EV Load Forecasting Guide

A Report by the
Energy Systems Integration Group's
EV Load Forecasting Task Force

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ESIG
ENERGY SYSTEMS INTEGRATION GROUP

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Contents

Abbreviations

AMI	Advanced metering infrastructure
DCFC	DC fast charging [charger]
EV	Electric vehicle
EVSE	Electric vehicle supply equipment [EV charging infrastructure]
GIS	Geographic information system
HDV	Heavy-duty vehicle
ICE	Internal combustion engine
LDV	Light-duty vehicle
MDV	Medium-duty vehicle
MHDV	Medium- and heavy-duty vehicle
V2G	Vehicle-to-grid
VMT	Vehicle miles traveled

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Executive Summary

Forecasting electricity usage is a foundational planning activity for utilities, underpinning billions of dollars in grid investments that ensure system reliability. Historically, forecasting relied on trends in economic and population growth; however, transportation electrification presents a new and complex planning challenge. Unlike conventional loads, electric vehicle (EV) charging has relatively limited usage history. In addition, charging is driven by complex human behaviors, is mobile, and at the same time can concentrate geographically in ways that, without proper planning, can quickly overwhelm local distribution systems.

As market share for new light-duty EVs grows—from 2% to more than 10% between 2020 and 2024—so does the need for new forecasting approaches. Load from a single EV can equal nearly half the annual electricity consumption of an average U.S. household, and this new demand can materialize faster and with less notice than traditional loads. Planners must anticipate not only *how much* power will be needed, but also *when* and *where*.

To adequately prepare for future EV adoption, utility planners, regulators, and stakeholders require robust, fit-for-purpose forecasts that can better support planning for EV loads and help reduce the risk of service delays and inefficient grid investments. An EV load forecast is more than a prediction of future demand—it is a critical tool for evaluating potential solutions to meet load growth. As expanded upon throughout the report, scenario analysis is an increasingly important modeling technique that can help planners manage more effectively investment risks and design a more efficient, flexible grid.

The Energy Systems Integration Group (ESIG) developed this guide to articulate core principles for EV load forecasting, synthesize leading practices, and assist utilities, regulators, and stakeholders in adopting effective approaches.

Key Activities in EV Load Forecasting

This guide provides a practical framework for a diverse group of professionals involved in the three key forecasting activities, including:

- **Forecast scoping** (utility strategic planners, regulators, and stakeholders): Defining forecast objectives and scope, aligning the forecast with jurisdictional policies, and using outputs for high-level resource and infrastructure planning
- **Forecast implementation** (utility analysts and consultants): Executing the forecast, including data gathering, modeling, analysis, and documenting assumptions and results
- **Forecast review** (regulators and regulatory stakeholders): Evaluating submitted forecasts for methodological soundness, reasonableness of inputs and assumptions, compliance, and overall fitness for purpose

To better enable all stakeholders to develop, execute, and evaluate EV load forecasting models, the guide provides high-level summary information on the trade-offs and considerations for using different types of top-down and bottom-up data to develop robust EV load forecasts (see Table 1, p. 9), as well as detailed examples of inputs, assumptions, methods, and outputs associated with each step in the modeling process (see the "Implementing an EV Load Forecast" section).

The recommendations are informed by an industry advisory group, a regulatory advisory group, and interviews with subject matter experts. The resulting best practices are intended to improve forecast confidence, facilitate informed dialogue, and support the development of actionable strategies that keep pace with rapid changes in EV technologies and adoption.

The guide offers 20 best practices across the following core components of the EV load forecasting process:

- Scoping the forecast
- Implementing the forecast
- Reviewing the forecast
- Applying the forecast and advancing the practice

Each best practice includes explanations and examples. The following checklist summarizes all of these recommended practices. Given the resources required, small utilities in particular may benefit from using third-party or state forecasts and adapting them for their service area.

Best Practice Checklist for Performing EV Load Forecasting

Click on best practices to be taken to their discussion in the report below.

Scoping the Forecast

Best Practice 1

Define the forecast's **core requirements collaboratively**, including the forecast area, time horizon, and required spatial granularity, to align with its intended purpose.

Best Practice 2

Specify the **mix of vehicle segments** to be forecast (e.g., light-duty, fleet, off-road) based on their potential grid impact and relevance to the forecast area.

Best Practice 3

Explore the use of **multiple scenarios** to investigate a range of plausible futures by varying assumptions about technologies, market conditions, consumer behaviors, and policies.

Best Practice 4

Engage **stakeholders early and consistently** to shape scenarios, define assumptions, and build trust in the forecast results.

Implementing the Forecast

EV Adoption Forecasting

Best Practice 5

Use **comprehensive and clearly documented inputs** for adoption forecasts—including baseline vehicle stock, ownership types, market factors, and relevant policies—for each adoption scenario included in the forecast, and identify how inputs apply to each vehicle duty (light-, medium-, and heavy-duty).

Best Practice 6

Model the adoption of both **personally owned and fleet-owned vehicles**, recognizing that fleets prioritize total cost of ownership and operational needs while consumers are influenced by a broader set of factors.

Best Practice 7

Select adoption forecasting models and approaches (e.g., consumer preference, propensity, diffusion) that are **fit-for-purpose** based on data availability and desired granularity.

Best Practice 8

Calibrate and **validate** adoption models against historical registration data, and **benchmark** results against reputable third-party forecasts to ensure credibility.

EV Charging Infrastructure Forecasting

Best Practice 9

Base infrastructure forecasts on the outputs of the EV adoption forecast, including vehicle counts, characteristics, and spatial distribution.

Best Practice 10

Ground infrastructure assumptions in **empirical data** where possible, including real-world charging behavior, travel patterns, and observed charger utilization rates (see data table, p. 9).

Best Practice 11

Select **infrastructure forecasting methods** (e.g., needs-based simulation, EV-to-charger ratios) that are appropriate for the required level of detail, from high-level estimates to specific siting analysis.

EV Charging Profile Forecasting

Best Practice 12

Integrate vehicle, infrastructure, and grid data—including vehicle miles traveled, dwell times, charger power levels, and baseline grid conditions—to create **detailed load profiles**.

Best Practice 13

Model multiple charging scenarios to quantify a range of estimates for grid impacts of different behaviors, including unmanaged charging and various smart charging or demand response strategies.

Best Practice 14

Calibrate charging profiles by benchmarking against real-world metered data from sources like utility advanced metering infrastructure, charging network operators, or pilot programs.

Reviewing the Forecast

Best Practice 15

Ensure forecast **transparency** through comprehensive and accessible documentation of all data sources, assumptions, methodologies, and calculations.

Best Practice 16

Evaluate the forecast for **reasonableness and analytical robustness** by benchmarking against other forecasts (such as past forecasts, state agency forecasts, or forecasts by other parties) and conducting sensitivity analyses on key variables (e.g., baseline EV stock, fuel price projections, technology cost curves).

Best Practice 17

Confirm the forecast is fit-for-purpose by ensuring its outputs (e.g., granularity, time horizon) are relevant and clear for their intended use in planning or regulatory proceedings.

Applying the Forecast

Best Practice 18

Use the forecast as a tool to **inform actionable grid planning**, including identifying the need for targeted infrastructure upgrades and evaluating the potential of load management to mitigate costs.

Best Practice 19

Foster **coordination and data sharing** among all planning stakeholders—including utilities, regulators, other agencies, and other parties—to align assumptions and create more cohesive forecasts.

Best Practice 20

Incorporate **emerging technologies and modeling advances** into long-term scenarios to ensure forecasts remain forward-looking and account for potential market shifts like vehicle-to-grid (V2G) or ultra-fast charging.

The purpose of an EV load forecast is not to predict the future with perfect accuracy, but to provide a useful tool that enables robust, considered, and cost-effective electricity system planning. By adopting the fit-for-purpose, transparent, and collaborative principles outlined in this guide, the industry can develop forecasts that are useful, guiding the development of electricity grids that serve growing loads.

Introduction

Forecasting future electricity usage, in terms of total energy sales (kWh) and peak demand (kW), is a foundational planning activity for electric utilities. These forecasts underpin utility investment decisions—$202.7 billion projected in 2025 for U.S. investor-owned utilities (EEI, 2024)—and are a critical input for core planning functions, including generation resource adequacy, transmission and distribution system planning, and integration of distributed energy resources (Tsuchida et al., 2024). The increased adoption of electric vehicles (EVs) across all transportation modes and market sectors requires new forecasting approaches to serve this new load, and capture unique load profile characteristics and capabilities of EVs to ensure the efficient use of grid infrastructure.[1]

The increased adoption of EVs requires new forecasting approaches to serve this new load and capture unique load profile characteristics and capabilities of EVs to ensure the efficient use of grid infrastructure.

Traditionally, forecasting methodologies have sought to derive historical trends between electricity consumption and factors such as economic growth, population change, and weather conditions. This approach is effective when load patterns evolve predictably and suitable historical data are available. However, when technologies with new load patterns emerge, forecasters need to create new load profiles with no precedent. For example, the widespread adoption of air conditioning in the United States in the 1980s fundamentally reshaped daily demand by creating a distinct summer afternoon peak that strained existing infrastructure (Wilson, Zimmerman, and Gramlick, 2024). Today's accelerating transition to transportation electrification presents a similar, but more complex, planning challenge requiring new approaches to accurately forecast EV loads, including where and when these loads will emerge.

Load forecasting practitioners use a range of methodologies, from complex, data- and resource-intensive approaches to more straightforward and econometric methods. Regions with higher EV adoption often rely on granular, bottom-up techniques, while areas with lower adoption may reasonably use broader, top-down methods that focus less on spatial detail, though these approaches may need to adapt if EV adoption increases.[2] Because these methodologies differ in the models used, assumptions, and granularity, two practitioners could produce different forecasts for the same area—even when using the same data inputs—with implications for needed grid investments. For example, a granular bottom-up approach might reveal feeder or service transformer upgrades, while a top-down approach might only indicate substation-level upgrades—or none at all if equipment at that level is unaffected.

1 In this report, an EV is defined as either a battery electric vehicle or a plug-in hybrid electric vehicle. The powertrain for both of these vehicles is fueled either entirely (as for battery electric vehicles) or partially, for short distances (as for plug-in hybrids), by an electric battery that is energized using a vehicle charger whose ultimate source is the electric power grid.

2 *Bottom-up models* are built from granular datasets, such as individual households, vehicle owners, or localized charging behaviors. *Top-down models* begin with macroeconomic or system-level data, projecting trends based on high-level indicators such as vehicle stock, population growth, or regional energy consumption.

The Energy Systems Integration Group (ESIG) developed this guide to articulate core principles for EV load forecasting, synthesize leading practices, and assist utilities, regulators, and stakeholders to take steps toward standardizing and adopting these principles. ESIG convened dedicated sessions with an industry advisory group of forecast implementers, a regulatory advisory group, and individual interviews with subject matter experts. **The guide presents information from a wide variety of sources, vetted by technical and regulatory experts.**

A Practical Framework for Forecasting EV Charging Loads

By documenting common approaches and emerging best practices, this guide aims to facilitate informed dialogue, improve forecast confidence, and support the development of actionable strategies that keep pace with rapid EV adoption and evolving grid needs. The guide is also designed to improve engagement of regulators and stakeholders in the forecasting process, including alignment on a range of plausible scenarios to guide the analysis and ensure that the final product is widely accepted and actionable.

The guide provides a practical framework for addressing the complexities of forecasting EV charging loads. It details essential elements such as data inputs and assumptions, modeling methods, and outputs. It is designed to support three key activities:

- **Forecast scoping** (utility strategic planners, regulators, and stakeholders): Defining forecast objectives and scope, aligning the forecast with jurisdictional policies, and using outputs for high-level resource and infrastructure planning
- **Forecast implementation** (utility analysts and consultants): Executing the forecast, including data gathering, modeling, analysis, and documenting assumptions and results
- **Forecast review** (regulators and regulatory stakeholders): Evaluating submitted forecasts for methodological soundness, reasonableness of inputs and assumptions, compliance, and overall fitness for purpose

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How to Use This Guide

Those involved in **forecast scoping** (utilities, regulators, and stakeholders) can leverage the framework, particularly guidance on scope, requirements, and policy alignment, along with the component descriptions, to define appropriate forecast specifications and interpret results for strategic decision-making. **Forecast implementation** professionals (utilities) will value the guide's detailed discussions on data considerations and inputs, assumptions, methods, and outputs for each core forecasting component for guiding execution and aligning with best practices. Those involved in **forecast review** (regulators and stakeholders) can use the framework principles, data considerations, and component details to establish robust criteria for evaluating forecast validity, transparency, methodology, assumptions, and applicability.

Key Components of an EV Forecast

Key components of an EV forecast include EV adoption, EV charging infrastructure, and EV charging profiles. While these components are handled in sequential order in this guide, in practice they may be performed in a different order or recursively. EV adoption forecasting addresses how many EVs will enter the market over time, by vehicle type, ownership model, and geography. EV charging infrastructure projects where, when, and how charging infrastructure will be deployed to meet demand. And EV charging profiles convert vehicle and infrastructure forecasts into estimates of electricity consumption and demand.

While the guide mentions forecasting smart charging and vehicle-to-grid integration,[3] as well as grid impact assessment, mitigations, and cost estimation,[4] these complex topics warrant their own treatment and are beyond the scope of this guide.

The Distinct Challenges of EV Load Forecasting

Forecasting EV charging loads presents distinct challenges compared to both traditional electricity demand forecasting and forecasting distributed energy resources, like solar photovoltaics or stationary battery energy storage systems. While conventional forecasting primarily uses economic and weather data to forecast loads, and distributed energy resource forecasts rely on energy usage, weather patterns, and adoption patterns for fixed assets, EV forecasting must uniquely address several factors.

- **Less predictable adoption and energy usage patterns:** The relationship between technology adoption and energy usage patterns associated with most distributed energy resources, such as solar photovoltaics, battery energy storage systems, and demand response, is more predictable than for EVs, since most distributed energy resources are strongly associated with the premise's energy usage profile (the amount and timing of consumption). This important and relatively

3 Advanced EV functionalities, such as dynamic charging responses to price signals and vehicle export capabilities (e.g., V2G, V2H, V2X, and V1G), are expected to be major influences on future load profiles and are major sources of uncertainty. These functionalities should be included in scenario analysis given their growing importance (see the section "Smart Charging Scenarios").

4 Load forecasts are used to assess grid needs, identify solutions, and estimate the costs. This guide does not cover in detail how forecasted EV loads can be mapped to grid infrastructure for distribution system planning purposes.

The Time Is Right for Improved EV Load Forecasting

As Figure 1 shows, between 2020 and 2024 the market share of new light-duty EV sales rose from roughly 2% to over 10%, putting more than roughly 5.8 million light-duty EVs (battery electric vehicles and plug-in hybrid electric vehicles) on the road (AAI, 2024). The load from a single EV can be substantial, with an average light-duty EV for personal use consuming nearly half as much electricity annually as an average U.S. household today without an EV (Cantu, 2023).

Medium- and heavy-duty (MHD) EV adoption mirrors these trends, though at significantly lower levels. For example, from 2020 to the midpoint of 2024, sales of MHD battery electric vehicles grew from less than 1% of MHD sales (Sen et al., 2022) to roughly 2.6% of overall sales, reaching a total of more than 42,500 vehicles (Richard, 2025).

Although the future rate of EV adoption may differ from the 2020 to 2024 period, EV saturation levels in many highly populated jurisdictions are substantial, and overall EV growth is expected to continue, potentially at a more gradual pace.

For all these reasons, it is important for electricity system planners to integrate EV load forecasts into traditional load forecasting exercises to ensure that electricity is

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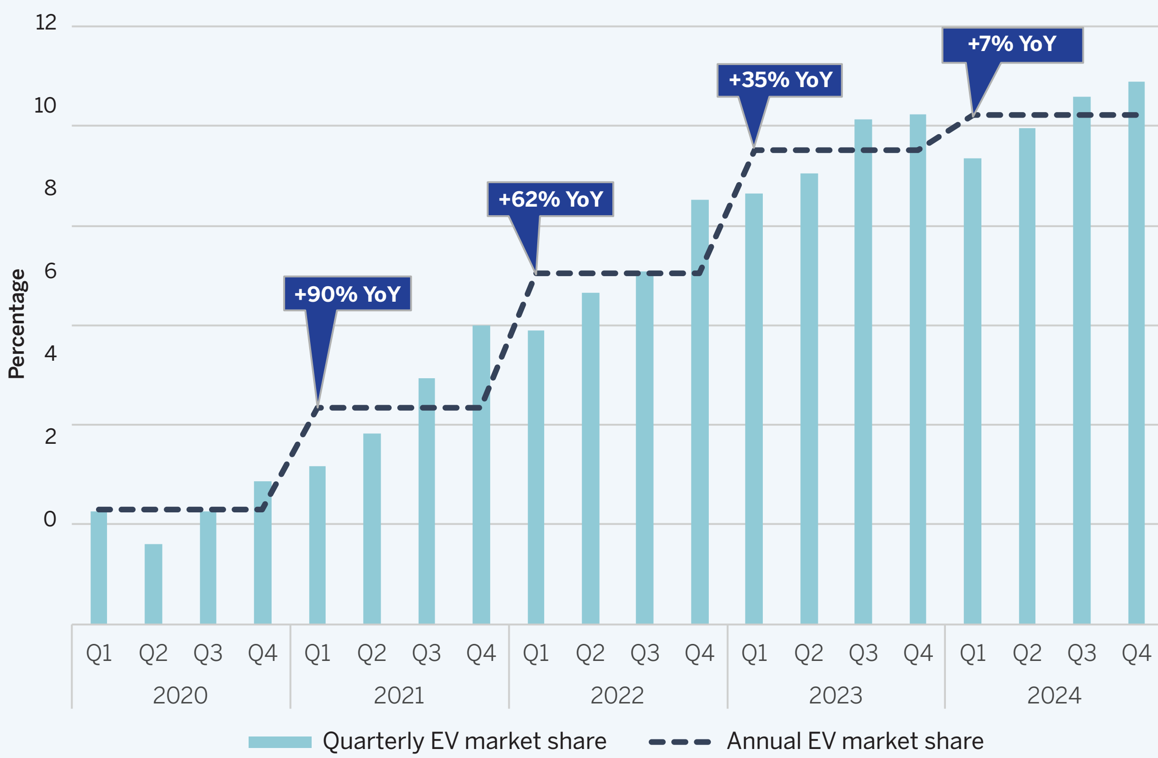
FIGURE 1
Light-Duty EV Market Share, Quarterly 2020–2024



Between 2020 and early 2025, the market share of new light-duty EV sales surged from roughly 2% to over 10%. This growth has put more than 5.8 million battery electric and plug-in hybrid EVs on the road.

Note: YoY = year over year.

Source: Alliance for Automotive Innovation.

The Time Is Right for Improved EV Load Forecasting (CONTINUED)

available when customers want it and the power system remains reliable and affordable. In regions with both high EV market share and utility distribution systems facing capacity constraints in the near to medium term, including EV loads in forecasting can identify necessary distribution system upgrades in a timely manner. Some jurisdictions are proactively addressing such infrastructure investment needs to improve customer service and meet state objectives for transportation electrification.

Unlike fixed assets, EVs are mobile loads whose charging patterns are shaped by complex human behaviors, rapid technological change in batteries, and evolving infrastructure availability and charging speeds. EV loads can materialize rapidly and concentrate geographically (e.g., fleet depots and public fast-charging plazas), with charging events varying widely in location (e.g., residential, workplace, public), timing, and power levels. Individually, each of these factors can create significant localized grid impacts. Integrating robust EV load forecasting into traditional load forecasting can help ensure that customers have the power they need when they need it.

predictable relationship makes customer load shapes a critical and reliable input for modeling distributed energy resource adoption and impacts on customer energy usage. In contrast, EV adoption is not tightly correlated with the customer's electricity usage profile.

- **Inherent locational and behavioral uncertainty:** EVs are mobile loads. While most light-duty vehicles (LDVs) and many medium- and heavy-duty vehicles (MHDVs) charge at home or at charging depots, some charging takes place en route. Charging location —and timing—depend on evolving human behaviors related to travel needs, convenience, cost awareness, and charging availability.
- **Potential for concentrated high-impact loads:** EV charging can concentrate geographically and appear rapidly—fleet depots and public fast-charging plazas can be built quickly, and EV adoption can be influenced by neighbors' choices (Generation180, 2023)—making it difficult for utilities to forecast EV loads.
- **Dynamic technology trajectory:** Rapid changes in EV battery technology that affect range and energy needs per vehicle, and charging capabilities that influence power demand and duration, create a moving target for forecasters. Emerging bidirectional capabilities that allow EVs to charge and discharge power to the grid add additional complexity.

Capturing these EV-specific dynamics requires integrating data from new sources (transportation agencies, vehicle manufacturers, and charging networks) and often requires different modeling techniques focused on charging behavior, spatial allocation, and technological diffusion, thus moving beyond traditional econometric load models. In addition, new methods are needed for modeling vehicle behavior, such as traffic flow and origin/destination data.

Effectively developing, evaluating, and using EV load forecasts requires acknowledging and managing uncertainty through robust scenario analysis, transparency and scrutiny of inputs and assumptions, considering spatial granularity, and adopting methods that differ substantially from historical utility forecasting practices.

Building an EV Load Forecast That Supports Diverse Planning Needs

The requirements of an EV load forecast are shaped by its intended use, and can vary based on the planning time horizon (short-, medium-, or long-term), the level of geographical and temporal detail required (system-wide vs. feeder-level, annual vs. hourly), and the specific grid or planning context (urban vs. rural, residential vs. fleet charging, etc.).

Choosing the Right Forecasting Approach

While a universal approach to EV load forecasting would help streamline planning processes and ensure consistency, it may not always be attainable. A highly granular, bottom-up, and long-term forecast aggregated to different spatial and temporal levels provides the most detail and can therefore be used for many distinct load forecasting needs. However, such a forecast is resource-intensive, and in practice, approaches that provide lower levels of spatial and temporal granularity may be able to meet specific load-forecasting objectives while being less resource-intensive.

Forecast practitioners and subject matter experts who contributed to this guide consistently cited the need for different approaches depending on the purpose of the forecast, and recognized the practical constraints created by data limitations, methodological complexity, and staffing capacity. These challenges are especially pronounced in regions where current levels of EV adoption are low, and the immediate need for detailed forecasting outputs may not justify substantial investment.

Planners' selection of appropriate time horizons, levels of spatial and temporal granularity, and modeling techniques is based on the specific questions the forecast aims to answer, the desired precision, and available resources (such as data, personnel, timelines, and budgets). It is critical to tailor the forecasting approach so it is fit-for-purpose in order to support well-planned, cost-effective EV integration across diverse planning needs—from localized distribution system upgrades to broad state-wide assessments.

Aligning Inputs and Assumptions for Comparable Forecasts

Forecasting approaches vary by purpose: a granular bottom-up forecast may be essential for circuit-level analysis, while a top-down approach may be more practical for system-wide scenarios. These different approaches may potentially lead to different modeling outputs without either forecast being "wrong," per se.

To make comparisons meaningful, practitioners should align on a common set of inputs and assumptions—such as baseline EV counts, adoption growth rates, vehicle efficiency, and charging behavior—regardless of the approach. When these factors are consistent, differences in results can be attributed to the methodology rather than underlying assumptions. This alignment allows planners to reconcile forecasts more easily and understand the impact of modeling choices.

If deviations from standard or previously used assumptions are necessary, practitioners should document them clearly. Transparency ensures that stakeholders can interpret differences correctly and avoid misinformed decisions.

Top-Down, Bottom-Up, and Mixed Forecasting Approaches, and Data Needs

Top-Down, Bottom-Up, and Mixed Forecasting Approaches

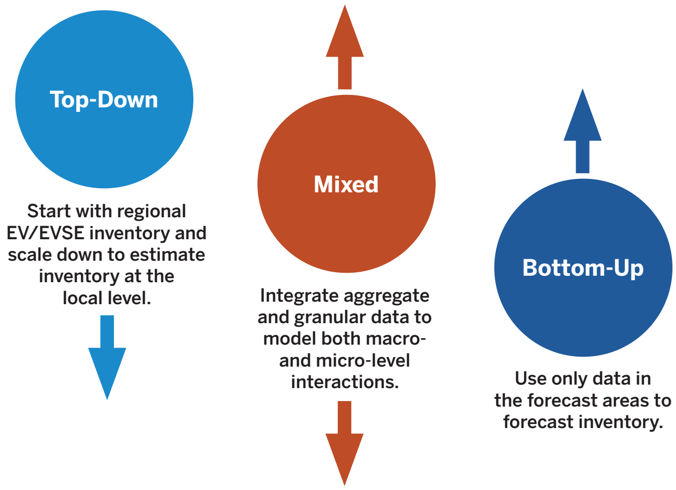
Forecasting approaches can be broadly categorized as top-down, bottom-up, or mixed (Figure 2). **Top-down models** begin with macroeconomic or system-level data, projecting trends based on high-level indicators such as vehicle stock, population growth, or regional energy consumption. They are typically suited to capturing long-term, large-scale trends. **Bottom-up models** are built from granular datasets, such as of individual households, vehicle owners, or localized charging behaviors. Techniques such as discrete choice modeling and agent-based simulation are often employed to represent decision-making processes and social diffusion dynamics at granular levels. **Mixed approaches** integrate top-down and bottom-up elements to balance scale with local detail.

For example, a forecaster may apply a top-down model to forecast total regional EV adoption based on market targets, while simultaneously using a bottom-up model to estimate siting needs for EV supply equipment (EVSE) based on household-level travel behavior, and a mixed approach to generate circuit-specific charging load profiles. The appropriate method depends on how the forecast is intended to be used—for example, bulk system capacity planning, localized infrastructure upgrades, rate design, or siting decisions.

In practice, many forecasters adopt a mixed approach, combining top-down projections with bottom-up modeling to balance scalability with detail. This hybrid strategy allows for better alignment of the forecast(s) with long-term planning goals while incorporating emerging trends and localized impacts in EV adoption and charging behavior. A mixed approach also allows the forecasters to leverage readily available data sources and methods as appropriate or incorporate third-party forecasts where such data may supplement the forecaster's efforts.

While these categories offer a conceptual structure, they are not mutually exclusive and can often be mixed or nested depending on the modeling objectives and data availability (Domarchi and Cherchi, 2023; Jochem et al., 2017).

FIGURE 2
High-Level Forecasting Approaches



EV load forecasting methodologies can be categorized into three main approaches. Top-down models scale regional or national data to the local level, while bottom-up models aggregate granular data to create a system-wide forecast. Mixed approaches, which are common in practice, integrate both to balance scale with local detail. Each approach has both strengths and limitations, with the main trade-offs being between data availability, method complexity, and output granularity.

Source: Energy Systems Integration Group.

Importantly, these modeling approaches can be applied independently to each component of EV load forecasting, described in sections in this report on Methods for Forecasting EV Adoption, Methods for Forecasting Charging Infrastructure, and Methods for Forecasting EV Charging Profiles.

Understanding Data Needs

Effective EV load forecasting relies heavily on the availability, quality, and appropriate application of diverse data-sets. Data inputs influence the forecast outcomes across the three core forecasting components: EV adoption, EV charging infrastructure needs, and EV charging profiles. The type and granularity of available data often shape the selection of forecasting methodologies.

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Unique Data Considerations for EV Load Forecasting

EV load forecasting introduces complexities beyond traditional load or distributed energy resource forecasts. While foundational inputs like weather, economic data, demographics, and existing baselines remain crucial, to accurately forecast EV impacts requires sourcing, integrating, and analyzing several new data dimensions that originate outside typical utility sources—such as transportation agencies, vehicle manufacturers, and charging networks. Types of data needed for EV load forecasting include the following:

- **Data on adoption motivators:** Forecasting why and when consumers and fleets adopt EVs requires different inputs than forecasting other loads and distributed energy resources. These inputs include detailed total-cost-of-ownership components, vehicle model availability, specific policy targets, and others.
- **Data on travel and charging behavior:** Unlike static loads, EV charging demands are driven by customer mobility needs, requiring data and assumptions related to travel patterns, charging location choices, pricing, and convenience.
- **More granular data:** Assessing the localized impacts from concentrated charging—such as charging depots, public hubs, neighborhood clusters—often demands finer spatial granularity in data and analysis than needed in typical system-level forecasts.
- **Data reflecting technological evolution and infrastructure interdependence:** Rapid changes in EV and EVSE technology and the feedback loop between charging availability and adoption introduce dynamic factors requiring specific assumptions.

Granularity

When developing an EV load forecast, the selection of data granularity is a foundational consideration with far-reaching implications for both model structure and accuracy. The modeling objectives must be clearly defined from the outset, as the chosen level of detail determines not only how well the forecast will address stakeholder needs but also the types of data sources and analytical tools required. Increased granularity in one dimension—such as detailed breakdowns by vehicle class, body type, or charging location—can enhance forecast accuracy, but it also requires corresponding granularity in supporting datasets. For instance, a highly disaggregated vehicle adoption forecast requires the same level of detail for data on registrations, vehicle characteristics (e.g., battery capacity, charging power), and extensive behavioral assumptions to ensure internal consistency across the modeling framework.

Establishing granular data sources early in the modeling process, particularly at the EV adoption stage, produces downstream benefits by enabling more nuanced scenario analysis and targeted infrastructure planning. However, this approach also introduces interdependencies: greater detail in one component may require enhancements in related datasets and modeling requirements, potentially increasing data acquisition and processing complexity. Aligning across these factors early in the process will help ensure that the forecast is both actionable and defensible, supporting effective decision-making for utilities, planners, and policymakers as they navigate the evolving landscape of transportation electrification.

Table 1 provides an overview of the main data categories required for each major step in the EV load forecasting process. The table contains example sources for top-down/less granular data and for bottom-up/more granular data, as well as considerations and trade-offs that forecasters and stakeholders can consider when selecting data sources for their modeling. These data types are described in detail in the "Inputs and Assumptions" subsections for each respective forecast component in "Implementing an EV Load Forecast."

TABLE 1

Summary of High-Level EV Data Types, Example Top-Down and Bottom-Up Sources, and Key Considerations

	Data Type	Data Purpose	Top-Down/ Less Granular Example Datasets	Bottom-Up/More Granular Example Datasets	Considerations and Trade-Offs
Foundational Data	**Utility service area boundaries and grid asset layers**	These data establish the geographical boundaries and level of geospatial granularity and specificity of the electricity system for which the EV load forecast is being developed. While the level of detail for a utility service area and its accompanying grid asset location data can be decoupled (i.e., a simple, high-level shape file for a utility can also include detailed geospatial data for grid assets), for simplicity, a high-level utility service shape file can be accompanied by simple, non-specific geospatial information on its grid assets.	The state of New York provides high-level geospatial electric utility service territory maps for the utilities in the state.	Pacific Gas & Electric Company's Grid Resource Integration Portal is an example of highly detailed geospatial utility boundary and grid asset data that utilities are beginning to make public.	Since electric utilities are typically directly involved in developing EV load forecasts, there is usually very limited friction or cost associated with gathering either top-down or bottom-up data for service area boundaries. However, the more granular the utility boundary and accompanying asset layers are, the more granular and geospatially specific the rest of the modeling data will need to be. As with most data selection decisions, the level of granularity selected will have cascading downstream impacts on the rest of the modeling choices.
Foundational Data	**Census socioeconomic data**	These data contain widely cited and utilized local socio-economic and community data ranging from education and income levels to housing type and vintage that can be analyzed with other data sources to identify correlations and other trends.	The U.S. Census Bureau collects vast amounts of data, from low levels of granularity, ranging from national and state, to higher levels of granularity, such as zip code to census block group (600 to 3,000 people).		Census data are free to obtain across all levels of granularity. While using more granular data adds complexity to the analysis, it can also yield better insights and correlational capabilities. A decision to use more granular socioeconomic data means the rest of the data source selections will likely need to be more granular to make use of the detailed information contained in the bottom-up data.
Foundational Data	**EV charging data**	Usually sourced from the utility or EV charging providers, these data contain charger-level (or sometimes port-level) energy consumption data, typically in the form of hourly or sub-hourly meter reading. They can be segmented by use case, such as residential, multi-unit dwelling, workplace, or fleet depot chargers. These data can help forecasters identify localized charging patterns unique to their service area.	The Maryland Statewide Electric Vehicle Portfolio Evaluation Mid-Course Evaluation Report (mail log: 237041) contains utility and program EV charging data and load profiles.	Granular (i.e., at the port or premise) EV charging data are typically confidential and maintained by either a utility or charging company. DOE maintains some granular examples, such as the EV Watts Public Database.	More detailed EV charging data, in terms of temporal and locational granularity as well as by use case, can provide forecasters with specific information that can help improve the accuracy, transparency, and explain-ability of charging behavior and its im-pact on the grid. However, the added complexity from the amount of data that must be managed and modeled, along with the larger number of assumptions that must be made, can erode the benefits associated with greater granularity.
Foundational Data	**Land use data and housing characteristics**	These data contain information on the type of structures that have been built on an area of land (e.g., county or a parcel) or the type of activities (e.g., commercial, industrial, or agricultural) that take place on the land.	U.S. Census Bureau data, such as the American Community Survey, contain aggregated data on the number of housing units, type of housing units, and building vintage.	Parcel data are typically aggregated at the county level, such as is seen in El Paso County, Colorado, but they can also be purchased nationally from third parties, such as Regrid.	Detailed land use and housing data can serve as an important variable to help forecasters analyze correlations associated with historical adoption patterns. However, doing so at a granular level requires multiple data-sets (such as vehicle registration data) of a similar level of granularity, which can be challenging or expensive to acquire.

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TABLE 1 (CONTINUED)

Summary of High-Level EV Data Types, Example Top-Down and Bottom-Up Sources, and Key Considerations

	Data Type	Data Purpose	Top-Down/ Less Granular Example Datasets	Bottom-Up/More Granular Example Datasets	Considerations and Trade-Offs
EV Adoption	**EV adoption forecast**	EV adoption forecasts contain data regarding what type of vehicles (both EV and internal combustion engine, by class and body type) will be adopted by the population within a given area and when those adoptions will take place across the forecast horizon.	Massachusetts' Clean Energy and Climate Plan 2030 state-wide targets for LDV, MDV, and HDV is an example of simplified, high-level adoption targets.	California Air Resources Board's 2020 Mobile Source Strategy LDV, MDV, and HDV forecasts provide details by year, vehicle class, and powertrain.	Simplified, less granular EV adoption forecasts, such as those that target LDV, MDV, and HDV but do not specify body type or class-level targets, can help make developing the rest of an EV load forecast more straightforward. However, the real population of vehicles is complicated, and this simplification may reduce the forecaster's ability to explain how a model's results will manifest realistically on the grid.
EV Adoption	**Historical vehicle registration and class data**	Vehicle registration data, which include information on the types or classes of vehicles that were registered over a given period for a given geography, contain critical information on purchasing behaviors of consumers. These data, when paired with other data listed above such as land use and demographic data, can yield deep insights and important trends that may inform future EV adoption choices.	State agencies, such as the Illinois Secretary of State, publish annual, county-level data on vehicle registrations by simplified vehicle class.	The California Air Resources Board's EMission FACtor (EMFAC) tool provides highly granular registration data for over a dozen vehicle classes at the census block level. Detailed national data can also be purchased from S&P Global or Experian.	A decision about the level of granularity a model's vehicle registration data to use must be made in the context of other data, such as the granularity of the adoption forecast the forecaster will be using for their model. For example, if the EV adoption forecast is highly granular, using equally detailed vehicle registration data is likely necessary to accurately allocate future EV adoption uptake in a realistic manner.
EV Adoption	**Vehicle characteristic data**	When developing an EV load forecast, forecasters must make assumptions regarding how much energy vehicles require to operate, their typical travel behavior, and other factors. Vehicle characteristics data capture this information and serve as an important input for critical energy calculations.	For LDVs, assumptions can be as simple as a single fuel-economy range cited by DOE's Alternative Fuels Data Center. For MDVs and HDVs, assumptions can be at the class level, such as those in this DOE study.	Appendix C of the California Energy Commission's 2024 AB 2127 report contains detailed LDV characteristics data. DOE's Annual Technology Baseline contains detailed information for MDV and HDV characteristics.	Using detailed vehicle characteristics data has the most impact when modeling MDV and HDV adoption because there is significant variation across these duty classes, and energy requirements are significantly larger than for LDVs. But leveraging these detailed data requires forecasters to gather equally detailed data on vehicle registration to support a detailed EV adoption forecast.
EV Infrastructure	**EVSE use case type**	The EVSE use case type conveys information about the location or type of building where the EVSE has been or will be sited (e.g., single-unit dwelling, multi-unit dwelling, office, highway corridor, or fleet depot). Where the EVSE has been sited determines the type of vehicles that will charge at the station, their charging requirements, and associated load profiles.	EV infrastructure data and assumptions are deeply interconnected and are typically determined in concert with one another. The California Energy Commission's 2024 AB 2127 report and appendices contain excellent primary data on LDV charger use cases, characteristics, and port count methods. For MHDV chargers, Lawrence Berkeley National Laboratory's HEVI-LOAD approach is an excellent source. The California Public Utilities Commission's Electrification Impact Study Part 1 provides an example of how to integrate these data.	For LDV EV infrastructure modeling, the National Renewable Energy Laboratory's *2030 National Charging Network* report provides the most comprehensive and granular example of the state of the industry. It contains an EVSE use case typology and an integrated EVSE port count method. For MHDV, the National Renewable Energy Laboratory's *Electric Medium- and Heavy-Duty Vehicle Charging Infrastructure Attributes and Development* report provides the latest data and thinking.	The choice to use more or less granular data for forecasting charging infrastructure is informed by the level of granularity used for the EV adoption forecast and EV charging profiles. If a forecaster has selected a top-down approach for EV adoption with low granularity (i.e., simplified vehicle classes and body types), the infrastructure forecast will most likely need to be executed at a similar level of granularity. If stakeholders want to use a low-granularity EV adoption forecast to generate a high-granularity infrastructure forecast (or vice versa), it requires developing a rationale and assumptions that may have limited basis on research or empirical data.
EV Infrastructure	**EVSE characteristics**	EVSE characteristics contain critical capacity and usage information for each EVSE use case including the peak charging capacity, how that capacity changes over the forecast horizon, typical load profiles, and the number of events per day.			
EV Infrastructure	**EVSE port counts method**	Once an EV adoption forecast has been determined, forecasters must estimate the number of EV charging stations and ports that will be required to supply the energy the EV population requires to operate. Station and port counts are typically estimated for each EVSE use case.			

(CONTINUED)

TABLE 1 (CONTINUED)

Summary of High-Level EV Data Types, Example Top-Down and Bottom-Up Sources, and Key Considerations

	Data Type	Data Purpose	Top-Down/ Less Granular Example Datasets	Bottom-Up/More Granular Example Datasets	Considerations and Trade-Offs
EV Charging Profiles	**EVSE use case load profiles**	Load profiles represent the EVSE port or station-level hourly energy consumption required to charge the number and type of EVs being served at the location where the EVSE has been sited. These load profiles are the manifestation of EV charging demand on the grid.	The California Energy Commission's EV Infrastructure Load Model used for its bi-annual Integrated Energy Policy Report has simplified load profiles.	The National Renewable Energy Laboratory's EVI-Pro Light (LDV) and Lawrence Berkeley National Laboratory's HEVI-LOAD (MHDV) represent more detailed, use case-specific profiles.	When forecasting for smaller utility service areas with a relatively homogeneous vehicle population, lower-granularity data for EV load profiles may simplify the complexity, time, and cost of developing the EVSE load forecast without compromising the accuracy or usefulness of the forecast. However, if the service area is large or has a relatively heterogeneous vehicle population, particularly with concentrated pockets of MHDV adoption, more granular EVSE load profiles may be warranted to accurately reflect a more realistic estimate of charging in regions with concentrated EV adoption.

Notes: DOE = Department of Energy; EVSE = electric vehicle supply equipment; HDV = heavy-duty vehicle; LDV = light-duty vehicle; MDV = medium-duty vehicle; MHDV = medium- and heavy-duty vehicle.

Source: Energy Systems Integration Group.

Using Data from Multiple Sources in EV Load Forecasting

In addition to multiple data types, EV load forecasting relies on data from various sources and entities. Figure 3 (p. 12) categorizes data sources that could contribute to an EV load forecast. A single load forecast may be informed by each of these data sources.

EV load forecasting often involves integrating data from multiple, sometimes overlapping, sources. This can create uncertainty for forecasters when trying to determine which data to use. For instance, baseline vehicle stock data can be sourced from the state Department of Motor Vehicles, but also from private data aggregators. Forecasters can leverage multiple data sources to bound uncertainty, create scenarios, calibrate models, and validate forecast results.

Data complexity is considered as part of a structured forecast scoping effort. Forecasters can document key assumptions regarding data used for the forecast. This transparency is vital because of the significant impact that assumptions have on results. Transparency of assumptions also helps build confidence between utilities, regulators, and stakeholders that the forecasts they are reviewing or using are reasonable.

Because data and related assumptions are subject to uncertainty, no single forecast can be considered definitive. **A collaborative forecast-scoping process can align utilities, regulators, and stakeholders on a range of plausible scenarios to guide the analysis and help ensure the final product is widely accepted and actionable.**

FIGURE 3

Summary of Data Sources

Utility Data

What is it?

Data generated and maintained internally by the electric utility. Can include operational data (SCADA, advanced metering infrastructure (AMI)), distributed energy resource program participation, billing data, or asset ratings.

How is it used?

- Provides location-specific historical EV charging behavior
- Provides EV rate enrollment for determining load profiles
- Assists in mapping EV adoption and EVSE to grid assets

Challenges

- Access may be restricted internally with data privacy requirements necessitating aggregation for external use.
- Legacy data systems may have poor reporting capabilities.

Public Data

What is it?

Data freely available from government-funded activities (Department of Energy, Energy Information Administration, Department of Transportation, state departments of motor vehicles, national laboratories) and nonprofits. Can include raw data (EV registrations), tools (National Renewable Energy Laboratory's EV-Pro), or studies (EPRI's eRoadMap).

How is it used?

- Establishes baseline EV adoption levels
- Provides socioeconomic info for adoption models
- Serves as a benchmark for national or regional trends

Challenges

- It may lag behind market changes.
- It may lack desired granularity or may not cover desired vehicle classes.
- It can be misused when methodologies are poorly understood.

Proprietary Data

What is it?

Data purchased or licensed from commercial data vendors, manufacturers, fleet owner/operators, or charging providers. Can include vehicle telematics, registration data, and consumer information.

How is it used?

- Improves spatial granularity for underlying data
- Informs observed travel patterns
- Refines market segment and cost assumptions

Challenges

- Cost, as these datasets typically require subscriptions or licensing fees.
- Data usage can be constrained by licensing agreements.
- Limited scope or coverage. For example, a dataset for medium- and heavy-duty vehicles might include commercially owned vehicles but exclude public transit and school buses.

Three primary categories of data are used in EV load forecasting: utility, public, and proprietary. Each data source offers unique benefits. Understanding the respective uses and challenges of each data type is essential for developing robust, transparent, and defensible EV load forecasts.

Source: Energy Systems Integration Group.

Scoping an EV Load Forecast

Forecast scoping occurs through various stakeholder engagement activities. Early engagement with stakeholders helps to define the forecast's extent, select relevant scenarios, and agree on initial assumptions. Stakeholders involved in scoping exercises may include utility planners (often a separate team from utility forecasters), regulatory commissions, researchers, state energy offices, utility consumer offices, transportation agencies, fleet managers, municipal planners, technology providers, and industry associations. Effective engagement does require time and coordination; however, it can lead to improved confidence in the forecast and greater overall planning efficiencies if it reduces the need for revisions or rework later in the forecasting process and results in more actionable outputs.

Defining Core Forecast Parameters

The scoping process moves from high-level strategy to defining practical boundaries that establish core parameters that shape the analysis: forecast area, time horizon, and level of spatial granularity. Each of these decisions involves significant trade-offs and is complicated by the unique nature of EVs. Making technically sound choices, deliberately and collaboratively with a wide variety of stakeholders, is essential for ensuring the final forecast is technically sound and aligned with its intended purpose.

Defining the Forecast Area

Forecast area refers to the specific geographical or electrical system boundary under consideration. The appropriate forecast area depends on the purpose and specific planning or operational questions being addressed.

State agencies or regional planners might define the forecast area as a state or region to inform policy or broad infrastructure strategies, while an electric utility or regulator might use a service territory boundary or planning zone as the forecast area for integrated resource planning or system-wide analysis. Utilities also define much smaller areas, such as specific substations or distribution feeders, to assess localized grid impacts and plan targeted upgrades. Throughout this guide, the term forecast area refers to the defined geographical region (e.g., state, county) and scope of the electricity system (e.g., distribution, transmission) of the specific forecast.

Defining the forecast area for EV charging can be relatively complex due to the "triple mobility" of EV loads:

- **Vehicles are transient.** They can move to different locations to charge inside and outside a given geographical area. Vehicles from outside the area can charge inside.

- **Vehicle owners can move.** Unlike with appliances, the vehicle will move with a relocating owner. This may be invisible in registration data, particularly for fleets.
- **Vehicles can change owners.** The secondary (used) vehicle market means that new registrations cannot indicate a vehicle's presence (or absence) in a given geographical area for its entire lifetime.

Establishing the Forecast Time Horizon

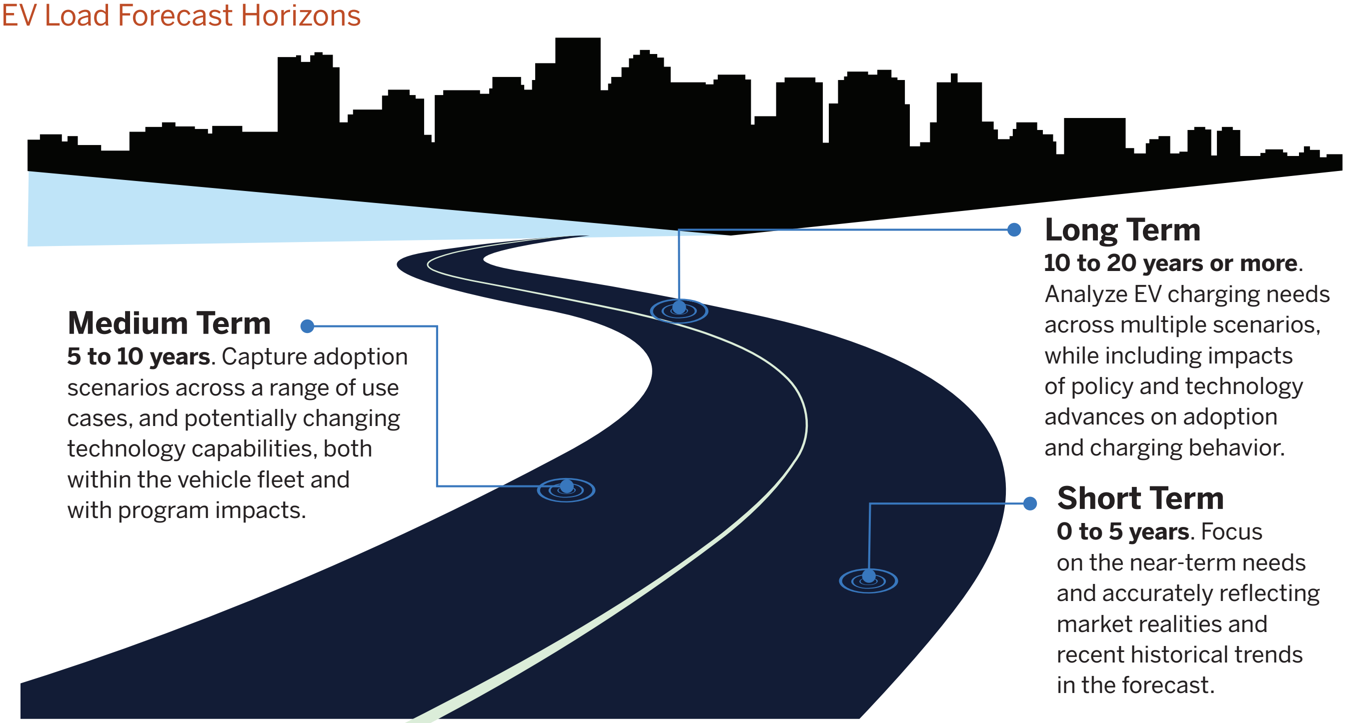
The forecast time horizon should be informed by how the forecast is to be used. The forecast horizon will directly impact assumptions related to vehicle adoption rates, infrastructure needs and availability, and technology advancements. Figure 4 describes three time horizons commonly used for EV forecasting: short term (5 years), medium term (10 years), and long term (20 years or more). Each horizon captures different stages of the evolution and infrastructure development needs of the EV market.

Near- to mid-term forecasts face less uncertainty because they are anchored by well-understood, slow-moving factors such as existing vehicle stock, known pace of vehicle turnover, and slate of currently available models and technologies, collectively known as system dynamics. In contrast, long-term forecasts are subject to much greater uncertainty related to disruptive technologies and fundamental shifts in consumer behavior over multiple decades. Clear long-term policy objectives, like a mandate for 100% zero-emission vehicle sales by a certain date, can reduce uncertainty by defining clear long-term objectives. This allows forecasters to "backcast" from the target to define a plausible pathway for achieving the goal (Yip et al., forthcoming).

Determining Forecast Spatial Granularity

The level of spatial granularity required for an EV load forecast depends on its purpose and objectives. For

FIGURE 4
EV Load Forecast Horizons



The forecast time horizon should align with planning objectives. Short-term forecasts focus on immediate needs based on current market data, medium-term forecasts capture broader adoption scenarios, and long-term forecasts analyze the impacts of major policy goals and technological shifts.

Source: Energy Systems Integration Group.

example, distribution system planners require granular forecasts at the feeder or substation level to identify local capacity constraints and plan grid upgrades, while regional or state-wide forecasts may suffice for policy development or budgetary estimates for financial planning. Figure 5 represents grid topology and geographical areas used in load forecasting, as well as the data types and identifiers that link different layers.

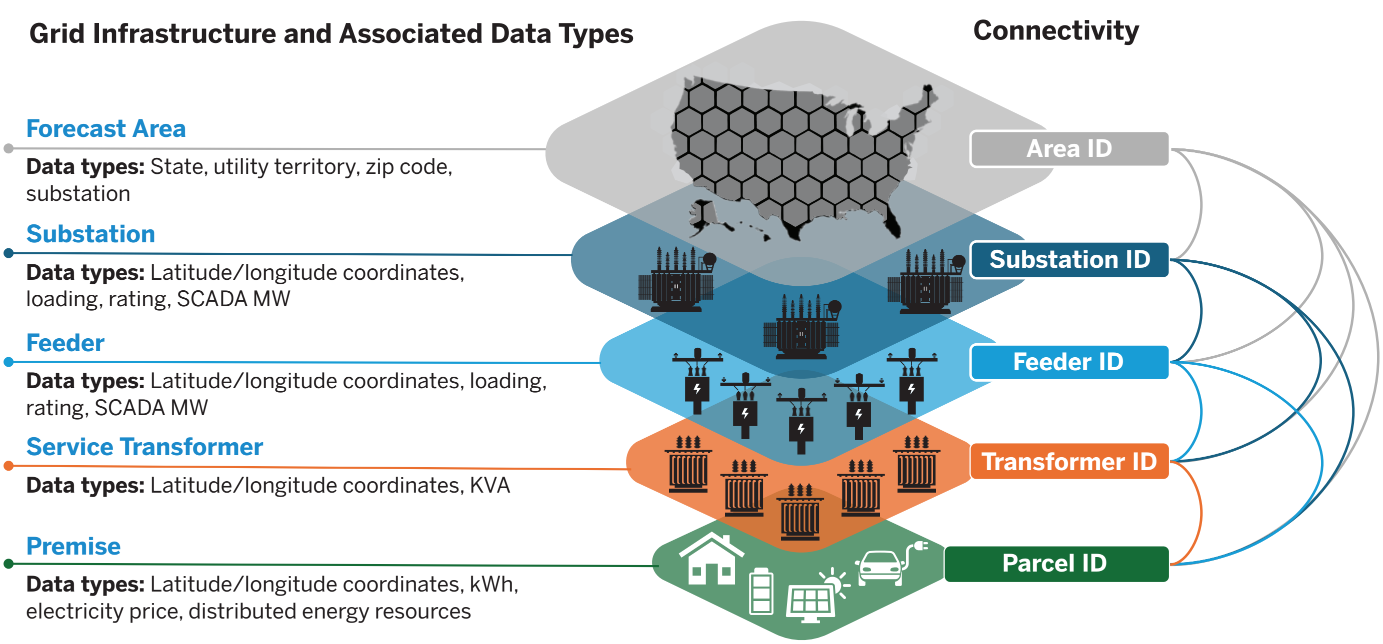
EV and EVSE adoption trends and behavior vary significantly by region, county, and even census block. When spatial granularity is matched to forecast objectives, this enables more precise allocation of resources and investments for specific areas, such as urban centers with dense EV populations or rural areas with minimal infrastructure. Using more granular spatial data can increase cost, time, and uncertainty, because as spatial data get more granular, data files grow in size and complexity and become more difficult to obtain and use. Errors in more granular data can cascade as small errors are aggregated to higher levels. If a data-intensive approach is required for the forecast to meet its objectives, the utility can make stakeholders aware that the resources and time required will increase accordingly.

Using granular data to predict individual behavior—such as whether a specific household will adopt an EV—tends to carry greater uncertainty (Yip et al., forthcoming). Aggregated predictions (such as adoption rates at the state level) may be more appropriate for bulk power

Forecast granularity should be matched to the scale and sensitivity of the decision being made, with uncertainty acknowledged, incorporated into planning assumptions, and hedged against by using scenario analysis to understand a range of possible futures.

FIGURE 5

Grid Infrastructure, Data Types, and Connectivity



A granular forecast requires mapping EV loads to the grid's hierarchical structure. Data from various levels—from the broad forecast area down to the individual premise—are linked using unique identifiers to allow planners to assess impacts on specific assets like feeders and service transformers.

Note: SCADA = supervisory control and data acquisition.

Source: Energy Systems Integration Group.

system planning and policy development, as they often provide more stable results due to the smoothing effect of larger sample sizes. **The key is to match forecast granularity to the scale and sensitivity of the decision being made, and to ensure that uncertainty is acknowledged, incorporated into planning assumptions, and hedged against by using scenario analysis to understand a range of possible futures.**

Specifying Types of EVs to Forecast

EVs come in many vehicle classes, body types, and charging power levels, and they have different charging profiles, use different types of charging, and are used in different ways. As part of scoping the EV load forecast, it is necessary to determine the mix of vehicles based on these factors. LDVs used for personal transportation are the dominant EV on the road today in many parts of the country, but that may change as fleets continue to electrify, technologies continue to improve, and policy targets take effect. Large concentrations of LDVs on a single transformer or circuit, or fast-charging at a fleet depot, may have significant impacts on local grids.

While fewer in number, MHDVs present unique and disproportionate challenges. For example, the infrastructure required for a single commercial fleet depot can be substantial, and costs for high-power chargers for heavy-duty trucks can be one or two orders of magnitude larger than for LDVs (NREL, 2024).[5] Further, MHDV charging needs are dictated by operational requirements that vary significantly by vehicle class and use case.

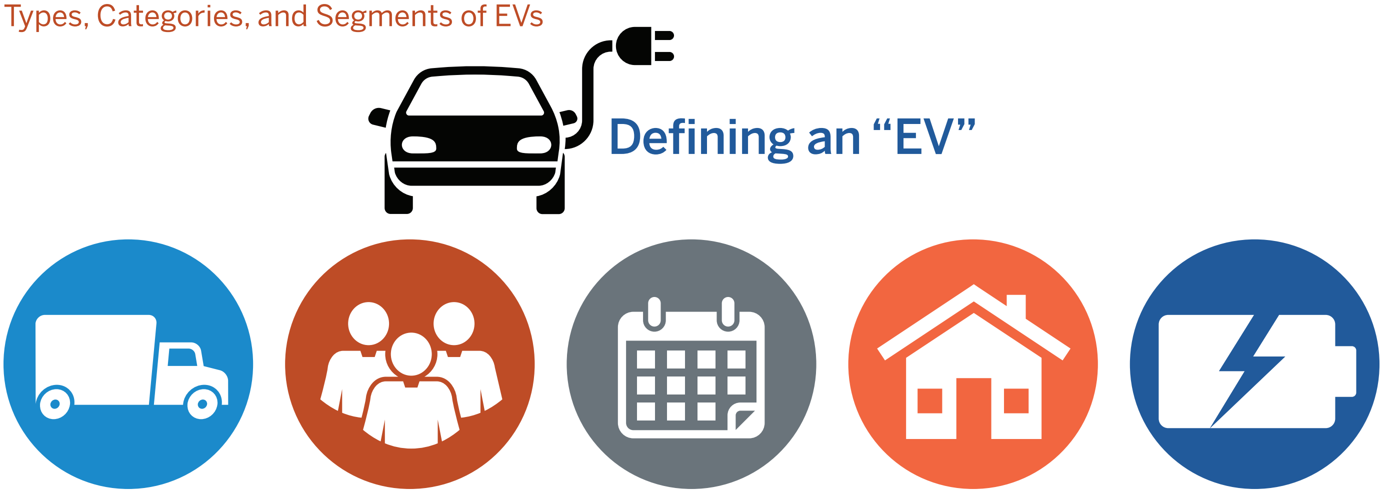
Figure 6 (p. 17) shows necessary considerations when defining the types of EVs that could be considered in a forecast.[6]

5 National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory, Kevala Inc., and U.S. Department of Energy. (2024). Multi-State Transportation Electrification Impact Study: Preparing the Grid for Light-, Medium-, and Heavy-Duty Electric Vehicles. U.S. Department of Energy. Report No. DOE/EE-2818.

6 This is sometimes referred to as dimensionality, to match with granularity above. Forecasters must simplify the heterogeneity of the population to simplify the model while providing a sufficient level of complexity, which is defined by the purpose of the forecast. If there are multiple forecast purposes (i.e., the number of forecast stakeholders and users increase), dimensionality also increases.

FIGURE 6

Types, Categories, and Segments of EVs



Vehicle Stock
- **Light duty:** Includes cars, vans, and some pickup trucks
- **Medium and heavy duty:** Includes trucks and hauling
- **Offroad:** Can be significant near ports and recreational centers

Ownership Segment
- Personal
- Municipal fleets
- Commercial

Usage
- Daily commuter
- Long-distance travel
- Seasonal transportation

Domicile Status
- Dwell location
  - Single-family dwelling
  - Multi-unit dwelling
  - Fleet depot
- Transient (passing through the area)

Technology
- Availability and affordability
- Electrification level (plug-in hybrid vs. fully electric)
- Battery size (kWh, range)
- Battery charge speed (kW)

Forecasters must define the types of EVs specified in the forecast, considering multiple dimensions. For example, key segments for analysis include the vehicle class, ownership, primary use case, domicile or parking status, and underlying technology, all of which influence its charging needs.

Source: Energy Systems Integration Group.

The types of vehicles being forecast can drive data needs, modeling approaches, and uncertainty considerations. For example, in areas where fleet electrification is expected to dominate, forecasters may seek higher-granularity fleet registration data as well as other data sources, such as purchase and survey information. Similarly, when fleet electrification decisions are driven by price, total-cost-of-ownership models may be needed. Finally, state policy may encourage EV adoption in specific market segments, influencing the mix of vehicles to consider in the forecast.

Shaping Scenarios and Assumptions

Given the deep uncertainty inherent in forecasting, relying on a single projection is insufficient for robust planning. Instead, using scenario analysis to explore a range of plausible futures supports more informed decision-making and can help bound uncertainty.

Each scenario represents a coherent and plausible future, built upon specific assumptions about technology (e.g., battery costs), market conditions (e.g., EV model availability), consumer behavior (e.g., charging preferences), and policies (e.g., state targets). Defining scenarios and aligning on assumptions are critical parts of the scoping process, where stakeholders collaborate to define which potential futures are most relevant to explore for specific planning needs.

Stakeholder Collaboration to Shape Scenarios

Developing relevant and trusted scenarios is a collaborative process, not a purely technical one. Early and consistent

stakeholder input helps establish a shared understanding of different potential futures among all parties, which can reduce subsequent disagreements and build trust in the forecast results by exploring the range of stakeholder visions and priorities.

It is essential to the forecasting process to keep parties informed, solicit input, and promptly adapt to evolving assumptions, such as new data sources, technological developments, regulatory changes, and market trends. Communicating with specificity how stakeholder feedback is incorporated into the forecasting process helps support credibility and confidence among all participants.

While broad engagement across utility planners, forecasters, regulators, and other key stakeholders requires careful coordination across multiple entities, regulatory proceedings, and rulemaking procedures, it can support more effective planning and decision-making. Such coordination supports forecast implementers in prioritizing their limited resources and balancing sensitive trade-offs, such as limited budgets, timelines, or data. A forecast scoping function allows relevant parties to collaborate so that these trade-offs can be prioritized, and it is especially needed as EV load forecasting continues to mature while uncertainties grow.

Aligning EV Load Forecasts and Scenarios with Regulatory and Policy Frameworks

EV load forecasts used for utility planning, rate cases, and other regulatory filings must navigate a complex landscape of regulatory and policy frameworks that influence their development, acceptability, and use. Adherence to an appropriate EV load forecasting framework, and using appropriate scenarios given the use case, is crucial for effectively informing decision-making. Scenario analysis is increasingly used to consider a range of stakeholder viewpoints, contingencies, and possible policies affecting electricity system reliability and affordability.

Regulatory Expectations and Processes

Regulatory bodies often establish expectations or formal guidelines for forecast methodologies, data sources, underlying assumptions, and model transparency. Key considerations for any forecast include the following:

- **Model transparency:** The choice between proprietary "black box" models and open-source alternatives can significantly impact regulatory and stakeholder acceptance. Some jurisdictions have specific rules designed to increase transparency and may require extensive utility documentation or justification for any proposed proprietary approaches.
- **Review and validation:** Forecasts submitted in regulatory contexts typically undergo rigorous scrutiny. This often involves formal discovery processes, technical conferences, stakeholder reviews (including input from intervenors), and potentially third-party validation or audits to ensure that assumptions are reasonable, methods are sound, and documentation is complete and aligns with best practices.

Incorporating Policy Goals and Targets

Beyond procedural requirements, forecasts are also expected to reflect the relevant policy environment to be useful for planning. Forecasters can accommodate these expectations by:

- **Using policy-driven scenarios:** Forecasts can use scenarios that align with applicable national, state, and local targets. This includes specific goals for EV adoption (e.g., vehicle counts or sales percentages by year), broader objectives like targets for reducing air pollutants, and related distributed energy resource integration strategies. Incorporating scenarios based on these targets (e.g., "500,000 LDVs by 2035" or "net-zero fleet emissions by 2040") allows stakeholders to assess the grid implications of achieving stated policy goals.
- **Understanding policy influence:** It is important to understand how specific governmental policies—such as zero-emission vehicle programs, the continuation or discontinuation of federal initiatives like the Inflation Reduction Act, or state-level programs—directly influence adoption drivers (e.g., through incentives or manufacturer requirements). Scenarios can be created using different assumptions about EV adoption rates, resulting charging patterns, and future infrastructure needs based on existing policies and potential changes in policies.

In summary, the scoping phase is foundational to creating a credible and useful EV load forecast. This process involves two primary activities: defining the forecast's core parameters and shaping the scenarios to be analyzed. Through collaborative stakeholder engagement, planners first establish the forecast's fundamental boundaries, including specific geographical or electrical system boundary, time horizon, spatial granularity, and specific vehicle types to be included. Then, building on these parameters, the process focuses on shaping relevant scenarios and transparent assumptions that align with policy goals and regulatory expectations, allowing for a robust exploration of potential futures.

Table 2 summarizes scoping and planning practices for EV forecasting.

TABLE 2

EV Load Forecast Scoping and Planning Practices

FORECASTING CHARACTERISTICS	
EV load forecast scope is identified up front with input from stakeholders and consideration of forecast purpose, data availability, and level of effort required.	
Good practices	• EV load forecast inputs, methods, and outputs are aligned with the purpose and requirements of how the forecast will be used. **Example:** National Grid's Electric Highways load forecasting study underpins distribution planning efforts along highways.[a]
Better practices	• EV load forecasts are fully documented and contain transparent assumptions, while differentiating between types of EVs, such as multiple light-, medium-, and heavy-duty vehicle classifications and uses. **Example:** Consolidated Edison (Con Ed) creates different EV load forecasts for school buses, utility trucks, and refuse trucks.[b]
Best practices	• EV load forecasts include multiple scenarios as defined through early and continual stakeholder input to identify data sources, assumptions, and methods used. **Example**: The New England Power Pool organizes a Load Forecast Committee to review ISO New England's methodologies for all aspects of load forecasting, including EVs.[c]

a National Grid, "Electric Highways: Accelerating and Optimizing Fast-Charging Deployment for Carbon-Free Transportation," white paper (2022), https://www.nationalgrid.com/us/EVhighway.

b Con Edison, "Response to EDF Interrogatories, Re: Proactive Planning for Upgraded Electric Grid Infrastructure," February 6, 2025, https://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7b20096895-0000-C17A-B9F2-D408A84865B6%7d.

c https://www.iso-ne.com/committees/reliability/load-forecast

Source: Energy Systems Integration Group.

Implementing an EV Load Forecast

EV load forecast models are fundamentally composed of the following three interrelated components:

- **EV adoption forecasting and allocation**, which estimates how many EVs will enter the market over time by vehicle type, ownership model, and geography
- **EV charging infrastructure forecasting**, which projects where, when, and what type of charging infrastructure will be deployed to meet demand
- **EV charging profile forecasting**, which computes vehicle and infrastructure forecasts into hourly, seasonal, and locational estimates of electricity consumption and demand

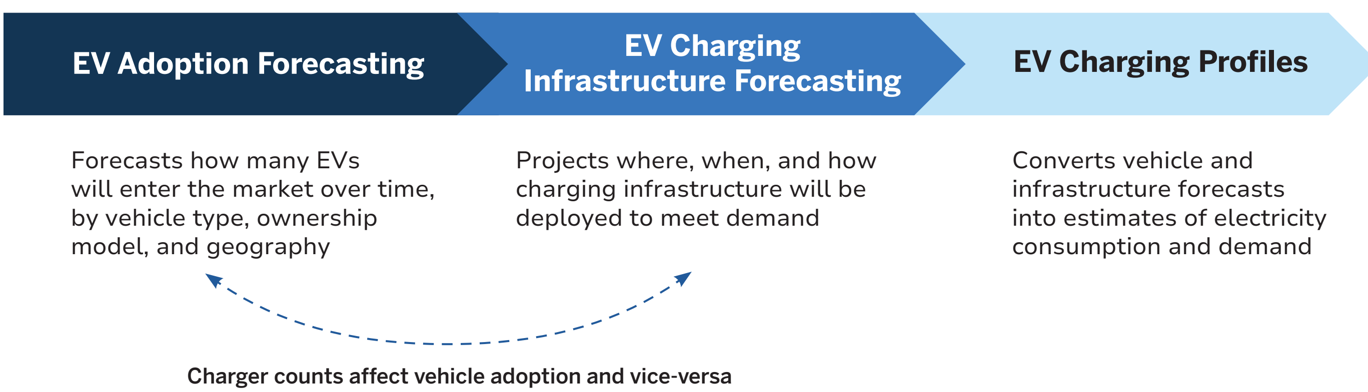
While it's helpful to describe EV load forecasting as sequential steps (Figure 7), it is inherently an iterative and integrated process that requires continual validation, refinement, and feedback across components.

The following sections describe each component in more detail and include subsections for key inputs and assumptions, modeling methods, and expected outputs (see box, p. 21).

Forecasting EV Adoption

EV adoption forecasting estimates how quickly EVs will enter the market and accumulate in the vehicle stock over time. While adoption is often expressed as the share

FIGURE 7
EV Load Forecasting Components



EV load forecasting is composed of three interconnected components. The forecast begins by estimating EV adoption (the number, type, and location of vehicles). This informs the projection of EV charging infrastructure needed to serve them. These two inputs are then synthesized to create EV charging profiles, which detail the resulting electricity consumption and demand. While presented sequentially here, the process is iterative, as the availability of charging infrastructure and the rate of vehicle adoption are mutually influential.

Source: Energy Systems Integration Group.

Definitions of Key Inputs and Assumptions, Modeling Methods, and Expected Outputs for EV Load Forecasting

Inputs and assumptions: The data (inputs) and expert judgments (assumptions) that serve as the basis for the entire EV load forecasting process, influencing projections across EV adoption, charging infrastructure needs, and resultant grid load

Methods: The range of analytical techniques, simulations, and computational frameworks used across forecasting components to translate data inputs and assumptions into projections of EV adoption, charging infrastructure deployment, and combined load impacts on the electricity system

Outputs: The projections resulting from the methods for each of the forecasting components, which typically include the quantity, types, and characteristics of EVs adopted over time; the amount, types, power levels, and locations of charging infrastructure required; and the final estimates of electricity consumption (kWh) and power demand (kW) profiles attributable to EVs, all presented across various time frames and geographical or electrical system granularities

of new vehicle sales that are electric, the actual number and types of EVs on the road—and therefore their impact on the grid—are also shaped by broader vehicle ownership patterns and dynamics of stock turnover. These include factors such as vehicle ownership rates of households or fleets, the lifespan of internal combustion engine (ICE) vehicles, and how quickly old vehicles are retired or replaced. Adoption factors also capture shifts in consumer vehicle preferences, such as purchasing larger trucks, which could increase EV loads compared to consumers more interested in smaller vehicles.

EV adoption forecasts are not monolithic; they include forecasts for different vehicle segments and can cover a range of future scenarios. Each vehicle segment requires distinct data sources and modeling approaches, and their inclusion in adoption forecasts should reflect both current market activity and anticipated shifts. Adoption trajectories can vary across scenarios to reflect different policy and regulatory environments, economic conditions, and technology assumptions, such as accelerated fleet turnover, aggressive zero-emission targets, and lagging consumer uptake. Robust electricity system planning requires stakeholder engagement, consistency across EV load forecasting for different types of planning processes, and transparent comparison of system outcomes under different futures.

This section outlines key inputs and assumptions, modeling approaches, and forecast outputs for EV adoption forecasting, and highlights how these factors can be used in scenario construction and inform downstream estimates of charging infrastructure and grid impacts. Load profile assumptions associated with these vehicles (e.g., charging behavior, location, and timing) are covered in the sections "Forecasting EV Charging Infrastructure" and "Forecasting EV Charging Profiles."

Inputs and Assumptions for Forecasting EV Adoption

EV adoption forecasts are built upon specific data inputs and key assumptions made about those inputs. It is crucial to clearly define and document both of these for forecast transparency and usability.

Forecast Scope: Vehicle Stock and Segments

Forecasters must decide which vehicle segments will be included in the analysis based on established classifications. These scope decisions are critical because market drivers, data availability, and operational profiles vary significantly across segments.

While LDVs are often the primary focus of EV load forecasts since they are currently the most electrified segment, MHDVs and off-road vehicles are electrifying rapidly and can create disproportionately large load requirements that can quickly overwhelm distribution equipment. Robust forecasts need to consider how adoption may evolve across different vehicle types:

- **LDVs:** These vehicles are typically owned by individuals and are influenced by factors such as income, vehicle turnover rates, state and federal incentives, model availability, and consumer preferences. Adoption forecasting for LDVs may use econometric, Bass-diffusion, or agent-based models, often informed by registration trends and household demographics.

- **MHDVs:** These vehicles are often part of commercial, municipal, or industrial fleets and follow different adoption pathways, influenced by factors such as compliance with zero-emission-vehicle programs, fleet turnover cycles, and total-cost-of-ownership calculations. Their adoption is more sensitive to policy, infrastructure availability, and duty cycle suitability. Forecasting adoption in this segment may require integrating vehicle stock turnover models, fleet registries, and sector-specific adoption constraints.
- **Off-road vehicles:** While less frequently included in system-level forecasts, off-road EVs that are used in applications such as drayage, ports, agriculture, construction, and recreation can be regionally significant and may be driven by specific rules (e.g., California's off-road diesel regulations). Inclusion in forecasts may be necessary in areas with major freight hubs or specialized equipment electrification programs.

These vehicle types are one way to segment vehicles. More granular segmentations may also be useful for some EV load forecasts—for example, parsing LDVs as daily commuters and taxi cabs, as discussed in the sections that follow.

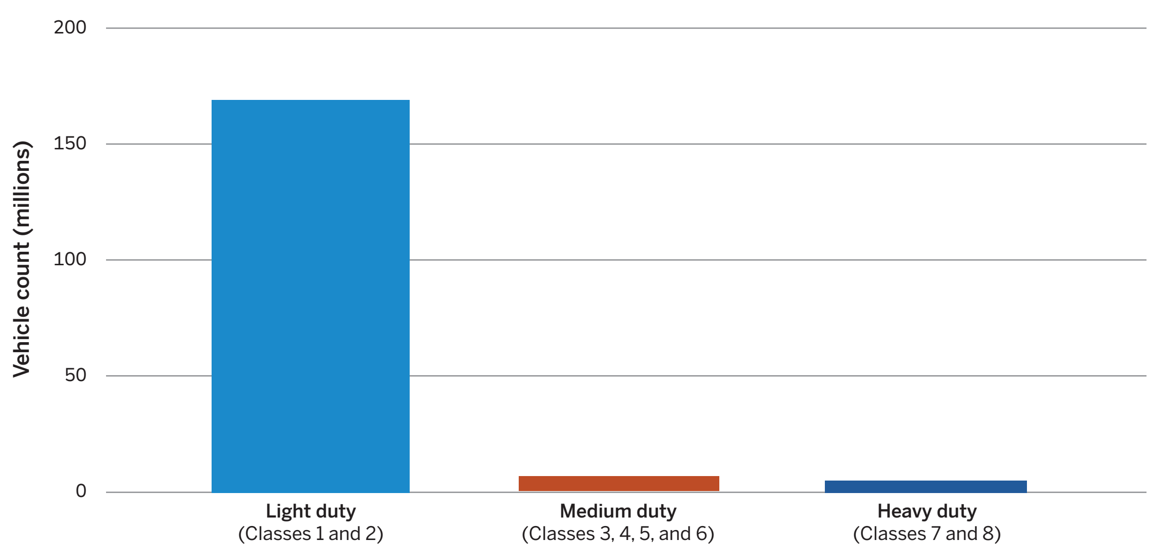
Baseline Vehicle Stock: Existing Vehicles, Characteristics, and Turnover

To project EV adoption accurately, forecasters establish the starting point (or baseline) composition of the current vehicle stock (both EV and ICE) and consider key factors driving its transformation over time. This involves analyzing vehicle characteristics that influence consumer choice and modeling the rate of stock turnover through retirements and new vehicle sales. Utilities can analyze the data themselves or hire vendors.

Because forecast areas (e.g., utility service territories) rarely align with jurisdictional data sources (e.g., national, state, or county), developing the baseline vehicle stock for the forecast area often requires (dis)aggregating available vehicle inventory data. For example, Figure 8 shows the total vehicles in operation in the United States by duty and class for 2022.

FIGURE 8

2022 Vehicles in Operation by Duty/Class



Establishing baseline vehicle stock is critical for forecasting. For example, in 2022 the U.S. "vehicles in operation" stock was overwhelmingly composed of light-duty vehicles (Classes 1 and 2), with medium-duty (Classes 3 to 6) and heavy-duty (Classes 7 and 8) vehicles constituting a much smaller share of the total fleet. Planners can use high-level distributions to estimate the vehicle stock for a smaller, specific area, like a single utility's territory.

Source: Bureau of Transportation Statistics, Statistics https://www.bts.gov/browse-statistical-products-and-data/surveys/vius/vehicle-stats-state-vehicle-type-and-model-year.

Fundamental elements for establishing baselines and developing forecasts for vehicle stock adoption include the following.

- **Key Inputs:** Data sources for key inputs include state registrations (e.g., from Departments of Motor Vehicles) and proprietary vehicles-in-operation data-sets, the Annual Technology Baseline by the National Renewable Energy Laboratory,[7] and manufacturer data, and often require geographical aggregation or disaggregation to match a forecast area.

  Key data inputs include:

  - Counts of existing vehicles (EV and ICE) by segment within the forecast area for the first year of the forecast (Year 0)
  - Vehicle class and body type categories to reflect the configuration and characteristics of vehicle types (e.g., battery capacity, range) included in the adoption forecast
  - Vehicle battery efficiency (kWh/mile) for each vehicle class and body type included in the forecast. This is necessary to determine how much energy (kWh) is required to charge an EV based on its travel behavior—annual VMT.
  - Age distribution of the existing fleet, historical vehicle retirement/scrappage rates, new/used market sales figures, and current/projected EV technical specifications (e.g., battery costs, range, energy efficiency)

- **Key Assumptions:** Assumptions are typically derived from a combination of those used in third-party market forecasts (e.g., BloombergNEF, S&P Global, Guidehouse), government policies and regulations (e.g., zero-emission-vehicle policies), manufacturer announcements, and internal analysis by utility subject matter experts. Assumptions pertain to:

  - Establishing the baseline EV powertrain mix (battery electric vehicles vs. plug-in hybrid electric vehicles), addressing potential data gaps between data sources, and defining the starting conditions for stock turnover models

  - The future pace of technological improvement (such as rate of battery cost decline or efficiency gains), average vehicle lifetimes used in turnover calculations, how quickly new EV sales replace retiring ICE vehicles, and the dynamics of used or secondary EV markets[8]

Ownership Types: Personal vs. Fleet

A critical aspect of EV adoption forecasting is distinguishing between personally owned vehicles (used by households) and commercial or municipal fleet vehicles. This segmentation is essential because these ownership types exhibit fundamentally different adoption drivers, purchase-making processes, typical vehicle types, operational characteristics, and sensitivities to economic and policy signals, requiring distinct inputs and assumptions within the forecast.

Consumer Factors (Primarily Light-Duty/Personal Vehicle)

- **Key Inputs**
  - Spatially linked socio-demographic data (income, age, education, housing type, population density) from sources like the U.S. Census Bureau
  - Data on current home/work charging accessibility
  - Consumer surveys regarding current preferences, awareness, or barriers

7 https://atb.nrel.gov/

8 The secondary (used) vehicle market impacts both LDV and MHDV modeling. For instance, drayage trucks are often refurbished fleet trucks.

- **Key Assumptions**
  - How different demographic factors are weighted to influence adoption likelihood in propensity models
  - Impact of charging accessibility on choice, the rate at which consumer awareness or experience grows
  - Influence of social "peer effects"

Fleet Operational Factors (Primarily Medium- and Heavy-Duty/Fleet Vehicles)

- **Key Inputs**
  - Typical fleet operations for relevant vocations, including duty cycles (daily mileage, routes), payload requirements, dwell times/locations, and potentially direct input from major fleets via surveys or targeted outreach regarding their specific needs and electrification plans
- **Key Assumptions**
  - How well available EV models meet specific duty cycle requirements for the specific fleet's operations (range, payload, refueling/charging time)
  - Expected fleet replacement schedules/strategies
  - Relative weighting of total cost of ownership versus operational factors in fleet procurement decisions

Market and Economic Factors: Vehicle Availability and Costs

The decision for consumers or fleets to acquire an EV depends significantly on market and economic factors. Inputs and assumptions in this category cover influences on purchasing behavior including supply-side market conditions (such as interest rates, oil prices, vehicle model availability, and expected vehicle suitability) as well as demand-side economic calculations (often synthesized as total cost of ownership). Key elements considered in utility or third-party forecasts include the following.

- **Key Inputs**
  - Current EV model availability across relevant vehicle segments, potentially including manufacturer production targets
  - Existing charging infrastructure availability and density
  - Current and historical data for vehicle purchase prices (EV vs. ICE), battery pack costs, fuel/energy costs (electricity rates, gasoline/diesel prices), estimated maintenance costs, details of available financial incentives (rebates, tax credits), and overall economic conditions (interest rates, unemployment, economic growth)

- **Key Assumptions**
  - Projected pace of new EV model introductions (especially in underserved segments like pick-ups or heavy-duty vehicles (HDVs))
  - Impact of supply chain constraints
  - Degree to which perceived or actual charging infrastructure availability influences consumer and fleet adoption decisions
  - Future trajectories of energy prices (e.g., from the U.S. Energy Information Administration's Annual Energy Outlook)
  - Persistence, structure, and uptake of incentives
  - Sensitivity of different market segments (e.g., personal LDV buyers vs. commercial fleets) to economic signals

Policy and Regulatory Factors: Existing and Proposed Policies

Government policies and regulations at the federal, state, and local levels act as powerful external drivers that shape the EV market and influence adoption rates. Accurately forecasting EV uptake requires incorporating policies and regulations and making informed assumptions about how their implementation may influence EV adoption in the utility's service area; scenario analysis is often used to consider plausible futures that bound uncertainty. Foundational elements include the following.

- **Key Inputs**
  - Existing and formally proposed policies, such as zero-emission-vehicle sales targets, fleet electrification requirements (e.g., the California Air Resource Board's Advanced Clean Trucks regulation), emissions standards, state and federal quantitative adoption targets, and potential restrictions on ICE vehicle sales
- **Key Assumptions**
  - Likelihood and timing of proposed policies
  - Expected level of manufacturer and market compliance
  - Overall policy stability
  - Effectiveness of policies and regulations in driving EV adoption

Methods for Forecasting EV Adoption

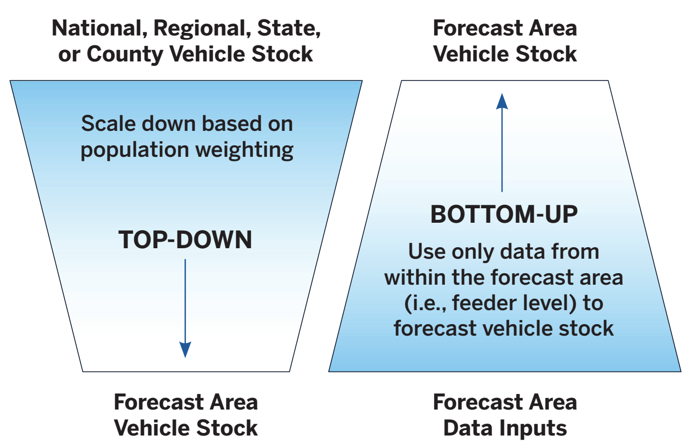
After establishing an EV baseline, forecasters define an approach for how those figures will grow over the forecast horizon. In some cases, there is a prescribed goal or target (e.g., a state-wide policy goal of 1 million light-duty EVs by 2030). In other cases, forecasters may project EV inventories based on market forces.

As shown in Figure 9, top-down approaches estimate EV adoption by starting with broad economic and demographic indicators (e.g., population growth, vehicle sales trends) and then project overall EV uptake. These forecasts are often aligned with policy goals or historical market trends and can provide high-level insights into aggregate impacts. However, they may overlook localized constraints, regional infrastructure readiness, consumer behavior, or manufacturing capacity.

In contrast, a bottom-up approach offers higher resolution and is particularly useful for assessing localized EV adoption, but requires granular data. This approach models EV adoption using detailed data on past customer

FIGURE 9

EV Adoption Approaches

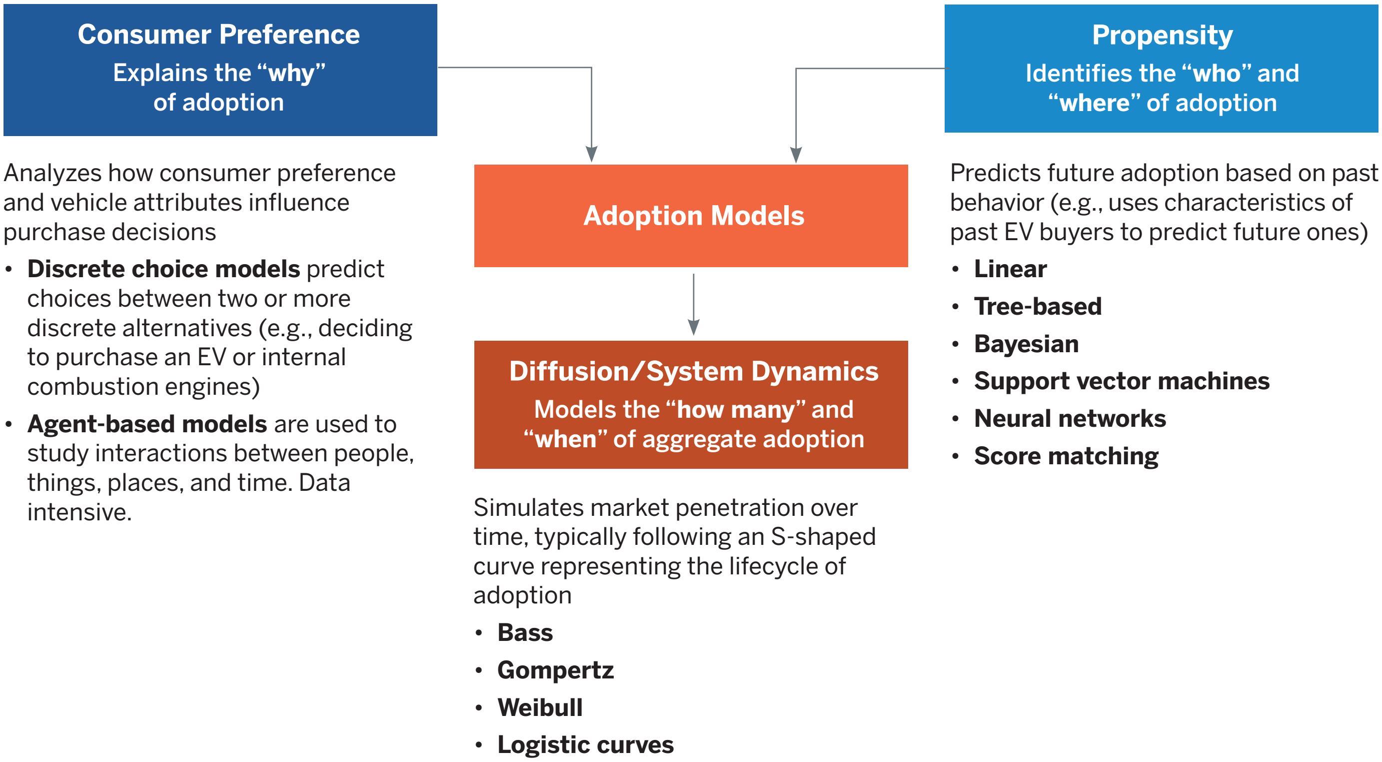


Top-down approaches estimate EV adoption, starting with broad economic and demographic indicators and then projecting overall EV uptake. Resulting forecasts are often aligned with policy goals or historical market trends and can provide high-level insights into aggregate impacts. Bottom-up approaches, in contrast, offer local detail but require more granular data. These methods estimate impacts on electricity demand by aggregating expected EV usage patterns across specific areas and times of day.

Source: Energy Systems Integration Group.

FIGURE 10

Commonly Used Models for Projecting EV Adoption



Source: Energy Systems Integration Group.

purchasing behavior, vehicle types, charging behaviors, customer segments, and regional factors. Forecasters estimate electricity demand impacts by aggregating expected EV usage patterns across specific geographical areas and times of day.

EV adoption forecasts are not developed in a vacuum. For instance, assumptions about future charging infrastructure availability (see the section “Forecasting EV Charging Infrastructure”) can significantly influence adoption rates, creating an interdependency where EV adoption modeling, rather than treat EVs and infrastructure independently, iterates with EVSE projections.

After settling on an approach that meets the requirements of the forecast, forecasters decide what model(s) to use for estimating EV adoption. Model selection is a technical decision made by forecast implementers based on forecast objectives, data and resource availability, and desired granularity, with all factors ultimately constrained by the available resources. While the models described in Figure 10—consumer preference, propensity, and diffusion models—represent common techniques, they are not exhaustive, and the field continues to evolve. These approaches, detailed in “Appendix A: EV Adoption Methods,” simulate how individual charging events aggregate to create impacts on the grid.[9]

Outputs

Outputs of EV adoption forecasts serve multiple purposes, both for the modeling process and for forecast reviewers assessing the results of the model for reasonableness and acceptability. The first question is, “what activity is happening over the forecast horizon?”

In the case of EV adoption forecasting outputs, this “activity” is the number, type, and location of EVs that customers are projected to adopt in the forecast area. Given differences in battery capacity, peak charging capabilities, and travel distances, EV energy demand can significantly, so it is vital to categorize adoption model

9 This report’s appendices can be found at https://www.esig.energy/ev-load-forecasting.

TABLE 3

Example Outputs for Light-Duty Plug-In Hybrid and Battery EV Categories

Vehicle Powertrain	Vehicle Category	Vehicle Battery Capacity (kWh)	Vehicle Efficiency (Wh/mile)	Charging Speed AC (kW)	Charging Speed DC (kW)	Electric Range (miles)
Plug-in hybrid electric vehicle	Large car	15	277	6.5	0	54
	Large sport utility vehicle	20	376	6.4	0	53
	Pickup truck	19	378	6.1	0	50
	Small car	12	275	5.2	0	44
	Small sport utility vehicle	17	339	6.1	0	50
	Sport car	13	273	5.7	0	48
	Van	19	353	6.4	0	54
Battery-electric vehicle (Gen 1; model year 2011–2025)	Large car	136	349	12	281	390
	Large sport utility vehicle	172.7	500	12	311	346
	Pickup truck	179.1	611	12	232	293
	Small car	69.9	308	10.9	118	227
	Small sport utility vehicle	139.1	488	12	220	285
	Sport car	119	389	12	224	306
	Van	99.9	411	11.6	247	243

The outputs of an adoption forecast must include key vehicle characteristics that determine energy needs. This example from a California Energy Commission report details the battery capacity, efficiency, and charging speeds for different light-duty vehicle classes, which are critical inputs for calculating charging load.

Source: California Energy Commission and National Renewable Energy Laboratory, "Assembly Bill 2127 Second Electric Vehicle Charging Infrastructure Second Assessment Revised Staff Report," 2024, https://efiling.energy.ca.gov/GetDocument.aspx?tn=254161, pg. C-3 (137). Edited for clarity.

outputs by duty, class, or body type. Table 3 illustrates the output data of EV adoption forecasting.

The second critical question is, "how are these outputs used by the next modeling component?" For EV load forecasting modeling, the features of EV adoption outputs (number, type, location, and travel behavior of the adopted EVs) directly inform the type of charging infrastructure that is necessary to meet the energy demand required for the projected EV population. Thus, the EV adoption forecasting outputs (1) provide forecasters and other stakeholders with transparent information to evaluate the composition of the projected EV population, and (2) provide the EV charging infrastructure model with the data required to determine the portfolio of charging assets necessary to support the future EVs in the region. Figure 11 (p. 28) summarizes the outputs of an EV adoption forecast component.

The EV adoption forecasting outputs (1) provide forecasters and other stakeholders with transparent information to evaluate the composition of the projected EV population, and (2) provide the EV charging infrastructure model with the data required to determine the portfolio of charging assets necessary to support the future EVs in the region.

FIGURE 11

Summary of EV Adoption Forecast Outputs

 # EVs in Forecast Area

Total Vehicle Stock (Primary Output)

The primary output is the forecasted number of EVs (total vehicle stock, not only annual sales), within the defined forecast area for each year of the specified time horizon.

Composition of vehicle stock

- **Weight class:** Light-duty vehicle, medium-duty vehicle, heavy-duty vehicle
- **Powertrain:** Battery-electric vehicle vs. plug-in hybrid electric vehicle
- **Ownership type:** Personal vs. fleet

Spatial distribution

- **Adoption likelihood/ density:** Maps or rankings indicating areas with higher or lower EV adoption propensities

Temporal resolution

- **Annual vehicle stock counts:** Typical vehicle stock counts by year, though finer resolution may be required

Vehicle stock characteristics (advanced)

- **Battery capacity:** Battery sizes (kWh) for each vehicle segment
- **Battery efficiency:** kWh/mile per vehicle segment
- **Range:** EV range by segment
- **Travel behavior:** Travel patterns by location, ownership type, vehicle segment

The outputs of an EV adoption forecast provide a detailed picture of the future vehicle stock. Beyond the total number of EVs, key outputs include the composition of the fleet, its spatial distribution, and the specific characteristics of the vehicles, all of which are critical inputs for forecasting loads and infrastructure needs.

Source: Energy Systems Integration Group.

Calibration and Verification

Where possible, EV adoption forecasts should be validated against historical data by comparing model outputs with observed EV registration data and past EV adoption trends within the forecast area, or other relevant available data. This helps to assess the model's ability to replicate known EV market development outcomes. Calibration involves tuning EV adoption model parameters—such as those in Bass diffusion curves specific to new technologies or discrete choice models reflecting consumer preferences for EVs over ICE vehicles—using observed historical data (e.g., initial EV sales figures, market responses to EV-specific incentives, and EV stock turnover rates reflecting the replacement of ICE vehicles with EVs). This process ensures that the forecast aligns with established local market realities for EV uptake and improves the accuracy of future EV penetration projections.

Further, context and important benchmarking can be gained by comparing EV adoption forecast outputs with those from other reputable entities specializing in transportation electrification, such as national laboratories (e.g., National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory, Pacific Northwest National Laboratory), utilities with active EV programs and rates, academic institutions performing studies on EV adoption, and established industry consultancies. While differences in underlying assumptions and methodologies inevitably lead to variations in projected EV adoption numbers, such comparisons can highlight areas for further investigation, identify potential biases in the EV forecast, and increase overall confidence if results show general alignment or if deviations can reasonably be explained. Documenting these validation, calibration, and benchmarking efforts is crucial for forecast transparency and for reviewers to understand the robustness of the EV adoption forecast.

Inputs for Subsequent Forecasting Components

Outputs of the EV adoption forecast component are critical inputs for both the EV charging infrastructure and EV charging profile components, including:

- **EV Charging Infrastructure Forecasting**
  - The number, type, and location of forecasted EVs, which directly inform the demand for charging infrastructure (how many ports are needed and where, for all types of charging stations—utility, third party, and publicly owned)
  - Fleet characteristics (battery size, range, efficiency), which influence the type and power level of chargers required (e.g., Level 2 vs. DC fast charging (DCFC), high-power DCFC for HDVs)
- **EV Charging Profile Forecasting**
  - The number of EVs, combined with their characteristics (battery size, efficiency) and spatial distribution, forming the basis for calculating energy consumption (kWh)

These outputs, together with charging behavior profiles from EV load forecasting inputs and methods, determine the resulting load shapes for power demand (kW). For example, a higher proportion of large EVs versus small EVs results in significantly higher overall energy needs, and potentially different power demands, for the same number of vehicles.

Typical Formats and Scenarios

EV adoption forecasting outputs are typically presented as data tables, time-series charts (showing growth), and maps (showing spatial distribution) reflecting multiple scenarios—e.g., low, baseline, low, medium, high adoption —to address inherent forecast uncertainty and provide insights into the range of possible adoption futures.

Table 4 summarizes EV adoption forecasting practices.

Forecasting EV Charging Infrastructure

Forecasting EV charging infrastructure—or EVSE—estimates the amount, type, and location of charging

TABLE 4
EV Adoption Forecasting Practices

FORECASTING CHARACTERISTICS	
EV adoption models are performed at a granularity appropriate for the forecasting purpose.	
Good practices	• A baseline of existing EVs (light-duty and medium- and heavy-duty) is established based on the best available data. **Example:** Utilities in the state of Washington can use publicly available EV registration data from the state[a] to establish a baseline of what EVs are currently in use and approximately where, but additional information, such as vehicle mobility models,[b] are needed for more precision on where EVs will need to charge.
Better practices	• In addition to broad market shifts such as consumer preferences or national policy, the forecast considers local policy scenarios that may drive EV adoption in subregions of the forecast area. **Example:** Eversource modifies its base EV adoption forecasts based on state and local policy objectives.[c]
Best practices	• Adoption model input data, methods, and outputs align with the forecast purpose to create a mixed model that reflects both granular modeling inputs and system-level adoption policy targets. **Example:** When evaluating distribution system needs, the California Public Utilities Commission and Kevala developed land-parcel-level adoption forecasts.[d]

a State of Washington, *Electric Vehicle Population Data* (2025), https://data.wa.gov/Transportation/Electric-Vehicle-Population-Data/f6w7-q2d2/about_data.

b The state of Washington also has a publicly available EV Mapping and Planning Tool that includes a modeled trips layer to capture high-fidelity trip data. The EV Mapping and Planning tool is available at: https://ev-map-wsdot.hub.arcgis.com/apps/7e310dcd476640ec8c611c101f610c09/explore.

c Eversource Energy, *Forecasting and Electric Demand Assessment Methodology* (2023), https://www.mass.gov/doc/eversource-forecasting-and-electric-demand-assessment-methodology/download.

d Kevala, *CPUC Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates* (2023), https://www.kevala.com/resources/electrification-impacts-study-part-1.

Source: Energy Systems Integration Group.

infrastructure needed to support expected EV adoption. EVSE forecasts translate projected vehicle counts into charging infrastructure requirements by accounting for where and how vehicles will be charged across different customer segments.

EVSE forecasts can be used to evaluate a range of future scenarios. When paired with EV adoption forecasts, scenario variations may explore differences in charger availability (whether chargers exist and are operational in a given area or location), utilization rates, charging access (the ability of an EV owner to use a charger, considering factors like physical access, payment systems, and any restrictions such as membership or time-of-day limits), and infrastructure deployment policy. For example, one scenario may assume widespread residential access to Level 2 charging, while another may prioritize the build-out of public and workplace charging infrastructure in dense urban areas. Forecasting multiple EVSE scenarios allows planners to assess trade-offs between cost, charging access, and grid impacts and better coordinate EVSE investments with other distribution system upgrades.

Forecasting multiple EVSE scenarios allows planners to assess trade-offs between cost, charging access, and grid impacts and better coordinate EVSE investments with other distribution system upgrades.

This section outlines data inputs, assumptions, modeling approaches, and outputs for EVSE infrastructure forecasting, emphasizing how these elements support scenario-based planning and interact with vehicle adoption and load modeling.

Inputs and Assumptions

Forecasting EV charging infrastructure, for a utility service area or broader geographical area, involves translating projected EV adoption into the required number, type, and location of chargers to meet charging demand. This includes a range of data inputs and key assumptions regarding existing infrastructure, characteristics of the forecasted EV fleet, how and where drivers will charge, and relevant siting or policy factors.

EVSE Baseline: Stock and Types

As with EV adoption, it is necessary to establish an EVSE baseline, typically expressed as counts of charging ports by type (Level 1, Level 2, DCFC), location type (residential, public, workplace, depot), and geographical area.

Properly defining the EVSE baseline is critical for planning infrastructure investments, identifying coverage gaps, and evaluating the potential for managed charging, which can reduce demand spikes by encouraging charging during off-peak hours. It also helps ensure consistency when comparing scenarios or integrating EVSE planning with broader analyses of needed distribution system upgrades.

Like vehicle data, charging infrastructure data often do not align with utility service territories and may require spatial reallocation or adjustment to reflect actual use patterns in the forecast area. For example, charger locations might be mapped by ZIP code but must be reprocessed to align with circuit or substation boundaries.

- **Key Inputs**
  - Inventory of all existing public and private EVSE within the forecast area

- Counts of charging ports disaggregated by level (Level 1, Level 2, DCFC), power output (kW), specific location type (e.g., single-family home, multi-unit dwelling, workplace, public retail, highway corridor, fleet depot), and access type (public, private, semi-private)
- Data sources including national databases (e.g., the U.S. Department of Energy's Alternative Fuels Data Center,[10] utility interconnection records, and third-party charging network aggregators

- **Key Assumptions**
  - Accuracy and completeness of data
  - Operational status and availability of existing charging infrastructure
  - Utilization patterns of existing infrastructure

EV Adoption Forecast: Primary Output of the EV Adoption Component

The EV adoption outputs for each year of the forecast horizon are critical inputs to the EV charging infrastructure forecast, as they directly define the scale and nature of the charging demand the infrastructure must be designed to serve.

- **Key Inputs**
  - Projected number of EVs (by weight class, powertrain (e.g., all electric, plug-in hybrid electric), ownership type)
  - EV spatial distribution
  - Key vehicle characteristics (battery size, range, energy efficiency)
- **Key Assumptions:** The EVSE forecast inherits the underlying assumptions of the EV adoption forecast, including:
  - Policy and market scenarios
  - EV adoption rates
  - Vehicle stock turnover
  - Vehicle segment, class, and powertrain mix

Charging Behavior and Locations: Where, When, and How Long Will EVs Charge?

Forecasting EV charging infrastructure involves estimating the number and type of chargers needed, how those chargers are distributed across use cases, and how they will likely be used over time. This includes assumptions

10 https://afdc.energy.gov/

about vehicle-to-charger ratios, utilization rates, and the coincidence of charging with system peak demand, each of which varies significantly across charging contexts—whether residential, workplace, fleet depots, urban public, or highway corridor locations.

- **Key Inputs**
  - Observed charging patterns (session duration, energy consumed, time of day, location type from network operators or telematics if available)
  - Vehicle travel behavior (VMT, dwell times at home/work/public locations, trip purpose from surveys or telematics)
  - Consumer surveys on charging preferences
  - Current participation rates in managed charging or EV-specific electricity rates
- **Key Assumptions**
  - **Primary charging location:** Where different EV segments (e.g., owners of personal LDVs, EV owners living in single- vs. multi-family dwellings, commercial fleets) will primarily seek charging—for example, home, workplace, public destination, fleet depot, highway corridor
  - **Charger type and power levels:** Mix of Level 1, Level 2, and DCFC power levels (e.g., less than 50 kW, 50 to 150 kW, 150 to 350 kW, and more than 350 kW for HDVs) needed at different location types to satisfy user needs (e.g., vehicle capabilities, dwell times, and operational requirements)
  - **Charging session characteristics**
    - How often different EV types charge (e.g., daily, 4 to 6 events per week for single-family dwelling Level 2, 2 to 4 events per week for multi-family dwelling Level 2)
    - Typical duration of charging sessions (e.g., 2 to 3 hours for single-family dwelling Level 2, 4 to 8 hours for multi-family dwelling Level 2, 15 to 45 minutes for corridor DCFC)
    - Average energy transferred per session (e.g., 7 to 12 kWh for single-family dwelling Level 2, 20 to 80 kWh or more for corridor DCFC), which is often influenced by state of charge at the start of charging and daily travel needs
  - **Vehicle-to-charger ratios:** Ratios common for shared charging environments, such as multi-family dwellings (3:1 to 6:1 vehicles per port), workplaces (1:1 to 2:1), and public stations (varies significantly by location, from 1:1 to 25:1 (in very rural areas) to more than 1,001:1) (Pew Research Center, 2024), to determine how many vehicles a single port can adequately serve
  - **Charger utilization rates:** Target or expected utilization rates for different EVSE types and locations—for example, single-family dwelling Level 2, 10% to 15% daily; multi-family dwelling Level 2, 25% to 40% daily; workplace, 1 to 2 sessions per day; fleet depots, often higher and more consistent utilization rates, with 3 to 4 sessions per day; urban DCFC, 4 to 10 or more sessions per day; corridor DCFC, 5% to 15% average daily but more than 50% on peak days
  - **Impact of managed charging and time-varying rates:** Effect of customer participation in, and effectiveness of, managed charging programs or time-varying electricity rates in shifting when and where charging occurs, which directly influences peak demand on chargers and the type of infrastructure needed (see Schwartz et al., 2025)
  - **Temperature and seasonal effects:** Potential adjustments or assumptions regarding how ambient temperature affects charging behavior or energy needs, or how seasonal travel patterns influence demand spikes at specific locations such as highway corridors

Siting and Land Use Factors: Identifying Suitable Areas for Charger Deployment

Determining where to locate charging infrastructure requires specific geographical and land-related inputs. To identify suitable areas, forecasters use geographic information system (GIS) data covering land use classifications (e.g., residential, commercial), local zoning ordinances, and parcel details. Other crucial inputs are the locations of key demand drivers like commercial centers, major transportation corridors, and known fleet operational hubs. Based on these data, forecasters make assumptions regarding the suitability of different land types for various EVSE deployments, practical charger density limits within those areas, and site accessibility considerations such as public right-of-way or how far users might typically travel to reach a charger.

- **Key Inputs**
  - GIS data: Viable and non-viable locations for EVSE are identified using land use classifications (residential, commercial, industrial, or mixed-use), zoning regulations, parcel data, locations of key commercial centers, major transportation corridors, known fleet operational areas/depots, and potentially Traffic Analysis Zones (TAZs), which are typically defined by state departments of transportation and metropolitan planning organizations.
- **Key Assumptions**
  - Suitability of different land use types for various EVSE deployments (e.g., commercial zoning for public DCFC plazas)
  - Charger deployment density targets (e.g., scaling with EV penetration in specific ZIP codes or counties)
  - Constraints or opportunities presented by local zoning, public right-of-way access
  - How far users travel to access different types of public chargers

Policy and Economic Factors: Infrastructure Deployment Drivers and Costs

Key drivers influencing the growth of EV charging infrastructure include government policies and the economic viability of charger deployment. Inputs detailing specific targets, funding mechanisms, and building codes, alongside assumptions about infrastructure costs and the impact of financial support, are essential for forecasting the development of EV charging networks.

- **Key Inputs**
  - Government targets for public charger deployment (e.g., number of ports per X number of EVs or along Y miles of highway)
  - Funding programs or grants available for EVSE installation
  - EV-ready building code requirements
  - Parameters of utility "make-ready" infrastructure programs
- **Key Assumptions**
  - Continuation of existing policies supporting infrastructure deployment
  - Overall effectiveness of policies
  - Funding levels

Methods for Forecasting EV Charging Infrastructure

Translating a forecast of EV adoption into infrastructure requirements can be done using a variety of methods, ranging from simple heuristics to complex simulations. These approaches aim to determine the necessary number, type, power level, and general location of chargers needed to serve the projected EV stock. This requires considering factors like vehicle-to-charger ratios, diverse charging behaviors, and desired service levels. The methods outlined in this section are illustrative of current practices but are not exhaustive.

To select a method, forecasters must decide how to address the feedback loop between EV adoption and EVSE deployment. An iterative approach, which models adoption and EVSE deployment in tandem, aims for greater consistency by capturing their mutual influence, but increases complexity and resource demands. Conversely, a linear approach that forecasts EV adoption and uses those figures to project EVSE needs is simpler, but may not fully account for how charger access influences adoption rates or charging behaviors. This fundamental trade-off requires balancing the desired level of detail and accuracy in reflecting real-world dynamics against practical constraints like model complexity, data availability, and computational resources.

Forecasting MHDVs presents unique challenges for infrastructure planning. More so than personal vehicles, MHDV adoption is driven by operational needs and total cost of ownership. Charging is often concentrated at centralized depots, which can significantly stress localized grid areas and require additional electricity supplies. Fleet vehicle registration data can be an unreliable indicator of where charging will occur, compounding this problem. For example, vehicles may be registered at a corporate headquarters but operate from a depot in an entirely different state.

Fleets also require larger batteries and higher charging speeds to minimize operational downtime. Accounting for this complexity requires specialized tools. An example of such a tool is Lawrence Berkeley National Laboratory's HEVI-LOAD model.[11] It integrates inputs on vehicle class, duty cycles, and battery size to determine the specific number, power level, and location of chargers needed to support a fleet without disrupting its operations.

These approaches, detailed in "Appendix B: EV Charging Infrastructure Methods," simulate how individual charging events aggregate to create impacts on the grid.[12]

Outputs

EV charging infrastructure outputs answer the question, "what activity is happening over the forecast horizon?" Outputs include number, type, and location of EV charging ports that are necessary to provide the projected EV population (from the adoption component) and the electricity required to meet the expected travel behavior for the specific vehicles in the region.

Similar to EVs themselves, EV charging infrastructure is not composed of assets with uniform characteristics. Different chargers deliver different quantities of energy, peak at different demand levels, and have different

TABLE 5

Example Outputs for Charger Types and Related Characteristics

Charger Type	Typical Input Voltage	Charge Power	Typical Charge Times	Typical Vehicle Utilization
Level 1	120 volts AC	Up to 1.4 kW	~4 miles range per hour	Light-duty vehicle, residential charging
Level 2	208/240 volts AC	Up to 19.2 kW	~32 miles range per hour (at 9.6 kW)	Light-duty vehicle, residential, workplace, and public charging
DC fast charger (DCFC)	Varies	Up to 350 kW with CCS connector	~139 miles range per 10 minutes (at 250 kW)	Light-duty vehicle, highway corridor charging
Megawatt	Varies	Up to several MW with megawatt charging system connector	250 miles in 5 minutes (1 MW)[a]	Medium- and heavy-duty vehicle, depot charging or highway corridor charging

EV charging infrastructure is categorized by power level, which determines charging speed. Forecasts must differentiate between slower Level 1 and Level 2 AC chargers, common for residential and workplace use, and high-power DC fast chargers needed for public and highway corridor charging.

a https://insideevs.com/news/755163/chinese-evs-1-megawatt-chargers/

Source: California Energy Commission, "Assembly Bill 2127 Second Electric Vehicle Charging Infrastructure Second Assessment Revised Staff Report," https://efiling.energy.ca.gov/GetDocument.aspx?tn=254161.

11 https://transportation.lbl.gov/hevi-load

12 This report's appendices can be found at https://www.esig.energy/ev-load-forecasting.

FIGURE 12

Summary of EVSE Component Outputs

EV Charging Infrastructure in Forecast Area

Total Charging Infrastructure Needs (Primary Output)

The primary outputs are the forecasted number of EVSE ports and/or the total charging capacity (kW or MW) required within the forecast area for each year of the forecast time horizon to serve the forecasted EVs (from EV adoption component).

Composition of EVSE

- **Charger level:** Level 1, Level 2, DC fast charging
- **Power output:** Power rating (kW)
- **Location type:** Home, workplace, public fleet, etc.
- **Access type:** Public, private, semi-private

EVSE characteristics (advanced)

- **Mix of power levels:** Distribution and count of EVSE by power and location type
- **Utilization:** Utilization rates by EVSE segments
- **Build-out rate:** Ports/capacity per year

+

Temporal resolution

- **Annual EVSE counts:** Typically EVSE counts by year, though finer resolution may be required

Spacial distribution

- **EVSE siting/density:** Maps or rankings indicating areas with higher or lower EV adoption propensities

The outputs of a forecast of EV charging infrastructure (electric vehicle supply equipment (EVSE)) specify the number, type, and location of chargers required to serve the projected EV fleet. This includes the composition of the charging network (e.g., Level 2 vs. DC fast charging, public vs. private) and its spatial distribution, providing the necessary inputs for grid impact studies.

Source: Energy Systems Integration Group.

utilization levels. It is important that the output contain features such as charger type, capacity level, and location. Table 5 (p. 34) illustrates some of the data provided by EV charging infrastructure model outputs.

These output characteristics answer another critical question, "how are these outputs used by the next modeling component—EV charging profile forecasting?" The EV charging infrastructure outputs (number, type, location, and load profile) directly inform the hourly energy and capacity requirements necessary to meet the energy demand required for the projected EV population.

Figure 12 (p. 34) summarizes the outputs of an EVSE forecast component.

Calibration and Verification

It is critical to validate and calibrate component outputs for EV charging infrastructure forecasts to ensure that projections for the number, type, and location of chargers are realistic and effectively meet the needs of the broader forecast. Primarily, the projected EVSE deployment logically stems from the validated EV adoption forecast, with justifiable vehicle-to-charger ratios for different segments, benchmarked against empirical data or established needs-based simulations using tools like the National Renewable Energy Laboratory's EVI-Pro. An accurate baseline of existing EVSEs, typically drawn from sources such as the DOE's Alternative Fuels Data Center, is critical. Also important is using observed data to ground assumptions about EV driver charging behaviors (including location preferences, charging session characteristics, and charger utilization rates). Observed data can be obtained from active networks, pilot programs, or robust simulation models that reflect real-world travel and energy needs.

If the forecast details charger locations, the spatial allocation methodology can consider factors like EV adoption hotspots, traffic, and land use. Sensitivity analysis on key assumptions can illuminate their relative impact on the overall EVSE forecast and help define ranges of potential need. Comprehensive documentation of these validation, calibration, and benchmarking efforts is vital for transparency so that reviewers can assess the forecast's reliability.

Inputs for Downstream Forecasting Components

- **EV Charging Profile Forecasting**
  - The number, type, location, and power rating of forecasted chargers define the maximum potential power demand (kW) and location for EV charging events used in load profile simulation.
  - EVSE infrastructure modeling outputs, EV adoption figures, and charging behavior models determine aggregated load shapes.
- **Grid Planning / Impact Studies**
  - Specific locations of forecasted charging infrastructure are needed to map to grid infrastructure.
  - Power requirements (kW/MW) of forecasted charging infrastructure are needed to understand the impacts on existing grid infrastructure.

Typical Formats and Scenarios

- Outputs are commonly presented as data tables (summarizing ports/capacity by type, location, year), time-series charts (showing infrastructure growth), and maps (visualizing spatial deployment needs).
- Outputs are usually generated across multiple scenarios, typically linked to the EV adoption scenarios (e.g., low, medium/base, high) and potentially varying key infrastructure assumptions (e.g., charging behavior, technology costs).

Table 6 summarizes forecasting practices for EV charging infrastructure.

Forecasting EV Charging Profiles

EV load forecasting estimates the amount, timing, and location of electricity demand from EVs as they interact with the grid via EVSE. While EV adoption forecasts determine how many vehicles will be on the road and EVSE infrastructure forecasts identify where and how they will be charged, EV load forecasting combines these

TABLE 6
Forecasting Practices for EV Charging Infrastructure

FORECASTING CHARACTERISTICS	
EV charging infrastructure forecasts consider the scale of need based on projected EV adoption and time of charging.	
Good practices	• Location of modeled charger availability is informed by traffic patterns. **Example:** Eversource uses anonymized Global Positioning System (GPS) vehicle tracking data to understand travel patterns in its service territory.[a]
Better practices	• EV adoption models are used to inform EV charger specifications. **Example:** When vehicles are modeled with faster charging speeds, the EV chargers are modeled to reflect their capacity to charge vehicles at the faster speed.
Best practices	• The availability of EV charging infrastructure informs EV adoption and load profile steps through non-linear (often recursive) forecasting processes across scenarios. **Example:** Guidehouse's VAST model uses system dynamics to capture the recursive feedback loop between EV adoption and charging infrastructure availability. As more chargers become available, the potential market for EVs grows. This growth is quantified by reducing a "consumer sacrifice penalty," modeled as a cost added to total cost of ownership.[b]

a G. Walker, "Vehicle Electrification and Grid Impact Modeling," Presentation by Eversource Energy at the Energy Systems Integration Group Long-Term Load Forecasting Workshop, June 13-15, 2023, Denver, CO, https://www.esig.energy/event/2023-long-term-load-forecasting-workshop/.

b Guidehouse, *Colorado Electric Vehicle and Charging Needs Forecast: Technical Guidance Report* (prepared for Xcel Energy) (2023), https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Rates%20&%20Regulations/Hearing%20Exhibit%20105,%20Attachment%20JLJ-1%20Colorado%20Electric%20Vehicle%20and%20Charging%20Needs%20Forecast_FINAL.pdf.

Source: Energy Systems Integration Group.

inputs to produce detailed projections of EV charging profiles.

Forecasters can create different forecast scenarios by varying behavioral assumptions, technology mixes, charger access, managed charging programs, rate structures, and grid management strategies. For example, scenarios might explore unmanaged residential charging versus time-of-use rates or managed charging programs, or contrast high public-charging futures with more home charging-centric futures.

This section outlines the key assumptions, data inputs, modeling approaches, and forecast outputs involved in EV charging profiles.

Inputs and Assumptions

EV load forecasting synthesizes information about the number and type of EVs on the road and the available charging infrastructure to estimate the resulting electricity consumption (kWh) and power demand (kW) over time and across different locations. This requires combining outputs from the previous forecasting modules with specific inputs and assumptions related to how vehicles are used and charged, alongside baseline grid conditions.

Inputs from EV Adoption and Charging Infrastructure Forecasts

EV charging profile forecasting synchronizes EV adoption with charging infrastructure components. Outputs from the EV adoption and EV charging infrastructure components specify the projected number, types, characteristics, and locations of both the EVs requiring energy and the EVSE network available to provide it. These outputs set the stage for charging profile load calculations, which inherit the scenarios and assumptions defined in those earlier modules. Alternatively, as previously noted, a different order of operations may be used to identify EV and EVSE needs. The analyses also may be recursive, with initial results feeding back through the process to build the final forecast.

- **Key Inputs**
  - Number, types, characteristics, and locations of EVs for each year of the forecast horizon
  - Number, types, power levels, and locations of EVSE ports for each year of the forecast horizon
- **Key Assumptions**
  - Same as those embedded within the scenarios, methodologies, and uncertainties from upstream adoption and infrastructure forecasts
  - Consistency in segmentation and geographical allocation across modules

Historical EV Load Profiles: Establishing Load Shapes

Historical EV load profiles can be used as a baseline for projecting future demand. This involves analyzing real-world charging data to discern typical patterns, including when, where, and how long EVs are plugged in and how much energy they consume. While subject to change as EV adoption matures and technologies evolve, historical profiles offer crucial insights into current charging behaviors and their aggregate impact on the grid.

- **Key Inputs**
  - Observed charging patterns, including data on the duration of charging sessions, energy consumed per session, time of day that charging occurs, and type of location where charging takes place (e.g., residential, workplace, public); data sources can include network operators, vehicle telematics, and utility direct metering of EV loads

- Historical EV load profiles (e.g., hourly 8,760 data) for the relevant geographical or electrical system level (e.g., system total, substation service area, feeder level), often sourced from advanced metering infrastructure (AMI) data

  – Observed participation in managed charging or EV-specific electricity rates and uptake, to help understand how current behaviors might already be influenced by grid signals

- **Key Assumptions**
  – That historical data often reflect the behavior of early EV adopters who may have different charging patterns and preferences than the general population as adoption expands
  – That, absent specific interventions (e.g., new policies or smart charging programs), historical charging patterns will continue to some extent into the future

Vehicle Usage and Travel Behavior: Establishing Energy Needs

Estimating EV energy requirements and identifying opportunities to charge at a specific location require inputs and assumptions that define the day-to-day driving patterns of different vehicle segments. To model usage patterns, forecasters use data and projections for VMT, typical trip characteristics pertaining to frequency and distance, vehicle dwell times at various locations (home, work, public), and distinct operational schedules for commercial fleets. Modeling results determine per-vehicle energy needs and identify when and where charging demand arises.

- **Key Inputs**
  – Average or segmented VMT per vehicle class/type (daily, weekly, annual)
  – Typical trip patterns (distance, frequency, purpose (e.g., commuting vs. long-distance travel))
  – Vehicle dwell times and locations (home, work, public sites)
  – Typical state-of-charge levels when charging is initiated

  – Specific operational schedules for commercial fleets (e.g., transit routes, delivery schedules)

Sources can include travel surveys (National Household Travel Survey),[13] telematics data, and fleet operator records.

- **Key Assumptions**
  – How average VMT is translated into daily charging energy requirements
  – How often vehicles need to charge based on range and usage
  – Where vehicles are located when charging demand occurs (especially for fleets whose operational base may differ from registration address)
  – Driver behavior related to maintaining a desired state of charge

Charging Process and Behavior: Translating Energy Needs into Electrical Loads

Modeling how to translate energy needs for an individual EV charging event into electrical load depends on technical specifications and assumed driver behaviors. Inputs define vehicle battery capabilities (e.g., maximum charge rate) and charger power output, alongside estimates for charging efficiency losses. Forecasters then make crucial assumptions about driver charging objectives (e.g., charge to full vs. meet next trip need) and responsiveness to

13 https://nhts.ornl.gov/

external signals like time-varying rates and managed charging commands, which collectively shape the resulting load profile of the charging session.

- **Key Inputs**
  - Technical specifications influencing the charging process, such as vehicle battery capacities (kWh)
  - Maximum charge acceptance rates (kW) for different vehicle types
  - Rated power output (kW) of different EVSE types (Level 1, Level 2, DCFC)
  - Typical charging efficiencies (accounting for energy losses)
  - Details of utility time-varying rate structures or specific managed charging program designs
- **Key Assumptions**
  - Charging efficiency factors
  - Shape of the charging curve (e.g., power tapering as the battery approaches a full charge)
  - EV driver charging strategy (e.g., charge when empty, charge daily, charge on weekends)
  - EV driver participation in managed charging programs or time-varying rate schedules
  - Behavioral response to programs or price signals (e.g., degree of load shifting)
  - Primary driver objective during charging (e.g., minimize time, minimize cost, charge to full, charge to 80%, charge to meet next trip needs)
  - Bidirectional or vehicle-to-grid (V2G) dispatch behavior (optional/advanced)

Temporal and Environmental Factors: Adjusting Profiles for Daily, Seasonal, and Weather Effects

Properly executed EV charging load forecasts account for expected variations based on time and environmental conditions beyond typical daily patterns. Forecasters incorporate inputs like historical weather data and calendar information (weekends, holidays, seasons) and apply assumptions regarding how these factors—particularly the effect of ambient temperature on vehicle efficiency and charging behavior—modify baseline charging profiles across different times of the year. Seasonal information also can modify driving behaviors, particularly in certain areas, such as college towns and ski resorts.

- **Key Inputs**
  - Historical weather data, particularly temperature, which impacts vehicle charging efficiency and vehicle heating and cooling use, thereby modifying driving efficiency (kWh/mile)
  - Data identifying weekends, holidays, or other special event periods
  - Seasonal variations in travel patterns
- **Key Assumptions**
  - Impact of temperature on EV efficiency (kWh/mile)
  - Adjustments made to typical daily load profiles to account for differences in charging behavior on weekends versus weekdays, during different seasons, and around holidays and major events

Smart Charging Scenarios

Many types of "smart charging" approaches, also known as managed charging, have the potential to influence EV charging behavior and its associated impacts on the grid. Mechanisms include time-of-use rates, dynamic price signals, program incentives, and more advanced methods like utility direct control and bidirectional functionality that enable EVs to both charge and discharge to the grid. All of these efforts modify load profiles compared to what would occur under unmanaged charging. While smart charging scenarios and load profiles may be developed independent of the EV load forecasting process, it is important that they be informed by load forecasters and EV adoption and EV charging infrastructure projections.

- **Key Inputs**
  - Historical participation in smart charging programs, which can inform the degree of modification that can be achieved through future programs
  - Future grid constraints
  - Incentives available to recruit enrollment and promote behavior change (more generous incentives are more likely to show meaningful impacts)

– Stakeholder interest in future program design to inform possible technologies, including innovative approaches

- **Key Assumptions**
  – Enrollment in a specific program (e.g., 30% of EVs are on time-of-use rates) and responsiveness to established incentives (e.g., 90% of charging occurs during the program's designated off-peak periods)
  – Vehicle-to-port ratios, which affect when charging can take place (without enough charge ports, charging will occur whenever ports are available, regardless of what smart charging options are in place)
  – Technology availability (e.g., number of vehicle models with bidirectional capabilities)

Methods for Forecasting EV Charging Profiles

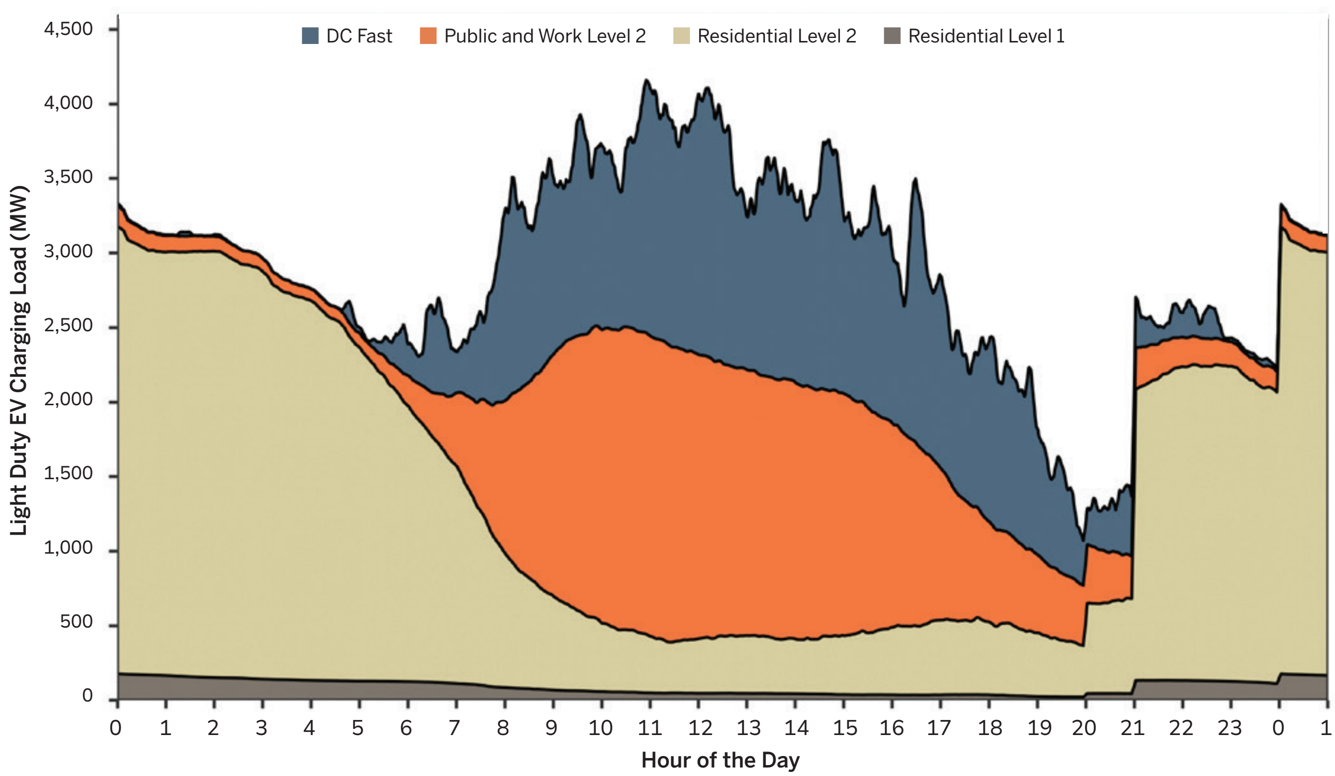
After forecasting EV adoption and required charging infrastructure, the next step is to estimate the resulting electrical load. These methods convert the number and types of EVs and chargers, along with their assumed usage patterns and behaviors, into spatial and temporal profiles of electricity consumption (kWh) and power demand (kW). These approaches, detailed in "Appendix C: EV Charging Profile Methods," simulate how individual charging events aggregate to create impacts on the grid.[14]

Outputs

The outputs of the EV load forecasting component synthesize vehicle adoption and charging infrastructure forecasts to quantify the projected EV electrical demand. This involves calculating total energy consumption

FIGURE 13

Load Curve from Light-Duty EV Charging in 2030 Under Primary Scenario



EV load profiles aggregate the demand from different charging segments. This example from a California study shows a distinct daytime peak driven by public, workplace, and DC fast charging, layered on top of a base of overnight residential charging.

Source: California Energy Commission, "Assembly Bill 2127 Second Electric Vehicle Charging Infrastructure Second Assessment Revised Staff Report," https://efiling.energy.ca.gov/GetDocument.aspx?tn=254161, pg. 51.

14 This report's appendices can be found at https://www.esig.energy/ev-load-forecasting.

(kWh) and, critically, the demand profiles (kW) at the temporal resolution required by the forecast purpose. Outputs characterize the magnitude, timing, and geographical distribution of EV charging loads, enabling an assessment of their impact on system peaks, overall load shapes, and operational limits of grid assets. Figure 13 (p. 40) shows an illustrative example of loads from different charger types for a single day. Figure 14 summarizes the outputs of an EV adoption forecast component.

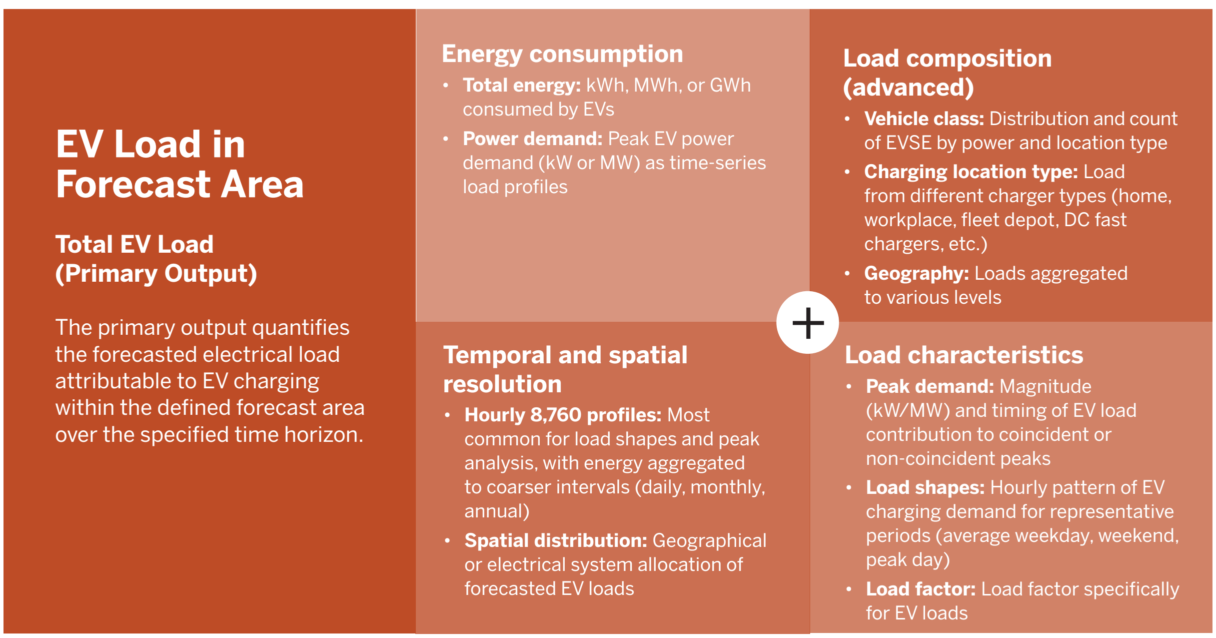
Calibration and Verification

To ensure credible outputs from EV load forecast components, projected electricity consumption (kWh) and power demand (kW) profiles require validation. This involves ensuring that energy needs align with EV numbers, efficiencies, and VMT and that peak demand is plausible given charger capacities and diversity. Assumed charging profiles for various segments can be benchmarked against real-world metered data (such as EV Watts[15]) from established simulation models (National Renewable Energy Laboratory's EVI-Pro,[16] Lawrence Berkeley National Laboratory's HEVI-LOAD,[17] EPRI's Load Shape Library[18]) or findings from pilot programs and research. This includes justifying assumptions about what drives charging behavior and the impact of managed charging programs and time-varying rates.

The methodology for aggregating individual charging events and applying appropriate diversity or coincidence factors at each grid level needs careful review, particularly

FIGURE 14

Summary of EV Charging Profile Component Outputs



The final output of the forecasting process quantifies the electrical impact of EVs. This includes total energy consumption (kWh) over time as well as detailed power demand profiles (kW) that characterize load shapes, contributions to system peaks, and distribution across the grid.

Source: Energy Systems Integration Group.

15 https://www.osti.gov/dataexplorer/biblio/dataset/1970735-ev-watts-public-database

16 https://www.nrel.gov/transportation/evi-pro

17 https://transportation.lbl.gov/hevi-load

18 https://loadshape.epri.com/

as EV charging patterns (especially under managed charging or time-varying rates) can reduce load diversity and create new, synchronized peaks. For example, if time-of-use rates incentivize charging at the start of an off-peak period, many EVs might start charging simultaneously. The robustness of the EV load projections will be further established through sensitivity analyses on key behavioral and input assumptions, alongside benchmarking overall energy and peak load contributions against other reputable forecasts. Transparent documentation of these processes is crucial for regulatory and stakeholder review.

Typical Formats and Scenarios

Outputs are commonly presented as data tables (summarizing energy/peak demand metrics), time-series charts (hourly profiles, load duration curves), and maps (visualizing geographical load concentration or grid asset impacts). Outputs are generated across multiple scenarios reflecting uncertainty in EV adoption, infrastructure availability, and particularly charging behavior assumptions (e.g., managed vs. unmanaged charging, V2G).

Table 7 summarizes EV load forecasting practices.

TABLE 7
EV Charging Profile Forecasting Practices

FORECASTING CHARACTERISTICS	
EV charging profile forecast scenarios are informed by historical charging behavior and assumed future driver behavior.	
Good practices	• Historical utility data, such as AMI data, inform local historical EV charging patterns. **Example:** Duke Energy Florida evaluates its EV managed charging programs using AMI data.[a]
Better practices	• EV load profiles are adjusted based on seasonal vehicle travel patterns and profiles are modified according to weather conditions. **Example:** PJM modified the efficiency of light-duty vehicle charging based on temperature.[b]
Best practices	• Uncertainty is quantified, for daily energy needs and on a temporal basis. **Example:** This is an aspirational best practice and area of ongoing innovation. The National Renewable Energy Laboratory's forthcoming *Deconstructing Uncertainty in Electric Vehicle Load Forecasting* report will provide more information and context on bounding load forecast uncertainty.[c]

a Itron, "Duke Energy Florida: Behavioral Managed EV Charging Program," 2024, https://na.itron.com/o/commerce-media/accounts/-1/attachments/6348202.

b S&P Global Commodity Insights, *Electric Vehicle Charging Power Demand Forecast: PJM Interconnection* (2024), https://www.pjm.com/-/media/DotCom/committees-groups/subcommittees/las/2024/20241125/20241125-reference---item04-spglobal---pjm-ev-forecast.pdf.

c A. Yip et al., forthcoming. *Deconstructing Uncertainty in Electric Vehicle Load Forecasting*, National Renewable Energy Laboratory.

Source: Energy Systems Integration Group.

Reviewing an EV Load Forecast

Regulators and stakeholders review EV load forecasts for reasonableness—founded on sound data inputs and assumptions—and appropriate application. Detailed review is critical, as the utility uses forecasts to identify needed grid investments that meet customer demand, grid reliability, and affordability and achieve long-term state objectives. Reviewers can begin their assessment by asking the following fundamental questions:

- Is this forecast a credible representation of potential future EV loads?
- Are the underlying data, assumptions, and methodologies transparent and justifiable?
- Is the forecast fit-for-purpose—for example, long-term resource planning, distribution system planning, or design of new electricity rate structures or programs?

This section aims to equip forecast reviewers with a structured approach for assessing the credibility, transparency, and overall efficacy of EV load forecasts.

A thorough evaluation hinges on an assessing how the forecast meets core principles of transparency, reasonableness, robustness, and fitness for its intended use. These principles provide a lens for scrutinizing specific elements of the forecast.

Transparency

Clarity of Purpose, Scope, and Definitions

This includes explicitly stating forecast objectives, the defined forecast area (geographical and/or electrical boundaries), time horizon (e.g., 5, 10, 20 years), and spatial and temporal granularity of outputs. Transparency also requires clear definitions of all key terms and segmentations (e.g., vehicle classes, charger types).

Accessibility and Thorough Documentation of Data Sources

Clear identification of all data used is important, whether from public sources (e.g., government statistics, national lab studies), proprietary vendors (e.g., market analytics firms, telematics providers), or internal utility systems (e.g., AMI), including vintage (date, time, and source of data). Documentation also includes methods used to process, clean, or adjust raw data.

Openness of Methodologies and Models

Another critical step is clearly explaining the forecasting methodologies employed for each component—EV adoption, EVSE charging infrastructure, and load profile determination. Any proprietary models used, including core logic, key parameters, and general functionality, can be described to the extent possible, along with a justification for their use over publicly available alternatives. Also included in this category are assumptions about model calibration and validation.

Explicit Articulation of All Key Inputs and Assumptions

Given the significant impact of assumptions in EV forecasting, it is important to explicitly state and justify all key inputs (e.g., baseline EV stock, fuel price projections, technology cost curves) and all major assumptions, especially those relating to consumer and fleet adoption, charging behavior, technological advancements, and policy effectiveness.

Traceability of Calculations and Outputs

Forecasters can document the path from inputs and assumptions, through modeling, to final forecast outputs. Summary tables, clear graphics, and accessible output files will facilitate traceability.

Reasonableness and Analytical Robustness

Consistency with Established State Objectives and Relevant Targets

Using scenarios, the forecast can clearly describe how impacts of existing and anticipated federal, state, and local policies (e.g., zero-emission-vehicle mandates, emissions reduction targets, infrastructure deployment goals) are accounted for. This includes any deviation from policy drivers in a "business as usual" or alternative scenario.

Aligning Modeling Sophistication with Forecast Purpose

A critical area for review is the fit of the forecasting approach with the forecast purpose. In some situations, broad-stroke, top-down approaches are sufficient, while in others, more granular, bottom-up approaches are needed. These forecasting decisions are not based solely on the granularity of the planning function (e.g., distribution system upgrades) but also include the level of granularity needed to deliver the appropriate level of accuracy and extent to which granularity may resolve inherent forecasting uncertainty.

Thorough Treatment and Presentation of Uncertainty

The forecast should adequately address the inherent uncertainties in EV adoption, technological change, and driver behavior. This typically involves developing multiple scenarios (e.g., low, base, high adoption; varying behavioral assumptions), conducting sensitivity analyses on critical variables, and clearly communicating the range of potential outcomes and key drivers of that range.

Evidence of Model Validation and Calibration Efforts

Where possible, it is important to validate models against historical data (back-casting) or calibrate models using observed trends. Comparisons with forecasts from other reputable entities (e.g., national laboratories, other utilities, studies from academic institutions) can provide valuable context and benchmarks.

Stakeholder Feedback Loop and Updates

Given the ongoing innovation in EV load forecasting, forecasts can benefit from industry expert input. Reviewers can assess how stakeholder feedback has been used to update forecasting inputs and assumptions and methodological approaches. These steps ensure that utility forecasts are not completed in isolation but are informed by lessons learned elsewhere and stakeholder input.

Fitness for Purpose

A forecast may be technically sound but still unsuitable for its intended application. Reviewers should assess whether the forecast's design, outputs, and integration into planning processes are appropriate for the specific decisions it is meant to inform.

Relevance and Clarity of Output Metrics

The forecast's level of detail must match its intended use. For instance, system-wide annual energy forecasts are appropriate for high-level resource planning, while feeder-level hourly peak demand forecasts are necessary for detailed distribution system investment analysis. Reviewers should confirm the forecast provides the specific metrics required for the planning context.

Integration into Utility Planning Processes

EV load forecasts need to be integrated into the utility's overall load forecast. Reviewers should verify that EV-related growth is not double-counted by confirming the base load forecast has been adjusted to remove embedded assumptions about electrification. They should also assess how the unique timing of EV charging combines with baseline loads and evaluate the range of possible impacts under different EV adoption scenarios.

The considerations identified above will build confidence among reviewers that the EV load forecast is robust and reasonable. An additional regulatory step is requiring the utility to track and report forecast accuracy over time. Such retrospective assessments allow all stakeholders to learn from previous iterations and improve forecasting data, assumptions, methods, and outputs over time.

Recommendations and Conclusions

The acceleration of EV adoption requires accurate load forecasting so that utilities and regulators can plan infrastructure needs and investments to ensure reliability and affordability. As this guide details, forecasting EV load requires different assumptions, considerations, and inputs from traditional utility loads because the load is mobile, influenced by complex human behaviors, and subject to the fast-changing pace of technology. While these factors introduce uncertainty, a structured, transparent, and collaborative approach enables planners, regulators, and stakeholders to make well-informed decisions about needed investments to meet growing electricity demands.

From Forecast to Action: Grid Investments and Mitigations

An EV load forecast is more than a prediction of future demand—it is a critical tool for evaluating potential solutions to meet load growth. Scenario analysis can help manage investment risks and design a more efficient, flexible grid.

An effective forecast requires adopting a fit-for-purpose forecasting approach, where the granularity of the model can effectively support the scale of the investment decision. By modeling different adoption and charging scenarios, planners can identify potential infrastructure bottlenecks ahead of need and can prioritize investments, weighing the risks of over-building against the risks of being unprepared for new load.

Informing Grid Upgrades

Supporting consumers' rising interest in EVs and the associated electricity demand may require grid infrastructure upgrades. An EV load forecast is the primary mechanism for identifying where and when to make targeted system upgrades. An effective forecast requires adopting a fit-for-purpose forecasting approach, where the granularity of the model can effectively support the scale of the investment decision. By modeling different adoption and charging scenarios, planners can identify potential infrastructure bottlenecks ahead of need and can prioritize investments, weighing the risks of over-building against the risks of being unprepared for new load.

Understanding Load Management Impacts

EV load forecasts can be used to model the impact of potential mitigation strategies. Instead of simply forecasting an unmanaged load, scenarios can be used to evaluate the effectiveness of the following approaches:

- **Load shaping and demand response:** To reduce the need for extensive physical infrastructure upgrades, utilities can implement smart charging technologies and demand response programs that shift EV charging to off-peak hours and help avoid distribution system constraints. Managed charging programs, as well as time-varying rates, can shape EV demand to defer or even eliminate the need for some upgrades.
- **Dynamic load management:** Real-time monitoring of grid conditions and automated control of charging infrastructure can help utilities manage localized peaks and improve overall grid efficiency. Enabling such systems allows utilities to control or influence when and how vehicles are charged, ensuring that demand remains within the grid's capacity limits.

- **Bidirectional charging:** Technology that allows EVs to feed energy to the grid when demand is high can help alleviate stress on the grid during peak periods and reduce the need for immediate infrastructure upgrades. Bidirectional charging requires consideration of control systems, communication protocols, and grid readiness.

Considering load management impacts includes mitigation strategies as part of the forecast itself, rather than treating them as after-the-fact solutions to a projected problem. Traditionally, forecasters provided distribution system planners a single "unmanaged" load forecast, and then it was up to planners to identify solutions, including grid upgrades and demand response programs, to solve for the projected overloads.

By transparently embedding mitigation measures like smart charging directly into forecast scenarios, planners can make more informed decisions from the start. They are no longer solving for a single worst-case outcome but instead are comparing the distinct grid needs and costs associated with multiple potential futures (e.g., a managed charging future vs. an unmanaged future). This allows the value of a mitigation measure—in terms of deferred or avoided infrastructure costs—to be embedded within the inputs of grid needs assessments, rather than identified through distribution planning.

By transparently embedding mitigation measures like smart charging directly into forecast scenarios, planners can make more informed decisions from the start.

Key Principles for Coordinated EV Load Forecasting

Effective load forecasting and grid planning cannot happen in isolation. Success requires deliberate coordination across a range of stakeholders adhering to a set of core principles.

Embrace Collaborative Scoping

Shaping a credible forecast is a collaborative process, not a purely technical one. Early and continual stakeholder engagement is an integral part of forecasting. Activities that create a collaborative environment include the following.

- **Engage a variety of stakeholders:** A wide range of participants need to be included, such as utilities, regulators, EV manufacturers, fleet operators, consumer advocates, and community organizations.
- **Incorporate community-level insights:** Local stakeholders provide area-specific insights into challenges like charging access or grid reliability concerns. Some utilities are developing Community Engagement Stakeholder Advisory Groups to ensure that local leaders and community representatives can participate directly in the planning process.
- **Create dedicated task forces:** Regional and local task forces are effective for coordinating planning and implementation of specific EV and grid-related initiatives for complex challenges across multiple state and local agencies.
- **Establish formal feedback loops:** Regular meetings can be held to present forecast assumptions and solicit feedback, providing transparency and incorporating diverse perspectives into the planning cycle.

Establish Integrated Data-Sharing Agreements

Effective coordination depends on shared data. A key step in forecasting is to formalize data-sharing agreements between organizations and agencies. This breaks down silos within utilities (e.g., grid vs. customer data), as well as between utilities, Departments of Motor Vehicles (e.g., vehicle registration data), and other state agencies (e.g., policy and emissions data).

Translate Policy into Forecast Scenarios

Forecasts must translate the policy landscape into scenarios. By building scenarios that reflect policy targets—e.g., modeling the infrastructure required to support a state goal of 1 million EVs by 2030—stakeholders can assess the grid implications and investment requirements for achieving these goals.

Ensure Forecast Alignment

Coordination is required for both strategic and technical alignment, including the following actions.

Aligning Inputs and Assumptions Across Planning Bodies

Different forecasting entities can work to align their core assumptions. This helps stakeholders understand and reconcile forecasts with different results for the same area. Misalignment leads to conflicting forecasts and uncoordinated investments across utility organizations, state energy offices, regional grid operators (independent system operators and regional transmission organizations), and state transportation agencies.

Preventing Methodological Double-Counting

Forecasts can clearly differentiate between base load and load modifier forecasts. This prevents the technical error of "double-counting" EV loads, which happens when EV demand is included both in the base load forecast and again as a separate load modifier. Failure to differentiate between base load and load modifier forecasts can overstate total load and lead to unnecessary utility spending for resources and grid upgrades.

Adapt Regulatory Frameworks to Support Proactive Grid Planning

Regulatory frameworks can evolve to support coordinated forecasting approaches. Regulators can establish mechanisms that encourage utility-state collaboration, require proactive investments in distribution systems to meet growing loads, and update rules to keep pace with the speed of EV adoption.

Incorporating Technology and Modeling Advances

Long-term forecasting looks beyond current market trends to account for foundational shifts in technology and modeling capabilities. Planners can anticipate and incorporate these advances into their scenarios to create more robust and forward-looking analyses.

Future Technologies

Forecasters can consider how emerging vehicle and charging technologies will alter energy demand, shift load profiles, and create new opportunities for EVs to provide grid services. Key technologies to monitor and incorporate into long-term scenarios include the following:

- **Ultra-high-speed charging:** While today's fast chargers operate in the 50–350 kW range, megawatt-level charging systems are in development to support HDVs, which will create highly concentrated, high-impact loads.
- **Improvements in EV and EVSE technologies:** Continued advancements in battery energy density and vehicle lightweighting may reduce the energy intensity of EVs, while new battery chemistries like solid-state could alter charging speeds and battery lifespans.

- **Bidirectional charging (V2G/V2X):** The ability of EVs to export power back to the grid or a home is transformational. As automakers release more models with V2G capability, the EV fleet could represent a massive source of distributed energy storage, dwarfing utility-scale batteries by an order of magnitude. Forecasts can begin to explore scenarios where this capability provides a variety of grid services and customer benefits.
- **Autonomous vehicles:** Expanded adoption of autonomous vehicles could fundamentally change travel behavior, vehicle ownership models, and charging patterns, requiring specific scenario analysis.

Co-adoption of EVs with Distributed Energy Resources and Building Electrification

While EV adoption is not happening in isolation, this guide does not make recommendations on how to manage compounding uncertainties across planning processes. However, there are opportunities and potentially large cost savings associated with designing energy systems to leverage synergies and efficiencies—for example:

- **Synergies with solar:** Smart charging programs that encourage daytime EV charging can absorb surplus energy from distributed solar photovoltaics that might otherwise be curtailed, turning a potential grid challenge into a benefit.
- **Compounding load growth:** Electrifying building heating and cooling with heat pumps creates new loads alongside growing loads from EV charging. Infrastructure planning can consider these combined loads to consider right-sizing the grid at the time the utility makes distribution system upgrades.

Taking advantage of these opportunities requires disentangling the impacts of different distributed energy resources and building electrification from the base load forecast and understanding interactive effects—a key challenge for the next generation of load forecasting.

Modeling Advancements

To ground long-term forecasts, planners can stay apprised of physics-based battery and energy system simulation models that define the upper and lower limits of what future technologies can achieve. These models are used to forecast the technical potential of systems (e.g., vehicle efficiency improvements, increases in maximum charging rates) based on engineering principles rather than simple historical extrapolation. This approach helps create more defensible long-term assumptions about how much energy EVs will consume in the future.

Conclusion

Forecasting future electricity system loads with rapidly changing technologies is an inherently uncertain endeavor. As statistician George E. P. Box wrote, "all models are wrong, but some are useful."[19] The purpose of an EV load forecast is not to predict the future with perfect accuracy, but to provide a useful tool that enables robust, considered, and cost-effective electricity system planning. By adopting the fit-for-purpose, transparent, and collaborative principles outlined in this guide, the industry can develop forecasts that are useful in guiding the development of electricity grids that serve growing loads.

19 G. E. P. Box and N. R. Draper, *Empirical Model-Building and Response Surfaces* (New York: John Wiley & Sons, 1987), p. 424.

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EV Load Forecasting Guide

A Report by the Energy Systems Integration Group's EV Load Forecasting Task Force

This report and its online appendices are available at https://www.esig.energy/reports-briefs/ev-load-forecasting.

To learn more about the recommendations in this report, please send an email to info@esig.energy.

The Energy Systems Integration Group is a nonprofit organization that marshals the expertise of the electricity industry's technical community to support grid transformation and energy systems integration and operation. More information is available at https://www.esig.energy.

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