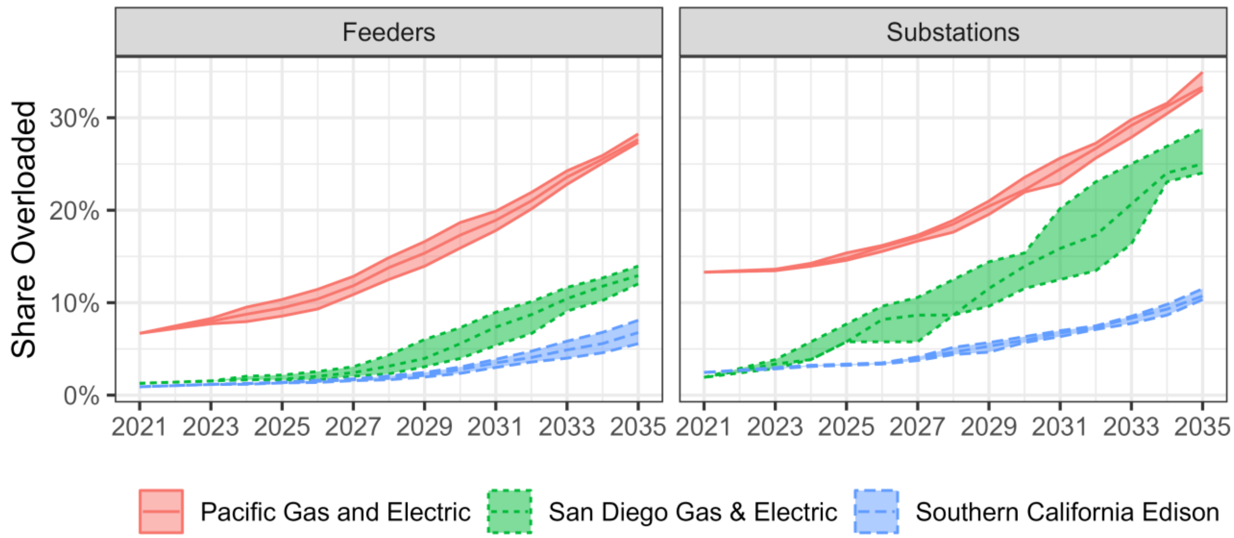

Figure 3-5. Share of overloaded feeders and substations as a percentage of the total number of feeders and substations in each IOU's service territory. Lines show median, maximum, and minimum share of overloaded infrastructure across scenarios.

PG&E has the largest share of overloads across the study period for both feeders and substations. SDG&E and SCE have significantly lower shares of overloaded feeders, about seven percent lower in 2021 and 15 – 20 percent lower in 2035. SDG&E and SCE both have low rates of substation overloads in 2021, but SDG&E's overload rate climbs the fastest. SDG&E's overload rate approaches PG&E's overload rate toward the end of the study period. SCE's rate of substation overloads remains small, one-half to one-third of the other IOUs in 2035.

Our result for PG&E indicates that there were many capacity exceedances in its service territory in 2021. The relatively high share of exceedances is partially due to real infrastructure insufficiencies and partially due to data issues (see Appendix A.1.4). Nevertheless, PG&E's infrastructure is more affected by TE and other types of electrification and shows more overloads than the other IOUs.

3.5 The pace of primary distribution upgrades

As shown in Table 3-2, the forecasted pace of primary distribution upgrades is significant. The pace accelerates toward the latter third of the study period (i.e., the average upgrade rate between 2030 and 2035 is always above the average for the entire period). The upgrade rate for PG&E is approximately twice that for SCE, and the rate for SCE is approximately twice that for SDG&E. Since the service territories of PG&E and SCE are approximately four-and-a-half times the size of the service territory of SDG&E,[90] the share of infrastructure requiring upgrades each year will be similar for PG&E and SDG&E while SCE's rate is about half.

Table 3-2. Median forecasted annual rate of upgrades for each IOU and facility type. Ranges for planned investments show only new distribution feeders at the low end and include reconductoring and other potentially smaller feeder projects at the high end.

Facility Type	IOU	Forecasted Annual Upgrades		Historic Pace[91]		
		2023 - 2035	2030 - 2035	2020	2021	2022
Feeders	PG&E	46	58	18 - 68	21 - 49	40 - 90
Feeders	SCE	19	32	22 - 49	15 - 36	15 - 56
Feeders	SDG&E	7	12	2 - 7	4 - 15	1 - 10
Substations	PG&E	10	13	1	4	13
Substations	SCE	5	7	9	6	8
Substations	SDG&E	2	2	1	0	0

Table 3-2 also provides historical data for comparison based upon planned investments in the IOUs' 2022 distribution deferral opportunity reports (DDORs). With this context, the results are not alarming: future rates tend to be close to present rates. If only new feeders are included in historic data (the lower numbers in Table 3-2), the average number of forecasted future annual feeder upgrades is higher than the peak of the historic pace for PG&E and SDG&E: 15 percent and 75 percent, respectively; however, if all DDOR projects are included, the forecasted annual feeder upgrades are lower than the maximum historic pace for all IOUs. For substations, the future pace is similar to the historic pace for PG&E and SCE, and higher (twice the recent historic peak) for SDG&E.

These data come with several caveats. First, we compared forecasts of needed infrastructure upgrades to planned investments. Planned investments receive much more scrutiny than our forecasted upgrades. Second, we did not explicitly consider the *scope* of upgrades. It is possible that future feeder or substation upgrades will tend to be larger in size than past upgrades, such that while the number of projects remains similar, the labor force required to implement them could substantially grow.[92]

3.5.1 In comparison to Elmallah et al.

We found that PG&E will require 46 new feeders annually and ten new substations annually between 2022 to 2035 (see Table 3-2). Elmallah et al. found that, with vehicle electrification, PG&E would need to annually upgrade 95 to 260 feeders and two to five substations through

[90] Based upon 2019 retail electricity sales data, available in map metadata: CEC, *Electric Load Serving Entities*.

[91] See Appendix C for data sources.

[92] Elmallah et al. at 19.

2030.[93] Our annual feeder upgrade estimates are about one-fifth to one-half the upgrade estimates that Elmallah et al. anticipated, while our substation upgrade estimates are two to five times higher. The former difference may partially or fully be because Elmallah et al. analyzed various sections of each feeder while the DGEM assessed only the feeder head. That is to say that we compared load to the maximum feeder capacity while Elmallah et al. compared load to the capacity of each feeder section. Elmallah et al. suggest that their methods lead to underestimation of substation upgrades because they "sum bank capacity to evaluate total substation capacity"[94]; however, this does not explain the difference between our two studies because we apply the same simplifying assumption. Rather, the difference may come from the way that Elmallah et al. aggregate load from feeders to substations, or other factors.

3.6 Cost of infrastructure upgrades

This section delineates the feeder, substation, and secondary infrastructure upgrades that may be needed to cure the modeled deficiencies in grid capacity. Feeder and substation upgrades may not be the only solution to meeting the load growth due to increased electrification (a high electrification future). Rate structures that favor off-peak energy consumption and the integration of DERs into the grid could delay or obviate the need for infrastructure investments and reduce the costs of necessary upgrades.[95] Other infrastructure solutions like load transfers and DERs could also mitigate some of the infrastructure needs. These alternative approaches are not considered in the DGEM.

One of the primary points of uncertainty in the DGEM is the cost of the upgrades that could be expected to be undertaken whenever grid capacity is deficient (see Section 4). The cost of upgrades will depend on many factors, including which IOU is responsible for the upgrade, what length of feeder needs replacement, whether the feeder will be new or reconductored, and whether a transformer bank or substation will need to be added or upgraded. Determining how to solve each forecasted asset overload requires an engineering evaluation, which is impractical for a forecast over an entire IOU service territory. To attempt to cover the uncertainty in the costs of upgrades, we used several cost scenarios for substation and feeder replacements to generate an array of possible outcomes. Appendix A.8 elaborates on the cost scenarios.

Because of uncertainty in cost estimates (see Table 2-3 for a brief review and Appendix A.8 for more thorough discussion), especially for feeders, our maximum and minimum cost estimates are quite far from our central estimate (200 percent and 40 percent, respectively). These upper and

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[93] Elmallah et al. at 13-14.

[94] Elmallah et al. at 14.

[95] See Elmallah et al.; M. Kintner-Meyer et al., *Electric Vehicles at Scale - Phase II - Distribution Systems Analysis*, Pacific Northwest National Laboratory (PNNL), September 21, 2022 at 25. Available at: https://www.pnnl.gov/publications/electric-vehicles-scale-phase-ii-distribution-systems-analysis.

lower bounds should not be viewed as projections themselves but as bounding the uncertainty in the central estimate.

The range of unit cost scenarios allowed us to see the array of possible total costs of grid infrastructure upgrades needed to meet increased load from vehicle electrification and non-EV load sources. This strategy also reinforces the uncertainty of these cost estimates, which underscores the fact that no single forecast can account for all possibilities and nuances in future load growth. Figure 3-6 shows the average cumulative upgrade costs forecasted and a range of one standard deviation. We include primary and secondary costs. The figure also includes a black line, which represents the Replicate scenario.[96] As with total upgrade needs, PG&E is predicted to require the most infrastructure investments.

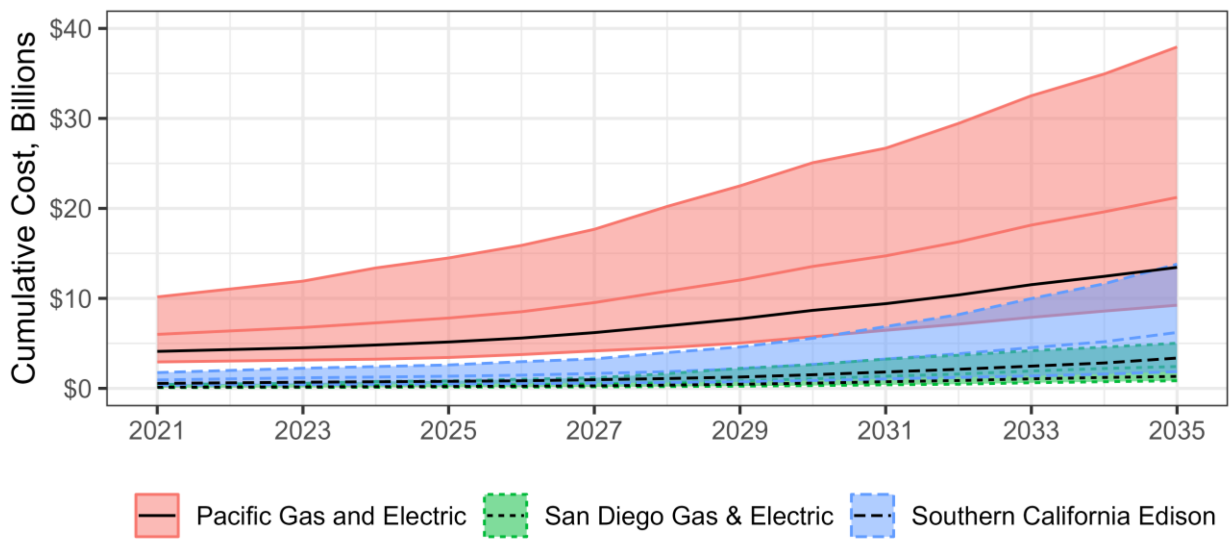

Figure 3-6. Total cost including primary and secondary distribution upgrades forecasted for each utility. Bands show the maximum and minimum values across scenarios and the black lines depict the Replicate scenario.

Table 3-3 shows the DGEM's central cost estimates for each IOU along with the uncertainty range. Maximum cost estimates are drawn from the scenario with the maximum cost and include costs of upgrades identified by the DGEM as being needed in 2021, while minimum estimates are drawn from the scenario with the minimum cost and exclude costs of upgrades identified by the DGEM in 2021.

[96] The Replicate scenario used the same unit costs and substation upgrade frequency as the EIS. This scenario evaluated how factors *other than* unit cost led to differences between the DGEM and the EIS (see Section 3.7).

Table 3-3. Central cost estimates for 2035 in billions with upper and lower uncertainty (i.e., our lowest estimate for PG&E is $6.3 billion – which is the result of $18.2 minus $11.9 billion). The central scenario is the mean of all cost estimates and includes half of possible 2021 costs. These costs include both primary and secondary distribution costs.

Cost Estimate	PG&E	SCE	SDG&E	Total
Central estimate	$18.2	$5.7	$2.3	**$26.3**
Upper uncertainty	$19.7	$8.1	$2.7	$30.5
Lower uncertainty	-$11.9	-$4.2	-$1.5	-$17.7

It is unclear whether 2021 modeled costs are due to real causes (versus data issues), and whether they are due to electrification in particular (see Appendix A.1.4). Therefore, the central estimate ($26.3 billion total) depicts the mean 2035 costs less half of the 2021 costs. We included half of the 2021 modeled costs in our central estimate because this gives the best central representation of the uncertain result.

3.6.1 Comparison to the preliminary results

We published two documents with preliminary results in June 2023.[97] In these reports, we estimated the cost of distribution grid upgrades to be $15 to $20 billion, including the cost of secondary distribution infrastructure. Our cost estimates are now higher, with a total central estimate of $26.3 billion.

These differences from the preliminary results are primarily due to the inclusion of higher unit costs for feeders based on research conducted during the intervening months; the preliminary results used unit costs for feeders from the EIS based in most cases on two miles of feeder having to be upgraded for each instance of an overload. We now use four estimates: 1.35 miles, 9.5 miles, and 10.9 miles based upon various empirical data provided by the IOUs and two miles based on the EIS's assumptions (see Appendix A.8 for additional data and discussion). This results in an average length estimate of 5.9 miles. The variation of these cost estimates is significant and a major driver in uncertainty in our result as discussed in Sections 4.2 and 4.5.

Secondary differences stem from updated assumptions of the frequency that new substations are needed, based on data from the EIS, and the per-foot cost of feeders. We previously assumed that new substations would be needed zero percent to 25 percent of the time; now, following the EIS, we assume new substations are needed up to 42 percent of the time for PG&E. We

[97] The Public Advocates Office, *Cal Advocates' Distribution Grid Electrification Model (DGEM) – Preliminary Results*, June 2, 2023. Available at: https://www.publicadvocates.cpuc.ca.gov/press-room/reports-and-analyses/distribution-grid-electrification-model-preliminary-results. The Public Advocates Office, *Public Advocates Office Study on the Costs of Upgrading the Distribution Grid for Electrification*, June 14, 2023. Available at: https://www.publicadvocates.cpuc.ca.gov/-/media/cal-advocates-website/files/reports/230614-cal-advocates-distribution-grid-impacts-study-fact-sheet.pdf.

previously used the EIS's estimate for the per-foot cost of feeders; we now explore a variety of scenarios) as described in Appendix A.8).

The Replicate scenario, which retains cost data from the EIS, remains closer in its cost estimate to our preliminary results (see Section 3.7). The differences in this scenario from the preliminary results are due to substation upgrade frequency and other minor updates to the DGEM.

3.7 The DGEM vis-à-vis the EIS

This section provides a comparison between the DGEM and the EIS. We begin with a comparison of the bottom-line costs before diving into the source of the differences between the studies, which we attribute to charging load shape. As an initial point, the EIS is intended to evaluate "unmitigated" scenarios,[98] which are not necessarily the same as what our charging load shapes (from the IEPR) evaluate.[99] To the best of our understanding, the EIS assumes lower participation in EV-TOU rates than the IEPR does. EV-TOU rates have low-price periods later in the day with the intent of encouraging different charging behavior. This is discussed in more detail below.

Since the DGEM has a wide variation in unit cost assumptions, we included a cost scenario (Replicate) that exclusively uses the unit cost data from the EIS to make a more straightforward comparison possible.[100] The total predicted cost for 2035 – including primary and secondary upgrades for all IOUs using the EIS's cost data – is $15.7 billion,[101] which is just over 30 percent of the EIS's preliminary estimate of $51 billion.

Table 3-4. Cost estimates for the Replicate scenario. Costs shown are less half 2021 costs.

IOU	Total Cost (Billions)		
	2025	2030	2035
PG&E	$3.1	$6.6	$11.4
SCE	$0.5	$1.2	$3.1
SDG&E	$0.1	$0.5	$1.3
Total	$3.8	$8.4	**$15.7**

[98] See EIS ES-1 to ES-2:

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 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.

[99] Though the EIS does not provide a totally clear definition of "unmitigated."

[100] EIS at 117.

[101] As with our central estimate, this cost includes half of 2021 costs.

Figure 3-7 provides a visual representation of the 2035 costs in Table 3-4 split into primary and secondary infrastructure. Distribution system upgrade cost estimates in the EIS are higher in all regions. The most drastic difference is in SCE's service territory.

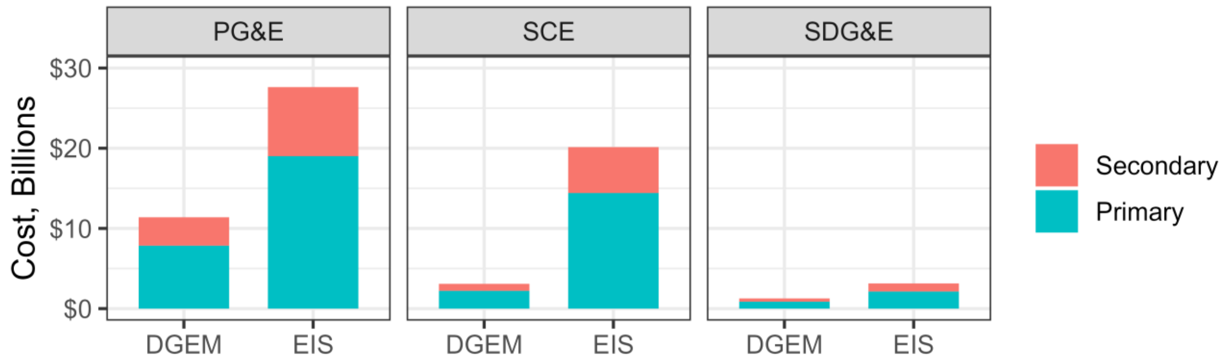

Figure 3-7. Cost comparison between the DGEM (using the Replicate scenario) and EIS in 2035. Infrastructure costs are split between primary and secondary. Costs shown are less half 2021 costs.

Because the total costs for the DGEM (Replicate scenario) and the EIS, as shown in Figure 3-7, use identical unit costs, differences are due to other factors. We found that the key cause of differing total costs (excluding unit costs) is differing rates of peak load growth between the two studies. The DGEM draws its peak load growth from the IEPR (in some cases indirectly[102]). By comparison, the EIS's peak load growth, which is largely due to EV charging,[103] is the result of its assumptions around when EVs are charged, which do not align with the IEPR (this is discussed below). Figure 3-8 depicts the difference in peak load growth rate.

[102] For example, we did not copy the peak load contribution of EVs from the IEPR, but since we use the same number of vehicles, energy consumption assumptions, and charging assumptions, our peak load contribution is nearly identical. (See Section 3.3.)

[103] EIS at ES-7.

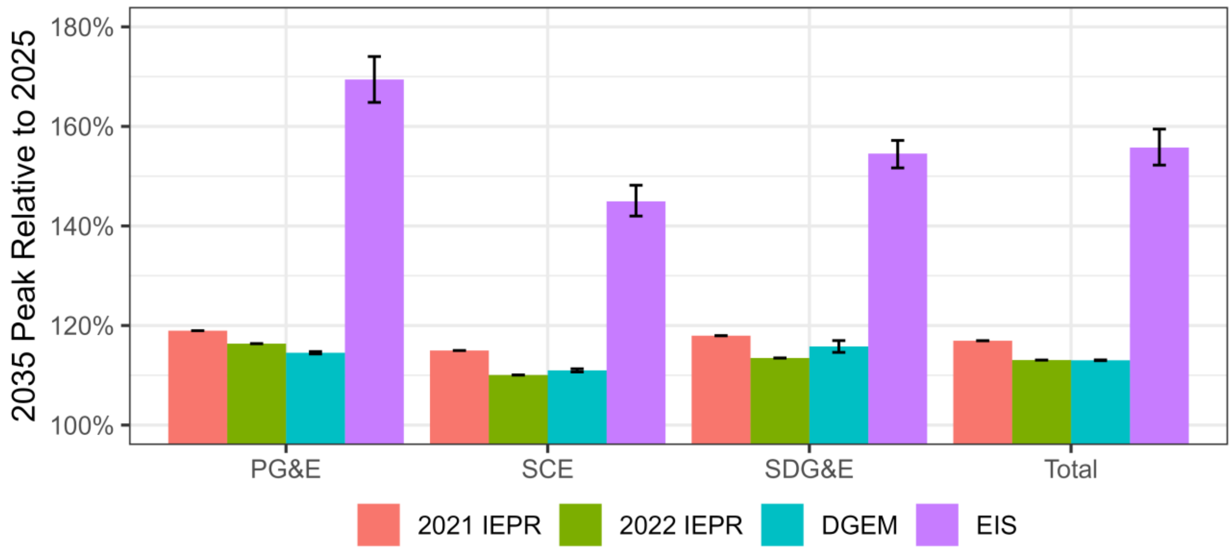

Figure 3-8. Comparison of peak load growth. I-bars show variation across scenarios (we removed the EIS's baseline scenario from this comparison). The DGEM closely aligns with the IEPR, as intended.

The peak load increase in the EIS study appears to be largely or entirely driven by a significant amount of charging starting at 9 p.m. In the EIS, this charging assumption was enough to shift the peak load hour of all IOUs to 9 p.m. in 2035.[104] In addition to the shape of the profile, another important factor in the differences between peak load for the IEPR and the EIS is that the total energy consumed during the peak day is 43 percent higher in the EIS than in the 2022 IEPR. This could be caused by differing assumptions around energy consumption per mile driven, miles driven per year, or day-to-day variance in charging patterns.

[104] EIS at 159.

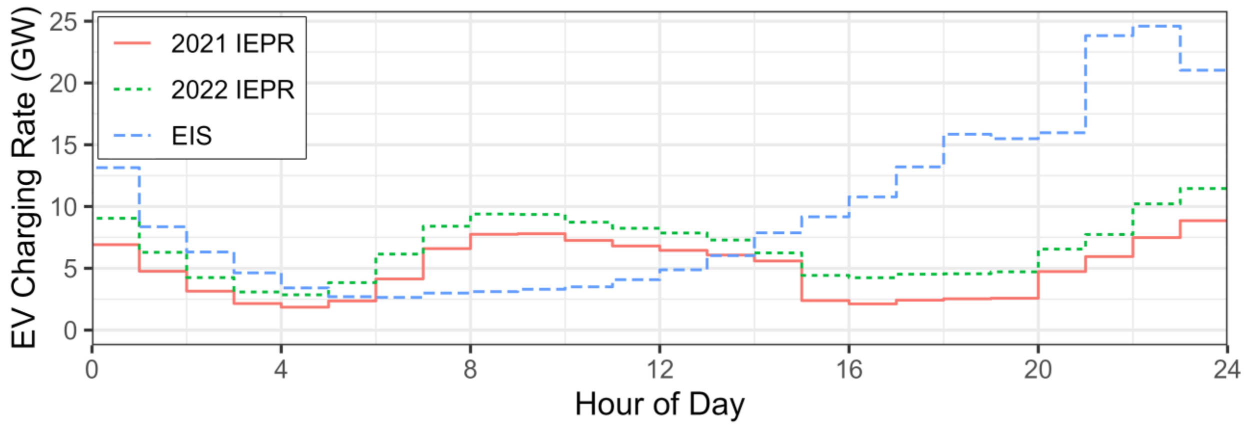

Figure 3-9. Hourly peak-day charging demand from the EIS and two IEPR vintages. Sources: 2021 and 2022 IEPR data, the EIS (digitized).[105]

In summary, the differences in total cost estimates between the DGEM (in the Replicate scenario) and the EIS are primarily due to differences in assumptions regarding when EVs will charge. This finding has several noteworthy implications. First, the TOU rates already included in the IEPR can reduce the cost of grid upgrades by about two-thirds (i.e., from the EIS's result to the DGEM's Replicate result). Second, despite significant differences in methods between the DGEM and the EIS, the two studies achieve similar results, which suggests that both models are reasonable representations of reality, at least within a factor of about two.

The other significant difference between the DGEM in general (not the Replicate scenario) and the EIS is the unit cost assumptions. The differences in total costs between our central estimate and the Replicate scenario summarize the aggregate unit cost differences between the EIS and the DGEM's central estimate: Our unit costs for PG&E are 44 percent higher, our unit costs for SCE are 56 percent higher, and our unit costs for SDG&E are 49 percent higher.

3.8 Residential rate impacts

Both the absolute magnitude of forecasted distribution upgrades and the uncertainty in upgrade costs are significant. Without context, however, it is difficult to understand the burdens that these upgrades will place on ratepayers. Calculating the electric rate impact for residential customers can put this into perspective: How much upward pressure on rates (in $/kWh) might infrastructure upgrades apply?[106] How much downward pressure on rates might the increase in

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[105] 2021 IEPR data from 2021 CED, Hourly Demand Forecast Files, High Baseline Scenario; 2022 IEPR data from 2022 CED, Hourly Demand Forecast Files, Planning Scenario; EIS data provided by Energy Division Staff and Kevala as an informal response to the June 12, 2023 email *R2106017 EIS Ruling Data Request*, Question 5. See also *Administrative Law Judge's Ruling Setting Deadline to Receive Data Requests on Electrification Study*, June 9, 2023; issued in R.21-06-017.

[106] Distribution feeders and substations are paid for through electric rates at present; we assume this structure continues without endorsing it.

energy sales apply (because increasing load spreads infrastructure investment across more electricity units)? Will the net effect of electrification be upward or downward pressure on rates?[107]

Figure 3-10 shows forecasted impacts to the average residential consumer cost of electricity for the IOUs (in present-day dollars). This rate impact is the difference between 2023 electricity rates and the rates that would be achieved with the electrification impacts modeled in this report with no other changes to utility costs and revenues. The DGEM predicts downward pressure on electric rates for all IOUs in the central case. The downward pressure is greatest for SDG&E, and less for SCE and PG&E.

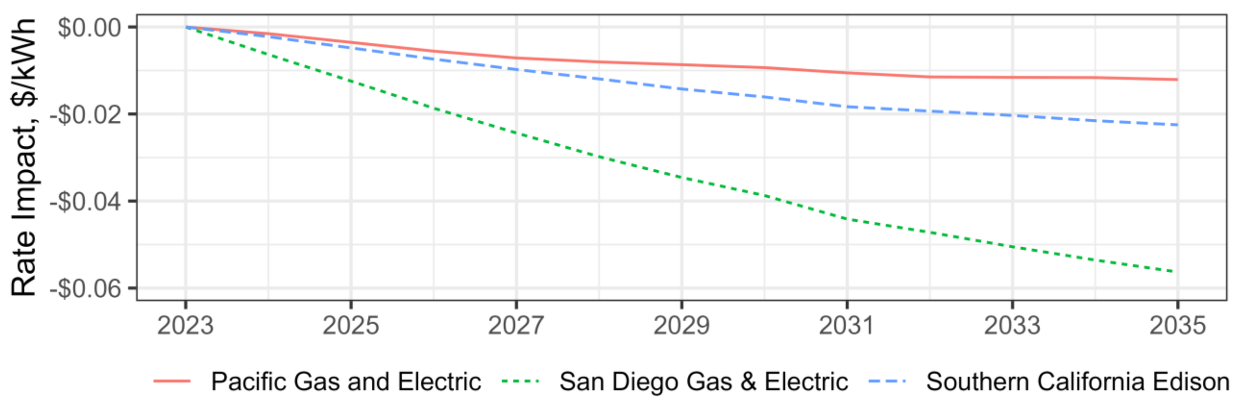

Figure 3-10. Project rate impact of electrification using our central cost estimate.

Rate impact helps to put the infrastructure costs in perspective. In our central cost estimate, upward pressure on rates due to infrastructure costs is more than offset by downward pressure on rates due to the increased consumption of electricity resulting from electrification. More importantly, a reduction in electricity rates means that customers who cannot (or choose not to) electrify need not be negatively impacted by electrification. Ultimately, because Figure 3-10 depicts impacts to the average residential electric rates, the specifics of rate design will determine the impact to non-electrifying customers. For example, if EV owners are allowed to select a rate that does not recover the marginal cost to provide electricity, electricity rates for other customers could still rise.

There is one important limitation that applies to SCE only: We did not assess sub-transmission costs. This means that the rate impact for SCE is somewhat understated; however, since we expect SCE to make well under half of PG&E's forecasted distribution investment needs, we expect SCE's downward rate pressure to be at least equal to PG&E's, even if sub-transmission costs equal distribution costs.

[107] This is a different question from 'will rates go up or down?' Other utility costs could drive rates up in net even if electrification applies downward pressure on rates.

Next, we explore the variation in rate impacts across our model scenarios. Scenarios with lower unit costs of feeders and substations lead to larger rate decreases, as shown in Table 3-5. PG&E experiences just over one cent per kWh in upward rate pressure in the highest cost scenario and nearly three cents per kWh of downward pressure in the lowest cost scenario. SCE experiences almost zero downward pressure in the high-cost scenario and three cents per kWh of downward pressure in the low-cost scenario. SDG&E experiences the most downward pressure, nearly three cents per kWh in the high-cost scenario and almost seven cents per kWh in the low-cost scenario.

Table 3-5. Rate impacts across cost scenarios. Rate impacts are shown in $/kWh.

IOU	High cost	Central	Low cost
PG&E	$0.013	-$0.012	-$0.028
SCE	-$0.006	-$0.022	-$0.030
SDG&E	-$0.026	-$0.056	-$0.069

Furthermore, these data show that even with the relatively high uncertainty in total grid upgrade costs based upon available data, there is an unambiguous forecast of downward pressure on rates provided by electrification for SDG&E and SCE—under the assumptions of the DGEM (see Section 4 for a discussion of key assumptions). For PG&E, there is a small chance of upward rate pressure but only with the least optimistic infrastructure unit costs (i.e., if infrastructure turns out to be very expensive). The unit costs we used are relatively high – higher than those used in the EIS – and relatively unlikely to underestimate cost. Therefore, there will likely be a small downward pressure on residential rates for PG&E's customers.

These data are, therefore, consistent with a vision of affordable electrification. Climate change mitigation need not raise costs for all consumers, and falling electricity rates may help to spur additional electrification. However, one should not conclude that the analysis presented herein guarantees declining electricity rates, even for SDG&E. Other factors, such as wildfire mitigation, can drive rates up in net. Moreover, appropriate policies are needed to ensure that the possible rate decreases are realized in customers' rates.

We have not attempted to calculate the overall bill impact for typical customers that our results might represent. In the context of electrification, estimating the electricity bill impact in isolation for a household can be misleading without understanding how total home energy costs might change. To take a simple example, a household that converts from a gasoline vehicle to an EV would expect additional electricity costs due to adding the EV charging load, but correspondingly lower gas costs by not having to regularly fill the tank of a conventional car. An estimate of the changes in total household energy costs is beyond the scope of this report.

4 Assumptions and Limitations

California's electric distribution grids include thousands of distribution feeders spanning hundreds of thousands of miles, thousands of distribution substations, over a million service transformers, and countless capacitors, sectionalization devices, fuses, and other pieces of distribution infrastructure.[108] The DGEM accounts for the addition of eleven million electric vehicles, each of which may have a unique spatial and temporal charging profile over the course of the 8,760 hours in a year. Modeling such a vast and complicated system – to say nothing of forecasting twelve years into the future – necessitates many simplifying assumptions to make the problem tractable—from the perspectives of computation and comprehension. These simplifying assumptions lead to limitations. We begin by describing the most important assumptions in Section 4.1. Next, we provide in Section 4.2 a quantitative analysis of those factors for which we have been able to reasonably bound the range. Finally, we qualitatively discuss further limitations on the scope and accuracy of the model in Sections 4.3 through 4.5.

Future work, whether by The Public Advocates Office or others, could seek to provide greater certainty and reduce the need to use assumptions of the sorts described here. Section 5.5 discusses some of these further research needs.

4.1 Major assumptions of the DGEM

The four most important assumptions of the DGEM model are the time of vehicle charging, the number of vehicles deployed, the types of grid mitigations used, and assessment of overloads at the feeder level.

4.1.1 EVs charge at midday and overnight

The time at which EVs charge is critical to the resulting grid impacts. As discussed in Section 3.7, on-peak charging could double our cost estimates. The DGEM's charging load shape, illustrated in Figure 2-4 of Section 2.2.1, is drawn from the IEPR, which is based upon empirical charging data and existing rates and policies. The IEPR's charging load shape predicts significant amounts of midday and overnight charging.

More managed charging provides opportunities for reducing infrastructure investments and electric rates.[109] Unmanaged charging – i.e., charging taking place during peak load hours, as in

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[108] See EIS at 115; PG&E, *Company Profile*, n.d. Available at: https://www.pge.com/en_US/about-pge/company-information/profile/profile.page; SCE, *Powering Southern California for 130+ Years*, n.d. Available at: https://www.sce.com/about-us/who-we-are; and SDG&E, *CPUC Rule 20 Programs: Overhead-to-Underground Conversion of Electric Power Lines*, n.d. Available at: https://www.sdge.com/major-projects/Rule20Undergrounding.

[109] See: Zhuk et al., *The Impact of Electric Vehicles on the Outlook of Future Energy System*, IOP Conference Series: Materials Science and Engineering, February 2018. Available at: https://doi.org/10.1088/1757-899X/315/1/012032.

the EIS – could drive investment and rates higher than forecasted by the DGEM. We do not consider alternative charging profiles at this time.

4.1.2 California will deploy 15.5 million EVs through 2035

The DGEM relies on the EV deployment forecasts for the state of California underlying the 2022 IEPR Planning Scenario (see Appendix A.3.1). The 2022 IEPR Planning Scenario's forecasts are based upon policy compliance, including compliance with the Advanced Clean Cars II and Advanced Clean Fleets regulations.[110] The DGEM treats vehicle deployment as exogenous and does not consider what might happen if the forecasts go unmet or are exceeded.

4.1.3 No alternative mitigations are used

The DGEM always applied wires solutions—new feeders, transformer banks, and substations. The DGEM does not assess alternative mitigations such as DERs or load transfers that may provide mitigations at a lower cost in some cases.

4.1.4 Overloads at the feeder are a good proxy for all overloads

The DGEM only assesses loads at the feeder head (i.e., near the substation, where all load has developed). This is similar to the methods of prior studies.[111] It is possible that there are overloads at distant feeder segments with small conductors. We assume that this situation is rare and relatively cheap to solve.

4.2 Sources of uncertainty quantified in the DGEM

Distribution upgrade costs are uncertain due to many factors. We have attempted to quantify the impacts of four factors impacting uncertainty: personal EV adoption trends, fleet EV adoption trends, feeder costs, and substation costs. We developed multiple EV adoption scenarios to bound the possibilities of spatial dispersion and the number of distribution assets that would exceed capacity. We also developed a series of infrastructure cost scenarios to evaluate the impact of differing assumptions on the total upgrade cost estimates and rate impact estimates (see Appendix A.8).

Figure 4-1 shows that the uncertainty in total cost (among quantified factors) is primarily a result of feeder cost uncertainty; better data on feeder costs are needed to improve future analysis on how these assets influence the total infrastructure upgrade costs. Accurate modeling of feeder upgrades and upgrade costs is fundamental to pinpointing the total infrastructure costs relating to electrification. Substation cost uncertainty is important but small relative to feeder cost

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[110] CEC, *2022 Integrated Energy Policy Report Update*, May 10, 2023 at 48-49. Available at: https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update.

[111] For example, see EIS at 118: "Kevala calculated the coincident peak at each of the 8,256 feeders and compared it to the feeder rating to determine the overload."

uncertainty. Better fleet and personal vehicle modeling may not be a dominant factor in cost uncertainty.

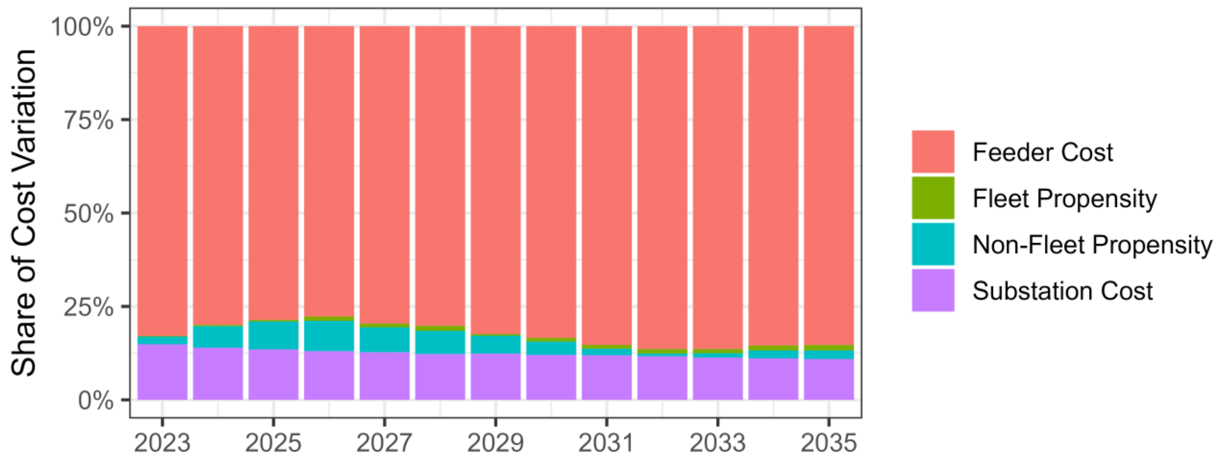

Figure 4-1. Analysis of model variation over the study period.

The DGEM scenarios for feeder upgrades included four different unit costs varying from $1,000,000 per mile to $2,800,000 per mile and four different lengths of feeder from 1.35 miles to 10.9 miles. This wide variation in unit costs and feeder lengths – based upon empirical data provided by the IOUs – contributes to the large share of total model variation shown in Figure 4-1. However, without more data, the uncertainty of feeder unit costs cannot be reduced.

4.3 Charging location

Not all dimensions of charging location uncertainty were quantified in Section 4.2. Additional dimensions of uncertainty are discussed below.

The DGEM, at present, assumes that every vehicle in the state is *always* charged at its registered mailing address. There are two main ways in which this differs from reality: First, it ignores the reality of public charging, which currently makes up a small but significant portion of all charging and may compose a smaller or larger portion of charging across California in the future.[112] Second, our assumption ignores the fact that vehicles, particularly fleet vehicles, may operate out of a location other than the registered mailing address. For example, a fleet may register its vehicles to an administrative office rather than an operations site. These simplifications were made because data on public chargers and fleets are far sparser than the

[112] Gil Tal et al., *Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior (Carb Contract 16RD009)*, UC Davis Plug-In Hybrid & Electric Vehicle Research Center, April 19, 2021. Available at: https://ww2.arb.ca.gov/sites/default/files/2023-06/Emerging%20Technology%20Zero%20Emission%20Vehicle%20Household%20Travel%20and%20Refueling%20Behavior%2816RD009%29.pdf.

registration dataset we used. Furthermore, we assume that the load is placed on the geographically closest feeder, which may not always be the case.

While these assumptions are not ideal, the impact they have on our result is likely small—smaller than it might appear. If we were attempting to plan specific feeder and substation upgrades, the precise location of charging is critical; however, for a total cost estimate, what matters is the quality of the aggregate. As shown in Section 4.2, different models that place vehicles differently – including highly concentrated and highly dispersed – show that charging location makes up a relatively small portion of uncertainty in the total cost. This does not bound the impact of these other effects, which are not measured in the DGEM, but the result suggests that the order of magnitude of spatial effects is small.

4.4 Time of charge

Our model assumes that each vehicle in California follows the same typical charging pattern. In reality, individual vehicles will not always follow this charging pattern. But as long as the charging aggregated to the feeder level approximates the statewide load shape, this departure from reality will not impact our cost estimates. However, any remaining variance in this charging pattern on each feeder will not be captured, which will cause an underestimation of the variation in charging profiles.[113] This effect is mitigated by the approach we took of using the worst-day non-EV load for each hour because EV load will tend to be near its average on the worst day.

More generally, the DGEM assesses typical charging in terms of energy consumption rather than peak charger power. For example, an HD truck would typically consume 80 kWh per day and be recharged at a peak load of 7.5 kW in our model. In reality, it could be recharged using a much larger 350-kW EV supply equipment (EVSE) that could have significantly different impacts to primary and secondary distribution infrastructure. The DGEM assumes that these effects average out at the feeder level because all 350-kW EVSEs will not tend to simultaneously operate.

4.5 Infrastructure, limits, planning, and costs

The DGEM directly assesses only primary distribution infrastructure needs, so the DGEM's estimates of the costs of secondary distribution infrastructure are coarse, drawn directly from the EIS (by ratio). Moreover, the DGEM only accounts for upgrades needed for distribution infrastructure, not sub-transmission, transmission, or generation infrastructure.

[113] In general, aggregating across the state will tend to remove variation in time of charge; therefore, in principle, adding variation when disaggregating will improve accuracy.

In addition to not directly assessing the cost of secondary distribution infrastructure, the DGEM does not assess the (potentially beneficial) impact that secondary distribution limits may have on electrification in practice. These effects could limit the actual cost of distribution upgrades because secondary infrastructure can limit the peak power that needs to be delivered by primary distribution infrastructure. For example, if the collective power ratings of service drops[114] (or service panels) connected to a particular service transformer are not sufficient to overload it, one or more service drops would need to be upgraded before the service transformer would need to be replaced. Similarly, if the load capacity of service transformers is collectively insufficient to overload a feeder or transformer bank, investments in primary distribution infrastructure could be delayed or obviated.

How the limitations imposed by secondary infrastructure play out in practice is impossible to predict. But because there are, at present, wait times to upgrade service and costs that the customer must bear, there is a potential that the customer opts for a different solution, such as a smart service panel[115] that manages load to limit peak load to what the customer's level of service allows. A smart service panel could be cheaper and faster for customers and reduce IOU investments and could help provide customers with other benefits, such as supporting resiliency solutions.

In contrast to the assumptions of the DGEM, the IOUs will perform an engineering study before upgrading a piece of distribution infrastructure. An engineering study entails planning out the most cost-effective solution to resolve capacity exceedance on an asset, which could be significantly different from the DGEM's solution of a typical infrastructure upgrade. For example, the DGEM will trigger the installation of a new feeder if an existing feeder is overloaded. In practice, an IOU might choose to switch load temporarily or permanently, particularly for small overloads. Conversely, the DGEM will not trigger an upgrade unless the model calculates an overload, but in practice, an IOU might upgrade a feeder that is nearing capacity due to uncertainty in future loading conditions. In general, if IOUs build more infrastructure than the DGEM deems necessary, total costs could be higher than modeled.

Another limitation of the DGEM is its treatment of feeders operating at archaic distribution voltages, mainly 4-kilovolt (kV). Because of the limitations of the available data, the DGEM assumes that any 4-kV overloaded feeder in PG&E's service territory is upgraded to a 12-kV feeder, but does not assume so for SCE or SDG&E. In practice, the infrastructure solution will be made on a case-by-case basis, considering, among other things, the voltages of nearby feeders such that load transfers remain possible. Furthermore, we do not make any cost differentiation

[114] I.e., the wires connecting the service transformer to the service panel.

[115] For example, see the products of the home electrification technology company SPAN.

for these feeders, while in practice costs may be significantly different from the costs of more typical 12-kV primary distribution upgrades.

Finally, the DGEM's cost model is relatively coarse. As discussed in Appendix A.8, we cannot directly assess the length of distribution feeder upgrades. The length of upgrades is critical to cost and highly uncertain. Moreover, we assume that the most common distribution voltage is used regardless of the number of units of infrastructure required. For example, the DGEM would solve a 30 MW overload with three 12-MW (12-kV) feeders. The IOU likely could instead install a single 34-MW (33-kV) feeder at a lower cost. Substation costs, too, have a significant degree of cost uncertainty. The cost of a substation can vary significantly with location. Additionally, we assume that utility infrastructure design standards remain static over time, while typical unit sizes may increase under electrification (for better economies of scale) and unit costs may otherwise inflate. We approach these limitations by applying high- and low-cost scenarios, which lead to different total costs.

One way to improve cost estimates is to develop a better database of historic costs for feeder and substation upgrades. However, this is not a wholly satisfactory approach because experience is also not necessarily a reliable indicator of future upgrades. This is because future upgrades may serve much more distributed loads than past upgrades (i.e., EVs at 100 houses versus one large industrial customer). Therefore, in the future, a *significantly* greater length of each branching distribution feeder may need to be upgraded. This could lead to future costs significantly departing from historical costs.

Directly estimating the length of feeder upgrades can remove the need to assume a fixed length. A direct feeder length estimation can eliminate the most significant source of uncertainty in the unit cost but requires different and more resource-intensive methods than those applied in the DGEM. Specifically, the model would need to assess load at a feeder segment or section level and calculate upgrade needs over the same unit length. Such an assessment can, in principle, be accomplished in the EIS Part 2 by leveraging section-level infrastructure (i.e., ratings and hierarchy) data available through the IOUs' Wildfire Mitigation Plans[116] and the AMI data already used to model load.

5 Key Findings

We highlight the key findings of our work below.

[116] State of California Office of Energy Infrastructure Safety, *Data Guidelines - Version 3.1*, February 17, 2023 at 37-38. Available at: https://efiling.energysafety.ca.gov/eFiling/Getfile.aspx?fileid=53475&shareable=true.

5.1 Electrification will cost $26 billion through 2035 without additional mitigations

The mass electrification of vehicles, buildings, and other sectors – which is crucial for meeting California's decarbonization goals – will result in higher energy usage and necessitate distribution grid infrastructure upgrades. Our study assessed the effects of projected load growth on the distribution systems of PG&E, SCE, and SDG&E from EV and non-EV sources through 2035 and the associated costs of upgrades to the system to meet the projected load. We found that load growth on the three IOUs' distribution systems will necessitate upgrades on 1,100-1,300 feeders and 310-340 substations. We estimated the cost of upgrades to be $26 billion. This number has significant uncertainty and could be as much as $18 billion lower or $31 billion higher based mainly on the unit costs of upgrades.

It is important to note, however, that no single study, particularly at this point in the electrification process, can definitively answer such a complex question as what the costs of distribution grid upgrades will be through 2035. The DGEM provides a variety of forecasts in an attempt to bound some of the uncertainties involved. These forecasts reasonably align with prior research, lending credence to both the DGEM and prior studies. Nonetheless, our results cannot be seen as definitive. Rather, our results support discourse on the costs and benefits of electrification in California

5.2 Increased energy sales due to electrification may put downward pressure on residential rates

The DGEM predicts that the increase in electricity sales from electrification may outweigh the costs of distribution investments, resulting in downward pressure on residential rates compared to 2023 rates. Importantly, this decrease in rates is resilient to differing unit cost assumptions: We predict downward pressure on rates for SDG&E's and SCE's residential customers under all unit cost assumptions, and downward pressure on rates for PG&E's residential customers under nearly all unit cost assumptions. Decreasing rates are beneficial to California's residential ratepayers, who experience the highest rates in the contiguous United States.[117] Significantly, decreasing pressure on rates benefits all ratepayers, including those who choose not to (or cannot afford to) electrify by, for example, purchasing an EV. Lower electric rates can also help to spur additional electrification as the upfront investment needed for customers to electrify becomes more cost-effective.

Achieving this downward pressure on residential electricity rates is contingent upon five key model assumptions. Downward pressure on residential rates might not be achieved if:

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[117] Data reflect 2021 rates. See U.S. Energy Information Administration, *US Electricity Profile 2021*, November 10, 2022. Available at: https://www.eia.gov/electricity/state/.

6. EVs mostly charge in the evening, near peak hours (i.e., 6 p.m. to 10 p.m.), which would drive a higher peak load and, therefore, higher upgrade costs.
7. Electric rates rise to cover additional electrification programs, such as deploying EV chargers.[118]
8. New feeders and substations are more expensive than the DGEM estimates.
9. Expected load growth due to electrification does not occur.
10. Utilities build more infrastructure than is needed or build infrastructure in the wrong locations because upgrade costs will be higher.

Good forecasting and planning are key parts of achieving this downward pressure on rates. Utility forecasts must be accurate and not lead to infrastructure over-building. If overbuilding occurs, electrification could cause *upward pressure* on rates. Utility distribution planning processes should, therefore, be based upon realistic forecasts. Planning processes should be flexible and adaptable to provide for incremental infrastructure build and include offramps so that investment plans can be reshaped if it becomes clear that load will not appear as expected. This point is important for all IOUs but, based on our analysis, it is the most critical to PG&E's customers who, as established, are the most vulnerable to rate increases under electrification.

Even if electrification leads to downward pressure on rates, we cannot conclude that electric rates *will* fall. Other utility costs, such as wildfire mitigation, clean energy procurement, or other climate change mitigations, could cause rates to rise in net. Moreover, effective policies, particularly around rate design, are needed to ensure that potential rate decreases are realized. For example, if EV owners are allowed to select a rate that does not recover the marginal cost to provide electricity, electricity rates for other customers could still rise.

5.3 Reducing the peak load could avoid $35 billion or more in distribution investments

Our work on the DGEM has identified the key factors that drive distribution investments. As discussed throughout our report, the time at which EV owners charge their vehicles is one of these key drivers. If many EVs charge at the same time – or at the same time as significant non-EV loads – the peak load on the system and the need for new distribution investments can be significantly higher.

Although we only evaluated a single load profile for each vehicle class, we can provide a first-order estimate of the investment that can be saved under current EV-TOU rates by comparing the DGEM's result using the EIS's cost with the EIS's results. This is because the EIS assumes

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[118] Ratepayers do not typically fund BTM infrastructure such as EVSE because "the primary role of ratepayers [is] to fund utility-side infrastructure upgrades." See Decision (D.) 22-11-040, *Decision on Transportation Electrification Policy and Investment*, November 17, 2022 at 89-90, issued in R.18-12-006. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M499/K005/499005805.PDF.

much higher peak charging due to the assumption that EV-TOU rates are eschewed. Approximately 70 percent of the costs identified in the EIS – $35 billion – vanish under charging assumptions consistent with EV-TOU rates.

Further work should be undertaken to understand in more detail the benefits and costs of mitigations such as encouraging EV owners to charge at times that could reduce the impact on the distribution grid. This could be accomplished through the promulgation of EV-TOU rates.

5.4 The present pace of primary distribution upgrades is nearly sufficient for future grid needs

Prior research found that the pace of primary distribution upgrades needed in the future may far surpass the present upgrade pace for PG&E, which could cause future upgrades to bottleneck electrification efforts across California.[119] Our study does not corroborate this result. We predict that the pace of upgrades to meet future load growth will be approximately equal to the present planned pace of upgrades for each of the IOUs. Furthermore, it is worth considering that new substations must already be planned well in advance because regulatory affairs and permitting can be lengthy.[120]

5.5 Better data can improve study accuracy

Reliable and readily accessible datasets make research possible. The datasets required to forecast distribution upgrades and the associated costs generally lack depth and quality. Our team had access to confidential datasets, such as utilities' historic load data and vehicle registration data from the DMV, that made this study possible. Nevertheless, there are several areas where data were notably absent. For instance, data on medium- and heavy-duty fleets are sparse though the CPUC currently has a *Freight Infrastructure Planning* (FIP) process underway to improve data on that sector.[121] Moreover, utility asset cost data were significantly lacking. Utilities do not use reference materials to establish the typical costs of upgrades. They instead rely on engineering studies to forecast costs. As such, the "typical" cost of a feeder upgrade has little meaning to the IOUs. We relied on relatively small samples from historic feeder data to infer the length and cost of feeder upgrades. Substations had similar – even more acute – issues since new substations are substantially rarer than new feeders. Improvement in datasets,

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[119] Salma Elmallah et al., *Can Distribution Grid Infrastructure Accommodate Residential Electrification and Electric Vehicle Adoption in Northern California?*, Environmental Research: Infrastructure and Sustainability, November 9, 2022 at 1. Available at: https://doi.org/10.1088/2634-4505/ac949c.

[120] For example, SCE's 2009 application to build the Alberhill substation, A.09-09-022, remains pending before the Commission.

[121] CPUC, *Freight Infrastructure Planning,* n.d. Available at: https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/infrastructure/transportation-electrification/freight-infrastructure-planning.

particularly cost datasets, would lead to a convergence in study results toward a consensus on the future cost of grid upgrades to meet electrification needs.

6 Potential for Future Work

This publication aims to continue the discourse on distribution planning, the future of California's distribution grids, and electrification. Research on load forecasting and infrastructure upgrade costs remains critically important for ratepayers, and further work is needed to deepen the shared understanding of these issues. Below we outline the work that we intend to undertake, as well as possible contributions from other stakeholders.

The Public Advocates Office plans to expand the DGEM to systematically evaluate the possible impacts of managed charging on infrastructure investments and electric rates across PG&E, SCE, and SDG&E. Future studies, broadly, should also source more comprehensive cost data, evaluate alternatives to traditional wires investments, and improve data on MD and HD fleet locations.

Cost data can be improved through collaboration with IOUs or through improved distribution grid modeling by third parties. A more thorough collation of historic data, created with IOU support, could aid in the development of a statistically sound estimate of future upgrade costs. Alternatively, distribution grid models that are spatially explicit below the feeder level (i.e., to the line section or segment level) could be used to better estimate the length of feeder upgrades, which will significantly reduce cost uncertainty. These models need to begin with load at the meter or service transformer level rather than the feeder level and assess feeder capacity on the section or segment level based upon granular geospatial data. The IOUs could create such models; the model underlying the EIS appears to have this capability.[122]

Future work should consider how alternative strategies can mitigate some of the upgrade costs. One such alternative is managed charging (e.g., through TOU rates or flexible interconnections[123]). Another alternative is smart home panels that could mitigate the need for primary upgrades, secondary upgrades, and customer-side upgrades.

Because the DGEM relies heavily on the IEPR for data and generally aligns with the IEPR in forecasting, as typified by growth in peak load, the DGEM can be loosely seen as an application of the IEPR to the IOUs' distribution grids. As such, the DGEM's distribution cost forecasts are an appropriate source of distribution costs in whole-system models that consider generation, transmission, and distribution. The DGEM's results, data, or methods could be incorporated into the Pathways Model used in the CARB's 2022 Scoping Plan.

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[122] Most importantly, the EIS's model is developed from meter-level data. See EIS at 84.

[123] For a discussion of flexible interconnections, see Electric Power Research Institute, *Understanding Flexible Interconnection*, September 2018. Available at: https://www.epri.com/research/products/000000003002014475.

We elected to calculate only the total cost of upgrades and the expected rate impact rather than customer bill impacts or total home energy cost. We did not calculate customer bill impact because it has little meaning in the context of electrification; electric bills may go up but could be more than made up for by decreasing gasoline or natural gas bills. Total home energy cost paints a fuller picture of the impacts of electrification on the finances of California's IOU customers but would have required analysis that are beyond the scope of our model. The CEC may be well-positioned to make this calculation.

Better data on MD and HD fleet locations and charging behavior can improve the precision of grid models by more precisely placing the load from those EVs on the grid in space and time. The spatial dimension of MD and HD EV charging is less critical to the bottom-line result (i.e., the total cost identified) of the DGEM than unit cost and LD load shape assumptions. Nevertheless, more spatially accurate MD and HD adoption forecasts would improve accuracy and better align whole-distribution modeling with utility planning, which aims to identify the upgrade needs of specific assets.

We have provided estimates of the cost of distribution grid upgrades, electric rate impacts, and the uncertainty as well as sources of uncertainty in those factors. We have also identified important next steps for future grid assessments. Understanding the degree of uncertainty in the DGEM and other studies can help decision makers and utilities to develop planning methods appropriate for a highly unpredictable future. These contributions will help stakeholders to understand the impacts of electrification, make policy choices, and determine where future research is needed.

Appendix A Detailed Methods

A.1. Establishing the baseline total load forecasts, ratings, and topology

The first methodological step entailed collating sets of data from California's three major electric IOUs – PG&E, SCE, and SDG&E – and calculating hourly peak loads on each feeder within the three IOUs' service territories. The IOUs provided data in response to data requests. The IOUs provided confidential planning data of differing origins and methodologies.

PG&E supplied loading data for 2022 while SCE provided loading data for 2021, and SDG&E provided loading data covering the start of 2018 through September 2021. Table A-1 summarizes the key characteristics of the load data.

Table A-1. Utility loading data details.

IOU	Data range	Observations per year
PG&E	2022	576 (month, hour, weekday/weekend)
SCE	2021	8,760 (hour interval)
SDG&E	1/1/2018 – 9/31/2021	105,120 (5-minute interval)

We first took the 99th percentile of the 5-minute interval data for each hour of each month from SDG&E's data.[124] This resulted in 288 observations per feeder for SDG&E,[125] along with 8,760 observations per feeder for SCE and 576 observations per feeder for PG&E.

We then reduced each load dataset down to the maximum demand for each feeder in each hour (24 records per asset). This was informed by the charging load shapes for LD EVs and for MD and HD EVs from the IEPR (see Section A.5). The IEPR's EV charging load shapes vary mostly by year and hour; we found day-to day variations in EV charging to be insignificant.

We also received load ratings from the utilities in megawatts of real power capacity. These limits were calculated from the ampacity ratings and voltage level and assume a power factor of 1.0. This tends to slightly overestimate the ability to transfer real power, which is, in reality, reduced by the flow of reactive power. SCE provided planned loading limit data, whereas SDG&E and PG&E provided thermal limits. PG&E applies higher thermal ratings to infrastructure in some areas during winter. This is because the cooler air mitigates feeder and

[124] We initially tried using the 95th percentile value for each hour of the year (8,760 hours), but this produced many records with power exceeding infrastructure capacity. It appears that this original method was not sufficient to remove erroneous records (or, perhaps, values representing real, unusual switching events).

[125] SDG&E provided 288-hour ICA data for 39 feeder with no available SCADA data. We combined the 288-hour files provided by SDG&E with the other data at this stage.

transformer overheating.[126] To account for this, for PG&E only, we used 48 loading records per feeder instead of 24 loading records. This refers to 24 loading records for summer (April – October) and 24 loading records for winter (November – March). We took the same approach with PG&E's rating data – each infrastructure with a cold-weather rating received a summer value and a higher winter value.

We reduced our dataset down to all feeders for which we had ratings and loading data. We excluded all substations and feeders for which the max load was exactly zero. We kept all substations that were loaded by any feeders and had ratings. We used the same IOU data to create infrastructure topologies and to track infrastructure ratings. It is worth noting that feeder attrition (either in this step or when aligning this set of data with the feeder data associated with vehicles) leads to an underestimation of the load on substations. This became apparent in the modeling process when correcting some misaligned names increased substation utilization (e.g., Peoria Flat 1701 in one dataset might be Peroria 1701 in another).

The dataset reduction process resulted in the number of pieces of infrastructure shown in Table A-2. There was a substantial amount of attrition due to pieces of infrastructure appearing in one dataset and not in others. The IOUs indicated that the Grid Needs Assessment (GNA)[127] generally provides the most up-to-date planning information. Other datasets might include data from retired feeders, idle feeders, planned feeder installations or feeders with no load. For example, of the 4,468 feeders that SCE provided, 4,252 are included in the GNA. Of these, 4,239 have loading data (i.e., 13 have not operated long enough to provide load data). The DGEM captured 4,191 (or 99 percent) of the 4,239 feeders with loading data. Additionally, for PG&E specifically, we eliminated all low voltage (≤ 4.16 kilovolt) substations.[128]

Table A-2. Initial and final infrastructure counts after cleaning IOU data and keeping only records with loads and ratings.

	Initial Dataset		Final Dataset	
IOU	**Substations**	**Feeders**	**Substations**	**Feeders**
PG&E	714	3,417	633	3,128
SCE	927	4,468	816	4,191
SDG&E	109	835	109	818

[126] While this is true for infrastructure in general, it is relevant mostly for PG&E because its territory contains colder regions that are winter peaking.

[127] The GNA is a CPUC mandated process in which the major electric IOUs annually report which infrastructure across their transmission, generation, and distribution systems need to be upgraded and opportunities for upgrade deferrals. For more information, see CPUC, *Distribution Planning*, n.d., Available at: https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/infrastructure/distribution-planning.

[128] We did this because the connectivity map available for PG&E allowed us to re-attribute this load to the upstream, higher voltage substations. This approach is consistent with the PG&E's trend of upgrading these systems to higher voltages when more capacity is needed.

More relevant than the lost feeders and substations is the lost EV load (i.e., from EVs which we identify to be in an IOU service territory but for which we cannot calculate a feeder or substation upgrade cost). This is discussed further in Appendix A.2.1.

The following subsections provide additional details specific to the datasets from each IOU.

A.1.1. PG&E

The DGEM used the following information provided by each IOU: substation and feeder ratings, historical loading data, and hierarchy information (i.e., how infrastructure is connected; also referred to as topology or connectivity). Specifically, PG&E provided us with the following information:

1. Load ratings at the levels of feeder, bank, and group bank for summer and winter. These files included hierarchical information (i.e., parent infrastructure identification number).
2. 95th percentile 576-hour (12 months times 24 hours times weekday/weekend) loading for feeders. According to PG&E, these data are from 2022. These profiles were created by PG&E by scaling historical meter data to the net peak load on the substation circuit breaker for each feeder.
3. The length of each feeder.

We calculated the total present substation capacity by summing bank capacities across each substation. PG&E conveyed that this type of information is not useful for distribution planning because loading of each bank is important for reliability. While we understand PG&E's concerns with this approach, we use this information not for planning substation builds but to estimate future costs, as discussed in more depth in Appendix A.1.4.

PG&E's infrastructure in the San Francisco Bay Area has some notable hierarchical structures. For example, PG&E's Potrero substation feeds 12-kV feeders *and* 12-kV tie-lines. The 12-kV tie-lines feed 12-kV feeders connected to the SF E substation (which are, therefore, not fed by the transformer banks in the SF E Substation). The SF E substation also feeds 4-kV feeders through 12-to-4-kV transformers. Finally, one of the 12-kV feeders wired into the SF E Substation feeds a 12-to-4-kV transformer in the Castro substation which in turn feeds a 4-kV feeder.

To use the Bay Area feeder data in the DGEM study, the hierarchical infrastructure necessitated either restructuring the entire topology analysis to allow arbitrary levels of hierarchical information or introducing simplifications to flatten into the typical distribution substation-to-feeder hierarchy. We opted for the latter approach, as depicted in the lower half of Figure A-1. While a significant amount of information is lost, this information is inconsequential since PG&E is unlikely to expand its 12-to-4-kV substations. Instead, consistent with PG&E's (and SCE's) general approach of eliminating 4-kV feeders during upgrades, it is likely that PG&E would replace the 4-kV feeders with 12-kV feeders and eliminate the corresponding substations, if practical. Our cost accounting approach is consistent with this interpretation though it does not account for these costs being higher than typical, in the case they are. This approach eliminated all of PG&E's 4-kV substations from the DGEM study.

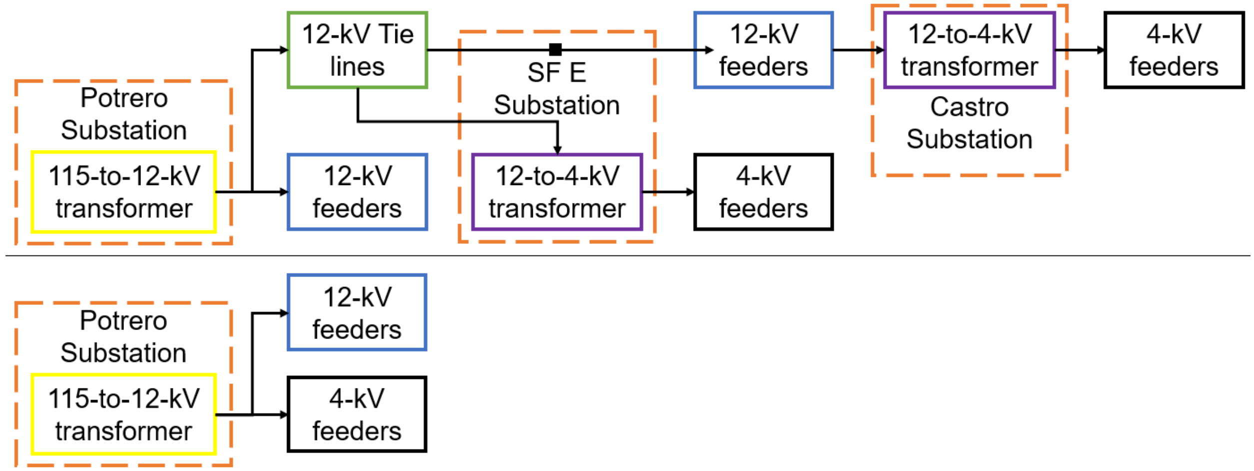

Figure A-1. Full hierarchy (top) and assumed hierarchy (bottom).

One shortcoming of our approach is that substation hierarchies above 4 kV are not cleanly mapped. For example, a 21-to-12 kV substation *should* be dealt with using the full hierarchy. Since the full hierarchy approach added too much complexity to the DGEM, we followed load from the feeder to the 12-kV substation but not back up to the 21-kV substation that feeds it. In practice, there are *very few* transformers (i.e., 15 banks and two group banks) with both high-side and low-side voltages at distribution voltages above 4 kV (between 12 and 44 kV) in PG&E's service territory.

A.1.2. SCE

SCE provided us with the following information:

1. 8,760-hour distribution feeder net load profiles from 2021, with hierarchy information (i.e., feeder-substation connections).
2. A list of feeder and substation ratings that also includes hierarchy.
3. A report of feeder lengths.

We used the hierarchical data embedded in the feeder and substation ratings (rather than hierarchical data in the load profiles) to determine the distribution system topology. Using the hierarchy data embedded in the net load profiles was untenable because the naming conventions of the substations in load data did not match the naming conventions in the rating data. For example, a high-side voltage (included in a substation name) might be 66 in the rating data and 69 in the loading data.

A.1.3. SDG&E

SDG&E provided the following information:

1. Feeder net load at 5-minute interval at the approximate connection of the feeder to the substation. Data spanned the period January 1, 2018 through the third quarter of 2021.
2. Each feeder's gross load capacity, in MW, the feeder length, and the substation name to which the feeder is connected, current as of August 15, 2022.
3. Aggregate adjusted transformer ratings in MW for each substation, current as of August 15, 2022.

We mapped the hierarchy using both the provided GNA (gross load capacity) data *and* the SCADA data. While there were some records that did not overlap, only one conflicted: Feeder 138 connects to Vine in the GNA data and SCADA data show that it switched from Kettner to Vine in August 2018. Therefore, we removed Kettner data to avoid overrepresenting load on Vine.

A.1.4. Data Limitations

The feeder loading data provided by all three IOUs, combined with the EV uptake modelling and geospatial data, serves as the basis for the rest of the analysis. As mentioned above, these data were acquired through data requests. Each IOU submitted data and written responses to each of the data requests. In addition to providing contextual information for their data, the IOUs also provided several notes and limitations to their data. The above sections describe the data we received for each of the IOUs, while this section focuses on caveats and limitations to the data we received and how this information may affect the DGEM.

In relation to the feeder data, we requested the feeder identifiers and names, hourly load data for a year, feeder capacity, and feeder length. For substations, we requested the substation identifiers and load capacity.

SDG&E and PG&E both noted that their provided load capacity is the thermal rating of the feeder gateway converted from amperage to MW with a power factor of one. This tends to overestimate the ability to transfer real power, which is reduced by the flow of reactive power.

SDG&E noted that some overloads were erroneously recorded due to conversion from amps to MW. Another overload was caused by SDG&E not providing all equipment at a substation which, therefore, made our substation capacity lower than the actual capacity available. Like PG&E and SCE, there were some discrepancies between data sources due to certain feeders being energized after the data collection occurred. These data were sometimes replaced by data modeled by the IOUs.

PG&E noted that its net load peak data do not include generation by the largest DER on each feeder. This results in an overestimate of the net peak load for PG&E, which results in an overestimate of utilization in the DGEM in turn.

A key challenge of PG&E's data is that many of its feeders and substation transformers exceed rated capacity in 2021 and 2022. This is due to two reasons: 1) genuine overloads that are recognized by PG&E and generally have planned solutions in flight, and 2) forecasting or data issues. Since some but not all PG&E's overloads are valid, we included the overloads as reported and consider costs with and without the impacts of those overloads in our final cost estimates.

In addition to noting some of the reasons that its feeders may be at or above capacity, PG&E also noted that deficiencies inside a substation will be missed if all substation transformers are summed to obtain a "substation capability." If one transformer is loaded beyond normal capability and another is not fully loaded, work may be required to reconfigure feeders or add feeders to the more lightly loaded transformer to take load from the overloaded transformer. Therefore, the DGEM's use of "substation capacity" may miss intricacies of loading within the substation (i.e., assume a substation is not at capacity when a transformer bank within the substation may be). We acknowledge that we may miss some of the distribution upgrade costs by not factoring the individual capacity of all the equipment within a substation.

SCE did not specify any limitations to its feeder and substation data, but there were some discrepancies in the feeder and bank data that SCE originally provided. SCE noted that the data may vary from team to team depending on the planning needs, so it provided an updated document noting which feeders and banks should be excluded from the analysis. Additionally, several of SCE's feeders and substation banks were above their rated capacity in the provided data, not to the scale of PG&E's, but still at a significant rate. SCE noted that many of these exceedances were due to data quality issues that are not representative of true peak load conditions. However, some of these exceedances occurred due to temporary or permanent transfer of load from adjacent feeders to alleviate loading. Other feeders have legitimate overloads for which SCE has mitigations in flight.

A.2. Calculating vehicle population by class in California

The energy needs of electric vehicles differ most significantly by vehicle class. For that reason, our analysis aggregates vehicles by class. To determine the number of total vehicles in California, we acquired confidential vehicle registration data from the DMV with registrations dated through December 31, 2021. The data include addresses of the registered vehicles, vehicle class, ownership (e.g., personal, commercial, government), and drivetrain (e.g., gasoline, electric). Each of these vehicle characteristics informed our analysis. The dataset contains a total of 31,035,599 registered vehicles. We used the CEC's vehicle classification system – which classifies vehicles by their gross vehicle weight rating (GVWR) – to categorize all the registered vehicles in the DMV data.[129] For instance, LD vehicles have a GVWR up to 10,000 pounds, MD vehicles have GVWR up to 26,000 pounds, and HD vehicles have a GVWR of

[129] CEC, *Medium- and Heavy-Duty Zero-Emission Vehicles in California*. See the section "Understanding Vehicle Weight Class" on the webpage.

26,001 pounds. and above. We use the resulting total number of vehicles in each class as one of the bases for estimating EV load in subsequent steps.

A.2.1. Associating registered vehicles with proximal feeders

In order to accurately estimate EV energy demand over time and space, we had to know the exact locations where EVs are expected to charge and the demand that EV charging will place on the distribution system. We assumed that charging would take place at each vehicle's registration address. We employ this assumption for two reasons: 1) our study draws upon vehicle registration data, and 2) approximately 80 percent of charging occurs at the household.[130] As such, to the best of our knowledge, our study is the first to estimate energy demand due to increased EV adoption and the costs required to upgrade distribution infrastructure to meet EV charging demand using DMV data, which is more granular and geographically precise than other datasets.

As a first step, we geocoded the DMV dataset by matching each address to geographic latitude and longitude coordinates using ESRI StreetMap Premium. Geocoding is the process of transforming a description of a location, such as an address, to geographic coordinates that can be mapped to a location on the Earth's surface.[131] The positional accuracy of geocoding can vary greatly depending on many factors, including but not limited to: the vintage and quality of the reference data that the locator is built on, the quality of the input address data, and the geographic region. Since the majority of the DMV registration addresses fell in relatively urban or suburban residential areas and the quality of the DMV address data was high, the geocoding process for the DMV dataset produced a high match rate from address to latitude and longitude. However, not all matches were utilized in our study's resultant Study Area. We eliminated records that were unable to be geocoded due to poor address quality (e.g., typos, misspellings, duplicates, P.O. boxes, and redactions), as well as records for which their positional accuracy was not considered granular enough for the nature of the DGEM analysis.

Approximately 899,380 vehicles in the DMV dataset were registered at an address that could not be geocoded. We removed the vehicles that could not be geocoded from the total registered vehicle count, which resulted in the functional number of vehicles that we could use in the study dropping from 31,035,599 to 30,120,564. See Table A-3 for more information.

Next, we associated the locations of EVs with feeders within the service territories of the three major IOUs, which cover the majority of California. Feeders provide the electricity from the primary distribution system to the houses where electric vehicles are assumed to charge. As

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[130] Michael Blonsky et al., *Incorporating Residential Smart Electric Vehicle Charging in Home Energy Management Systems*, National Renewable Energy Laboratory, April 2021 (Blonsky et al.) at 1. Available at: https://www.nrel.gov/docs/fy21osti/78540.pdf.

[131] Environmental Systems Research Institute, *What's Included in the Geocoded Results*, n.d. Available at: https://pro.arcgis.com/en/pro-app/latest/help/data/geocoding/what-is-included-in-the-geocoded-results-.htm.

described above, all EVs are presumed to charge at the registered address found in the DMV vehicle registration dataset, and every address represents a building that is drawing electricity from the grid for household and related purposes. We assume that the closest feeder to a building with a registered address supplies the electricity to that building. This assumption is justified by the fact that there is typically only one feeder that supplies energy close to a residence. Nevertheless, in some regions like compact urban environments, there could be multiple feeders within proximity to one or more buildings that could result in a misalignment between a registered address and the feeder that serves the building. Due to the granular level of this analysis, the number of misalignments was observed to be a very small phenomenon that was far outweighed by the quantity of valid associations.

We focused the DGEM analysis on EV adoption trends and the resulting impacts on energy demand within the service territories of PG&E, SCE, and SDG&E. These three electric utilities in aggregate supply 82 to 83 percent of power in the state[132], as shown in Figure A-2, and their service territories contained 77 percent of all registered vehicles in California in 2021. In order to isolate the EVs within the service territories of PG&E, SCE, and SDG&E, we clipped the geocoded DMV data to the IOU service territory boundaries. We used the CEC's publicly available shapefiles for the three IOUs' service territories.[133]

Figure A-2. Share of energy demand in the combined service territories of PG&E, SCE, and SDG&E (Three IOU).

After geocoding the registered vehicles, we spatially joined the geocoded data with the primary distribution feeders provided by the IOUs' Quarter 3 2022 Quarterly Data Reports.[134] This

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[132] 2021 CED, Baseline Forecast files for the three IOUs and the state under the Baseline Demand Forecast Files. This is based upon analysis of the 2021 Baseline Demand Forecast files for State / PG&E + SDG&E + SCE.

[133] CEC, *Electric Load Serving Entities*.

[134] The primary distribution feeder data came from the confidential versions of the Wildfire Mitigation Plans of PG&E, SCE, and SDG&E. We only included feeders for which we also had load and rating data. The publicly available versions are available: PG&E, 2022 Quarterly Reports. Available at: https://www.pge.com/en_US/safety/emergency-preparedness/natural-disaster/wildfires/wildfire-mitigation-plan.page; SCE, Wildfire Mitigation Plan Update & Related Documents. Available at: https://www.sce.com/safety/wild-fire-mitigation; SDG&E, 2022 Wildfire Mitigation Plan, February 11, 2022. Available at: https://www.sdge.com/2022-wildfire-mitigation-plan. The asset data used in this research came from the Quarter 3, 2022 submittal.

process associated each vehicle record to the closest distribution feeder as the crow flies.[135] Then, we further filtered the vehicle data based on the number of feeders with a known location, rating, connectivity to a substation, and existing load data, as described in Appendix A.1. The result of these reductions from the total DMV dataset to the matched dataset, to the IOU area, to the Study Area are shown in Table A-3.

Two types of duplicates were encountered in the DMV database. For true duplicates, which were identical in every field, we retained one record. For duplicates with different addresses but the same VIN, we counted each VIN once in the Total column but removed all of them at the Matched stage. This aligns with our approach for tied geocoding matches, which are similar because each VIN would geocode to multiple addresses.

Table A-3. Funneling of DMV data into the DGEM's Study Area. Summary values are provided as used in the study and for the entire dataset.

Class	IOU	Total (T)	Matched (M)	3-IOU (I)	Study Area (S)	S/I	S/M	M/T
LD	All	30,013,130	29,185,643	22,498,935	21,906,860	-	75.1%	
MD	All	661,923	611,871	460,185	450,353	-	73.6%	-
HD	All	360,546	323,050	243,557	238,574	-	73.9%	-
All	PG&E	-	-	9,896,459	9,765,311	98.7%	-	-
All	SCE	-	-	10,469,094	10,208,696	97.5%	-	-
All	SDG&E	-	-	2,837,124	2,621,780	92.4%	-	-
All	All	31,035,599	30,120,564	23,202,677	22,040,146	97.4%	75.0%	97.1%

Table A-3 also shows three important ratios.

1. S/I indicates the share of vehicles in the area comprising the three IOUs' combined service territories (I) (e.g., 97.4 percent) that we consider in our model.[136]
2. S/M approximates the share of vehicle sales in California that occur within the Study Area (S).[137]
3. M/T reflects the share of vehicles from the 2021 DMV registration dataset with known addresses (i.e., 2.9 percent of records did not match with an address, a trend which we expect to hold within the Study Aea. This trend leads to the assumption that 2.9 percent of vehicles in each of the IOU's service territories have an unknown location).[138]

[135] "As the crow flies" refers to the straight line distance from one point to another. In this case, one point is the geocoded registration address, and the other is the closest point on the nearest distribution feeder to the geocoded registration address.

[136] We divided the study's total cost and energy forecast by S/I (for each IOU) to estimate the IOU total cost and energy impacts from our study result.

[137] We divided the statewide vehicle deployment forecasts by S/M (by class) to determine how many vehicles to allocate into the Study Area.

[138] We divided 2021 TE demand by M/T before subtracting TE demand from baseline load to calculate baseline load without TE.

We use these ratios later in the analysis as correction factors for the changes we made to the initial DMV vehicle registration dataset to harmonize with the constraints of other datasets.

As noted above, a major assumption of the study is that all vehicles charge at their registration addresses. For LD vehicles, this assumption reflects the charging behavior of most drivers: recent data indicate that 80 percent of early LD EV adopters charge at home.[139] The MD and HD sector, however, has different charging characteristics, but there are limited literature and data on the sector's charging behavior. Research indicates that MD and HD vehicles are expected to predominantly charge at their home base.[140] Based on those data, we assumed in our analysis that MD and HD electric vehicles also would charge at their operating center.[141] We assume that the registration addresses of the MD and HD vehicles are the operation centers even though the addresses might actually be the administration offices. The implications of this assumption are discussed in Section 4.3.

These assumptions demonstrated odd outcomes in a few cases, which provide insight into possible improvements but does not significantly impact the modeling result. For example, in the DGEM, one feeder in San Francisco (Hunters Point 1101) at times showed more forecasted 2021 load from EV charging than total measured load. Our methods allotted nearly 300 electric buses to the Hunters Point 1101 feeder, likely because it is the closest feeder to the registration address of SF's electric bus fleet. We also observe that since these buses run mostly on wires, their demand load shape will be quite different than the general MD and HD load shape that we employ in the DGEM, and the buses' location of load will be based upon the interconnection point of the city's overhead bus lines, not the buses' registration address. Nevertheless, while accurate spatial load forecasting is critical in a grid needs assessment, we do not attempt to fix them on an individual basis for the type of large-scale total-cost estimate we yield in the DGEM. Future studies may seek to improve spatial load forecasting. See Section 4 and Appendix A.3.6 for further discussion of MD and HD fleet data improvements.

Though the limitations are important, the assumption that vehicles charge at their registration address may limited issues for the following reasons. First, if a vehicle charges *near* its registration address – i.e., on the same distribution feeder – it makes no difference in the DGEM compared to charging at the registration address itself. For example, if an apartment building resident charges an EV down the street, it is likely that the load impact from charging would be identical to the load impact that the DGEM predicts. Second, the clustering of EVs on a feeder is

[139] Blonsky et al. at 1.

[140] MJB&A at 6, and 17.

[141] A terminal serves as a hub for fleet management activities, such as dispatching drivers, scheduling maintenance, and managing cargo. Terminals may also provide facilities for drivers, including parking areas, restrooms, and break rooms. Depending on the size and scope of the fleet, a terminal may be a large complex with multiple buildings and extensive infrastructure, or it may be a smaller, more basic facility.

more important than the precise location of EVs on a feeder. On average, a large fleet load on feeder A would not look notably different cost-wise from a large fleet on feeder B. Therefore, if some large fleets are at a different address than their registration address, the bottom-line upgrade costs may be the same. Random feeder-to-feeder variability will tend to wash out over the large number of fleets in the DGEM. Nevertheless, systematic differences – such as if industrial areas where fleets are located tend to have less capacity than business parks where vehicles are registered – in the DGEM could underestimate the total number of overloads and the resulting cost.

A.2.2. Classifying registered vehicles by class and ownership

In order to make data usable across datasets, we made a new dataset of vehicles matched to geocoded addresses and to feeders with load and rating data within the service territories of PG&E, SCE, and SDG&E (i.e., the Study Area, S). The new dataset excluded registered vehicles that could not be geocoded, vehicles outside the IOUs' service territories, and vehicles on feeders with incomplete data. For more information, see Appendix A.2.

We applied different propensity models to fleet vehicles and personal vehicles, so in addition to classifying vehicles by class, we also classified vehicles by ownership. Table A-4 summarizes the results of classification by class and ownership.

Table A-4. Share of vehicles by class and ownership category.

Ownership	LD	MD	HD	MD + HD
Personal	92.7%	16.9%	6.2%	13.2%
Commercial	6.6%	76.2%	82.1%	78.2%
Gov - transit	0.0%	0.6%	2.1%	1.1%
Gov - other	0.7%	6.3%	9.5%	7.5%

Note: This table illustrates the percentage breakdown of vehicles by class and ownership category within the Study Area (S).

A.3. Predicting LD, MD, and HD vehicle adoption using propensity modeling

To forecast load increases on feeders and substations due to EV charging, we designed a spatially explicit methodology for determining *where* EVs will appear on the grid every year between 2023 through 2035. First, we estimated the number of EVs expected to be in California's vehicle population in each year. Second, we developed a series of propensity models that predicted which conventional vehicles[142] from each class across the Study Area would become EVs annually until the established EV population set forth in the IEPR was reached. We used one set of models for non-fleet vehicles (i.e., personal LD vehicles) and another set for fleet vehicles (i.e., all medium- and heavy-duty vehicles, as well as non-personal vehicles. Non-personal vehicles consisted of government and commercial vehicles).[143] Each model result was calculated in parallel with the others to create a set of scenarios that captured the range of possibilities for needed distribution system upgrades and total infrastructure upgrade costs.

A.3.1. Vehicle population through 2035

To assess the amount of load that EV charging will place on the grid, we needed to know how many EVs will be added to the state's vehicle population annually through 2035. The CEC has estimated the number of BEVs and PHEVs per vehicle class[144] that will be on the road in California between 2023 through 2035.[145] We assume that the electric vehicles that the CEC predicts will be on the road annually are replacing the same number of conventional vehicles of the same subclass. We assume that every electric vehicle (i.e., BEV and PHEV) entering the state's annual vehicle population based on the IEPR's projections take the place of a conventional vehicle of the same subclass registered in the DMV dataset. Once a vehicle becomes an EV, it is assumed to remain an EV for the remainder of the study period. Moreover, we assess only new vehicle purchases and ignore transfers of EVs (along with the corresponding replacements of EVs).

To generate annual EV populations that are appropriate for the geographic area of our study, we multiplied the IEPR's forecasted populations by the share of vehicles with known addresses that are in the Study Area by vehicle class (e.g., S/M for LD vehicles is 75.1 percent; see Table A-3). Next, we split the IEPR's forecast of annual LD vehicle population into non-fleet and fleet vehicles based on the percentage of LD vehicles in the 2021 DMV dataset that are registered as categories other than personal (this step allocated 92.7 percent of LD vehicles to personal, or non-fleet; see Table A-4). As described in Appendix A.3.3, these vehicles were fed into different propensity models.

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[142] Conventional vehicles exclude only BEV and PHEV by our categorization. This results in the inclusion of typically non-conventional vehicles like hydrogen, but the vehicles of this type in the 2021 DMV dataset are small in number.

[143] We elected not to consider personal MD and HD vehicles within the personal model for the following reasons: 1) it is likely that many of these vehicles are personally owned but used for commercial purposes, 2) the share of these vehicles registered as non-personal is minimal, and 3) the relative impact of MD and HD compared to LD is minimal.

[144] The IEPR forecasts population at subclass (e.g., compact car, heavy pickup truck, and shuttle bus), but we used these data at the class level (LD, MD, HD).

[145] Data provided by CEC on April 20, 2023. These are internal model data that are not published.

A.3.2. Propensity models

We developed six propensity models to capture a diversity of spatial distribution scenarios for EV adoption and to compensate for some of the uncertainty in the spatial deployment of EVs. Two of the models were applied to non-fleet vehicles (i.e., personal LD vehicles) and four were applied to fleet vehicles (non-personal LD vehicles plus all MD and HD vehicles).[146] Below, we outline the justification and mechanics of each propensity model. The propensity models generated a score for each conventional vehicle to determine the likelihood that the vehicle would be replaced by an EV of the same subclass in the future. Second, we elaborate on how the propensity scores were applied to determine which conventional vehicles become EVs until the annual EV population per vehicle category (fleet or personal) was reached. Third, we reveal the results of the propensity models and the spatial depiction of EV distribution in the Study Area.

A.3.3. Personal propensity model variables

We used two LD vehicle propensity models. The first model reflects current conditions, which principally favor EV adoption in wealthier and more highly educated areas. We applied a logistic regression on the 2021 DMV registration dataset to assess the influence of current factors[147] that impact adoption and then utilized those variables to assign a propensity score to each conventional vehicle. The second model produced a more even distribution of LD EVs across the Study Area, reflecting the potential longer-term results of state policies driving EV affordability and widespread adoption. In this scenario, we assume that the current factors that determine EV adoption are not the driving factors of adoption between 2023 and 2035. For that reason, we assigned each vehicle a random adoption propensity score for EV adoption. These two forecasts are likely to bound what will happen in reality: the propensity scoring method based on current trends will supply a greater clustering of EV adoption while the random propensity scoring method will provide a more spatially dispersed LD EV adoption. The regression model does not result in the densest possible clustering of EVs[148] but is almost certainly denser than what will actually occur because historically important factors will lose significance as EV prices come down and EVs become more commonplace.

A.3.3.1. Personal regression score

Several factors have been correlated with personal LD EV adoption. We selected factors that corresponded to higher rates of EV adoption and were available at a spatial scale that corresponded to the household scale of the DMV dataset (see Table A-5). For these reasons, we considered the following factors in the LD propensity model: income, commute length,

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[146] The EIS splits vehicles along the same lines. See EIS at 109.

[147] We based one of the light-duty propensity models on available literature that demonstrates factors associated with light-duty EV adoption. See Appendix A.3.3.1 for more relevant literature.

[148] The densest clustering of EVs would have resulted from converting conventional vehicles to electric vehicles substation-by-substation and feeder-by-feeder.

educational attainment, home ownership, building type, and household size. We utilized the U.S. Census Bureau's five-year American Community Survey (ACS) data for 2016-2020 and the DMV vehicle registration dataset.[149] The ACS provides demographic and socioeconomic factors at the Census block group level, the most granular scale provided by the Census Bureau and the most reliable dataset at a scale closest to the household scale. The Census Bureau defines a block group as a statistical division of census tracts that generally contain between 600 and 3,000 people.[150] Table A-5 summarizes the factors considered in the DGEM's propensity regression model for personal vehicles, along with their justification, source, and the spatial scale at which data were available.

Table A-5. Factors included in the DGEM's propensity regression model.

Factor	Justification	Literature Citations	Data Source	Spatial Scale
Household income	Studies have correlated higher income with higher rates of EV adoption.	Coffman et al., 2018; Gehrke et al., 2021; Langbroek et al., 2017; Westin et al., 2018.[151]	ACS 5-year estimate (2016-2020)	Census block group
Educational attainment	Studies have linked higher rates of education with an increase in EV ownership.	Langbroek et al., 2017; Coffman et al., 2018; Westin et al., 2018.[152]	ACS 5-year estimate (2016-2020)	Census block group
Home ownership	Homeownership has been connected to EV adoption.	Campbell et al., 2012; Tiwari et al., 2020.[153]	ACS 5-year estimate (2016-2020)	Census block group

[149] U.S. Census Bureau, 2016-2020 5-year ACS data. Available at: https://data.census.gov/. At the time of carrying out the DGEM methods, the 2016-2020 5-year ACS data were the most up-to-date dataset available.

[150] U.S. Census Bureau, *Glossary*, n.d. Available at: https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_4. We used the definition for Block Group from the glossary.

[151] See Michael Coffman et al., *Who Are Driving Electric Vehicles? An Analysis of Factors That Affect EV Adoption in Hawaii*, The Economic Research Organization at the University of Hawaii, May 30, 2018 (Coffman et al.). Available at: http://www.ourenergypolicy.org/wp-content/uploads/2018/06/Hawaii-EVs.pdf; Steven R. Gehrke et al., *Patterns and Predictors of Early Electric Vehicle Adoption in Massachusetts*, International Journal of Sustainable Transportation, June 1, 2022 (Gerhke et al.). Available at: https://www.tandfonline.com/doi/abs/10.1080/15568318.2021.1912223; Joram Langbroek et al., *Electric Vehicle Users and Their Travel Patterns in Greater Stockholm*, Transportation Research Part D: Transport and Environment, May 1, 2017 (Langbroek et al.). Available at: https://doi.org/10.1016/j.trd.2017.02.015.; and Kerstin Westin et al., *The Importance of Socio-Demographic Characteristics, Geographic Setting, and Attitudes for Adoption of Electric Vehicles in Sweden*, Travel Behaviour and Society, October 1, 2018 (Westin et al.). Available at: https://doi.org/10.1016/j.tbs.2018.07.004.

[152] Langbroek et al.; Coffman et al.; and Westin et al.

[153] Amy R. Campbell, *Identifying the Early Adopters of Alternative Fuel Vehicles: A Case Study of Birmingham, United Kingdom*, Transportation Research Part A: Policy and Practice, October 1, 2012. Available at: https://doi.org/10.1016/j.tra.2012.05.004; and Vibhor Tiwari et al., *Public Attitudes towards Electric Vehicle Adoption Using Structural Equation Modelling,* Transportation Research Procedia, Recent Advances and Emerging Issues in Transport Research – An Editorial Note for the Selected Proceedings, January 1, 2020. Available at: https://doi.org/10.1016/j.trpro.2020.08.203.

Factor	Justification	Literature Citations	Data Source	Spatial Scale
Commute time	Studies have found that EVs are typically used for shorter and briefer commutes rather than longer commutes.	Coffman et al., 2018; Jakobssen et al., 2016.[154]	ACS 5-year estimate (2016-2020)	Census block group
Building type (i.e., stand-alone household or multi-unit dwelling)	Research has found that people who live in stand-alone households are more likely to own an EV than people who live in apartment buildings	Langbroek et al., 2017; Gehrke et al., 2021; Westin et al., 2018.[155]	2021 DMV vehicle registration dataset	House hold

In order to match the socioeconomic data with the registered vehicles, our team joined vehicles to 2020 Census block groups. The block group level is as close to the household scale that our study can achieve and is the most comprehensive, efficacious dataset on local socioeconomic characteristics available. However, even at this level, our study assumes that all registered vehicles in a block group share the same characteristics.[156]

The ACS does not provide data on building type. Research indicates that owners of single-family homes are more likely to adopt an LD EV, in part because stand-alone houses have more room for EV chargers and more accessible parking for private vehicles. In order to represent building type in the non-fleet propensity model, we distinguished between address types – stand-alone buildings and multi-unit buildings by the presence of a unit number with the address. We selected this method because, to the best of our knowledge, there is no publicly available dataset showing building type (e.g., single family residential, multi-unit dwellings) available for all of California.

We trained a logistic regression model on 95 percent of the DMV registration data within the Study Area, achieving the parameters shown in Table A-6.

Table A-6. Regression model parameters.

Term	Coefficient	P Value
Vehicle is in a standalone building*	0.46	0
Share of households earning $150,000 or more annually	0.87	0

[154] See: Coffman et al.; Niklas Jakobsson et al., *Are Multi-Car Households Better Suited for Battery Electric Vehicles? – Driving Patterns and Economics in Sweden and Germany*, Transportation Research Part C: Emerging Technologies, April 1, 2016. Available at: https://doi.org/10.1016/j.trc.2016.01.018. Even though these papers find that early EV adopters tend to use their EVs for shorter commutes and trips that take less time, it is important to note that newer EVs have longer battery range, which makes newer EVs able to fill more of the same functions as a conventional vehicle.

[155] See: Langbroek et al.; Westin et al.; and Gehrke et al.

[156] The DGEM's usage of U.S. Census Bureau data for local socioeconomic and demographic information reflects the industry standard. Researchers studying the grid impacts of electric vehicle adoption have made similar assumptions, given the trustworthiness and availability of U.S. Census Bureau data. For example, see Gehrke et al., and Coffman et al.

Share of households earning $200,000 or more annually	0.33	0
Share of residents with bachelors as highest degree	2.43	3.04E-70
Share of residents with a postgraduate degree	2.64	0
Share of owner-occupied units	-0.10	0
Share of commutes 20-45 minutes	0.25	3.43E-46
Share of commutes 45+ minutes	0.53	2.03E-123

*If a sub-address (e.g., apartment A) was matched in geocoding, the building was assumed not to be standalone.

After training the model, we visually evaluated the model using the remaining five percent of data. This result is shown in Figure A-3. In the training data set, PHEVs receive a higher score, in general, than non-electric vehicles, while BEVs receive the highest score. This confirms that the model has some explanatory power.

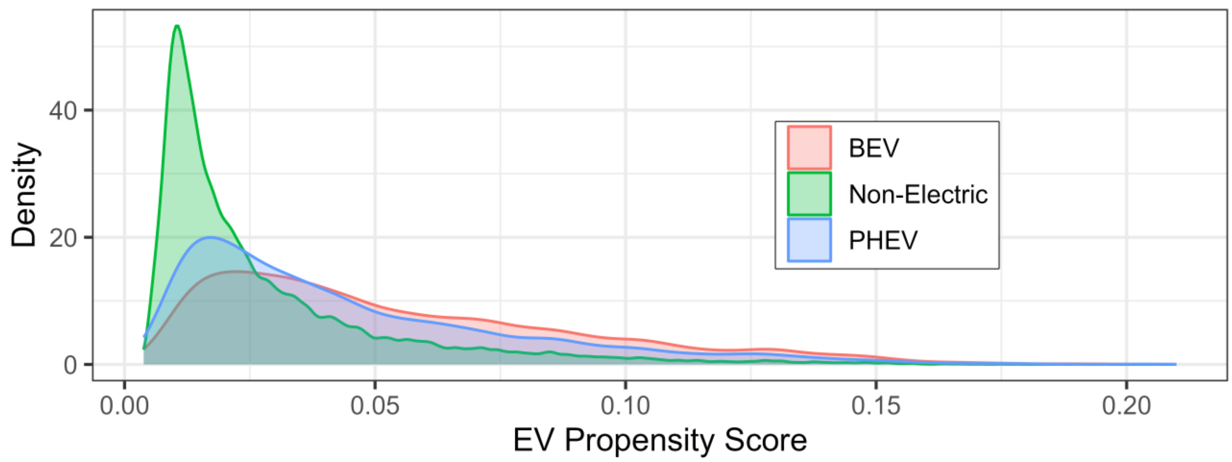

Figure A-3. Depiction of the predictive power of our propensity model. PHEV and BEV propensities are shifted significantly to the right (i.e. they have higher propensity scores). BEVs are shifted furthest to the right. This indicates success in the predictive model.

A.3.3.2. Personal random score

In this model, each LD vehicle was assigned a random score. We used a random propensity score for one model because this will achieve an approximately even density of EVs and thus spread out the load as much as possible. The historically informed model, on the other hand, will cluster EVs into higher-income, more educated neighborhoods.

A.3.4. Fleet propensity model variables

Because the MD and HD and commercial EV sectors are less mature than the LD sector and there is less research on the factors that influence uptake, we developed four propensity models that combined three categories – MD and HD vehicles and fleet LD vehicles (e.g., commercial, government) – to generate various fleet vehicle adoption models across the Study Area through 2035. Two of the propensity models rely on different empirical data gleaned from registration data, while the other two models are entirely random. We review the characteristics of the four propensity models below, including the advantages and limitations of each model. These models principally represent vehicles, especially fleet vehicles, used for commercial, government, and industrial purposes.

A.3.4.1. Feeder adoption score

Each fleet vehicle received a propensity score equal to the ratio of PHEV + BEV to total vehicles on its feeder in its same class (LD, MD, or HD). Vehicles on feeders without any EVs in their class (i.e., vehicles assigned a score of zero from the scoring process) received a random score between zero and negative one to ensure that such vehicles are randomly selected after vehicles with some EV adoption in their class and body type. This method will tend to cluster EV adoption for fleet vehicles where EV adoption is already occurring.

A.3.4.2. Fleet body-type score

Each fleet vehicle received a score equal to the ratio of PHEV + BEV to total vehicles with the same body type in its class (LD, MD, or HD). All vehicles with a score of zero received a random score between zero and negative one to ensure that such vehicles are randomly selected after vehicles with some EV adoption in their class and body type. This method will tend to predict EV adoption in sectors with early adoption.

A.3.4.3. Fleet random score

The methodology is the same as the random personal propensity model.

The strength of this random propensity score is that it will achieve an approximately even density of fleet EVs, spreading out their load as much as possible. This model acknowledges that EV adoption across fleets remains nascent and the exact feeders on which load from these vehicles will concentrate is unknown. However, a limitation of this model is that fleet vehicles will likely not convert to electric on a vehicle-by-vehicle basis, as this model implies, and instead will probably convert on a fleet-by-fleet basis. Additionally, the current locations of fleet hubs are a strong indicator of the sites where electrified fleets will charge overnight, which detracts from the efficacy of a random propensity by vehicle model.

A.3.4.4. Fleet random-by-feeder score

This propensity model assigns a random score to each feeder rather than each vehicle. The advantage of this propensity model is that it clusters fleet vehicles nearly as much as is possible. As such, it serves as an upper bound for fleet adoption density. Furthermore, it may more accurately simulate whole-fleet transitions.

A.3.5. Application of propensity score to generating the statewide distribution of EVs

We assigned each vehicle in the Study Area a propensity score based on its likelihood to switch from a conventional vehicle to an electric vehicle. As described in Appendix A.3.1, we used the

2022 IEPR projections for EV population per vehicle class in California as the estimation for the number of EVs that will annually replace conventional vehicles.[157] The conventional vehicles with the highest scores became EVs until the projected population per vehicle class was met.

We differentiated between conventional vehicles that were replaced by BEVs and PHEVs: the conventional vehicles with the highest scores became a BEV until the BEV population target was met, then the conventional vehicles with the next-highest propensity scores became PHEVs. This is consistent with the observation that PHEV buyers have lower propensity scores than BEV adopters but higher propensity scores than non-adopters, as shown in Figure A-3. The conventional vehicles with the highest scores that did not convert to EVs in the previous year rollover to the next year and are replaced by EVs in that year. Table A-7 illustrates an example: five BEVs and two PHEVs are added in year two, and three BEVs and one PHEV are added in year three. We continued this analysis year over year from 2023 through 2035 because the IEPR data end in 2035.

Table A-7. Notional conversions from conventional vehicles to BEV or PHEV.

Vehicle	Propensity Score	Rank	Drivetrain - Year 1	Drivetrain - Year 2	Drivetrain - Year 3
#1	0.9	1	Conventional	BEV	BEV
#2	0.85	2	Conventional	BEV	BEV
#3	0.84	3	Conventional	BEV	BEV
#4	0.84	4	Conventional	BEV	BEV
#5	0.82	5	Conventional	BEV	BEV
#6	0.82	6	Conventional	PHEV	PHEV
#7	0.8	7	Conventional	PHEV	PHEV
#8	0.75	8	Conventional	Conventional	BEV
#9	0.6	9	Conventional	Conventional	BEV
#10	0.55	10	Conventional	Conventional	BEV
#11	0.54	11	Conventional	Conventional	PHEV
#12	0.31415	12	Conventional	Conventional	Conventional

The results of this methodological step consisted of tables of adoptions of electric vehicles by feeder and year for each propensity scenario, grouped by subclass.

With respect to the propensity models looking at the feeder level, when the population reaches its target a fraction of the way into converting conventional vehicles into EVs on one feeder in a given year (e.g., 2025), the model will stop converting the vehicle at the population target for that year. Then, when the subsequent year (e.g., 2026) begins, the remaining conventional vehicles on that feeder will become EVs first and subtract from the population target for the

[157] Data provided by CEC on April 20, 2023. These are internal model data that are not published.

subsequent year (e.g., 2026). The standard method for applying the propensity score to the conversion of conventional to electric vehicles year over year resumes, as described in Appendix A.3.5.

A.3.6. Methodological limitations

A lack of published literature and lack of corroborating information in the DMV dataset regarding where fleet vehicles charge overnight meant we were not able to confirm whether the registered address of a MD or HD EV functioned as the home base for overnight parking or was an administrative office separate from the fleet hub. Due to the lack of data on truck refueling behavior and overnight parking data, among other factors, we were not able to create a more spatially precise MD and HD adoption propensity model in this study. An improved model for estimated MD and HD fleet electrification would require a dataset showing the locations of fleet operation centers and high-trafficked truck stops across California. From correspondence with numerous TE experts, it appears that no database of fleet home bases yet exists.[158] Datasets showing the locations of fleet operation centers and high-trafficked truck stops would provide a more precise picture of where fleet charging would occur and where load demand due to charging would take place. However, company privacy concerns and competition might hinder the near-term completion of these types of datasets. The FIP workstream being undertaken by CPUC's Energy Division may produce more meaningful data in this regard.

A.4. Calculating the annual energy demand of EVs

To determine the total energy demand that EVs place on the grid, we first calculated the annual energy demand by vehicle subclass for each year from 2021 through 2035. Next, we summed annual demand by vehicle class (i.e., LD or MD and HD) across each feeder. LD vehicles were kept separate because we established different charging load shapes for LD vehicles, as discussed in Appendix A.5.

One notable caveat of this step and the study overall is that we do not consider public charging; all charging is assumed to take place at a vehicle's registration address, as discussed in Section 4.3.

We used VMT per year by vehicle subclass and powerplant-to-wheels efficiency from the 2022 IEPR.[159] These data vary by vehicle subclass and year (i.e., vehicles in 2035 have different VMT and efficiency assumptions modeled than vehicles in 2030). These efficiency changes are on an average fleet basis, and we interpret them as such rather than applying different efficiencies to EVs based upon adoption year. Thus, we assume that an EV adopted in 2030 will

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[158] e.g., CALSTART staff, email correspondence, April 21, 2023.

[159] Data provided by CEC on April 20, 2023. These are internal model data that are not published.

operate with different efficiency and VMT assumptions in 2031. PHEVs are assumed to be driven 60 percent on electric-powered miles, consistent with the IEPR's data.

The CEC (through the IEPR) provided us with data on electric shuttle bus and school bus energy[160] consumption, which could be used to make a more granular energy consumption calculation for these vehicle types compared to other MD and HD vehicles in the same class. However, since the DMV data were coded no more specifically than "bus," we elected to leave them with other vehicles of the same gross vehicle weight rating.

We converted the miles per gallon equivalent (MPGe) from the IEPR data to kWh/mile. California has a distinct MPGe to kWh conversion factor due to its unique fuel blend: 32.7 kWh/gallon. In order to determine the annual energy usage (AEU) for each EV subclass, we used the following calculations:

- BEV AEU $\left[\frac{\text{kWh}}{\text{year}}\right] = 32.7 \left[\frac{kWh}{Gallon}\right] \cdot \frac{1}{MPGe} \left[\frac{Gallons}{Mile}\right] \cdot \text{VMT} \left[\frac{Miles}{Year}\right]$
- PHEV AEU $\left[\frac{\text{kWh}}{\text{year}}\right] = 32.7 \left[\frac{kWh}{Gallon}\right] \cdot \frac{1}{MPGe} \left[\frac{Gallons}{Mile}\right] \cdot \text{VMT} \left[\frac{Miles}{Year}\right] \cdot 0.6 \left[\frac{Electric\ miles}{mile}\right]$

Table A-8 provides an excerpt of the results drawn from the IEPR for 2021 and 2035.

Table A-8. Vehicle consumption information. Source: 2022 IEPR data with modifications.[161]

	kWh/mile		Miles/year		kWh/year	
Subclass	**2021**	**2035**	**2021**	**2035**	**2021**	**2035**
Car-Sport	0.35	0.31	6,790	6,666	2,400	2,059
Car-Subcompact	0.28	0.28	8,762	10,144	2,473	2,856
Car-Compact	0.29	0.30	9,043	10,317	2,616	3,087
Car-Midsize	0.26	0.28	12,407	12,047	3,282	3,418
Car-Large	0.29	0.27	7,458	9,599	2,134	2,618
Pickup-Compact	0.41	0.41	8,234	13,009	3,396	5,365
Pickup-Std	0.44	0.44	11,307	11,714	4,993	5,144
Pickup-Heavy	0.58	0.53	6,742	11,159	3,943	5,882
SUV-Subcompact	0.30	0.38	12,455	13,608	3,795	5,173
SUV-Compact	0.29	0.30	10,240	10,780	2,985	3,264
SUV-Midsize	0.42	0.42	9,009	11,704	3,750	4,947
SUV-Large/Heavy	0.58	0.51	10,100	13,474	5,817	6,890
Van-Minivan	0.44	0.43	8,841	14,194	3,870	6,158
Van-Std	0.41	0.40	8,708	12,889	3,610	5,180
Van-Heavy	0.47	0.43	8,838	13,879	4,163	5,994
GVWR 3	0.62	0.59	16,409	15,887	10,156	9,312
GVWR 4/5	1.16	1.05	19,661	17,290	22,803	18,104

[160] Data provided by CEC on April 20, 2023. These are internal model data that are not published.

[161] Data provided by CEC on April 20, 2023. Data for 2021 is copied from 2023 for all vehicles. For pickup-compact, we added 2023 data copying 2024 and 2025. SUV Heavy is copied from SUV-Large because the IEPR does not predict any heavy SUVs. We assumed other MD and HD vehicles, such as "demand response", "shuttle bus", and "school bus," had equivalent values by GVWR.

	kWh/mile		Miles/year		kWh/year	
Subclass	**2021**	**2035**	**2021**	**2035**	**2021**	**2035**
GVWR 6	1.10	1.03	13,782	15,973	15,163	16,489
GVWR 7	1.08	1.03	17,397	26,068	18,842	26,894
GVWR 8	1.85	1.77	38,825	34,881	71,856	61,773

Both drivetrain efficiency and charging efficiency affect an EV's energy demand from the grid and must be factored into a calculation of total EV energy usage. Drivetrain efficiency refers to the amount of energy in the battery used to power the vehicle's wheels.[162] Charging efficiency describes the amount of energy drawn from the wall (in kWh) that is converted into usable energy for the EV battery (versus energy expended in route to the battery). The same charging efficiency assumptions that the U.S. Environmental Protection Agency (EPA) uses are included in the CEC's MPGe value.[163] In fact, the number used by EPA and CEC overestimates the impact of EV charging on the distribution grid (for our purposes) because it includes transmission losses.

Because we know the location of every electric vehicle on each feeder in the three IOUs' service territories, we can calculate the annual load placed on each feeder due to EV charging. To do so, we summed the annual energy demand of each registered vehicle, based on subclass, on each feeder for each year of the study. We kept MD and HD separate from LD at this stage due to the differing charging load shapes.

A.5. Calculating hourly EV load on each feeder and substation

Our next step entailed developing typical EV load shapes by class for the purpose of identifying when the load serving capacity of the distribution system will be exceeded and when upgrades will be needed.[164] EV charging typically follows a predictable schedule that varies based on time of the day (as shown in Figure A-5). The 2022 IEPR provides hourly load profiles for LD as well as MD and HD vehicles in the 2022 IEPR Planning Scenarios.[165] We considered only the

[162] Ossian Muscad, *An Overview of the Electric Vehicle (EV) Drivetrain System*, Datamyte, July 17, 2022. Available at: https://www.datamyte.com/ev-drivetrain/.

[163] See D. Good, *EPA Test Procedures for Electric Vehicles and Plug-In Hybrids*, DRAFT Summary – Regulations take Precedence, November 14, 2017. Available at: https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf.

[164] Jenn et al. used a similar methodology for determining when the aggregated load of EV adoption would exceed the carrying capacity of feeders throughout PG&E's service territory. See: Alan Jenn et al., *Distribution Grid Impacts of Electric Vehicles: A California Case Study*, IScience, January 21, 2022 (Jenn et al.). Available at: https://doi.org/10.1016/j.isci.2021.103686.

[165] CEC, *California Energy Demand Update, 2022-2035,* the Planning Scenario under the Hourly Demand Forecast Files. Available at https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2022-integrated-energy-policy-report-update-2.

load shapes for the IEPR Planning Scenarios, which includes additional achievable TE (AATE).[166]

In order to reduce the computational complexity of calculating the hours of peak demand on the grid, we developed a load forecast that represented typical load charging behavior over time while retaining most of the variability in the IEPR model's hourly charging consumption. To do so, we divided the forecasts between weekends and weekdays and across the years of the study – 2023[167] through 2035. Figure A-4 shows the result.

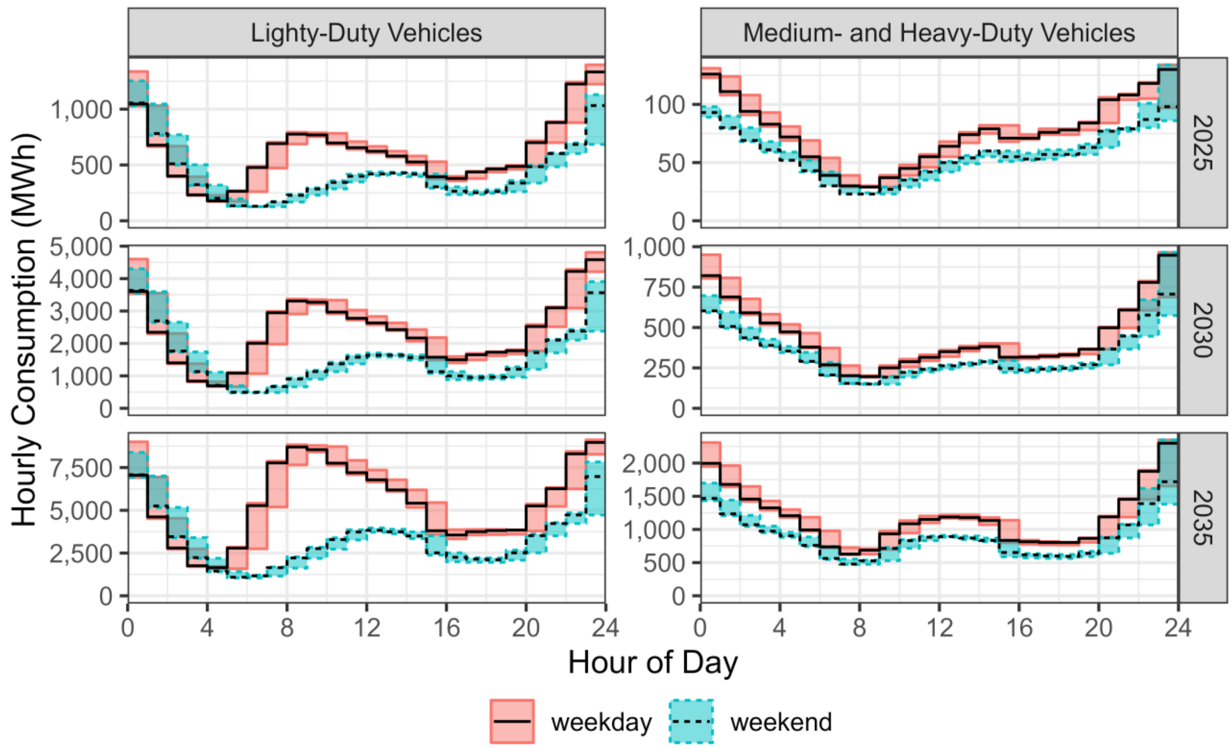

Figure A-4. The 2022 IEPR's aggregate charging behavior. Colored areas show the full variability within each group and the black line shows the median.

The IEPR's 24-hour energy consumption data show variation in charging patterns: on weekdays, peak charging occurs mid-morning (approximately 8 a.m. to noon) and late at night (approximately 10 p.m. to 2 a.m.) while weekend charging mostly occurs between 10 p.m. to 4 a.m., with a small demand surge in the middle of the day. Meanwhile, the peak charging of MD and HD EVs takes places between approximately 10 p.m. to 2 a.m., with another demand surge at about 2 p.m. that is equivalent to about half of the daily peak demand. The magnitude of variation within each model is relatively small (shown by the size of the colored bands in Figure

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[166] The baseline scenario's load shape is similar to the load shape including AATE, but AATE has a slightly larger noon peak.

[167] 2023 is the first year of hourly forecast data.

A-4). Furthermore, the median corresponds with the maximum value or minimum value nearly all the time; thus, the median adequately represents the typical hourly charging behavior. For this reason, we used the median hourly load profiles for LD as well as MD and HD models.

Next, we scaled the 24-hour load profiles for EV charging to hourly consumption rates aggregated over the course of the year (Figure A-5). The result provides a factor for converting annual consumption to hourly consumption. It is important to note that we consider only typical charging behavior over the course of a given year. This is consistent with our isolation of peak baseline load—it would be too conservative to assume that the peak charging day *and* the peak non-charging day coincide. On the other hand, this assumption may be too liberal: for example, the 90th percentile charging day and 90th percentile base-load day may coincide and be worse than our forecast. Nevertheless, we had to select a single assumption for the DGEM and we chose maximum baseline load combined with median EV charging load shape. This limitation of the model is discussed in Section 4.4.

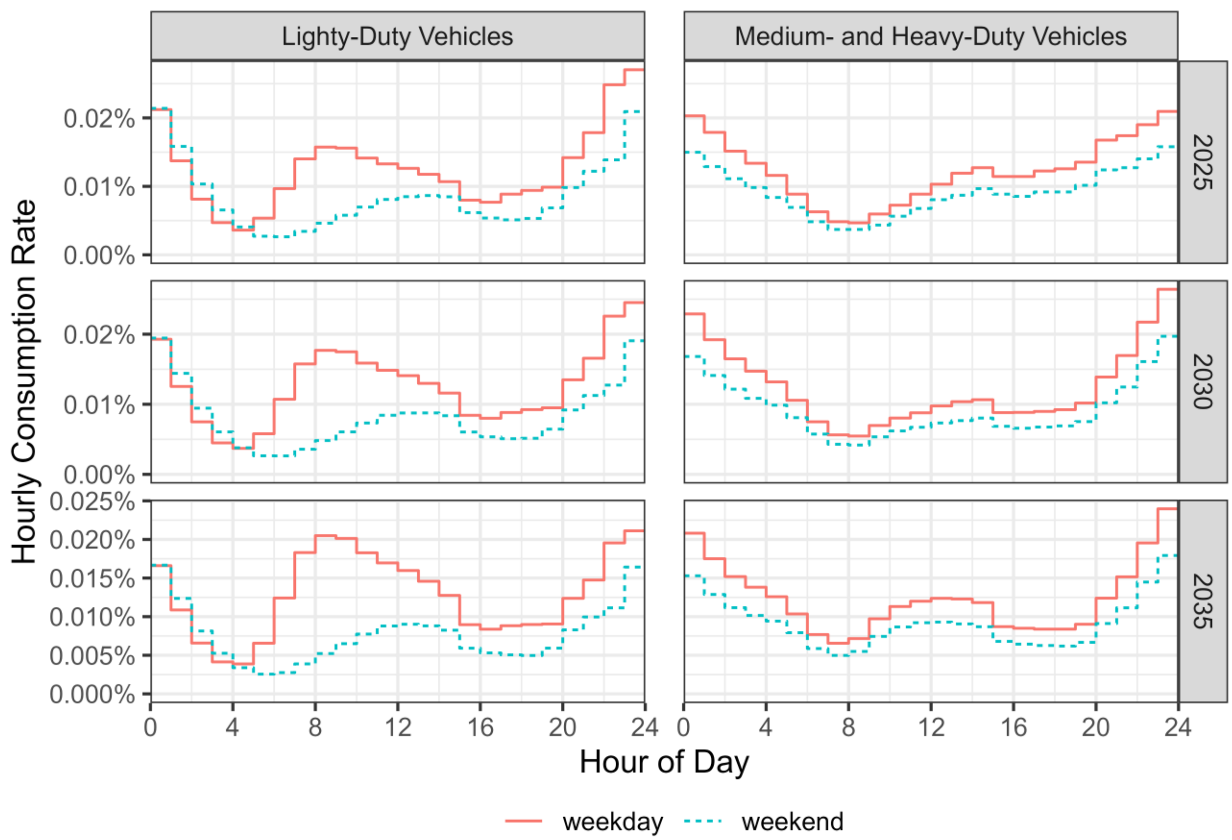

Figure A-5. Select typical charging behavior (median) across select years, vehicle classes, and weekday-vs-weekend. The hourly consumption rate is the energy consumption of each hour divided by total energy consumption in that year.

The *Hourly Consumption Rate* is the hourly consumption (MWh) in hour *i* divided by the sum of consumption across all hours in the year. We use the following equation to calculate the hourly consumption rate:

$$Hour\ Consumption\ Rate_i = \frac{Hourly\ Consumption_i}{\sum_{k=1}^{8760} Hourly\ Consumption_k}$$

The hourly load profiles per year demonstrate two significant patterns that informed our selection of representative charging behavior:

1. LD vehicles charge at different times than MD and HD vehicles. The MD and HD sector typically charges overnight, whereas many LD vehicles charge during the day at workplaces or public locations, such as shopping centers.
2. Weekday charging exceeds weekend charging (except in early morning hours when weekend charging is slightly greater). Therefore, we see little benefit to considering weekend charging in our analysis.

Given these results, we selected the representative EV charging load shapes as: 24-hour load profiles based on the median value of the AATE scenario for each year of hourly EV charging data provided by the IEPR (Figure A-6). We used the load shapes from 2023 for 2021 (our analysis does not consider 2022).

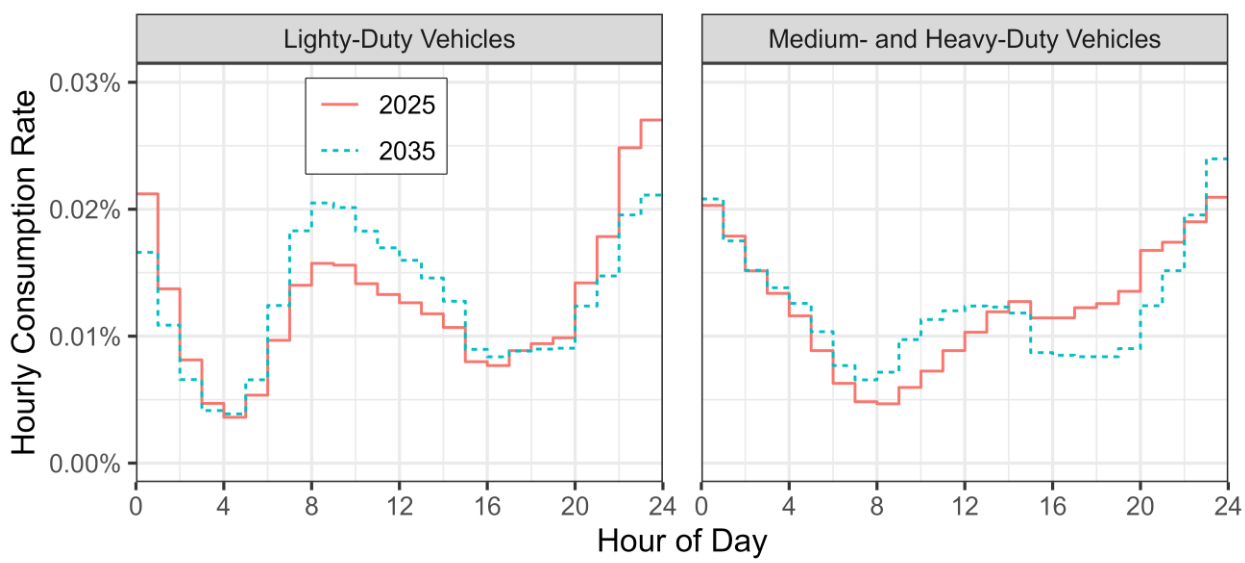

Figure A-6. Selected load examples for two years. Hourly consumption rate is the consumption in each hour divided by the annual consumption.

Next, we determined the hourly load placed on all the feeders and substations in the Study Area using a three-step process:

1. Calculate hourly annual consumption for each vehicle class (LD and MD and HD).
2. Sum the annual hourly load for LD and MD and HD EVs on each feeder.

3. For each substation, sum up the hourly load on each of its feeders to calculate its total load.

Because our analysis assumes that all LD vehicles are charged with a single load shape and all MD and HD vehicles are charged with another load shape, we did not distinguish between public and private chargers. This method is consistent with the DGEM's simplifying assumption that vehicle charging happens at the registered address. Accordingly, we also assume that each household will have EV chargers sufficient to charge every EV at the registered address. That said, the load shape does include the temporal impacts of public charging.

Our methodology does not account for the differing impacts of charger types. For example, providing 50 kWh to an electric vehicle will cause different grid impacts depending upon whether the energy is spread over one hour (50 kW) or over ten minutes (300 kW). By using averaged hourly forecasts, we ignore the impacts that highly concentrated direct-current fast chargers (DCFCs) can place on the electric grid. For example, a cluster of ten 350-kW DCFCs drawing on the same feeder and charging EVs simultaneously would generate a peak load of 3.5 MW, but these DCFCs during typical, non-congruous charging events would have a significantly lower load. Our estimates are consistent with a typical spread, not necessarily the highest peak events. High peak events, which we do not account for, could necessitate grid upgrades beyond the upgrades that we identify. See Section 4 for further discussion.

A.6. Calculating non-EV load on each feeder and substation

Next, we determined how EV load interacts with other load types and affects the three IOUs' distribution systems. These loads include baseline resources and loads on the grid today as well as additions of PV, EE, BE, and BESS. Load changes also include population growth, cultivation, and other factors. All these non-EV loads are captured, in aggregate, in the IEPR's hourly load forecasts.[168]

In order to understand how EV load combines with other loads in the distribution system, we calculated the hourly load profiles and expected load of non-EV electricity consumption and generation from 2021-2035. This step is critical not only because several load types are expected to increase but also because the exact year that the combined demand of all the consumption exceeds the carrying capacity of distribution systems across utilities remains a moving target. Studies using more granular data could refine annual load projections and estimate the date by which a distribution system will require upgrades.

To calculate non-EV load from 2021 through 2035 and associated distribution system impacts, we followed a four-step process:

1. Calculate the baseline non-EV load.

[168] 2022 CED, Hourly Demand Forecast Files, Planning Scenario.

2. Determine a growth rate for non-EV load.
3. Forecast the non-EV load on feeders using the established growth rate.
4. Sum up non-EV load on each substation.

A.6.1. Calculating base-year non-EV load

The first step was to calculate the base-year non-EV load for the three IOUs (2022 for PG&E, and 2021 for SCE and SDG&E). To do this, we subtracted the calculated 2021 EV load from the baseline load provided by the IOUs. This created our best estimate of base-year non-EV loading.

To slightly improve our calculation, we divided EV load by the ratio M/T (see Table A-3). This results in an adjusted EV load that slightly increases the amount of load that we attribute to EVs. This step accounts for the vehicles lost in the geocoding process because they lacked an address that could be geocoded. See Appendix A.2.1 for a fuller description of this methodological step.

As noted in Appendix A.2.1, this resulted in negative maximum loads on certain assets in certain hours. This is neither a problem nor the only basis for negative maximum load estimates. For example, PG&E's Goose Lake 1103 feeder reports a maximum load less than zero from 10 a.m. to 3 p.m., peaking at –5.5 MW.

A.6.2. Calculating the growth rate of non-EV load from the IEPR

We needed non-EV growth rates to project SCE's and SDG&E's 2021 load data through 2035 as well as to establish the 2021 load from PG&E's 2022 load. We relied on hourly forecasts from the 2021[169] and 2022[170] IEPR vintages to determine annual load growth over the study timeframe. The IEPR's load forecasts tabulate energy consumption by hour, year, and sector. Since the 2022 IEPR only forecasts from 2023 onward, we used the 2021 IEPR as the source for the 2021 and 2022 hourly loads.[171] We calculated hourly non-EV energy consumption in each IOU's service territory over the period 2021 to 2035 from the total managed net load minus the load attributable to electric vehicles.[172]

A.6.2.1. Calculating annual growth rates

For each dataset, we calculated the annual growth rate in each year (*n)* and each hour (*h)* as follows:

$$Growth\ Rate_{n,h} = \frac{Demand_{n,h} - Demand_{n-1,h}}{Demand_{n-1,h}}$$

[169] 2021 CED, Hourly Demand Forecast Files, Mid Baseline Scenario.

[170] 2022 CED, Hourly Demand Forecast Files, Planning Scenario.

[171] 2021 CED, Hourly Demand Forecast Files, Mid Baseline Scenario.

[172] Non-TE energy consumption = MANAGED_NET_LOAD – MEDIUM_HEAVY_EV – LIGHT_EV – AATE_LDV – AATE_MDHD.

For example, the *Growth Rate*$_{2022,1}$ is the relative amount that 2021 demand in the 1 a.m. hour increased to become 2022 demand in the 1 a.m. hour. This is an atypical method for defining the growth rate, but this method allowed us to apply the growth rate in year n to calculate the demand in year n from demand in year n-1:

$$Demand_n = (1 + Growth\ Rate_n) \cdot Demand_{n-1}$$

From there, we used the growth rates calculated for 2022-2035 as shown in Figure A-7 (2021 cannot be calculated because there is no $Demand_{n-1}$). A change in the data sources for growth rates caused a jump in year 2023.

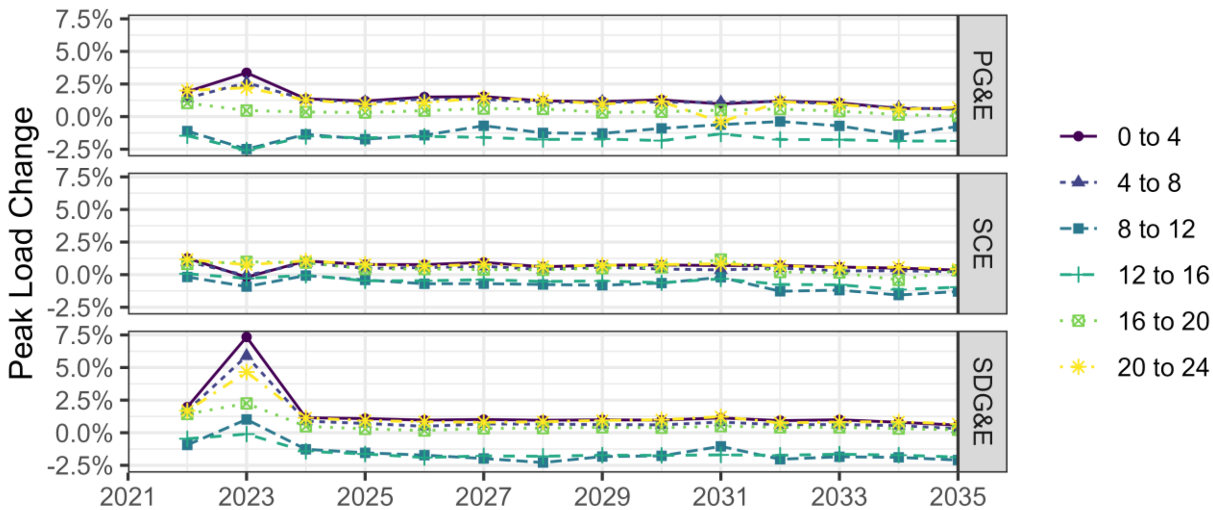

Figure A-7. Annual change in peak demand from non-EV sectors. We averaged the data used in our analysis across small bins to make these figures easier to read.

A.6.2.2. Calculating cumulative growth rates

Next, we calculated the cumulative growth rates, forecasting future growth for SCE and SDG&E as well as backcasting from 2022 to 2021 for PG&E. For each IOU, we set the cumulative growth rate to one in the year that the IOUs' feeder load data represent (i.e., 2021 for SCE and SDG&E, and 2022 for PG&E). Then we forecasted a cumulative growth rate (CGR) for future years n as:

$$CGR_n = \prod_{k=b+1}^{n} 1 + Growth\ Rate_k$$

Where b is the base year.

Backcasting takes a similar form, wherein:

$$CGR_n = \prod_{k=b}^{n-1} \frac{1}{1 + Growth\ Rate_k}$$

The resulting CGRs are shown in Figure A-8.

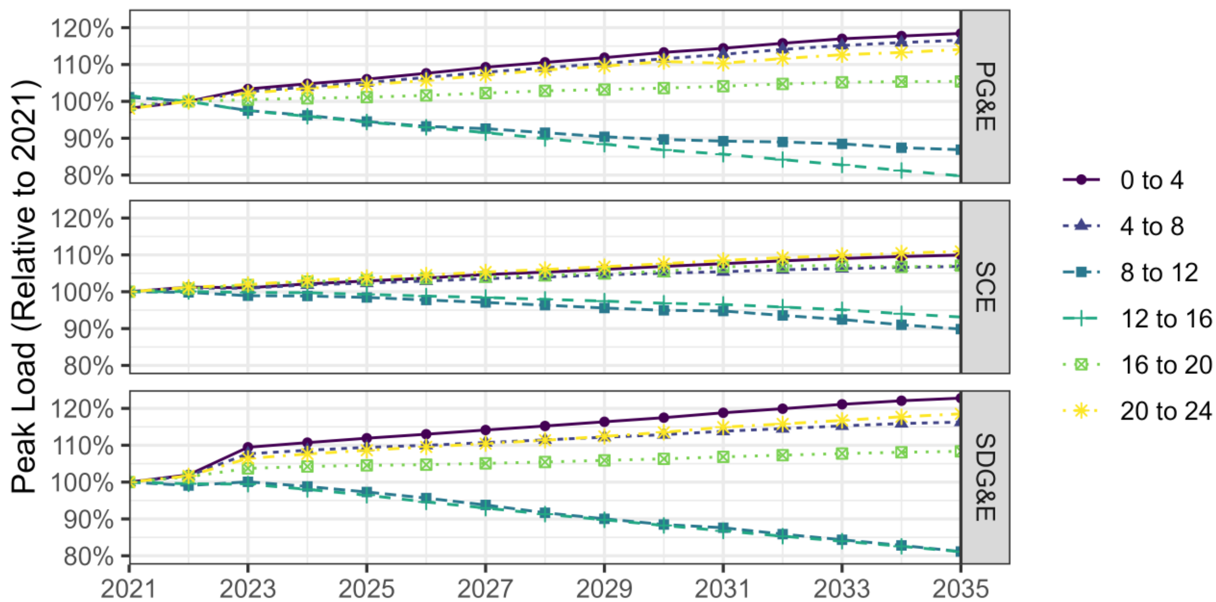

Figure A-8. CGR of hourly peak demand from non-EV sectors. We averaged the data used in our analysis across small bins to make these figures easier to read. Note that PG&E's CGR is keyed (set to a value of 100 percent) to 2022, while the other IOUs' CGRs are keyed to 2021.

A.6.3. Forecasting non-EV load

Once we determined the base year demand and the annual, hourly CGRs, we multiplied the base-year demand by the calculated CGRs to forecast non-EV load on each feeder in future years. Finally, we returned the small amount, *X*, that was lost by dividing the 2021 EV load by M/T (see Table 2-2):

$$X = TE\ load - TE\ load\ / \left(\frac{M}{T}\right)$$

A.6.4. Summing non-EV load across substations

At this final step, we summed hourly load across each of the feeders connected to each substation:

$$SL_{i,h} = \sum_{i} feeder_{i,h}$$

That is, the load for substation (*SL*) *i* in hour *h* is the sum of the load in hour *h* on all feeders connected to it (each $feeder_i$). Because computational power limited us to assessing only 24 hours rather than all hours in the year, this method tends to overestimate the load on substations to the extent that peak days for feeders fed by a particular substation differ. This effect is likely small because weather, a key driver of peak load, will be similar over the small geographic area served by one distribution substation.

A.7. Calculating total peak loads and overloads

We calculated 24 peak loads (one for each hour) for each distribution asset (i.e., feeder or substation) and selected the maximum value of peak hourly load.

Overloads were also straightforward to calculate. We subtracted the rating of each infrastructure asset (using the map created in Appendix A.1) from its peak load and applied a lower bound of zero (i.e., there are no negative overloads). At this stage, we retained the existence of overloads and their magnitudes. The magnitude of overloads impacts the cost, as discussed in Appendix A.8.

A.8. Calculating total cost

At a high level, in each year of the analysis, we identified the distribution system assets experiencing capacity overloads and calculated the cost of the minimum infrastructure necessary to cure these overloads. The costs considered in the DGEM study include building new feeders, installing new transformer banks in substations, and building new substations. Building new feeders can solve feeder overloads.[173] Installing new transformer banks or constructing new substations can solve substation overloads. In general, costs are highly variable and difficult to estimate.[174]

Establishing when a new substation might be needed is a challenge. From a cost perspective, it is best to avoid building new substations. The utility will only build a new substation if additional transformers cannot be sited within the existing substation footprint. However, establishing whether there is space in each substation requires a case-by-case study, data which were not available to us. Because of this, we assumed a share (see Table A-11) of new transformers in substations would trigger building a new substation.

Additionally, the length of feeder that needs to be replaced or supplemented with an additional feeder is highly uncertain and significantly affects infrastructure upgrade costs. In fact, the length of feeder replacement is so integral to upgrade costs that costs are generally provided on a per-foot basis.[175]

Generally, we do not know the location of overloads within feeders because the spatial scale of the DGEM is only as granular as the feeder, not the specific feeder section or segment at which

[173] Feeder overloads can also sometimes be solved by reconductoring or increasing the feeder voltage, referred to by the IOUs as a voltage cutover. The cost of cutovers is difficult to assess because cutovers entail installing new service transformers, substation transformers, and potentially different poles. The applicability of cutovers as a mitigation is constrained by the need to maintain operational flexibility.

[174] For example, 25th percentile and 75th percentile costs can differ by more than an order of magnitude. See Elmallah et al., *Supplementary Information* at Tables 5 and 6.

[175] PG&E TY 2023 GRC Exhibit PG&E-4 at 165.

overloads occur.[176] Data and computational limitations contributed to the spatial scale of the distribution system used in this study. Establishing the length of feeder that may need to be upgraded is a particular challenge because feeders are highly branched, as shown in Figure A-9. No single overload would require reconductoring an entire feeder, but it is not possible to know precisely how much of the feeder must be reconductored based on available data. At minimum, it is plausible that each overload would necessitate the replacement of the feeder's mainline;[177] replacement length beyond the mainline is unknown.

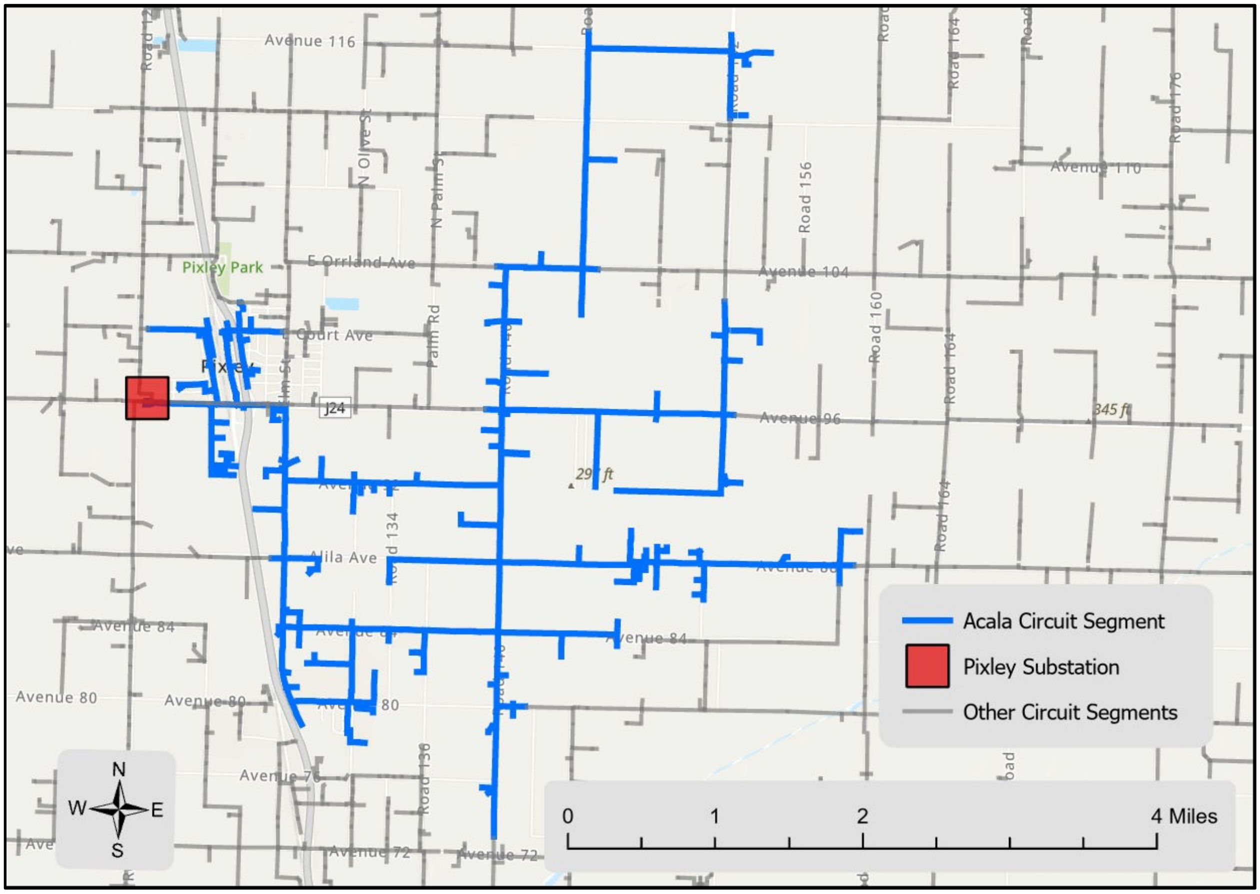

Figure A-9. Example feeder (Acala, 12-kV) in SCE's service territory.

The EIS assumed that two miles of feeder would need to be replaced on every overloaded feeder.[178] The EIS further assumed that transformers could be accommodated at substations with

[176] A section is separated by sectionalizing devices (devices which can open to stop power flow). A segment is the length of feeder between two poles.

[177] The mainline is the highest amperage portion of the distribution feeder, the backbone, to which other feeder segments connect.

[178] EIS at 116. This is the case for SDG&E and PG&E. SCE did not explicitly state a length, but costs are consistent with two-mile runs for other utilities.

fewer transformer banks than a typical substation footprint would allow.[179] This assumption could lead the EIS to underestimate costs associated with substations designed for a lower number of transformer banks and overestimate the costs of building a new substation if the original could have accommodated more banks.

As with the DGEM's propensity model, we approached uncertainty with scenario analysis. We gathered three feeder length replacement estimates based on data provided by PG&E and SCE. We also used data from the EIS to create a fourth feeder length replacement estimate. First, PG&E provided the average feeder upgrade length for the past five years (across 242 projects[180]), which is 1.35 miles. PG&E also provided the total length of both mainline and non-mainline conductors within its service territory. We calculated the ratio of mainline to total length and multiplied PG&E's average feeder length by this ratio, resulting in a value of 9.5 miles. Additionally, SCE provided an average length for new feeder projects across ten projects over the past two years. The average replacement length is 10.9 miles. Our final scenario used the EIS's assumption of two-mile feeder length replacements. These data are summarized in Table A-9.

Table A-9. Four feeder upgrade length scenarios used in the DGEM's cost analysis.

Source	Length (miles)	Scenario
SCE Average New Feeder Length	10.9	High
PG&E Average Non-Mainline Length	9.50	Medium
PG&E Average New or Reconductoring Feeder Length	1.35	Low
EIS	2.00	Replicate

Using a wide range of estimates to create our scenarios may provide more insight into the uncertainty around total upgrade cost projections. Figure A-10 shows that the length of nearly all feeders is longer than two miles, and most feeders are longer than ten miles. Thus, our range of scenarios may not necessarily bound the actual cost. Nevertheless, the scenarios significantly improve the DGEM's total upgrade cost projections relative to any single scenario.

[179] EIS at 118.

[180] The projects included reconductoring, installing a new overhead line, re-pulling underground lines, and installing new underground lines.

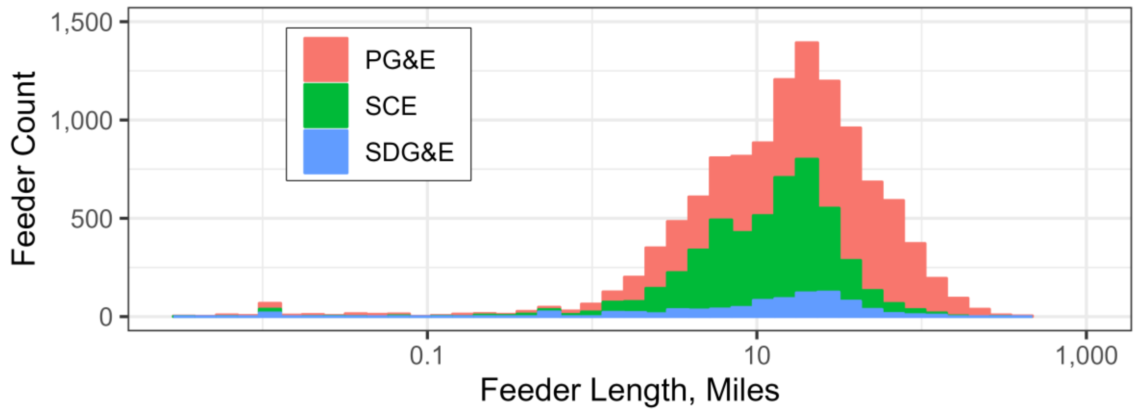

Figure A-10. Histogram of feeder lengths. Note the logarithmic x-axis.

The IOUs' data on feeder length replacement averages also may not reliably indicate the length of future upgrades. This is because future upgrades may serve a greater amount of distributed load than past upgrades (i.e., EVs at 100 houses versus one large industrial customer). Therefore, future asset upgrades may need to cover a significantly longer percentage of branching distribution lines than past upgrades.

To calculate the unit cost of each IOU's grid assets, we used PG&E's and SDG&E's per-foot costs for both underground and overhead conductors.[181] We averaged the per-foot costs for the medium cost scenario (see Table A-10) and used plus and minus one standard deviation for the high and low cost scenarios, respectively. The per foot costs were then multiplied by the lengths show in Table A-9. For the Replicate scenario, we used the unit costs directly from the EIS.[182] The resulting costs are shown in Table A-10.

Table A-10. Feeder costs across the four scenarios.

IOU	Size	Low Cost	Medium Cost	High Cost	Replicate
PG&E	12 MW	$2,855,879	$20,014,888	$32,399,013	$6,363,200
SCE	12 MW	$2,855,879	$20,014,888	$32,399,013	$5,473,094
SDG&E	12 MW	$2,855,879	$20,014,888	$32,399,013	$6,689,760

We also created four scenarios for substation upgrades. For the Replicate scenario, we used three different substation upgrade frequency values for the three IOUs based on data provided by the EIS team. Table A-11 shows the upgrade frequencies for each scenario and IOU. The Replicate scenario uses values calculated from the EIS for each IOU; the other scenarios (low, medium, and high) used the same three IOU substation frequency values sorted from low to

[181] SDG&E, *San Diego Gas & Electric Unit Cost Guide,* March 31, 2023. Available at: https://www.sdge.com/sites/default/files/documents/SDGE%20Updated%20Rule21%20Unit%20Cost%20guide%20-%202023_0.pdf; and PG&E TY 2023 GRC Exhibit PG&E-4 at 165.

[182] EIS at 117.

high, paired with the three different substation costs to attempt to bound uncertainty in upgrade cost estimates.

Table A-11. Substation upgrade frequencies.

IOU	Low	Medium	High	Replicate
PG&E	6.4%	20.4%	42.2%	42.2%
SCE	6.4%	20.4%	42.2%	20.4%
SDG&E	6.4%	20.4%	42.2%	6.4%

Instead of rolling the substation cost into the bank cost, we kept the values separate and we limited the need for substations to one per upgrade even if multiple banks were needed. We kept these costs separate because, according to PG&E, a typical substation can accommodate three 45 MVA transformers and the DGEM estimates that, at maximum, two transformer banks will be needed to accommodate estimated overloads. For the Replicate scenario, we reference the exact costs from the EIS for new substations and transformer banks.

Since PG&E's standard transformer size is larger than the other two IOUs, we used the cost estimate values provided by PG&E for three of its scenarios. For the other two IOU banks and substations, we use the highest and lowest credible estimates. This excluded EIS data on bank costs for SCE because we received an updated estimate and substation costs for SDG&E because the EIS's estimate does not account for all aspects of building a substation.[183] Table A-12 summarizes the resulting costs.

Table A-12. Substation and transformer bank upgrade costs, in millions of dollars. L/M/H = low/mid/high.

		L/M/H	Low	Mid	High	Replicate cost	
IOU	**Size**	**Bank**	**Substation**			**Bank**	**Substation**
PG&E	45 MW	$11.80	$15.20	$25.80	$36.40	$11.80	$15.20
SCE	28 MW	$3.40	$15.20	$25.80	$36.40	$2.00	$37.60
SDG&E	28 MW	$4.70	$15.20	$25.80	$36.40	$4.70	$16.20

The precise data sources are as follows:

- For all three IOUs, the mid scenario's substation costs are an average of the high and low substation costs.
- PG&E's transformer bank unit cost for all four scenarios were drawn from data provided by PG&E[184] (which matches the EIS). The high substation cost is from SCE's updated estimate and low and Replicate substation costs are from the EIS.

[183] E.g., land acquisition, site development, permitting, and some hardware. See EIS at 116.
[184] PG&E TY 2023 GRC Exhibit PG&E-4 at 165.

- SCE's transformer bank costs for the low, mid, and high scenario were drawn from the updated bank costs provided by SCE, while the Replicate cost is from the EIS.[185] The substation cost for the low scenario uses PG&E's substation cost from the EIS,[186] the high scenario uses the updated substation cost provided by SCE, and the Replicate scenario uses SCE's substation cost from the EIS.
- SDG&E's transformer bank costs use the EIS's data for all four scenarios.[187] For the substation costs, the low scenario uses the EIS's PG&E estimate, the high scenario uses SCE's updated cost estimate, and the Replicate scenario uses the EIS's SDG&E cost estimate.[188]

In addition to replacing feeders, transformer banks, and substations, the DGEM analysis also considers secondary costs. Secondary costs include any equipment needed between distribution systems and the customer including, but not limited to, distribution transformers, service drops, and secondary lines.[189] The costs of these upgrades are significant but are not often studied. The DGEM assesses secondary costs by adding a percentage of the primary costs for each IOU drawn from the Replicate scenario. The EIS provided the secondary cost percentages, as displayed in Table A-13.[190]

Table A-13. Secondary cost percentage by IOU from the EIS.

IOU	Secondary costs as a percentage of primary cost
PG&E	45%
SCE	47%
SDG&E	40%

A.9. Calculating rate impact

To estimate the residential rate impact, we accounted for the expected increase in distribution capital and maintenance expenses allocated to residential rates, plus forecasted transmission and generation costs allocated to residential rates and weighed them against the forecasted increase in residential electricity sales.

$$\Delta Rate = \frac{RR_{2023} + \Delta RR_{distribution} + \Delta RR_{transmission} + \Delta RR_{generation}}{ES_{2023} + \Delta ES} - \frac{RR_{2023}}{ES_{2023}}$$

The incremental change in residential rate is equal to the new residential rate (the left half of the equation) minus the 2023 residential rate (the right half of the equation). The 2023 rate is equal

[185] EIS at 117.

[186] EIS at 117.

[187] EIS at 117.

[188] EIS at 117.

[189] See Brown.

[190] EIS at 26-29. Data show the average from the year 2035, excluding the EIS's Baseline scenario.

to the 2023 revenue requirement (RR_{2023}) divided by the 2023 energy sales (ES_{2023}). All rate components, including sales and revenue requirements, were allocated to residential using the currently representative factors for each IOU. The new rate was calculated from the new revenue requirement divided by the new energy sales. The new revenue requirement is equal to the 2023 revenue requirement plus the incremental revenue requirements from distribution, transmission, and generation (the three ΔRRs). The new sales are equal to the 2023 sales plus the incremental sales associated with electrification (ΔES). Table A-14 provides the 2023 sales and revenue requirements.

Table A-14. 2023 system residential revenue requirements and system residential sales.

IOU	System residential revenue requirement ($ Billion)	System residential sales (kWh)
PG&E	$6.425	27,986,000,000
SCE	$6.513	26,274,000,000
SDG&E	$2.447	6,059,000,000

The revenue requirement for distribution infrastructure was calculated by depreciating capital over forty years and including the depreciation and the return on undepreciated capital (at the weighted-average cost of capital) in the revenue requirement. To account for distribution O&M, we assumed an incremental O&M cost of 3.5 percent per year on the undepreciated value of incremental capital. This was informed by data from the most recent general rate cases of PG&E, SCE, and SDG&E and accounts for wildfire mitigation costs.[191] The residential component of this cost was added to the revenue requirement. Table A-15 shows the weighted-average cost of capital and the residential allocation of distribution costs alongside the residential allocation of generation costs (discussed later).

Table A-15. Weighted average cost of capital and residential allocation of distribution costs for the three IOUs.

IOU	Weighted-average cost of capital[192]	Residential allocation of distribution costs	Residential allocation of generation costs
PG&E	7.27%	41%	38%

[191] For PG&E, we used data from A.21-06-022. Electric distribution rate base for 2020 through 2023 was drawn from workpapers to Exhibit PG&E-10, Chapter 15 (at 15-1, 15-4, 15-7, and 15-10). Distribution expenses were drawn from workpapers to Exhibit PG&E-4, Chapter 2 (at 2-2) excluding costs of "Customer Request & Load Growth" and "Risk Reduction." For SCE, we used data from A.23-05-010. Distribution rate base for 2025 was drawn from workpapers to Exhibit SCE-07 Vol.02 Book A (at 11) and compared to O&M expenses including inspections and maintenance, substation, poles, vegetation management, and "other" from Exhibit SCE-02 Vol. 10 at 1. For SDG&E, we used data from A.22-05-016. Distribution capital for 2021-2024 were drawn from workpapers to Exhibit SDG&E-35-R (at 12) and compared to distribution capital expenses, from workpapers to Exhibit SDG&E-12-R (at 2) plus wildfire expenses from workpapers to Exhibit SDG&E-13-R at 1.

[192] D.22-12-031, *Decision Addressing Test Year 2023 Cost of Capital for Pacific Gas and Electric Company, Southern California Edison, Southern California Gas Company, and San Diego Gas & Electric Company*, December 15, 2022 at 1; issued in A.22-04-008 et al. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M500/K015/500015851.PDF.

IOU	Weighted-average cost of capital[192]	Residential allocation of distribution costs	Residential allocation of generation costs
SCE	7.44%	50%	47.3%[193]
SDG&E	7.18%	45%	49.9%[194]

Transmission costs were accounted for through the TAC, which is projected to rise to $20/MWh in 2029 and exceed $25/MWh in 2035.[195] This growth rate was used to forecast increases in the current IOU-specific TAC and then multiplied by the incremental energy sales (ΔES) to account for the new transmission revenue requirements associated with the sales. Table A-16 summarizes the TACs used in our rates analysis.

Table A-16. Summary of TACs used in our rate model.

Year	PG&E	SCE	SDG&E
2023	$0.006	$0.001	$0.016
2024	$0.006	$0.001	$0.017
2025	$0.007	$0.001	$0.018
2026	$0.007	$0.001	$0.018
2027	$0.007	$0.001	$0.020
2028	$0.008	$0.002	$0.021
2029	$0.008	$0.002	$0.022
2030	$0.008	$0.002	$0.022
2031	$0.008	$0.002	$0.022
2032	$0.009	$0.002	$0.023
2033	$0.009	$0.002	$0.023
2034	$0.010	$0.002	$0.026
2035	$0.011	$0.002	$0.028

Generation costs were derived from the 2022 avoided cost calculator (ACC),[196] including costs associated with generation energy, generation capacity, ancillary services, greenhouse gases, and high global warming potential gases. Generation costs are a pass-through cost, so the revenue requirement is equal to the cost per MWh of generation multiplied by the incremental energy sales (ΔES). The cost per MWh of generation was calculated from the hourly ACC values weighted by the hourly peak consumption change (i.e., the electrification load minus additional

[193] This is not the same number used in our model. The number in our model is confidential. The publicly available value provides an indication. See SCE, *Joint Motion of Southern California Edison Company (U 338-E) And Settling Parties for Adoption of Marginal Cost and Revenue Allocation Settlement Agreement*, December 13, 2021 at Attachment A - Page 20; issued in A.20-10-012.

[194] This is not the same number used in our model. The number in our model is confidential. The publicly available value provides an indication. See SDG&E, *Chapter 2 Prepared Direct Testimony of Ray C. Utama on Behalf of San Diego Gas & Electric Company*, January 17, 2023 at RU-5; issued in A.23-01-008

[195] See The Public Advocates Office, comments on draft transmission plan of the California Independent System Operator, April 25, 2023 at Section 9, Table 1. Available at: https://stakeholdercenter.caiso.com/Comments/AllComments/3b5eb926-9bce-4c7f-806c-9ae156a4f9f3#org-b4bc96db-9bb3-478b-a339-41f5d6e8413c.

[196] See *2022 Distributed Energy Resources Avoided Cost Calculator Documentation*.

self-generation, energy efficiency, etc.).[197] We used the same ACC values for all IOUs since little variation was observed.[198] Table A-17 summarizes the average prices from the ACC and the weighted average prices used in our rate model. We calculate the revenue requirement from incremental generation as the product of the weighted-average price, the incremental sales (see below), and the share of generation costs allocated to residential customers for each IOU.

Table A-17. Summary of ACC prices and weighted average prices used in our rate model.

Year	Average price	Weighted-average price
2023	$0.071	$0.094
2024	$0.083	$0.11
2025	$0.082	$0.11
2026	$0.085	$0.11
2027	$0.088	$0.11
2028	$0.086	$0.11
2029	$0.088	$0.11
2030	$0.069	$0.088
2031	$0.075	$0.092
2032	$0.079	$0.097
2033	$0.078	$0.094
2034	$0.080	$0.097
2035	$0.079	$0.095

The strategy to forecast residential electricity sales was to apply the growth rate of energy sales to the baseline system residential sales for each IOU. Table A-18 provides the geometric average annual growth rate in energy sales that we calculated and used in the DGEM.

Table A-18. Annual growth rates of energy sales used in the rate model.

IOU	Annual growth rate
PG&E	1.81%
SCE	1.45%
SDG&E	2.14%

One limitation of the DGEM is that it does not estimate total energy consumption directly, only hourly total peaks and annual EV energy. We used the annual EV energy from the DGEM combined with non-EV forecasts from the 2022 IEPR hourly and annual tables to derive total energy to serve load. The hourly tables[199] for the Planning Scenario provided the non-EV energy to serve load (i.e., gross generation – self generation) for 2023 to 2035. From the annual

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[197] Average hourly consumption would provide a better representation. But since DGEM does not produce full hourly load profiles, only hourly peak loads, these data were not available.

[198] We used values for SCE climate zone 9.

[199] 2022 CED, hourly Planning Scenario forecast data for each of the three IOUs under Hourly Demand Forecast Files.

tables[200] we extracted the losses[201] as a percentage of total energy to serve load in all years of the study (i.e., 2023-2035). Sales are total energy to serve load minus losses.

[200] 2022 CED, annual Baseline Forecast data for each of the three IOUs under Baseline Demand Forecast Files.

[201] In the IEPR, percent losses in all years varied little for each IOU (calculated as a percentage of total energy to serve load). We used the average values: 8.3 percent for PGE, 6.4 percent for SCE, and 7.6 percent for SDG&E.

Appendix B EV Deployment by IOU Service Territory

While the DGEM's projected total annual electricity consumption by all EVs aligns closely with the 2022 IEPR, there is more variation between the IOUs, as shown in Figure B-1. Relative to the IEPR, the DGEM predicts less EV adoption in PG&E's service territory in most propensity scenarios and more uptake in SCE's and SDG&E's service territories.

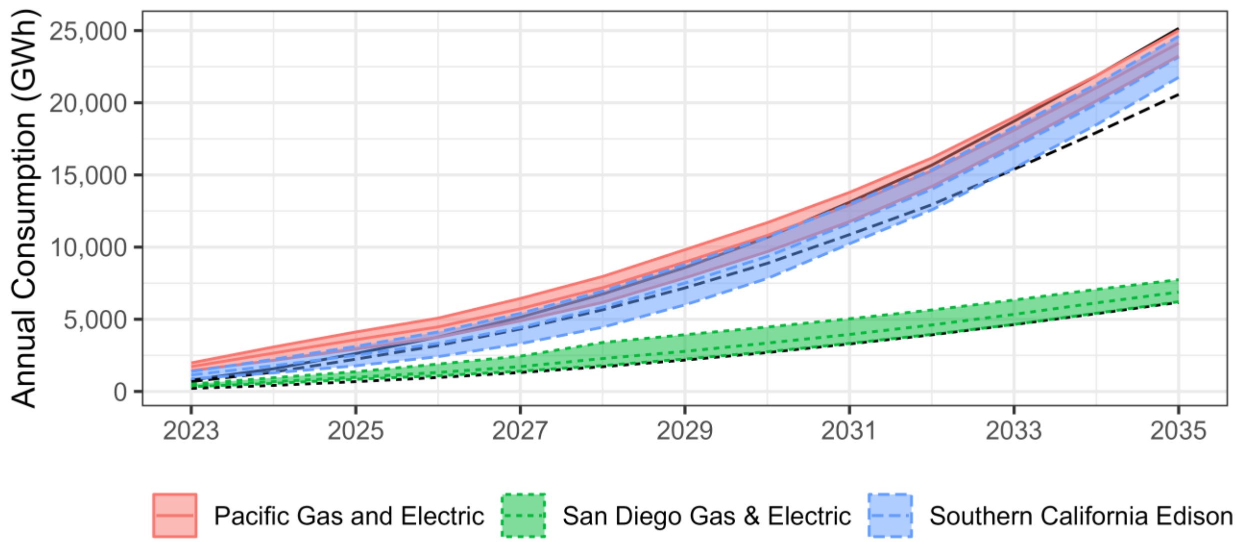

Figure B-1. Consumption forecasts relative to the IEPR (shown in black). The DGEM predicts more adoption in SCE's and SDG&E's territories and less in PG&E's service territory than the 2022 IEPR.

Table B-1 explores the DGEM's maximum and minimum forecasted EV consumption in each IOU's service territory and the EV adoption scenarios that achieve these outcomes. These results are provided alongside the IEPR's forecasted electric consumption for comparison. The DGEM's consumption forecasts in PG&E's service territory align with the 2022 IEPR in the maximum case and are about 2,000 GWh/year less in the minimum case. The DGEM's forecast for SCE ranges from 1,000 to 4,000 GWh/year above the IEPR. Moreover, the DGEM's forecast for SDG&E ranges from aligned with the IEPR in the minimum case to nearly 2,000 GWh/year above the IEPR in the maximum case.

Table B-1. Comparison of the DGEM's minimum and maximum forecasts of EV consumption in each IOU service territory and the corresponding scenarios for 2035. IEPR load consumption for 2035 is shown for reference.

	Consumption, GWh/year			Propensity model scenarios			
				Minimum consumption		Maximum consumption	
IOU	IEPR	Min	Max	Personal	Fleet	Personal	Fleet
PG&E	25,150	23,293	25,044	Random	Body Type	Regression	By Feeder
SCE	20,574	21,881	24,568	Regression	Body Type	Random	Random By Vehicle

	Consumption, GWh/year			Propensity model scenarios			
SDG&E	6,174	6,225	7,852	Random	By Feeder	Regression	Body Type

More importantly, Table B-1 shows which vehicle deployment models lead to which outcome: the regression model leads to the least uptake in SCE's service territory and the most in the other IOUs' territories. This implies that demographic factors considered in the regression model favor adoption in SDG&E's and PG&E's territories (i.e., these territories tend to have customers who are more educated and wealthier).

The fleet propensity model outcomes are more complicated. PG&E sees the most adoption using the by-feeder propensity model. This means that PG&E currently has a higher EV adoption rate. SDG&E shows the lowest adoption with the by-feeder propensity model, which means that SDG&E has low EV adoption rates at present. But SDG&E shows the most adoption under the by-body-type adoption model, which means that SDG&E has many vehicles of body types with high rates of EV adoption across the state. This could favor near-term adoption of fleet vehicles in SDG&E's service territory. SCE sees the greatest adoption of MD and HD vehicles in the random scenario, implying that SCE has neither a high MD and HD adoption to date nor many vehicles of the types with high EV adoption across California.

Appendix C Calculation of the 2020-2022 Pace of Upgrades for the IOUs

For each IOU, we categorized planned upgrades into three categories: new substation equipment, new distribution feeders, and possible new distribution feeders or upgrades to existing feeders. Possible new distribution feeders or feeder upgrades are included in the high end of the range for "Historic Pace" of feeder upgrades presented in Table 3-2. For all three IOUs, we examined the planned upgrades for three years spanning 2020 through 2022. For SCE and PG&E, we looked at the planned upgrades in the Distribution Deferral Opportunity Reports (DDOR) for the years 2020 through 2022 and counted the upgrades planned for each year, removing redundant records. For SDG&E, we used the 2022 DDOR dataset, which included records for 2020 and 2021. We also removed redundant records for SDG&E's DDOR dataset. The following paragraphs provide IOU-specific details on the categorization process.

We used data from SCE's 2020,[202] 2021,[203] and 2022[204] DDORs. We categorized entries using the "Type of Equipment To Be Installed" data column. We counted entries containing "Primary Feeder - New Distribution Line" as new distribution feeders. We counted entries with "Substation – Transformer" as new substation equipment. We included "Primary Feeder – Cable" and "Primary Feeder - Overhead Conductor" as possible new distribution feeders or feeder upgrades. We excluded all projects that required voltage distribution services. We further excluded projects with only switches, switch racks, service transformers, capacitors, bus cables, upgrades for protection equipment, transmission infrastructure projects, projects whose purpose was unclear, and other assets not included in the DGEM's level of infrastructure analysis.

For SDG&E we used data from the 2022 DDOR,[205] which included planned upgrades in 2020, 2021, and 2022. We categorized using the "Description" column. We categorized entries of "New Circuit" as new distribution feeders. We categorized the entry of "New Transformer" with

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[202] SCE, *Reports of the Southern California Edison Company (U 338-E) of its 2020 Grid Needs Assessment and 2020 Distribution Deferral Opportunities Report*, August 17, 2020 at Appendix C: 2020 Distribution Deferral Opportunities Report Redacted Dataset (PUBLIC VERSION); filed in R.14-08-013. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M345/K926/345926397.PDF.

[203] SCE, *Reports of Southern California Edison Company (U 338-E) of its 2021 Grid Needs Assessment and 2021 Distribution Deferral Opportunities Report*, August 16, 2021 at Appendix C: 2020 Distribution Deferral Opportunities Report Redacted Dataset (PUBLIC VERSION), filed in R.14-08-013. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M400/K580/400580035.PDF.

[204] SCE, *2022 Grid Needs Assessment and Distribution Deferral Opportunity Report of Southern California Edison Company (U 338-E) Public Version*, January 13, 2023 at Attachment D: 2022 Distribution Deferral Opportunities Report Redacted Dataset (PUBLIC VERSION); filed in R.21-06-017. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M501/K533/501533114.PDF.

[205] SDG&E, *2022 Grid Needs Assessment and Distribution Deferral Opportunity Report of San Diego Gas & Electric Company (U 902 E) Public Version*, August 16, 2022 at Appendix A – August 15, 2022 DDOR; filed in R.21-06-017. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M496/K592/496592463.PDF.

"Substation transformer bank" as the "Equipment Involved" under new substation equipment. We categorized "Reconductor" and "Transfer with new equipment" as possible new distribution feeders or feeder upgrades (because these are ways to mitigate distribution feeder overloads).

We used data from PG&E's 2020,[206] 2021,[207] and 2022[208] DDORs. We categorized entries using the "Project Name" and "Project Type" columns for 2020 and 2022. In 2021, PG&E featured a "Project Description" column that included more detail than the other two years. For 2020 and 2022, we counted entries of "Feeder" in "Project Type" as new distribution feeders unless the "Project Name" indicated new or replacement switches, disconnects, risers, regulators, capacitors, or other protection equipment identifiably out of the scope of the DGEM. We also counted entries of "Bank" in "Project Type" as new substation equipment. Other "Project Name" entries such as "line work," "reconfigure," "transfer," "line section," and "recable" were all counted as possible new distribution feeders or feeder upgrades. For 2021, we generally followed the same procedure, but the "Project Description" column provided more detail on the scope of the projects, so the "Project Description" column served as the primary source for parsing out the projects into the three categories.

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[206] PG&E, *PG&E's 2020 Distribution Deferral Opportunity Report*, August 17, 2020 at Appendix A – Planned Investments, Appendix B – Candidate Deferral Opportunities; filed in R.14-08-013.

[207] PG&E, *PG&E's 2021 Distribution Deferral Opportunity Report*, August 16, 2021 at Appendix A – Planned Investments, Appendix B – Candidate Deferral Opportunities; filed in R.14-08-013. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M400/K593/400593924.PDF.

[208] PG&E, *Corrected Project Cost Data to the 2022 Distribution Deferral Opportunity Report of Pacific Gas and Electric Company (U 39 E) Public Version*, March 24, 2023 at Appendix E: LNBA – Planned Investments – Results; filed in R.21-06-017. Available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M505/K748/505748651.PDF.