U.S. DEPARTMENT OF ENERGY

Multi-State Transportation Electrification Impact Study

Preparing the Grid for Light-, Medium-, and Heavy-Duty Electric Vehicles

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Kevala Inc.: County-to-Parcel Charging Load Assignment, Non-Transportation Loads, Distribution Grid Capacity Expansion and Cost Estimation (parcel level), National Extrapolation of Distribution Grid Costs, Capacity-Aware Charge Management

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Acronyms and Abbreviations

Acronym	Definition
AB	assembly bill
AFDC	Alternative Fuels Data Center
ATB	Annual Technology Baseline
BAU	business as usual
BEV	battery electric vehicle
C/SUV	compact crossover sport utility vehicle
CAGR	compound average growth rate
CARB	California Air Resources Board
CEC	California Energy Commission
CPUC	California Public Utilities Commission
DC	direct current
DCFC	direct current fast charging
DER	distributed energy resource
DOE	U.S. Department of Energy
EIA	U.S. Energy Information Administration
ELR	economic load reach
EMFAC	EMission FACtor
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EV	electric vehicle
EVI-X	Electric Vehicle Infrastructure Analysis Suite
EVSE	electric vehicle supply equipment
FERC	Federal Energy Regulatory Commission
FR	Federal Register
FUSE	Flexible charging to Unify the grid and transportation Sectors for EVs at scale
GHG	greenhouse gas
GPS	global positioning system
GTFS	General Transit Feed Specification
GVWR	gross vehicle weight rating
GWh	gigawatt-hour(s)
HD TRUCS	Heavy-Duty Technology Resources Use Case Scenario
HDV	heavy-duty vehicle
HEVI-LOAD	Medium- and Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment
HHD8	Class 8a and 8b trucks (GVWR > 33,000 lbs.)
Hz	hertz
IOU	investor-owned utility
IPM	Integrated Planning Model
IRA	Inflation Reduction Act
kV	kilovolt(s)
kW	kilowatt(s)
kWh	kilowatt-hour(s)

Acronym	Definition
L1	Level 1
L2	Level 2
LA100	Los Angeles 100% Renewable Energy Study and Equity Strategies
LBNL	Lawrence Berkeley National Laboratory
LDV	light-duty vehicle
LHD45	Class 4 and 5 trucks (14,000 lbs. < GVWR <= 19,500 lbs.)
MDV	medium-duty vehicle
MHD67	Class 6 and 7 trucks (19,500 lbs. < GVWR <= 33,000 lbs.)
MOVES	Motor Vehicle Emission Simulator
MVA	megavolt ampere(s)
MW	megawatt(s)
MWh	megawatt-hour(s)
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory
NTD	National Transit Database
NWA	non-wire alternative
OCPI	Open Charge Point Interface
OD	origin/destination
OMEGA	Optimization Model for reducing Emissions of Greenhouse gases from Automobiles
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
PV	photovoltaics
SOC	state of charge
TEIS	Multi-State Transportation Electrification Impact Study
UCR	University of California, Riverside
VMT	vehicle miles traveled
VOMS	vehicles operated in maximum service
ZEV	zero-emission vehicle

Executive Summary

The National Renewable Energy Laboratory (NREL), Lawrence Berkeley National Laboratory (LBNL), and Kevala Inc. (Kevala), in partnership with the U.S. Department of Energy, conducted this study to help answer key technical and deployment questions about whether the electric grid can accommodate new demands from transportation electrification. This study illuminates, at unprecedented local resolution, the charging network and associated distribution grid infrastructure needed to support increasing plug-in electric vehicle (PEV) adoption. In particular, the study examines the anticipated impact of the U.S. Environmental Protection Agency's (EPA's) rulemakings if finalized as proposed on greenhouse gas (GHG) emission standards for light-, medium-, and heavy-duty on-road vehicles (LDVs, MDVs, and HDVs, respectively).[1,2] This study provides in-depth analysis of PEV charging infrastructure and distribution grid upgrades for five states: California, Illinois, New York, Oklahoma, and Pennsylvania, which are indicative of a variety of U.S. transportation demand and utility distribution infrastructure.

If finalized as proposed, the EPA rules are likely to accelerate the ongoing adoption of PEVs beyond current policies and incentives. This report provides in-depth analysis of this incremental PEV adoption locally, as well as the investment required in charging infrastructure and distribution grid upgrades that the rules could motivate. As part of the proposed rules, the EPA developed potential modeled compliance pathways describing the potential number of PEVs on the road by 2032, and those pathways are examined in this work. Under the EPA's projected compliance pathways, an additional 3.9 million PEVs could be on the road by 2032 across the five states under study, bringing the five-state total to 20 million PEVs. The key takeaways of the analysis are that the proposed rules could—effectuated from 2027 to 2032—for those five states:

1. Result in an incremental increase of 3% in annual electric vehicle charging infrastructure installations (including public and private infrastructure),
2. Result in an incremental distribution grid investment that equates to approximately 3% of current annual utility investments,
3. Result in a 30% reduction of those annual utility investments using basic managed charging techniques, illustrating the potential for additional cost savings from local load optimization, and,
4. Result in net consumer benefits, primarily in fuel savings, 2.5 times greater than the incremental charging and distribution grid costs.

The report provides an in-depth presentation of the inputs, methodology, and context for the analysis. The report also presents key avenues for future work and the context of ongoing investment in charging and distribution infrastructure. The rest of the executive summary provides an overview of the report and more discussion of each of the key findings from the analysis.

§

[1] Proposed Rule by the EPA, Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles, Docket ID No. EPA–HQ–OAR–2022–0829 (May 5, 2023), https://www.federalregister.gov/documents/2023/05/05/2023-07974/multi-pollutant-emissions-standards-for-model-years-2027-and-later-light-duty-and-medium-duty.

[2] Proposed Rule by the EPA, Greenhouse Gas Emissions Standards for Heavy-Duty Vehicles, Phase 3, Docket ID No. EPA–HQ–OAR–2022–0985 (April 27, 2023), https://www.federalregister.gov/documents/2023/04/27/2023-07955/greenhouse-gas-emissions-standards-for-heavy-duty-vehicles-phase-3.

U.S. climate goals for economy-wide net-zero GHG emissions by 2050 require the rapid decarbonization of the on-road transportation sector, and PEVs are poised to become a key technology for achieving this end.[3] Recent EPA notices of proposed rulemakings for GHG emissions standards for light-, medium-, and heavy-duty on-road vehicles would further incentivize advancements already happening in the industry because of private investment, consumer demand, state-level policies, and federal incentives (notably from the Bipartisan Infrastructure Law and Inflation Reduction Act). This study provides timely estimates for the investments in charging infrastructure and grid upgrades necessary to support a possible PEV adoption scenario consistent with emissions reduction requirements in the proposed rulemaking.

This study examines two scenarios of PEV adoption:

- An **"Action"** scenario is used to reflect the adoption of two national GHG standards – one for LDVs and MDVs and the other for HDVs – as proposed by EPA in April 2023. These rules would regulate emissions from new motor vehicles for model years 2027 through 2032.[4]
- A **"No Action"** scenario is used to reflect the absence of new national GHG standards for LDVs, MDVs, and HDVs but includes current state and federal policies and regulations.[5]

Based on EPA's modeling and assumptions of modeled compliance pathways, the Action scenario of this study examines one potential compliance pathway in which a total of 55 million PEVs are on the road nationally by 2032, including 920,000 HDVs. This contrasts with the No Action scenario, EPA's baseline assuming no new federal GHG standards, which assumes that 41 million PEVs are on the road nationally by 2032, including 540,000 HDVs.

Grid data from five states were leveraged for this study, with state selection capturing diversity in urban/rural populations, utility distribution grid composition, freight travel demands, and state-level PEV policies. The following five states were selected for detailed analysis: **California, Illinois, New York, Oklahoma, and Pennsylvania.**

The EPA estimates that, under one possible compliance pathway, the proposed rules in the Action scenario could result in a total of 20 million PEVs— across all weight classes (including 260,000 heavy-duty PEVs, Class 4–8)—on the road in these five states by 2032. The No Action scenario assumes that 16 million PEVs (including 220,000 heavy-duty PEVs, Class 4–8) will be on the road in these five states by 2032.

With the goal of evaluating the potential infrastructure costs of the EPA's proposed rules, this study focuses on the delta between the Action and No Action scenarios. As such, the term **incremental** is used

[3] Michael Berube, Andrew Wishnia, Karl Simon, Alexis Pelosi, Matteo Muratori, Tatjana Kunz, Aaron Hula, and Michael Freedberg, *The U.S. National Blueprint for Transportation Decarbonization*, Washington, D.C.: U.S. Department of Energy, DOE/EE-2674, 2023, https://www.energy.gov/sites/default/files/2023-01/the-us-national-blueprint-for-transportation-decarbonization.pdf.

[4] LDV and MDV adoption is based on Alternative 3 from the 2027 and Later Light-Duty and Medium-Duty Vehicle Multipollutant proposed rule with HDV adoption based on an interim set of inputs and assumptions built off the Greenhouse Gas Emissions Standards for Heavy-Duty Vehicles – Phase 3 Proposed Rule (HDP3).

[5] Includes electric vehicle provisions from the Inflation Reduction Act within the Optimization Model for reducing Emissions of Greenhouse gases from Automobiles (OMEGA) compliance model and compliance with 2023 and later GHG standards (86 FR 74434 2021), with the addition of heavy-duty vehicle (Class 4–8) charge demand estimated for the California Advanced Clean Trucks (ACT) Program.

in this study to reflect the difference between the Action and No Action regulatory scenarios, including differences in the number of PEVs on the road, the size of the necessary charging network, and the associated upgrades to local distribution networks. Across the five selected states in 2032, this translates to an estimated **3.9 million incremental PEVs** on the road (including 40,000 incremental heavy-duty PEVs, Class 4–8).

This work quantifies the value of proactive and intelligent vehicle grid integration by modeling two load flexibility scenarios. These scenarios have been designed to temporally shift charging loads at residential and depot locations within the bounds of simulated vehicle arrival and departure times. The simulated network size shown above is constant among the study's two charge management scenarios:

- A baseline **"Unmanaged"** scenario that assumes vehicles begin charging at full power immediately upon arrival (relative to the capabilities of the vehicle and the simulated charging infrastructure).
- A **"Managed"** scenario that assumes that vehicles arriving at select charging locations will intentionally minimize charging power so that the session is completed just prior to the vehicle's departure from that location.

Key Finding #1: Annual charging infrastructure needs could increase by 3% across five states in scenarios consistent with the EPA proposals.

Five-state simulation results (Table ES-1) show that 14.3 million public and private charging ports are estimated as necessary to support 20 million PEVs across five states in the 2032 Action scenario. This represents 2.3 million incremental ports relative to the No Action scenario, an increase of 19%. As the EPA proposals apply to model years 2027 through 2032, this averages to an annual increase of 3% over six years. The vast majority of these incremental ports (97%) are used for alternating current (AC) charging of light- and medium-duty vehicles. However, incremental costs (including grid upgrades) for high-power direct current (DC) charging of heavy-duty vehicles remain significant because of unit costs that are 1–2 orders of magnitude larger.

The $7.5 billion in funds currently available via the National Electric Vehicle Infrastructure Formula Program pursuant to the Infrastructure Investment and Jobs Act provide a foundational incentive to develop a national charging network across the states, both from an installation and manufacturing perspective. For context, based on current publicly-announced quantified capabilities, U.S. manufacturers can produce over 1,000,000 chargers each year, including 60,000 DC chargers.[6] Furthermore, though not quantified here, the Inflation Reduction Act of 2022 extended the Internal Revenue Code Section 30C tax credit, incentivizing up to 30 percent of the cost of recharging property (up to $100,000 for each item of depreciable property, and up to $1,000 otherwise) until 2032.[7]

[6] U.S. Department of Energy. Building America's Clean Energy Future. February 25, 2024. Available at: https://www.energy.gov/invest.

[7] U.S. Internal Revenue Service. Alternative Fuel Vehicle Refueling Property Credit. February 2, 2024. Available at: https://www.irs.gov/credits-deductions/alternative-fuel-vehicle-refueling-property-credit

Table ES-1. *Simulated 2032 Network Size for the Five-State Study by Vehicle Weight Class and Electric Vehicle Supply Equipment Type. AC ports include Level 1 and Level 2 charging; DC ports include units rated for peak powers between 50 kW and 1.5 MW per port.*

		Simulated Five-State Network Size (ports)			
Vehicle Class	**EVSE Type**	**No-Action**	**Action**	**Incremental**	**Percent Increase**
L/MDV (Class 1-3)	AC Ports	11,800,000	14,000,000	2,200,000	19%
	DC Ports	68,000	85,000	17,000	25%
HDV (Class 4-8)	AC Ports	23,000	38,000	15,000	64%
	DC Ports	173,000	207,000	34,000	19%
Total		12.0 million	14.3 million	2.3 million	19%

Key Finding #2: Incremental distribution grid investment needs represent approximately 3% of current annual utility investments in the distribution system for scenarios consistent with the EPA proposals.

As shown in Table ES-2, this study estimates an incremental distribution grid investment of $2.3 billion over six years for the five states under study (2023 dollars). Incremental distribution grid upgrade investment needs[8] can be compared to existing utility distribution system investments. Based on utility reports to the Federal Energy Regulatory Commission, data from electric co-ops, and extrapolation for the remaining utilities, we estimate that as of 2021, utility investments in distribution systems, nationwide, exceeded $60 billion annually.

We estimate the share of that utility distribution investment for the five states evaluated in this study is $15 billion per year. Based on this, the EPA proposals represent approximately 3% of current annual utility investments in distributions systems between 2027 and 2032 across the five states studied. As also shown in the table, incremental charging infrastructure capital investment needed across the five states under study for 2027 is $865 million and gradually increases the deployment of charging to total $9.7 billion by 2032.

Across the five states the study estimated a combined investment of $12.0 billion in incremental charging and distribution grid infrastructure in 2032. Over the six model years from 2027 through 2032, this averages to an annual incremental investment of $2.0 billion in charging and distribution grid infrastructure. This investment would support the incremental manufacturing and installation of 2.3 million charging ports, eight distribution substations, 125 feeders, and 30,000 service transformers,

[8] By design, this study presents incremental grid upgrade results describing the relative investment difference between PEV adoption scenarios that could occur with and without the pending EPA regulations. The study identifies where and when the electric distribution grid may require capacity enhancements under certain PEV adoption and charging behavior scenarios. The study does not predict the absolute levels of distribution grid investment needed in the long term.

without the use of managed charging. Notably, substation, transformer bank and service transformers built by 2027 mostly cover 2032 needs based off size assumptions for existing and new substations; feeder upgrades are still triggered in 2032.

Table ES-2. *Incremental 2027 and 2032 Simulation Results for the Five-State Study (relative to No Action)*

Five-State Scenarios (2027)	**Action vs. No Action**	
	Unmanaged	**Managed**
Incremental PEV adoption (all weight classes)	300,000	
Incremental charging ports (all types)	250,000	
Incremental charging infrastructure capital investment	$865 million	
Incremental substations	1	0
Incremental feeders	9	5
Incremental service transformers	2,800	2,400
Incremental distribution grid capital investment	$195 million	$82 million
Combined incremental infrastructure capital investment	$1.1 billion	$947 million

Five-State Scenarios (2032)	**Action vs No Action**	
	Unmanaged	**Managed**
Incremental PEV adoption (all weight classes)	3.9 million	
Incremental charging ports (all types)	2.3 million	
Incremental charging infrastructure capital investment	$9.7 billion	
Incremental substations	8	4
Incremental feeders	125	75
Incremental service transformers	30,000	21,000
Incremental distribution grid capital investment	$2.3 billion	$1.6 billion
Combined incremental infrastructure capital investment	$12.0 billion	$11.3 billion

Identification of these costs, while important, is just the first step in understanding how to equitably allocate them. A key finding from this study is the importance of taking the next step to allocate distribution costs to PEV loads served by new distribution capacity as well as non-PEV loads that could also be served by such new capacity, the latter of which was out of scope. Follow-on analysis is needed to allocate distribution costs among these multiple types of customers.

Key Finding #3: Managed charging techniques can decrease incremental distribution grid investment needs by 30%, illustrating the potential for significant cost savings by optimizing PEV charging and other loads at the local level.

Proactive utility planning, tariff structures, and vehicle-grid integration technologies and strategies will mitigate grid infrastructure investment needs. The incremental distribution grid capital investment of $2.3 billion estimated by this study is reduced 30% to $1.6 billion when PEV charging loads at home and depot locations are managed. This result is driven by the ability of PEVs to shift charging to off-peak hours based on parking durations that exceed the time necessary to charge and by strategically locating chargers, thereby avoiding potential overloading and thermal violations that otherwise drive distribution equipment upgrades. Managing charging could substantially reduce incremental grid components needs, including for substations by 50%, feeders by 40%, and service transformers by 30%. A 30% reduction in PEV peak load was simulated in the Action–Managed scenario.

When considering all electric loads, this translates to a reduction in total peak load of between 0.4% and 4.5% depending on the state. Although this management strategy ensures that peaks from PEV charging are reduced, within the context of this study, the strategy is agnostic to non-PEV residential, commercial, and industrial loads on the distribution network (meaning simulated PEV loads are not optimized relative to non-PEV loads). Accordingly, the results present a conservative estimate of the potential distribution grid savings from managing charging load locally.

Key Finding #4: Consumer benefits from vehicle electrification significantly outweigh the estimated cost of charging and grid infrastructure costs in scenarios consistent with the EPA proposals.

Based on levelized cost of driving from NREL's 2022 Transportation Annual Technology Baseline,[9] by 2030, PEVs are expected to provide $8,300 per vehicle in lifetime net benefits to consumers, including fuel savings but excluding the value of avoided emissions (fleet-weighted average using the EPA's adoption scenario and infrastructure costs consistent with this study). This conservative estimate of net benefits ($33 billion for the 3.9 million incremental PEVs by 2032), which does not allocate distribution costs among other potential loads that might use incremental grid infrastructure, is more than 2.5 times greater than the combined capital investment in charging infrastructure and grid upgrades estimated by this work.

[9] National Renewable Energy Laboratory, "Annual Technology Baseline," https://atb.nrel.gov/.

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Introduction

U.S. climate goals for economy-wide net-zero greenhouse gas (GHG) emissions by 2050 require the rapid decarbonization of the on-road transportation sector, and plug-in electric vehicles (PEVs) (including battery electric vehicles [BEVs] and plug-in hybrid electric vehicles [PHEVs]) are poised to become a key technology for achieving this end.[10] U.S. Environmental Protection Agency (EPA) proposed rulemakings for GHG emissions standards in light-, medium-, and heavy-duty on-road vehicles[11,12] would incentivize continued ongoing advancements already happening in the industry because of private investment, consumer demand, federal incentives (notably from the Bipartisan Infrastructure Law and Inflation Reduction Act), and state-level policies. Questions have been posed regarding the cost of the requisite charging infrastructure and associated upgrades to the nation's electric grid.

Charging infrastructure deployment costs are location-specific, with estimates requiring granular information on planned deployment, flexibility potential, and grid readiness. This multi-disciplinary team conducted a Multi-State Transportation Electrification Impact Study (TEIS) that quantitatively assesses the incremental investment necessary to enable the levels of vehicle electrification that may be induced by pending EPA regulation and to estimate the potential value of deferred investments in electric distribution infrastructure that would be enabled by proactive vehicle–grid integration planning and deployment.

Research Team and Modeling Tools

Given the technical challenges posed by this analysis, the DOE, the National Renewable Energy Laboratory (NREL), Lawrence Berkeley National Laboratory (LBNL), and Kevala, Inc. (Kevala) partnered to develop a novel national framework for estimating charging infrastructure costs across all on-road vehicle weight classes and the associated upstream electricity distribution system upgrade costs. This national framework leverages critical data and state-of-the-art modeling capabilities from each organization.

NREL's Electric Vehicle Infrastructure Analysis Suite (EVI-X) models light-duty vehicle (LDV) (Class 1–2a) charging demands across multiple use cases, including drivers with and without access to home charging, long-distance road trips, and ride-hailing electrification with national-level scope and county-level resolution. EVI-X is also used within this study to model medium-duty vehicles (MDVs) (Class 2b–3), transit buses, and school buses. EVI-X was a key analytic component of the EPA's regulatory impact

[10] Michael Berube, Andrew Wishnia, Karl Simon, Alexis Pelosi, Matteo Muratori, Tatjana Kunz, Aaron Hula, and Michael Freedberg, *The U.S. National Blueprint for Transportation Decarbonization*, Washington, D.C.: U.S. Department of Energy, DOE/EE-2674, 2023, https://www.energy.gov/sites/default/files/2023-01/the-us-national-blueprint-for-transportation-decarbonization.pdf.
[11] Proposed Rule by the EPA, Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles, Docket ID No. EPA–HQ–OAR–2022–0829 (May 5, 2023), https://www.federalregister.gov/documents/2023/05/05/2023-07974/multi-pollutant-emissions-standards-for-model-years-2027-and-later-light-duty-and-medium-duty.
[12] Proposed Rule by the EPA, Greenhouse Gas Emissions Standards for Heavy-Duty Vehicles, Phase 3, Docket ID No. EPA–HQ–OAR–2022–0985 (April 27, 2023), https://www.federalregister.gov/documents/2023/04/27/2023-07955/greenhouse-gas-emissions-standards-for-heavy-duty-vehicles-phase-3.

analysis and was central to NREL's evaluation of national light-duty infrastructure needs, as published in *The 2030 National Charging Network* report.[13]

LBNL's Medium- and Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment (HEVI-LOAD) tool provides nationwide travel demand modeling capabilities for medium- and heavy-duty zero-emission vehicles (ZEVs) and projects load profiles and charging/refueling infrastructure needs at granular temporal and spatial scales. HEVI-LOAD leverages agent-based simulation techniques to resolve the integrated driving, parking, and charging/refueling behaviors of ZEVs over large-scale transportation networks and was central to the California Energy Commission's (CEC's) evaluation of statewide medium- and heavy-duty infrastructure needs, as published in the Second Assembly Bill (AB) 2127 Assessment.[14]

Kevala is a data and analytics company that develops software solutions designed to empower energy market participants to plan for a more robust, environmentally sustainable, effective, and safe grid. In this analysis, Kevala utilized high-resolution, distribution-level grid data synthesized through its proprietary data platform. The platform is organized around a foundational grid infrastructure data set mapped to geographic, parcel, and other socioeconomic data. This architecture enables Kevala to create load and distributed energy resource (DER) adoption propensity models at the parcel[15] level, which are then associated with grid assets and used to perform grid capacity analysis. These capabilities were leveraged by the California Public Utilities Commission (CPUC) in a statewide *Electrification Impacts Study*, completed in 2023.[16] This California study developed a highly granular load forecast of baseline load and DER adoption for more than 12 million premises across the state, which was then associated with the grid infrastructure from the parcel to the substation to evaluate when, where, and how much California's major investor-owned utilities (IOUs) may need to invest in grid upgrades.

Study Design

This study's parameters, inputs, and assumptions closely align with elements of the EPA proposal. Two scenarios of PEV adoption in **2027** and **2032** are considered to bookend the relevant vehicle model years.

- An **"Action"** scenario is used to reflect the adoption of national GHG standards as proposed by the EPA in April 2023 (which would regulate emissions from new motor vehicles for model years

[13] Eric Wood, Brennan Borlaug, Matt Moniot, Dong-Yeon (D-Y) Lee, Yanbo Ge, Fan Yang, and Zhaocai Liu, *The 2030 National Charging Network*, Golden, CO: National Renewable Energy Laboratory, NREL/TP-5400-85654, 2023, https://www.nrel.gov/docs/fy23osti/85654.pdf.
[14] California Energy Commission, Second Assembly Bill (AB) 2127 Electric Vehicle Charging Infrastructure Assessment, Assessing Charging Needs to Support Zero-Emission Vehicles in 2030 and 2035, CEC-600-2023-048, 2023, https://www.energy.ca.gov/publications/2023/second-assembly-bill-ab-2127-electric-vehicle-charging-infrastructure-assessment.
[15] A parcel is a real estate property or land and any associated structures that are the property of a person with identification for taxation purposes.
[16] Kevala Inc., *Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates*, prepared for the CPUC in support of Proceeding R.21-06-017 (Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future), May 9, 2023, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M508/K423/508423247.PDF.

2027 through 2032) and potential PEV adoption by vehicle manufacturers in response to standards across all on-road vehicle weight classes (Class 1–8).[17]

- A **"No Action"** scenario is used to reflect the absence of new national GHG standards but includes current state and federal policies and regulations (as of April 2023).[18]

Both the Action and No Action scenarios used in this report were developed by the EPA. PEV adoption scenarios for LDVs and MDVs (Class 1–3) were developed using the Optimization Model for reducing Emissions of Greenhouse gases from Automobiles (OMEGA).[19] PEV adoption scenarios for heavy-duty vehicles (HDVs) were developed using the Heavy-Duty Technology Resources Use Case Scenario (HD TRUCS) model[20] and the MOtor Vehicle Emission Simulator (MOVES).[21]

Based on EPA modeling, a total of **55 million PEVs** are assumed to be on the road nationally by 2032 in the Action scenario across all weight classes. This contrasts with the No Action scenario, which assumes **41 million PEVs** on the road nationally by 2032. Both the Action and No Action scenarios represent an increase in the national PEV population relative to today. For reference, as of November 2023, a total of 4.5 million PEVs have been sold cumulatively in the United States since 2010.[22] Although both scenarios may entail investments in charging infrastructure and grid upgrades, this analysis is designed to estimate the potential incremental charging infrastructure and grid upgrade costs associated with the EPA's proposed rulemakings.

A key challenge in assessing the grid impacts of transportation electrification is that charging forecasts do not necessarily spatially align with utility electric grid infrastructure. Prior studies have illustrated the benefits of using actual distribution feeder models in strategic investment and planning for PEVs;[23] however, a feeder can cross multiple geographic aggregation levels commonly used in PEV adoption and travel demand forecasting, such as census blocks[24] or traffic analysis zones.[25] Ultimately, a reliable and granular method of aligning charging forecasts and utility grid infrastructure is to disaggregate the

[17] LDV and MDV adoption is based on Alternative 3 from the 2027 and Later Light-Duty and Medium-Duty Vehicle Multipollutant proposed rule with HDV adoption based on an interim set of inputs and assumptions built off of the Greenhouse Gas Emissions Standards for Heavy-Duty Vehicles – Phase 3 Proposed Rule (HDP3).

[18] Includes electric vehicle provisions from the Inflation Reduction Act within the OMEGA compliance model and compliance with 2023 and later GHG standards (86 FR 74434 2021), with the addition of heavy-duty vehicle (Class 4–8) charge demand estimated for the California Advanced Clean Trucks (ACT) Program.

[19] EPA, "Optimization Model for reducing Emissions of Greenhouse Gases from Automobiles (OMEGA), last updated September 21, 2023, https://www.epa.gov/regulations-emissions-vehicles-and-engines/optimization-model-reducing-emissions-greenhouse-gases#omega-2.1.0.

[20] Lang Sui, Memorandum to Docket EPA-HQ-OAR-2022-0985, "Heavy Duty Technology Resource Use Case Scenario Tool (HD TRUCS)," April 14, 2023, https://www.regulations.gov/document/EPA-HQ-OAR-2022-0985-0830.

[21] Evan Murray, Memorandum to Docket EPA-HQ-OAR-2022-0985, "MOVES4.R3," February 2024.

[22] Argonne National Laboratory, "Light Duty Electric Drive Vehicles Monthly Sales Updates," Energy Systems and Infrastructure Analysis, n.d., https://www.anl.gov/esia/light-duty-electric-drive-vehicles-monthly-sales-updates.

[23] J. Coignard, P. MacDougall, F. Stadtmueller, and E. Vrettos, "Will Electric Vehicles Drive Distribution Grid Upgrades?: The Case of California," *IEEE Electrification Magazine* 7, no. 2 (June 2019): 46–56, https://doi.org/10.1109/MELE.2019.2908794.

[24] Alan Jenn and Jake Highleyman, "Distribution Grid Impacts of Electric Vehicles: A California Case Study," *iScience* 25, no. 1 (2022): 103686, ISSN 2589-0042, https://doi.org/10.1016/j.isci.2021.103686.

[25] California Energy Commission (CEC), EVSE Deployment and Grid Evaluation (EDGE) Tool, data last updated May 11, 2023, https://www.energy.ca.gov/data-reports/reports/electric-vehicle-charging-infrastructure-assessment-ab-2127/evse-deployment.

forecast at the parcel level.[26] This method allows the associated PEV load to be attributed from the parcel to individual grid feeders and substations.

Given the localized nature of charging infrastructure installation costs and grid upgrades, high-resolution spatial analysis of the electric distribution system is necessary. Although Kevala has developed an extensive inventory of high-resolution grid data at scale, full coverage of this information at the national level has yet to be synthesized and validated. Thus, the novel approach developed for this initial study was applied to a subset of states. The states were selected to capture diversity in urban/rural populations, utility distribution grid composition, freight travel demands, and state-level PEV policies. With this selection plan, and with guidance from Kevala on the spatial coverage of their data, the following five states were selected for detailed analysis:

- California
- Illinois
- Oklahoma
- Pennsylvania
- New York

A new statistical extrapolation method was developed by Kevala for this study, such that detailed modeling from these five states could be used to approximate incremental costs at the national level. This approach is discussed in Chapter 2 and 0

Finally, this work attempts to quantify the value of proactive, intelligent vehicle–grid integration by modeling two load flexibility scenarios:

- An **"Unmanaged"** scenario serves as the baseline in which vehicles arrive at locations where they intend to charge and begin doing so immediately and at full power (relative to the capabilities of the vehicles and the simulated charging infrastructure).
- A **"Managed"** scenario is applied in which vehicles arriving at select charging locations will intentionally minimize charging power such that the session is completed just prior to the vehicle's departure from that location.

Arrival time, departure time, and charging energy (but not power) are enforced as identical in both the Managed and Unmanaged scenarios. Given these constraints, charging flexibility is exercised only at home and depot locations, which are considered most likely to have margin for adjusting the charging power without negative impacts on vehicle availability. Although this management strategy ensures that peaks from PEV charging are reduced, it ultimately was agnostic to non-PEV residential, commercial, and industrial loads on the distribution network and is therefore unable to more aggressively optimize charging schedules to better use extra capacity on the local distribution system. Therefore, the results of this grid integration strategy could be considered a conservative estimate of the benefits of managed charging.

An additional charging management scenario, illustrated in 0, optimizes EV charging load with respect to local feeder loading conditions. Comparing the principal local capacity-agnostic approach with one that considers local constraints illustrates that grid integration strategies can be designed to dispatch load

[26] Jeremy Keen, Julieta Giraldez, Elizabeth Cook, Andy Eiden, Scott Placide, Alan Hirayama, Brian Monson, David Mino, and Fathalla Eldali, *Distribution Capacity Expansion: Current Practice, Opportunities and Decision Support* (Golden, CO: National Renewable Energy Laboratory, 2022), NREL/TP-6A40-83892, https://www.nrel.gov/docs/fy23osti/83892.pdf.

control to support different reliability objectives at the transmission or distribution scales. Harmonizing multiscale control strategies could be the subject of future analysis as the scope of field load management techniques expands to mitigate local loading. As of January 2024, the UL 3141 Outline of Investigation describes testing procedures for power control systems, which begins to standardize an additional technology for managing charging load.[27] This critical step toward standardizing load control technologies opens the door for more manufacturers to develop compliant products to manage charging as envisioned in this study. Further, these savings could be leveraged by electric utilities on behalf of their customers (independent of the EPA rules) via programs to incentivize cost-optimized vehicle charging patterns and demand response.

This study design results in a total of eight scenarios across the following three dimensions:

- Analysis years: 2027, 2032
- PEV adoption (national, Class 1–8):
    - Action: 55 million PEVs
    - No Action: 41 million PEVs
- Load flexibility: Managed, Unmanaged

Potential differences between these scenarios are conceptually visualized for a single analysis year in Figure 1. The gray line is intended to depict theoretical future electric demands, absent PEVs. The blue lines reflect theoretical increased electric load with the addition of PEVs from the No Action scenario under two load shapes: Managed (solid) and Unmanaged (dashed). Two analogous shapes are captured with incremental demand from the Action scenario in orange. Though conceptual, these curves intend to convey potential interactions between PEV fleet size and load flexibility explored in this work.

[27] UL, an organization that develops standards for the electronics industry, drafted UL 3141, Outline of Investigation for Power Control Systems. Manufacturers will be able to use this outline when developing devices that utilities can use to limit the energy consumption of BEVs. The outline identifies five potential functions for power control systems. One function is to serve as a power import limit or power export limit. In these use cases, the power control system controls the flow of power between a local electric power system (most often the building wiring on a single premises) and a broader area electric power system (most often the utility's system). Critically, the standardized power import limit function will enable smarter vehicle–grid integration by leveraging the flexibility of BEVs to charge during off-peak periods. Conforming products will give utilities a clear technological framework for use in load management programs.

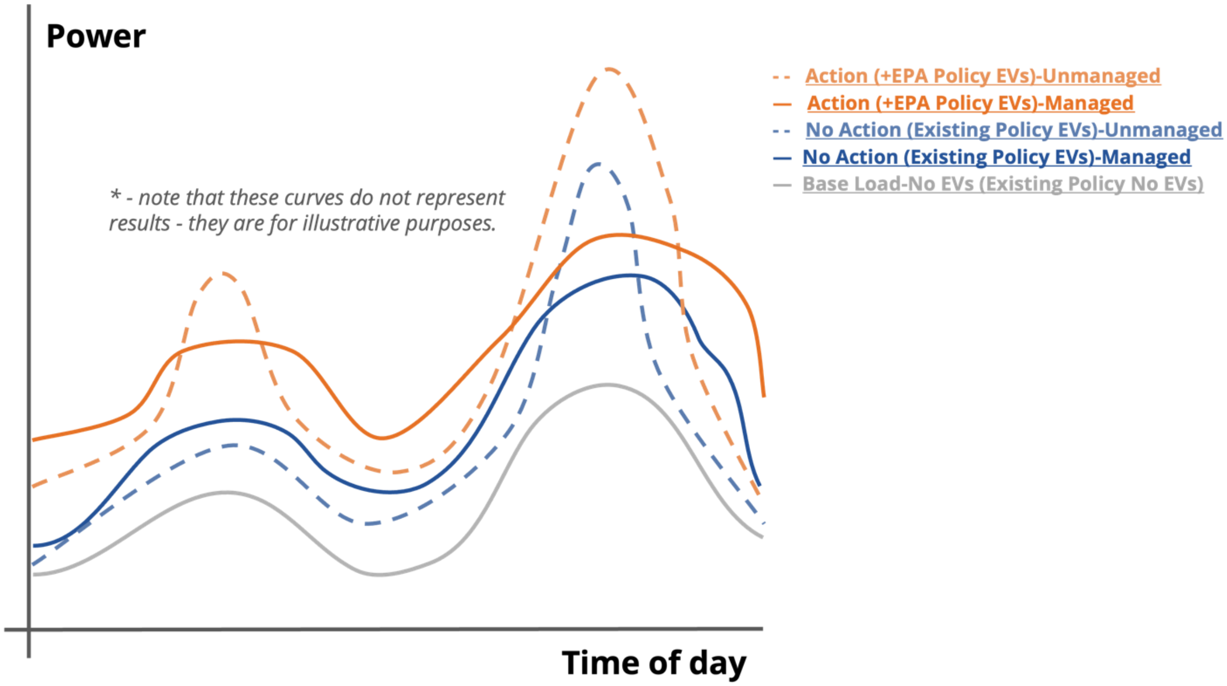


Figure 1. Illustrative example of the four PEV policy and charging behavior scenarios compared in this study

Absolute Versus Relative Scenario Analysis

We define the study scope to identify where and when the electric distribution grid may require *capacity enhancements* under a relative comparison of certain PEV adoption policy and charging behavior scenarios. However, the study does not predict the absolute levels of electric distribution grid investment needed in the long term. Relative scenario comparisons were used in this study to isolate the effect of electrification and reduce confounding effects from including other variables. The study did not examine the benefit of non-wire alternatives (NWAs) to manage load, nor did the study account for ongoing investments related to resilience and aging infrastructure; when investments will occur; or drivers of asset failures, such as calendar age, temperature, and actual loading patterns. Though the study employs publicly available high-resolution grid asset data, the prevalence of underground lines introduces some uncertainty in cost estimation. It is important that these factors be considered in absolute cost analyses, but their absence here will have a muted effect on the relative costs between scenarios.

Literature Review and Ongoing Studies

This study is the first of its kind, owing to the unique combination of scale of the analysis (e.g., five-state with national extrapolation), load and distribution spatial and asset granularity (parcel- and feeder-level, respectively), scope of the EV impacts (L/M/HDV), and time horizon of the analysis (2032 and extrapolated 2050 impacts). A comparison of key DOE, Electric Power Research Institute (EPRI), Kevala, and NREL studies in this space is presented in Table 1. National-scale studies to date either have not included distribution impacts or have taken high-level econometric approaches to performing impact analysis. Detailed studies that have performed parcel-level load analysis (i.e., allocating load profiles and electrification growth at the building level) have typically involved smaller spatial extents (i.e., LA100 analysis was for Los Angeles Department of Water & Power’s [LADWP’s] service area, EVs@Scale/FUSE is investigating specific feeders in Virginia, and the CPUC's Electrification Impact Study focused on IOU service areas in California). This study is unique in the large spatial extent (i.e., five states) coupled with the detailed load spatial resolution (parcel-level) conducted for the analysis.

Table 1. *Comparison of Multi-State Transportation Electrification Impact Study (TEIS) to other key DOE, NREL, EPRI, and Kevala Studies*

Project	Final Analysis Year	EV Adoption (Class-Dependent)	EV Weight Class	Charging Infrastructure Needs	Spatial Extent	Load Spatial Granularity (Demand)	Generation Impacts	Distribution Impacts	Distribution Assets Granularity/ Analysis Method
LA100[28]	2050	80% Stock 2045	LDV	Yes	LADWP	Parcels	Yes	Yes	Distribution Transformer/ Power Flow
2030 NCN (NREL)[29,30]	2030	15% Stock (50% Sales)	LDV	Yes	National	County	No	No	No
DECARB (DOE)	2050	80% Stock	L/M/ HDV	No	National	County	Yes	Yes	Econometric
EVs on Bulk Power Systems (DOE)[31]	2050	80% Stock	L/M/ HDV	No	National	County	Yes	No	No
EVs2Scale2030 /eRoadMap (EPRI)[32]	2030	15% Stock (50% Sales)	L/M/ HDV	No	National	~0.28 mi^2 Cells	No	Yes	Feeder (Selected Utilities)
EVs@Scale/ FUSE (DOE)[33]	2040	50% Stock	L/M/ HDV	Yes	Virginia	Parcels	No	Yes	Feeder/ Power Flow
Electrification Impact Study (CPUC)[34]	2035	30% Stock	L/M/ HDV	Yes	California	Parcels	No	Yes	Distribution Transformer/ Capacity Analysis
Multi-State TEIS	**2032**	**20% Stock**	**L/M/ HDV**	**Yes**	**5-State**	**Parcels**	**No***	**Yes**	**Feeder/ Capacity Analysis**

* EPA independently simulated generation capacity expansion using the PEV charging loads from this study.

A key aspect of electrification impact studies is how load is modeled. The focus of this work is on examination of transportation electrification grid impacts and required upgrades. Models are developed to predict how specific types of loads will behave with regard to the amount and rate of energy they

[28] Bryan Palmintier, Meghan Mooney, Kelsey Horowitz, Sherin Abraham, Tarek Elgindy, Kwami Sedzro, Ben Sigrin, Jane Lockshin, Brady Cowiestoll, and Paul Denholm, "Chapter 7: Distribution System Analysis," in *The Los Angeles 100% Renewable Energy Study*, edited by Jaquelin Cochran and Paul Denholm (Golden, CO: National Renewable Energy Laboratory, 2021), NREL/TP-6A20-79444-7, https://www.nrel.gov/docs/fy21osti/79444-7.pdf.

[29] E. Wood, B. Borlaug, M. Moniot, D-Y Lee, Y. Ge, F. Yang, and A. Liu, *The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure*, NREL Technical Report 85654, June 2023, https://www.nrel.gov/docs/fy23osti/85654.pdf.

[30] E. Wood, B. Borlaug, M. Moniot, D-Y Lee, Y. Ge, F. Yang, and Z. Liu, *The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure*, NREL Technical Report 85654, June 2023, https://www.nrel.gov/docs/fy23osti/85654.pdf.

[31] B. Borlaug, E. Hale, P. Jadun, L. Lavin, C. Ledna, M. Muratori, and A. Yip, "Managing Increased Electric Vehicle Shares on Bulk Power Systems," NREL Technical Presentation 86000, June 2023, https://www.nrel.gov/docs/fy24osti/86000.pdf.

[32] EPRI, "EVs2Scale2030," accessed 2023, https://msites.epri.com/evs2scale2030.

[33] Andrew Meintz, "Electric Vehicles at Scale (EVs@Scale) Laboratory Consortium," VGI/SCM Pillar, presentation at the DOE Vehicle Technologies Office (VTO) Annual Merit Review, June 22, 2022, https://www.nrel.gov/docs/fy22osti/82828.pdf.

[34] Kevala, "Electrification Impacts Study Part I: Bottom-up Load Forecasting and System-Level Electrification Impacts Cost Estimates," prepared for CPUC Energy Division, 2023, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M508/K423/508423247.PDF.

need. Examples of load models developed for this study include baseline loads for various building types that reflect typical loads found in residential, commercial, and industrial locations. Models were also developed to predict loading from electric vehicle battery charging, and these were adjusted to reflect charging needs of different types of vehicles (L/M/HDVs of various types). Vehicle projections are provided by EPA modeling, with non-electrification load provided from projections from ICF Consulting. The EPA projections for LDVs and MDVs (Class 1–3) were developed using OMEGA,[35] and projections for HDVs were developed using the EPA's HD TRUCS model[36] and MOVES.[37]

Future work may consider refining the assumptions for the type and size of charging infrastructure under the managed charging scenario. This study predicts that for the baseline (No Action scenario) in California, there will need to be a total of 7,248,724 public and private chargers (charging ports) to serve around 10 million PEVs by 2032. The CEC forecasts that by 2030, California will need 1.01 million chargers to serve 7.1 million PEV passenger vehicles. By 2035, PEV passenger vehicle adoption is expected to reach 15.2 million vehicles and require 2.11 million chargers.[13] The CEC report projects that by 2030, California's fleet of 155,000 medium and heavy-duty electric vehicles will require 114,500 chargers. By 2035, this will increase to a fleet of 377,000 vehicles requiring 264,500 chargers at depot and public en route locations. The CEC study notes that "[w]hile today's average electric passenger vehicle driver charges at home in a single-family dwelling, many Californians do not have convenient access to this option. People who live in multifamily dwellings or have no access to electricity where they park need convenient charging options. In addition, all electric vehicle drivers will need charging on long trips."[38] The CEC adjusted the number of public and private ports accordingly.

The current study assumes that charging infrastructure is available and operational whenever it is needed. Future work may refine this assumption. Charger reliability has been raised as a concern in California,[39] although it was recognized that more information is needed to understand this issue more clearly. Accordingly, the California Legislature required the CPUC 1) to develop charger uptime recordkeeping and reporting standards receiving for state-incentivized chargers and 2) to conduct biennial assessments of charger uptime. The current assumption for managed charging is that all home and depot charging participate in some form of managed charging. Future studies may choose to refine this assumption based on further analysis of customer adoption scenarios. For example, U.S. Energy Information Administration (EIA) data show that, for the five states that are a focus of the current study,

[35] For overview information on OMEGA, see EPA's page at https://www.epa.gov/regulations-emissions-vehicles-and-engines/optimization-model-reducing-emissions-greenhouse-gases#overview. Additional documentation on the model is provided at https://omega2.readthedocs.io/en/2.1.0/.
[36] Sui, Lang. Memorandum to Docket EPA-HQ-OAR-2022-0985. "Heavy Duty Technology Resource Use Case Scenario Tool (HD TRUCS)". April 14, 2023. Available online: https://www.regulations.gov/document/EPA-HQ-OAR-2022-0985-0830.
[37] Murray, Evan. Memorandum to Docket EPA-HQ-OAR-2022-0985. "MOVES4.R3". February 2024.
[38] California Energy Commission Staff Report "Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Assessing Charging Needs to Support Zero-Emission Vehicles in 2030 and 2035", August 2023, CEC-600-2023-048, (Executive Summary, page 2)
[39] California Energy Commission Staff Report "Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Assessing Charging Needs to Support Zero-Emission Vehicles in 2030 and 2035", August 2023, CEC-600-2023-048. An overview of the report and link to the report is at https://www.energy.ca.gov/data-reports/reports/electric-vehicle-charging-infrastructure-assessment-ab-2127

only 13% of customers are enrolled in demand response programs and 58% are enrolled in dynamic pricing programs (e.g., time-of-use).

Distributed energy resources (DERs) are impacting utility net load and are not the focus of this study. Distributed battery energy storage systems, which act like traditional loads when they are charging and act like “negative loads” when they are discharging, can help manage utility peak demand. Other types of DERs include photovoltaic (PV) systems that appear as negative load when operational. PV system models were developed in this study. This study did not include additional PV adoption beyond what was included in the base case. Large-scale PV adoption can change the overall net load, resulting in large mid-day load valleys or duck curves,[40] and has raised discussions on night versus day EV charging patterns to flatten the overall net load curve. The effect of PV systems was modeled based on an extrapolation of existing PV. To do this, Kevala’s Sunspot computer vision algorithm was used to identify locations and dimensions of existing rooftop PV systems, and then NREL’s PVWatts Calculator was used to estimate the time series generation (negative load) from the PV systems. PVWatts is typically configured to assume PV systems are installed at the ideal tilt and orientation for the specified location. Future work may refine the models based on more information about tilt and orientation of the PV systems, which are rarely ideal, owing to differing orientations of rooftops in housing developments. This may affect the shape (timing) of PV generation relative to load.

Building electrification and other emerging load sectors were also not a focus of this study. Building electrification could be an important element to examine in future work, as it can *share* added grid capacity if the end-use peaks for each sector are not time-coincident. Recent work has shown that, for some regions, building electrification may account for more than half of future peak load growth, particularly in regions with electrification of high heating loads (i.e., heat pump adoption).[41] Examining multi-sector electrification forecasts[42] in the future, across multiple states, will further help delineate cost allocation and capacity expansion in the context of multiple drivers for load growth.

For distribution analysis, the five-state TEIS in this report performs capacity analysis of distribution assets at a feeder level and aggregates the distribution transformer capacity for the analysis. Studies that take a more detailed distribution analysis approach (e.g., distribution primary power flow down to the distribution transformer) have typically focused on single utility service areas or performed analysis on selected feeders (e.g., LA100, EVs@Scale), using real utility datasets. A key enabling capability to perform state-level analysis has been Kevala’s synthesis of distribution asset data and connectivity. Kevala has used machine learning algorithms, trained on real distribution data, to be able to estimate distribution assets and topologies. This enables the analysis to leverage synthetic data, as opposed to trying to obtain datasets across the tens or hundreds of utility service areas that make up a typical U.S. state.

[40] R. Bowers, E. Fasching, and K. Antonio, “As solar capacity grows, duck curves are getting deeper in California,” EIA, June 2023, https://www.eia.gov/todayinenergy/detail.php?id=56880.

[41] National Grid, "Future Grid Plan: Empowering Massachusetts by Building a Smarter, Stronger, Cleaner and More Equitable Energy Future", September 2023, https://www.nationalgridus.com/media/pdfs/our-company/massachusetts-grid-modernization/future-grid-full-plan-sept2023.pdf

[42] Mai, Trieu, Paige Jadun, Jeffrey Logan, Colin McMillan, Matteo Muratori, Daniel Steinberg, Laura Vimmerstedt, Ryan Jones, Benjamin Haley, and Brent Nelson. 2018. Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States. National Renewable Energy Laboratory. NREL/TP-6A20-71500. https://doi.org/10.2172/1459351.

This study focuses on the investment required as a result of transportation electrification, along with other load growth present in the Integrated Planning Model (IPM) forecasts that were used as inputs. Cost allocation and comparisons of other investment analysis become challenging because of the nature of how studies define cost categories. Utility rate cases delineate operational expenses and capital investments. One challenge of identifying “cost causation” due to electric vehicles is that individual distribution investments often achieve multiple objectives. Utilities’ increased use of integrated distribution planning promotes reliability alongside resilience, sustainability, and equity goals, while examining a broad solution space including customer programs and NWAs as an alternative to traditional grid upgrades or as potential bridge toward deferring or meeting load growth until load can be served with conventional expansions. Notable recent integrated distribution plans include those submitted to the Massachusetts Grid Modernization Advisory Council and those by the large IOUs in California and New York. These plans examine multiple investment drivers, such as aging infrastructure, reliability and resilience needs, and customer electrification. Building upon this study, future analysis decomposing the drivers of multipurpose investments that are out of scope here could reduce the estimated cost of transportation electrification, as could the use of NWAs.

Report Structure

The remainder of this report details assumptions and methodologies and discusses scenario results.

- **Chapter 2** presents methods for simulating charging needs to support transportation electrification scenarios, introduces assumptions for charging infrastructure capital costs, and explains estimating distribution grid upgrade costs.
- **Chapter 3** presents transportation electrification scenario results, including adoption scenarios, charging load shapes, and charging network costs.
- **Chapter 4** presents results from the relative scenario analysis on the distribution grid, including incremental costs of the EPA’s proposed rulemakings.
- **Chapter 5** discusses the key assumptions and approaches used and contextual information to aid in the interpretation of results.
- **Chapter 6** concludes with key takeaways from this study.

The document’s appendices include additional details related to the results, methods, and study context.

Modeling Approach

Data were passed from one organization to another through a one-way data pipeline (see Figure 2) that began with the EPA's PEV adoption scenarios and ended with capital cost estimates (charging equipment and grid infrastructure). LBNL used HEVI-LOAD to simulate the charging needs for HDVs (Class 4–8), while NREL performed the same task in parallel using EVI-X for LDVs (Class 1–2a), MDVs (Class 2b–3), and battery electric transit and school buses. NREL then translated charging needs into capital cost estimates for charging equipment and installation (on the customer side of the meter). Finally, Kevala took the county-level charging load profiles and infrastructure needs from both NREL and LBNL, spatially disaggregated charging demand to the parcel level, and overlaid this demand with non-PEV demands to estimate distribution capacity expansion needs and associated capital costs. This chapter discusses the methods used in each step of this data pipeline, including the modeling assumptions and input data sources.

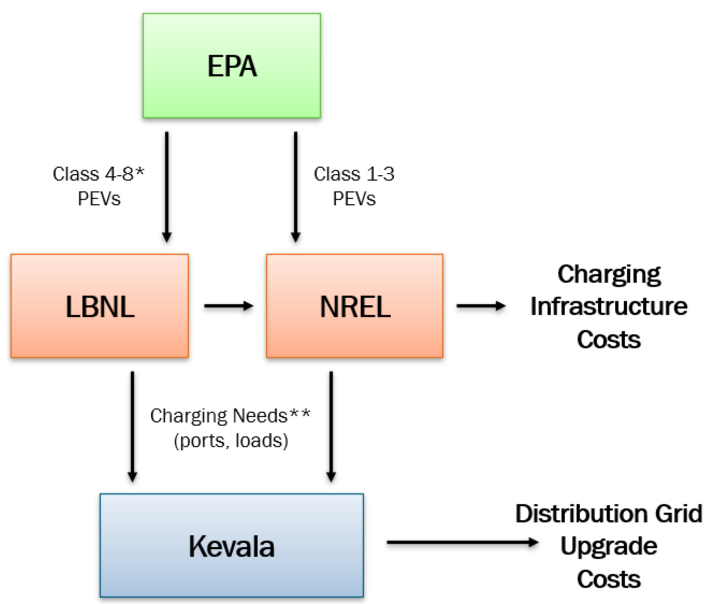


Figure 2. Multi-organization data pipeline

* Excluding school/transit buses, which are simulated by NREL

** Data were used by EPA for production cost and capacity expansion modeling.

Simulating Transportation Electrification

Charging infrastructure terminology used in this report is consistent with definitions used by the U.S. Department of Transportation Federal Highway Administration[43] and aligns with Open Charge Point Interface (OCPI) terminology for the hierarchy of PEV charging stations, as shown in Figure 3 (adapted from the DOE Alternative Fuel Data Center [AFDC]):

[43] Federal Highway Administration, National Electric Vehicle Infrastructure Standards and Requirements, February 28, 2023, https://www.federalregister.gov/documents/2023/02/28/2023-03500/national-electric-vehicle-infrastructure-standards-and-requirements.

- **Station location** refers to a site with one or more electric vehicle supply equipment (EVSE) ports at the same address. Examples include a parking garage or a mall parking lot.
- An **EVSE port** provides power to charge only one vehicle at a time, even though it might have multiple connectors. The unit that houses EVSE ports is sometimes called a charging post, which can have one or more EVSE ports.
- A **connector** is what is plugged into a vehicle to charge it. Multiple connectors and connector types (e.g., Tesla [SAE J3400], Combined Charging System, CHAdeMO) can be available on one EVSE port, but only one vehicle will charge at a time. Connectors are sometimes called plugs.

As discussed in Wood et al. (2017)[44], charging infrastructure needs can be thought of in terms of coverage and capacity, wherein coverage needs tend to be defined in terms of number of stations and capacity needs tend to be defined in terms of number of ports. This analysis is primarily concerned with estimating future charging capacity, and thus it presents results in terms of port counts (as opposed to stations).

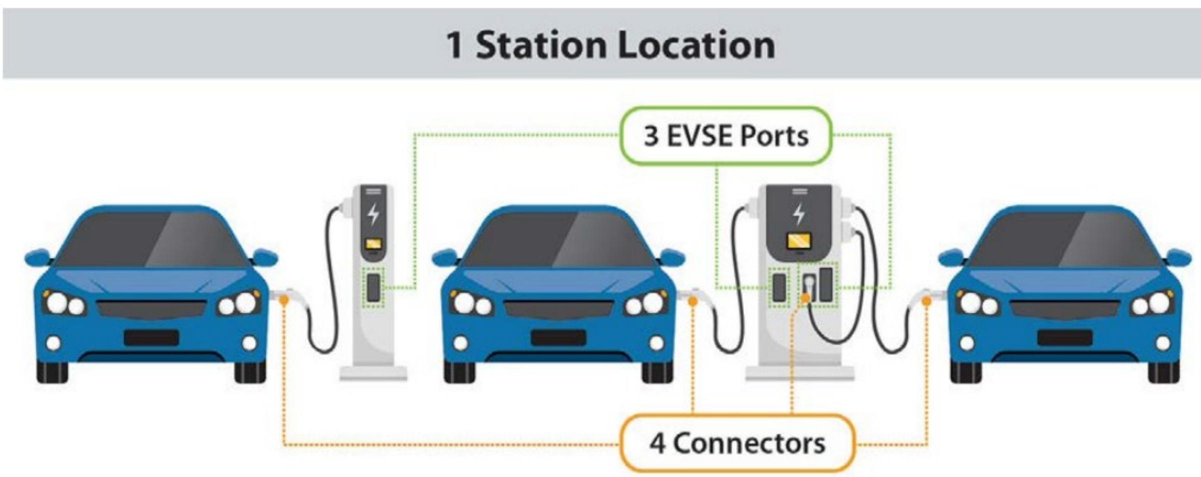


Figure 3. PEV charging infrastructure hierarchy *(Source: AFDC (2023a))*[45]

Charging Demand from Light- and Medium-Duty Vehicles

Light-duty PEV modeling in this report builds on the foundation of years of research and collaboration at NREL and beyond, most notably the recently published *2030 National Charging Network* report.[13] A brief explanation of this modeling approach is provided here; readers are directed to this previous work for more detailed explanations of the modeling approach and assumptions.

In addition to modeling tools, several assumptions must be made to define vehicle use scenarios and estimate the corresponding charging demands. These include scenario-specific assumptions on vehicle adoption (number of PEVs with regional variation), fleet composition (PEV chassis types and preference for BEVs/PHEVs), technology attributes (e.g., vehicle efficiency/range, charging efficiency/speed), and

[44] Eric Wood, Clément Rames, Matteo Muratori, Sesha Raghavan, and Marc Melaina. 2017. National Plug-In Electric Vehicle Infrastructure Analysis. Washington, D.C.: U.S. Department of Energy Office of Energy Efficiency & Renewable Energy. DOE/GO-102017-5040. https://www.nrel.gov/docs/fy17osti/69031.pdf.
[45] Alternative Fuels Data Center: Electric Vehicle Charging Stations, 2023. https://afdc.energy.gov/fuels/electricity_stations.html

driving/charging behavior. A key determinant of charging behavior—particularly the demand for public charging—is the share of PEV owners able to access charging at their primary residences. Home charging is typically the most convenient and affordable charging location for those who have access, but many do not—as discussed at length by Ge et al. (2021).[46]

The core tools used for modeling LDV charging demands in this study are:

- **EVI-Pro**: For typical daily charging needs
- **EVI-RoadTrip**: For fast charging along highways supporting long-distance travel
- **EVI-OnDemand**: For electrification of transportation network companies.

The development and application of individual models dedicated to specific use cases provide at least two benefits:

1. Increased modularity maximizes the flexibility in our modeling—namely, models can be combined or run in isolation (where appropriate), as demonstrated in many studies listed in Wood et al. (2023).[47]
2. Each model can be tailored to the unique driving and charging behaviors of their associated use cases.

The models used in this study are a subset of the larger EVI-X modeling suite maintained by NREL for network planning, site design, and financial analysis across light-, medium-, and heavy-duty vehicles (NREL 2023).[48]

LDV use cases vary widely and have unique infrastructure requirements that must be accommodated to facilitate a seamless transition to PEVs. Typical daily use of LDVs tends to be characterized by short trips with long dwell periods (e.g., 70% of daily driving less than 40 miles and 95% less than 100 miles, with vehicles typically parked 95% of their lifetimes). These periods present ample opportunities for destination charging (most notably at home and workplace locations) that is "right-speeded" to match typical dwell times. EVI-Pro assumes such an opportunistic approach to charging, attempting to make use of low-cost destination charging where convenient and rely on fast charging only when necessary.[49]

[46] Yanbo Ge, Christina Simeone, Andrew Duvall, and Eric Wood. 2021. There's No Place Like Home: Residential Parking, Electrical Access, and Implications for the Future of Electric Vehicle Charging Infrastructure. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-81065. https://www.nrel.gov/docs/fy22osti/81065.pdf.

[47] Eric Wood, et al. 2023. The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-85654. https://www.nrel.gov/docs/fy23osti/85654.pdf

[48] NREL EVI-X Modeling Suite of Electric Vehicle Charging Infrastructure Analysis Tools, 2023. https://www.nrel.gov/transportation/evi-x.html

[49] EVI-Pro assumes that fast charging is necessary only when long-dwell-time opportunities to charge slowly are not present in the detailed driving pattern data sets used as inputs. In reality, charging preferences will be dictated by myriad conditions that are challenging to anticipate in a model. Therefore, in this analysis, EVI-Pro has been configured to simulate a minority of BEV drivers (10%) as preferring fast charging over slower alternatives, including opportunities to charge at home. The size of this behavior cohort is believed to be consistent with the limited set of real-world charging behavior observations available in the literature. BEV manufacturers are arguably in the best position to observe actual charging behavior in the field and are encouraged to consider publishing aggregated charging behavior statistics to inform the efficient deployment of charging infrastructure.

In contrast, the use of PEVs for long-distance travel and in ride-hailing applications requires that they can pull over in convenient locations and quickly charge to either resume a road trip or return to service. EVI-RoadTrip and EVI-OnDemand both employ this charging behavior philosophy but rely on distinct data sets to describe the geographic footprint of long-distance versus ride-hailing travel patterns. Long-distance travel requires a network of fast-charging stations along highways (including urban and rural areas that these highways pass through), whereas ride-hailing electrification necessitates access to fast charging within the urban areas where such services are most common (such as near urban centers and airport locations). Additional details of each model are discussed in the following subsections of this report.

Each individual LDV model is integrated into a shared simulation pipeline (see Figure 4). Models are provided with a self-consistent set of exogenous inputs that prescribe the size, composition, and geographic distribution of the national PEV fleet; technology attributes of vehicles and charging infrastructure; assumed levels of residential/overnight charging access; and regional environmental conditions. Each model uses these inputs in bottom-up simulations of charging behavior by superimposing the use of a PEV over travel data from internal combustion engine vehicles. By relying on historical travel data from conventional vehicles, these models implicitly design infrastructure networks capable of making PEVs one-to-one replacements for internal combustion engine vehicles, effectively minimizing impacts to existing driving behavior and identifying the most convenient network of charging infrastructure capable of meeting driver needs.

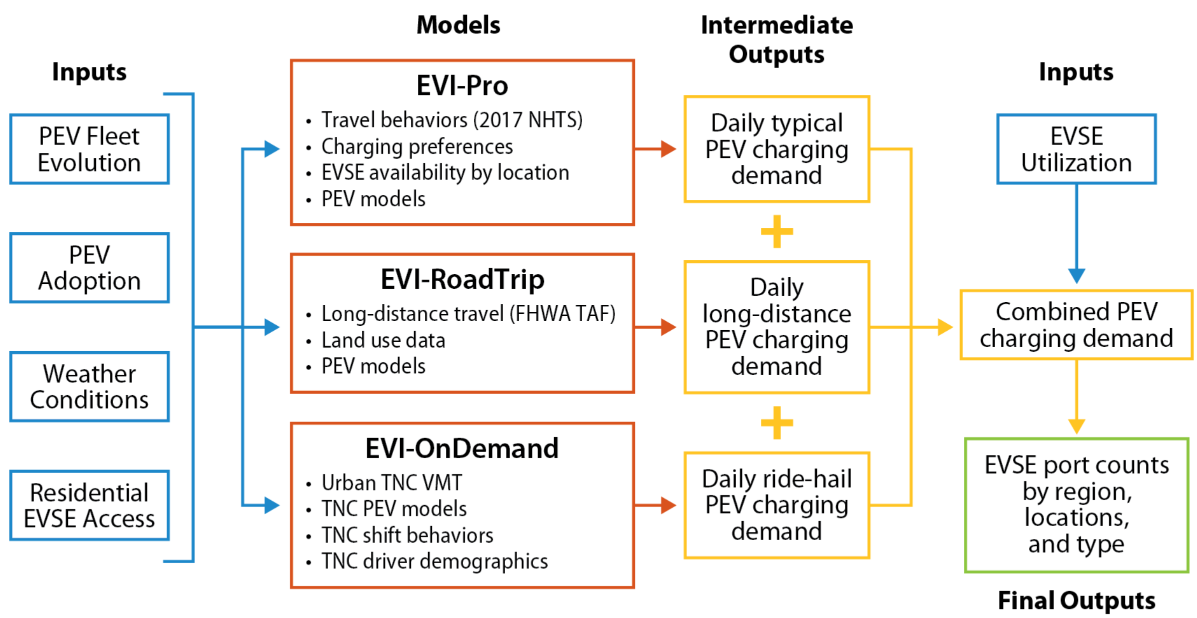


Figure 4. Shared simulation pipeline integrating EVI-Pro, EVI-RoadTrip, and EVI-OnDemand

The independent (but coordinated) simulations produce a set of intermediate outputs estimating daily charging demands for typical PEV use, long-distance travel, and ride-hailing electrification. These intermediate outputs are indexed in time (hourly over a representative 24-hour period) and space (core-based statistical area or county level) such that they can be aggregated into a composite set of charging demands across multiple use cases. Once combined, the peak hour for every combination of charging type (e.g., Level 1 [L1], Level 2 [L2], direct current [DC]), location type (e.g., home, work, retail), and geography (e.g., core-based statistical area) is identified for the purpose of network sizing. Rather than sizing the simulated charging network to precisely meet the peak hourly demand in all situations, the simulation pipeline uses an assumed network-wide utilization rate in the peak hour to “oversize” the network by a margin that accounts for the fact that charging demands tend to vary seasonally and around holidays.

Because the EVI-X modeling ensemble simulates demand on a typical day, the network sizing approach attempts to account for periods of peak demand, which could far exceed what is experienced on a typical day. This margin is calibrated based on an analysis of real-world utilization data, as described later in this section. The resulting final output of the LDV pipeline is a set of charging infrastructure port counts by region, location type, and charging type that can be aggregated to the national level or reported out for individual states or core-based statistical areas.

The simulation of MDVs (Class 2b–3, gross vehicle weight rating [GVWR] 8,500–14,000 lbs.) leverages the EVI-X LDV pipeline with some key updates:

- MDVs are disaggregated from the national level to counties in a manner proportional to existing registrations, as observed through data licensed from Experian. This contrasts with the LDV approach, which relies on a likely adopter model to assign PEVs to households with characteristics shown to correlate with PEV adoption. The development of a likely adopter model for MDVs is a potential subject of future research.
- MDV travel patterns are derived from two sources based on chassis type: (1) vans are simulated based on data from NREL’s FleetDNA database, and (2) pickups are simulated based on data licensed from Wejo. This contrasts with the LDV approach, which relies on the 2017 National Household Travel Survey (NHTS). Bruchon et. al. collected additional driving data for MDVs.[50]
- MDVs are owned by a variety of businesses, both in terms of company size and business type, and are often used for both personal and commercial use. Therefore, medium-duty PEVs in this study are assumed to be domiciled during off-shift periods at either a commercial property (e.g., a depot) or a private residential property (e.g., a single-family home). This study assumes that 75% of medium-duty PEVs are domiciled at depots and 25% at single-family homes. Further research into the domicile locations of MDVs is warranted because data on this topic are scarce, especially at the national level.

Table 2 summarizes the modeling assumptions used in the national LDV/MDV pipeline. Where necessary, these assumptions have been harmonized with EPA modeling.

Table 2. *2032 Nominal EVI-X Modeling Assumptions Used for Light- and Medium-Duty PEVs*

Modeling Parameter	Light-Duty (Class 1–2a)	Medium-Duty (Class 2b–3)
PEV fleet size	No Action = 40 million Action = 53 million	No Action = 0.4 million Action = 1.4 million
PEV powertrain shares	BEV = 99%	BEV = 100%

[50] Bruchon, Matthew, Brennan Borlaug, Bo Liu, Tim Jonas, Jiayun Sun, Nhat Le, and Eric Wood. 2024. Depot-Based Vehicle Data for National Analysis of Medium- and Heavy-Duty Electric Vehicle Charging. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-88241. https://www.nrel.gov/docs/fy24osti/88241.pdf.

Modeling Parameter	Light-Duty (Class 1–2a)	Medium-Duty (Class 2b–3)
	PHEV = 1%	PHEV = 0%
PEV body type distribution (Action scenario)	Sedan = 34% C/SUV = 56% Pickup = 10%	Pickup = 17% Van = 83%
Average PEV electric range	BEV = 300 miles PHEV = 50 miles	BEV van = 150 miles BEV pickup = 300 miles
BEV minimum DC charge time (20%–80% state of charge [SOC])	20 minutes [a]	
Maximum DC power rating (per port)	350 kW	
Geographic distribution	Scaled proportional to existing PEV and gasoline–hybrid registrations with a ceiling of 35% of LDVs on the road in 2030 representing PEVs in high-adoption areas, and a floor of 3% in low-adoption areas	
PEVs with reliable access to overnight charging	No Action: 87% Action: 84%	100%
Weather conditions	Typical ambient conditions are used for each simulated region, affecting electric range accordingly	
Driving behavior	EVI-Pro: Consistent with the Federal Highway Administration 2017 NHTS EVI-RoadTrip: Directly applies the Federal Highway Administration Traveler Analysis Framework EVI-On Demand: Consistent with Balding et al. (2019)[51]	
Charging behavior	All models attempt to maximize the use of home/depot charging (when available) and use charging away from home only as necessary. When fast charging is necessary, the preference for BEVs is the fastest compatible option, up to 350+ kW.	

Tesla recently reported an average charge duration of 27.5 minutes on their Supercharger network[52] and a median duration of 36 minutes has been calculated from public 50 kW DC chargers as part of the EV WATTS program[53]. These estimates are provided as context for the 2030 modeling assumption, even though neither statistic necessarily aligns with 20%–80% SOC events in all cases.

Charging Demand from Heavy-Duty Vehicles

Class 4–8 vehicles are modeled in LBNL's HEVI-LOAD tool, an agent-based simulation tool that aims to inform charging infrastructure needs of, and provide charging load profiles for, HDVs with a GVWR of more than 10,000 lbs. The tool provides granular temporal and geospatial resolutions ranging from the

[51] Balding, M., T. Whinery, E. Leshner, and E. Womeldorff. 2019. "Estimated TNC Share of VMT in Six US Metropolitan Regions." Fehr & Peers memorandum, Aug. 6, 2019. https://www.fehrandpeers.com/what-are-tncs-share-of-vmt/.

[52] Mark Kane. "Tesla Reveals Charging Stats: Almost 2 Million Sessions Per Day." InsideEVs, Motorsport Network. March 13, 2023. https://insideevs.com/news/656779/tesla-charging-supercharging-stats/

[53] Energetics EV WATTS Vehicle Dashboard, 2023. https://www.energetics.com/evwatts-vehicle-dashboard

site (i.e., station location) level to traffic analysis zone, county, state, and freight corridors to national scale. HEVI-LOAD streamlines the complex modeling process—including trip generation, vehicle behavior design, dynamic routing, load profiling, and infrastructure assessment—to determine the type, quantity, and statistically informed charger locations. The tool can subsequently be used to provide informed decision support to various stakeholders.

The HEVI-LOAD workflow consists of three major steps, as visually summarized in Figure 5:

1. **Data preprocess and scenario generation**, wherein the tool takes input data for travel demand, charging infrastructure, and road networks to create simulation scenarios.
2. **Agent-based simulation**, wherein the tool executes a detailed simulation using preprocessed input data, accounting for adopted heavy-duty ZEV truck trips, charging location details, and road network information, thus emulating real-world ZEV driving, parking, and charging behaviors for a specified analysis region.
3. **Results post-analysis**, wherein the tool summarizes event-based output data and provides an energy demand analysis and infrastructure assessment.

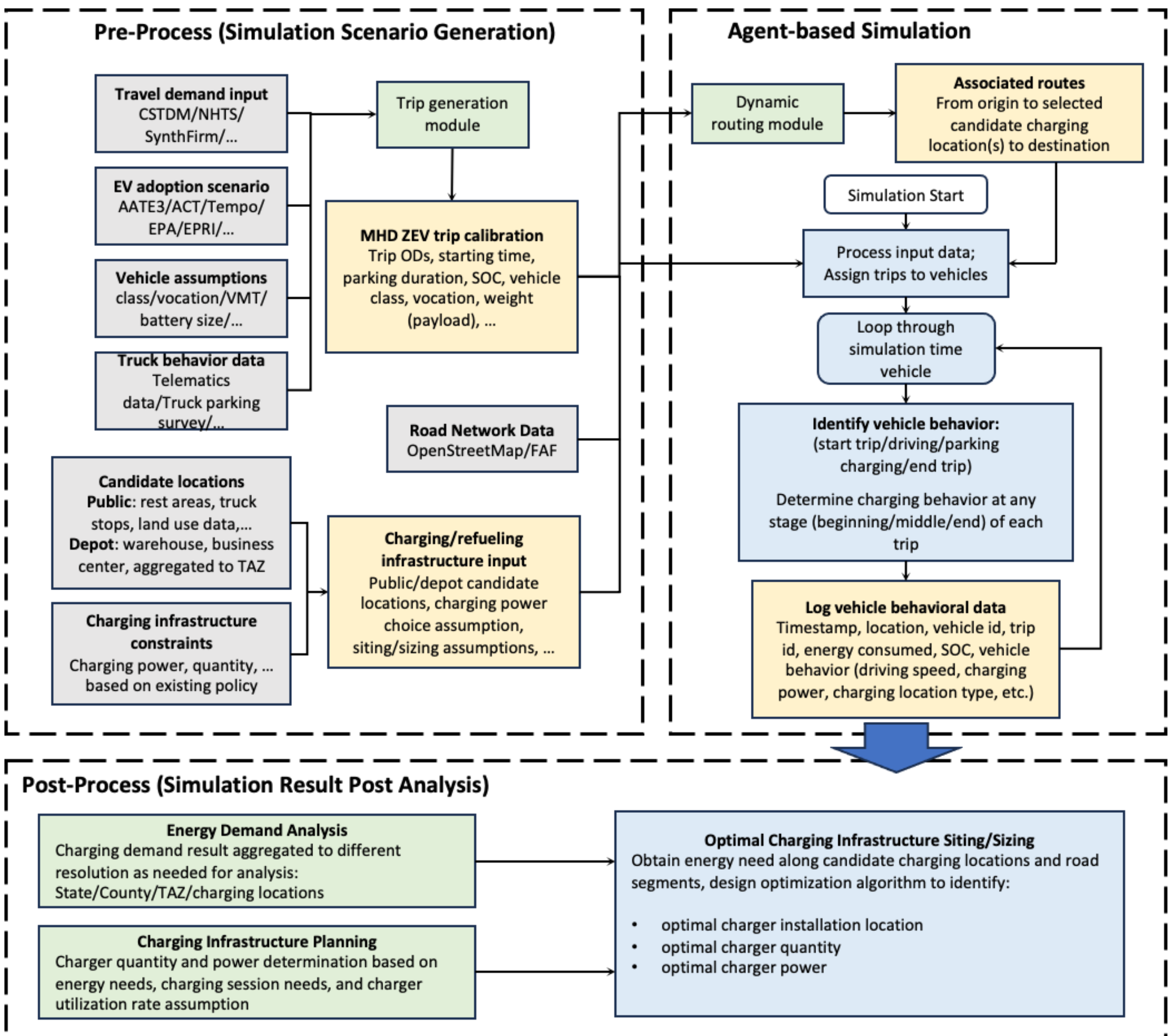


Figure 5. HEVI-LOAD tool flowchart. The gray boxes are data inputs, the green and blue boxes are methodology modules, and the yellow boxes are outputs of data from HEVI-LOAD.

Heavy-Duty ZEV Trip Synthesis

The heavy-duty ZEV trips in this study are generated based on a variety of national-scale data sets, including NHTS truck origin/destination (OD) data[54] (county-level business patterns that provide the number of businesses, business size, and business type distribution at the county level), Experian vehicle registration data,[55] INRIX OD data hosted on the DOE Livewire platform,[56] and truck telematics data.[57] This approach creates a combined sampling and disaggregation methodology for the baseline travel demand synthesis. At the same time, additional constraints are applied to ensure that the synthesized trips match the geospatial distribution patterns of the trip ODs, the vehicle miles traveled (VMT), and the energy consumption metrics at the aggregated level. The detailed sampling and disaggregation method is shown in Figure 6–Figure 8.

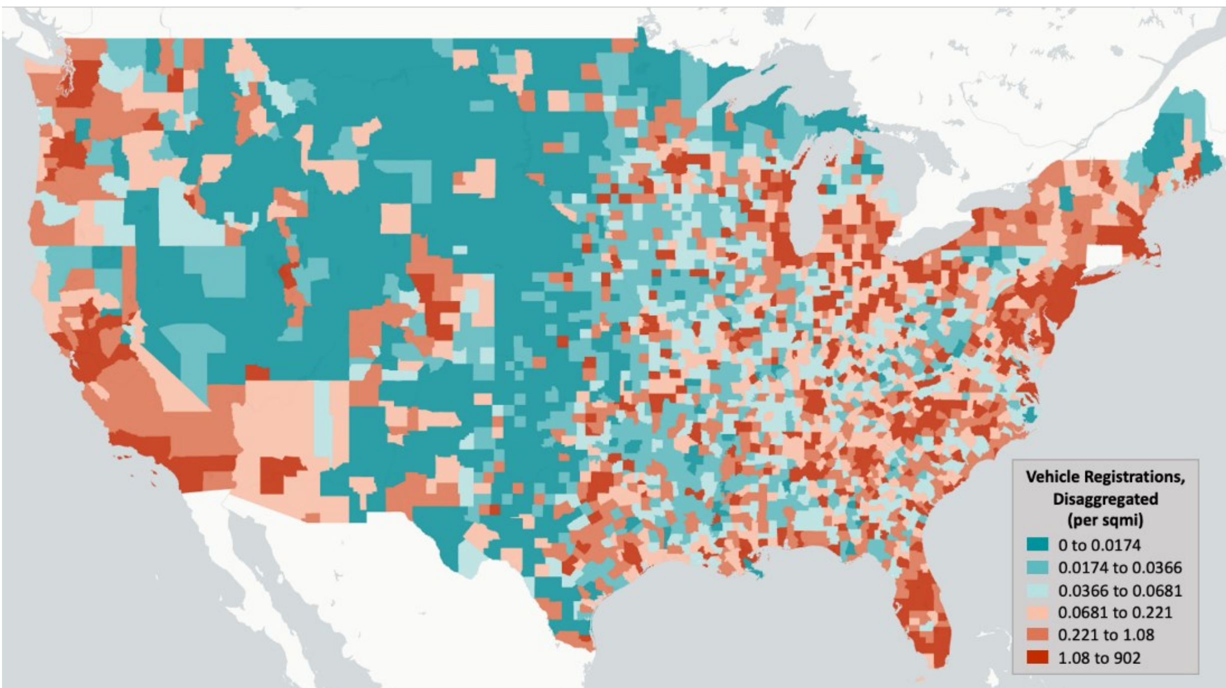


Figure 6. Experian registration data

[54] NHTS, "NextGen NHTS OD Data," 2022, accessed January 16, 2024, https://nhts.ornl.gov/od/.
[55] Experian Automotive, "Vehicle in Operation Market Data & Reports (Data Set)," 2022, https://www.experian.com/automotive/vehicles-in-operation-vio-data.
[56] L. S. Luhring, "Livewire Data Platform: A Catalog of Transportation and Mobility Data" (Golden, CO: National Renewable Energy Laboratory, March 2021), DOE/GO-102021-5520, https://www.osti.gov/biblio/1784501.
[57] NREL, "Fleet DNA: Commercial Fleet Vehicle Operating Data," Transportation and Mobility Research, accessed January 16, 2024, https://www.nrel.gov/transportation/fleettest-fleet-dna.html.

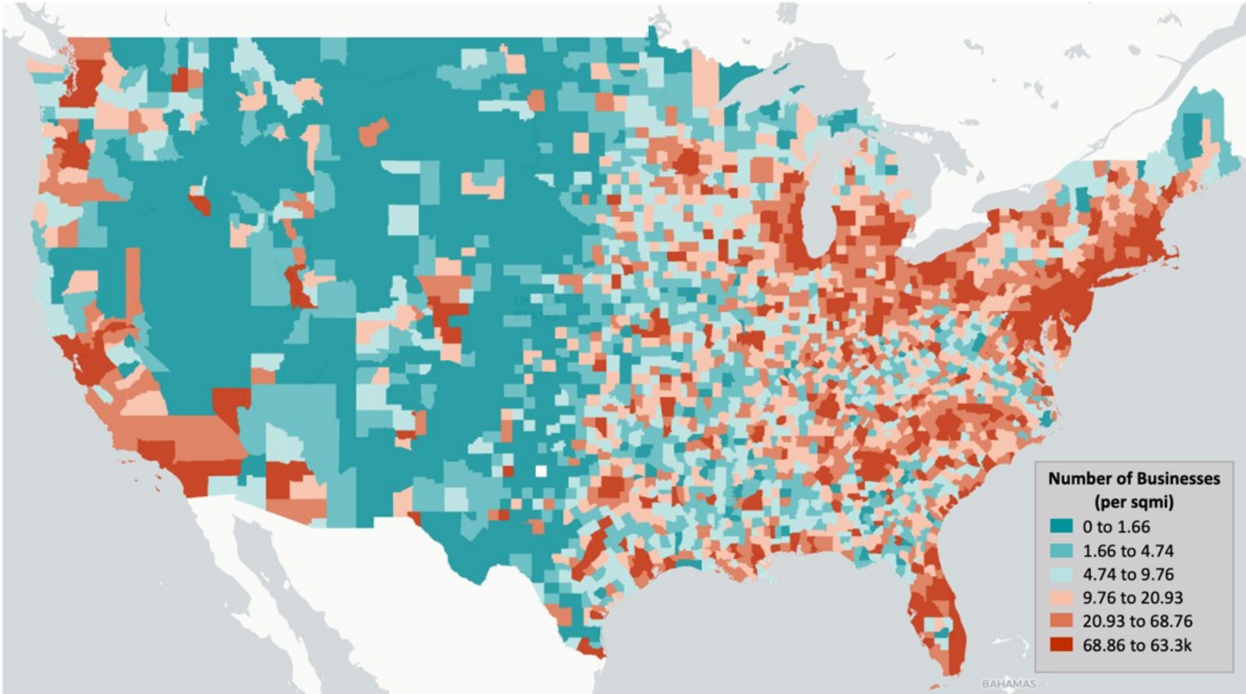


Figure 7. County business pattern data

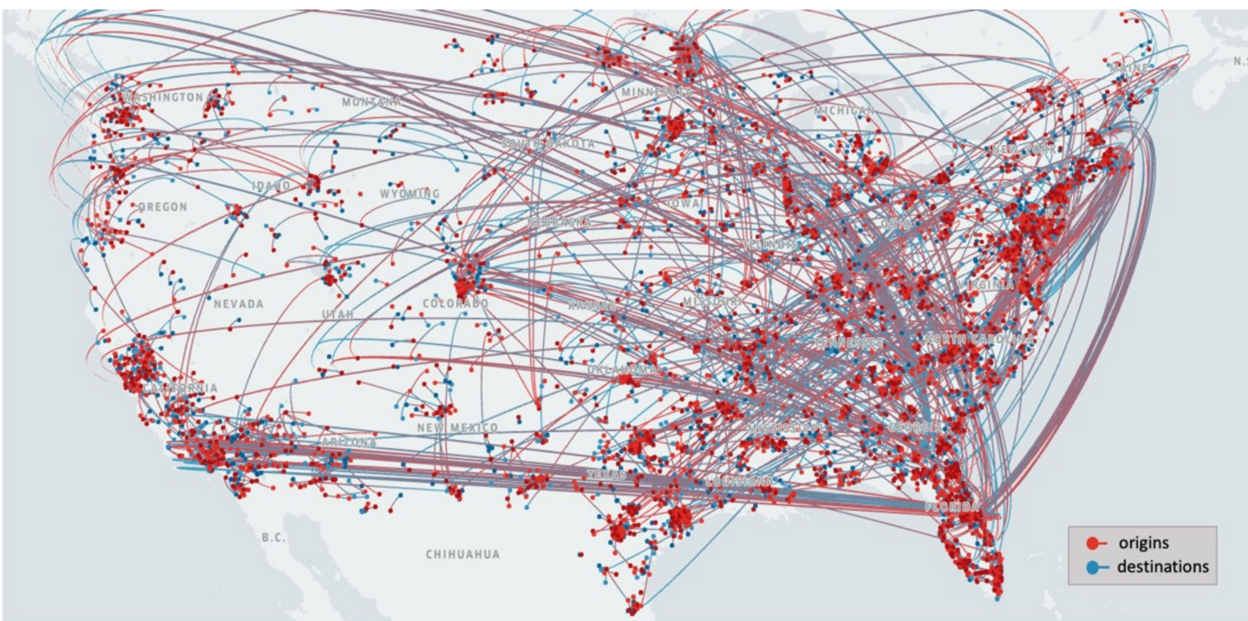


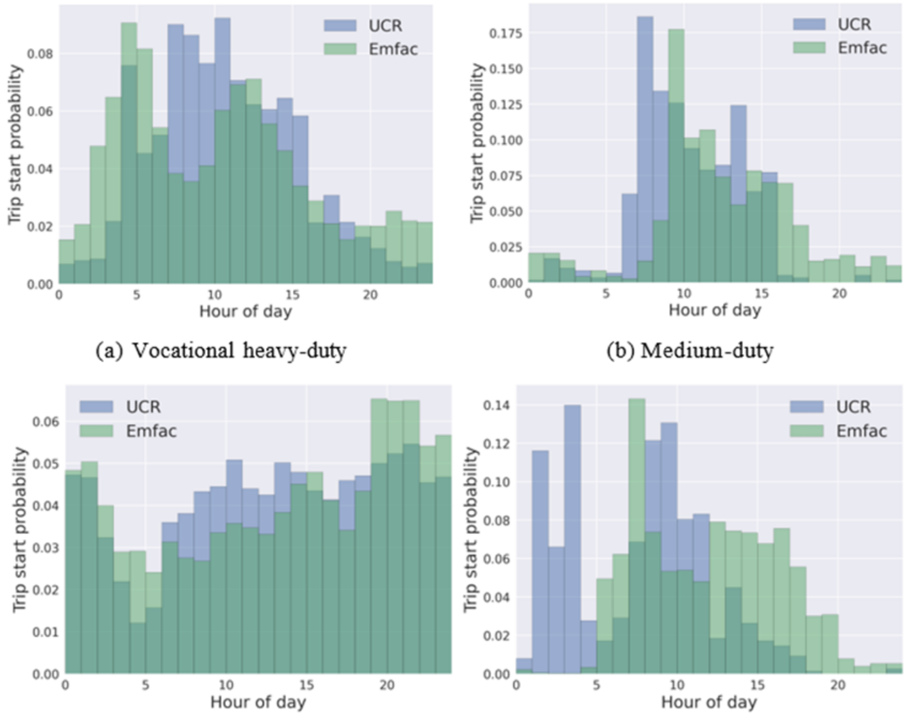
Figure 8. Example travel demand model of heavy-duty ZEVs at the national scale from HEVI-LOAD

Vehicle/Trip Behavior Assumptions

To include vehicle type identification in the trip data, vehicle classes, vocations, and weights were assigned for each trip based on vehicle information leveraged from various data sets, such as NHTS truck OD data, the Freight Analysis Framework,[58] the EMission FACtor (EMFAC) from the California Air Resources Board (CARB),[59] and FleetDNA. Because of the time differences in charging versus refueling behavior, we also investigated truck parking studies, chiefly the Federal Highway Administration's Jason's Law Truck Parking Survey,[60] and truck telematics data such as parking duration, trip start time, and the initial battery SOC as ZEV trip inputs.

Start time distribution. Vehicle start time assumptions are based on state-of-the-art travel demand data for trucks from EMFAC and Global Positioning System (GPS) location data from the University of California, Riverside (UCR) based on California trip start time data.[61] As shown in Figure 9, significant variance in the trip start time has been identified among multiple vocations. The HEVI-LOAD analysis averaged start time distributions based on EMFAC and UCR GPS data to generate vehicle-specific trip start times. Such data collected in California has a more comprehensive and balanced HD truck stock representation in terms of vehicle type, vocation, and weight class. Thus, the California data was the primary data source in this study to inform temporal truck behaviors at the national scale, i.e., trip start times, although limited truck telematics data collected in other states, especially for the long-haul applications, were also used to augment the fidelity of truck behaviors.

[58] U.S. Department of Transportation Federal Highway Administration, "Freight Analysis Framework," Freight Management and Operations, accessed January 16, 2024, https://ops.fhwa.dot.gov/freight/freight_analysis/faf/.
[59] CARB, "EMission FACtor (EMFAC)," accessed January 16, 2024, https://arb.ca.gov/emfac/.
[60] U.S. Department of Transportation Federal Highway Administration, "Jason's Law Truck Parking Survey Results and Comparative Analysis: Introduction," Freight Management and Operations, accessed January 16, 2024, https://ops.fhwa.dot.gov/freight/infrastructure/truck_parking/jasons_law/truckparkingsurvey/ch1.htm.
[61] Z. Wei, D. Brown, P. Hao, and K. Boriboonsomsin, "Real-World Heavy-Duty Truck Trajectories on Signalized Corridors," Dryad, 3698578 bytes, June 2, 2022, https://doi.org/10.6086/D1BT3K .



(a) Vocational heavy-duty (b) Medium-duty

(c) Short-haul heavy-duty (d) Long-haul heavy-duty

Figure 9. Start time distribution for different vehicle types

Travel distance distribution. The trip distance depends on several factors, including the statistical distribution of existing trip data sets, VMT, geospatial OD pair distribution, and geospatial vehicle stock distribution. The trip statistics in the FleetDNA and UCR truck GPS data sets were compared with the HEVI-LOAD trip distance distribution to validate the trip generation process. The trip distance distribution was combined with the assumption of vehicle specifications—such as VMT, energy consumption rate, and battery capacity—from the adoption scenario shown in Table 3.

Table 3. *EPA Scenario Vehicle Simulation Assumptions*

	VMT (50 percentile) per Vehicle per Day (mile)	Energy Consumption (kWh/mile)	Range (mile)	Battery Capacity (kWh)
Long-haul	**391**	**3.11**		**1175**
HHD8	391	3.12	**350**	**1200**
MHD67	391	3.06	250	600
Short-haul	**198**	**2.9**		**1024**
HHD8	197	2.98	**350**	**1200**
MHD67	198	2.7	250	600
Vocational	**55.7**	**1.12**		**380**
HHD8	58.6	2.08	**300**	**600**
LHD45	55.9	0.75	250	300
MHD67	53.4	1.25	250	400

In addition, travel demand data, including the NHTS truck OD data, are used to inform the geospatial OD pair distribution. Finally, geospatial vehicle distributions were derived by disaggregating to a finer resolution the OD pair data at the Federal Highway Administration zone level from the NHTS OD data at the county/census block level using Experian vehicle registration data, county business pattern data, and INRIX OD data. Figure 10 shows the national average trip distance histogram for different vehicle classes (vocational versus short-haul) generated from the UCR data, FleetDNA, and HEVI-LOAD.

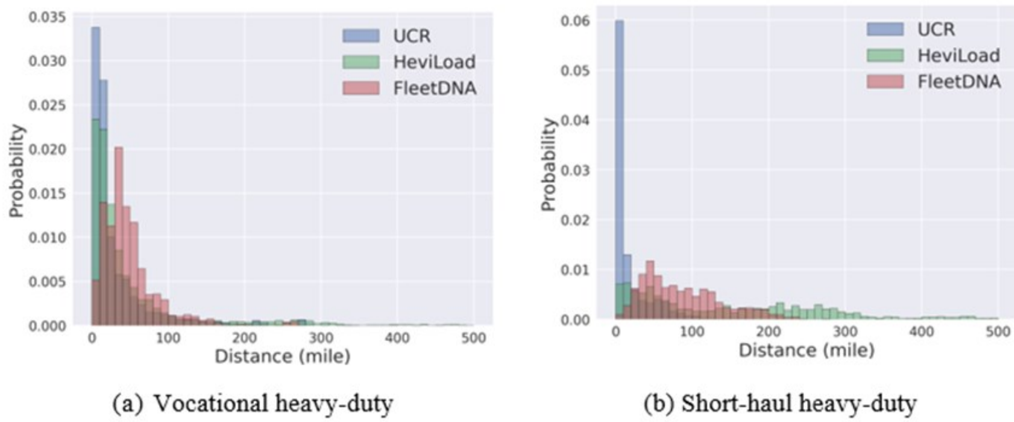


Figure 10. Trip distance histogram comparison – national average

Energy consumption rate. The energy consumption rates (kWh/mile) used in this study stem from the Action scenario based on HD TRUCS and MOVES, which considered a number of factors to determine the energy consumption rates observed on the grid side (between the step-down transformer and the charger). These factors include but are not limited to the electricity consumption by air conditioning, battery weight, the power loss caused by the AC/DC and DC/DC conversion within the charging stations, etc.—in addition to the powertrain energy consumption. Adopting such rates ensures consistency of energy consumption values at the state level. Therefore, grid-end energy consumption rates are utilized to quantify the encompassing energy demand by heavy-duty EVs on the distribution grids.

Starting SOC distribution. Another critical parameter in the simulation is the initial SOC of the vehicle batteries at the beginning of trips. Unlike passenger EVs or gasoline/diesel trucks, there are limited existing data sets to show battery SOC/fuel tank status at the beginning of trips for PEV trucks; thus, assumptions are needed to characterize the driver's/fleet operator's baseline refueling behaviors. Based on the Jason's Law Truck Parking Survey (on the refueling and rest behaviors of gasoline/diesel truck drivers) and the Run on Less project by the North American Council for Freight Efficiency,[62] we assume the starting SOC in Figure 11. For trips starting in the early morning (2 a.m.–10 a.m.), the minimal starting SOC values are lifted from 40% to 65%, which suggests that these trips will likely have higher starting SOCs than trips starting during other time periods. Specifically, the minimal starting SOC increases between 12 a.m. and 5 a.m., due to the assumption that longer overnight charging time leads to more energy in vehicle batteries after 5 a.m. and more and more vehicles starting and then finishing

[62] North American Council for Freight Efficiency, "Run on Less – Electric," accessed January 16, 2024, https://nacfe.org/research/run-on-less-electric/.

their first trips of the day. Thus, the minimum starting SOC of the second trips will keep dropping but is assumed to remain above 40%.

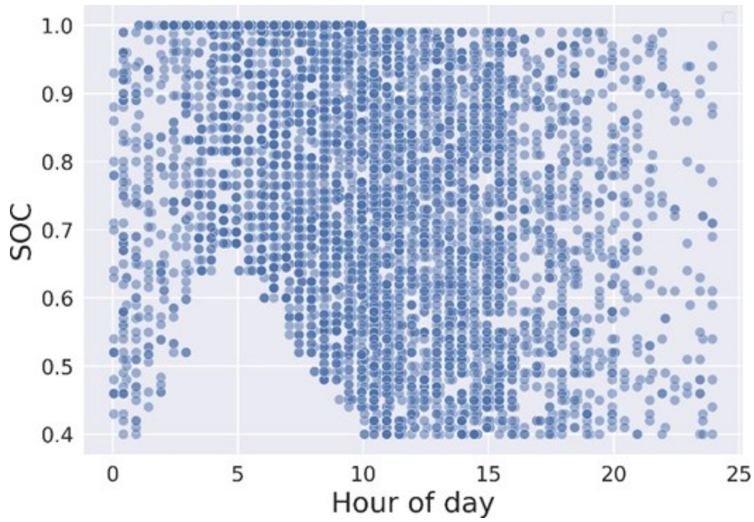


Figure 11. SOC versus trip start time distribution

Charging Infrastructure Scenario

Truck stops and rest areas along major freight networks were investigated to identify critical charging/ refueling locations. To preserve the privacy of the businesses at candidate locations, the exact location information was mapped to either the nearest freeway entrance of the freight network (public en route) or the centroid of the traffic analysis zones based on the required geospatial resolution. In addition, LBNL consulted with stakeholders on preferences in charger types, power levels, and quantities across location types. Figure 12 and Figure 13 show candidate parking locations for potential PEV public charger installations for California by location type and the United States, respectively, according to parking capacity. HEVI-LOAD constrains the size for the candidate charging stations, with a maximum of 100 charging ports per location, with options to select 350 kW–1.5 MW chargers for en route charging. Table 4 maps charger power and location specifications to vehicle types. For each vehicle class, there are constraints on the maximum power levels, and chargers are selected based on a pre-assigned distribution. Note that for purposes of this portion of the analysis, “L2-Low” describes Level 2 chargers with power levels of 7.2 kW; “L2” describes Level 2 chargers with power levels of 19.2 kW.

Figure 12. California candidate parking locations

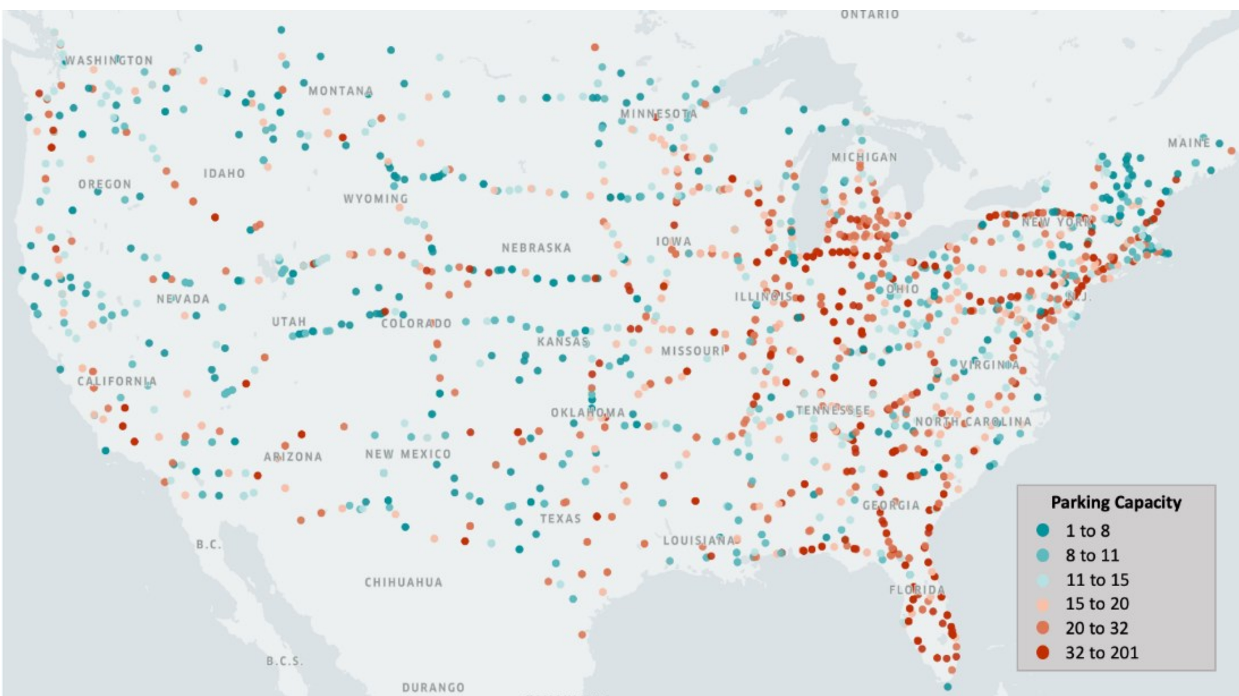


Figure 13. U.S. candidate parking locations from the Jason's Law Truck Parking Survey

Table 4. *EVSE Types for Heavy-Duty Applications*

Vehicle Type	Weight Class	Depot	Public En Route
Long-haul	HHD8	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500
	MHD67	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500
Short-haul	HHD8	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500
	MHD67	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500
Vocational	HHD8	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500
	LHD45	L2-Low, L2, DC50, DC150, DC250	DC350, DC500, DC1000
	MHD67	DC50, DC150, DC250	DC350, DC500, DC1000, DC1500

Managed Charging for Heavy-Duty Applications

Supplementing the explanation of the managed charging approach described in Chapter 1, LBNL developed a charging management strategy leveraging the load flexibility of the simulated depot charging sessions (i.e., the duration between plug-in time and plug-out time) from HEVI-LOAD. Specifically, the objectives of the charging management scheme include (1) reducing the peak load of the aggregated heavy-duty EV charging sessions at the depots and (2) flattening the load profile as much as possible. Two methods have been developed to manage the charging sessions in this study: a heuristics-based approach, which generates the managed charging load profiles that are fed into the Kevala grid upgrade analysis, and the optimization-based solution for comparison. In the heuristics-based approach, the duration of all charging sessions was extended to twice the original duration. After the extension, if the new departure time is later than 7 a.m., it is then set to 7 a.m. The charging power is set to an average of the energy demand over the time duration of the session. The managed charging load (red) successfully reduces the evening load peak (blue) and the energy demand during daytime to avoid a possible coincidental peak period with the commercial baseload. Alternatively, the optimization-based approach takes the same objectives and assumes perfect knowledge of the session parameters (session start time, end time, energy demand, etc.) and of the base demand profile on all feeders, leveraging empirical building load data sets.[63] This assumes that all feeders share the same baseload shape, which might not be realistic; however, it serves as a benchmarking test case compared with the heuristic-based solution. Solving the optimization problem results in the optimized charging load profile (green curve in Figure 14). Specifically, the optimized charging load profile shows more sensitivity to the underlying baseload—as the baseload ramps up in the early morning, the optimized charging load suddenly drops. In addition, the original load peak in the evening is removed, and the overall load shape is flattened due to some charging activities that shifted from evening to after midnight.

[63] F. Angizeh, A. Ghofrani, and M. A. Jafari, “Dataset on Hourly Load Profiles for a Set of 24 Facilities from Industrial, Commercial, and Residential End-use Sectors,” Version 1, August 21, 2020, https://doi.org/10.17632/rfnp2d3kjp.1.

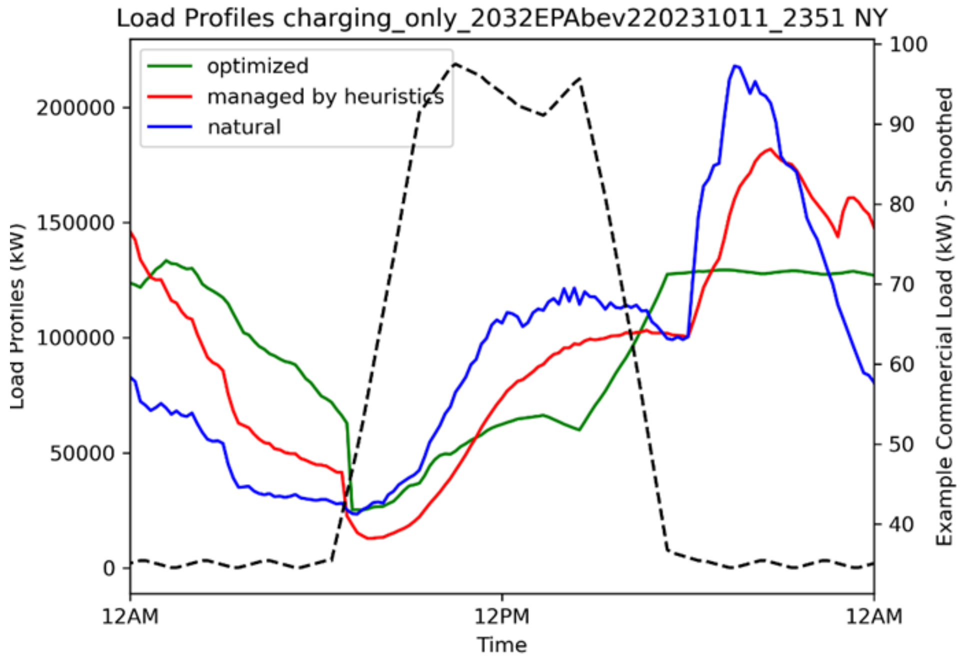


Figure 14. Preliminary managed charging load profiles using the heuristics-based approach (red) and the optimization-based approach (green). The original unmanaged charging load is shown as the blue curve, and the assumed circuit baseload is shown as the black dashed curve.

Charging Demand from Transit and School Buses

A relatively small part of the heavy-duty fleet (Class 4–8), transit and school buses, feature unique driving schedules that are particularly well suited to electrification. Based on this and the wealth of publicly available data to describe transit bus driving schedules, in this analysis, transit and school buses are independently simulated from the rest of the heavy-duty fleet to represent charging demand more accurately. This transit and school bus modeling approach is described in greater detail.[64]

Transit Buses

At time of publication, there were more than 106,000 transit buses across 1,591 U.S. counties (Figure 15). Transit bus modeling primarily relies on two major data sources (Figure 16):

- The National Transit Database (NTD), which serves as a centralized hub for financial, operating, and asset information of transit agencies in the United States.[17] The 2021 annual database was used to calculate transit bus population and support the generation of transit bus travel profiles.
- The General Transit Feed Specification (GTFS), an open standard that transit agencies use to publish their service schedules (referred to here as the "GTFS Schedule") and real-time operations ("GTFS Realtime") for various software applications.

Not every transit agency publishes its schedules or real-time operations in the GTFS format, and collecting every agency's real-time operations data would be highly labor-intensive and computationally expensive; thus, we conduct a clustering analysis of transit agencies to extrapolate bus operations at a

[64] Bruchon et al., 2024.

larger scale using the information from representative transit agencies with publicly available GTFS data sets.

We apply log transformation to all four variables to reduce skewness and to standardize the data to make variables comparable.

To determine the optimal number of clusters, we use direct methods (i.e., elbow and average silhouette methods) and statistical testing methods (i.e., the gap statistic and 30 other indices) to compare results from two to six clusters. The results show that most methods suggest two and five as the optimal number of clusters. Given our goal of having a larger number of groups to represent various transit agency operating characteristics, we perform the final analysis and extract the results using five clusters for agencies with fleet sizes of less than 750 transit buses; thus, we categorize the NTD agencies into six clusters.

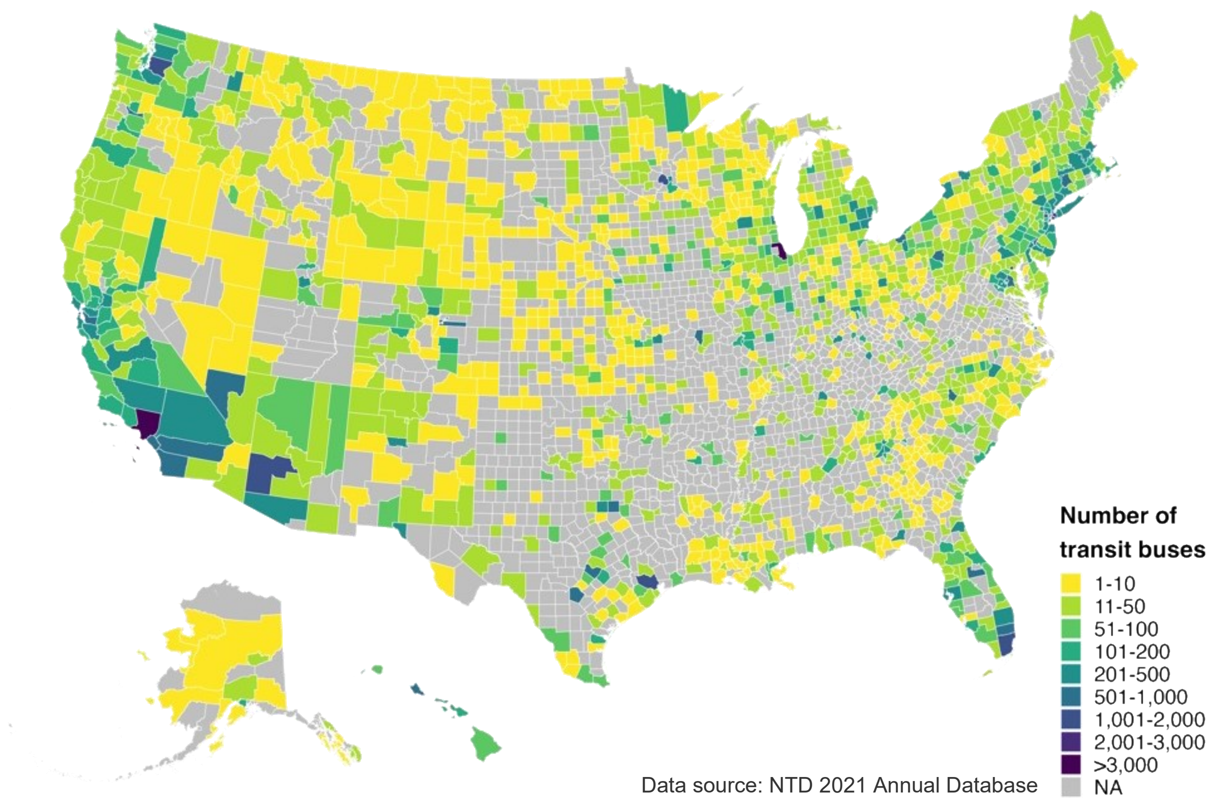


Figure 15. County-level transit bus inventory in the United States

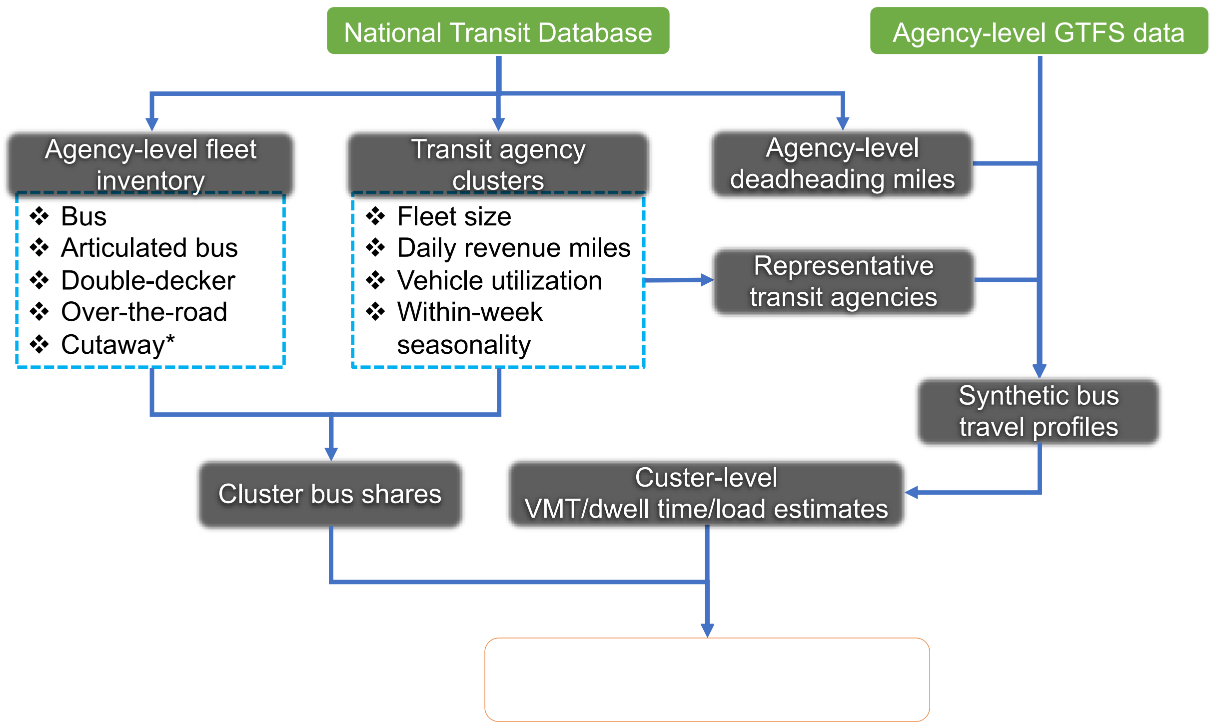


Figure 16. Overview of transit bus modeling approach
* According to the NTD 2021 annual database, 86% of cutaways are used for demand response, and GTFS data are available only for fixed-route services. For this reason, cutaways are included only in the fleet inventory and are not included in generating cluster bus shares for VMT/dwell time/load estimates.

We rely on GTFS Schedule data sets, the estimated optimal time intervals, and the reported agency-level deadheading miles in the NTD to generate the travel profiles. We obtained GTFS Schedule data (Oct. 14–16, 2023) for 37 transit agencies across all six clusters. The VMT estimates are calculated using Eq. 1.1–Eq. 1.3, using the variables shown in Table 5. The deadheading time is estimated using the deadheading distance divided by the agency-level average deadheading speed, which is based on the NTD reported total deadheading miles and hours at the agency level. The deadheading time is added to the beginning and the end of each block that has associated deadheading trips.

Figure 17 illustrates the distribution of the nationally scaled weighted average daily VMT of transit buses on a typical weekday. On average, the daily VMT of transit buses ranges from 57 miles (10th percentile) to 230 miles (90th percentile), with most buses traveling 141 miles (50th percentile) on a weekday. Figure 18 illustrates the distribution of the weighted average daily domicile dwell duration per vehicle on a typical weekday. Half the buses have a dwell time of at least 10.5 hours per day at the domicile, which exhibits great potential for nighttime depot charging with lower charger power requirements. For transit buses with shorter domicile duration, chargers with higher power levels can potentially support service provision without changing current schedules.

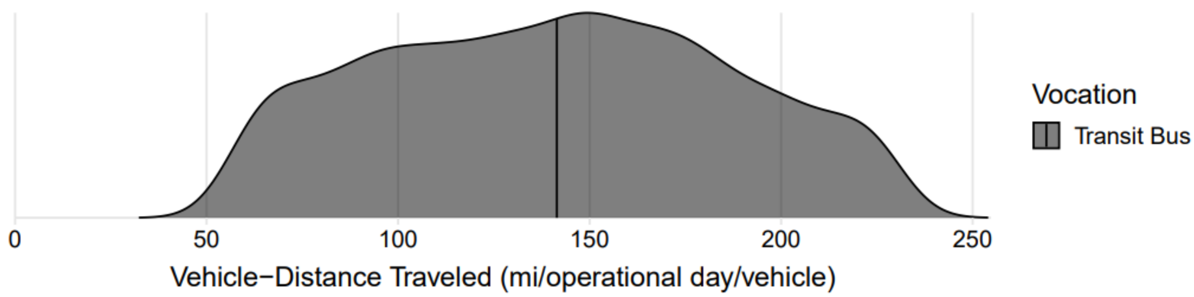


Figure 17. Distribution of daily VMT for transit bus data. The vertical line marks the median. (Weekdays, 10th–90th percentile range)

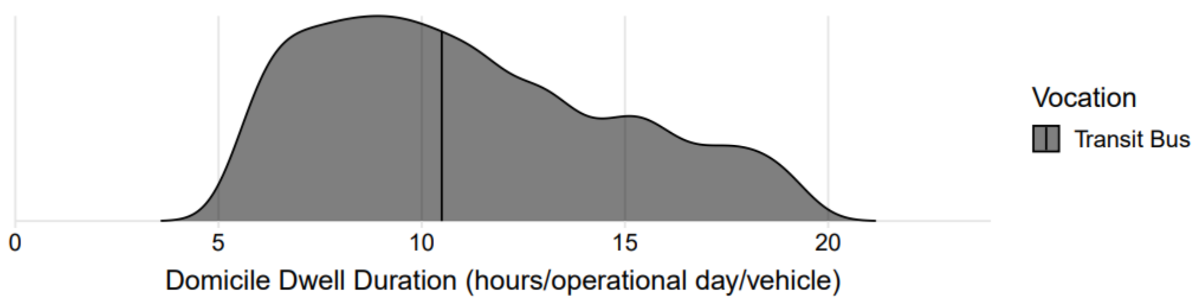


Figure 18. Distribution of domicile dwell duration for transit bus data. The vertical line marks the median. (Weekdays, 10th–90th percentile range)

We assume an energy consumption rate of 2.28 kWh/mile for battery electric transit buses, taken from the April 2023 version of the EPA's HD TRUCS and MOVES tools and an overall charging efficiency of 91.4%.[2] We start by estimating the charging power and time for each bus with VMT and dwell time estimates. The minimal charging power for each bus is determined by its daily VMT and the dwell time (Eq. 1.1). When the minimal charging power needed is no greater than 19 kW, we assume that L2 chargers of 19 kW would be deployed. When the minimal charging power needed is greater than 19 kW, the charging power is rounded up to the nearest 50 kW level. The charging time is then estimated using the rounded charging power level (Eq. 1.3).

$$power_v^{\mathrm{MIN}} = miles_v^{\mathrm{TOTAL}} * \frac{2.28\ kwh/mile}{91.4\% * time_v^{\mathrm{DEPOT}}} \tag{1.1}$$

$$power_v^{\mathrm{ADJUSTED}} = \begin{cases} 19,\ when\ power_v^{\mathrm{MIN}} \leq 19\ kW; \\ 50 * ceiling\left(\frac{power_v^{\mathrm{MIN}}}{50}\right), when\ power_v^{\mathrm{MIN}} > 19\ kW \end{cases} \tag{1.2}$$

$$time_v^{\mathrm{CHARGE}} = miles_v^{\mathrm{TOTAL}} * \frac{2.28kwh/mile}{91.4\% * power_v^{\mathrm{ADJUSTED}}} \tag{1.3}$$

When the operating time of the bus is longer than 24 hours, we assume that the bus is not operated the next day and that charging spans from the end of the current service day to the beginning of its next service day. The bus-level load profiles are aggregated to the cluster level for each hour during a 24-hour period and then normalized to obtain the per-vehicle hourly load profiles for each cluster. The cluster bus shares are used to generate the national weighted average per-vehicle hourly load profiles.

School Buses

Approximately 480,000 school buses are operating in the United States today.[65] According to vehicle registration data curated by Experian, school buses falling under Classes 2–5 represent less than 2% of the national total, while 25% are classified as Class 6, 41% as Class 7, and 32% as Class 8. This section explains the approach taken to describe the operating patterns through the analysis and modeling of real-world data. First, we introduce the FleetDNA school bus data sample used to characterize and represent school bus operations in this study. Next, we describe how school bus depot dwell times are assigned for subsequent analysis.

NREL hosts a database of real-world commercial vehicle operating data, called FleetDNA, hosted on the FleetREDI platform.[4,5] FleetDNA offers statistical summaries derived from 1 Hz drive cycle data captured using onboard data loggers for commercial fleets spanning diverse vocations and geographic regions. To produce the data sets described in this report, we deduce from the 1 Hz speed and location data the daily driving (i.e., trip) patterns of school buses, including their driving distances and durations. We also determine when and how long they are parked at their depots, presenting potential charging opportunities for BEVs. Table 5 summarizes the sample of conventional school bus operating data used in this study, comprising 7 fleets, 279 buses, and more than 1,700 travel days with more than 106,000 miles driven. The representation of GVWR classes in the sample closely aligns with the distribution of classes observed in the United States.

Table 5. *FleetDNA School Bus Operating Data Summary*

Location	Year	Bus Count	GVWR	Travel Days	VMT
Austin, TX	2009	2	6	10	429
Thornton, CO	2010	99	6	428	29,371
Schenectady, NY	2010	3	6	22	565
Redmond, WA	2011	108	6	468	14,712
Torrance, CA	2015	33	2,3,8	231	11,454
Napa, CA	2015	8	8	88	4,830
Rialto, CA	2017	26	8	492	45,381
Total	**2009–2017**	**279**	**2,3,6,8**	**1,739**	**106,742**

EVSE Capital Cost Assumptions

Charging infrastructure costs are used within this study as a postprocessing step to estimate the cumulative capital investment required to deploy the simulated network. These costs are based on historical observations from public reports, as shown in Table 6. These costs include charging equipment

[65] World Resources Institute, "Dataset of Electric School Bus Adoption in the United States, accessed December 12, 2023, https://datasets.wri.org/dataset/electric_school_bus_adoption.

and installation costs that are intended to reflect labor and materials for construction on the customer side of the meter.

Cost estimates exclude the costs of utility upgrades (such as new transformers and line extensions), DERs (such as onsite storage or generation), operating costs (such as utility energy and demand charges), maintenance costs (necessary to ensure a high level of reliability), and certain construction soft costs (such as delays associated with local permitting of the utility service connection). Although these additional cost elements are beyond the scope of this analysis (primarily because of a lack of publicly accessible data), they are nontrivial and could significantly contribute to overall costs for the national charging network. Additionally, lead times for these upgrades will dictate the pace of deployment. Previous studies have estimated that although charging infrastructure projects can often take 3–10 months to complete, situations requiring feeder upgrades can add a year to this timeline, and substation upgrades can potentially add up to four years.[66]

Table 6. *Base-Year EVSE Capital Cost Assumptions*

Charger Hardware	Unit Cost per Port in 2021	Installation Cost per Port in 2021	References
L1	$0	$550	Mid values from Wood et al. (2023)
L2 commercial	$2,696	$3,810	Bloomberg New Energy Finance (2022)[67]
L2 residential	$800	$1,100	Mid values from Wood et al. (2023)
DC 50 kW	$23,000	$12,000	Inferred from DC 150 kW costs (linear extrapolation by power level)
DC 150 kW	$69,000	$36,000	Bloomberg New Energy Finance (2022)
DC 250 kW	$75,500	$60,000	Bloomberg New Energy Finance (2022)
DC 350 kW	$82,000	$84,000	Bloomberg New Energy Finance (2022)
DC 500 kW	$117,143	$120,000	Inferred from DC 350 kW costs (linear extrapolation by power level)
DC 1,000 kW	$234,286	$240,000	Inferred from DC 350 kW costs (linear extrapolation by power level)

[66] Borlaug, B., Muratori, M., Gilleran, M., Woody, D., Muston, W., Canada, T., Ingram, A., Gresham, H., McQueen, C., 2021. Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems. Nature Energy 6, 673–682.

[67] Fisher, Ryan. Bloomberg New Energy Finance. Commercial EV Charger Price Survey 2022: Pressure Mounts. September 16, 2022.

Charger Hardware	Unit Cost per Port in 2021	Installation Cost per Port in 2021	References
DC 1,500 kW	$351,429	$360,000	Inferred from DC 350 kW costs (linear extrapolation by power level)

Wright's law is a common model-based approach for estimating future technology costs because of learning by doing or economies of scale. Originally identified as an empirical pattern by Wright in 1936, it posits that each doubling of experience (i.e., often proxied by cumulative production) for a given technology is associated with a cost reduction that is determined by a fixed and technology-specific learning rate.[68] We applied Wright's law to forecast how charging equipment costs may evolve in the future (Eq. 2).

$$y_{t+1} = y_t(\frac{X_{t+1}}{X_t})^{-W_{t+1}} \quad \text{Eq. 2}$$

where y is the unit technology cost, t is the year, and the exponent is determined by the learning rate, defined as $r = 1 - 2^{-w}$

Although there is no analysis estimating learning rates for EVSE cost reduction, recent studies have estimated or reviewed learning rates for various energy supply technologies (Meng et al. 2021; Rubin et al. 2015[69]; Way et al. 2022[70]), lithium-ion battery technology (Ziegler and Trancik 2021[71]), and other energy-related technologies (Wei et al. 2017[72]). Results from these studies indicate that learning rates vary by technology and deployment stage, and the empirically estimated learning rates range from 1.4%–23% for energy supply technologies and 3.5%–30% for lithium-ion battery technology. NREL assumed conservative learning rates for forecasting charging equipment cost reductions, i.e., 5% under the business-as-usual scenario, 10% under the mid-EVSE advancement scenario (Mid), and 15% under the high EVSE advancement scenario (High). We obtained reported L2 (public, workplace, and multifamily home) and DCFC (public and workplace) port counts in 2021 from Brown et al. (2022[73]) and used them as proxies for the cumulative production of L2 chargers and DCFCs, respectively. Projected L2 and DCFC port counts under the same access types were used to approximate the cumulative production of EVSEs in 2027 and 2032. With these assumptions, we estimated the average annual

[68] Meng, L., et al. (2021). Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. https://doi.org/10.1073/pnas.1917165118.
[69] Edward S. Rubin, Inês M.L. Azevedo, Paulina Jaramillo, Sonia Yeh, A review of learning rates for electricity supply technologies, Energy Policy, Volume 86, 2015, Pages 198-218, ISSN 0301-4215, https://doi.org/10.1016/j.enpol.2015.06.011.
[70] Rupert Way, Matthew C. Ives, Penny Mealy, J. Doyne Farmer, Empirically grounded technology forecasts and the energy transition, Joule, Volume 6, Issue 9, 2022, Pages 2057-2082, ISSN 2542-4351, https://doi.org/10.1016/j.joule.2022.08.009.
[71] Ziegler, Micah S. and Trancik, Jessika E., Re-examining rates of lithium-ion battery technology improvement and cost decline, The Royal Society of Chemistry, Volume 14, Issue 4, 2021, Pages 1635-1651, ISSN 1754-5692, https://pubs.rsc.org/en/content/articlelanding/2021/ee/d0ee02681f.
[72] Max Wei, Sarah Josephine Smith, Michael D. Sohn, Non-constant learning rates in retrospective experience curve analyses and their correlation to deployment programs, Energy Policy, Volume 107, 2017, Pages 356-369, ISSN 0301-4215, https://doi.org/10.1016/j.enpol.2017.04.035.
[73] Brown, Abby, Jeff Cappellucci, Emily White, Alexia Heinrich, and Emma Cost. 2022. Electric Vehicle Charging Infrastructure Trends from the Alternative Fueling Station Locator: Second Quarter 2022. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-84263. https://www.nrel.gov/docs/fy23osti/84263.pdf.

percentages of charging equipment cost reductions for 2022–2027 and 2028–2032 (Table 7). Similarly, installation costs could decrease as installers continue to accumulate experience with charging projects and identify efficiencies, but installation costs are notorious for being site-specific (proximity to an existing transformer is a key consideration), and per-site costs could plausibly increase as low-hanging fruit continues to be picked. For these reasons, this analysis assumed no reductions in installation costs. The base-year installation costs were applied to all future years to generate future EVSE capital cost trajectories (Figure 19).

Table 7. *Estimated Average Annual Percentages of Equipment Cost Reductions by EVSE Technological Advancement Scenarios and Charger Type*

EVSE Scenarios	Learning Rate	L2 Chargers		DCFCs	
		2022–2027 (Action/ No Action)	2028–2032 (Action/ No Action)	2022–2027 (Action/ No Action)	2028–2032 (Action/ No Action)
Business as Usual	5%	2.9%/2.8%	2.1%/1.7%	3.0%/2.7%	1.9%/1.8%
Mid	10%	5.9%/5.7%	5.7%/3.4%	6.0%/5.4%	3.9%/3.7%
High	15%	8.9%/8.6%	8.6%/5.1%	9.1%/8.2%	6.0%/5.6%

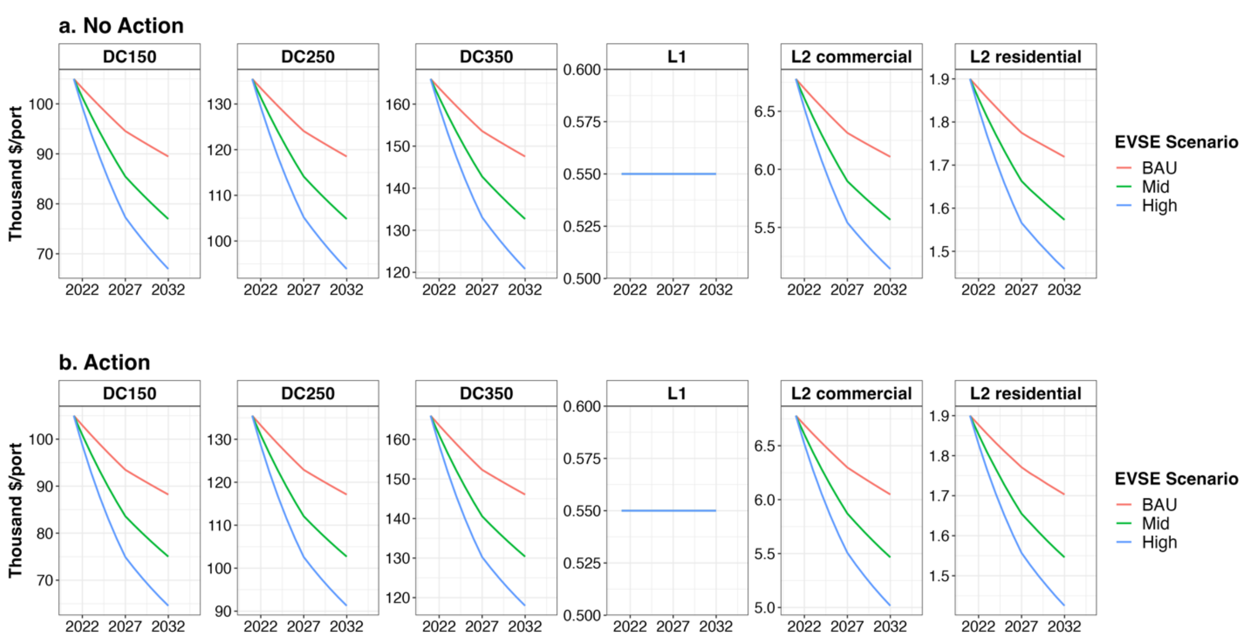


Figure 19. Projected EVSE capital cost (combined equipment and installation cost) trajectories for 2021–2032: (a) No Action scenario and (b) Action scenario.

Estimates for out-of-scope costs—including the strategies charging networks might take to account for utility, DER, operations and maintenance, and construction costs, as well as solutions to reduce the magnitude of these cost and time requirements—are the subject of forthcoming Argonne National Laboratory technical report, “Innovative Charging Solutions for Deploying the National Charging Network,” conducted in parallel with this electrification impact analysis.

EVSE County-to-Parcel Disaggregation

Kevala ingested NREL and LBNL county-level EVSE adoption targets and used them to allocate charging ports to parcels. The EVSE adoption targets were specified by several attributes:

- **Forecast year:** 2027 or 2032
- **Forecast scenario:** No Action–Unmanaged, No Action–Managed, Action–Unmanaged, Action–Managed
- **Vehicle segment:** LDV, MDV, HDV, school bus, transit bus
- **Location type:** home – single family, home – multifamily, destination – all, destination – retail/recreational, workplace, en route, depot, public, truck stop
- **Access type:** public, private, semiprivate
- **EVSE capacity:** L1, L2, DC50, DC150, DC250, DC350, DC500, DC1000, and DC1500

The methodology to disaggregate EVSE to parcels consisted of four steps:

1. **Eligibility:** For each EVSE target, Kevala filtered the parcels in the relevant county to create a list of parcels that could potentially adopt the specified type of EVSE. The model specified which of NREL's ResStock™ and ComStock™[74] building types were allowed to adopt ports with a given vehicle segment, location type, and access type. A parcel could be eligible for more than one type of EVSE based on its building type.
2. **Adoption scoring:** Each parcel selected in the eligibility step was then given a random adoption score, given the low quality of predictive features during this early market phase.
3. **Sizing:** Kevala then determined how many ports a parcel would adopt if it were to be selected for adoption in the allocation step.
4. **Allocation:** Once all eligible parcels were assigned an adoption score and port counts, Kevala allocated the available ports across parcels in descending order of adoption score until no ports remained unassigned.

Each step is further described in the following subsections.

[74] ResStock (https://resstock.nrel.gov/) and ComStock (https://comstock.nrel.gov/) are physics-based simulation models that represent the energy use of the U.S. residential and commercial building stocks with high granularity at national, regional, and local scales. The models use a large number of representative building energy models—tens of thousands or hundreds of thousands, depending on the application—to represent the building stock with high fidelity. The building characteristics used in those energy models are statistically sampled from the full stock to create a set of buildings with a realistic diversity of building types, vintages, sizes, construction practices, installed equipment, appliances, occupant behavior, and climate zones.

Eligibility

In the load simulation step (see Section 0), Kevala assigned each parcel a building load profile from ComStock or ResStock based on its customer class and building square footage. Additionally, parcels known to contain truck stops according to the Jason's law dataset were assigned a "truck stop" building type for the EVSE allocation.[75]

Figure 20, Figure 21, and Figure 22 show which ResStock and ComStock buildings as well as truck stops were considered to be eligible to adopt each EVSE type. For a parcel to be eligible for a particular EVSE adoption target, it needed to be included on the list of eligible buildings for the vehicle segment, location type, and access type associated with the target.

[75] Kevala was not able to allocate 7% of truck stop ports because the parcel data set did not have complete coverage of all land mass in the continental United States. Even with a 200-meter buffer, some truck stops could not be associated with a parcel.

LDV	MDV	LDV+MDV	HDV	Bus – School	Bus – Transit
			Truck Stop	Truck Stop	Truck Stop
Single-Family Attached		Single-Family Attached			
Single-Family Detached		Single-Family Detached			
Mobile Home		Mobile Home			
Multifamily 2-4 Units					
Multifamily 5+ Units					
Small Hotel		Small Hotel			Small Hotel
Large Hotel	Large Hotel	Large Hotel			Large Hotel
Outpatient					Outpatient
Hospital	Hospital				Hospital
Quick Service Restaurant		Quick Service Restaurant			Quick Service Restaurant
Full Service Restaurant		Full Service Restaurant			Full Service Restaurant
Warehouse	Warehouse		Warehouse	Warehouse	Warehouse
Retail Standalone	Retail Standalone	Retail Standalone			Retail Standalone
Retail Stripmall	Retail Stripmall	Retail Stripmall			Retail Stripmall
Small Office	Small Office		Small Office	Small Office	Small Office
Medium Office	Medium Office		Medium Office	Medium Office	Medium Office
Large Office	Large Office		Large Office	Large Office	Large Office
Primary School	Primary School				
Secondary School	Secondary School				

Figure 20. Vehicle segment mapping to ResStock and ComStock buildings (blue) and truck stop parcels (green) *(Source: Kevala)*

Public	Private	Semi-Private
Truck Stop		
	Single-Family Attached	
	Single-Family Detached	
	Mobile Home	
	Multifamily 2-4 Units	Multi-Family 2-4 Units
	Multifamily 5+ Units	Multi-Family 5+ Units
Small Hotel	Small Hotel	
Large Hotel	Large Hotel	
Outpatient	Outpatient	Outpatient
Hospital	Hospital	Hospital
Quick Service Restaurant	Quick Service Restaurant	Quick Service Restaurant
Full Service Restaurant	Full Service Restaurant	Full Service Restaurant
	Warehouse	
Retail Standalone	Retail Standalone	Retail Standalone
Retail Stripmall	Retail Stripmall	RetailStripmall
	Small Office	
	Medium Office	
	Large Office	
	Primary School	
	Secondary School	

Figure 21. EVSE access type mapping to ResStock and ComStock buildings (blue) and truck stop parcels (green) *(Source: Kevala)*

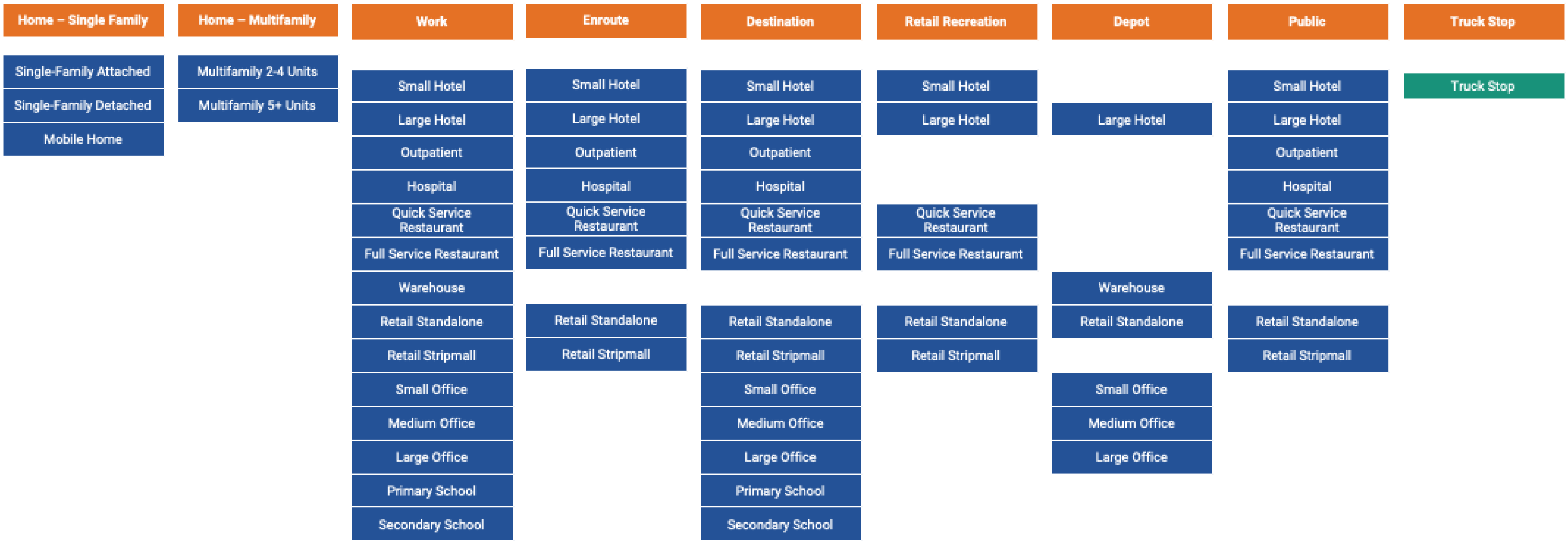


Figure 22. EVSE location type mapping to ResStock and ComStock buildings (blue) and truck stop parcels (green) *(Source: Kevala)*

Adoption Scoring

As previously mentioned, adoption scores are currently random, given the lower quality of predictive features. This is not necessarily unexpected because the PEV market is still in its infancy.[76]

Adoption Sizing

Kevala customized the approach to adoption sizing to each type of charging location. Note that the port counts from this step were not necessarily the final numbers adopted at each parcel (see Section 0).

Residential Sizing

Single-family parcels were all sized for one port. Multifamily parcels received a port count based on the number of parking spots they contained. Kevala assumed that one parking spot would be available for each unit and used the California Building Standards Commission building codes (as summarized by the AFDC)[77] to assign an appropriate number of ports for a given parking lot size.

Nonresidential Sizing

For nonresidential sizing, Kevala derived distributions of parcel port counts based on real-world data from four datasets:

- **AFDC EVSE locations[78]:**
  - **Destination locations:** Selected chargers in public locations where the facility was not a parking lot, car dealer, or government.
  - **Retail/recreational locations:** Selected chargers in public locations where the facility was one of the following types: brewery, convenience store, co-op, grocery, hardware store, hotel, library, museum, national park, other entertainment, park, recreational sports, restaurant, retail, shopping center, shopping mall, travel center.
  - **HDV charging:** Used the six entries for L2 chargers and two entries for direct current fast charging (DCFC) included in the dataset.
  - **Transit bus DCFC sizes:** Used the same options as for HDV public charging.
- **Vehicle counts from a northeast utility:** Used these vehicle counts to create distributions of port counts for depot locations by applying a 1:1 PEV:EVSE ratio for L1 and L2 ports and a 1:2 PEV: EVSE ratio for DCFC ports.
- **National Transit Database[79]:** Derived the distribution of transit bus counts per depot by assuming that one port would be available for every two buses or a 1:1 ratio if fewer than five buses were present.

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[76] NREL, LBNL, and Kevala discussed other attributes, such as income, and collectively decided that randomized scoring was the appropriate path.
[77] AFDC, "Mandatory Electric Vehicle (EV) Charging Station Building Standards," U.S. Department of Energy Office of Energy Efficiency and Renewable Energy, https://afdc.energy.gov/laws/11068.
[78] AFDC, "Electric Vehicle Charging Station Locations," U.S. Department of Energy Office of Energy Efficiency and Renewable Energy, accessed 2023, https://afdc.energy.gov/fuels/electricity_locations.html#/find/nearest?fuel=ELEChttps://afdc.energy.gov/fuels/electricity_locations.html#/find/nearest?fuel=ELEC.
[79] Federal Transit Administration, "NTD Data," https://www.transit.dot.gov/ntd/ntd-data.

- **Clean School Bus Program[80]:** Used the recent EPA Clean School Bus Rebate Program awards to build a distribution of school bus counts per depot and applied NREL's assumption of 0.8 ports per bus to create the port count distribution.

For each possible combination of vehicle segment, location type, and EVSE type, Kevala chose four port counts that could be selected with equal probability. These counts corresponded to the medians of the four quartiles of the relevant dataset. For example, in the AFDC dataset, the median of the fourth quartile (i.e., the 87.5th percentile, halfway between the 75th and 100th percentiles) of the distribution of the L1 port counts at the destination locations was 10 ports. The final sizing options are included in Table 8.

[80] EPA, "Clean School Bus Program Rewards," Awarded CSB Rebates, last updated Sept. 29, 2023, https://www.epa.gov/cleanschoolbus/awarded-clean-school-bus-program-rebates.

Table 8. *Parcel Port Count Sizing Options (Source: Kevala)*

Vehicle Segment	Location Type	EVSE Capacity	No. of Ports—12.5 Pctl	No. of Ports—37.5 Pctl	No. of Ports—62.5 Pctl	No. of Ports—87.5 Pctl
LDV, MDV, LDV+MDV	Home: single family	Any	1	1	1	1
LDV, MDV, LDV+MDV	Home: multifamily	Any	Based on no. of units in the building			
LDV, MDV, LDV+MDV	Destination	L1	1	1	2	10
LDV, MDV, LDV+MDV	Destination	L2	1	2	3	7
LDV, MDV, LDV+MDV	Destination	DCFC	2	4	8	12
LDV, MDV, LDV+MDV	Retail recreation	L1	1	1	1	5
LDV, MDV, LDV+MDV	Retail recreation	L2	1	2	2	4
LDV, MDV, LDV+MDV	Retail recreation	DCFC	2	6	12	16
LDV, MDV, LDV+MDV	Work	L1	1	1	2	4
LDV, MDV, LDV+MDV	Work	L2	1	2	4	16
LDV, MDV, LDV+MDV	Work	DCFC	1	1	2	7
LDV	Depot	L1	2	3	5	15
LDV	Depot	L2	2	3	5	15
LDV	Depot	DCFC	1	2	3	8
MDV	Depot	L1	2	4	8	25
MDV	Depot	L2	2	4	8	25
MDV	Depot	DCFC	1	2	4	13

Vehicle Segment	Location Type	EVSE Capacity	No. of Ports—12.5 Pctl	No. of Ports—37.5 Pctl	No. of Ports—62.5 Pctl	No. of Ports—87.5 Pctl
HDV	Depot	L2-Low	1	2	5	10
HDV	Depot	L2	1	2	5	10
HDV	Depot	DCFC	1	1	3	5
Bus transit	Depot	DCFC	1	4	14	62
Bus school	Depot	L2	1	2	7	17
HDV	Truck stop	L2	1	2	5	12
HDV	Truck stop	DCFC	2	2	2	2
Bus transit	En route	DCFC	2	2	2	2

Allocation

Allocation was performed in two phases. In the first phase, for each EVSE target, Kevala sorted eligible parcels in descending order of adoption score and allocated ports until the target was reached. Because it was possible to allocate ports to all parcels in a county without reaching the target, in the second phase, Kevala distributed any remaining ports equally across all parcels in the county. The following example shows how this worked for 10 parcels in a county with a target of 25 ports.

1. If the first allocation phase resulted in 1 port per parcel, 15 ports would remain at the beginning of the second phase.
2. Kevala then gave each of the 10 parcels 1 additional port, and the 5 parcels with the highest adoption scores would be allocated 1 additional port.

Residential parcels that adopted EVSE in the 2027 forecast year were not allowed to adopt again in 2032. This restriction did not apply to any other location types. Two important things to note about this restriction:

- It applied only to a specific EVSE type. This means that a single-family home parcel could adopt both an L1 and an L2 port in the same year or different years.
- The second allocation phase allocated remaining ports regardless of prior year adoptions. For example, if a single-family home parcel adopted one port in 2027, and the county was not meeting its target for 2032 adoptions, that parcel could be assigned more ports in 2032.

Estimating Baseline Load and Existing Photovoltaics

This section describes the approach to modeling parcel-level baseline load, existing solar rooftop photovoltaics (PV), as well as load growth throughout the study forecast horizon.

Estimating Baseline Load

Kevala assigned parcels a load profile using building stock information from ResStock and ComStock. Each parcel from the Kevala software was assigned a simulated load based on building and parcel properties. The following properties were used to match the Kevala parcels to the NREL ResStock and ComStock load profiles:

- State
- County
- Customer class
- Building footprint (i.e., square footage)

For each parcel, Kevala selected the residential or commercial building that had the closest footprint to the Kevala parcel's building footprint from an eligible subset of NREL individual building models. If building square footage data were not available for the parcel, then the building was selected at random from the eligible subset. The eligible subset of building models was filtered to buildings in the same county and that have the same customer class (residential, commercial, or industrial).

The "Commercial - Warehouse" building type from the ComStock database was used to model all industrial parcels, except for those in New York and Illinois. For New York and Illinois, Kevala approximated industrial parcels to have a flat load profile after assessing the “Commercial - Warehouse” building profile and determining that it had a high load factor (see Figure 23 and Figure 24) that was distorting the overall contribution of industrial loads to the midday load.

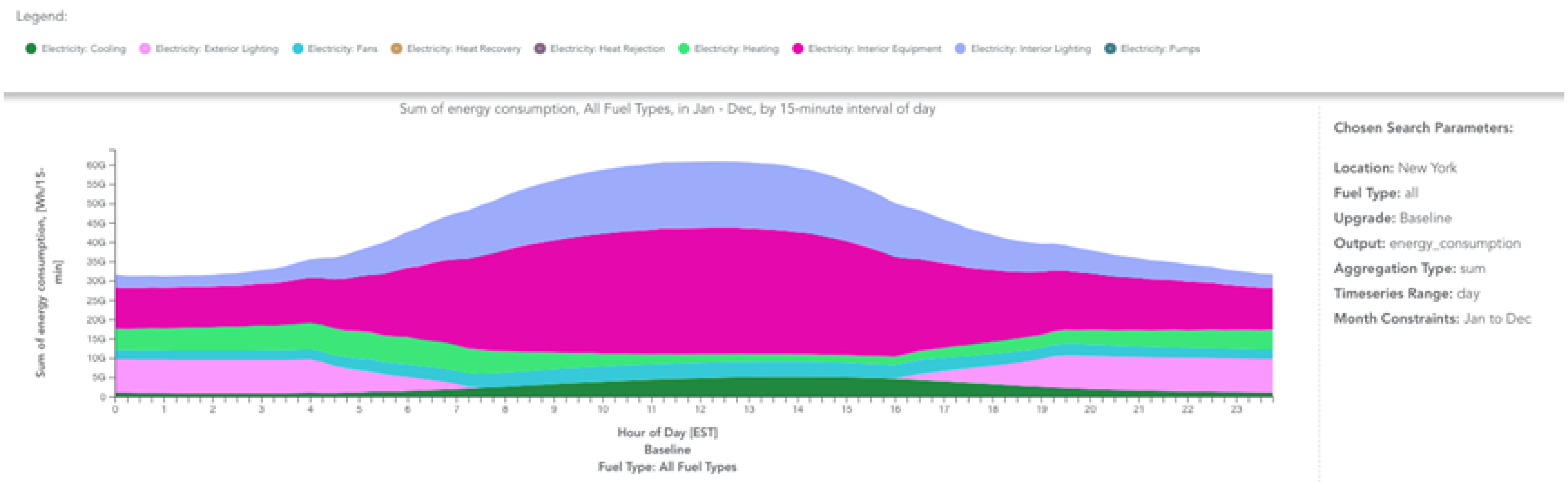

Figure 23. Aggregate electricity consumption of "Commercial–-Warehouse" buildings in New York *(Source: NREL ComStock)*

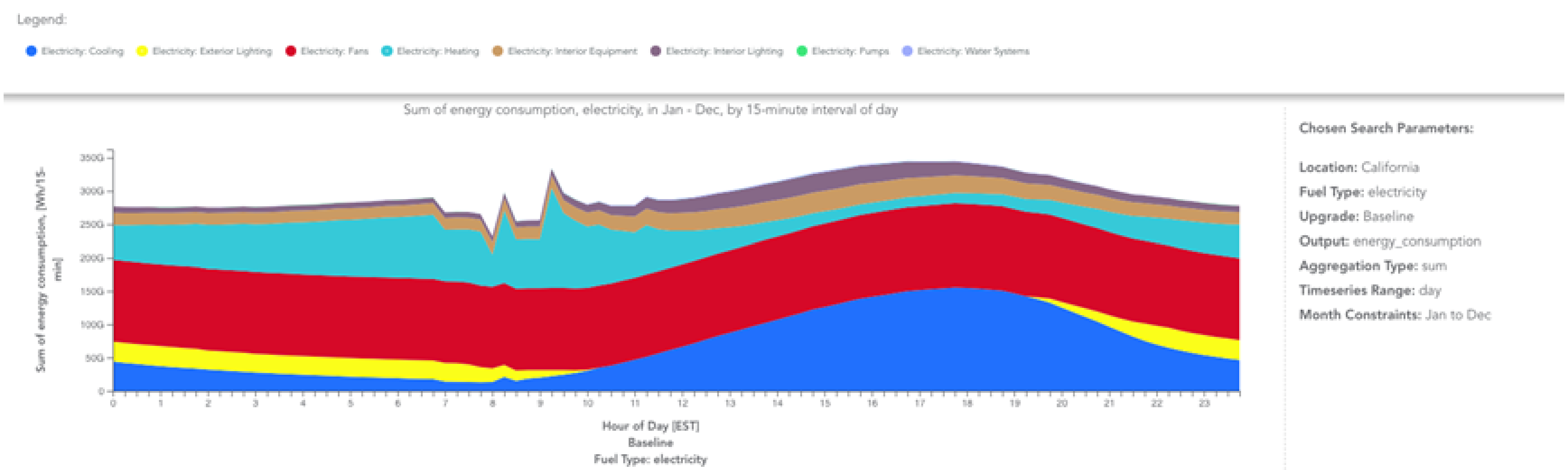

Figure 24. Aggregate electricity consumption of "Commercial–-Warehouse" buildings in California *(Source: NREL ComStock)*

Approximately 20% of Kevala's parcels did not have any customer class label. To address this, Kevala:

1. Calculated the relative frequency of each customer class across a range of building and parcel sizes.

Imputed a missing customer class value for a parcel by drawing at random from the distribution with the corresponding building or, if building square footage was not available, parcel square footage. For example, if a parcel had no known customer class, its building square footage was unknown, and its area slightly exceeded 10,000 square feet, Kevala would select the column just to the right of the "10^4" tick mark shown in

2. Figure 25 and choose a customer class at random. In this example, "Residential - single family" would be the most likely selection.

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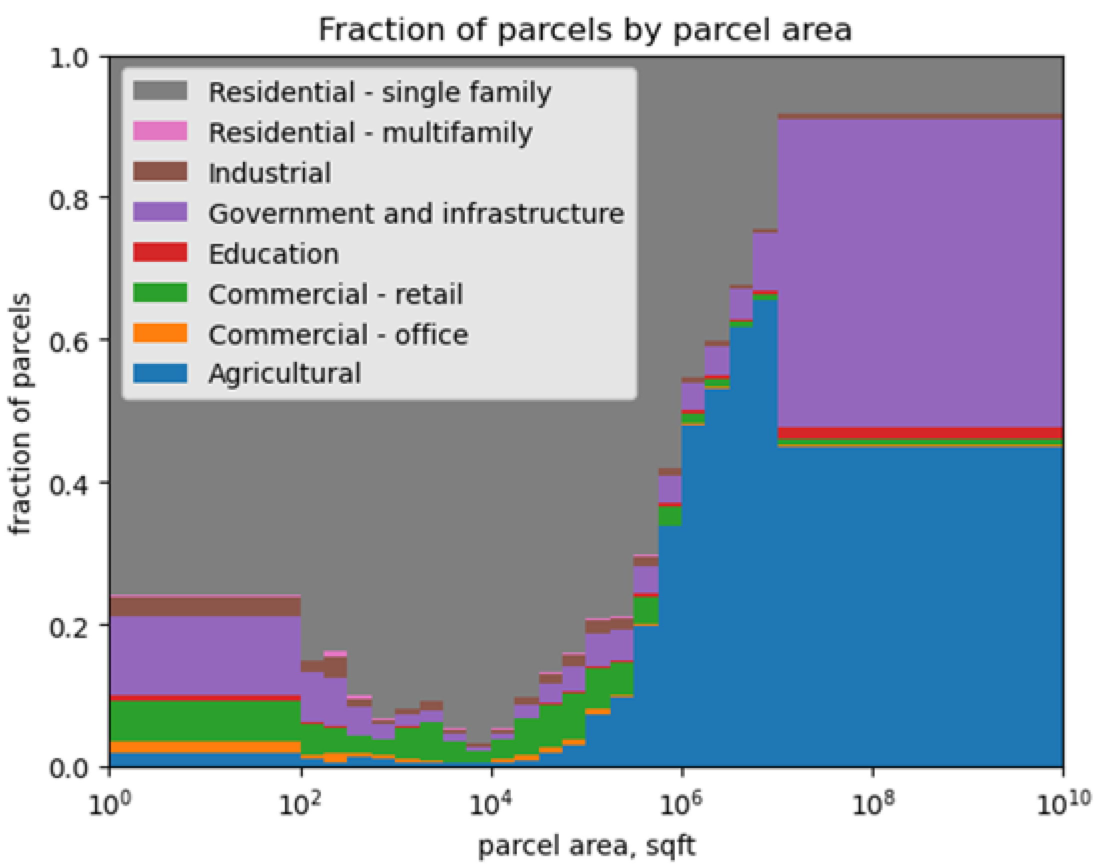


Figure 25. Fraction of parcels versus parcel area and building square footage *(Source: Kevala)*

Finally, the aggregated annual energy demand by state was calibrated to the 2021 aggregated energy gross load by state published by the EIA, so that the total gross load demand by state in the study matches the latest published historical numbers.

Estimating Existing PV

The Kevala platform identifies existing solar rooftop PV using a proprietary computer vision algorithm called Sunspot. Sunspot identifies solar systems that are visible on rooftops via satellite imagery processing and sizes the PV systems using the dimensions of the spotted rooftop system. After identifying and sizing the existing visible solar systems via satellite imagery, Kevala uses NREL's PVWatts® Calculator[81] to estimate a time series of the solar rooftop system, which is added to the parcel-level baseload previously described.

Non-PEV Load Growth

To coordinate the study assumptions, the EPA provided the total energy growth for the No Action scenario throughout the study forecast horizon. Kevala subtracted the transportation electrification load provided by NREL and LBNL from the EPA-provided total energy to obtain the non-PEV-related load growth. The load growth was then added as an annual percent energy load growth to the baseline load to determine the non-PEV baseload for the study horizon.

Distribution System Cost Methods

The distribution system investments from the total load growth include the baseline load growth from the EPA (this is assumed to include new customers and other non-PEV-related DER growth) and PEV load growth, as Figure 26 shows. Grid capacity cannot be sized to perfectly meet the load additions and is discrete in nature (a choice to add a new transformer of available capacity, to add a new feeder line, etc.), meaning that upgrades will include the buildout of excess capacity. Although PEVs might result in the need for grid upgrades, they might not use the full capacity of new asset additions, and the remaining capacity can be used for other load growth (e.g., new customers, building electrification, new commercial or industrial loads).

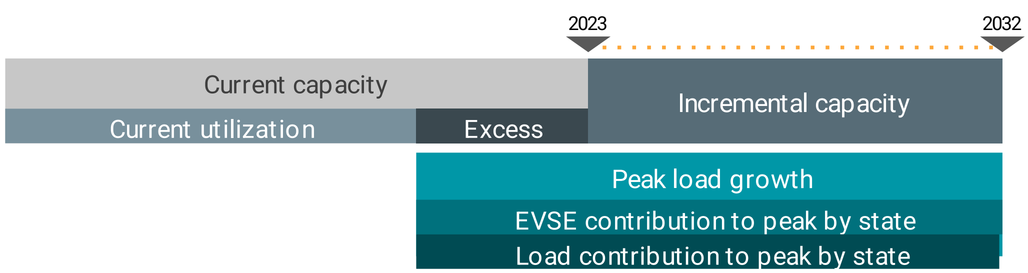


Figure 26. Incremental capacity from distribution system new infrastructure requirements due to load growth and PEV growth. *(Source: Kevala)*

The new distribution infrastructure requirements and costs derived in this study are triggered by capacity needs only; other grid planning investment categories such as resiliency or asset aging are not evaluated. Operational grid investments such as program management, grid modernization technology, and new hardware/software investments are not included in the distribution system costs evaluated.

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

[81] NREL, "NREL's PVWatts Calculator," https://pvwatts.nrel.gov/

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

Creating parcel-level hourly disaggregated load profiles enables Kevala to calculate the peak load at different aggregation levels. For this study, Kevala calculated the distinct peak load for all feeders and substations to determine long-term thermal capacity upgrades for the different forecast scenarios and time horizons.

A simplified grid diagram depicting the grid infrastructure assets and their connectivity is provided in Figure 27. From left to right, a transmission line feeds a distribution substation that typically has between two and four transformer banks. Each transformer bank serves several feeders to distribute power in the neighborhoods. From the feeders that serve thousands of customers, the service transformers on poles or underground pad-mounted transformers step down the voltage for a few customers (up to a dozen) to the customer utilization voltage.

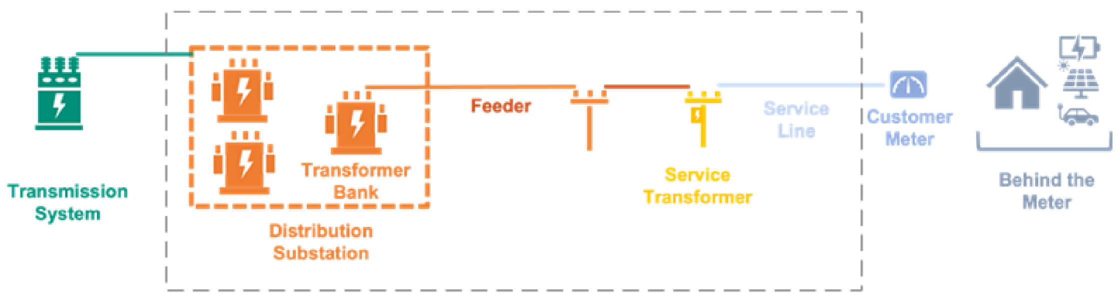


Figure 27. Grid infrastructure diagram. The dashed line highlights the grid assets in this study, including distribution substations, feeders, service transformers, and service lines. *(Source: Kevala)*

New Infrastructure Requirements

Kevala calculated the upgrade costs based on the following unit costs of grid assets and distribution design assumptions.

Substation assumptions:

- Evaluated overload at the substation level using a limit of 100%. Every substation was able to be expanded by adding one 30 MW substation transformer if the substation size was less than 100 MW or a substation transformer sized to 35% of the existing substation size if the substation was larger than 100 MW.
- If the substation expansion was not sufficient to mitigate the overload, a new 60 MW substation was built if the overload was less than 60 MW. A substation right sized to the overload was built if the substation overload was larger than 60 MW.

Feeder assumptions:

- Evaluated overload at every feeder connected to the same substation using a limit of 100%.

- Calculated the overload amount as well as the available capacity for every feeder and then simulated the load transfer capability.
    - If the overload on feeders reaching the thermal limit was less than 15% of the substation capacity, it could be transferred to feeders with available load hosting capacity.
    - If an overloaded feeder had EVSE public chargers, the location of such chargers could be transferred to feeders with remaining load hosting capacity. These geographically proximal feeders may often be served by the same substation, but that was not always the case.
- If the feeder was still overloaded after the load transfer, a new feeder was added using the voltage-to-new feeder capacity size shown in Table 9. The new feeder voltage class was assumed to be the same as the existing overloaded feeder voltage class, except for 4 kV feeders that were assumed to be replaced with a 15 kV class conductor.

Table 9. *New Feeder Capacity Size (MW) by Voltage Class (Source: Kevala)*

	Voltage Class		
	0 kV–15 kV	16 kV–25 kV	26 kV–35 kV
Overhead	11	24	30
Underground	11	24	30

- After determining the need to build a new feeder, feeder length was estimated. Kevala's approach used the properties of the existing feeders of the substation the new feeder will be connected to and the economic load reach (ELR)[82] of the ideal feeder sizes under a typical loading condition of the feeder. All the line segment lengths of the new feeder were sized to follow the ELR guidelines in which the cost-per-unit distance stays within the desired limits. The ELR is found to be dependent on the operating voltage of the feeder, which is presented in Table 10.

Table 10. *ELR by Voltage Class (Source: Kevala)*

Voltage Class (kV)	Distance (mi)
15	3.8
25	7.1
35	9.7

- When a new feeder was required to solve an overload, two cases could arise:
    1. All existing feeders had the same ratings.
    2. Existing feeder ratings differed.

The distance l_{ELR} provided by the ELR table bounded the set of lengths that could be considered to determine the length of the new feeder. The upper and lower bounds (ub, lb) were assumed

[82] ELR is the length of a feeder needed to deliver power while maximizing its economic lifetime use and keeping the voltage drop problems at bay.

to be ub =2 * l_{ELR} and lb = 0.2* l_{ELR}, respectively, to include the range of lengths expected for different loading conditions and the geography of a feeder.

- For the first case, l_{ELR} corresponded to the ratings of that feeder as provided by Table 10. If the observed length of an existing feeder was within its bounds, the new feeder was assigned the observed length. If not, the new feeder length was assigned as l_{ELR}.
- In the second case, a distance l_{ELR} was obtained for each distinct voltage rating of the feeders connected to the substation. The length of all the feeders with a common voltage rating was checked against the bounds. The feeders with feeder lengths that fell outside the bounds were filtered out from the candidate set. The median of the feeder lengths, after applying the filter, was selected as the length of the new feeder. If the resulting candidate was empty, the new feeder length was assigned as l_{ELR}.

Service transformer assumptions:

- Evaluated overload in aggregate for service transformers connected to the same feeder using a 125% overloading criteria and excluding the DCFC contribution to feeder peak load.
  - Used diversity factors[83] to estimate the aggregate service transformer peak load derived from the service transformer to the feeder peak load factors from the CPUC *Electrification Impacts Study*[84] results in California: 0.77 in 2027 and 0.75 in 2032.
  - If the aggregate service transformer peak load was greater than 125% of the aggregate service transformer capacity connected to a feeder, then Kevala calculated the number of 50 kW service transformers required to serve the increase in load.

DCFC service transformer assumptions:

- Each parcel that adopted a DCFC charger had a dedicated three-phase service transformer assigned, following the sizing design parameters provided by NREL based on the DCFC charger size and number of ports per parcel (see Table 11).
- The transformer size was determined by calculating the sum of the diversity factors multiplied by the DCFC charger size and number of ports.

Table 11. *Parcel-Level Diversity Factors by DCFC Port Power Rating, Vehicle Class, and Station Size (Source: NREL)*

DC Power, kW	≤ 3 Port	LD (3 < Port ≤ 8)	LD (Port > 8)	MD (2 < Port ≤ 8)	MD (Port > 8)	HD (2 < Port ≤ 8)	HD (Port > 8)
50	1	1	1	1	1	1	1
150	1	1	0.5	1	1	1	1
350	1	0.75	0.5	1	0.5	1	1
500	1	0.75	0.5	1	0.5	1	0.5

[83] A diversity factor is the ratio of the sum of the individual noncoincident maximum loads of various subdivisions of the system to the maximum demand of the complete system. In this case, the subdivisions of the system are service transformers, and the complete system is the feeder.

[84] Kevala, *Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates*, prepared for the CPUC in support of Proceeding R.21-06-017 (Order Instituting Rulemaking to Modernize the Electric Grid for a High Distributed Energy Resources Future), May 9, 2023, https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M508/K423/508423247.PDF.

DC Power, kW	≤ 3 Port	LD (3 < Port ≤ 8)	LD (Port > 8)	MD (2 < Port ≤ 8)	MD (Port > 8)	HD (2 < Port ≤ 8)	HD (Port > 8)
750	1	0.75	0.5	0.75	0.5	1	0.5
1,000	1	N/A	N/A	0.75	0.5	0.75	0.5
1,500	1	N/A	N/A	0.75	0.5	0.75	0.5

Unit Costs for New Infrastructure

Kevala used the following assumptions to determine the new grid infrastructure costs by asset type. Table 12 provides the installed unit cost assumptions for a 30 MVA substation transformer and the equipment premium adder of $300,000/MVA for substation transformers larger than 30 MVA. Table 13 provides new substation costs for rural, suburban, and urban substations, as well as a $/MVA cost for substations larger than 60 MVA.

Table 12. *New Substation Transformer Cost Calculations (Source: Kevala)*

X: Substation Capacity (MVA)	Transformer Bank (MVA)	Cost ($ Millions)
X < 100	30	10
X > 100	0.35*X	10 + 0.3*(0.35*X-30)

Table 13. *New Substation Cost Calculations by Type (Source: Kevala)*

X: Overload	Type	Cost ($ Millions)
X < 60 MVA	Rural	20
X < 60 MVA	Suburban	30
X < 60 MVA	Urban	60
X > 60 MVA	Rural	20+ (X-60)*0.3
X > 60 MVA	Suburban	30+ (X-60)*0.4
X > 60 MVA	Urban	60+ (X-60)*0.5

Table 14 shows the conductor costs in $/foot used by voltage class and overhead and underground categories for rural and urban feeders.

Table 14. *New Feeder Conductor Costs ($/ft) by Voltage Class, Type, and Rural Versus Urban (Source: Kevala)*

	Voltage Class			
	Type	0 kV–15 kV	16 kV–25 kV	26 kV–35 kV
Rural	Overhead	100.00	100.00	100.00
Rural	Underground	558.27	558.27	558.27
Urban	Overhead	156.25	156.25	156.25
Urban	Underground	872.30	872.30	872.30

The following are the feeder breaker costs by feeder voltage class:

- 0 kV–15 kV: $1 million
- 16 kV–25 kV: $1 million
- 26 kV–35 kV: $1.5 million

National Extrapolation

To derive a national estimate, Kevala extrapolated the results of the bottom-up study of representative states to the contiguous 48 states and the District of Columbia through 2055. Kevala performed this task by developing an average cost per EVSE type for the five study states and applying it to the nationwide EVSE forecasts produced by LBNL and NREL through 2055. These results were broken out by distribution upgrade costs required to serve baseline load growth and those costs required to serve transportation electrification in each of the four scenarios in the five-state study. Further, Kevala delivered these costs by Integrated Planning Model (IPM)[85] region, while the cost results of the five-state study are defined by county.

Figure 28 shows a high-level overview of Kevala's extrapolation approach. Appendix B provides a more extensive description of the extrapolation method.

[85] EPA, "Post-IRA 2022 Reference Case, EPA's Power Sector Modeling Platform v6 Using IPM," Power Sector Modeling, https://www.epa.gov/power-sector-modeling/post-ira-2022-reference-case.

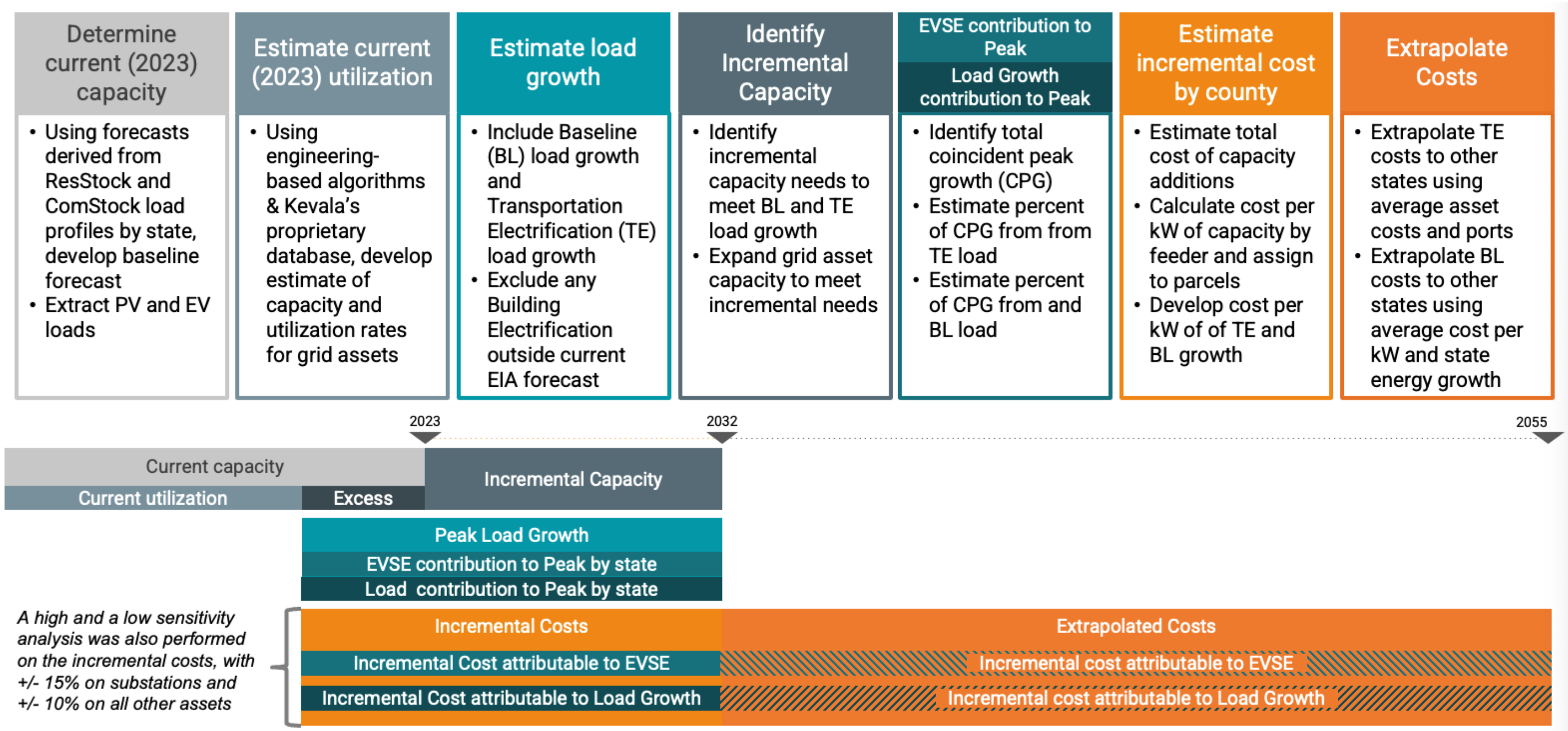


Figure 28. Overview of extrapolation approach *(Source: Kevala)*

Transportation Electrification Scenarios

This chapter presents the PEV adoption scenarios, simulated charging load shapes, and network size requirements for light-, medium-, and heavy-duty PEVs (Class 1–8).

Vehicle Adoption Scenarios

The study's parameters closely align two scenarios of PEV adoption in 2027 and 2032, to bookend the analysis with the model years under EPA consideration:

- An **"Action"** scenario is used to reflect the adoption of two national GHG standards – one for LDVs and MDVs and the other for HDVs – as proposed by EPA in April 2023. These rules would regulate emissions from new motor vehicles for model years 2027 through 2032..
- A **"No Action"** scenario is used to reflect the absence of new national GHG standards for LDVs, MDVs, and HDVs but includes current state and federal policies and regulations.

Based on EPA modeling, a total of 55 million PEVs are assumed to be on the road by 2032 in the Action scenario across all weight classes. This contrasts with the No Action scenario, which assumes 41 million PEVs on the road by 2032.

Figure 29 provides a PEV adoption summary for the five states included in this work (California, Oklahoma, Illinois, Pennsylvania, and New York) broken down by scenario (2027 and 2032, and Action and No Action). Percentage annotations provide the relative increase in PEVs on the road between the Action and No Action scenarios for each simulation year.

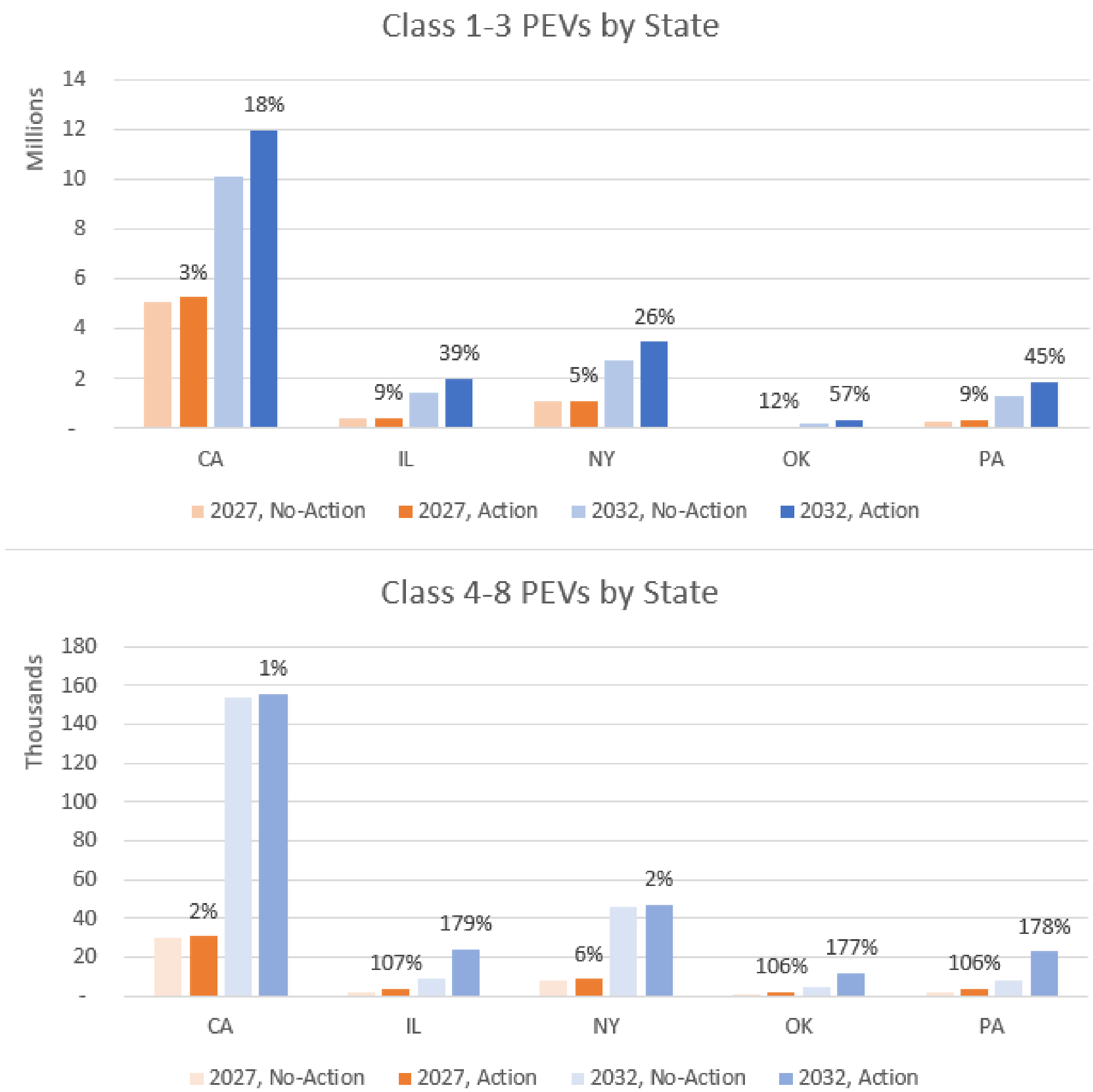


Figure 29. PEV adoption (absolute and relative increases) by weight class and scenario for the five selected states

Charging Load Shapes

This section presents simulated charging load shapes for light-, medium-, and heavy-duty PEVs (Class 1–8). This analysis attempts to quantify the value of proactive vehicle–grid integration by modeling two load-flexibility scenarios:

- An **"Unmanaged" scenario** serves as the baseline in which vehicles arrive at locations where they intend to charge and begin doing so immediately and at full charging speed (relative to the capabilities of their vehicle and the simulated charging infrastructure).
- A **"Managed" scenario** is implemented such that vehicles arriving at select charging locations will intentionally minimize their charging speed such that the session is completed just prior to departure from that location.

In this analysis, arrival time, departure time, and charging energy (but not charging power) are enforced as identical in both the Managed and Unmanaged scenarios. Given these constraints, charging flexibility is exercised only at home and depot locations, which are considered most likely to have margins for adjusting charging speed without negatively impacting vehicle availability. Although this management strategy ensures that peaks from PEV charging are reduced, it ultimately was agnostic to non-PEV loads on the distribution network and is therefore unable to more aggressively optimize charging schedules and better utilize the local distribution system.

Light- and Medium-Duty Vehicles

Figure 30 provides an example of PEV load shapes for the Managed and Unmanaged charging scenarios of LDVs and MDVs. As previously discussed, the Unmanaged scenario assumes that vehicles begin charging immediately and at full power. Given the high level of overnight (residential and depot) charging assumed for LDVs/MDVs, the Unmanaged scenario tends to peak in the early evening as vehicles return to their domicile. Conversely, the Managed scenario is relatively flat with respect to time of day. By prolonging charging events (informed by departure time but agnostic of other grid loads), the peak of the Unmanaged scenario in the early evening is dampened in the Managed scenario, with said energy deferred to fill the load "valley" in the overnight hours.

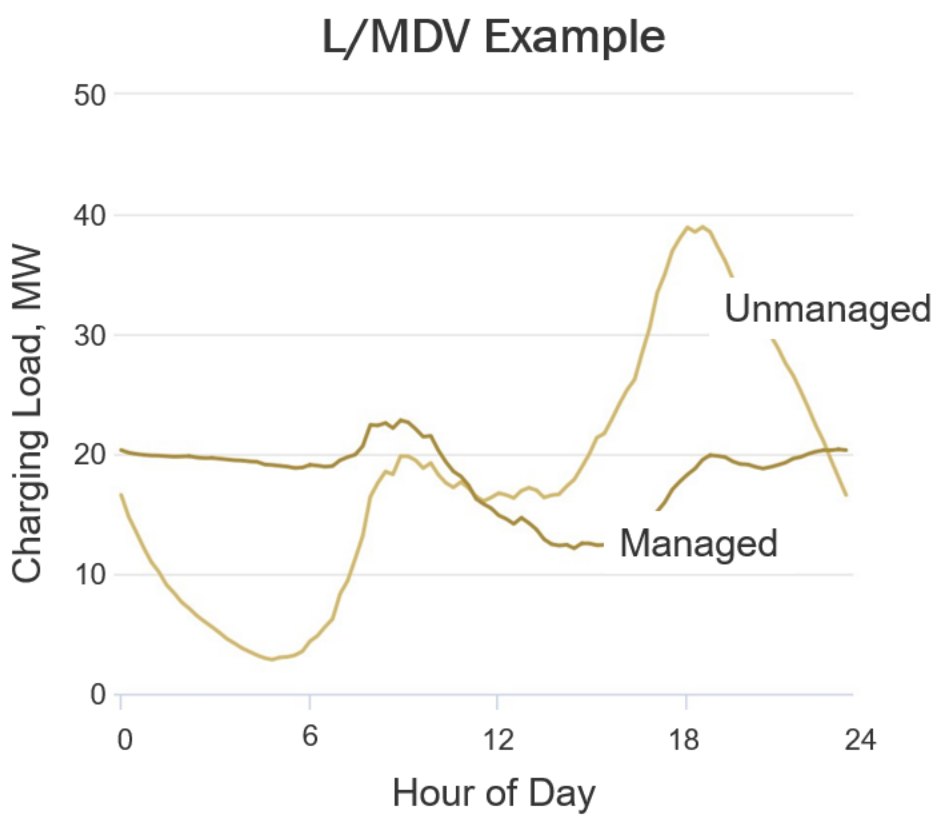


Figure 30. Example load profiles for Managed and Unmanaged charging of LDVs and MDVs

Composite Charging Profiles (Class 1–8)

Figure 31 and Figure 32 provide the composite charging profiles across all weight classes (Class 1–8) for California in the Action scenario (Unmanaged and Managed, respectively). In the case of California, a

30% reduction in the EV charging peak load can be observed in the Managed scenario, and this example is representative of the other four states under study. As expected, the Managed scenario tends to reduce EV coincident peaks by deferring charging from the evening to overnight hours. Given that the Managed scenario was developed agnostic to the baseline non-transportation loads, there is no guarantee that the Managed scenario reduces the total load across all parts of the distribution system (as further discussed in the chapter Load and Distribution System Impacts and Costs).

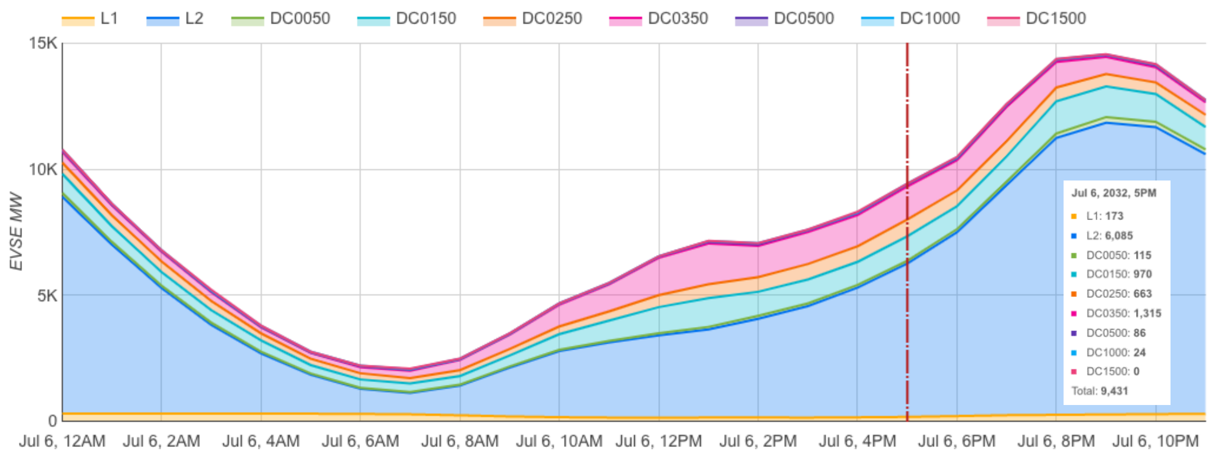


Figure 31. Composite (Class 1–8) PEV charging load profile for California by EVSE type in 2032 (Action–Unmanaged scenario)

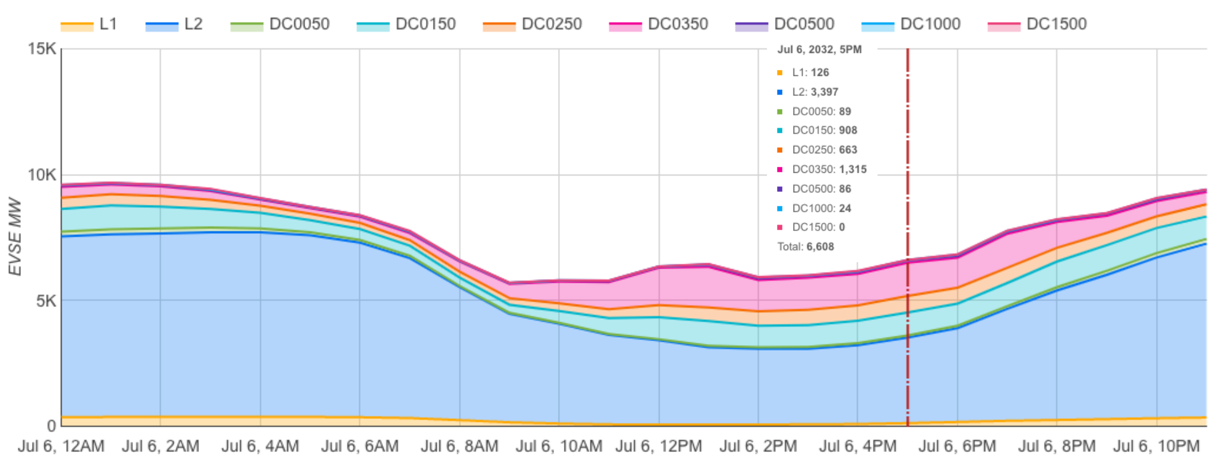


Figure 32. Composite (Class 1–8) PEV charging load profile for California by EVSE type in 2032 (Action–Managed scenario)

The Action scenario has a generally homogenous impact in increasing overall energy consumption and peak loads relative to the No Action policy scenario across the five states, as shown in Figure 33. The increase between the No Action–Unmanaged and Action–Unmanaged scenarios ranges from 1.6% (Oklahoma) to 2.7% (California) in energy consumption by 2032 and from 0.6% (Oklahoma) to 3.0% (Illinois) in peak load by 2032. Those same ranges are less differentiated by 2027: from 0.1% (Oklahoma) to 0.3% (California) for energy and 0.1% (New York and Oklahoma) to 0.2% (California, Illinois, and

Pennsylvania) for peak load. Additional statistics regarding peak load and energy can be found in Table 21 and Table 22, respectively.

The increase in energy consumption between the No Action and Action scenarios occurs regardless of whether the Managed or Unmanaged scenario is used; however, the increase in peak load is reduced to 0.4%–1.4% in the presence of charge management, as shown in Figure 34.

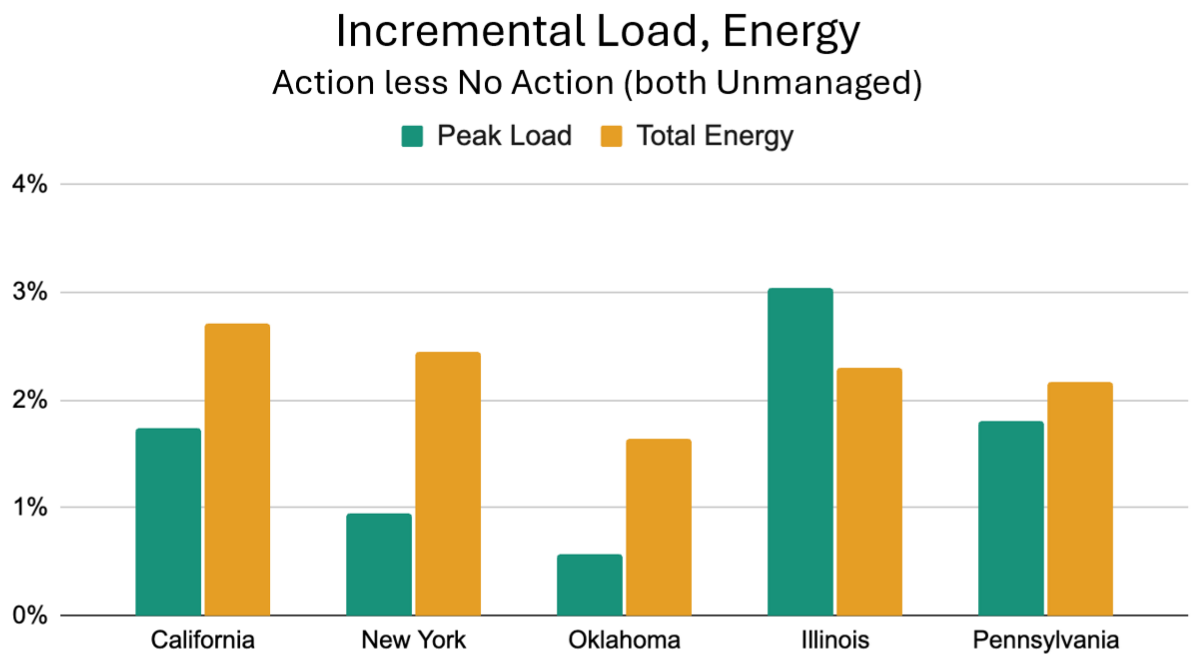


Figure 33. Peak load and energy increases (expressed as a percentage) in 2032 of the Action–Unmanaged scenario relative to the No Action–Unmanaged scenario

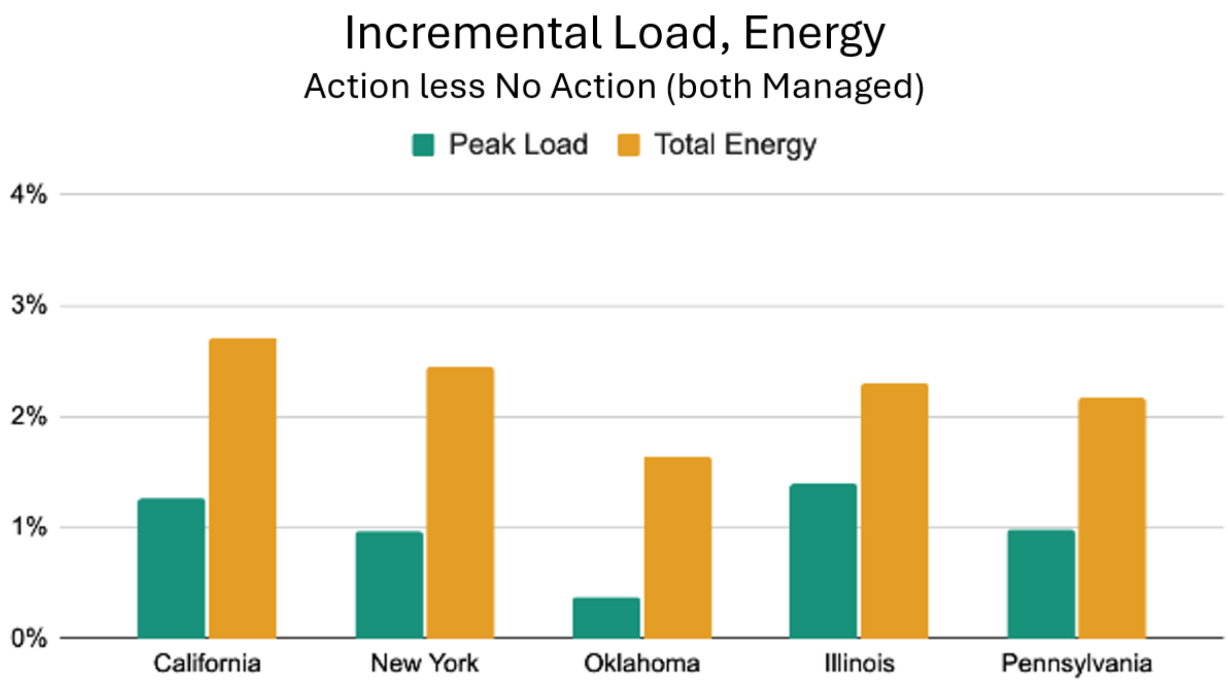


Figure 34. Peak load and energy increases (expressed as a percentage) in 2032 of the Action–Managed scenario relative to the No Action–Managed scenario

Charging Network Size and Cost

We used the combined equipment and installation costs and projected port count by EVSE type, access type, and scenario to estimate charging network costs in 2027 and 2032. We have considered potential effects of economies of scale in developing equipment cost trajectories for future years. In this section, we summarize the estimated cost impacts with respect to both total charging network capital costs and average charging network capital costs on a per-port basis.

Table 15 through Table 19 provide state-level summaries of the charging network size and cost for each of the five states in the study, including breakouts by scenario and access type (public or private). In 2032, the Action scenario is estimated to increase the relative charging network capital costs by as little as 13% in California and as much as 62% in Oklahoma. As with other parts of this study, there are key differences between the relative and absolute costs. Due to significant differences in the simulated PEV fleet size, California and Oklahoma are inverted when ranking the absolute incremental charging network capital costs; California sees a $3.8-billion increase in charging network capital costs under the Action scenario, whereas Oklahoma sees a $0.5-billion increase. Except for L1 chargers, the average capital costs on a per-port basis for EVSEs are estimated to be lower under the Action scenario than the No Action scenario in both 2027 and 2032 (Table ***20***) due to economies of scale. By 2032, the average capital cost ranges from $550 per port for L1 chargers to $630,165/$639,207 per port for 1.5-MW DCFCs.

Table 15. *California Simulated PEV Charging Network Size and Capital Cost (Excluding Grid Upgrades) by Scenario and Access Type (Public/Private). The percentage increases in the network capital costs in 2027 and 2032 resulting from the Action scenario are provided in the bottom row. The small decrease in costs in 2027 results from economies of scale. (BAU = business as usual)*

CA	Network Size (Ports)					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	4,131,964	4,256,181	124,217	6,915,555	7,716,900	801,345
public	95,705	98,272	2,567	333,169	405,476	72,307
total	4,227,669	4,354,453	126,784	7,248,724	8,122,376	873,652
	Network Cost (millions) - EVSE BAU Scenario					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	$ 8,709	$ 9,062	$ 353	$ 19,171	$ 21,837	$ 2,666
public	$ 3,115	$ 3,063	$ (52)	$ 10,519	$ 11,701	$ 1,182
total	$ 11,824	$ 12,125	$ 301	$ 29,690	$ 33,538	$ 3,848
			3%			13%

Table 16. *Illinois Simulated PEV Charging Network Size and Capital Cost (Excluding Grid Upgrades) by Scenario and Access Type (Public/Private). The percentage increases in the network capital costs in 2027 and 2032 resulting from the Action scenario are provided in the bottom row.*

IL	Network Size (Ports)					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	361,583	394,792	33,209	1,252,753	1,665,327	412,574
public	5,121	5,643	522	18,731	50,491	31,760
total	366,704	400,435	33,731	1,271,484	1,715,818	444,334
	Network Cost (millions) - EVSE BAU Scenario					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	$ 804	$ 939	$ 135	$ 2,777	$ 4,096	$ 1,319
public	$ 182	$ 204	$ 22	$ 799	$ 1,445	$ 646
total	$ 986	$ 1,143	$ 157	$ 3,576	$ 5,541	$ 1,965
			16%			55%

Table 17. *New York Simulated PEV Charging Network Size and Capital Cost (Excluding Grid Upgrades) by Scenario and Access Type (Public/Private). The percentage increases in the network capital costs in 2027 and 2032 resulting from the Action scenario are provided in the bottom row.*

NY	**Network Size (Ports)**					
	2027			**2032**		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	936,360	981,803	45,443	2,101,338	2,499,428	398,090
public	26,245	27,401	1,156	87,173	118,545	31,372
total	962,605	1,009,204	46,599	2,188,511	2,617,973	429,462
	Network Cost (millions) - EVSE BAU Scenario					
	2027			**2032**		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	$ 2,660	$ 2,821	$ 161	$ 8,132	$ 9,440	$ 1,308
public	$ 722	$ 741	$ 19	$ 2,428	$ 2,953	$ 525
total	$ 3,382	$ 3,562	$ 180	$ 10,560	$ 12,393	$ 1,833
			5%			17%

Table 18. *Oklahoma Simulated PEV Charging Network Size and Capital Cost (Excluding Grid Upgrades) by Scenario and Access Type (Public/Private). The percentage increases in the network capital costs in 2027 and 2032 resulting from the Action scenario are provided in the bottom row.*

OK	**Network Size (Ports)**					
	2027			**2032**		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	43,246	48,566	5,320	218,525	338,855	120,330
public	796	918	122	3,513	5,269	1,756
total	44,042	49,484	5,442	222,038	344,124	122,086
	Network Cost (millions) - EVSE BAU Scenario					
	2027			**2032**		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	$ 127	$ 167	$ 40	$ 551	$ 944	$ 393
public	$ 61	$ 73	$ 12	$ 251	$ 357	$ 106
total	$ 188	$ 240	$ 52	$ 802	$ 1,301	$ 499
			28%			62%

Table 19. *Pennsylvania Simulated PEV Charging Network Size and Capital Cost (Excluding Grid Upgrades) by Scenario and Access Type (Public/Private). The percentage increases in the network capital costs in 2027 and 2032 resulting from the Action scenario are provided in the bottom row.*

PA	Network Size (Ports)					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	334,687	372,812	38,125	1,056,106	1,462,503	406,397
public	8,228	8,873	645	38,080	50,367	12,287
total	342,915	381,685	38,770	1,094,186	1,512,870	418,684
	Network Cost (millions) - EVSE BAU Scenario					
	2027			2032		
Access Type	No Action	Action	Delta	No Action	Action	Delta
private	$ 741	$ 883	$ 142	$ 2,406	$ 3,644	$ 1,238
public	$ 250	$ 283	$ 33	$ 1,112	$ 1,446	$ 334
total	$ 991	$ 1,166	$ 175	$ 3,518	$ 5,090	$ 1,572
			18%			45%

Table 20*. Average Network Capital Cost ($/Port) by Scenario and EVSE Type across the Five States*

EVSE Type	2021	2027		2032	
		Action	No Action	Action	No Action
L1	$ 550	$ 550	$ 550	$ 550	$ 550
L2 residential	$ 1,900	$ 1,771	$ 1,775	$ 1,734	$ 1,748
L2 commercial	$ 6,779	$ 6,298	$ 6,314	$ 6,118	$ 6,183
DC50	$ 35,000	$ 31,158	$ 31,517	$ 29,714	$ 30,192
DC150	$ 105,000	$ 93,475	$ 94,550	$ 89,439	$ 90,725
DC250	$ 135,500	$ 122,889	$ 124,065	$ 118,498	$ 119,887
DC350	$ 166,000	$ 152,304	$ 153,581	$ 147,283	$ 149,014
DC500	$ 237,143	$ 217,577	$ 219,402	$ 210,776	$ 213,004
DC1000	$ 474,286	$ 435,154	$ 438,803	$ 421,604	$ 425,372
DC1500	$ 711,429	$ 652,731	$ 658,205	$ 630,165	$ 639,207

Load and Distribution System Impacts and Costs

Impact on Peak Load Between Scenarios

Table 21 compares all scenarios to the No Action–Unmanaged scenario in terms of peak load increase or decrease for 2027 and 2032. Table 22 makes the same comparison on an energy basis. Note the following:

- The No Action–Managed scenario has a lower peak load than the No Action–Unmanaged scenario for all states and years simulated.
- The Action–Unmanaged scenario has a higher peak load than the No Action–Unmanaged scenario, ranging from 0.6% to 3% by 2032.
- The Action–Managed scenario can reduce the peak-load impact relative to the Action–Unmanaged case.
    - In California, Illinois, and Pennsylvania, in 2032, the peak load of the Action–Managed case is less than the peak load in the No Action–Unmanaged scenario.
    - In New York and Oklahoma, the Action–Managed scenario reduces the peak load by 44% and 83%, respectively, compared to the Action–Unmanaged scenario, but it is still slightly higher than the No Action–Unmanaged scenario, with increases of 0.5% and 0.1%, respectively, by 2032.
- The energy requirements do not change based on whether or not PEV charging is managed.

Table 21. *Percentage (%) Difference in Peak Load by Scenario as Compared to the No Action–Unmanaged Scenario in 2027 and 2032 (Source: Kevala)*

Year	Scenario	California	New York	Oklahoma	Illinois	Pennsylvania
2027	No Action–Unmanaged	—	—	—	—	—
	No Action–Managed	-2.3	-0.2	-0.1	-0.9	-0.6
	Action–Unmanaged	0.2	0.1	0.1	0.2	0.2
	Action–Managed	-2.0	-0.1	0.0	-0.8	-0.5
2032	No Action–Unmanaged	—	—	—	—	—
	No Action–Managed	-3.1	-0.4	-0.3	-2.8	-1.5
	Action–Unmanaged	1.7	0.9	0.6	3.0	1.8
	Action–Managed	-1.8	0.5	0.1	-1.5	-0.5

***Table 22.** Percentage (%) Difference in Energy by Scenario as Compared to the No Action Scenarios in 2027 and 2032* (Source: Kevala)

Year	Scenario	California	New York	Oklahoma	Illinois	Pennsylvania
2027	No Action–Unmanaged/Managed	–	–	–	–	–
	Action–Unmanaged/Managed	**0.3**	**0.2**	**0.1**	**0.2**	**0.2**
2032	No Action–Unmanaged/Managed	–	–	–	–	–
	Action–Unmanaged/Managed	**2.7**	**2.4**	**1.6**	**2.3**	**2.2**

Peak Load Demand Shapes

Figure 35 is an illustrative example of the daily load shapes for the different scenarios in California on the day of the peak load. The chart inset indicates that the Action–Managed peak load value is 1.8% *lower* than the No Action–Unmanaged peak load value, reflecting the critical benefit of managing charging to integrate incremental PEV loads and infrastructure into the grid *without* commensurate additions to system capacity.

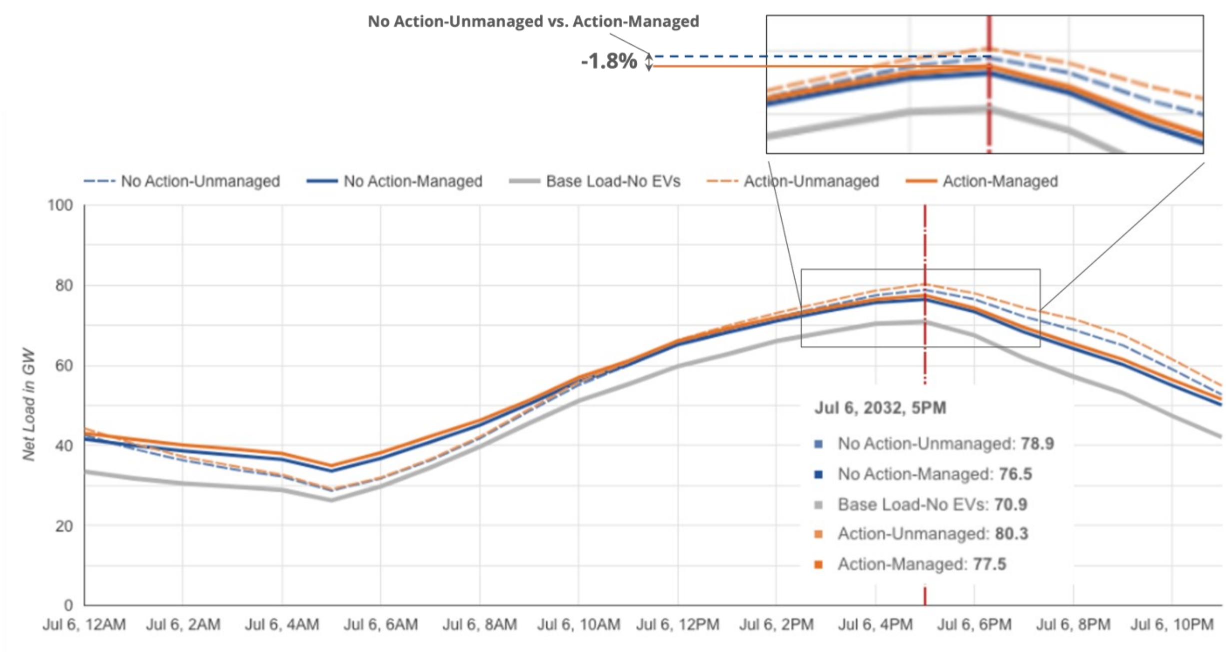


Figure 35. Peak-day load shapes for California in 2032 for all scenarios *(Source: Kevala)*

Peaks by Time of Day at Grid Asset Levels

The peak load value was calculated at multiple grid asset levels. Figure 36 compares the peak load time of day for distribution feeders in California for different pairs of scenarios:

- **Baseload–No EVs scenario versus Action–Unmanaged (left):** The charging infrastructure increases the frequency of the feeders peaking in the evening, particularly from 7 p.m. to 9 p.m.

- **No Action–Unmanaged versus Action–Managed (middle) and Action–Unmanaged versus Action–Managed (right):** The Managed charging scenario is effective at reducing the evening peak loads, particularly at 7 p.m. and 8 p.m., compared to the Unmanaged scenarios; however, it increases the frequency of the feeders peaking in the morning at 6 a.m. and 7 a.m.

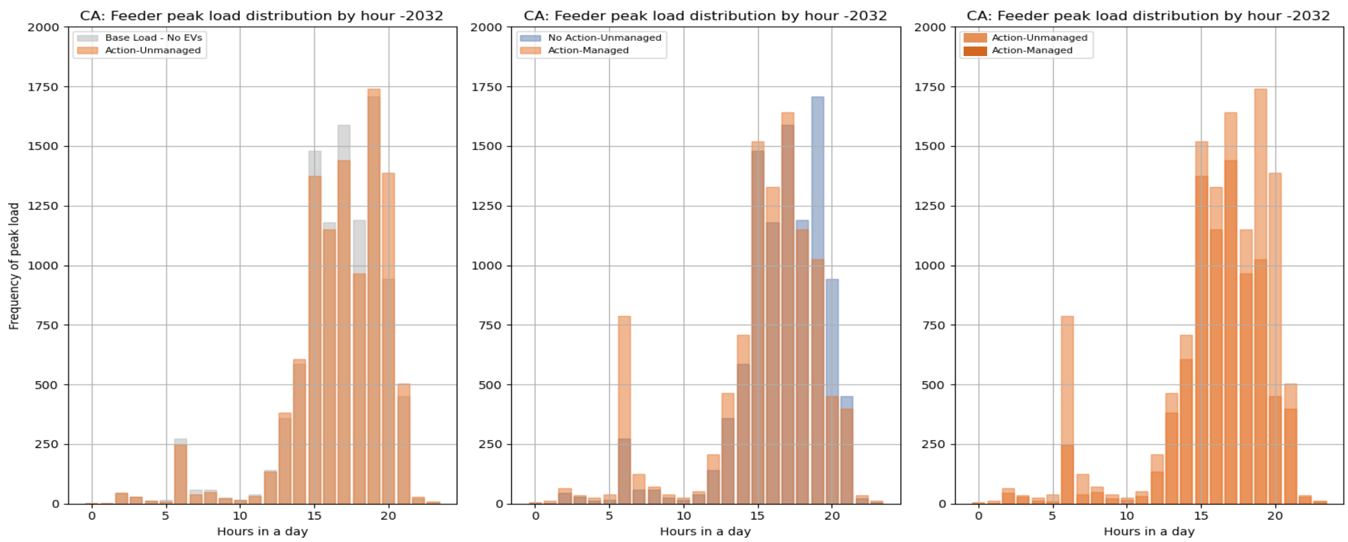


Figure 36. Frequency of peak load time of day for feeders in California in 2032 between the Baseload–No EVs and Action–Unmanaged (left), No Action–Unmanaged and Action–Managed (middle), and Action–Unmanaged and Action–Managed scenarios (right) *(Source: Kevala)*

Cost Comparison Between Scenarios

Table 23 compares all scenarios to the No Action–Unmanaged scenario in terms of peak load increase or decrease for 2027 and 2032. Note the following:

- The Action–Unmanaged scenario increases grid capacity upgrade costs by between 3.3% and 4.3% across the five states by 2032.
- Managed charging reduces grid capacity upgrade costs relative to scenarios that allow charging to remain unmanaged for both the No Action and Action cases.
    - In California, Illinois, and Pennsylvania, the Action–Managed scenarios require less total distribution grid investment cost than the No Action–Unmanaged scenario in 2032.
    - In New York, the Action–Managed scenario has a slightly higher total grid investment cost in 2032 than the No Action–Unmanaged case; however, managed charging would reduce costs 75% compared to the Action–Unmanaged scenario (i.e., 0.8% versus 3.3%).
    - In Oklahoma, the Action–Unmanaged and Action–Managed scenarios do not impact the distribution investment costs in 2027. Counterintuitively, in 2032, the No Action–Managed scenario results in 0.4% higher costs than the No Action–Unmanaged scenario. This is because the algorithm to delay charging for home- and fleet-based EVSE was not effective at reducing local distribution capacity criteria due to the Oklahoma Baseload–No EVs scenario's load shape being higher in the morning than in the evening hours.

Table 23. *Percentage (%) Difference in Total Distribution Costs by Scenario as Compared to the No Action–Unmanaged Scenario in 2027 and 2032 (Source: Kevala)*

Year	Scenario	California	New York	Illinois	Pennsylvania	Oklahoma
2027	No Action–Unmanaged	—	—	—	—	—
	No Action–Managed	**-1.6**	**-0.8**	**-0.5**	**0.2**	**-0.4**
	Action–Unmanaged	**0.7**	**0.1**	**0.6**	**0.3**	**0.0**
	Action–Managed	**-1.4**	**-0.8**	**-0.1**	**0.4**	**0.0**
2032	No Action–Unmanaged	—	—	—	—	—
	No Action–Managed	**-3.3**	**-1.4**	**-3.9**	**-0.6**	**0.4**
	Action–Unmanaged	**3.6**	**3.3**	**4.3**	**3.3**	**3.5**
	Action–Managed	**-0.8**	**0.8**	**-0.9**	**-1.8**	**3.1**

National Extrapolation

National extrapolation of the bottom-up results mirrored trends observed in the five study states. For example, the Action scenarios resulted in greater degrees of distribution grid investments, scaling more rapidly beyond 2032. This is largely due to a parallel increase in EVSE counts, the parameter on which the extrapolated costs are largely based. Further, the scale of those investments was tempered in the Managed scenarios, as expected. By the end of the forecast period (2055), there is a larger impact of managed charging on distribution costs in the Action scenario due to higher overall EVSE counts as well as a more rapid scaling of EVSE adoption types eligible for management (i.e., LDVs and fleets) in the context of the study.

The cumulative national distribution costs resulting from support of PEV/EVSE growth, by scenario, are shown in Figure 37 and are further explored in Appendix B.

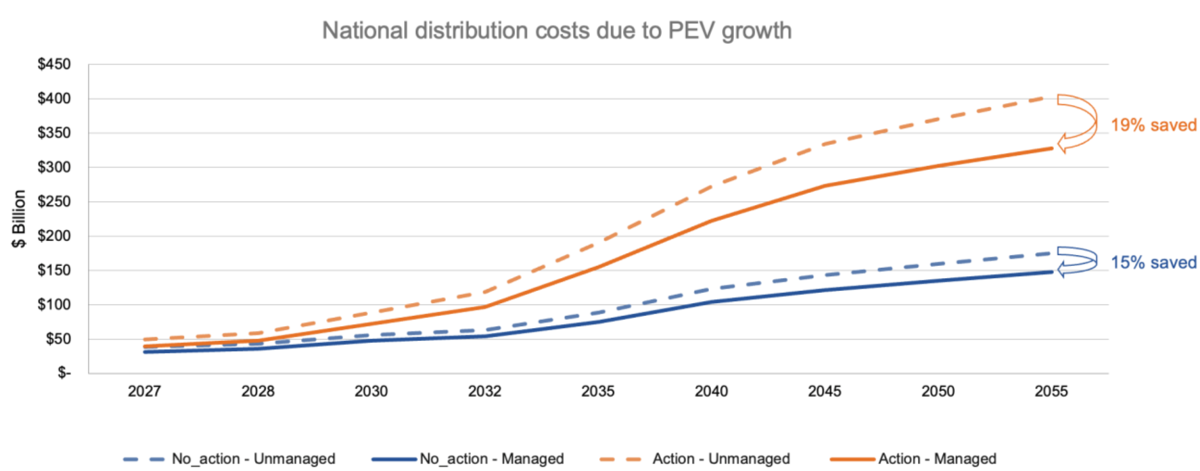


Figure 37. Extrapolated nationwide cumulative distribution costs for all scenarios from 2027 through 2055. Although these costs are national, the extrapolation is conducted to reflect the cost components of the five study states in 2027 and 2032 in the bottom-up study. *(Source: Kevala)*

As referenced elsewhere, the widening gap between each set of colored lines in Figure 37 is a testament to the growing impact of charge management over the forecast horizon; there is an increasing proportion of EVSEs eligible for charge management in later years under the Action scenarios. Furthermore, comparing the scenarios in Figure 37 reveals that implementing managed charging in the Action case could reduce grid upgrade costs by approximately 19%.

To confirm these results, Kevala examined the share of EVSE costs from the five-state study and compared them to the extrapolated nationwide results. Figure 38Figure 38 shows that the five states account for approximately 30%–35% of total costs, depending on the scenario, with Unmanaged scenarios showing a greater share of the total costs than the Managed scenarios. This is explored further in 0

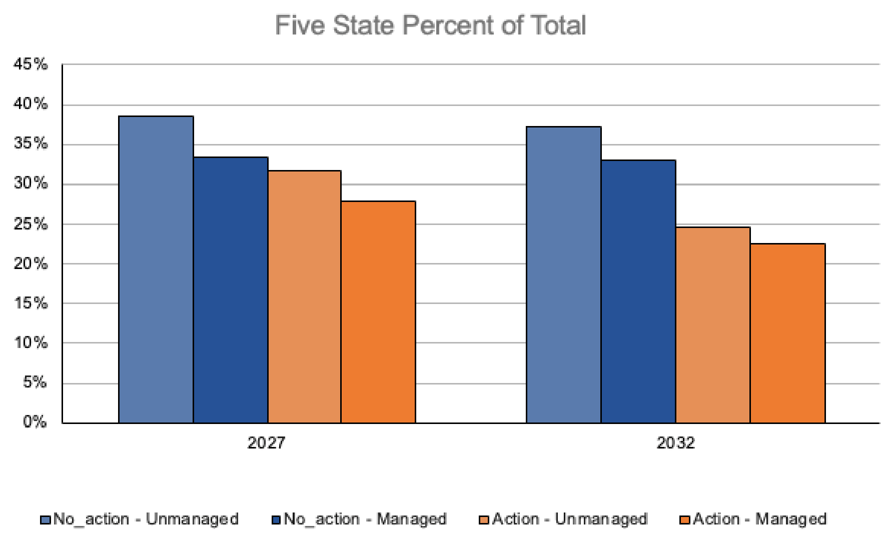


Figure 38. Five-state costs as a percentage of the nationally extrapolated costs *(Source: Kevala)*

Although this proportion of costs seems sufficient based on EVSE, PEV, economic, and demographic factors, more study is needed to determine how best to support national cost analyses with bottom-up electrification impact studies. For example, variable regulation, labor and procurement costs, driving habits, and dynamic charge management could play major roles in the overall impacts of transportation electrification. With increased support and additional location-specific data availability, the project team could conduct additional bottom-up studies for other U.S. states.

The final results of the national extrapolation were broken down by IPM region (see Appendix F for a list of these IPM regions); relative costs between these regions are shown in Figure 39. Note that there is a "long tail" of IPM regions with significantly lower costs, which is driven by those areas having a lower proportion of vehicles forecasted to be adopted and operated.

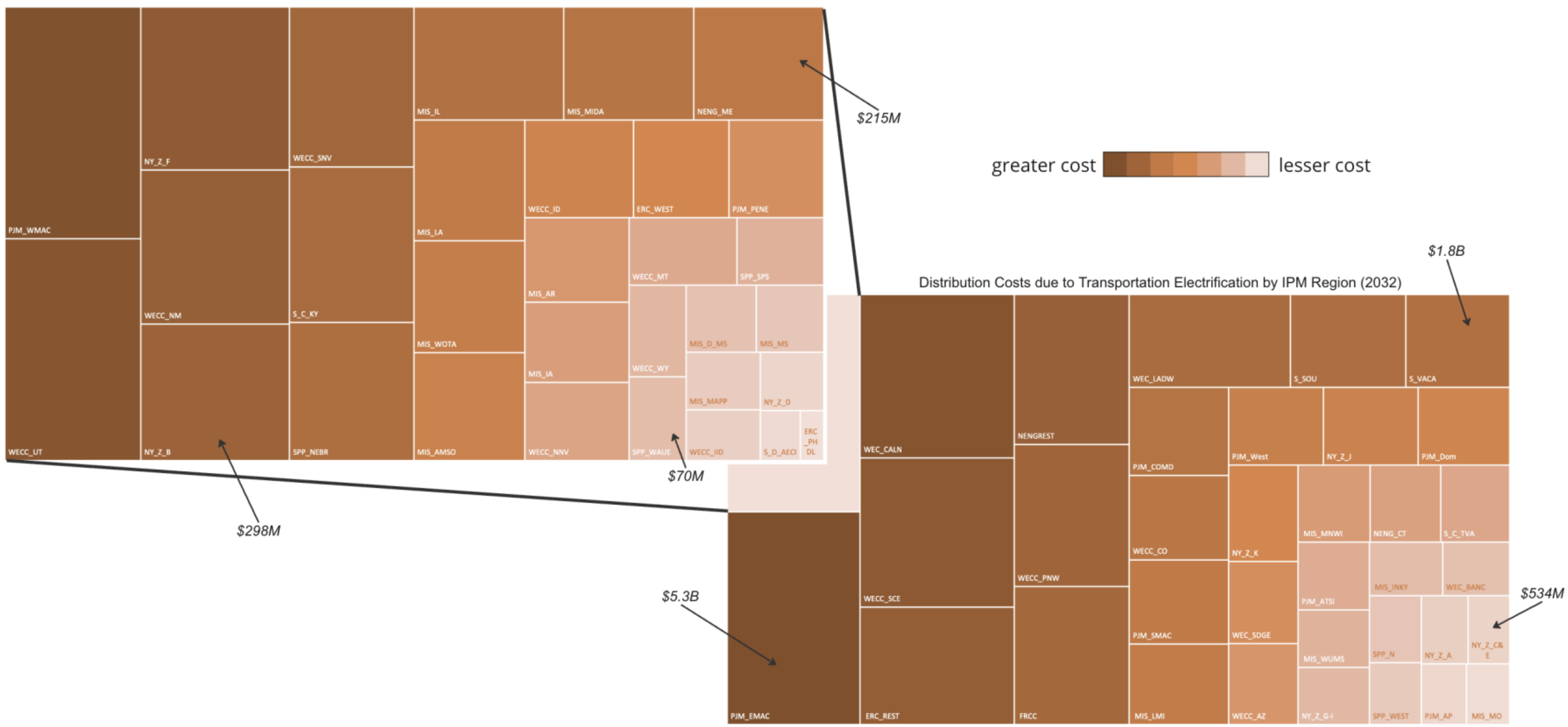


Figure 39. Extrapolated nationwide distribution costs by IPM region for the No Action–Unmanaged scenario in 2032 *(Source: Kevala)*

Discussion

Contextualizing Costs

As shown in Table 24, this study estimated a $12.0-billion incremental charging and distribution grid infrastructure investment as being necessary to support an additional 3.9 million light-, medium-, and heavy-duty PEVs on the road in 2032 across five states, as are estimated to be induced under the Action scenarios. Of this $12.0 billion, $9.7 billion (81%) is estimated as necessary for capital expenses related to charging equipment and installation at publicly and privately accessible locations. The remaining $2.3 billion (19%) of the infrastructure estimate is allocated for grid upgrades, including service transformers, feeders, and substations.

Table 24. *Year 2032 Simulation Results for the Five-State Study*

Five-State Scenarios (2032)	Action vs No Action	
	Unmanaged	Managed
Incremental PEV adoption (all weight classes)	3.9 million	
Incremental charging ports (all types)	2.3 million	
Incremental charging infrastructure capital investment	$9.7 billion	
Incremental substations	8	4
Incremental feeders	125	75
Incremental service transformers	30,000	21,000
Incremental distribution grid capital investment	$2.3 billion	$1.6 billion
Combined incremental infrastructure capital investment	$12.0 billion	$11.3 billion

For context regarding the magnitude of these costs, consider the following:

- Distribution grid upgrade costs estimated in this work can be compared to existing utility distribution system investments. Based on utility reports to the Federal Energy Regulatory Commission, data from electric co-ops, and extrapolation for the remaining utilities, we estimate that the national investment in distribution systems exceeded $60 billion annually as of 2021. A high-level approach for scaling the national distribution system investment to the five states under study was applied to estimate that $15 billion of distribution system investment occurred in 2021. This study estimates the incremental investment in distribution networks (to accommodate the estimated PEV growth under the Action scenario) to be an additional $2.3 billion of grid investment for PEVs in the Unmanaged scenario. Annualizing this between 2027 and 2032 results in an estimated annual cost of $0.4 billion, or approximately 3% of existing annual distribution investments, from the EPA's proposed rules across the five states (see Appendix D).

- Based on NREL's 2022 Transportation Annual Technology Baseline (ATB),[86] by 2030 PEVs are expected to provide $8,300 per vehicle in lifetime net benefits accrued to EV users, primarily from fuel cost savings (based on a fleet-weighted average using the EPA's adoption scenario and consistent infrastructure costs). Scaling these net benefits to a fleet of 3.9 million PEVs implies a fleet-weighted net benefit of $33 billion across the lifetime of the 2032 PEV fleet in the five states under study. This is at least 2.5 times greater than the capital investment needs for charging infrastructure and grid upgrades estimated by this work.
- The $9.7 billion increase in charging network capital costs is approximately a 19% increase over what would be necessary for charging infrastructure in the No Action scenario, with the majority of the cost (approximately 70%) expected to be needed at privately accessible locations (including single-family homes and commercial depots).

Proactive utility distribution planning, dynamic tariff structures, and vehicle–grid integration technologies provide levers to efficiently forecast grid infrastructure investment needs for PEVs and other loads and serve them with the least associated costs. The incremental distribution grid capital investment of $2.3 billion (Action–Unmanaged versus No Action–Unmanaged) is reduced to $1.6 billion when assuming that charging loads at home and depot locations are managed (Action–Managed versus No Action–Managed). This result is driven by the ability of PEVs to shift charging to off-peak hours based on parking durations that exceed the time necessary to charge. For example, a 30% reduction in California's PEV peak load was simulated in the Action–Managed scenario, and this example is representative of the other four states under study. When considering all electric loads, this translates to a reduction in total peak load between 0.4% and 4.5% (depending on the state).

Although this management strategy ensures that peaks from PEV charging are reduced, it is agnostic to non-PEV residential, commercial, and industrial loads on the distribution network in the context of this study, and therefore charging schedules were not further optimized in this study to better use the local distribution system. Exploratory research presented in Appendix E suggests that further savings, in the form of deferred grid upgrade costs, can be achieved by managing the charging patterns of particular vehicle classes to actively respond to local, feeder-level congestion and capacity constraints. These potential savings are more significant on feeders with greater adoption of more easily manageable vehicle classes (namely, those at locations with home and depot charging).

Comparisons to Other Work on a Marginal Cost Basis

To check the validity of PEV grid costs, results can be compared with grid costs associated with historical load increases. The *marginal cost of service* metric is used to perform this check, defined as the cost of infrastructure investments relative to the change in peak load (i.e., $ investment divided by MW change in peak load). To be consistent with this five-state study, only capital costs are examined. Yearly operations and maintenance and capital carrying costs are not included. Using this definition, the marginal cost of service for the Action–Unmanaged scenario for 2032 is $640/kW-peak-load averaged across the five states in the study.

The calculated ($640/kW-peak-load) marginal cost of service for the five-state study is higher than other reported values in the literature and suggests that actual costs may be lower than reported in this study.

[86] National Renewable Energy Laboratory, "Annual Technology Baseline," https://atb.nrel.gov/.

Using a regression on Federal Energy Regulatory Commission (FERC) Form 1, data[87] results in an average marginal cost of service of $34/kW from 1994 to 2014. This value derived from FERC Form 1, however, is lower than values reported by utilities. In New York, 2018 data from New York State Electric And Gas Corporation (NYSEG) reports[88] a $169/kW-peak-load marginal cost of service. ConEdison reports[89] values ranging from $59/kW-peak-load to $186/kW-peak-load. Beyond these comparisons, the 2032 $640/kW-peak-load figure may be further reduced under other accounting methods (such as the discounted total investment method) that levelize investment between (for example) 2027 and 2032 on a year-over-year, as opposed to stepwise, basis.

The difference between the marginal cost of service in this study and other reported values might, in part, be attributed to the lumpiness of distribution investments and the fact that this study does not attempt cost allocation. The capacity utilization of assets needed to meet PEV load growth in 2032 is low. For example, the capacity utilization of a substation in 2032 for the Action–Unmanaged scenario is 5%. This suggests the potential for more efficient infrastructure investments (for example, using load balancing, non-wire alternatives, or right-sizing assets).

Future Work for Refining the Analysis

With a study of this breadth, there are several key areas for future work to refine the analysis. The identified key areas for future work are as follow. We expect many of the areas for future work to have a lower impact on the overall incremental analysis of this study than their impact on total investment (i.e., the investment differences between the Action and No Action scenarios). A more detailed breakdown of the key caveats and context for the areas for future work are given in Appendix C.

1. **Contingency conditions for substations:** The study examined the need for future substation capacity growth. One key area for future work should consider how substation capacity can accommodate electrification growth while considering power-flow, reliability, and N-1 conditions (i.e., contingency for load transfer). Not considering that substations keep overhead capacity for load transfer in contingency conditions can underestimate the upgrades required.

2. **Large standard deviation of loading/capacity of grid assets:** Many assets are overloaded in the 2023 asset utilization dataset, which would require upgrades that should not be attributed to electrification. Refining loading estimates and electrical asset capacities might reduce incremental upgrades required for electrification.

3. **Low utilization of new substation transformer banks and new substations:** The buildout of new substations and the expansion of existing substations results in many transformer banks with low loading conditions. Conducting a cost allocation among benefitting customer classes other than PEVs could help account for the costs associated with expanded substation capacity, which

[87] Robert L. Fares and Carey W. King, "Trends in transmission, distribution, and administration costs for U.S. investor-owned electric utilities," *Energy Policy* 105 (June 2017): 354–362, https://doi.org/10.1016/j.enpol.2017.02.036.

[88] New York State Electric And Gas Corporation (NYSEG), "Derivation of Systemwide Marginal Costs," 2018, https://www.nyseg.com/documents/40132/5899056/NYSEG%2BElec%2BLSRV%2BDRV%2BMC%2B2018-07-30.xlsx/3327dcf5-7e8f-a58b-30e7-2110729877fb?version=1.0&t=1645136501943.

[89] P.Q. Hanser, T.B. Tsuchida, P. Donohoo-Vallet, L. Zhang, and J. Schoene, "Marginal Cost of Service Study," prepared for conEdison, published July 30, 2018, https://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7BF99CFC43-2D67-44DB-AB02-A7ACDA5E6341%7D.

could be used for future load growth but would not be used by electrification for the study's focal years (2027–2032). An important area for future work is examining how much of the added electrical infrastructure is utilized by PEVs. PEV load growth may result in grid capacity asset additions with low utilization, where overhead capacity can be used for load growth in other sectors (e.g., building electrification). Using cost allocation of utilized capacity may appropriately lower the investment attributed to vehicle electrification.

4. **Undergrounding costs:** Estimating underground distribution infrastructure is challenging and does not lend itself well to machine-learning- and satellite-image-based estimation techniques. A more detailed examination of underground infrastructure will be important for future studies to improve cost estimation given that undergrounding costs five to 10 times more than overhead costs.
5. **Drivers of grid investment not considered**: The key focus of this study was to examine relative grid capacity investment from the perspective of incremental electrification between the No Action and Action scenarios. Given that utilities are motivated to continue investment in the distribution system based on other factors (e.g., resilience investments and replacing aging assets), to the extent that these investments also result in capacity expansions, this analysis would overestimate grid costs attributable to transportation electrification.
6. **PEV demand profiles:** This study examines two PEV charging profiles. Given that there are several ways to optimize charging profiles—e.g., based on location (public versus at home), the provision of grid balancing services (such as coincident with midday solar or nighttime-valley filling), or to reduce emissions (while matching charging with the geographic and temporal attributes of generators)—additional sensitivity analysis would refine the investment associated with PEV grid integration and provide greater insight into which forms of managed charging and utility programs may provide the greatest benefits.
7. **Sensitivity analysis of unit costs for grid equipment:** This study applies unit costs for grid equipment (e.g., transformer, overhead line, and underground conductor costs) based on 2023 dollars. Future studies could account for supply chain dynamics in cost forecasting that reflect recently announced[90] and expected additional domestic supplies for grid component manufacturing in response to improved demand forecasting, utility regulators' valuation of NWA (including the deployment of station- and distribution-level power control systems), and efforts to standardize transformer design.
8. **Refining forecasted demand for other sectors:** Other non-PEV sector demand (e.g., building electrification, energy efficiency, and commercial and industrial load growth) and the growth of DERs (e.g., rooftop solar and behind-the-meter storage) are not the focus of this study, but both can impact the costs of vehicle electrification and its impact on system peak demand (e.g., using transactive controls among PEVs and other end uses to ensure that sector demand does not coincide with system peak demand, using DERs as an NWA). For example, distributed solar can change the timing and magnitude of system peak demand, which may, given coordinated charging, lower the impact of transportation demand on system peak.

[90] CorePower Magnetics, "CorePower Magnetics Awarded $20M from DOE to Establish Domestic Manufacturing Facility in Pittsburgh," published November 28, 2023, https://www.corepowermagnetics.com/post/corepower-magnetics-awarded-20m-from-doe-to-establish-domestic-manufacturing-facility-in-pittsburgh.

9. **Capacity-aware charge management:** The Managed scenarios modeled in this study were based on behaviors observed to date in existing high-penetration PEV markets, and thus they did not precisely suit each state or utility's baseline load. The distribution grid investment costs in Oklahoma for the No Action–Managed scenario resulting in, counterintuitively, 0.4% higher costs than the No Action–Unmanaged scenario, illustrate the need to implement charge management strategies that account for and are aware of the relevant local patterns in electric demand and asset-specific capacity constraints. The project team anticipates that more technologies will be developed and deployed to directly orchestrate charging in certain market segments to reduce peak load impacts on distribution infrastructure. Accordingly, Kevala ran an additional management scenario specifically designed to migrate charging load from peak times to less costly periods to minimize capacity investments, where dwell times allow, resulting in the potential for capacity savings that increase in proportion to charging load. The approach and the detailed results of this scenario are discussed in Appendix E.

10. **Expansion of utility-level analysis to reduce reliance on extrapolation:** The five study states account for approximately 25% of electric customers in the United States and 20% of overall utility peak demand across the country.[91] Additionally, the states overall represent those with high IOU presence; the five-state average for IOU service is ~84% of customers, whereas IOUs serve approximately 69% of customers nationwide. Extrapolation from a five-state study to national-scale is challenging due to the diversity in U.S. distribution systems (i.e., variations in load density, underground versus overhead lines, loading conditions, and historic investment across different service areas). Conducting further analysis using utility-specific datasets and examining the diversity in utility distribution systems would enhance the accuracy of any future work. As previously referenced, while not a central aspect of this study, the costs for the five-state study were extrapolated to the rest of the continental United States (including the District of Columbia); this approach and the corresponding results are detailed in Appendix B.

[91] Based on NREL analysis of 2021 EIA Form 861 data.

Study Conclusions

Key Finding #1: Annual charging infrastructure needs could increase by 3% across five states in scenarios consistent with the EPA proposals.

Five-state simulation results (Table 25) show that 14.3 million public and private charging ports are estimated as necessary to support 20 million PEVs across five states in the 2032 Action scenario. This represents 2.3 million incremental ports relative to the No Action scenario, an increase of 19%. As the EPA proposals apply to model years 2027 through 2032, this averages to an annual increase of 3% over six years. The vast majority of these incremental ports (97%) are used for alternating current (AC) charging of light- and medium-duty vehicles. However, incremental costs (including grid upgrades) for high-power direct current (DC) charging of heavy-duty vehicles remain significant because of unit costs that are 1–2 orders of magnitude larger.

The $7.5 billion in funds currently available via the National Electric Vehicle Infrastructure Formula Program pursuant to the Infrastructure Investment and Jobs Act provide a foundational incentive to develop a national charging network across the states, both from an installation and manufacturing perspective. For context, based on current publicly-announced quantified capabilities, U.S. manufacturers can produce over 1,000,000 chargers each year, including 60,000 DC chargers.[92] Furthermore, though not quantified here, the Inflation Reduction Act of 2022 extended the Internal Revenue Code Section 30C tax credit, incentivizing up to 30 percent of the cost of recharging property (up to $100,000 for each item of depreciable property, and up to $1,000 otherwise) until 2032.[93]

Table 25: *Simulated 2032 Network Size for the Five-State Study by Vehicle Weight Class and EVSE Type. AC ports include Level 1 and Level 2 charging; DC ports include units rated for peak powers between 50 kW and 1.5 MW per port.*

		Simulated Five-State Network Size (ports)			
Vehicle Class	**EVSE Type**	**No-Action**	**Action**	**Incremental**	**Percent Increase**
L/MDV (Class 1-3)	AC Ports	11,800,000	14,000,000	2,200,000	19%
	DC Ports	68,000	85,000	17,000	25%
HDV (Class 4-8)	AC Ports	23,000	38,000	15,000	64%
	DC Ports	173,000	207,000	34,000	19%
Total		12.0 million	14.3 million	2.3 million	19%

[92] U.S. Department of Energy. Building America's Clean Energy Future. February 25, 2024. Available at: https://www.energy.gov/invest.
[93] U.S. Internal Revenue Service. Alternative Fuel Vehicle Refueling Property Credit. February 2, 2024. Available at: https://www.irs.gov/credits-deductions/alternative-fuel-vehicle-refueling-property-credit

Key Finding #2: Incremental distribution grid investment needs represent approximately 3% of current annual utility investments in the distribution system for scenarios consistent with the EPA proposals.

As shown in Table 26, this study estimates an incremental distribution grid investment of $2.3 billion over six years for the five states under study (2023 dollars). Incremental distribution grid upgrade investment needs[94] can be compared to existing utility distribution system investments. Based on utility reports to the Federal Energy Regulatory Commission, data from electric co-ops, and extrapolation for the remaining utilities, we estimate that as of 2021, utility investments in distribution systems, nationwide, exceeded $60 billion annually.

We estimate the share of that utility distribution investment for the five states evaluated in this study is $15 billion per year. Based on this, the EPA proposals represent approximately 3% of current annual utility investments in distributions systems between 2027 and 2032 across the five states studied. As also shown in the table, incremental charging infrastructure capital investment needed across the five states under study for 2027 is $865 million and gradually increases the deployment of charging to total $9.7 billion by 2032.

Across the five states the study estimated a combined investment of $12.0 billion in incremental charging and distribution grid infrastructure in 2032. Over the six model years from 2027 through 2032, this averages to an annual incremental investment of $2.0 billion in charging and distribution grid infrastructure. This investment would support the incremental manufacturing and installation of 2.3 million charging ports, eight distribution substations, 125 feeders, and 30,000 service transformers, without the use of managed charging. Notably, substation, transformer bank and service transformers built by 2027 mostly cover 2032 needs based off size assumptions for existing and new substations; feeder upgrades are still triggered in 2032.

[94] By design, this study presents incremental grid upgrade results describing the relative investment difference between PEV adoption scenarios that could occur with and without the pending EPA regulations. The study identifies where and when the electric distribution grid may require capacity enhancements under certain PEV adoption and charging behavior scenarios. The study does not predict the absolute levels of distribution grid investment needed in the long term.

Table 26. *Incremental 2027 and 2032 Simulation Results for the Five-State Study (relative to No Action)*

Five-State Scenarios (2027)	**Action vs. No Action**	
	Unmanaged	**Managed**
Incremental PEV adoption (all weight classes)	300,000	
Incremental charging ports (all types)	250,000	
Incremental charging infrastructure capital investment	$865 million	
Incremental substations	1	0
Incremental feeders	9	5
Incremental service transformers	2,800	2,400
Incremental distribution grid capital investment	$195 million	$82 million
Combined incremental infrastructure capital investment	$1.1 billion	$947 million

Five-State Scenarios (2032)	**Action vs No Action**	
	Unmanaged	**Managed**
Incremental PEV adoption (all weight classes)	3.9 million	
Incremental charging ports (all types)	2.3 million	
Incremental charging infrastructure capital investment	$9.7 billion	
Incremental substations	8	4
Incremental feeders	125	75
Incremental service transformers	30,000	21,000
Incremental distribution grid capital investment	$2.3 billion	$1.6 billion
Combined incremental infrastructure capital investment	$12.0 billion	$11.3 billion

Identification of these costs, while important, is just the first step in understanding how to equitably allocate them. A key finding from this study is the importance of taking the next step to allocate distribution costs to PEV loads served by new distribution capacity as well as non-PEV loads that could also be served by such new capacity, the latter of which was out of scope. Follow-on analysis is needed to allocate distribution costs among these multiple types of customers.

Key Finding #3: Managed charging techniques can decrease incremental distribution grid investment needs by 30%, illustrating the potential for significant cost savings by optimizing PEV charging and other loads at the local level.

Proactive utility planning, tariff structures, and vehicle-grid integration technologies and strategies will mitigate grid infrastructure investment needs. The incremental distribution grid capital investment of $2.3 billion estimated by this study is reduced 30% to $1.6 billion when PEV charging loads at home and depot locations are managed. This result is driven by the ability of PEVs to shift charging to off-peak hours based on parking durations that exceed the time necessary to charge and by strategically locating chargers, thereby avoiding potential overloading and thermal violations that otherwise drive distribution equipment upgrades. Managing charging could substantially reduce incremental grid components needs, including for substations by 50%, feeders by 40%, and service transformers by 30%. A 30% reduction in PEV peak load was simulated in the Action–Managed scenario.

When considering all electric loads, this translates to a reduction in total peak load of between 0.4% and 4.5% depending on the state. Although this management strategy ensures that peaks from PEV charging are reduced, within the context of this study, the strategy is agnostic to non-PEV residential, commercial, and industrial loads on the distribution network (meaning simulated PEV loads are not optimized relative to non-PEV loads). Accordingly, the results present a conservative estimate of the potential distribution grid savings from managing charging load locally.

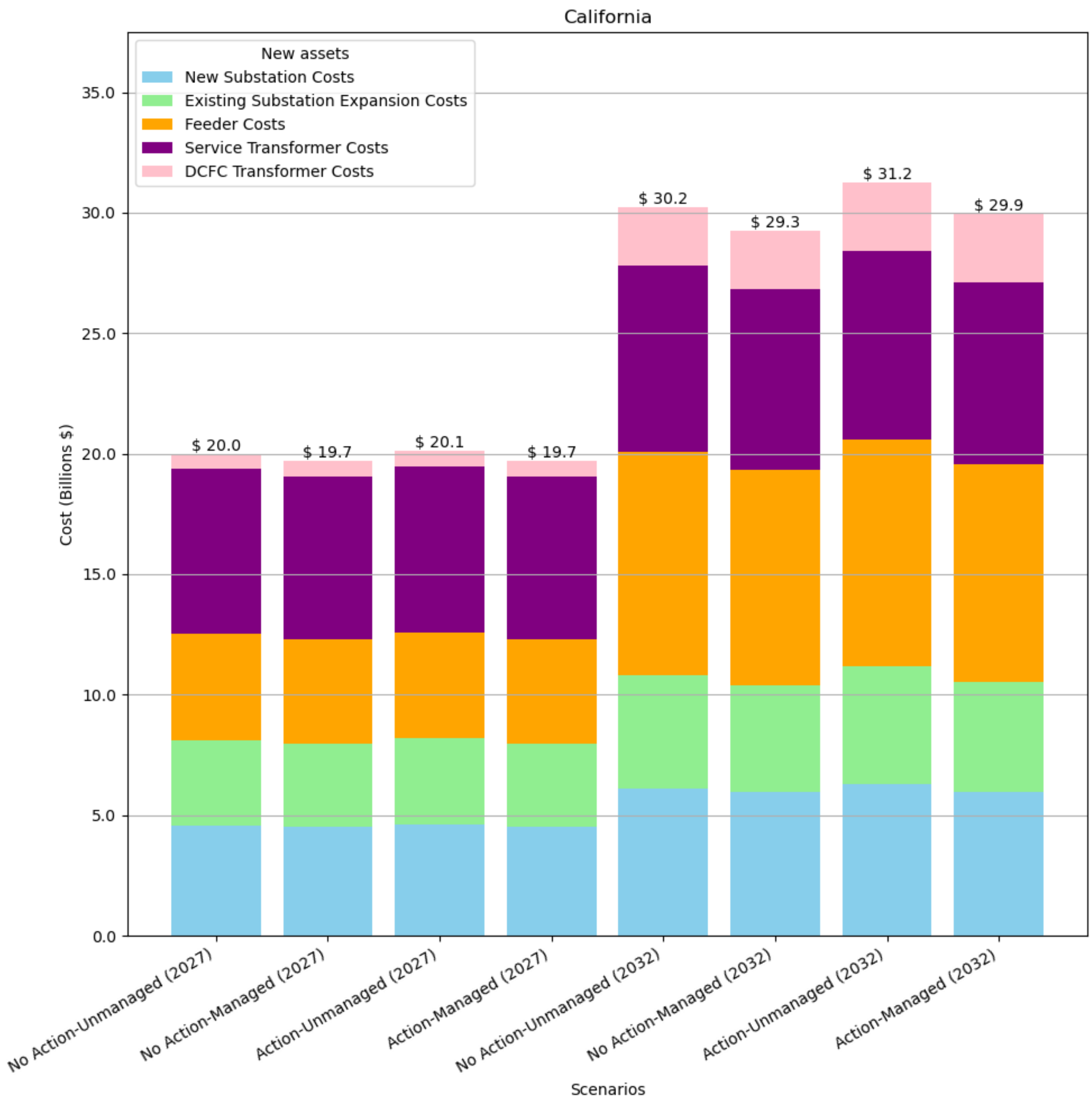
Key Finding #4: Consumer benefits from vehicle electrification significantly outweigh the estimated cost of charging and grid infrastructure costs in scenarios consistent with the EPA proposals.

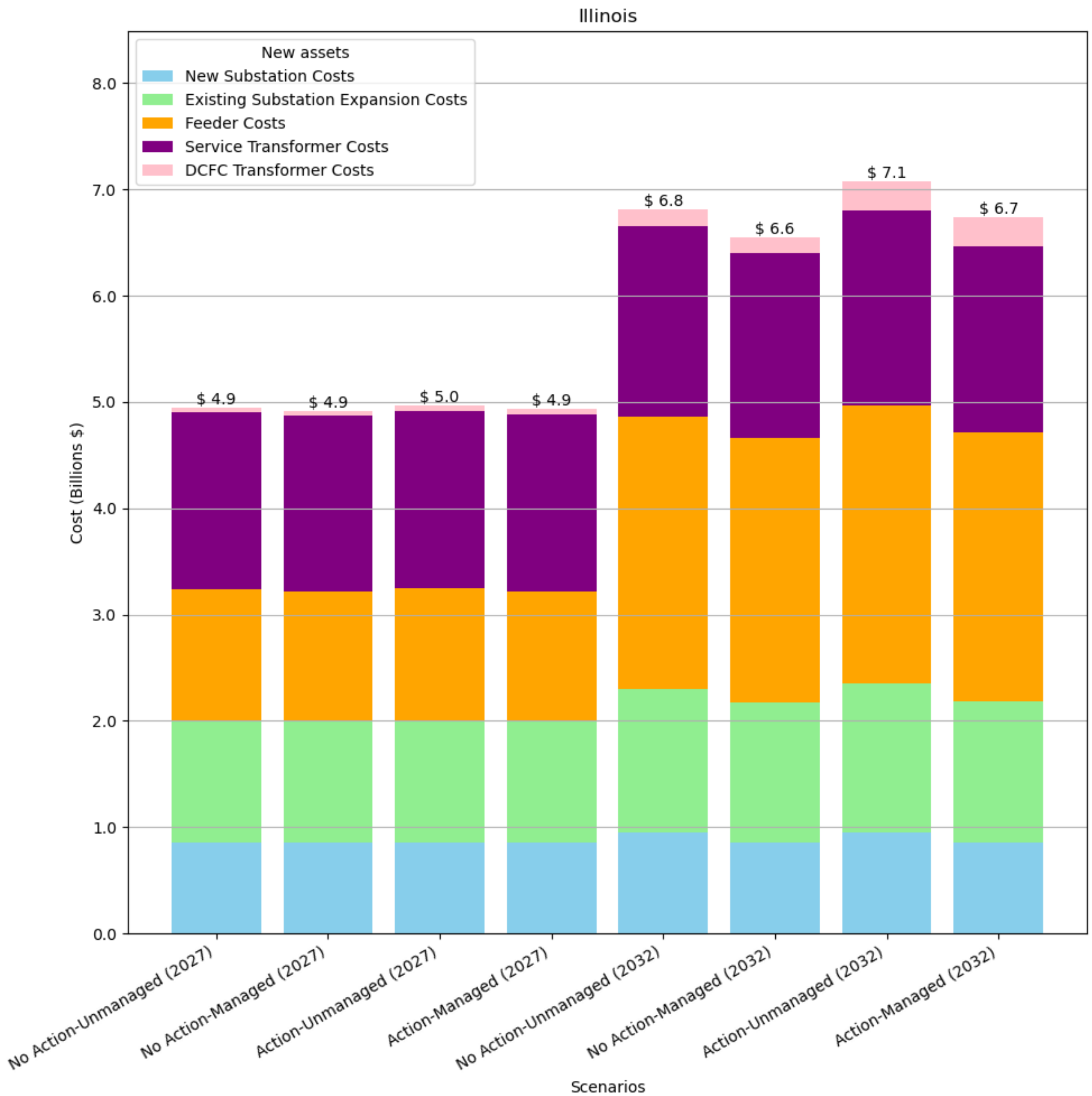
Based on levelized cost of driving from NREL's 2022 Transportation Annual Technology Baseline,[95] by 2030, PEVs are expected to provide $8,300 per vehicle in lifetime net benefits to consumers, including fuel savings but excluding the value of avoided emissions (fleet-weighted average using the EPA's adoption scenario and infrastructure costs consistent with this study). This conservative estimate of net benefits ($33 billion for the 3.9 million incremental PEVs by 2032), which does not allocate distribution costs among other potential loads that might use incremental grid infrastructure, is more than 2.5 times greater than the combined capital investment in charging infrastructure and grid upgrades estimated by this work.

[95] National Renewable Energy Laboratory, "Annual Technology Baseline," https://atb.nrel.gov/.

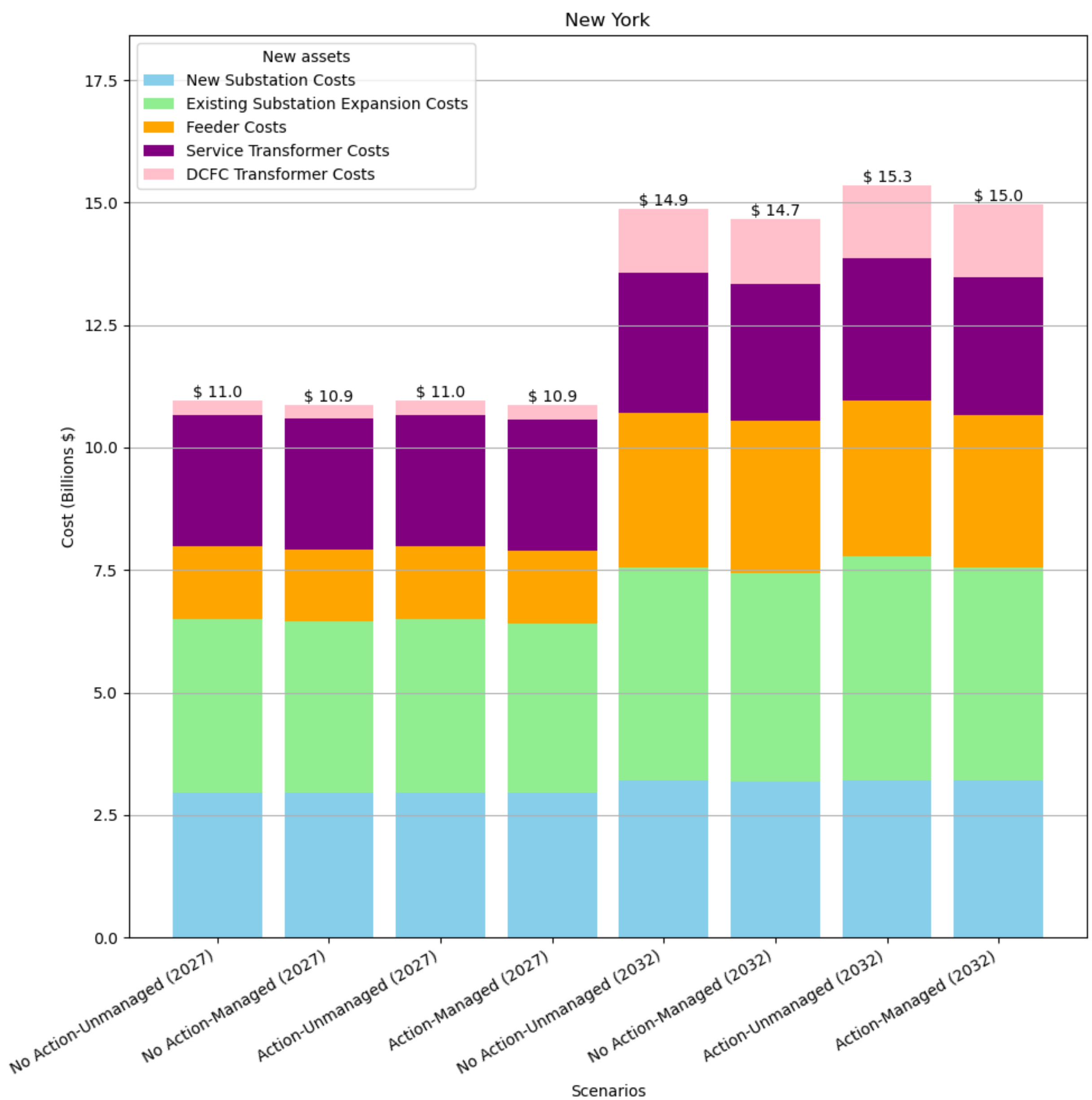
Appendix A. State Distribution Investment Costs

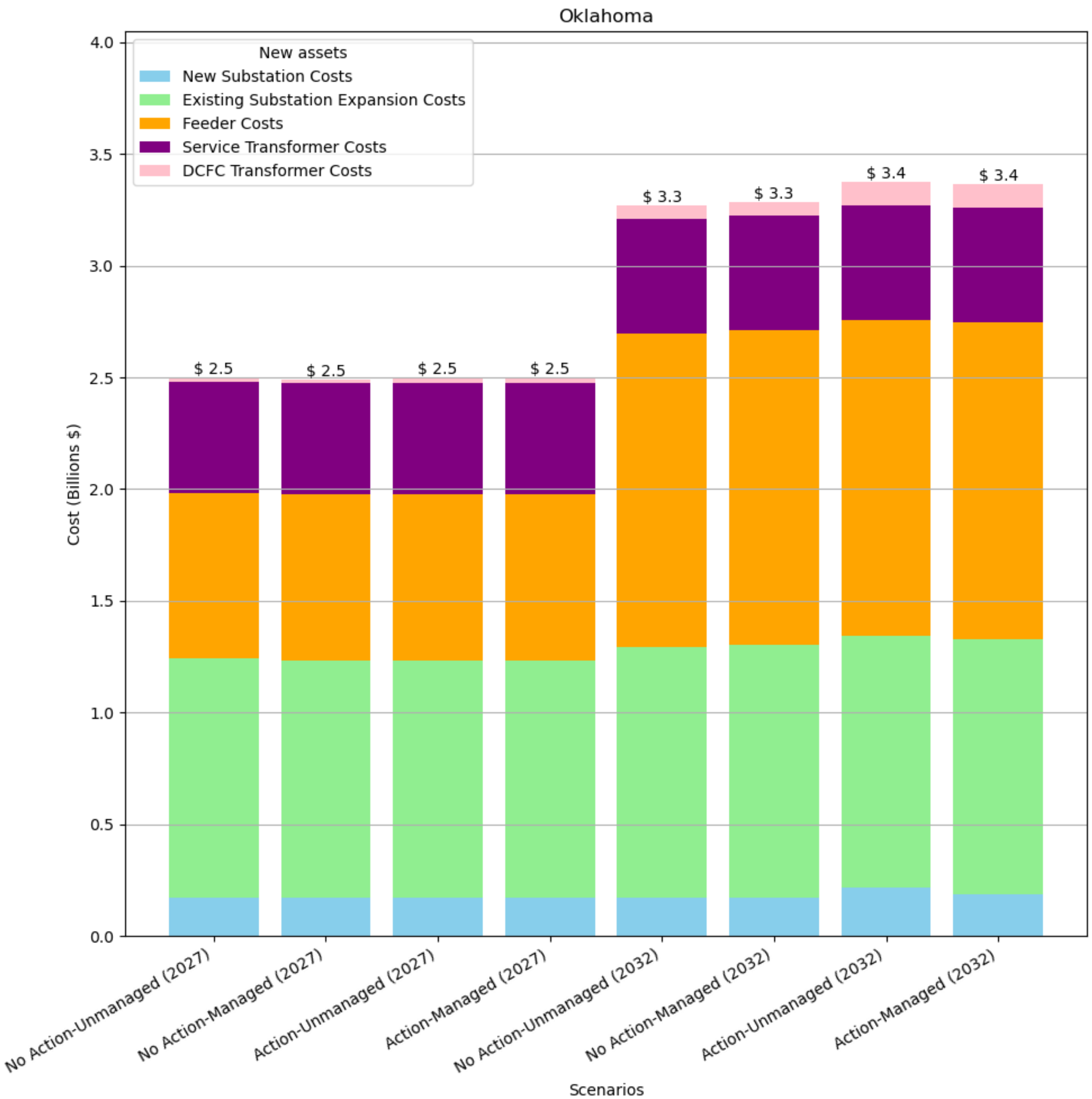
The total costs for all scenarios for 2027 and cumulative through 2032 by grid asset category type are shown in the following figures. Note that "New Substation Costs" specifically refers to new substations in each figure in this Appendix section.

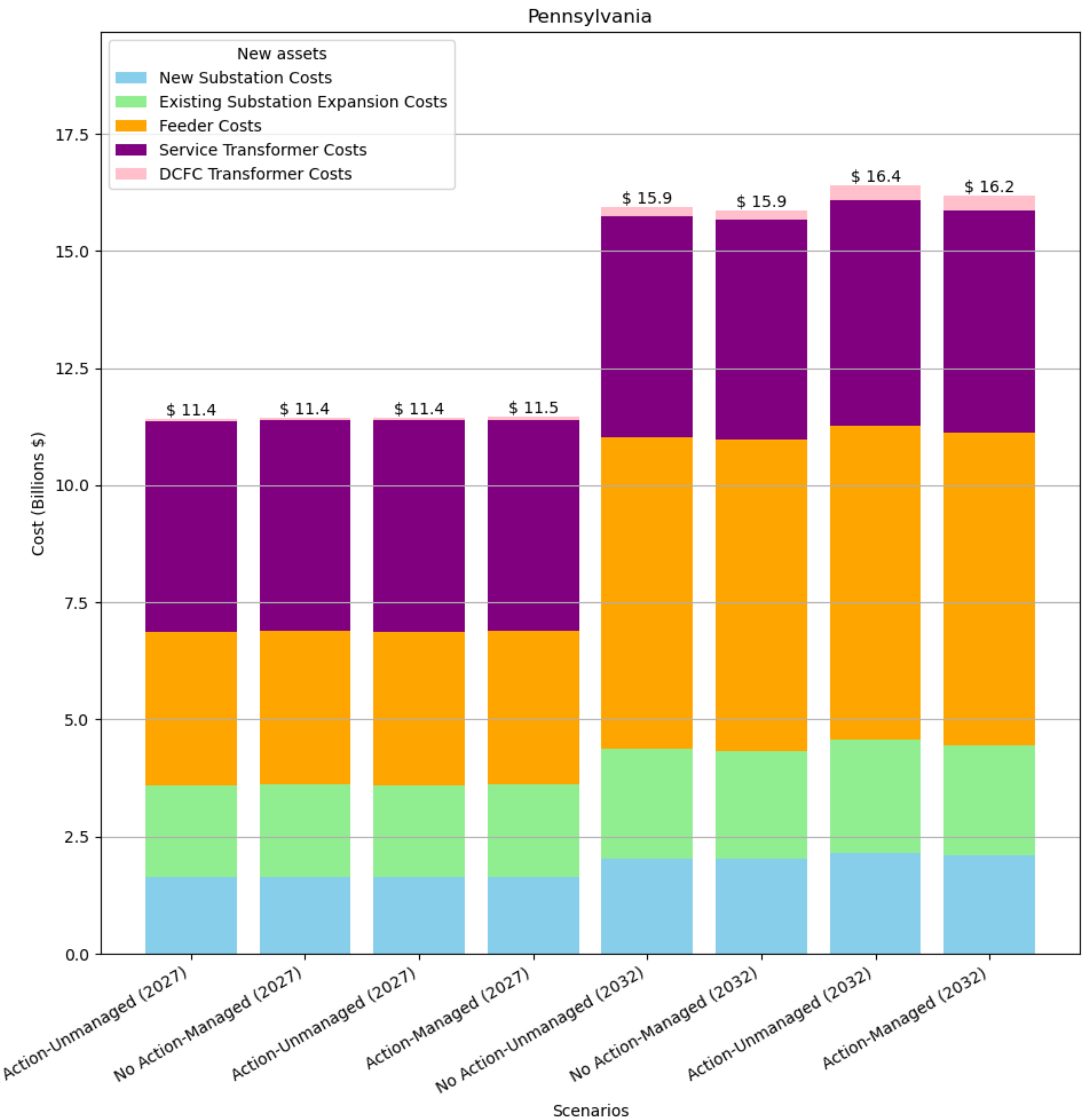




Illinois
New assets
New Substation Costs
Existing Substation Expansion Costs
Feeder Costs
Service Transformer Costs
DCFC Transformer Costs
Cost (Billions $)
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
$ 4.9
$ 4.9
$ 5.0
$ 4.9
$ 6.8
$ 6.6
$ 7.1
$ 6.7
No Action-Unmanaged (2027)
No Action-Managed (2027)
Action-Unmanaged (2027)
Action-Managed (2027)
No Action-Unmanaged (2032)
No Action-Managed (2032)
Action-Unmanaged (2032)
Action-Managed (2032)
Scenarios


New York
New assets
New Substation Costs
Existing Substation Expansion Costs
Feeder Costs
Service Transformer Costs
DCFC Transformer Costs
Cost (Billions $)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
$ 11.0
$ 10.9
$ 11.0
$ 10.9
$ 14.9
$ 14.7
$ 15.3
$ 15.0
No Action-Unmanaged (2027)
No Action-Managed (2027)
Action-Unmanaged (2027)
Action-Managed (2027)
No Action-Unmanaged (2032)
No Action-Managed (2032)
Action-Unmanaged (2032)
Action-Managed (2032)
Scenarios


Oklahoma
New assets
New Substation Costs
Existing Substation Expansion Costs
Feeder Costs
Service Transformer Costs
DCFC Transformer Costs
Cost (Billions $)
$ 2.5
$ 2.5
$ 2.5
$ 2.5
$ 3.3
$ 3.3
$ 3.4
$ 3.4
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
No Action-Unmanaged (2027)
No Action-Managed (2027)
Action-Unmanaged (2027)
Action-Managed (2027)
No Action-Unmanaged (2032)
No Action-Managed (2032)
Action-Unmanaged (2032)
Action-Managed (2032)
Scenarios


Pennsylvania
New assets
New Substation Costs
Existing Substation Expansion Costs
Feeder Costs
Service Transformer Costs
DCFC Transformer Costs
Cost (Billions $)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
$ 11.4
$ 11.4
$ 11.4
$ 11.5
$ 15.9
$ 15.9
$ 16.4
$ 16.2
No Action-Unmanaged (2027)
No Action-Managed (2027)
Action-Unmanaged (2027)
Action-Managed (2027)
No Action-Unmanaged (2032)
No Action-Managed (2032)
Action-Unmanaged (2032)
Action-Managed (2032)
Scenarios

Appendix B. Extrapolation of Results

The bottom-up distribution network cost results for the five states developed by Kevala corresponded to a county-wide geography and the years 2027 and 2032. The EPA benefit-cost analysis has a different scope, namely 2028–2055 at IPM-region resolution. This scope required an extrapolation of the five-state cost results (see Figure 28 in the Modeling Approach chapter for a high-level overview of the methodology to take the five-state study costs to the national level).

Specifically, the extrapolation required extending the five-state costs to the 64 IPM regions for the contiguous 48 states, including the District of Columbia, in 2027 and 2032. Kevala used these results to interpolate costs between 2027 and 2032 and extrapolate temporally to 2055 in five-year increments starting in 2035.

Because the five-state cost estimates Kevala developed were based on load growth between 2023 and 2027 and then from 2027 to 2032, the costs needed to differentiate between baseline load and transportation electrification load growth. Kevala used its baseline load forecast and the EVSE load curves provided by NREL and LBNL to estimate the contribution to the change in coincident peak from 2023 to 2027 and 2027 to 2032 for each driver of growth. Table Error**! No text of specified style in document.**-1 shows the percentage change in incremental coincident peak attributable to EVSE load by state, year, and scenario.

***Table** Error! No text of specified style in document.**-1.** Contribution to Incremental Coincident Peak Resulting from EVSE Load (Source: Kevala)*

	2027				2032			
	No Action		Action		No Action		Action	
State	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed
CA	42%	29%	42%	30%	40%	31%	43%	35%
IL	30%	18%	33%	20%	40%	26%	56%	34%
NY	23%	21%	24%	22%	29%	27%	33%	31%
OK	17%	13%	20%	15%	30%	23%	40%	32%
PA	18%	10%	20%	11%	23%	14%	31%	20%

The relationship of costs by scenario for EVSE also changed because of applying the contribution to peak values. As Figure **Error! No text of specified style in document.**-1 shows, the difference between the Managed and Unmanaged scenarios is much greater.

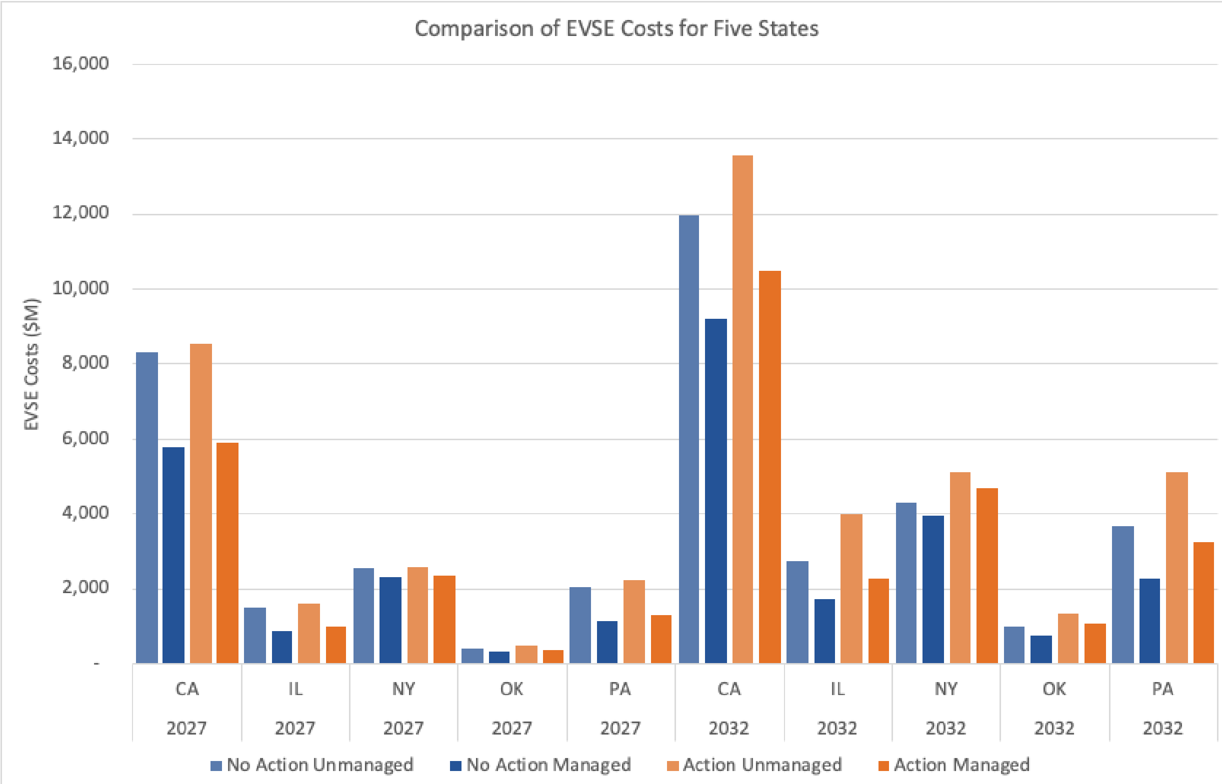


Figure Error! No text of specified style in document.**-1.** Comparison of EVSE distribution costs for five states in 2027 and 2032 *(Source: Kevala)*

Kevala then developed two methodologies for extrapolating the baseline load and EVSE-related costs. To extrapolate the baseline load, Kevala estimated a cost per gigawatt-hour (GWh) using the annual energy and baseline allocated costs for each state in 2027 and 2032. Table Error**! No text of specified style in document.**-2 shows these estimates.

***Table** Error! No text of specified style in document.**-2.** Cost ($) per GWh of Load (Source: Kevala)*

	2027				2032			
State	No Action		Action		No Action		Action	
	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed
CA	1,650	1,964	1,636	1,951	2,575	2,829	2,492	2,746
IL	506	593	491	581	597	711	454	656
NY	6,529	6,654	6,502	6,595	8,214	8,328	7,958	7,974
OK	251	262	241	256	275	303	243	277
PA	2,544	2,785	2,494	2,753	3,326	3,676	3,057	3,498
AVG	**1,288**	**1,434**	**1,270**	**1,419**	**1,746**	**1,902**	**1,630**	**1,818**

These costs per GWh were then applied to the forecasted loads, less transportation, for each IPM region in 2027 and 2032. These results were then interpolated for 2028 and 2032 using the compound average growth rate (CAGR) between 2027 and 2032, calculated as shown in Equation B-1.

Equation** Error! No text of specified style in document.**-1. Estimation of CAGR

$$CAGR_{2032}^{2027} = \left(\frac{Load_{2032}^{IPM}}{Load_{2027}^{IPM}}\right)^{\left(\frac{1}{5}\right)} - 1$$

This same CAGR was then used to extrapolate 2032 through 2055. Note that the load growth is slightly different across the four scenarios because the contribution to peak due to baseline load growth differed among the scenarios. Kevala chose to use a cost per kilowatt-hour (kWh) rather than a cost per coincident peak because the coincident peak of each IPM region was not available.

To extrapolate the EVSE-related costs, Kevala developed a multistep method. The primary challenge was to develop a method that could translate cost estimates based on asset type (feeder, service transformer, and substation) to geographically defined costs (IPM region). Kevala chose to estimate a cost per EVSE derived from the five-state costs attributed to EVSE. The first step was to compute a cost per kilowatt (kW) of additional capacity, defined as the asset's rating (see ***Equation** Error! No text of specified style in document.**-2***).

Equation** Error! No text of specified style in document.**-2. Estimation of cost per kW for each asset

$$kWCost_{Asset} = \frac{Cost_{Asset}}{Rating_{Asset}}$$

Figure Error**! No text of specified style in document.**-2 shows the average cost per kilowatt by asset type and state. These costs per kilowatt by asset type were assigned to parcels connected to and making use of that particular asset.

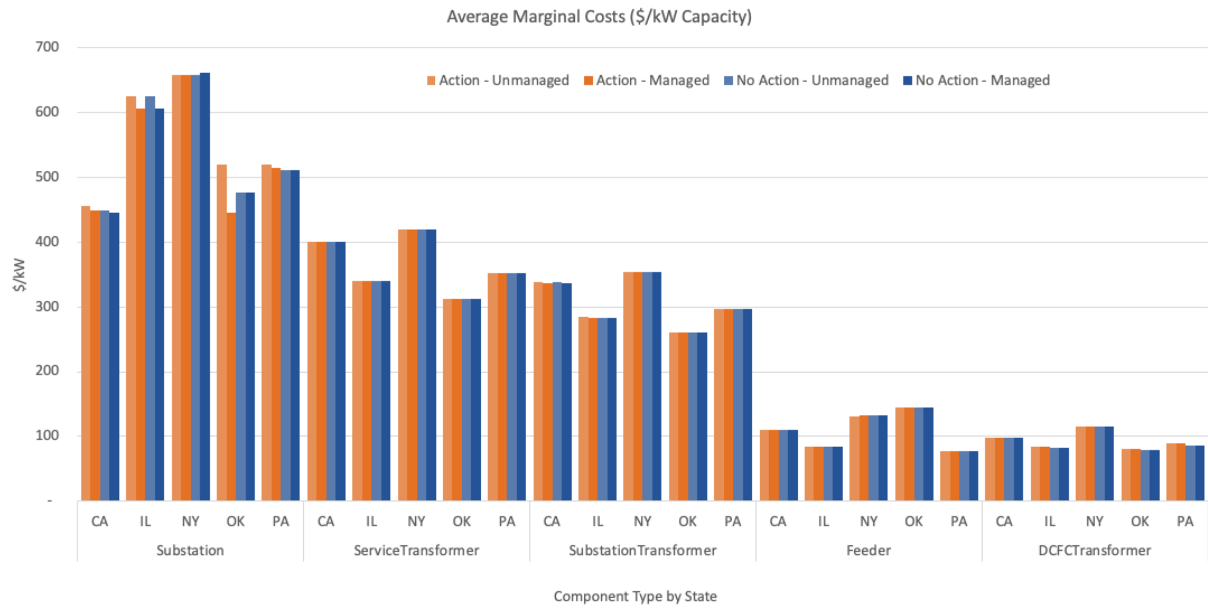


Figure Error! No text of specified style in document.**-2.** Average marginal costs per kW of capacity *(Source: Kevala)*

To estimate the cost of an EVSE at a parcel, Kevala first estimated the cost per kilowatt of EVSE demand at the parcel by applying a contribution to the noncoincident peak of an EVSE type, by county, relative to the cumulative noncoincident peak of all EVSE in the county. This contribution to noncoincident peak value was then applied to the $/kW cost at the parcel to reflect the costs allocated to that parcel. Last, Kevala applied the cost per EVSE kW attributable to the parcel to the noncoincident peak of the EVSE load at the parcel to derive the total cost at the parcel for the EVSE load and then aggregated the parcel costs and parcel ports by county to estimate a port-weighted cost per EVSE by county.

Initially, Kevala tried to use these county estimates of costs per EVSE along with key census data (e.g., commuting by car, homeownership, population density, and income) at a county level to develop a statistical model to extrapolate the EVSE costs to all counties nationwide using county-specific census data; however, Kevala could not find a reliable statistical relationship among these variables. This is due to the lack of correlation between existing and additional grid infrastructure capacity and demographics, which is reasonable given that energy delivered via the electric grid has evolved largely independently from transportation demand. As a result, Kevala adopted a weighted average approach using the EVSE cost for all counties in the five states and calculating an average cost per EVSE type, weighted by ports.

Kevala applied this cost per EVSE type to the forecasts of ports by IPM region in 2027, 2028, 2030, 2032, 2035, 2040, 2045, 2050, and 2055 provided by NREL and LBNL. The sum total provided the estimate of EVSE costs out to 2055. Because this method involved several averaging steps, the results deviate from the five-state result. Similarly, because costs were estimated at two points in time (2027 and 2032), the change in cost per EVSE between these two periods needed to be interpolated to better reflect the gradual change in 2028 and 2030 of the cost per EVSE rather than a step-function change in 2032.

Kevala used two techniques to calibrate and smooth these results. To calibrate, Kevala calculated the equivalent of the extrapolation values for the five study states in 2027 and 2032 and applied the CAGR for the cumulative cost change to obtain an estimate of extrapolated costs in 2028 and 2030. Interpolating 2028 and 2030 costs from the five-state study costs allocated to EVSE by CAGR from 2027 to 2032, Kevala was able to estimate equivalent study results for all four years. Kevala applied the ratio of extrapolated costs to the five-state costs to scale the final results and smooth the cost between 2027 and 2032 (see Figure Error**! No text of specified style in document.**-3).

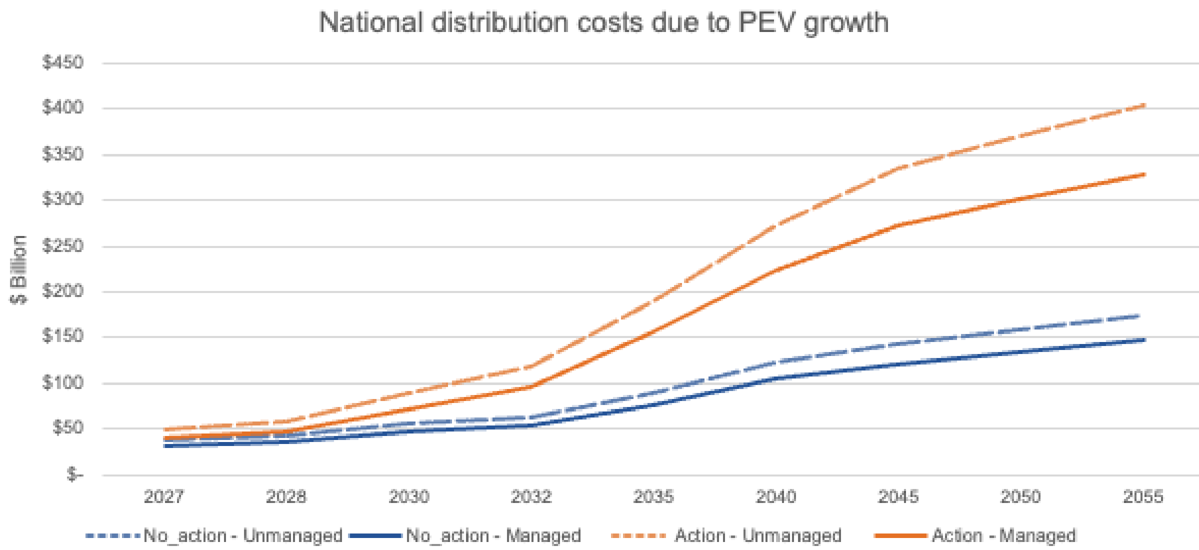


Figure Error! No text of specified style in document.**-3.** Extrapolated nationwide cumulative distribution costs for all scenarios from 2027 through 2055. Although these costs are national, the extrapolation is conducted to reflect the cost components for the five study states in 2027 and 2032 in the bottom-up study. *(Source: Kevala)*

To confirm the results, Kevala examined the share of EVSE costs from the five-state study and compared them to the extrapolated nationwide results. Figure Error**! No text of specified style in document.**-4 shows that the five states include approximately 30%–35% of the total costs, depending on the scenario, with the Unmanaged scenarios showing a greater share of total costs than the Managed scenarios.

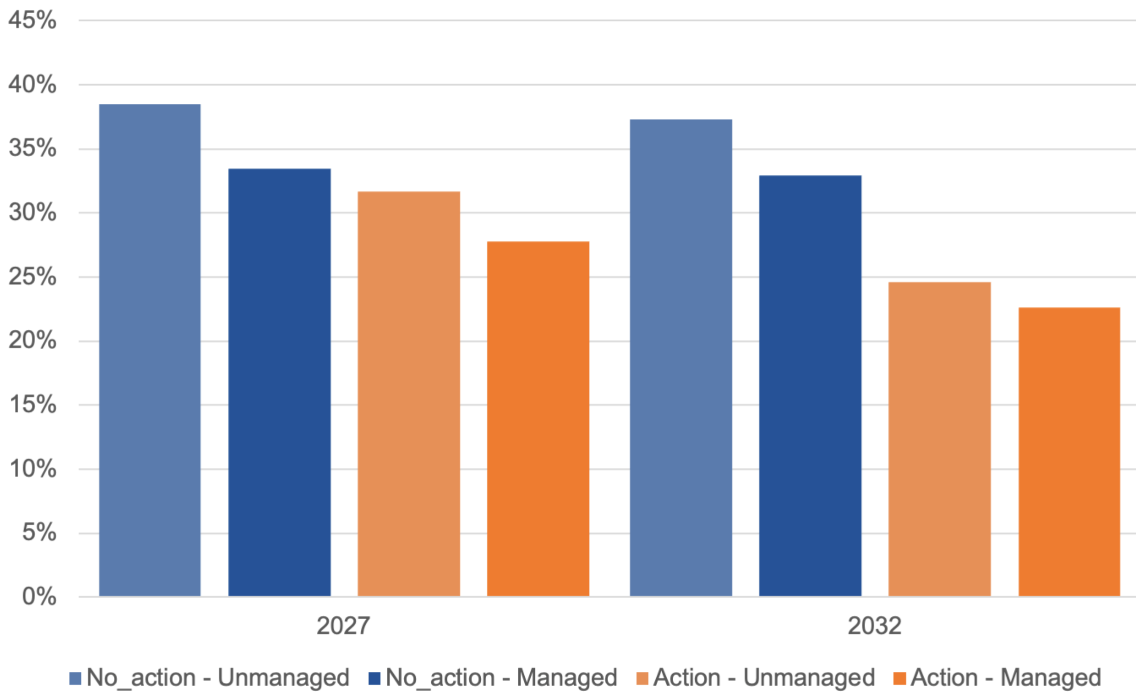


Figure Error! No text of specified style in document.**-4.** Comparison of five-state costs to national cost *(Source: Kevala)*

Because the extrapolation for EVSE costs is greatly driven by EVSE port forecasts, Kevala also looked at the level ports adopted by EVSE type and the change in that forecast from the No Action to the Action scenarios. Figure Error**! No text of specified style in document.**-5 and Figure Error**! No text of specified style in document.**-6 show the distribution of ports by EVSE type by scenario in 2032. Figure Error**! No text of specified style in document.**-7 shows the change in port forecasts by EVSE type.

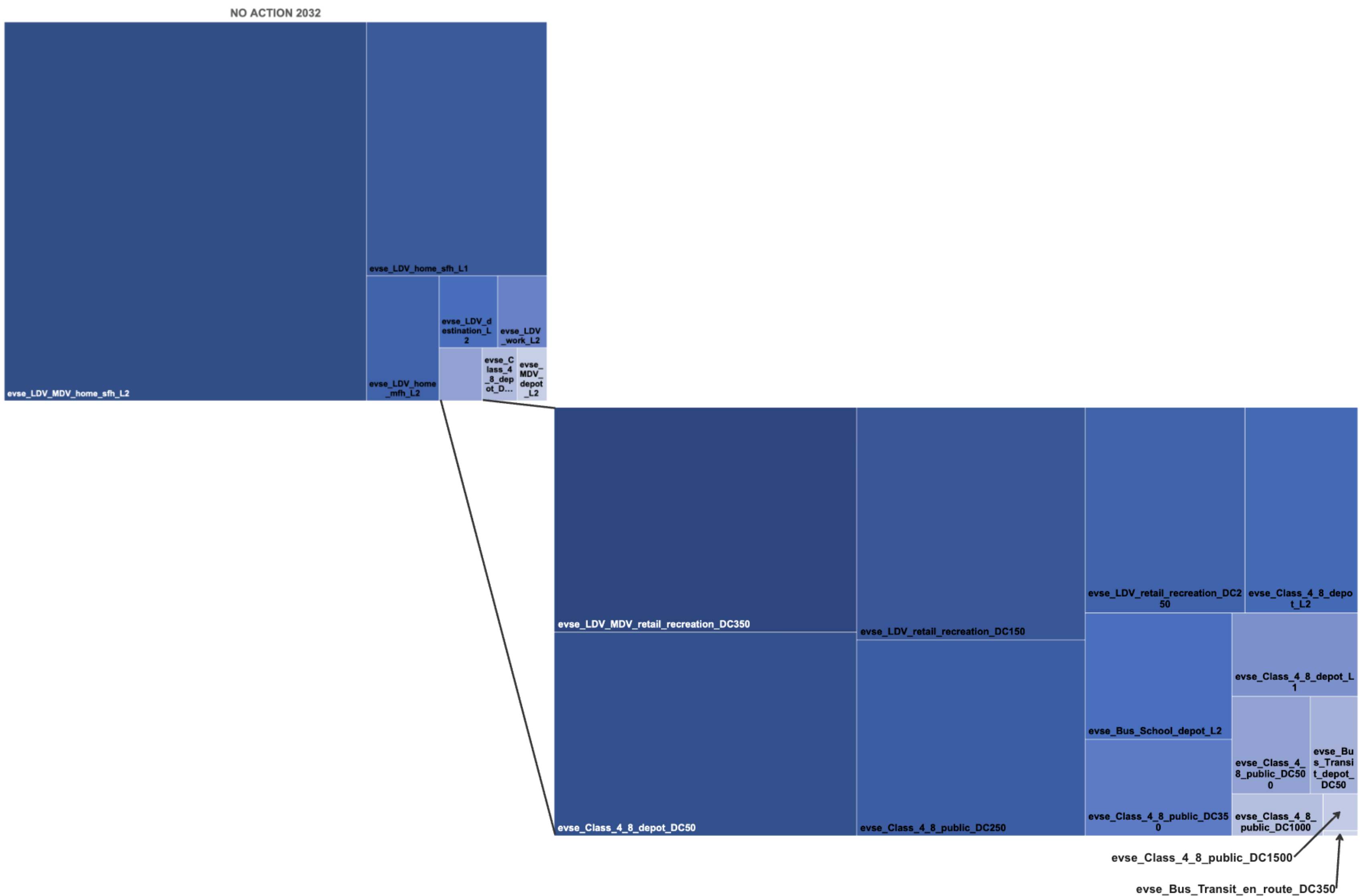


Figure Error! No text of specified style in document.**-5.** Distribution of ports by EVSE type in 2032 (No Action scenario) *(Source: Kevala)*

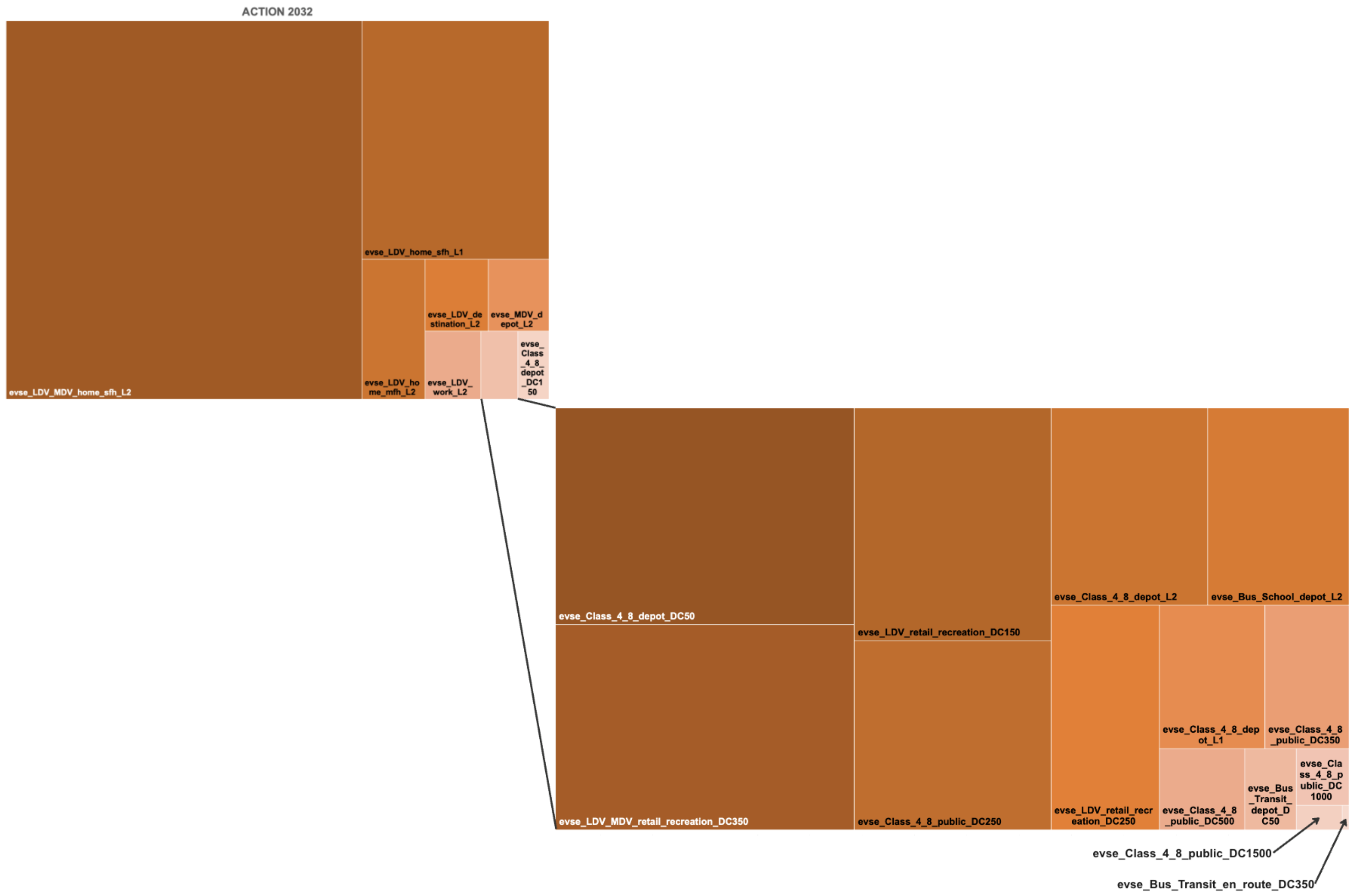


Figure Error! No text of specified style in document.**-6.** Distribution of ports by EVSE type in 2032 (Action scenario) *(Source: Kevala)*

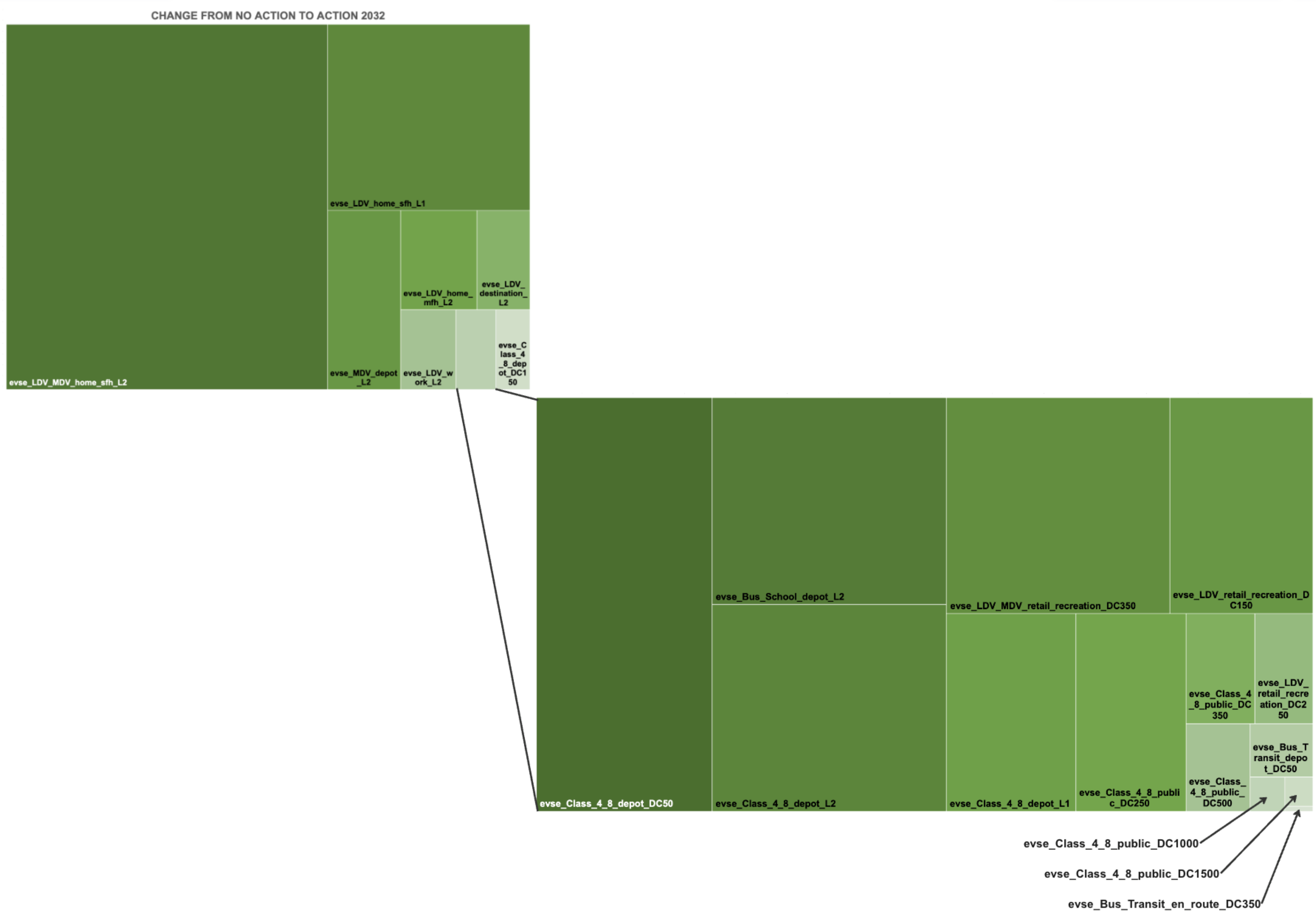


Figure Error! No text of specified style in document.**-7.** Change in port forecasts by EVSE type in 2032 based on policy adoption *(Source: Kevala)*

The final step was to derive the cost per EVSE type by scenario that could be applied to other studies. This involved scaling the weighted average cost per EVSE derived from the five-state study to the calibration targets used. These distribution grid upgrade costs per EVSE are shown in Table Error**! No text of specified style in document.**-3.

Figure Error**! No text of specified style in document.**-8 shows the extrapolated distribution costs by region. This shows that 10 IPM regions (PJM_EMAC, four Western Electricity Coordinating Council regions [CALN, SCE, PNW, and LADW], NENGREST, FRCC, ERC_West, S_VACA, and S_SOU) comprise approximately 50% of the total EVSE costs (see Appendix F for a list of IPM regions).

In the future, additional studies could be undertaken using parcel-level granularity similar to that of the five states analyzed in this study.

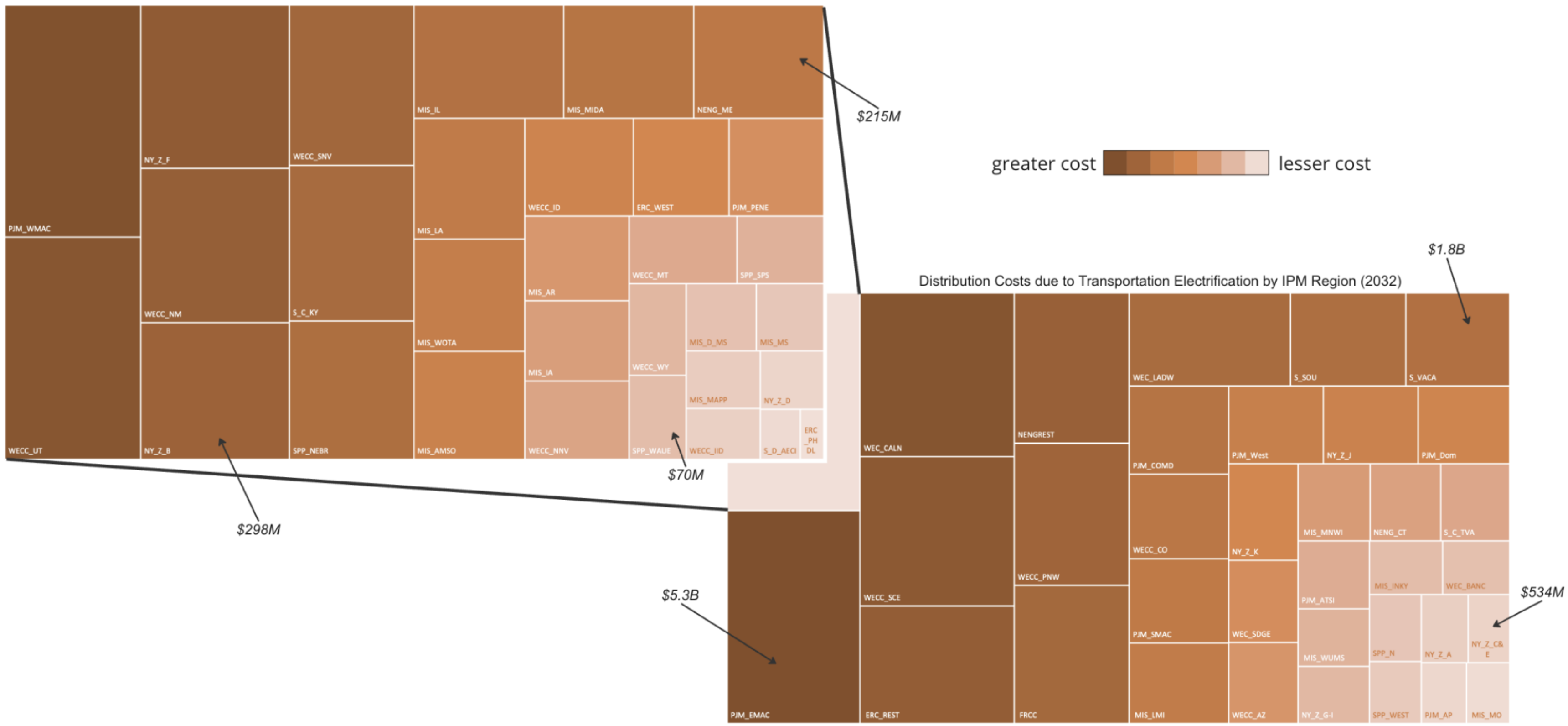


Figure Error! No text of specified style in document.**-8.** Extrapolated nationwide distribution costs by IPM region for the No Action–Unmanaged scenario, EVSE costs by IPM *(Source: Kevala)*

***Table** Error! No text of specified style in document.**-3.** Total Distribution Grid Upgrade Costs per EVSE Type (Source: Kevala)*

EVSE Type	2027				2032			
	No Action		Action		No Action		Action	
	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed	Unmanaged	Managed
evse_Bus_School_depot_L2	16,773	5,839	33,603	14,391	9,718	3,579	21,857	9,797
evse_Bus_Transit_depot_DC50	37,177	27,371	44,932	32,770	22,188	17,446	31,004	24,040
evse_Bus_Transit_en_route_DC350	8,197	7,269	8,824	7,888	9,410	8,883	11,125	10,363
evse_Class_4_8_depot_DC150	64,990	50,433	70,947	53,947	37,160	30,967	47,054	37,979
evse_Class_4_8_depot_DC50	74,944	49,769	61,711	42,722	41,267	29,674	40,279	29,838
evse_Class_4_8_depot_L2-Low	12,441	10,635	16,726	14,650	7,114	6,539	11,415	10,627
evse_Class_4_8_depot_L2	51,469	35,878	44,584	35,339	28,338	21,629	28,963	24,729
evse_Class_4_8_public_DC1000	117,918	88,918	123,388	92,560	74,372	60,096	92,763	73,547
evse_Class_4_8_public_DC1500	210,406	150,903	365,946	248,219	145,342	113,096	256,578	187,379
evse_Class_4_8_public_DC250	41,921	32,617	33,923	26,305	24,450	20,384	23,866	19,575
evse_Class_4_8_public_DC350	57,184	43,691	54,973	42,377	34,253	28,121	39,422	32,178
evse_Class_4_8_public_DC500	68,719	53,527	82,419	66,705	41,773	34,874	57,923	49,316
evse_LDV_destination_L2	5,056	4,955	4,962	4,913	2,982	3,094	3,500	3,625
evse_LDV_home_mfh_L2	2,039	1,438	2,194	1,544	1,218	906	1,554	1,137
evse_LDV_home_sfh_L1	196	305	208	322	116	188	146	232
evse_LDV_MDV_home_sfh_L2	1,992	1,679	2,105	1,783	1,189	1,039	1,499	1,296
evse_LDV_MDV_retail_recreation_DC350	84,942	72,214	87,604	74,855	51,066	46,481	62,836	56,702
evse_LDV_retail_recreation_DC150	41,585	35,726	41,569	36,197	25,091	23,058	29,743	27,354
evse_LDV_retail_recreation_DC250	60,723	51,183	66,304	56,444	39,368	34,945	48,713	44,200
evse_LDV_work_L2	7,220	7,017	7,187	7,090	4,253	4,391	5,017	5,207
evse_MDV_depot_L2	31,371	17,596	33,730	19,109	17,377	10,336	22,718	13,334

Cost Scenarios and Sensitivity Analysis

To better understand the sensitivities of the results, Kevala generated high-case and low-case scenarios. The high case was based on assuming that substation costs are 15% higher and all other asset costs are 10% higher. Similarly, the low case was based on assuming that substation costs are 15% lower and all other asset costs are 10% lower. Table Error**! No text of specified style in document.**-4 shows the percent change in the high and low cases relative to the baseline. These percentages can be applied directly to the extrapolated value to develop high and low extrapolation results.

***Table** Error! No text of specified style in document.**-4.** Scenario Costs and Percent (%) Change From Base (Source: Kevala)*

	2027				2032			
	No Action		Action		No Action		Action	
State	Un-managed	Managed	Un-managed	Managed	Un-managed	Managed	Un-managed	Managed
High Case (percent from base)								
California	111	111	111	111	111	111	111	111
Illinois	111	111	111	111	110	110	110	110
New York	111	111	111	111	110	110	110	110
Oklahoma	110	110	110	110	110	110	110	110
Pennsylvania	111	111	111	111	110	111	110	110
Low Case (percent from base)								
California	89	89	89	89	89	89	89	89
Illinois	89	89	89	89	90	90	90	90
New York	89	89	89	89	90	90	90	90
Oklahoma	90	90	90	90	90	90	90	90
Pennsylvania	89	89	89	89	90	89	90	90

Appendix C. Future Work and Context of the Analysis

This section provides detailed qualitative and, where available, quantitative indications of where the upgrade analysis will benefit from future work to refine results with respect to absolute investment costs. The key focus of the study was on the incremental investment projected to be needed under the Action and No Action scenarios; it is expected that incremental costs may be less sensitive to some of the areas of future work raised here. Key areas identified include the following:

1. **Contingency conditions for substations:** Substation expansion and new substation investment represent more than one-third of the study's calculated total grid investment costs (see Appendix A). The study was able to identify both expansions of existing substations and new substation requirements. Utilities operate substations for N-1 contingency conditions, meaning that, typically, they are neither loaded at nor exceed nameplate capacity to facilitate load transfer in a contingency event (e.g., for a substation with four transformer banks, loading should not exceed 75%[96] such that the failure of any one bank can be absorbed by the other transformers). The loading threshold could be revisited in future studies to account for reduced available capacity that reflects utility practices for contingency ratings.
2. **Large standard deviation of loading/capacity:** Accurate estimates of capacity are critical for estimating available capacity and overloading. Future work will benefit from ensuring that errors in capacity estimates are not a significant driver of simulated capacity replacements. In this five-state study, the standard deviation for grid asset loading for some states sometimes exceeded 100%, resulting in substations that are overloaded even before vehicle electrification takes place. These should be examined in detail, and efforts should be taken to ensure that assets are not overloaded before electrification growth is added and, specifically, that upgrades required by existing overloads are not attributed to electrification growth.
3. **Low utilization of new substation transformer banks and new substations:** The mean utilization of new substations transformer banks (4.65% across all scenarios and all states in 2032, not adjusting for state capacity) and new substations (3.18% across all scenarios and all states in 2032, not adjusting for state capacity) is very low. As this utilization level could be used to support additional non-PEV loads, it is critical to perform cost allocation only to the capacity used by PEVs. If significant grid capacity were added that could be used for future electrification and other load growth, the overall impact would result in a lower cost allocation to PEVs.
4. **Undergrounding costs:** Estimating underground distribution infrastructure is a challenge, particularly when using machine-learning- and satellite-image-based estimation techniques. Estimates from 2007 calculated that, nationwide, approximately 18% of the distribution system was underground. For four of the states in this study, the estimates for the volume of underground grid infrastructure appear lower than other state and national statistics. Improving estimated underground infrastructure could provide significant impacts to estimated investments given that underground costs can be five to 10 times those of overhead costs.[97]

[96] Liberty Utilities, *Electric Distribution Planning Criteria* (Londonderry, NH: 2019), New Hampshire Public Utilities Commission, https://www.puc.nh.gov/Regulatory/Docketbk/2019/19-120/INITIAL%20FILING%20-%20PETITION/19-120_2019-07-15_GSEC_ATT2_TESTIMONY_JOHNSON_RIVERA_STRABONE_TEBBETTS.PDF.
[97] EIA, "Power Outages Often Spur Questions Around Burying Power Lines," Today in Energy, July 25, 2012, https://www.eia.gov/todayinenergy/detail.php?id=7250.

5. **Drivers of grid investment not considered:** The focus of this study was on examining the incremental investment required by Action and No Action scenarios, with a brief examination of how the incremental investment relates to ongoing investment. The study focus was not to quantify the total relative investment increase for electrification versus regular investment nor any potential overlap with ongoing and other investment categories (i.e., the analysis does not present how upgrades increase the rate of ongoing regular annual investment). Future work examining absolute investment costs would be critical to understand the overlap in investments for replacing aging infrastructure (i.e., utilities practicing upsizing, rather than like-for-like replacement, when assets fail) and resilience programs (again, where utilities might upsize assets while executing undergrounding programs).

6. **PEV demand profiles:** The composite hourly demand from EVs was developed by NREL using the EVI-PRO, EVI-RoadTrip, and EVI-OnDemand models (see Figure 35 in the Load and Distribution System Impacts and Costs chapter, which shows the composite hourly demand for the Transportation Electrification Impact Study). Changes to the demand profile, such as when peak charging occurs, affect the forecast for peak load growth. The study focus was on two PEV charging profiles for unmanaged and managed charging. Examining further sensitivities regarding how to optimize managed charging—based on location (public and workplace versus home), provision of grid services (peak shaving and interconnection agreements), and timing (nighttime-valley filling or midday solar coincident charging)—will help inform the design of utility programs and provide greater insights into future demand profiles.

7. **Sensitivity analysis for unit costs of grid equipment**: The study assumes the unit costs shown in Table **Error! No text of specified style in document.**-5. Additional cost sensitivity analysis can provide context by utility and asset class to inform future investment needs.

***Table** Error! No text of specified style in document.**-5.** Unit Cost Assumptions for California, No Action–Unmanaged Scenario*

	2027		2032	
Category	**Median Cost**	**Mean Cost**	**Median Cost**	**Mean Cost**
Substation	$30,000,000	$51,162,646	$30,000,000	$40,526,316
Substation transformer bank	$10,000,000	$10,274,259	$10,000,000	$10,850,913
New feeder[98]	$611,420	$1,606,343	$611,420	$1,602,036
Feeder $/ft	$30.49/ft		$30.49/ft	
Service transformer—non-DCFC	$20,000	$20,000	$20,000	$20,000
Service transformer—DCFC	$50,000	$75,401	$50,000	$69,421

8. **Refining forecasted demand from other sectors**: The study focus was on PEV growth and impacts. An important area for future work will be examining net load curves to see how other electrification and distributed resources impact overall peaks and investment needs. Explicitly forecasting load growth and other distributed energy resources—such as photovoltaics, battery energy storage systems, energy efficiency, and building electrification—from the bottom up can

[98] Divergences in median and mean costs for new feeders can be attributed to calculating feeder breaker costs as a function of voltage rating, causing more variability and "lumpiness" in discrete asset costs.

improve the locational synergies of customer-sited resources in the distribution system demand profiles. These can identify investments that will share network capacity and explore how DERs may change overall peak demand.

9. **Capacity-aware charge management:** The Managed scenarios modeled in this study were based on behaviors observed in existing high-penetration PEV markets, and thus they did not precisely suit each state's baseline load. The project team anticipates that more technologies will be developed and deployed to directly orchestrate charging in certain market segments to reduce peak load impacts on distribution infrastructure. Accordingly, Kevala ran an additional "Capacity-Aware Charge Management Scenario" (discussed in Appendix E) specifically designed to migrate charging load from peak times to less costly periods to minimize capacity investments where dwell times allow. Future studies may build upon this approach to estimate the potential for additional local avoided costs.

Caveats for National Extrapolation

Caveats for the national extrapolation are an extension of the limitations mentioned for the five-state study. Additionally, this study does not reflect the variation of network characteristics (such as loading, percentage of overhead and underground feeders, length of lines, load density, voltage classes, etc.) by state. Future extrapolations should consider state-level distribution statistics and variations by state for more accurate estimates.

<u>Results:</u>

We found that the sum of the five states' EV distribution costs is 28%–39% of the 2027 national costs and 23%–37% of the 2032 national costs, depending on the scenario. These numbers are potentially high based on other investment indicators of the relative ongoing distribution investment for the five states compared to national investment. For example, the five states represent approximately 19.4% of 2021 nationwide utility noncoincident peak demand and account for 28% of investor-owned utility national investment (IOUs serve 83% of customers in the five states). The five states do represent those with more aggressive EV targets and adoption rates, which might partially explain the relatively high investment in these states. For example, California will enforce an Advanced Clean Cars II regulation, which requires all new cars sold in the state to be zero emissions by 2035; therefore, the PEV load and contribution to the total investment might be higher than in a state where there are no regulations on vehicles sold. Special consideration of EV legislation for each state might be required to provide more accurate PEV load estimates.

<u>Discussion on Benchmarking:</u>

The national extrapolation to 2055, presented in the final section of the Load and Distribution System Impacts and Costs chapter, established distribution costs attributed to PEV load increases of between $147 billion and $375 billion and total national distribution investments due to PEVs, other load growth, and added distribution capacity of between $1.07 trillion and $1.245 trillion across all scenarios. For context, the 2021 IOU investment in distribution system capital expenses was $39 billion, which includes all investment across multiple programs (e.g., replacements, resilience, new customers, electrification, metering, etc.). Extracting the specific investment categories that Kevala analyzed, utilities invested $33.2 billion (or approximately 85% of the total investment) in line transformers, underground conduit, underground conductors and devices, overhead conductors and devices, pole towers and fixtures, and substation equipment. The analysis of ongoing national investment is detailed in Appendix D, which extrapolates to obtain ongoing national distribution system investment (including cooperatives, municipals, and other utilities) of approximately $48.7 billion in 2021. If the same rate of investment stayed constant, and not controlling for inflation or including higher rates or load growth and investment in modernization and hardening, utilities would invest $1.37 trillion between 2023 and 2050. This provides some context to the total investment, not the incremental investment, estimated in this study. Finally, additional work is required to understand how much the national extrapolation of investments from PEVs and other load growth would overlap or be purely additive to the rate of ongoing and planned utility investments.

Appendix D. Context of Ongoing Utility Investment

Part of the analysis in this work presents costs for upgrading and expanding distribution system capacity. An important area of context is the volume of ongoing and planned investment in the distribution system that covers ongoing maintenance and replacement, hardening, upgrading, grid modernization, resilience, and other investment categories. In this section, NREL examines the context of the ongoing and planned utility investment. Obtaining annual investment by utilities in the distribution system is challenging; however, the Federal Energy Regulatory Commission collects data for investor-owned utilities on an annual basis through its Form 1 – Electric Utility Annual Report (see Figure **Error! No text of specified style in document.**-9). These data provide some insights into the level of annual investment specifically for IOUs and help benchmark investment. Note that there are more than 3,000 distribution utilities in the United States, with approximately 140 IOUs, 2,000 municipal utilities, and 900 cooperative utilities. IOUs accounted for 69% of electricity customers in 2021.[99] For 2021, IOU total distribution investment accounted for more than $39 billion, which includes all investment across multiple programs (e.g., replacements, resilience, new customers, electrification, metering, etc.).

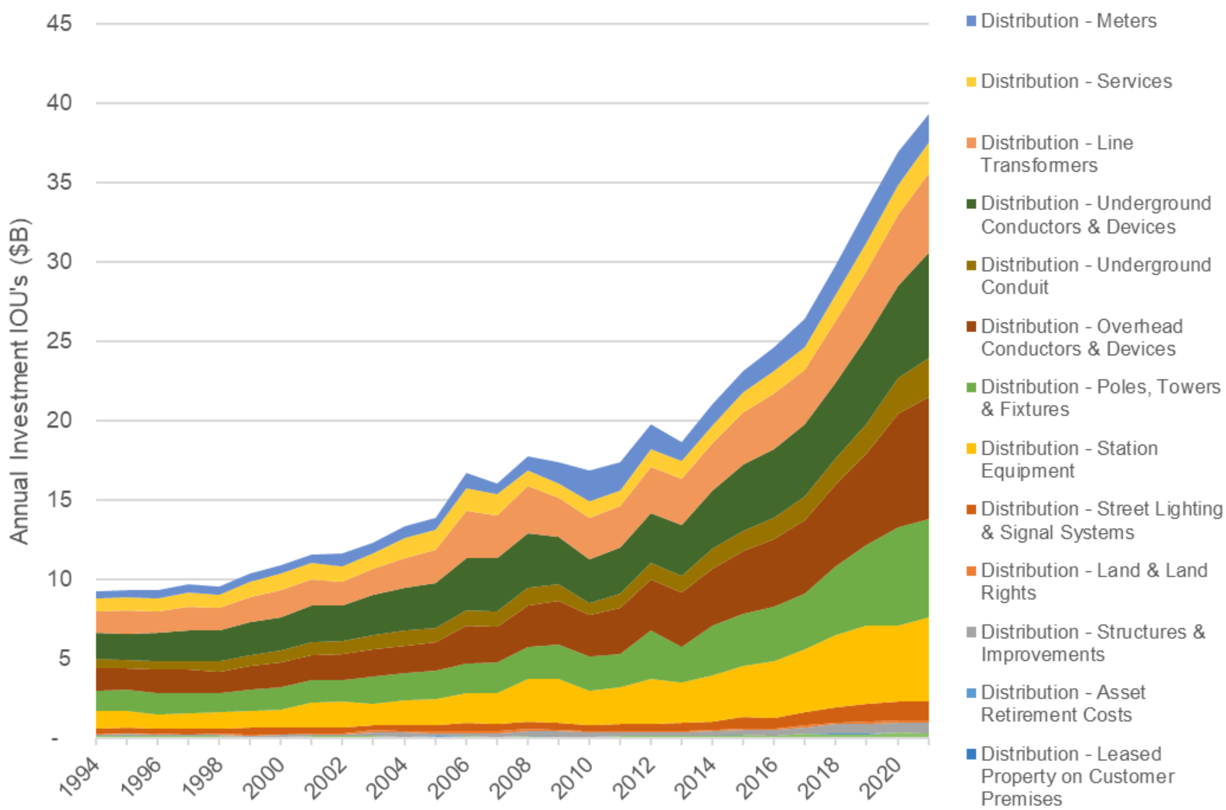


Figure Error! No text of specified style in document.**-9.** FERC Form 1 annual distribution system investments by investor-owned utilities

Using the 2021 capital investment data from FERC Form 1 and extracting the specific investment categories that Kevala analyzed, utilities invested $33.2 billion in line transformers, underground

[99] EIA, "Investor-Owned Utilities Serve 72% of U.S. Electricity Customers in 2017," Today in Energy, August 15, 2019, https://www.eia.gov/todayinenergy/detail.php?id=40913.

conduits, underground conductors and devices, overhead conductors and devices, pole towers and fixtures, and substation equipment. Again, these investments would cover all capital investment categories, such as ongoing and planned maintenance, replacement, hardening, grid modernization, and growth.

Expanding to examine non-IOU spending is challenging due to a lack of data. The National Rural Electrical Cooperative Association commissioned a report, published in October 2023, that stated that cooperative utilities' annual average capital expense spending from 2018–2022 was $9.4 billion.[100] Extrapolating IOU and cooperative utility investment to municipal, political subdivision, and other state and federal utilities with power delivery, we estimate the annual capital investment for distribution utilities to be approximately $60.4 billion. Straight-lining investment from 2023 to 2050 would result in approximately $1.633 trillion in distribution investment, not controlling for any growth rate or increase in investment above those seen in 2021.

Additional key areas for comparison are 5- and 10-year utility investment plans. We examined investment plans that use key elements of proposed integrated distribution planning processes[101] and have holistic load forecasting (planning across multiple investment categories) and some consideration for load management and non-wire alternatives. These plans include detailed future forecasts for net load growth due to electrification. Key investment plans include the following highlights:

1. The Massachusetts Grid Modernization Advisory Council has requested detailed Electric Sector Modernization Plans[102] from the major regulated IOUs. These future grid plans, including 5- and 10-year investment plans, present detailed analysis of the current state of the distribution system (asset ages, loading, etc.) and load forecasts and are best-in-class examples of how to examine grid upgrade needs. Key highlights from individual utility plans include the following:

    i. **The National Grid** utility serves approximately 1.3 million customers in Massachusetts. The utility's base peak demand is 4,614 MW, and the utility forecasts peak growth that includes a base growth of 988 MW, PEV growth of 3,103 MW, and heating electrification growth of 2,837 MW. The utility is proposing $6.035 billion in capital investments from 2025–2029, with $2.34 billion of that covering "future grid" investments (which include network, information technology/operational technology/digital, customer, and EV categories) and, of that, $1.89 billion covers "future grid – network" investments. From 2025–2034, the utility is proposing more than $13 billion in capital investments, which includes $5.68 billion for "future grid," and $4.7 billion covers "future grid – network" investments.

[100] National Rural Utilities Cooperative Finance Corporation and National Rural Electric Cooperatives Association, *Economic Powerhouses: The Economic Impacts of America's Electric Cooperatives* (October 2023), https://static1.squarespace.com/static/5f8721831dd8c167b78e87b1/t/653aad11fc65411ee1bb6a7a/1698344212103/Strategen_Economic_Powerhouses_Final.pdf.
[101] U.S. Department of Energy, Office of Electricity, *Modern Distribution Grid DSPx, Next-Generation Distribution System Platform: Strategy & Implementation Planning Guidebook* (June 2020), Pacific Northwest National Laboratory, https://gridarchitecture.pnnl.gov/media/Modern-Distribution-Grid_Volume_IV_v1_0_draft.pdf.
[102] Commonwealth of Massachusetts Grid Modernization Advisory Council (GMAC), "Electric Sector Modernization Plans (ESMPs)," 2023, https://www.mass.gov/info-details/grid-modernization-advisory-council-gmac#electric-sector-modernization-plans-(esmps)-information-.

ii. **Eversource** serves approximately 1.475 million customers in Massachusetts. The investment plan forecasts a 20% increase in net electric demand in the next 10 years, from 6.1 GW to 7.4 GW,[103] and a 150% increase in demand by 2050—50% of this increase is electric heating, 25% is transportation, and 25% is normal load growth. Eversource has proposed $6.1 billion in capital investments from 2025–2029 covering electric operations, clean energy enablement, and resilience.

iii. **Unitil,** a utility with approximately 30,500 customers, proposes to invest $131 million in capital spending from 2025–2029[104] across multiple categories, with more than $38 million planned across distribution, substation, grid modernization, and "EV charging and make ready" investments.

2. The Joint Utilities of New York[105] are also requesting detailed capital investment plans. Key highlights from individual utility plans include the following:

   i. **ConEdison**, a utility of 3.6 million customers, is forecasting an investment of $14.1 billion between 2022 and 2031 for clean energy investments in energy efficiency, building electrification, and EVs. ConEdison has also identified multi-value categories that include clean energy hubs and asset reinforcement and reliability totaling $23.3 billion. Both these investments are part of their capital and regulatory asset investments, which total $53.5 billion across multiple initiatives.

3. Recent analysis by Wood Mackenzie[106] examining 25 investment filings by IOUs accounted for $36.4 billion for grid modernization. Of those investments, 80% focus on grid hardening, distribution automation, and advanced metering infrastructure, with more than $15 billion solely focused on hardening.

[103] Eversource, *Electric Sector Modernization Plan* (September 2023), Commonwealth of Massachusetts, https://www.mass.gov/doc/gmacesmp-drafteversource/download?_gl=1%2Ako8zfs%2A_ga%2ANzUwNDI5MDE3LjE.
[104] Unitil, *Electric Sector Modernization Plan* (September 2023), Commonwealth of Massachusetts, https://www.mass.gov/doc/gmacesmp-draftunitil/download.
[105] Joint Utilities of New York, "Capital Investment Plans," June 30, 2023, https://jointutilitiesofny.org/utility-specific-pages/system-data/capital-investment-plans.
[106] Wood Mackenzie, "US$36.4B of Grid Modernization Planned by Investor-Owned Utilities," April 18, 2023, https://www.woodmac.com/press-releases/$36.4b-of-grid-modernization-planned-by-investor-owned-utilities/.

Appendix E. Capacity-Aware Charge Management Scenario

As an extension of the scope of the Transportation Electrification Impact Study, Kevala developed and implemented a capacity-aware managed charging model. This model orchestrates and schedules PEV charging to minimize daily peak demand on a given feeder, thereby quantifying deferred upgrade costs, particularly compared to the scenarios described in this study. This methodology was applied to every feeder for the five study states (California, Illinois, New York, Oklahoma, and Pennsylvania) for each day of the forecast years of 2027 and 2032.

Electric vehicle supply equipment with location types of single-family home, multifamily home, and fleet depot were considered eligible for capacity-aware managed charging given that those locations are more likely to be schedulable and dispatchable. EVSE with location types of work, retail, destination, en-route transit, and truck stop were not considered eligible for managed charging due to the smaller and less predictable charging windows of vehicles using these EVSE.

The EVSE type (L1, L2, and DC) from the capacity-agnostic Managed scenario was used to set the upper limit of the available charging capacity on the feeder. To realistically limit the available flexible loads at any given hour, each combination of individual location type and vehicle segment used representative weekday and weekend driving schedules to determine the available amount of EVSE capacity for each type of charger on an individual feeder. In addition, the methodology required that the total kilowatt-hours of daily EVSE charging in the capacity-agnostic and capacity-aware scenarios be equal, preventing load shedding or load shifting across multiple days and limiting differences in the scenario to charging strategy alone. Table **Error! No text of specified style in document.**-6 shows the different combinations of EVSE categories available at each feeder and the modeled maximum kilowatt output per port for each EVSE category. These values provide constraints to the charging levels used, but charging levels did not necessarily reach these output levels. For example, Class 4–8 depot charging did not exceed 11.1 kW, which is the maximum value seen from LBNL's profiles for this class and charger type.

***Table** Error! No text of specified style in document.**-6.** EVSE Categories and Max EVSE Output per Port (kW) (Source: Kevala)*

Vehicle Segment	Location Type	EVSE Type	Max EVSE Output per Port (kW)
LDV	home_sfh	L1	1.9
LDV	home_mfh	L2	7.2
LDV+MDV	home_sfh	L2	7.2
MDV	depot	L2	19.2
Class 4–8	depot	L2-Low	7.2[107]
Class 4–8	depot	L2	19.2
Class 4–8	depot	DC50	50
Class 4–8	depot	DC150	150
School bus	depot	L2	19.2

[107] Although exceeding typical power output ratings for "Level 1" chargers commonly used by LDVs, this L1 EVSE is named as such as a model parameter where its value was empirically derived from the LBNL-provided county-level charging curves by comparing average county-level charging curves with the number of installed Class 4–8 L1 chargers.

Transit bus	depot	DC50	50

To determine the total demand on each feeder, the linear optimization model must consider all load on the feeder for each day of the forecast period. To account for this, each 1-day period includes the following constants:

- Hourly baseline demand (kW) and
- Hourly inflexible EVSE demand (kW).

Objectives

Each linear optimization model includes two objectives:

1. **Minimize the total hourly peak demand on the feeder during a 1-day period**. This objective considers the sum of all hourly load on the feeder, including non-EVSE load and inflexible EVSE load. This objective is heavily weighted for importance in the model, and Kevala performed testing to ensure that the secondary set of objectives did not change the daily minimum peak demand value on the feeder.
2. **Minimize the Euclidean distance between each capacity-agnostic and capacity-aware EVSE charging hourly kilowatt value for each EVSE category**. This results in charging curves that resemble the capacity-agnostic curves as closely as possible while minimizing the overall peak demand on the feeder.

This second objective prevents the model from allocating electric vehicle charging to unlikely or inconvenient hours for vehicles on that feeder. Although the charging hours are defined by the average weekday and weekend driving schedules of the vehicles using each category of EVSE, without this set of objectives the model can arbitrarily place charging in any feasible hour without considering the hourly continuity of charging sessions for individual vehicles. This second objective leverages the highly detailed modeling of vehicle and charger interactions by NREL and LBNL in their capacity-agnostic Managed charging scenario to guide the capacity-aware managed charging model toward hours in which to allocate charging load without negatively impacting the feeder-level peak demand.

Model Criteria

The linear optimization model must account for the minimum and maximum kilowatt output for each hour of each EVSE category. These parameters are calculated by multiplying the EVSE installed capacity on the feeder for each EVSE category by the hourly fraction of vehicle availability for each EVSE category.

Kevala derived the installed capacity of EVSE on the feeder by multiplying the adopted EVSE port count on each feeder by the max output rating (kW) of each EVSE category (Table **Error! No text of specified style in document.**-6). This fraction of vehicle availability represents the proportion of vehicles that would be available at the EVSE location to charge in each hour of the day. The fraction of vehicle availability was found for a typical weekday and weekend and used across the forecast year.

The fraction of vehicle availability was derived from two data sources:

1. **Single-family and multifamily homes** used the 2017 National Household Travel Survey[108], where the fraction of vehicle availability was calculated for an average weekday and weekend day for each state (California, Illinois, New York, Oklahoma, and Pennsylvania) in the study. Vehicle trips departing and arriving from traveler homes were used to find the fraction of vehicles at home during each hour of the day for weekdays and weekends.
2. **Fleet vehicles** leveraged the NREL Fleet DNA: Commercial Fleet Vehicle Operating Data[109] set to calculate the fraction of vehicle availability. First, a representative vehicle type in the Fleet DNA dataset was chosen to represent the vehicle types using each category of EVSE. Next, the first depot departure and final depot return time stamps of all available vehicle trips by that vehicle type were used to find the fraction of vehicles available at the charging depot for each hour of the day. Where vehicle types had a sufficient sample size of trip data, separate weekday and weekend fractions of vehicle availability were calculated. Because only the day start and day end of this dataset can be confidently mapped to depot location, the fraction of vehicle availability derived does not consider inter-day stops at the depot and might underestimate vehicle availability between first departure and last arrival.

The optimization model must also meet the following criteria:

- **Capacity-agnostic total flexible charging (kWh) = capacity-aware total flexible charging (kWh)**: This energy balance criterion ensures that the total flexible charging over a 1-day period from the capacity-agnostic scenario for that feeder is equal to the capacity-aware total flexible charging. The model will not perform load shedding or load shifting across separate days.
- **Peak hourly feeder demand (kW) >= baseline load (kW) + inflexible EVSE (kW) + flexible EVSE (kW)**: This criterion defines the peak hourly demand as the sum of the baseline load, inflexible EVSE, and flexible EVSE. In practice, the peak demand always equals the sum of its parts and is not greater than them because the objective function aims to minimize the peak hourly feeder demand.
- **Similarity metric for each hour of each EVSE category >= Euclidean distance between capacity-agnostic and capacity-aware kW charging value for each hour and each EVSE category**: This criterion defines the similarity metric for each EVSE category as the Euclidean distance between the capacity-agnostic and capacity-aware kilowatt charging value for each hour and each EVSE category. In practice, the similarity metric is equal to the right-hand side of the equation and not greater than it, given that the objective function aims to minimize the similarity metric across all hours and EVSE categories.

Results

This approach yielded encouraging results, indicating that additional savings across all scenarios are possible. For example, in California, feeder peak energy was depressed by an average of 2% compared to the 2032 Action–Capacity-Agnostic Managed scenario, with reductions of up to 27% on feeders with especially high PEV penetration (see Figure **Error! No text of specified style in document.**-10).

[108] U.S. Department of Transportation Federal Highway Administration, "National Household Travel Survey," 2019, https://nhts.ornl.gov/.
[109] NREL, "Fleet DNA: Commercial Fleet Vehicle Operating Data," n.d., https://www.nrel.gov/transportation/fleettest-fleet-dna.html.

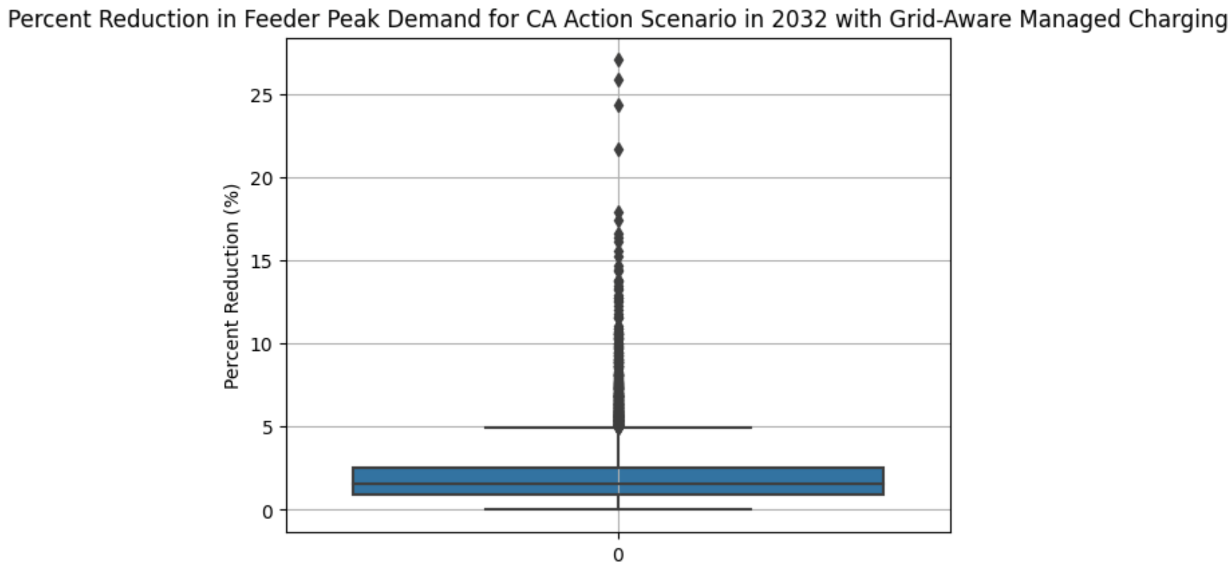


Figure Error! No text of specified style in document.**-10.** Percentage reduction in California feeder peak power via capacity-aware PEV charge management for the Action Scenario in 2032 *(Source: Kevala)*

The project team developed comparisons in cost between this capacity-aware management scenario and other scenarios modeled as part of the five-state study. Following the same pattern in reduced peak demand across assets, costs were lower in the capacity-aware management case, as shown in Figure **Error! No text of specified style in document.**-11

through Figure **Error! No text of specified style in document.**-15. Note that the scenario compared is the Action–Managed scenario, which is used as the baseline to determine how much additional cost savings are achievable by more intelligent, grid-responsive orchestration of charging patterns.

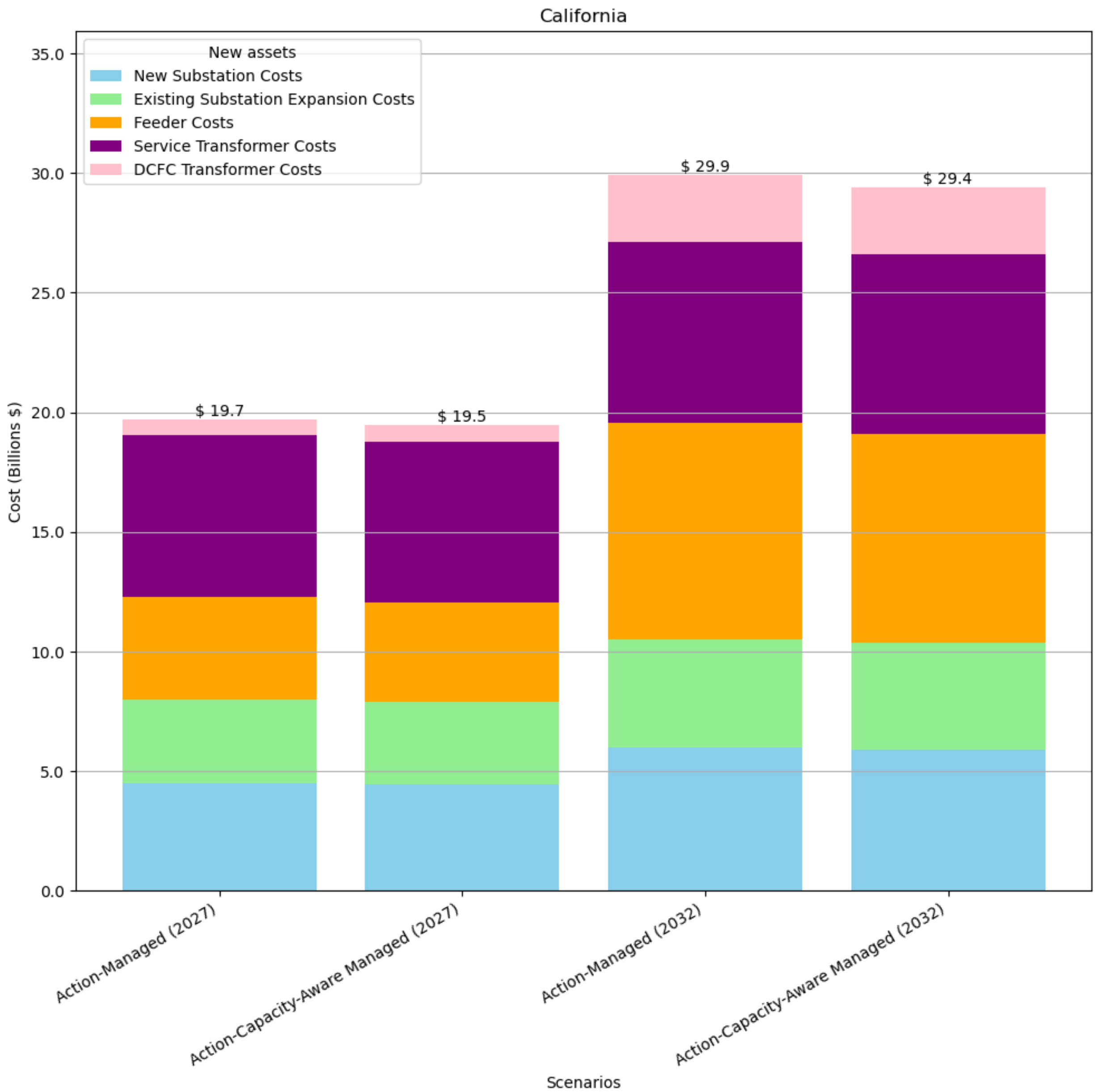


Figure Error! No text of specified style in document.**-11.** Comparison of Action–Managed and Action–Capacity-Aware Managed scenario costs by asset type for California in 2027 and 2032 *(Source: Kevala)*

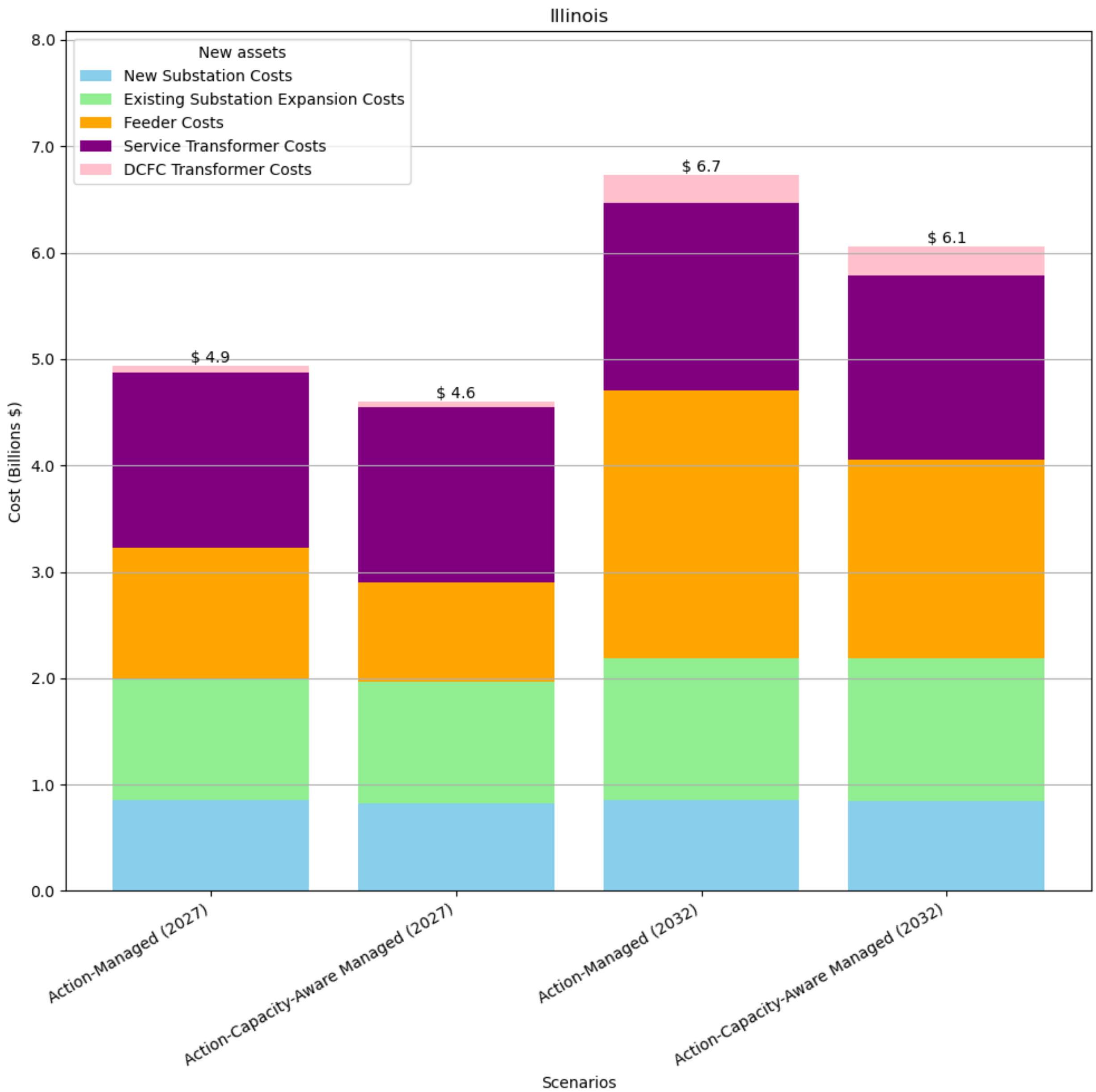


Figure Error! No text of specified style in document.**-12.** Comparison of Action–Managed and Action–Capacity-Aware Managed scenario costs by asset type for Illinois in 2027 and 2032 *(Source: Kevala)*

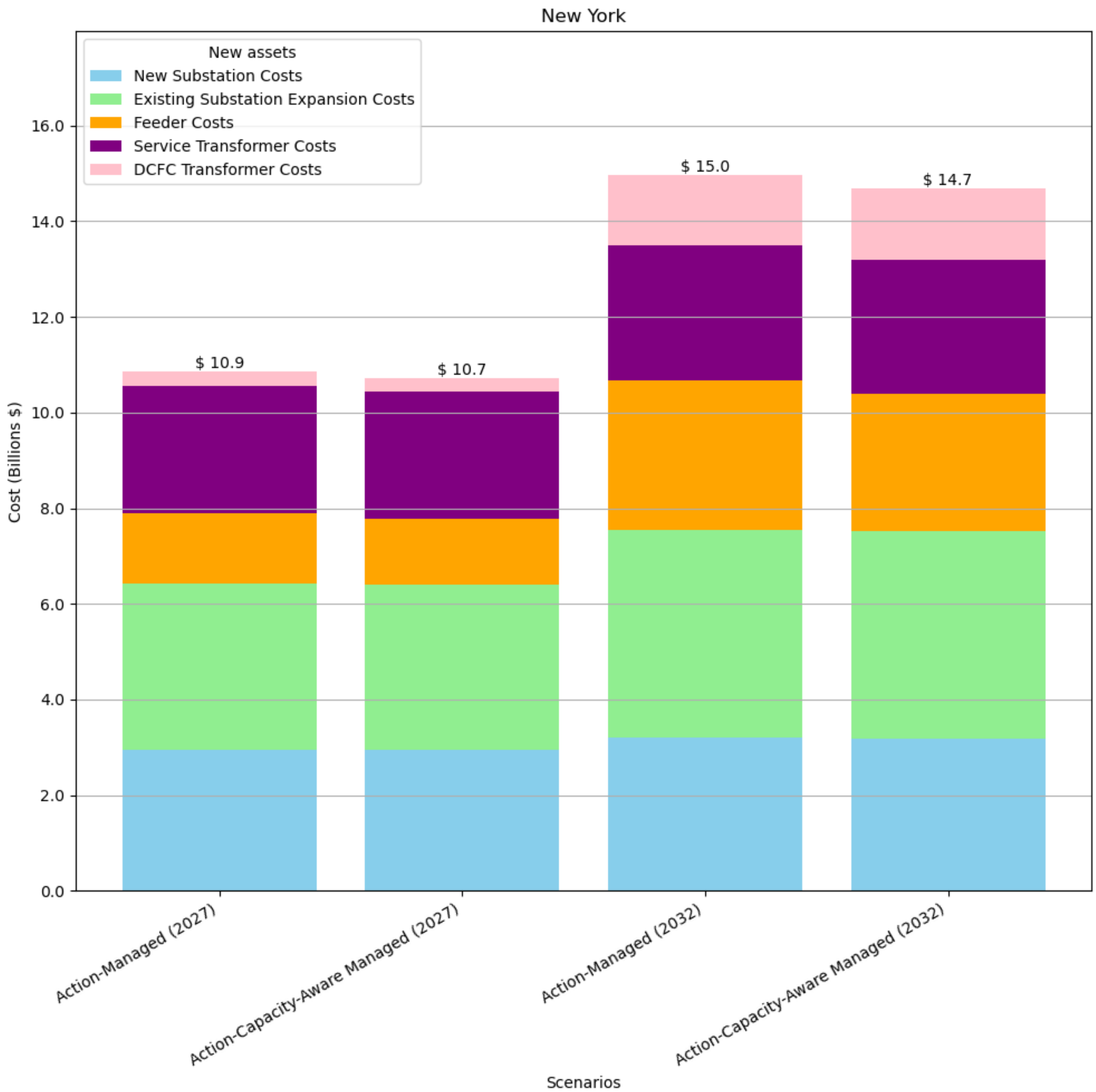


Figure Error! No text of specified style in document.**-13.** Comparison of Action–Managed and Action–Capacity-Aware Managed scenario costs by asset type for New York in 2027 and 2032 *(Source: Kevala)*

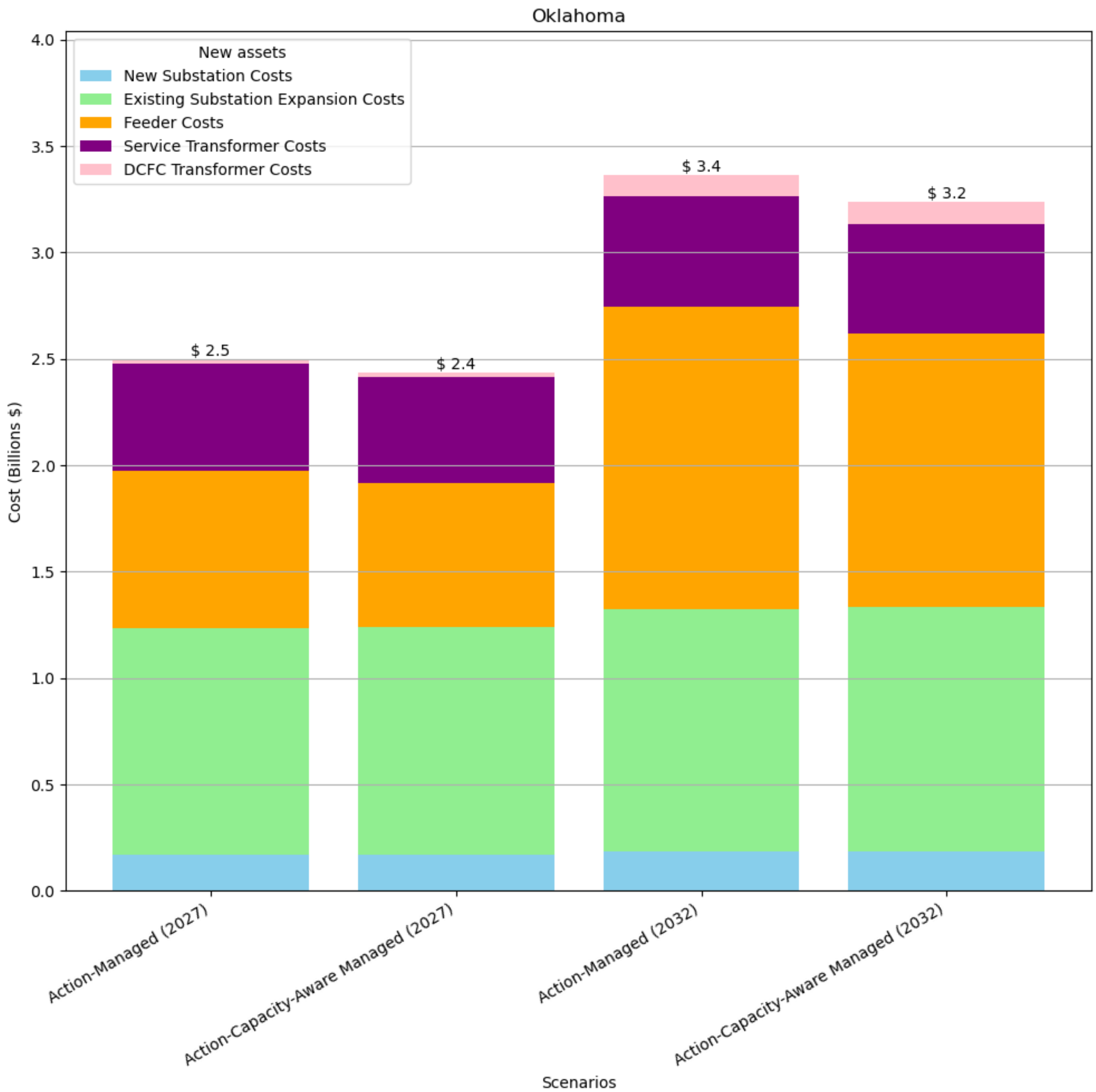


Figure Error! No text of specified style in document.**-14.** Comparison of Action–Managed and Action–Capacity-Aware Managed scenario costs by asset type for Oklahoma in 2027 and 2032 *(Source: Kevala)*

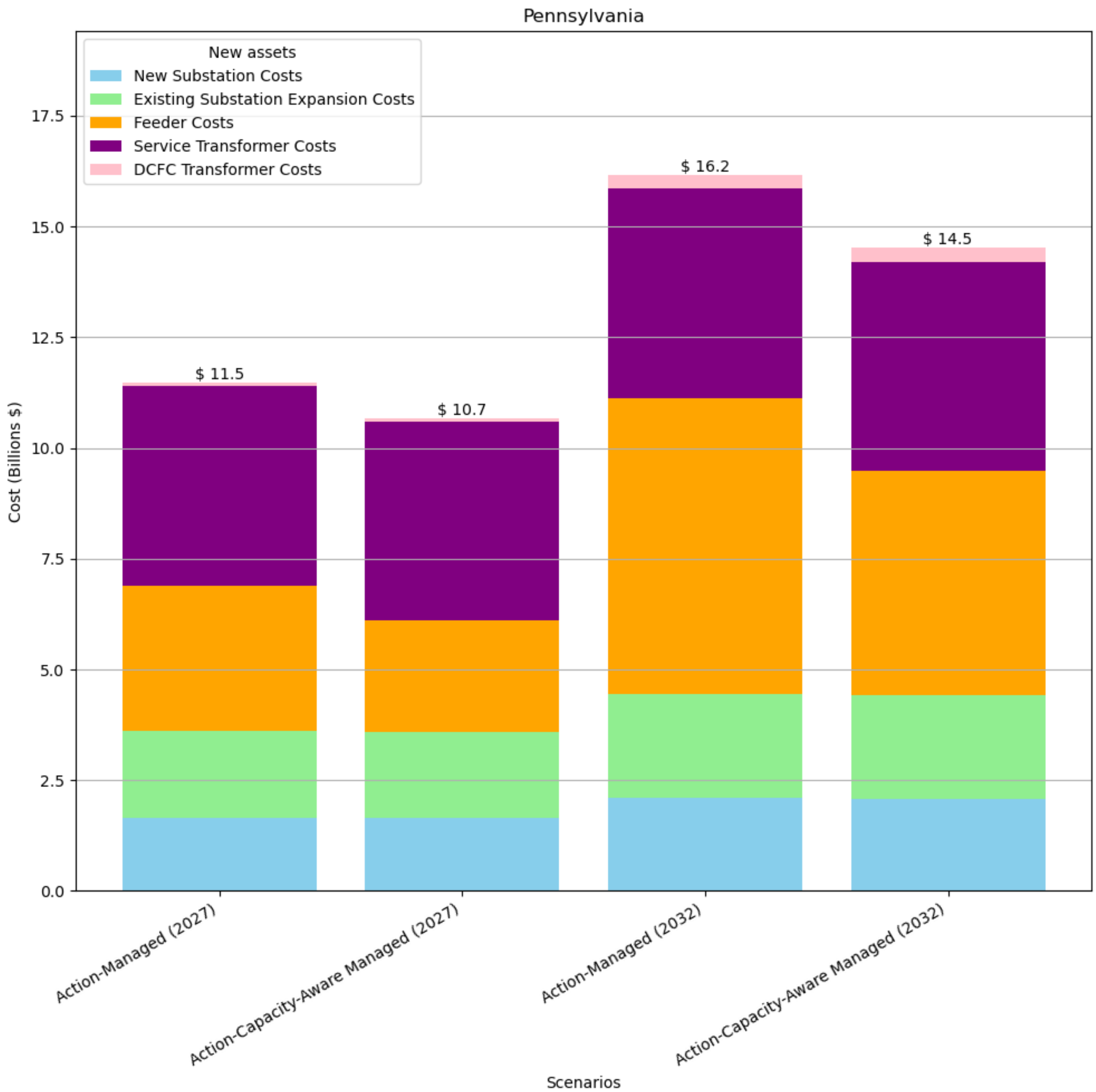


Figure Error! No text of specified style in document.**-15.** Comparison of Action–Managed and Action–Capacity-Aware Managed scenario costs by asset type for Pennsylvania in 2027 and 2032 *(Source: Kevala)*

Appendix F. IPM Regions

***Table** Error! No text of specified style in document.**-7.** Integrated Planning Model (IPM) Regions and Descriptions*

IPM Model Region	Model Region Description	Notes
ERC_FRNT	ERCOT_Tenaska Frontier Generating Station	Electric Reliability Council of Texas (ERCOT)
ERC_GWAY	ERCOT_Tenaska Gateway Generating Station	
ERC_PHDL	ERCOT_Panhandle	
ERC_REST	ERCOT_Rest	
ERC_WEST	ERCOT_West	
FRCC	Florida Reliability Coordinating Council (FRCC)	
MIS_AMSO	MISO_Amite South (including Downstream of Gypsy [DSG])	Midcontinent Independent System Operator (MISO)
MIS_AR	MISO_Arkansas	
MIS_D_MS	MISO_Mississippi	Has also been represented as “MIS_MS”
MIS_IA	MISO_lowa	
MIS_IL	MISO_Illinois	
MIS_INKY	MISO_Indiana (including parts of Kentucky)	
MIS_LA	MISO_Louisiana	
MIS_MAPP	MISO_MT, SD, ND	
MIS_LMI	MISO_Lower Michigan	
MIS_MIDA	MISO_lowa-MidAmerican	
MIS_MNWI	MISO_Minnesota and Western Wisconsin	
MIS_MO	MISO_Missouri	
MIS_WOTA	MISO_WOTAB (including Western)	West of the Achafalaya Basin (WOTAB)
MIS_WUMS	MISO_Wisconsin–Upper Michigan (WUMS)	
NENG_CT	ISONE_Connecticut	ISO New England (ISONE)
NENG_ME	ISONE_Maine	
NENGREST	ISONE_MA, VT, NH, RI (Rest of ISO New England)	
NY_Z_D	NY_Zone D (North)	
NY_Z_G-I	NY_Zone G-I (Downstate NY)	
NY_Z_A	NY_Zone A (West)	
NY_Z_B	NY_Zone B (Genesee)	
NY_Z_C&E	NY_Zone C&E	
NY_Z_F	NY_Zone F (Capital)	
NY_Z_J	NY_Zone J (New York City [NYC])	
NY_Z_K	NY_Zone K (Long Island [LI])	
PJM_WMAC	PJM_Western Mid-Atlantic Area Council (MAAC)	
PJM_West	PJM_West	

IPM Model Region	Model Region Description	Notes
PJM_ATSI	PJM_American Transmission Systems, Incorporated (ATSI)	
PJM_AP	PJM_Allegheny Power (AP)	
PJM_COMD	PJM_ComEd	
PJM_EMAC	PJM _EMAAC	
PJM_PENE	PJM_Pennsylvania Electric Company (PENELEC)	
PJM_SMAC	PJM_SWMAAC	
PJM_Dom	PJM_Dominion	
S_C_KY	SERC_Central_Kentucky	SERC Reliability Corporation (SERC)
S_C_TVA	SERC_Central_TVA	Tennessee Valley Authority (TVA)
S_D_AECI	SERC_Delta_AECI	Associated Electric Cooperative Incorporated (AECI)
S_SOU	SERC_Southeastern	
S_VACA	SERC_VACAR	Virginia–Carolinas (VACAR)
SPP_KIAM	SPP_Klamichi Energy Facility	Southwest Power Pool (SPP)
SPP_N	SPP_North (Kansas, Missouri)	
SPP_NEBR	SPP_Nebraska	
SPP_SPS	SPP_SPS (Texas Panhandle)	Southwestern Public Service Company (SPS)
SPP_WAUE	SPP_Western Area Upper Great Plains East (WAUE)	
SPP_WEST	SPP_West (Oklahoma, Arkansas, Louisiana)	
WEC_CALN	WECC_Northern California (not including Balancing Authority of Northern California [BANC])	Western Electricity Coordinating Council (WECC)
WEC_LADW	WECC_LADWP	
WEC_SDGE	WECC_San Diego Gas and Electric	
WECC_AZ	WECC_Arizona	
WECC_CO	WECC_Colorado	
WECC_ID	WECC_Idaho	
WECC_IID	WECC_Imperial Irrigation District (ID)	
WECC_MT	WECC_Montana	
WECC_NM	WECC_New Mexico	
WECC_NNV	WECC_Northern Nevada	
WECC_PNW	WECC_Pacific Northwest	
WECC_SCE	WECC_Southern California Edison	
WECC_SNV	WECC_Southern Nevada	
WECC_UT	WECC_Utah	
WECC_WY	WECC_Wyoming	
WEC_BANC	WECC_BANC	

Appendix G. Glossary

Agent-based simulation techniques: Agent-based modeling is a computational method for the simulation of complex systems, enabling autonomous decision-making entities (i.e., agents) to perform prescribed activities, assess their own situations, and make rule-based decisions. In this study, medium- and heavy-duty ZEVs are defined as agents in the simulation to perform activities related to driving (route selection), parking (en-route charging location selection), and charging (when- and where-to-charge decision-making).

Bottom-up grid impact study: A bottom-up method forecasts the generation and load impact from distributed energy resources based on adoption models that are run at a lower level of resolution—in this case, at the customer level—and aggregated up to determine the impact at higher aggregation levels, such as feeders, substations, or an entire service territory.

Coincident peak: Local (e.g., at a meter, feeder, or service transformer) power demand at the time of a system-wide peak demand for a given time period.

Connector: What is plugged into a vehicle to charge it. Multiple connectors and connector types (e.g., Tesla [SAE J3400], Combined Charging System, and CHAdeMO) can be available on one EVSE port, but only one vehicle will charge at a time. Connectors are sometimes called plugs.

Diversity factor: Ratio of the sum of the individual noncoincident maximum loads of various subdivisions of the system to the maximum demand of the complete system.

Economic load reach (ELR): The length of a feeder needed to deliver power while maximizing its economic lifetime use and avoiding voltage-drop problems.

Electric vehicle supply equipment (EVSE) port: Provides power to charge only one vehicle at a time even though it might have multiple connectors. The unit that houses EVSE ports is sometimes called a charging post and can have one or more EVSE ports.

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

Incremental: In this study, "incremental" is used to refer to the difference between the U.S. Environmental Protection Agency's Action and No Action policy scenarios, including differences in the number of PEVs on the road, the size of the necessary charging network, and the associated upgrades to local distribution networks.

Linear optimization model: A linear optimization model includes constraints and an objective, all of which are modeled as linear functions. The goal of a linear optimization model is to maximize the output of the objective function while remaining compliant with the model's constraints. In this study, we refer to the model's constraints as "Model Criteria" in Appendix E.

Long-haul: The transport of heavier goods with larger vehicles over a long distance, typically 250 miles or more. Long-haul truckers typically drive on highways more than on city roads and will spend more time away from their home locations.

Noncoincident peak: Local (e.g., at a meter) maximum power demand for a given time period.

On-road vehicle weight classes:

- Light-duty vehicle (LDV): Class 1–2a
- Medium-duty vehicle (MDV): Class 2b–3
- Heavy-duty vehicle (HDV): Class 4–8

Parcel: A real-estate property or land and any associated structures that are the property of a person with identification for taxation purposes.

Plug-in electric vehicle (PEV): Includes battery electric vehicles and plug-in hybrid electric vehicles.

Short-haul: The transport of large goods with smaller vehicles over a shorter distance, typically within a 150–250 mile radius of the truck's home location. Short-haul trucks often operate on city roads and return to their home location each day.

Station location: A site with one or more EVSE ports at the same address. Examples include a parking garage or a mall parking lot. Additional location types are defined for heavy-duty applications to include depots and public en-route locations, such as truck stops and rest areas.

Vocation heavy-duty: All other types of truck vocations except long-haul and short-haul. Examples include mobile homes, service trucks, and refuse trucks.

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