

APPENDICES

EV Load Forecasting Guide



Appendices for a Report by the
Energy Systems Integration Group

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About ESIG

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APPENDIX A

EV Adoption Methods

Consumer Preference Models

Forecasters use consumer preference models to simulate vehicle purchasing decisions by analyzing how factors like vehicle attributes (e.g., cost, range) and consumer characteristics influence the choice between EVs and internal combustion engine vehicles or between different EV types. Common approaches within this category include discrete choice models and agent-based models.

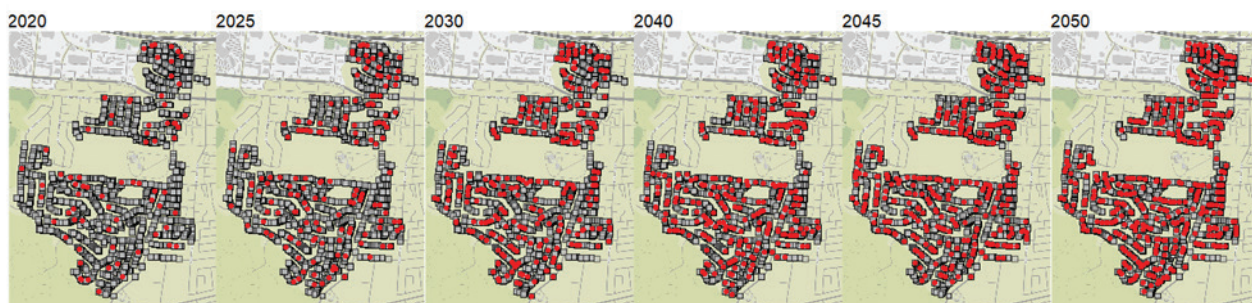
Discrete Choice Models

Discrete choice models are often used in top-down approaches and predict choices between two or more discrete alternatives (e.g., deciding to purchase an EV or internal combustion engine vehicle) (LBNL, 2023). As Figure A1 shows, to understand customer EV adoption

at the circuit level, forecasters create a probability of EV adoption for each household based on factors like housing type, household income, and other census data. Discrete choice models are causal and assume that a defined set of factors determine the agent's choice.

- **Suitability:** Best for top-down or mixed approaches analyzing substitution choices (e.g., EV vs. internal combustion engine vehicle) based on quantifiable vehicle/consumer attributes; useful for scenario testing sensitivity to price, EV range, or specific incentives.
- **Key data requirements:** Detailed consumer socio-demographics linked to location and vehicle attribute data (e.g., prices, operating costs, range).
- **Strengths:** Strong theoretical basis; explicitly link attributes to adoption probability; good for evaluating specific feature trade-offs.

FIGURE A1
Projection of EV Adoption by Household



Bottom-up adoption models can project the spatial distribution of EVs at a granular (i.e., neighborhood) level over time. This simulation by PNNL shows how EV adoption might concentrate in a specific area, allowing planners to anticipate localized grid impacts on feeders and transformers.

Note: PNNL = Pacific Northwest National Laboratory.

Source: PNNL and DOE Grid Modernization Initiative. <https://www.osti.gov/servlets/purl/1882799/>.

- **Limitations:** Can be complex to specify and calibrate; may not capture dynamic social network/peer effects; assume rational decision-making based on defined attributes.
- **Example:** Figure A4 (p. 5) shows an EV adoption forecast based on household propensity, developed by Pacific Northwest National Laboratory for Southern California Edison.

Agent-Based Models

Agent-based models simulate interactions between people, as EV purchasing decisions depend on the decisions of other agents and the overall market or network context the decisions are being made within. The flexibility of these models makes them suitable for testing the effects of economic variables and public attitudes and awareness (Domarchi and Cherchi, 2023).

- **Suitability:** Best for bottom-up forecasts needing high spatial/temporal granularity, exploring impacts of local interactions (e.g., peer effects, word-of-mouth, charging constraints), complex policy scenarios, or emergent system behaviors.
- **Key data requirements:** Highly data-intensive; require detailed agent profiles (e.g., household/fleet characteristics, preferences), behavioral rules/algorithms, network information (e.g., spatial, social), and potentially electric vehicle supply equipment (EVSE) and grid data.
- **Strengths:** High flexibility; capture heterogeneity, dynamic interactions, and feedback loops; excellent spatial detail.
- **Limitations:** Complex to develop, calibrate, and validate; computationally intensive; results can be highly sensitive to agent behavior rules and parameter assumptions.
- **Example:** Figure A2 (p. 3) shows an agent-based EV adoption tool, the Agent-based Transportation Energy Analysis Model (ATEAM), developed by Argonne National Laboratory in collaboration with Exelon. The model simulates agents making decisions about whether to switch from internal combustion engine vehicles to EVs. Decisions are based on many factors, including whether charging locations are near typical routes that drivers take in their community. If

the agent “sees” more chargers, they are more likely to switch over to an EV (ANL, 2019).

Propensity Models

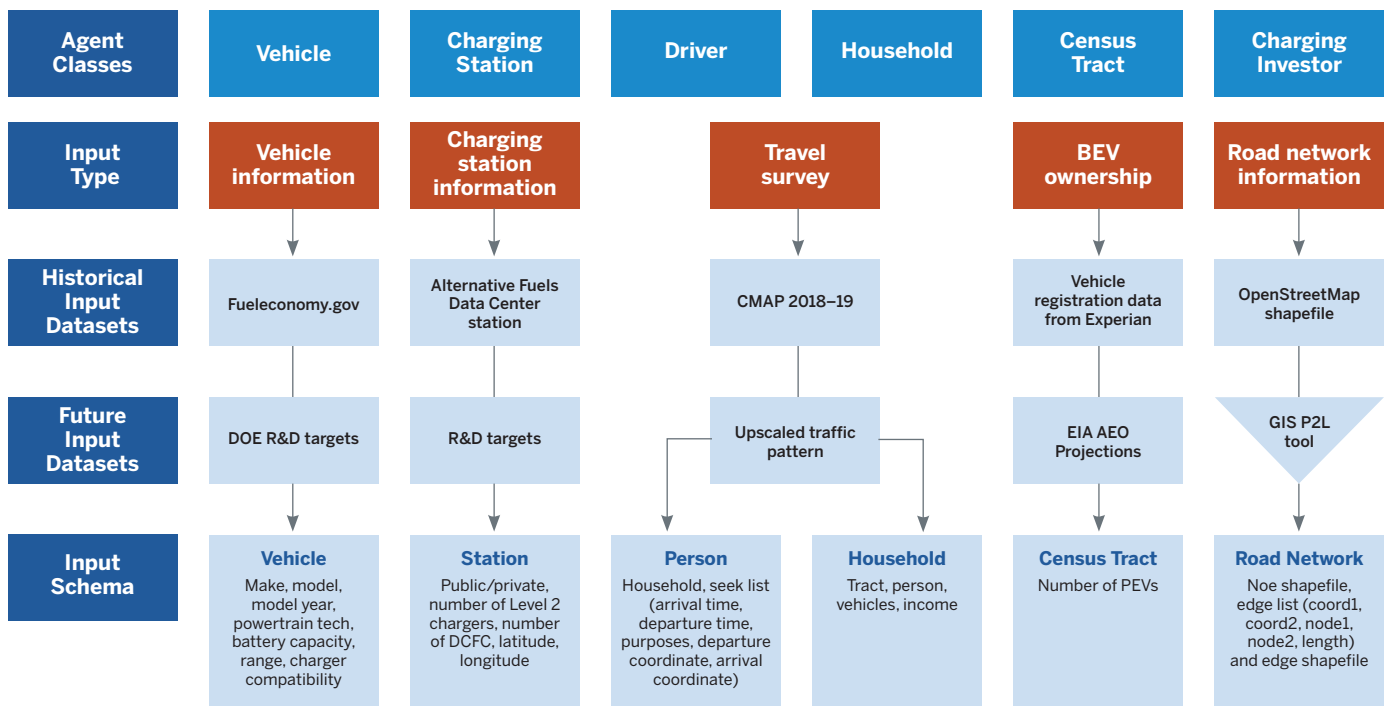
This category represents a set of approaches for building predictive models based on past behavior. For example, these models can identify the characteristics of customers who purchased a hybrid vehicle and use them to predict who else will buy one.

- **Suitability:** Primarily used in bottom-up spatial allocation to identify where adoption is most likely (e.g., census tract/ZIP scoring for “hotspot” analysis) or which customer segments are most likely to adopt based on historical correlations.
- **Key data requirements:** Granular historical adoption data (e.g., registrations) linked geographically to relevant predictor variables (e.g., demographics, housing types, charger locations, income).
- **Strengths:** Data-driven approach; can identify complex or non-linear correlations; effective for spatial targeting and customer segmentation.
- **Limitations:** Less explanatory than choice models (i.e., more correlational than causal); predictive power depends heavily on historical data quality and representativeness; may struggle to predict adoption of new technologies or new customer segments not present in historical data.
- **Example:** Pacific Gas and Electric (PG&E) uses propensity model results to drive the market potential component of an S-curve adoption model (LBNL, 2023).

Diffusion/System Dynamics Models

Models in this category simulate market penetration by following a characteristic S-shaped adoption curve. The forecast begins with a known starting point, typically based on current EV registrations, and grows over time toward a saturation point. The specific model used (e.g., Bass, Gompertz, Weibull, or Logistic) determines the shape of the growth curve. The saturation point is influenced by factors like state zero-emission-vehicle targets, population growth, and charging accessibility. This framework allows forecasters to develop multiple

FIGURE A2
Agent-Based Transportation Energy Analysis Model



Agent-based models like Argonne National Laboratory’s ATEAM rely on a wide range of granular inputs to simulate the complex interactions that drive EV adoption and charging behavior. The model integrates vehicle data, travel surveys, and demographic information to forecast how individual agents will respond to their environment.

Notes: AEO = Annual Energy Outlook; BEV = battery electric vehicle; DCFC = DC fast chargers; GIS = geographic information system; PEV = plug-in electric vehicle.
Source: Argonne National Laboratory, <https://publications.anl.gov/anlpubs/2024/08/190134.pdf>.

scenarios—such as low, medium, and high adoption—by varying the assumptions that drive market growth.

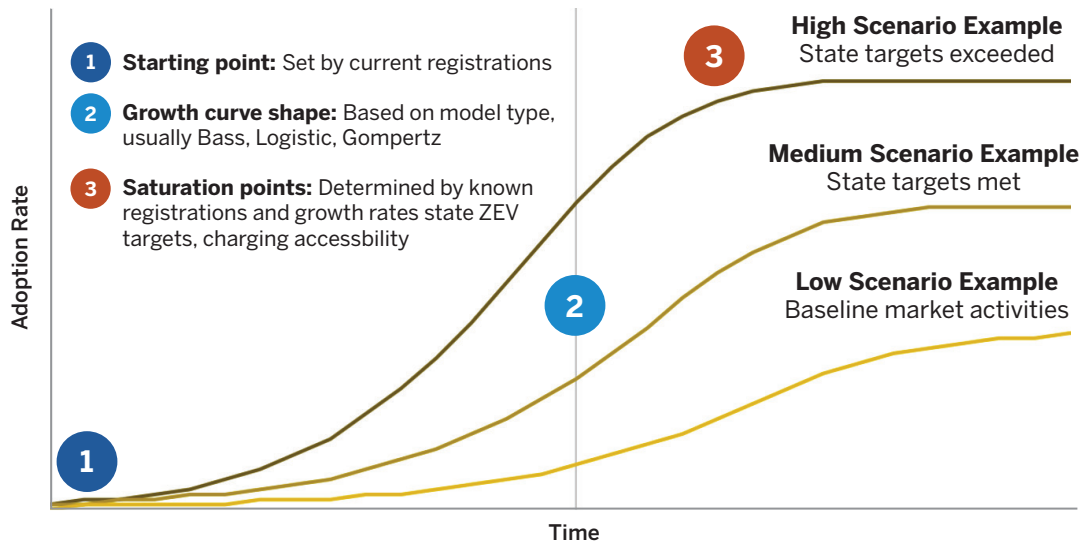
- **Suitability:** Best for top-down, long-term, aggregate forecasts (e.g., state/utility-level total EV stock or market share) focused on capturing overall market penetration and saturation dynamics (S-curve); often used when detailed behavioral data are scarce or for aligning with high-level policy targets.
- **Key data requirements:** Baseline EV stock/market share; estimates of total market potential; historical adoption data points for calibrating diffusion parameters.
- **Strengths:** Relatively simple to implement; less data-intensive than behavioral models; established methodology for technology diffusion; transparent structure.

- **Limitations:** Limited ability to explain why adoption occurs; less sensitive to specific economic/policy shifts unless parameters are externally adjusted; poor native spatial resolution (requires separate allocation step if local detail is needed).
- **Example:** Figure A3 (p. 4) illustrates a generalized diffusion model.

While generalized diffusion curves show the “what” of adoption, system dynamics models aim to explain the “why” by capturing the complex feedback loops between various market drivers. Figure A4 (p. 5) shows an example of this approach, Guidehouse’s Vehicle Analytics & Simulation Tool model, which illustrates how external inputs like fuel prices and incentives influence core modules such as total cost of ownership and consumer

FIGURE A3

Example of a Generalized Diffusion Model



Diffusion models are often used to forecast aggregate market penetration over time. They typically follow an S-shaped curve, starting with early adopters, accelerating as the technology becomes mainstream, and finally leveling off as the market reaches saturation.

Source: Concept by Grid Modernization Initiative, U.S. Department of Energy, https://eta-publications.lbl.gov/sites/default/files/forecasting_workshop_2_public_full_deck20230324.pdf. Adapted by Energy Systems Integration Group.

awareness (Guidehouse, 2023). These factors, in turn, drive vehicle sales and registrations, which then influence awareness and availability of charging infrastructure.

Fleet Adoption

The decision-making processes for fleet EV adoption are different than for personal vehicles; therefore, modeling fleet adoption requires weighing variables differently. For medium- and heavy-duty vehicle (MHDV) fleets, economics and cost minimization are central, particularly the total cost of ownership, where higher upfront costs may be offset by long-term savings in fuel and maintenance. Declining battery costs and increased efficiencies further enhance the economic viability of MHDVs for fleet operators who prioritize operational cost reductions (Qian and Szinai, 2023) or emission reductions. To develop reasonable and explainable forecasts for fleet EV adoption, it is important to carefully consider total cost

of ownership, along with fleet-specific duty cycle requirements, such as route length, freight loads, and delivery schedule.

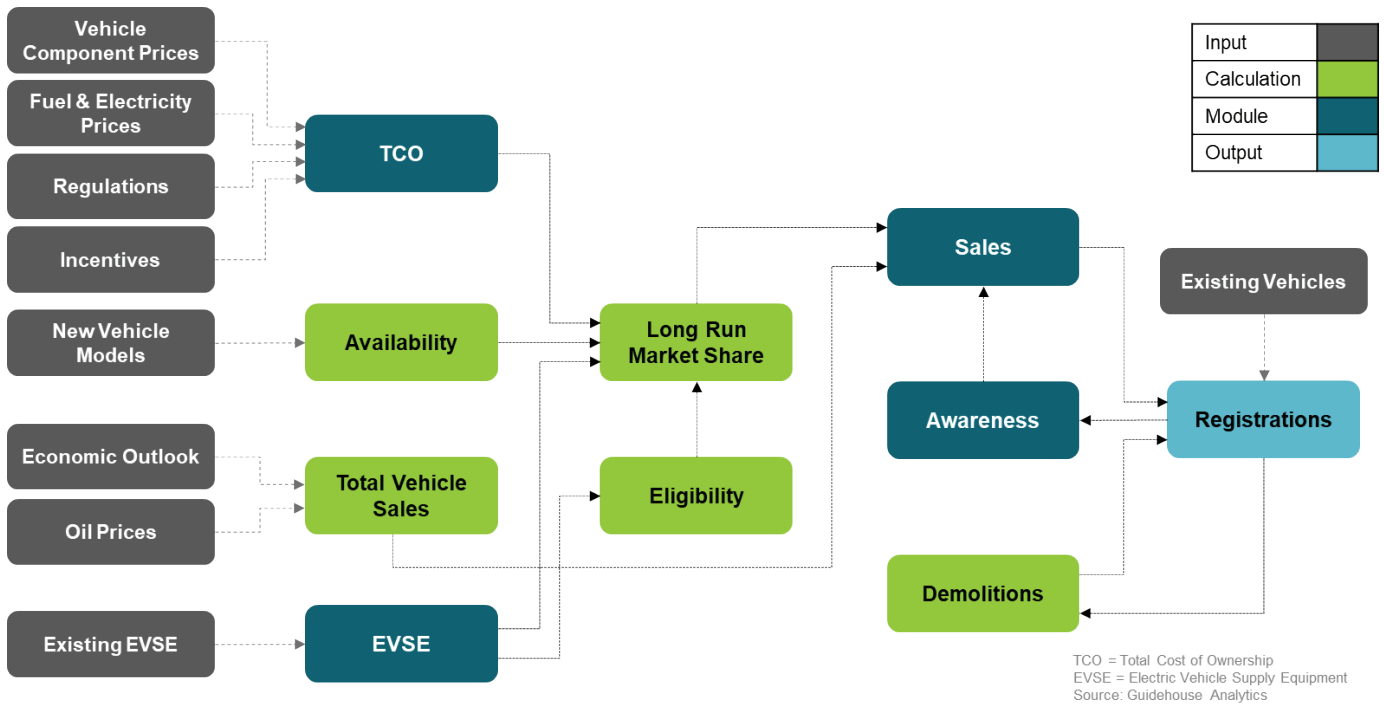
Policy decisions also drive MHDV adoption, especially specific fleet types. For example, the Advanced Clean Trucks regulation¹ established by the California Air Resources Board sets targets for zero-emission-vehicle sales and has been adopted by 18 other states and the District of Columbia (CARB, 2025). New York's electric school bus initiative is also driving MHDV fleet conversions.² Federal subsidies and investments in charging infrastructure and MHDV internal combustion engine replacement complement these policies, supporting electrification in segments such as urban delivery and transit, where adoption already is progressing (EPA, 2025). For long-haul trucking, however, broad adoption will depend on technological advancements in battery energy density or alternative fuels (Lee et al., 2023).

1 <https://ww2.arb.ca.gov/our-work/programs/advanced-clean-trucks/about>

2 <https://www.nysed.gov/All-Programs/Electric-School-Buses/All-About-Electric-School-Buses>

FIGURE A4

Example of a System Dynamics Innovation Diffusion Approach



System dynamics models capture the feedback loops between various market drivers. In this example, factors like vehicle cost (total cost of ownership) and charging availability (EVSE) influence consumer awareness and sales, which in turn affect the total number of registered vehicles on the road.

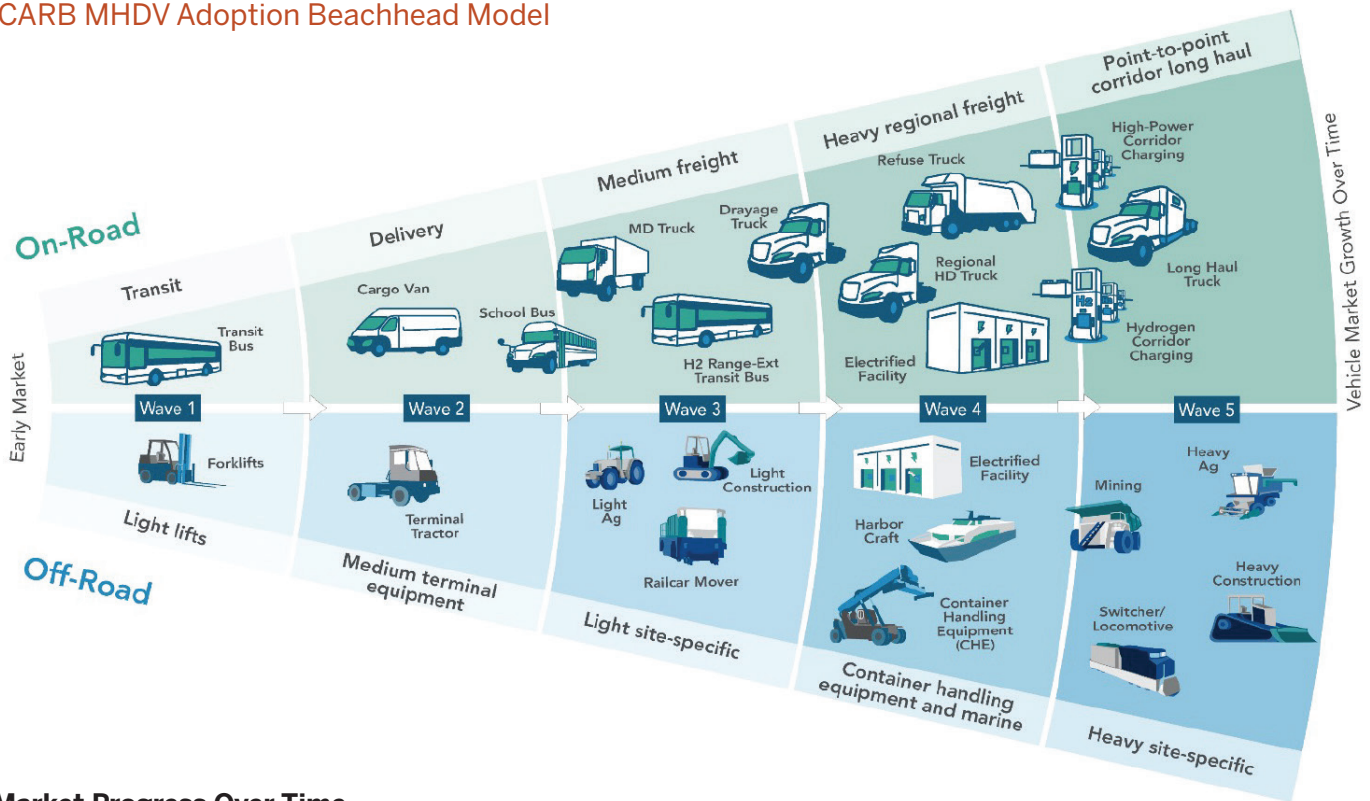
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There are well-established methods to forecast fleet EV adoption. The California Air Resources Board Beachhead Model for MHDV adoption in Figure A5 (p. 6) provides an example approach for projecting MHDV adoption that considers segment- and operational-specific factors and constraints. Beachhead models target initial, high-potential market segments to establish a foothold before expanding to more challenging applications. Under this model, MHDV electrification is organized into a series of waves, beginning with early market, on-road applications like transit buses and off-road equipment like forklifts. The model’s logic is that success in these initial segments allows for the scaling of similar drivetrains to other near-term applications. Over time, as market penetration progresses through subsequent waves—from delivery vans to medium freight and eventually long-haul trucking—expanded supply chain capabilities and increased volumes lead to price reductions and

strengthened performance confidence, enabling the eventual electrification of the most difficult segments.

A 2023 study by National Grid and Hitachi Energy provides a practical example of a bottom-up approach to forecasting the grid impacts of MHDV fleet electrification (National Grid and Hitachi Energy, 2023). Planners aimed to capture the highly localized and clustered nature of fleet charging by modeling individual fleet behaviors and aggregating their impacts on the distribution network. The analysis translates a long-term, large-scale fleet adoption scenario into specific feeder- and substation-level impacts to inform proactive grid planning. The study starts with data for individual fleets and then aggregates projected charging loads to assess the impact on specific grid assets, such as distribution feeders. The core methodology involves several steps:

FIGURE A5
CARB MHDV Adoption Beachhead Model



Market Progress Over Time

Similar drivetrain and component sizing can scale to early near applications.

Expanded supply chain capabilities and price reductions enable additional applications

Steadily increasing volumes and infrastructure strengthen business case and performance confidence

Beachhead models reflect a phased approach to fleet electrification, starting with vehicle segments best suited for early adoption. Success in initial “waves,” such as transit buses and terminal tractors, helps build the supply chain and performance confidence needed to tackle more challenging applications like long-haul trucking in later waves.

Source: California Air Resources Board, https://ww2.arb.ca.gov/sites/default/files/2021-10/fy21-22_fundingplan_appendix_d.pdf.

- **Fleet identification:** Researchers identified 51 major fleet operators using online maps and satellite imagery and estimated vehicle counts and classes (e.g., box trucks, regional freight trucks, school buses) for each fleet depot.
- **Driving pattern simulation:** The study used the National Renewable Energy Laboratory’s Fleet DNA dataset³ to model realistic driving patterns, including trip start times, durations, and distances for different vehicle classes.
- **Charging profile generation:** Monte Carlo simulation generated thousands of potential daily fleet schedules and resulting charging load profiles, considering both full charging and minimum charging strategies.

3 <https://www.nrel.gov/transportation/fleettest-fleet-dna>

APPENDIX B

EV Charging Infrastructure Methods

EV-to-EVSE Ratios (Heuristics)

These methods apply a fixed ratio (e.g., X number of EVs per public Level 2 port, Y number of EVs per DC fast charging (DCFC) port) based on benchmarks or targets.

- **Suitability:** Only suitable for top-down, high-level, preliminary estimates of total charger port counts (system-wide/regional) or translating broad policy goals (e.g., X chargers per 1,000 EVs) into rough numbers.
- **Key data requirements:** Total EV adoption forecast number; externally sourced benchmark or target EV:EVSE ratio values, which vary widely.
- **Strengths:** Extremely simple; minimal data required.
- **Limitations:** Insufficiently accurate for determining specific infrastructure needs (type, power, location); ignore critical factors like vehicle miles traveled (VMT), consumer behavior, vehicle types, utilization, and geography; do not provide actionable siting guidance.
- **Example:** The National Renewable Energy Laboratory and Portland General Electric used the AdopDER model⁴ to predict a mix of public Level 2 and DCFC chargers to meet unmet charging demand from another model that uses historical data (and therefore did not meet future charging needs). The model used two key heuristics: (1) it maintained an 8:1 ratio of Level 2 to DCFC chargers to align with benchmarks from other tools and studies, and (2) chargers were

grouped into sites by fours. The model then used typical consumption of residential EV owners to calculate the number of chargers needed for EVs without access to home charging (PGE, 2021).

Needs-Based Simulation Models

Needs-based simulation models, such as the National Renewable Energy Laboratory's EVI-Pro,⁵ Lawrence Berkeley National Laboratory's HEVI-LOAD,⁶ and custom models, simulate vehicle travel and charging behavior to estimate energy demand over time and space, then determine the necessary infrastructure (e.g., ports, power levels, locations) required to meet that demand adequately while limiting wait times.

- **Suitability:** The most common and comprehensive bottom-up approach for detailed forecasting for infrastructure needs when specific outputs are required for charger quantity, type, power level, and location; essential foundation for detailed grid impact studies.
- **Key data requirements:** Detailed EV adoption forecast outputs (numbers, types, locations, specifications from the EV adoption component); granular travel behavior data (e.g., VMT, dwell time at the facility); charging behavior assumptions (e.g., location preference, state of charge [SOC] management); existing EVSE inventory; land use data.
- **Strengths:** Provides detailed outputs (ports by type/power/location); grounded in vehicle energy needs and travel patterns; flexible for scenario analysis.

⁴ <https://www.adopder.com/>

⁵ <https://www.nrel.gov/transportation/evi-pro>

⁶ https://www.energy.ca.gov/sites/default/files/2021-09/5%20BLNL-FTD-EAD-HEVI-LOAD%20Medium-%20and%20Heavy-Duty%20Load%20Shapes_ADA.pdf

- **Limitations:** Highly sensitive to the quality and granularity of input data and behavioral assumptions; can be computationally complex depending on scale and detail.
- **Example:** The National Renewable Energy Laboratory’s report, *The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure*, uses EVI-Pro to estimate how much EV charging infrastructure is needed to meet a given demand (Wood et al., 2023).

Propensity Models

Propensity models help utilities and planners pinpoint areas where EV adoption is likely to be high, allowing for targeted infrastructure investments. For example, this type of model might predict higher adoption in urban areas with government incentives, highlighting regions that may need more public charging stations. This straightforward, data-driven approach offers a focused forecast by quantifying the adoption potential of different communities.

- **Suitability:** Bottom-up approach effective for identifying and prioritizing where to potentially site future infrastructure (i.e., “hotspot” analysis) by correlating factors linked to high demand (EV density, traffic, points of interest, demographics) with specific locations.
- **Key data requirements:** Geocoded data on existing EVSE and/or EV adoption; relevant spatial/demographic predictor variables (traffic, income, housing type, etc.); geographic information system (GIS) capabilities.
- **Strengths:** Useful for spatial targeting and suitability analysis; data-driven site identification.
- **Limitations:** Models do not determine the number or type/power of chargers needed, only relative locational propensity; predictive power depends on quality of historical correlations.
- **Example:** The Brattle Group’s *ERCOT EV Allocation Study* employs a methodology to determine EV load impact at the substation level by assigning a propensity score to geographical areas (Sergici et al., 2023). This score is derived by correlating local socio-economic and industry-specific data, such as the employment

level in the transportation and warehousing industry within a given ZIP code, with the likelihood of EV adoption. This “hotspot” analysis enables planners to identify and prioritize specific substations (Sergici et al., 2023).

Machine Learning Models

Machine learning models can process large datasets to predict charging demand patterns across locations and times. By analyzing historical charging behavior, they can uncover complex, non-linear demand patterns for different charging locations (home, public, workplace) and optimize demand forecasts accordingly. They can be top-down if using macro inputs to predict aggregate regional metrics or bottom-up if predicting utilization at specific stations.

- **Suitability:** Can predict utilization or demand patterns at existing charging locations based on historical data and factors like time, weather, and events; can contribute to site suitability scoring or short-term operational forecasts for specific stations/areas.
- **Key data requirements:** Large datasets of historical charging sessions (energy, duration, time) linked to location and relevant predictor variables.
- **Strengths:** Can capture complex, non-linear patterns in charger usage data.
- **Limitations:** Require significant, high-quality historical data (often unavailable or proprietary); less effective for forecasting needs at new locations or under future conditions different from historical patterns.
- **Example:** One study used observed driver behavior to create “scalable probabilistic estimates” of EV charging (Powell, Cezar, and Rajagopal, 2022).

System Dynamics Models

System dynamics models represent a system through feedback loops and interconnected variables, capturing time-dependent interactions and dependencies within the system. This approach is useful for understanding how variables like demand, infrastructure capacity, and policy interventions influence each other over time.

- **Suitability:** Best for strategic, long-term analysis exploring feedback loops between infrastructure

deployment, perceived charging availability or cost, and subsequent EV adoption rates; typically used in mixed forecasting approaches because these models are less suited for detailed spatial planning.

- **Key data requirements:** System stocks (EVs, chargers) and flows (adoption rate, deployment rate) and calibrating parameters governing feedback loops.
- **Strengths:** Uniquely capture system-level interactions and long-term dynamics between adoption and infrastructure.
- **Limitations:** Can be complex to build and calibrate; outputs are often aggregate; less useful for detailed spatial siting or specific charger type/power requirements.
- **Example:** The “Charging Needs” module within Guidehouse’s VAST model (Robinson, Kuss, and Owusu Agyeman, 2021) forecasts the charging infrastructure required to support the projected EV adoption using a dynamic market equilibrium model to determine the number of charger ports needed for a given number of vehicles (Guidehouse, 2023).

APPENDIX C

EV Charging Profile Methods

Load and Charging Profile Models

Load and charging profile models use historical data on the timing, frequency, and duration of charging sessions to create EV charging patterns that are used to forecast future loads.

- **Suitability:** A common approach for system-level or zonal forecasting, particularly when representative historical charging profiles (e.g., from advanced metering infrastructure (AMI), network data, or simulations) are available for key segments (e.g., residential, workplace Level 2, public DCFC); used to aggregate load based on forecasted numbers of EVs/chargers in each segment.
- **Key data requirements:** Representative hourly (or sub-hourly) load profiles for major EV charging segments; outputs from EV adoption and EVSE forecasts (counts by segment/location).
- **Strengths:** Conceptually straightforward; computationally less intensive than an agent-based model; directly use empirical shapes if available.
- **Limitations:** Accuracy heavily dependent on quality and representativeness of input profiles; assume profiles are static or require external adjustments for future conditions; aggregation can mask localized peak demand on the grid and diversity in peak demand times for EVs; require careful handling of profile scaling and aggregation.
- **Example:** Idaho National Laboratory's Caldera is a platform for developing and testing smart charging strategies.⁷

Bayesian Models

These models can dynamically adjust charging demand forecasts based on new data, such as changes in charging behavior due to policy or infrastructure improvements. For example, if a workplace charging program is implemented, a Bayesian model can update demand estimates to account for increased workplace charging.

- **Suitability:** Useful when needing to formally incorporate uncertainty in parameters and dynamically update forecasts as new charging data become available; can be applied within other modeling frameworks.
- **Key data requirements:** Prior distributions for model parameters; likelihood function relating data to parameters; ongoing stream of new data for updates.
- **Strengths:** Explicitly handle uncertainty; principled way to update forecasts over time.
- **Limitations:** Can be conceptually and computationally complex; require expertise in Bayesian statistics; results depend on choice of priors.
- **Example:** Researchers from the National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory, and Iowa State University developed a short-term EV load forecasting model using a specific type of Bayesian method known as Gaussian Process Regression (Shi et al., 2024).

Machine Learning Models

These models can process large datasets to predict charging demand patterns across locations and times. By analyzing historical charging behavior, they can uncover

⁷ <https://inl.gov/document/electric-vehicle-charging-simulation-platform/>

complex, non-linear demand patterns for different charging locations (home, public, workplace) and optimize demand forecasts accordingly.

- **Suitability:** Primarily effective for short-term operational forecasting (i.e., hours/days ahead) at specific aggregation levels (e.g., substation, charging depot) where sufficient historical load data and relevant predictor variables (e.g., time, weather, events, recent load) exist; can capture complex, non-linear historical patterns.
- **Key data requirements:** Large volumes of historical load data at the target forecast granularity; corresponding time series of predictor variables.
- **Strengths:** Data-driven; often achieve high predictive accuracy for short horizons if underlying patterns persist.
- **Limitations:** Less transparent; performance often degrades over longer horizons or with structural changes (e.g., new policies, behaviors, technologies) not included in the training data; require substantial, clean training data.
- **Example:** The University of Texas at San Antonio demonstrated the efficacy of a transformer-based deep learning approach to predicting EV charging demand (Koohfar, Woldemariam, and Kumar, 2023).

Agent-Based Models

Agent-based models simulate interactions between individual “agents” (e.g., households, fleet operators), each behaving according to rules influenced by their environment, demographics, and preferences. For EV load forecasting, agent-based models can model neighborhood-level effects, like local peak loads due to synchronized charging behavior under time-of-use rates.

- **Suitability:** Best for detailed, bottom-up simulations where emergent load shapes resulting from individual agent interactions are of interest (e.g., drivers, vehicles, chargers, grid signals); excellent for analyzing impacts of complex managed charging strategies, price responses, or heterogeneous behaviors at a granular level (e.g., feeder impacts).
- **Key data requirements:** Very high, as these models require detailed agent characteristics, behavioral rules (e.g., charging logic, response to signals), EVSE network specifications, potentially grid topology and/or constraints.
- **Strengths:** Capture individual heterogeneity, complex interactions, feedback loops, emergent patterns; high spatial/temporal resolution.
- **Limitations:** Highly complex to develop, calibrate, and validate; computationally intensive; results very sensitive to assumed behavioral rules.
- **Example:** Cornell University leveraged agent-based models to forecast high-resolution charging demand for workplace and public charging in the Atlanta metropolitan area (Liu, Tayarani, and Gao, 2021).

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EV Load Forecasting Guide

Appendices for a Report by the Energy Systems Integration Group's EV Load Forecasting Task Force

The guide and these appendices are available at <https://www.esig.energy/reports-briefs/ev-load-forecasting>.

To learn more about this work, 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>.

