Integration of Electric Vehicle Charging Loads in Residential Building Stock Energy Modeling

Andrew Speake, Anthony Fontanini, Rajendra Adhikari, Philip White, Prateek Munankarmi, and Arthur Yip

National Renewable Energy Laboratory

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List of Acronyms

ACS	American Community Survey
ATUS	American Time Use Survey
BEV	battery electric vehicle
DOE	U.S. Department of Energy
EIA	U.S. Energy Information Administration
EMS	Energy Management System
EV	electric vehicle
FPL	federal poverty level
ft	foot
HPXML	Home Performance XML
kW	kilowatt
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory
PUMA	Public Use Microdata Area
PUMS	Public Use Microdata Sample
RECS	Residential Energy Consumption Survey
SoC	state of charge
SUV	sport utility vehicle
TEMPO	Transportation Energy & Mobility Pathways Options
TWh	terawatt-hour
VMT	vehicle miles traveled

Executive Summary

The adoption of electric vehicles (EVs) has led to a significant number of new electric loads in homes, which have the potential to change the way energy costs are incurred by homeowners, as well as the landscape of utility operations and energy infrastructure. While the growth and scale of residential and EV charging loads are influenced by different factors, the loads themselves are closely linked to the behavior of individual occupants and EV owners. This correlated relationship motivates the use of a common approach to analyze the coincident energy impacts, whereas separate domain-specific tools are required to accurately characterize the parameters of EVs and residential buildings.

In this report, the authors describe an approach for integrating data and assumptions from the Transportation Energy & Mobility Pathways Options (TEMPO™) tool into the ResStock™ model to generate accurate and flexible datasets that capture the concurrent behavior and energy outputs of residential building loads and EV charging. We present methods to characterize the national baseline EV ownership, EV charger, and charging behavior consistent with TEMPO assumptions and within the context of ResStock's existing housing characteristics data. We also describe a new approach for modeling EV batteries and charging loads in ResStock, which incorporates regional and demographic details of EV stock characterization into individual building models. The modeling approach leverages a detailed lithium-ion battery model and incorporates stochastic occupant behavior to generate realistic charging and discharging profiles. Finally, we analyze a nationwide simulation of ResStock with EVs and present trends and impacts on the baseline housing stock, which we then compare to external datasets.

The key outcome of our implementation is to improve the building stock modeling capabilities to account for the operation and adoption of EVs in ResStock's national baseline. We provide a solution for modeling current EV charging behavior that is consistent with other occupant-generated household loads while offering numerous pathways toward analysis of future scenarios. Through an internal analysis, we confirm that EV energy use and charging times are consistent with expected trends across different segments of the housing stock. The results also show that EV adoption, charging energy, and schedules are consistent with national survey data, vehicle registrations, modeled TEMPO data, and the U.S. Federal Highway Administration's National Household Travel Survey.

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1 Overview

As households adopt EVs, electrify end uses, and experience weather-driven demand, understanding the building stock-level impacts of EV adoption and occupant-aligned charging patterns becomes critical. These insights are essential for planning resilient energy systems, managing grid capacity, and informing equitable infrastructure and policy decisions. We present a methodology for integrating electric vehicle (EV) charging loads into the national-scale building stock modeling tool ResStock™ (Reyna et al. 2025), enhancing the potential for baseline and scenario analysis of residential electricity demand. Our approach begins with engaging relevant stakeholders to identify the most pressing aspects of EV adoption, home charging, and operations, which is discussed in Section 2. Insights from the stakeholder engagement serve as the foundation for the methodological decisions described in Sections 3–5. Core to all use cases is an accurate characterization of EVs and flexible modeling of EV charging in the baseline of ResStock. Section 3 describes the generation of ResStock input files that characterize EV-related parameters across the housing stock, and Section 4 discusses how these inputs translate to individual building energy models.

Section 5 describes the specific enhancements and assumptions of the EV model. We leverage an existing physics-based home battery model to accurately simulate vehicle charging and discharging while maintaining flexibility for more complex operational scenarios, such as bidirectional charging. Additionally, we introduce occupant-driven schedules of charging and discharging, which ensure diverse load patterns that align with other occupant-driven household loads, such as hot water usage or appliances. Our approach to modeling EV charging loads in ResStock results in annual and time series energy, costs, emissions, and utility bill outputs in the baseline housing stock while also providing pathways to model scenarios for vehicle adoption, charger adoption, and demand flexibility of EV charging. Results from a national-scale ResStock simulation with external dataset comparisons and further discussion of the impacts of this effort can be found in Section 5.3 and Section 7.

1.1 Project Motivation

EVs introduce new connections across residential buildings, building occupants, mobility choices, vehicle manufacturers, and electric utilities. Residential buildings offer a convenient and cost-effective charging option for EV owners while also influencing household electricity demand and the broader power grid. As EV adoption grows and production scales up, ensuring a reliable and efficient energy system will be increasingly important.

Utilities, auto manufacturers, charging providers, and EV supply equipment manufacturers are working together to develop technologies (such as smart chargers) and services (such as EV rates) that enable efficient EV-grid integration. With potential continued EV adoption (over 10% of sales in the United States in 2024 [IEA 2025] and 25.3% of sales in California [California Energy Commission 2025] in 2024), coordination between the residential energy sector, transportation sector, and electric grid will play a key role in maintaining affordability and reliability.

In 2022, the residential electricity sector accounted for 1,500 terawatt-hours (TWh) of consumption (38% of total electricity demand [EIA 2024]). Although the future trajectory of light-duty EV adoption and mobility needs remains uncertain, most studies project a significant rise in electricity demand. Yip et al. (2023) estimate that light-duty EVs could add approximately 900 TWh of demand by 2050[1], whereas Hoehne et al. (2023) provide a broader range (120–3,000 TWh, with a median of 1,000 TWh) depending on the adoption scenario. With about 80%[2] of EV charging currently happening at home, residential electricity use will be a major factor in supporting future EV growth.

Although EV charging can be coordinated through strategies such as time-based pricing, infrastructure investments, and grid modernization, unmanaged charging remains the simplest approach for many consumers. In this scenario, simultaneous charging of multiple EVs—often aligning with peak residential electricity use in the late afternoon—can create localized grid stress. However, by leveraging advancements in home energy management and distributed energy resources, EV charging can be optimized to reduce costs and enhance grid stability.

Managed charging strategies, such as unidirectional smart charging (i.e., V1G), enable EV owners to shift charging to lower-cost periods (Anwar et al. 2022), reducing stress on the grid. More advanced technologies, including vehicle-to-grid and vehicle-to-building integration, allow EVs to store and supply power when needed, improving energy resilience and providing potential cost benefits. Through continued development and deployment of vehicle-to-building and vehicle-to-grid technologies, EVs can serve as a flexible energy resource for both consumers and the broader electricity system. To accurately assess the potential benefits of these approaches, comprehensive modeling of buildings and vehicles is essential.

1.2 Residential and Transportation Sector Energy Models

The National Renewable Energy Laboratory (NREL) develops and maintains the Transportation Energy & Mobility Pathway Options (TEMPO™) model and ResStock, national-scale models for the transportation and residential building sectors, respectively. With these models, independent, sector-specific analyses of future energy scenarios can be modeled with detailed geographic and temporal resolution. However, differences in the underlying datasets and assumptions do not guarantee agreement when outputs of the tools are combined.

TEMPO is a vetted and validated U.S. national transportation energy demand and emissions model (NREL 2025b). The model projects U.S. transportation demand from household mobility needs and freight activity and the vehicles and infrastructure needed to meet those demands (Muratori et al. 2021). TEMPO currently models households at the county level, broken down by household size, income, and urban classification. National Household Travel Survey (NHTS) (Federal Highway Administration 2022) data are used to capture heterogeneity in travel behavior (e.g., number and duration of trips over time, mode choice). TEMPO produces hourly energy use for all transportation modes (including residential charging of EVs), which makes it possible to generate EV load profiles that are appropriately correlated with housing characteristics—and, therefore, end-use load profiles—for households of different sizes, locations, and income levels.

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[1] For the "All EV Sales by 2035" scenario in Yip et al. (2023).

[2] This value is based on the result of 81% from Borlaug et al. (2020), according to an EPRI study of 45 battery EVs from 2016 to 2018, and 76% from the U.S. Energy Information Administration's (EIA's) 2020 Residential Energy Consumption Survey (RECS) (EIA 2020).

For example, a high-income household with four drivers in a large, suburban house will have very different load profiles for both EV charging and heating/cooling/etc. compared to a medium-income household with one driver in a one-bedroom apartment in a dense urban area. At the time of this report, TEMPO does not distinguish between different housing types but does incorporate distributions of residential charging availability by household type and county from a study by Ge et al. (2021).

ResStock is a U.S. national residential building energy stock model (NREL n.d.). The model first describes the U.S. residential housing stock with over 100 building characteristics that impact energy consumption. These characteristics are related to appliance ownership and efficiency levels, the amount of insulation, building types, construction materials, floor area, heating fuel, income, tenure, and number of occupants. The building characteristic database is then sampled. A typical run of ResStock contains 550,000 statistically representative residential dwelling units. These representative models are simulated with the U.S. Department of Energy (DOE) Building Technologies Office's flagship physics-based building energy modeling platforms EnergyPlus®[3] and OpenStudio®[4]. ResStock produces 15-minute time series of the end-use-level (heating, cooling, refrigeration, cooking, etc.) energy consumption of electricity and fossil fuels for each representative dwelling unit. ResStock was recently calibrated to U.S. Energy Information Administration (EIA), utility meter, and submetering data through the End-Use Load Profiles project (NREL 2025a). Since that large-scale validation effort, the focus of ResStock has been shifted to producing nationally relevant datasets to be used in cross-sectoral and residential building stock analyses. ResStock is used to answer questions about how certain technologies will impact the energy landscape in the residential building stock. However, ResStock does not currently model EV charging.

Figure 1 shows the high-level workflow of ResStock, from stock characterization to final dataset generation. To introduce EVs, we made updates to the first two steps of the workflow, "Stock Characterization" and "Building Energy Model Articulation," with the remaining steps unchanged and executed to produce and analyze results. More detailed information regarding the existing baseline ResStock workflow can be found in the *ResStock Technical Reference Documentation, v3.3.0* (Reyna et al. 2025).

[3] For more information, visit https://energyplus.net/.
[4] For more information, visit https://openstudio.net/.

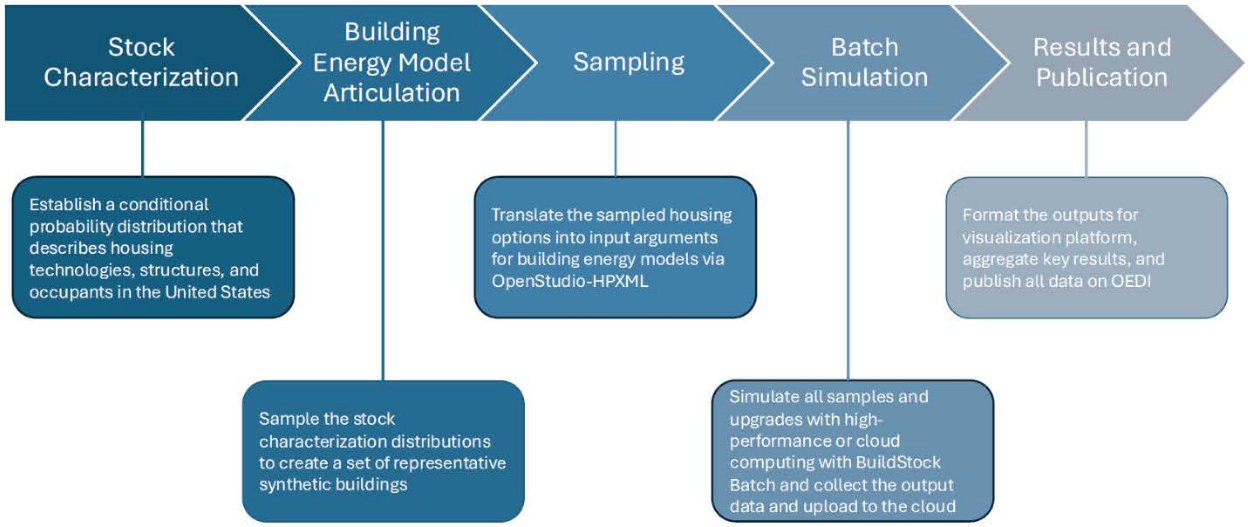

Figure 1. The full workflow to produce datasets using ResStock

Image from Reyna et al. (2025)

2 Stakeholder Engagement and Integration Plan

To identify industry needs and guide the implementation of our approach, we conducted a stakeholder engagement task involving utilities, automotive manufacturers, and other relevant parties. The objectives of the engagement included understanding the current and future needs of stakeholders and the possible analyses that would be of interest. This section describes the stakeholder profiles, interview responses, and the resulting integration plan designed to prioritize these needs.

2.1 Stakeholder Profiles

We identified the main stakeholders to be households, electric utilities, and manufacturers. Table 1–Table 3 include stakeholder descriptions, their needs, potentially beneficial analyses, and the considerations of working-class and middle-income households.

Table 1. Stakeholder Profile for Households

Stakeholder: Households	
Description of the stakeholder	A household that lives in a residential dwelling unit and may or may not own a vehicle
Needs	• Reliable and affordable transportation • Access and availability of charging infrastructure • Adequate range for household driving habits • Reliable backup power during power outages.
Analyses	• Monthly budget impacts • Utility bill impacts • Transportation and maintenance cost impacts • Amount of time their EV could provide backup power for critical loads.
Financial considerations	• High upfront costs to EVs and impacts to budget • Access to charging infrastructure is important for multi-family buildings • Renters may not be able to make changes to the residential dwelling to add charging infrastructure.

Table 2. Stakeholder Profile for Electric Utilities

Stakeholder: Electric utilities	
Description of the stakeholder	A utility that supplies residential buildings and the households living in them with electricity
Needs	• Data on ownership, driving habits, and charging behavior • Tools or models that help analyze a variety of scenarios • Load profile impacts of EV adoption • Rates based on electrification load profiles.
Analyses	• Integrated resource planning • Transmission planning

Stakeholder: Electric utilities	
	• Distribution system planning • Long-term load forecasting • Electrification planning • Energy efficiency programs • Demand-side management • Bill impact and rate design.
Working-class and middle-income household considerations	• Affordability and rate stability for working-class and middle-income households • Access to charging infrastructure in working-class and middle-income neighborhoods • Rate structures that help working-class and middle-income households save money • Provide education and outreach programs for households to learn the benefits of EVs.

Table 3. Stakeholder Profile for Manufacturers

Stakeholder: Manufacturers	
Description of the stakeholder	Private companies manufacturing or developing technologies related to and including EVs, charging technology, or home infrastructure
Needs	• Quantify the size and market potential of various customer segments • Improve EV technology to make EVs more affordable and increase range • Deployment of accessible and reliable charging infrastructure • Develop and deploy the technology necessary to enable vehicle-to-building and vehicle-to-grid integration • Ensure products are safe, reliable, and profitable.
Analyses	• Identifying and targeting customer segments • Value proposition for the company and customers • Impact of government regulation on the developed products
Working-class and middle-income household considerations	• Government programs that provide incentives and rebates for their products • Lower-priced EV models and related technology specifically designed for working-class and middle-income households • Affordable leasing or financing options to reduce upfront costs • Installation of accessible and reliable charging infrastructure in working-class and middle-income neighborhoods.

There are other stakeholder groups, like nonprofit, research, and government organizations. However, this report focuses on the three listed in Table 1–Table 3.

2.2 Stakeholder Responses

We performed an outreach effort to understand the perspectives of various stakeholders. A list of stakeholders the team communicated with is given in Table 4. Some of these stakeholders directly reached out to the ResStock and TEMPO teams via e-mail, whereas others were contacted by the ResStock and TEMPO teams. These entities either belong to one of the stakeholder groups discussed earlier or were able to represent their perspective.

Table 4. List of Stakeholders the ResStock and TEMPO Teams Have Engaged With

Name	Entity Description	Stakeholder Type	E-mail	Meeting
Rocky Mountain Institute	Nonprofit organization	Households	x	
Clean Coalition	Nonprofit organization	Utilities	x	
Electric Power Research Institute	Nonprofit organization	Utilities	x	x
LMN Architects	Consultant	Households	x	
Moixa	Software developer	Households	x	
New York Metropolitan Transportation Authority	Public benefit corporation	Households	x	
Northern California Power Agency	Utility	Utilities	x	x
Central Hudson Gas & Electric Corp.	Utility	Utilities	x	
National Grid	Utility	Utilities	x	
Lawrence Berkeley National Laboratory	National laboratory	Households/ Utilities	x	x
EIA	Government	Households/ Utilities	x	x
Toyota	Manufacturer	Manufacturers	x	
Ford	Manufacturer	Manufacturers	x	x
General Motors	Manufacturer	Manufacturers	x	
Tesla	Manufacturer	Manufacturers	x	

The responses from the stakeholders from both e-mail correspondence and virtual meetings were summarized. During the engagement process, a few use cases became evident:

1. **Load profile impacts of EVs and forecasting:** Load profiles and forecasted demand questions impact decisions made in other analyses, like distribution planning, rate design, and incentives programs. The load profiles and forecasted demand predicted by TEMPO and ResStock have been used as inputs for these other analyses.
2. **Charging infrastructure and strategies:** A vehicle owner's access to at-home charging, the type of charger, and the charging strategy impact the load profiles and household utility bills under certain rate structures.

3. **Demand response/flexibility:** Demand response and flexibility create a value proposition for utilities in delaying upgrades to the distribution system, aiding a shift in demand during peak periods or variations in renewable generation.
4. **Utility bills and rate design:** For the utility bills and rate design use case, the synergy impacts where the transportation costs show up for households and how rate design could impact various household types.
5. **Home infrastructure:** The home infrastructure could impact EV adoption if the existing electric panel size[5] is not large enough for the added service or there is no access to power where the vehicle is parked.
6. **Resilience:** In the event of a power outage, EVs could provide backup power to critical HVAC and other appliance loads to maintain a safe environment.

We categorized the stakeholder responses for each of the use cases and summarized them in Table 5. A given response can have more than one use case. For example, a respondent might be interested in how load profile changes in EV adoption impact customer utility bills and rate design.

The utilities engaged were mostly interested in the load profile impacts that charging strategies can have on customer utility bill and rate design. No direct responses related to demand response and flexibility came from the utilities surveyed. However, the utilities are looking for data (time series load profiles) to inform many analyses, one of which could be demand response. The automotive manufacturers surveyed mentioned how home loads can be coordinated with vehicle charging and individual home load profiles. The other stakeholder responses covered all the identified use cases. The variety of responses might be due to the broad range of applications performed by these stakeholders. To date, the most mentioned use cases among all groups are 1) load profile impacts and forecasting and 2) charging infrastructure and strategies. The results of these most frequently mentioned use cases also feed into other use cases, like rate design and demand response.

Table 5. Summary of Stakeholder Responses Relative to the Identified Use Cases

Stakeholder group	Resilience	Home infrastructure	Utility bills and rate design	Demand response and flexibility	Charging infrastructure and strategies	Load profile impact and forecasting
Utilities	0	0	2	0	2	3
Automotive manufacturers	1	1	1	1	3	4
Other stakeholders	2	4	2	6	8	7
Total	**3**	**5**	**5**	**7**	**13**	**14**

[5] Electric panel size information will be available in the 2025 ResStock dataset release.

2.3 Integration Plan

With the results from the stakeholder engagement, we designed an integration plan to meet the industry's desires and lay the groundwork to perform high-impact analyses. The following features drive the implementation of our methodology in the next sections:

1. Characterize nationwide household inputs for ownership and usage of EVs
2. Expose EV-related inputs within ResStock to align with potential scenarios of EV adoption, charger adoption, driving behavior, and charging flexibility.
3. Develop scheduling, battery modeling, and charger modeling capabilities in ResStock
4. Run ResStock simulations in the baseline year to verify expected behavior and energy outputs, and validate against external datasets where possible.

We designed our methodology to accomplish these steps while allowing flexibility to incorporate more advanced features in the future. However, some gaps remain in the current implementation. First, bidirectional charging to feed electricity back to the grid or to meet home loads is not yet supported. While we leverage a physics-based battery model that could enable bidirectional charging, important constraints would need to be addressed, such as inrush current limitations, available technology controls, and restrictions related to the vehicle, charging equipment, or regulatory requirements. Another limitation is that ResStock only models one EV per household. Supporting multiple EVs will require more sophisticated charging logic, particularly for homes equipped with one charger. Finally, only battery EVs (BEVs) are modeled; plug-in hybrid electric vehicles are excluded due to uncertainty in defining fuel and electricity use fractions.

3 Baseline Electric Vehicle Stock Characterization

ResStock and TEMPO use different data sources that affect their estimates of how many EVs are currently in the market, who will own them, and where they are (as well as where they will be in the future). ResStock is reliant on EIA's Residential Energy Consumption Survey (RECS)[6] for household characteristics, including energy technology ownership. The EIA 2020 RECS has data on EV ownership, charger types, home charging fraction, and parking proximity to outlets. Meanwhile, TEMPO uses a mix of the American Community Survey (ACS) Public Use Microdata Sample (PUMS), NHTS, and Experian vehicle registration data[7] to establish EV stock and ownership. In addition, survey data from Ge et al. (2021) and LightBox data have been used to inform TEMPO of residential charging availability and EV ownership. We leverage both the 2020 RECS data—so that existing housing characteristics and demographics in ResStock can be associated with EV inputs—and TEMPO data sources, which provide additional data points and can fill in gaps in the RECS data.

The ResStock workflow assigns individual building inputs by first distilling data from RECS and many other sources into common probability distribution input files, from which a sampling routine assigns specific housing parameters to building models that capture the dependencies of location, demographics, and other building inputs. These input files span hundreds of characteristics that may impact home energy usage or otherwise be useful in analyses, such as insulation levels, floor area, equipment efficiency, or income bins. Many of the input files are correlated with dependencies, which are input files that are sampled upstream and reflect physical constraints, regional factors, demographics, or correlations between technologies. To characterize EV-related inputs and ensure an appropriate level of diversity, we produced a total of six additional probability distributions that can map to one or more direct energy model inputs, be used to inform other input files, or be leveraged in designing scenario analyses. More details on these and other ResStock input files can be found in the *ResStock Technical Reference Documentation, v3.3.0* (Reyna et al. 2025).

Table 6 summarizes each input file and describes from what dataset they were sourced, while Figure 2 provides a visual representation of the inputs and their applicable dependencies.

Table 6. Summary of the ResStock Input Files Generated

ResStock Input File	Data Type	Description	Dependencies	Primary Data Sources	RECS Field
Electric Vehicle Ownership (Section 3.1)	bool	Shows whether the household owns or leases an EV	Building Type, Owner/Renter, Federal Poverty Level, County	2020 RECS and TEMPO (Experian)	ELECVEH
Electric Vehicle Charger (Section 3.2)	string	Indicates the presence and type of EV charging	EV Ownership, Building Type, Owner/Renter, Federal Poverty Level	2020 RECS	EVCHRGHOME

[6] For more information, visit https://www.eia.gov/consumption/residential/data/2020/.
[7] For more information, visit https://www.experian.com/automotive/auto-vehicle-data.

ResStock Input File	**Data Type**	**Description**	**Dependencies**	**Primary Data Sources**	**RECS Field**
Electric Vehicle Battery (Section 3.3)	string	Defines physical characteristics of the battery (efficiency, capacity, etc.)	None	TEMPO (Autonomie)	N/A
Electric Vehicle Miles Traveled (Section 3.4)	int	Assigns vehicle miles traveled and average speed	None	2022 NHTS	N/A
Electric Vehicle Charge at Home (Section 3.5)	string	Gives the fraction charged at home by energy	Building Type, Federal Poverty Level	2020 RECS	EVHOMEAMT
Electric Vehicle Outlet Access (Section 3.6)	string	Indicates whether there is access to an outlet within 20 feet (ft) of vehicle parking	Building Type, Owner/Renter, Federal Poverty Level, EV Charger, Vintage	2020 RECS and Ge et al. (2021)	OUTLET

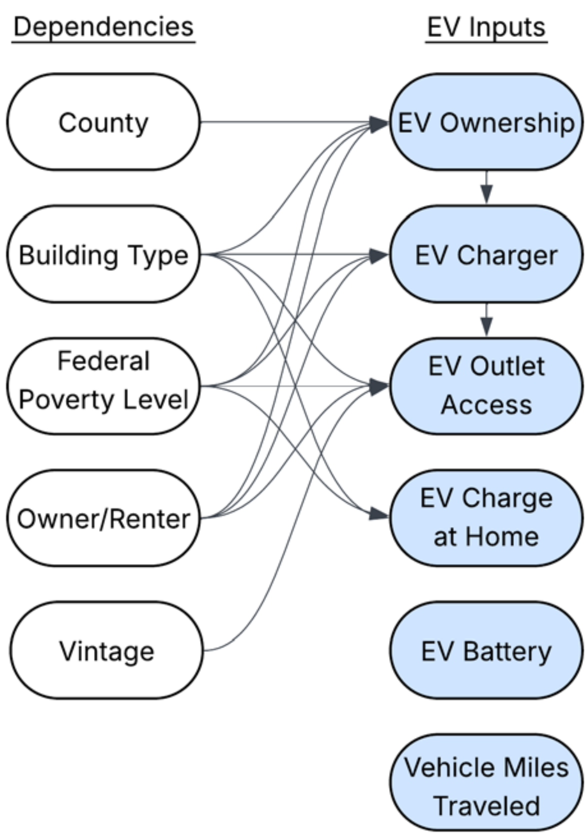

Figure 2. EV-related ResStock input files and their corresponding dependencies. Upstream dependencies that may implicitly impact EV inputs are not shown.

More information on how these files were generated is provided in the following subsections. Every model in ResStock is assigned an argument value for each of these inputs; although the

EV ownership and EV charger values may result in models with no EV charging demand, all the remaining inputs are still assigned a value so that the expected saturations of vehicle type and EV operation can still be captured in scenario analyses.

3.1 Electric Vehicle Ownership

The central input that drives EV charging loads in ResStock is the "Electric Vehicle Ownership" input file, which specifies whether the EV battery is simulated and introduces all other EV-related parameters found in Table 6.

Methodology

Each model in ResStock is assigned an EV ownership status, either true or false, based on probability distributions derived primarily from TEMPO registration data and the 2020 RECS. Models with EVs will simulate driving and charging events, whereas those without EVs disregard all other EV-related inputs at simulation. The characterization of EV ownership in the stock today uses a combination of four data sources that combine automotive registration data, spatial household and dwelling unit characteristics, and household characteristics:

- **Experian 2022[8]:** A database of automotive registration data by vehicle type for each county. This dataset is used to determine the number of BEVs in the U.S. vehicle stock, which aligns with TEMPO's baseline year.
- **2016 ACS[9]:** Data from ACS are used to characterize the number of vehicles per household for each county in the United States.
- **2019 5-Year PUMS[10]:** The PUMS datasets are microdata versions of the ACS. The 2019 5-year PUMS combines data from the PUMSs for the years 2015 to 2019. This dataset informs the dwelling unit characteristics: building type, tenure, and income.
- **EIA 2020 RECS[11]:** This dataset provides household technology characteristics of the residential building stock, including EVs.

The data from those sources were combined to capture correlations of BEV ownership as it relates geographically in the United States (by either county or Public Use Microdata Area [PUMA]) and by building type, income, and tenure. We first obtained the number of BEVs per household using the Experian and ACS vehicle data. The Experian dataset has registration information for every vehicle type. The dataset was filtered to include only BEVs. For each county, the total number of BEVs and total number of vehicles were calculated. Using these data, the fraction of BEVs for each county was determined. The fraction of BEVs was then joined to the county-level ACS vehicle data. These data included the number of vehicles per household. We could then calculate the number and fraction of households with a BEV by county.

Next, we mapped county-level BEV ownership to PUMA-level and joined it with PUMS housing characteristic data. Both counties and PUMAs are defined by the U.S. Census as a collection of census tracts. PUMAs and counties do not cross state boundaries. PUMAs are

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[8] For more information, visit https://www.experian.com/automotive/auto-vehicle-data.
[9] For more information, visit https://www.census.gov/programs-surveys/acs.
[10] For more information, visit https://www.census.gov/programs-surveys/acs/microdata.html.
[11] For more information, visit https://www.eia.gov/consumption/residential/data/2020/.

smaller in higher-population areas and larger in lower-population areas, and their boundaries may cross county lines. To map the county-level and PUMA-level BEV data we assumed that the county-level BEV data are uniform for all census tracts within a county. We then combined the fraction of households owning a BEV for every census tract with the PUMA data using a weighted average, with the weight being the number of dwelling units in each census tract.

With a geographic distribution of EV owners defined, we then obtained household EV ownership characteristics from EIA 2020 RECS. The EIA 2020 RECS included a question about whether a household owns an EV. The survey estimates that approximately 1.4% of households own an EV. Other interesting correlations identified were EV ownership by income, building type, and tenure (owner- or renter-occupied units), as shown in Figure 3. This characterization reflects expected trends that inform model inputs: 1) lower-income households are less likely to own an EV compared to higher earners, 2) single-family-attached and single-family-detached occupants are more likely to own an EV compared to the multi-family and mobile home categories, and 3) households that own their residence are more likely to own an EV.

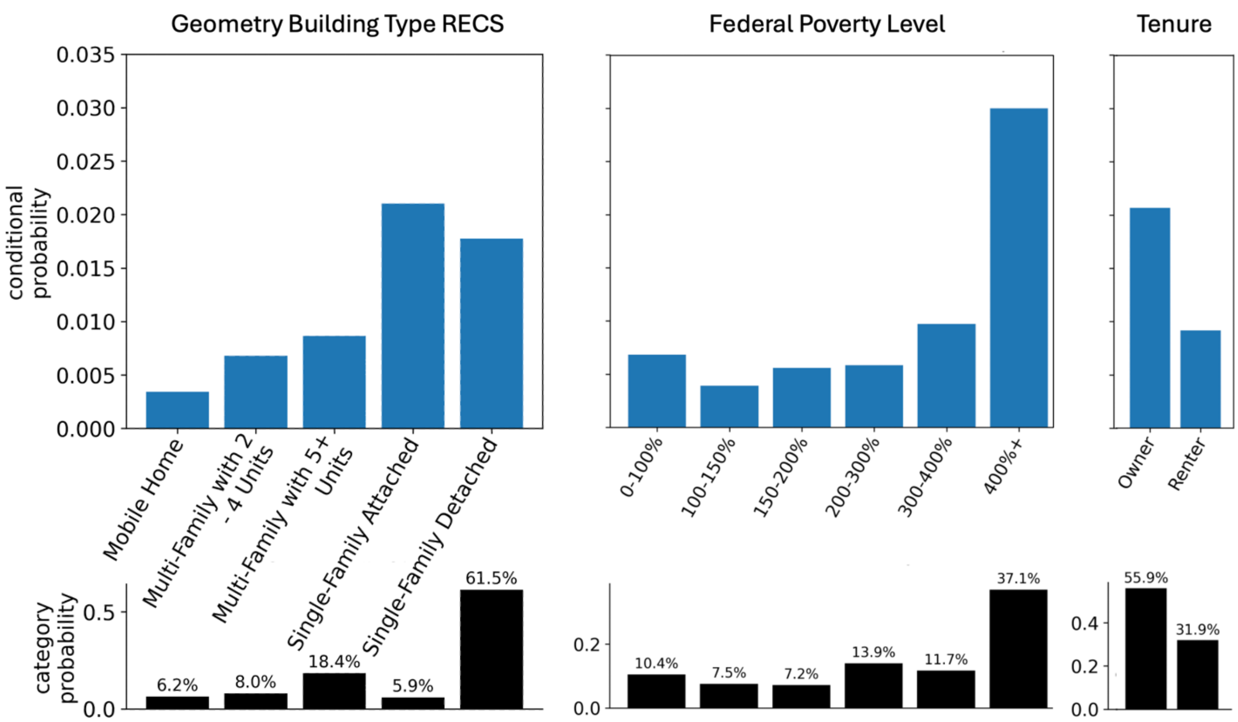

Figure 3. EV ownership from EIA 2020 RECS by federal poverty level (left), building type (middle), and tenure (right). The upper plots show the total saturation of EV ownership for each field, whereas the lower plots show the frequency of the field itself relative to all others.

Figure 3 displays probabilities along individual dimensions. To capture all three of these correlations in ResStock, a full cross-tabulation of these variables is needed. In total, there are 60 combinations of the three variables (six for federal poverty level [FPL], five for building type, and two for tenure). There are a limited number of samples in the 2020 RECS with EVs. Obtaining reliable distributions for all 60 combinations with these limited samples is not possible without applying some assumptions. A method of dimensional coarsening is applied to rows without enough samples. The successive rules for dimensional coarsening applied to the 2020 RECS data are as follows:

1. Original data
2. FPL combined every 100%
3. FPL combined every 200%
4. Building type is consolidated into three bins: 1) single-family, 2) multi-family, and 3) mobile home
5. Building type is consolidated into two bins: 1) single-family and 2) multi-family or mobile home.

If a row does not meet the minimum sample requirement (determined by engineering judgement based on the specific application and samples available in the survey), the next level of dimensional coarsening is applied. This method maintains distributions that have high sample counts while ensuring quality distributions for lower-sample rows. For EV ownership, we determined that the minimum number of samples required is 200 to reduce the number of binary distributions (a distribution with either 100% or 0% EV ownership in the segment). The resulting cross-tabulation of the building type, tenure, and FPL can be seen in Table 7.

Table 7. EIA 2020 RECS EV Ownership, the Number of Samples From RECS Informing the Probabilities Using the Dimensional Coarsening Hierarchy, and the Number of Dwelling Units by Building Type, Tenure, and FPL

		FPL					
Residential Building Type	**Tenure**	**0%–100%**	**100%–150%**	**150%–200%**	**200%–300%**	**300%–400%**	**400%+**
Mobile Home	Owner	0.33%	0.00%	0.00%	0.31%	0.20%	2.00%
Multi-Family With 2–4 Units	Owner	0.68%	0.68%	0.68%	0.26%	0.26%	1.47%
Multi-Family With 5+ Units	Owner	0.68%	0.68%	0.68%	0.26%	0.26%	1.08%
Single-Family Attached	Owner	0.00%	0.00%	0.00%	0.00%	1.43%	2.52%
Single-Family Detached	Owner	0.84%	0.22%	1.28%	0.74%	1.33%	3.09%
Mobile Home	Renter	0.87%	0.87%	0.87%	0.54%	0.54%	0.75%
Multi-Family With 2–4 Units	Renter	0.32%	0.00%	0.00%	1.47%	0.89%	0.41%
Multi-Family With 5+ Units	Renter	0.86%	0.18%	0.27%	0.24%	0.66%	0.84%
Single-Family Attached	Renter	0.14%	0.31%	0.31%	0.68%	0.68%	3.69%
Single-Family Detached	Renter	0.35%	1.51%	0.00%	0.31%	0.00%	1.25%
		Number of samples informing probabilities					
Mobile Home	Owner	242	227	384	230	345	414
Multi-Family With 2–4 Units	Owner	746	746	746	536	536	278
Multi-Family With 5+ Units	Owner	746	746	746	536	536	222
Single-Family Attached	Owner	266	213	213	269	232	700
Single-Family Detached	Owner	633	925	1,205	2,855	2,767	6,748
Mobile Home	Renter	212	212	212	1,261	1,261	1,047
Multi-Family With 2–4 Units	Renter	307	333	333	235	379	214

Multi-Family With 5+ Units	Renter	484	373	325	506	321	819
Single-Family Attached	Renter	379	210	210	295	295	212
Single-Family Detached	Renter	283	216	223	358	229	382
		Number of dwelling units (thousands)					
Mobile Home	Owner	1,497	1,054	703	957	538	632
Multi-Family With 2–4 Units	Owner	156	124	85	214	135	419
Multi-Family With 5+ Units	Owner	186	149	180	393	387	1,894
Single-Family Attached	Owner	231	292	265	674	606	2,558
Single-Family Detached	Owner	3,867	4,042	4,970	10,606	9,877	35,230
Mobile Home	Renter	717	257	170	192	55	62
Multi-Family With 2–4 Units	Renter	2,714	908	952	1,272	821	1,542
Multi-Family With 5+ Units	Renter	4,391	2,054	1,993	2,926	2,169	6,115
Single-Family Attached	Renter	701	338	269	464	360	694
Single-Family Detached	Renter	1,917	1,069	902	1,604	906	2,076

Finally, we merged the EIA 2020 RECS housing characteristics distributions with the PUMA-level data to generate a final ResStock input file. The EIA 2020 RECS data in Table 7 is not disaggregated spatially in the United States but is joined to the PUMA-level data. Each PUMA has its own distribution of building types, incomes, and tenure segments. For example, a PUMA that contains mainly wealthy suburbs might have more single-family detached owner-occupied 400%+ dwellings than a low-income inner-city PUMA and thus a higher rate of EV ownership. The result of this diversity is that simply using Table 7 will result in a different EV penetration than that of the vehicle registration data but will incorporate other housing characteristic factors beyond the spatial PUMA resolution. To resolve this issue, the ownership percentages in Table 7 are scaled according to the PUMA-level ownership percentages, thus maintaining the geographically resolved vehicle registration data while keeping the relationships between building type, income, and tenure.

Assumptions

We incorporated the following assumptions to produce the final input file for EV ownership:

- Households own one BEV. This is largely true about the stock, but there are some households with multiple BEVs.
- Households and dwelling units are synonymous. This is an assumption that allows the household data that TEMPO uses to be combined easily with the dwelling unit data in ResStock. In ACS and PUMS, this is not always the case, as there could be more than one household occupying a dwelling unit. The number of households and the number of dwelling units in the United States are roughly the same.
- To map between county and PUMA geographies, we assumed that the fraction of households owning a BEV is the same for all the census tracts in a county.
- Vacant units do not have EVs.

- Due to low sample sizes in the 2020 RECS, successive dimensional coarsening was applied until a minimum number of 200 samples was obtained for each conditional distribution, as discussed in the previous subsection.
- The 2020 RECS housing ownership characteristics in Table 7 were scaled to the PUMA-level vehicle registration ownership percentages to maintain both geographic granularity and housing characteristic relationships.

Results

The final generated "Electric Vehicle Ownership" input file has four dependencies: 1) PUMA, 2) residential building type, 3) tenure, and 4) FPL. These dependencies all have an isolated and significant influence on EV ownership; we show a selection of these impacts at varying geographic resolutions. Figure 4 shows the percentage of households owning EVs in each PUMA characterized by owner-occupied, single-family detached homes with incomes exceeding 400% of the FPL. This category exhibits the highest EV ownership among all categories. Within this category, urban PUMAs have the highest rates of EV ownership, with the highest concentrations in the San Francisco Bay Area of California.

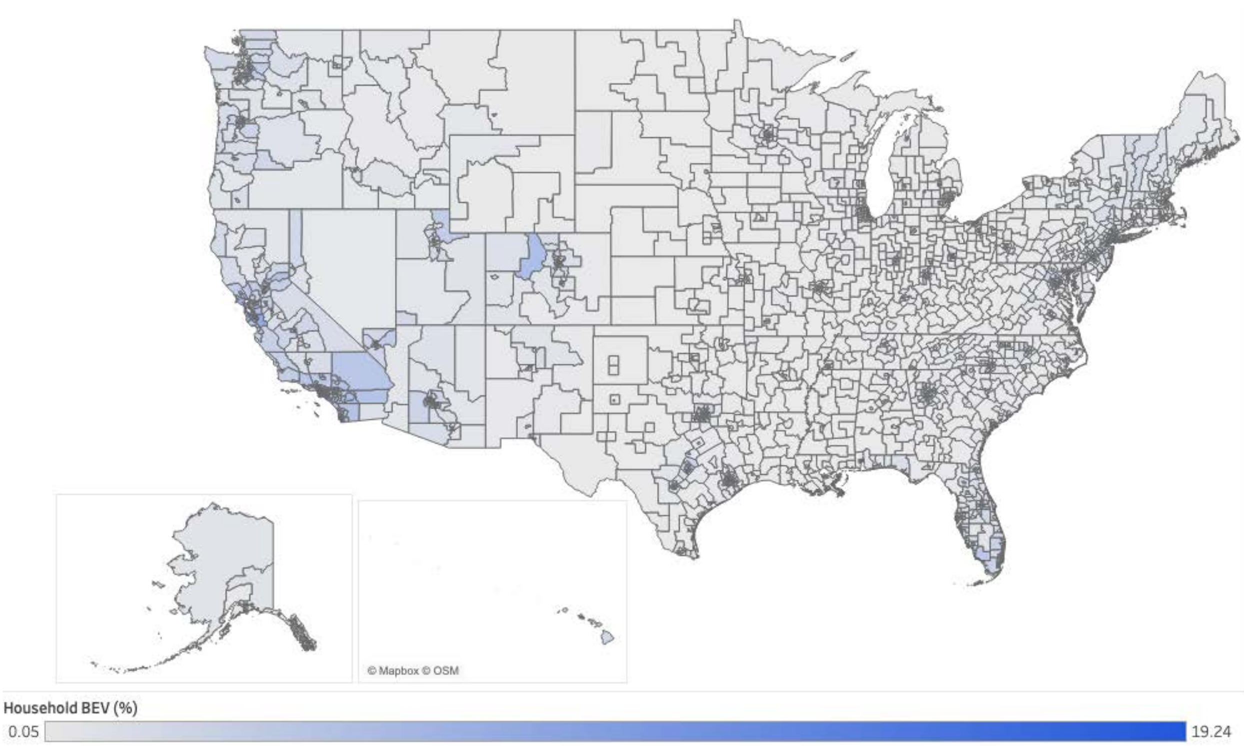

Figure 4. The percentage of households owning EVs in each PUMA with the following characteristics: high income 400%+ FPL, single-family detached homes, owner-occupied

Looking more closely into EV ownership in a particular state, Figure 5 compares the percentage of households with incomes exceeding 400% FPL across different building types (single-family detached vs multi-family 5+ units) and tenure status (renter versus owner) in California. As noted in the previous paragraph, owner-occupied, single-family detached households maintain significantly higher EV ownership compared to other categories, which is demonstrated in Figure 5. On average, across all PUMAs in California, EV ownership is 2.51% for owner-occupied, single-family homes, 3.06% for owner-occupied, multi-family 5+ unit buildings, and 2.34% for renter-occupied, multi-family 5+ unit buildings.

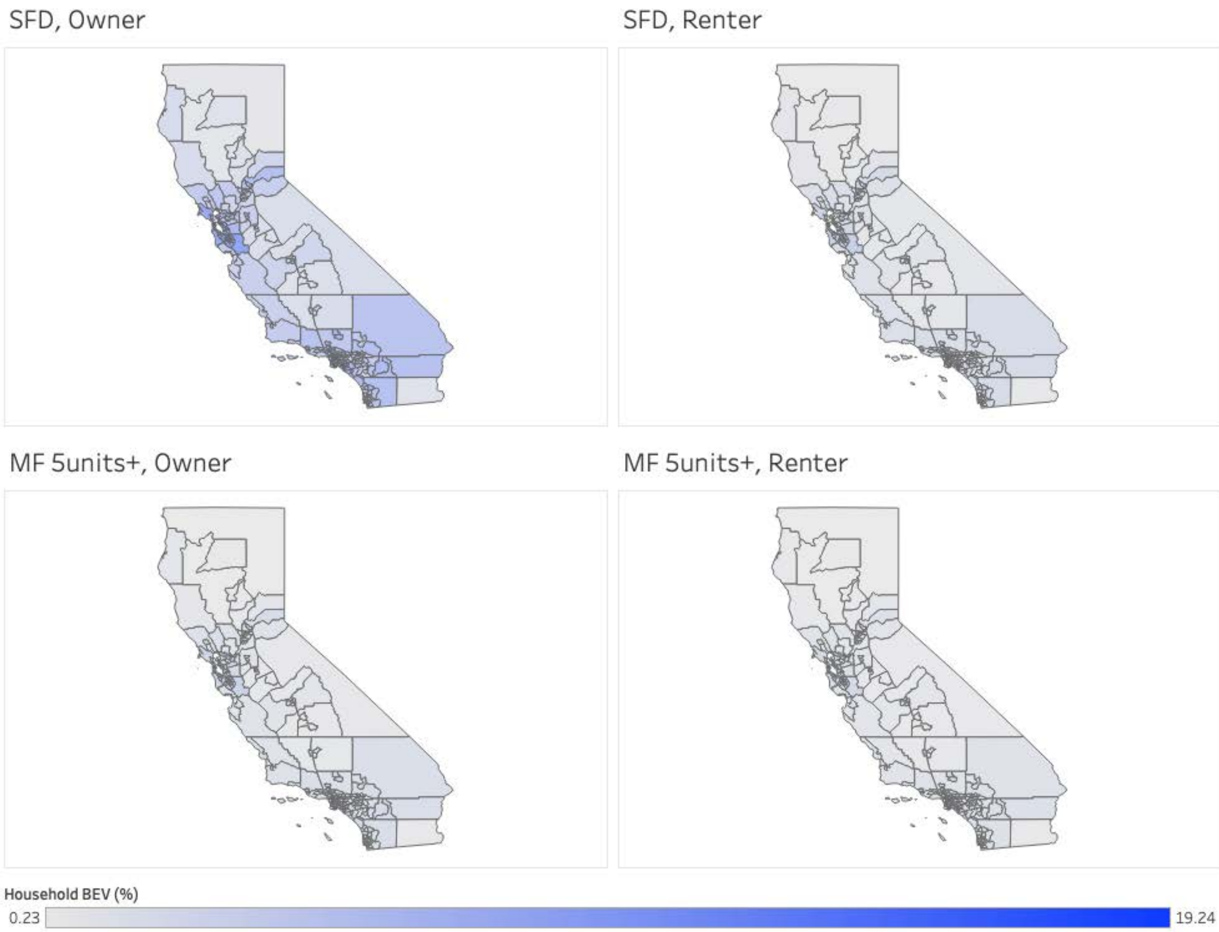

Figure 5. The percentage of EV ownership among households with 400% FPL for different building type and tenure scenarios. Maps are disaggregated by PUMAs in California.

SFD = single-family detached; MF 5units+ = multi-family 5+ units

To further illustrate the importance of geographic and housing granularity, Figure 6 displays EV ownership probabilities in the San Francisco Bay area for selected combinations of building type, tenure, and FPL bin. This figure includes all four "Electric Vehicle Ownership" dependencies, and the disparities between categories highlight how detailed segmentation supports more nuanced analyses across the housing stock. Among the cases shown, EV ownership is highest for higher-income, owner-occupied single-family homes and lowest for lower-income, renter-occupied multi-family buildings.

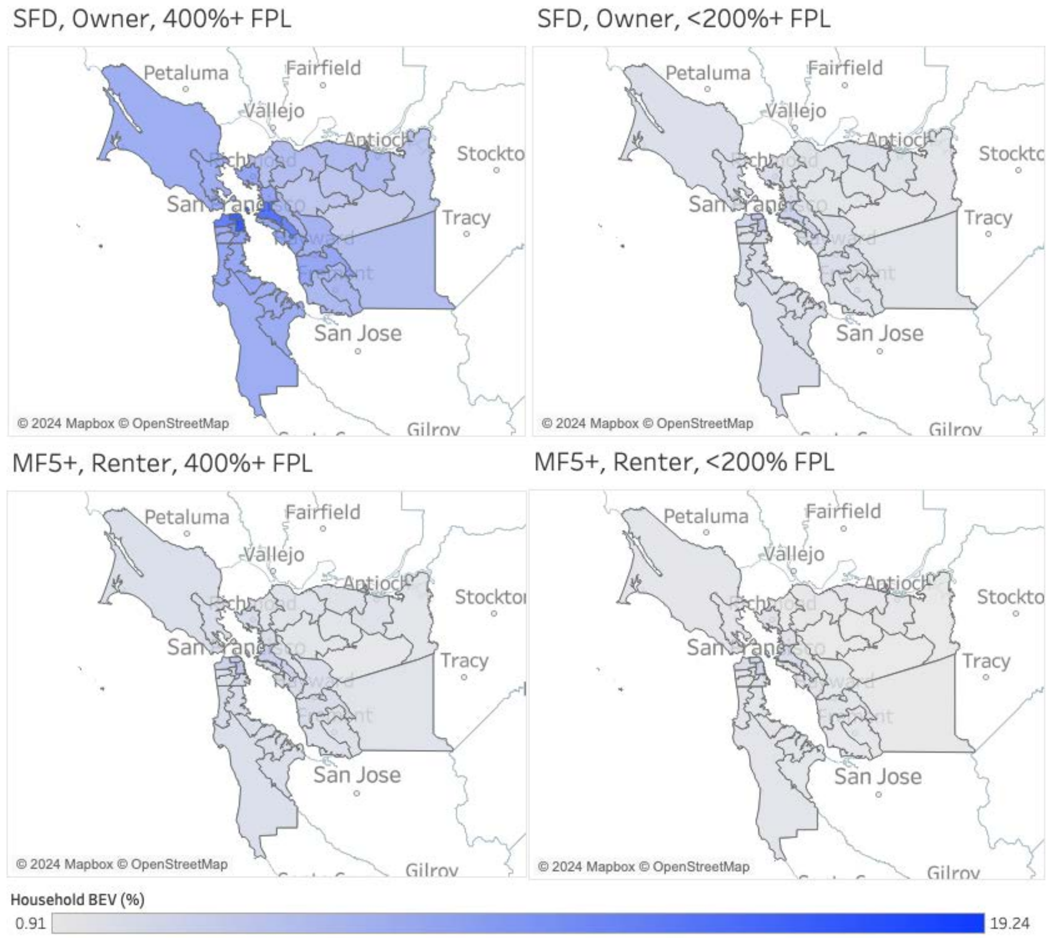

Figure 6. Comparison of percentage of EV ownership for different building types, tenures, and FPLs. Maps are disaggregated by PUMAs in the San Francisco Bay area.

SFD = single-family detached; MF5+ = multi-family 5+ units

3.2 Electric Vehicle Charger

We produced a ResStock input file that describes the distribution of home EV charger levels, which translates to model parameters indicating the presence of a home charger and its effective charging power.

Methodology

The 2020 RECS dataset provides information to characterize which households have level-1 and level-2 chargers with the EVCHRGTYPE (type of EV charger used at home) field. After an initial investigation, we selected the following characteristics as dependencies to the EV charger characteristic: 1) EV ownership, 2) building type, 3) FPL, and 4) tenure. The EV ownership characteristic was added so that households without an EV do not have an EV charger. The other dependencies are used to capture important demographic correlations, especially for low-income renters in multi-family and mobile home dwellings.

To ensure a sufficient sample size for each group of dependencies, we applied dimensional coarsening using the following steps until a minimum number of 12 samples was obtained:

1. Original data
2. FPL combined every 100%
3. FPL combined every 200%
4. Building type is reduced to two bins: single-family detached and all other building types
5. FPL is grouped into either 400%+ or <400% bins
6. All building types are combined.

Assumptions

We incorporated the following assumptions to produce the final input file for EV chargers:

- Dwelling units without an EV do not have an EV charger.
- Dwelling units with an EV need to have at least a level-1 charger.
- Vacant dwelling units do not have an EV charger.
- Due to low sample sizes in the 2020 RECS, successive dimensional coarsening is applied until a minimum number of 12 samples is obtained for each conditional distribution.

Results

Using the described methodology and assumptions, Figure 7 presents the high-level correlations for the variables of interest. Although Figure 7 shows relationships to single variables, the final output captures the cross-tabulation of these variables. Further, these relationships are derived from the raw 2020 RECS data and do not include the dimensional coarsening applied to the final outputs. The data show that for homes with EVs, roughly 41% have level-2 chargers. Larger apartment complexes have the lowest fraction of level-2 chargers in the 2020 RECS, whereas single-family detached homes have the highest fraction of level-2 chargers. Owner-occupied dwellings have a higher penetration than renter-occupied dwellings. The correlations with the FPL show an initial decrease followed by an increase of level-2 chargers with increasing FPL percentage. According to the microdata, there are three survey respondents with incomes less than $20,000 that have level-2 chargers. These three responses drive the higher percentage in the lowest FPL bin. Those responses correspond to single-family detached owner-occupied dwellings, which are generally more likely to have level-2 chargers compared to the other segments. The increase therefore seems to be likely due to small samples sizes in the 2020 RECS for EVs.

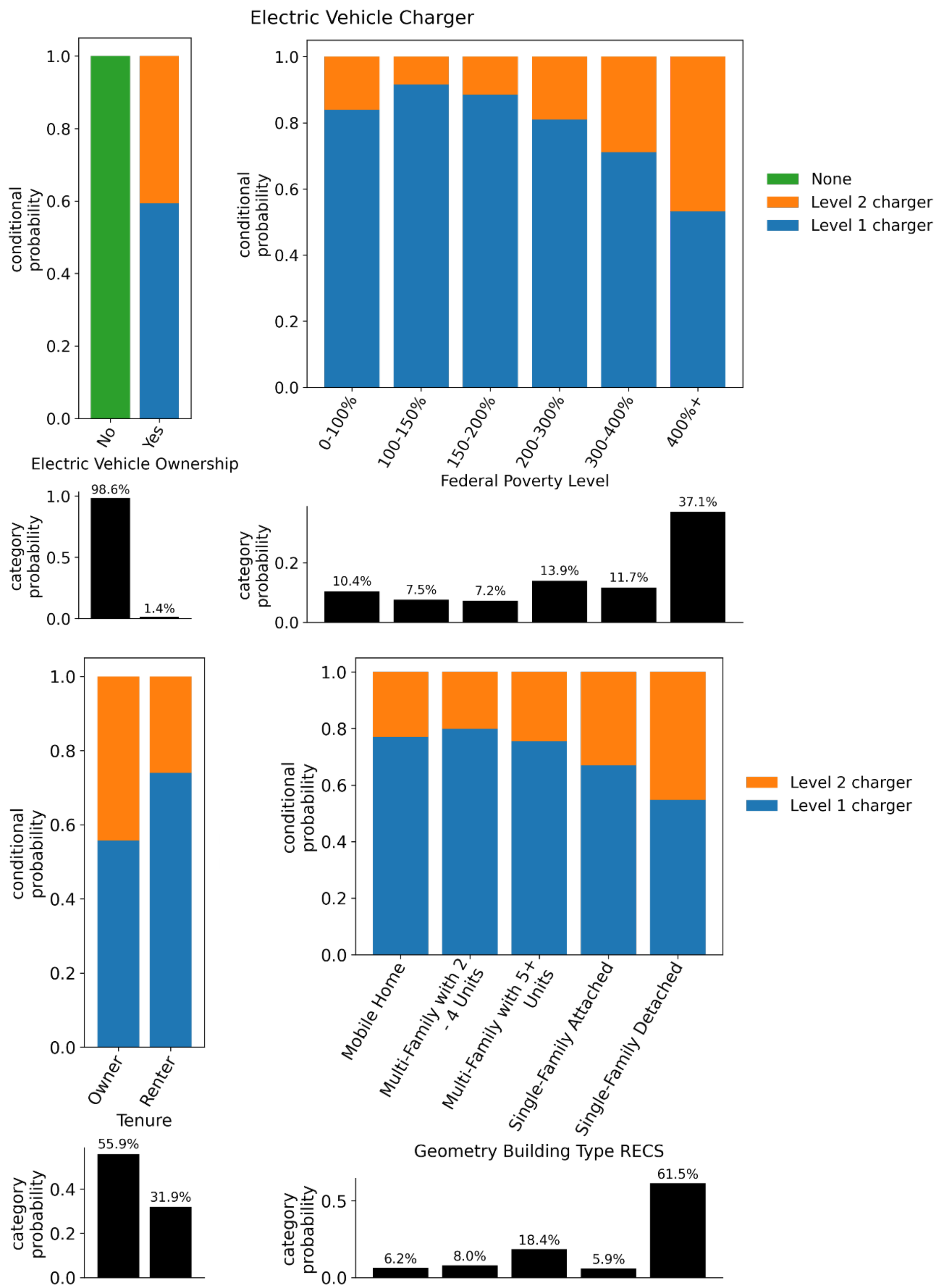

Figure 7. EV charger type by EV ownership, tenure, building type, and FPL. For the FPL, building type, and tenure plots, only units with EVs are shown.

We analyzed the correlation between charger type and a combination of three key dependencies—FPL, residential building type, and tenure—for households that own EVs (i.e., EV Ownership=Yes). Table 8 shows sampling probabilities of level-2 chargers for homes with EVs. For each combination, the sum of percentages of households with level-1 and level-2 chargers equals 100%, which assumes that dwelling units with EVs will have at least a level-1 charger. While trends exist across building types and FPL, many combinations have the same probability due to the dimensional coarsening steps.

Upon analyzing the correlation between charger type and these various dependencies, we found that significant variations are apparent, particularly in relation to single-family detached homes, households with an FPL exceeding 400%, and owner-occupied residences. It is evident that the prevalence of level-2 chargers tends to be higher in owner-occupied, single-family detached homes and households with an FPL exceeding 400% from the data in Table 8. Lower-income, owner-occupied, single-family detached homes (<400% FPL) have a higher level-2 charger saturation compared to higher-income, owner-occupied building types. This result is mainly due to there being more samples in the "single-family detached homes with EVs" category, whereas a limited number of samples exist for the other building types with incomes <400% FPL, thus requiring dimensional coarsening. For single-family detached owner-occupied households, 0%–100% FPL households have a higher saturation of level-2 chargers compared to 100%–300% FPL households, which is a result of there being two samples in the 0%–100% FPL bin and one sample in the 100%–150% FPL bin.

However, it's important to note that due to the limited availability of EV charger data in the 2020 RECS dataset, the coarsening of the data source resulted in similar distributions of level-1 and level-2 chargers for most of the other combinations.

Table 8. Correlation Between Level-2 EV Chargers and a Combination of Building Characteristics for Homes With EVs

		FPL					
Residential Building Type	**Tenure**	**0%–100%**	**100%–150%**	**150%–200%**	**200%–300%**	**300%–400%**	**400%+**
Mobile Home	Owner	10%	10%	10%	10%	10%	34%
Multi-Family With 2–4 Units	Owner	10%	10%	10%	10%	10%	34%
Multi-Family With 5+ Units	Owner	10%	10%	10%	10%	10%	28%
Single-Family Attached	Owner	10%	10%	10%	10%	10%	33%
Single-Family Detached	Owner	36%	12%	12%	29%	39%	49%
Mobile Home	Renter	9%	9%	9%	9%	9%	43%
Multi-Family With 2–4 Units	Renter	9%	9%	9%	9%	9%	43%
Multi-Family With 5+ Units	Renter	9%	9%	9%	9%	9%	43%
Single-Family Attached	Renter	9%	9%	9%	9%	9%	43%
Single-Family Detached	Renter	7%	7%	7%	7%	7%	43%

3.3 Electric Vehicle Battery

This section describes how the ResStock EV battery characteristic is developed from the data sources, including the correlations and results. The EV battery characteristic helps define the type of EV (e.g., midsize car, pickup) and its mileage range, which informs the battery size and capacity in the model.

Methodology

To generate the EV battery characteristics, we used the Experian dataset to characterize the distribution of BEVs and associated battery sizes in the vehicle stock. We used the latest data available for 2023, which ensures that our results are based on current information regarding the EV battery stock. Although the vehicle data included information on internal combustion engine vehicles as well, we filtered the dataset to focus exclusively on personal light-duty BEVs. In the dataset, there are four different categories of light-duty vehicles—compact, midsize, sport utility vehicle (SUV), and pickup truck—with information on two total mileage ranges for the battery—200-mile range and 300-mile range.

For each EV type, we draw from Argonne National Laboratory's Autonomie[12] vehicle powertrain simulation model for the EV energy consumption and battery capacity further downstream in the workflow. Autonomie is the source of the EV characteristics for both current day and future scenarios input into TEMPO.

Assumptions

We incorporated the following assumptions to produce the final input file for EV batteries:

- The dataset is derived from 2023 vehicle registration data.
- Only BEV datapoints are used; internal combustion engine vehicles and plug-in hybrid EVs are excluded.
- Only personal light-duty BEVs are considered in the characteristics, excluding commercial and heavy-duty vehicles.
- Every building model is assigned a vehicle type even if a BEV is not modeled so that adoption scenarios maintain diversity in the vehicle type input.

Results

Based on the described methodology and assumptions, Table 9 presents the percentage distribution of each vehicle type within the national BEV stock. No dependencies are associated with this input file; therefore, this distribution is applied evenly to each building model in ResStock. The total sample size for the BEV stock from the Experian data is 309,000.

Table 9. Percentage Distribution of Each Battery Vehicle Type

Compact, 200-mile range	Compact, 300-mile range	Midsize, 200-mile range	Midsize, 300-mile range	SUV, 200-mile range	SUV, 300-mile range	Pickup, 300-mile range
11.9%	33.9%	3.0%	7.6%	12.3%	30.6%	0.7%

[12] For more information, visit https://www.anl.gov/taps/autonomie-vehicle-system-simulation-tool.

The BEV stock is predominantly composed of 300-mile range compact vehicles and SUVs, which constitute over 64% of the total vehicle stock. This result highlights a significant consumer preference for longer-range EVs. Midsize vehicles and pickups make up a small percentage of the current BEV stock. Based on the BEV type distribution and the corresponding technical data from Autonomie, we derive the parameters for the battery, including battery capacity and energy efficiency. These parameters are crucial in modeling the energy requirements and performance characteristics of each vehicle type.

3.4 Annual Vehicle Miles Traveled

The annual vehicle miles traveled (VMT) input directly informs how discharging schedules are generated and is ultimately used to calculate the EV energy consumption power in the battery model. Miles traveled adds diversity across modeled EV owners and establishes more realistic bounds on EV behavior, which may influence the potential of scenarios.

Methodology

The 2022 NHTS data (Federal Highway Administration 2022) supports generation of the annual VMT input. This dataset provides self-reported annual miles traveled for all light-duty vehicles. Whereas light-duty VMT can depend on several factors such as urban classification, vehicle type, and building type, identifying the influences specific to EVs is more complicated. The amount of travel done by EVs has undergone some debate in recent scientific literature (Chakraborty, Hardman, and Tal 2022, Zhao et al. 2023). The hypothesized impact of vehicle electrification on VMT is multi-faceted. On the one hand, battery range may limit the ability of EVs to satisfy all required trips, and/or charging anxiety may lead to lower miles driven on EVs. This situation may be due to a self-selection bias in EV consumers who drive shorter distances, use certain vehicles less intensively, or have an alternative conventional vehicle in the household mix. Conversely, the lower cost of operating EVs may induce a rebound effect, where an increase in activity is associated with reductions in cost burden. For example, drivers may take longer routes or more frequent trips than they would have, induced by the lower energy costs. We currently assume a national distribution of EV miles traveled that mostly aligns with NHTS data for all light-duty vehicles; however, we cut off the maximum annual miles at 45,000 as the total probability of VMTs above this is under 1%.

Assumptions

We incorporated the following assumptions to produce the final input file for the annual VMT:

- The miles traveled reported for all vehicles in the 2022 NHTS data has the same expected distribution for EVs.
- No EV travels more than 45,000 miles in a year.
- Geographic influences of miles driven are ignored.
- Every building model is assigned a VMT even if an EV is not modeled so that adoption scenarios maintain diversity in the miles traveled input.

Results

Figure 8 shows the final distribution of the VMT input file in ResStock, which closely follows the data from NHTS. This distribution applies to all building models with EVs, as there are no dependencies. The distribution has a weighted average of 10,895 miles and a standard deviation of 8,436 miles.

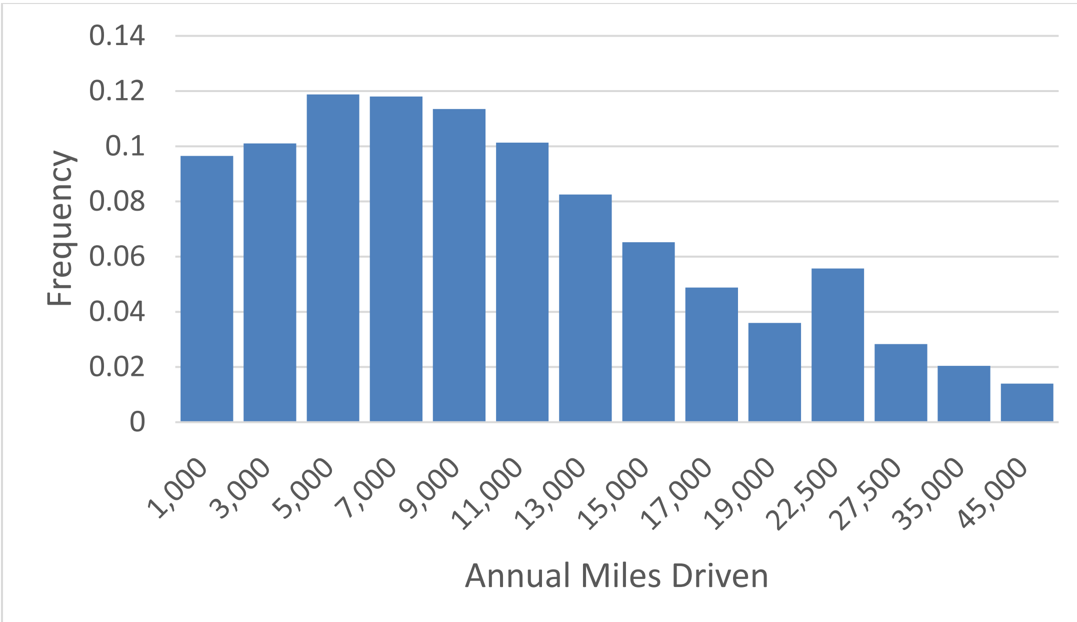

Figure 8. ResStock distribution of annual VMT

3.5 Home Charging Fraction

Today, approximately 80% of EV charging is done at home, and therefore most of the EV electricity consumption ends up on residential meters. However, not everyone has access to charging at their home, so it is important to provide a range of possibilities for at-home charging fractions to estimate the impacts of EVs on residential meters and utility bills. The home charging fraction specifies the fraction of charging energy provided by the at-home charger, ranging from 10% to 100%. This value scales the average EV energy consumption rate in the battery model so that the final charging demand excludes charging events that occur at charging stations outside of the home.

Methodology

The data used to generate the probability distributions were taken from the 2020 RECS. We selected the geometry building type RECS and FPL inputs as dependencies that influence the fraction of charging at home. Due to the low number of dwelling unit samples with EVs in the 2020 RECS, the conditional probability distributions were constructed by downscaling the selected dependencies. This approach captures the correlations for the dependency variables but ignores the conditional relationships between the dependencies.

Assumptions

Due to low sample counts, the characteristic conditional distributions were constructed by downscaling the following single-dependency variables until 10 samples were available for each row:

- Variable 1 dependency=geometry building type RECS
- Variable 2 dependency=FPL.

The percentage bins sampled directly from 2020 RECS are converted to scalar percentage values by using the midpoint of each bin.

Results

The relationships captured in the dependencies for the "EV charge at home" characteristic can be seen in Figure 9. Some of the most obvious trends include the following: Multi-family homes with 5+ units either always charge at home (100%) or rarely charge at home (0%–19%). Lower-income households (less than 400% FPL) charge less at home compared to households that are 400%+ FPL. The FPL bin with the lowest total charge-at-home fraction is 100%–150% FPL. We see that the lowest income group (0%–100% FPL) charges more at home than the 100%–150% FPL group. Similar trends are seen with other characteristics, as it is possible that the 0%–100% FPL bin includes some retirees that, through their savings, can afford some more charging at home compared to families that do not have the household funds to charge at home. This difference could explain why the 0%–100% FPL bin does not follow the same trend as the other FPL bins.

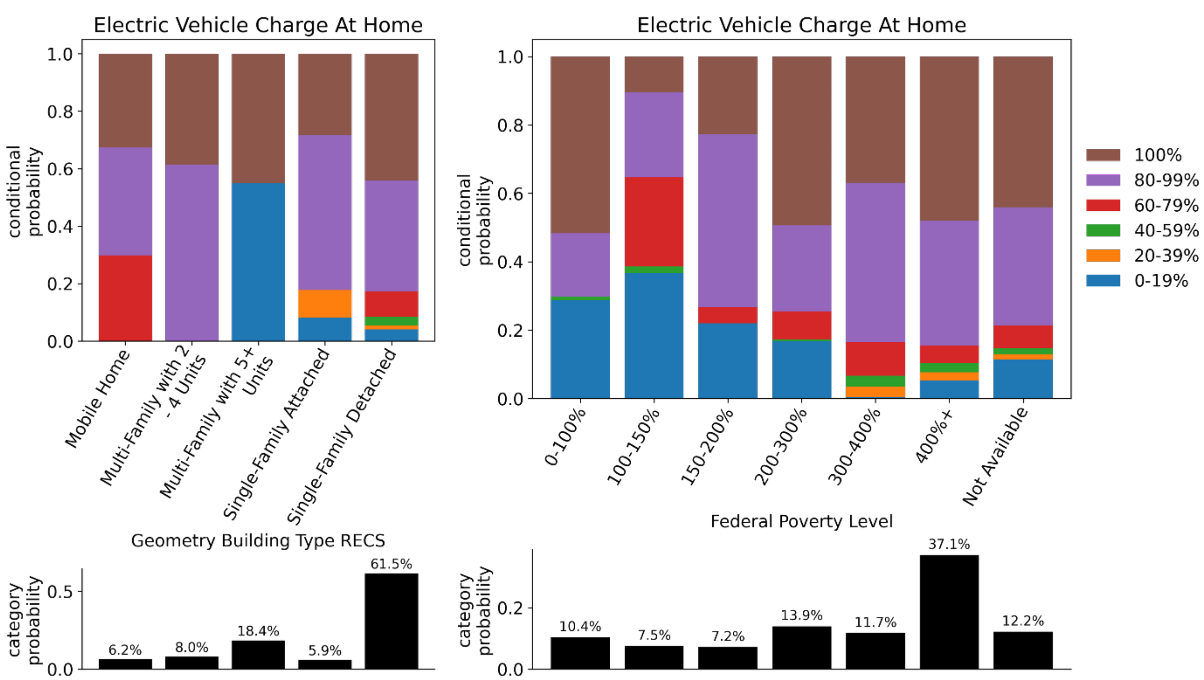

Figure 9. Percentage of EVs charged at home for the geometry building type RECS dependency (left) and FPL dependency (right)

3.6 Electric Vehicle Outlet Access

This section describes how the EV outlet access characteristic was created. Outlet access near vehicle parking is important for identifying charging patterns for EV owners today and EV adoption in the future. This input does not directly affect modeling outcomes but is useful for designing EV and EV charger adoption scenarios.

Methodology

The data used to generate probability distributions were mainly taken from the 2020 RECS. The Ge et al. (2021) survey (Scenario 2) was used to supplement data, as the 2020 RECS did not provide data for multi-family homes with 5+ units.

When investigating possible dependencies to correlate the units that have outlet access, five characteristics showed a significant correlation: “Geometry Building Type RECS”, “Vintage ACS”, “Electric Vehicle Charger”, “Tenure”, and “Federal Poverty Level”. Due to a low number of respondents having an EV in the 2020 RECS, some assumptions were required to capture correlations in all these dimensions. Thus, we created a set of sub-characteristics that can be blended to capture correlations among all dependencies. This process maintains certain relationships between the variables in each of the sub-characteristics but treats the relationships between dependencies and the sub-characteristics as independent. The two sub-characteristics created are a dwelling unit sub-characteristic and a household sub-characteristic.

The dwelling unit sub-characteristic has dependencies related to the dwelling unit construction: “Geometry Building Type RECS”, “Vintage ACS”, and “Electric Vehicle Charger”. To avoid small samples in the dwelling unit sub-characteristic, the vintage characteristic was coarsened to ignore this dependency if needed. Then, a second coarsening was applied to the building type characteristic, coarsening to two bins containing 1) single-family detached, single-family attached, and mobile homes and 2) multi-family with 2-4 units and multi-family with 5+ units.

The household sub-characteristic includes building type and dependencies related to occupants: “Geometry Building Type RECS”, “Tenure”, and “Federal Poverty Level”. No coarsening assumptions were made for the household sub-characteristic. After the creation of both the dwelling unit and household sub-characteristics, they were blended to obtain the final characteristic.

Assumptions

We incorporated the following assumptions to produce the final input file for EV outlet access:

- The 2020 RECS has multi-family homes with 5+ units marked as “Not Applicable.” These units are replaced with data from the Ge et al. (2021) study (Table 1, Scenario 2). Twelve percent of “Multi-Family 5+ Units” owners are assumed to have electrical access. This fraction is based on the average of mid-capacity apartments and high-capacity apartments. Twenty-eight percent of “Multi-Family 2–4 Units” owners are assumed to have electrical access. This fraction is based on the apartment owner data in the table.
- Units reported to have level-2 charger in the field EVCHRGTYPE are assumed to have outlet access.

- Level-1 chargers without outlet access are units with EVs that report no outlet access within 20 ft of vehicle parking.
- Due to the low sample count, the characteristic is constructed by downscaling a dwelling unit sub-characteristic with a household sub-characteristic. The sub-characteristics have the following dependencies:
    - Dwelling unit sub-tsv: ['Geometry Building Type RECS', 'Vintage ACS', 'Electric Vehicle Charger'] with the following fallback coarsening order:
        - Vintage ACS to the National distribution (ignoring the dependency)
        - Combining "Geometry Building Type RECS" together into [SFD, MF, SFA] and [MF 2–4, MF 5+] bins
    - Household sub-characteristic: "Geometry Building Type RECS", "Tenure", and "FPL"
- In combining the dwelling unit sub-tsv and household sub-tsv, the conditional relationships are ignored across (['Vintage ACS', 'Electric Vehicle Charger'], ['Tenure', 'Federal Poverty Level']).
- The "Void" option is assigned to impossible combinations of characteristics.

Results

The correlations according to the dependencies are shown in Figure 10–Figure 12. Lower incomes have a lower probability of an outlet being within 20 ft of parking than do higher incomes, as shown in Figure 10, which may be due to newer homes having better electrical access (Figure 11) and higher-income households tending to live in newer homes. Higher-income households are more likely to be in owner-occupied units, which are also more likely to have an outlet within 20 ft of vehicle parking, as shown in Figure 11. Likewise, higher-income households are more likely to live in single-family detached units, whereas lower-income households tend to live in multi-family buildings. Of all the building types, multi-family homes with 5+ units have the lowest access to an outlet near vehicle parking, as shown in Figure 12. Single-family detached units have the highest level of outlet access, which may be due to the higher likelihood of having an attached garage. Level-2 EV chargers are assumed to have outlet access, as the household can use their level-2 charger to charge their vehicle. For level-1 chargers, the chargers without outlet access are in units with EVs that report no outlet access within 20 ft of vehicle parking.

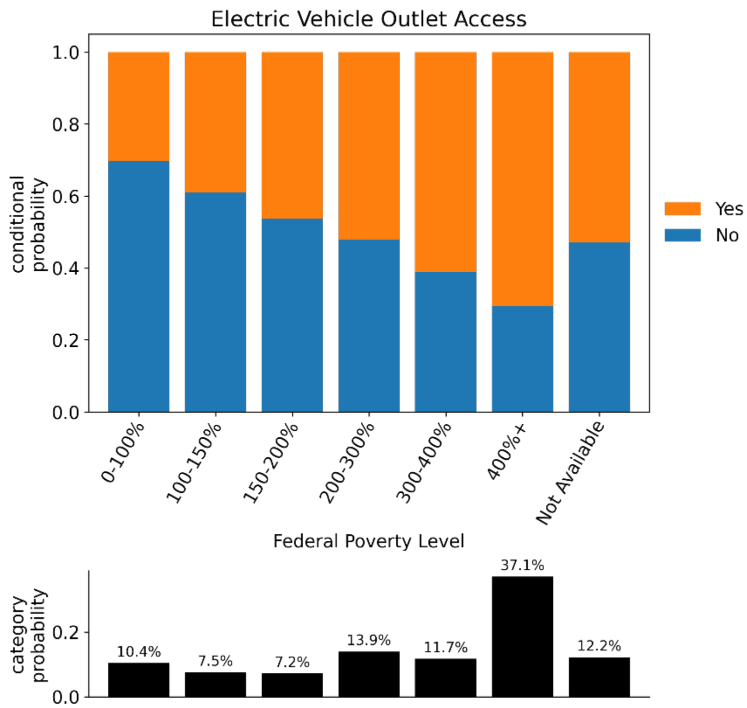

Figure 10. Outlet access as a function of FPL. "Not Available" are vacant units.

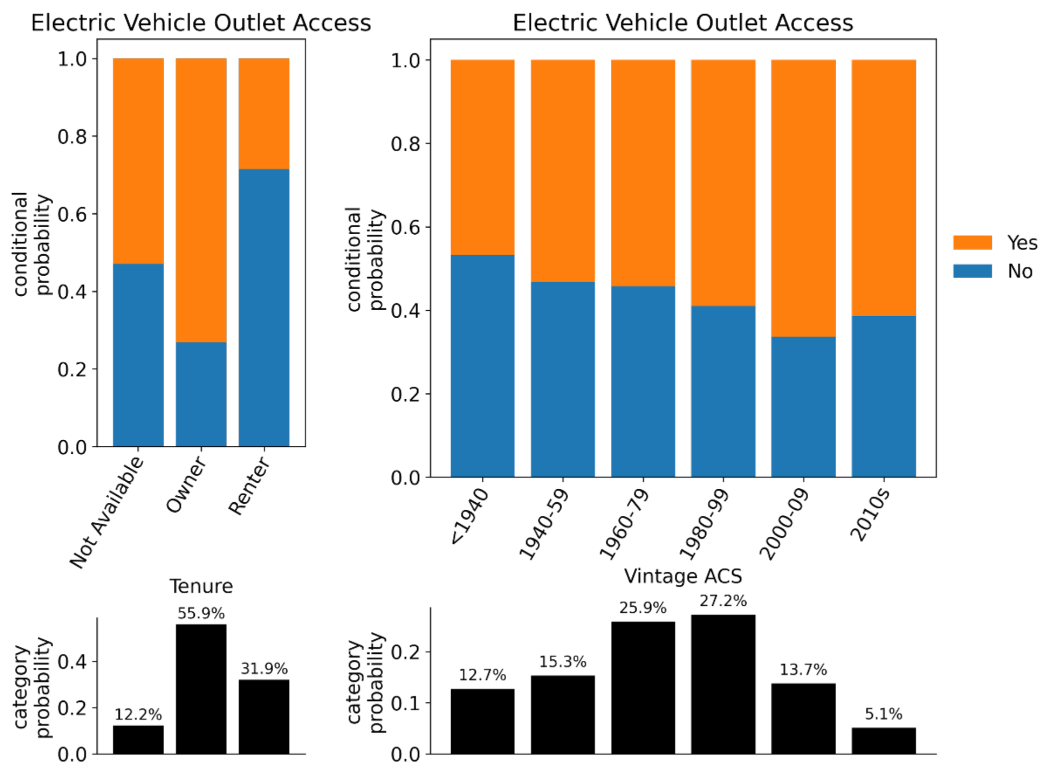

Figure 11. Outlet access as a function of (left) dwelling unit tenure ("Not Available" denotes vacant units) and (right) dwelling unit vintage

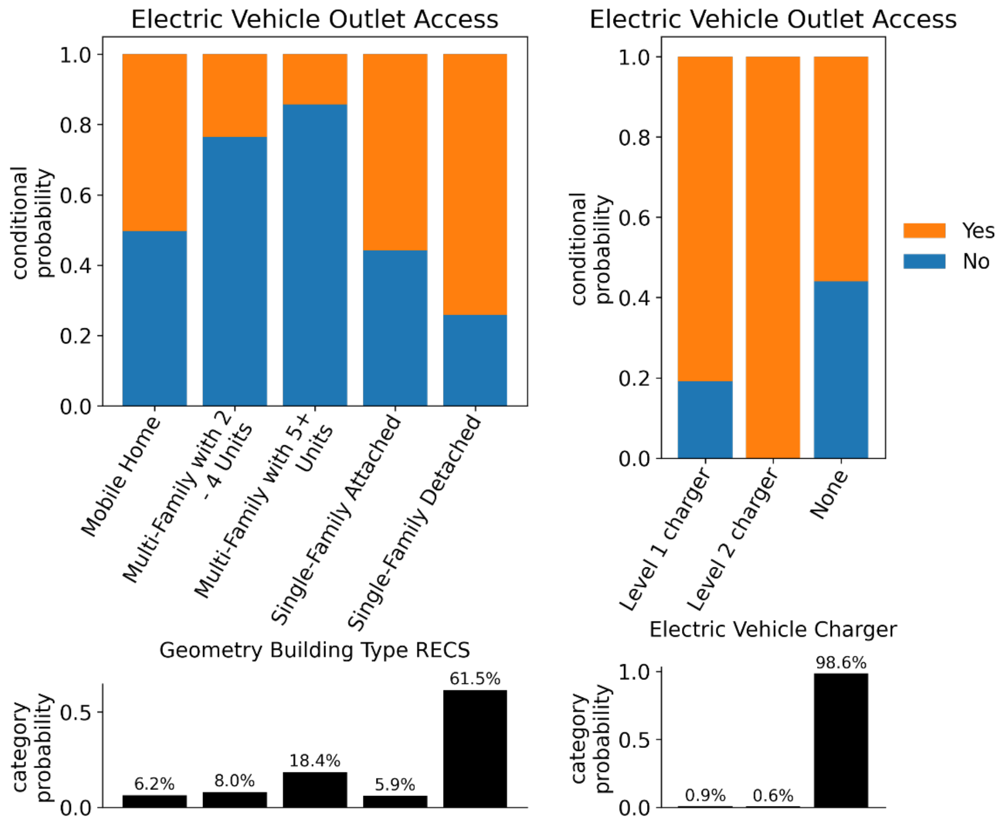

Figure 12. Outlet access as a function of (left) dwelling unit building type and (right) dwelling unit EV charger

4 Modeling Inputs

The national distributions defined in ResStock (Section 3) describe high-level EV details for individual building models, which are fed through several steps to define more specific model arguments and enable simulation. This section describes the process of assigning the more specific EV model inputs and summarizes the additional information integrated from TEMPO. Figure 13 visualizes this workflow, in which ResStock inputs are assigned to OpenStudio-Home Performance XML (HPXML) arguments that are then translated into HPXML fields before an OpenStudio model is generated then translated for simulation in EnergyPlus. Our methodology extended or updated each of the first four steps to support EV modeling, whereas the final translation to EnergyPlus is performed natively by OpenStudio.

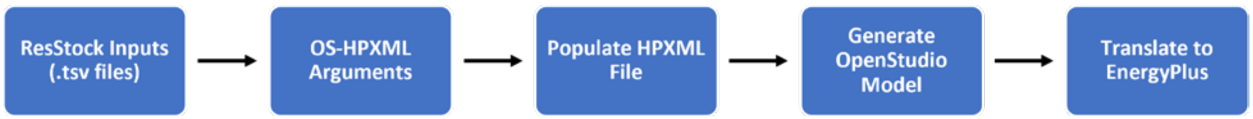

Figure 13. Steps to transform ResStock inputs into final building energy models

OS = OpenStudio

4.1 Translation of Electric Vehicle Stock Characteristics

ResStock datasets are composed of millions of building models through sampling the housing characteristic input distributions, mapping them to more resolved model arguments, and generating an HPXML file that is simulated using OpenStudio and EnergyPlus. To generate building model files, ResStock uses the OpenStudio-HPXML library[13], which produces HPXML files, translates them into OpenStudio models, and simulates them. We introduced numerous new OpenStudio-HPXML arguments to describe EV battery parameters, vehicle operation, and charger inputs, which were aligned with ResStock input files, where a single ResStock input file generally maps to one or more OpenStudio-HPXML arguments. Table 10 describes the arguments, the ResStock input file that informs the arguments, and the HPXML element that is populated. Section 4.2 provides more details about the HPXML elements, and Section 5 describes how these arguments influence the EV model. Arguments either influence the vehicle, which includes driving behavior and battery model parameters, or the EV charger, which sets the location and charging power of the charger.

Table 10. New OpenStudio-HPXML Arguments To Describe EVs and Chargers, and the HPXML Fields That They Populate

OpenStudio-HPXML Argument	ResStock Input File(s)	Data Type	HPXML Element[a]	Description
Vehicle: Type	Electric Vehicle Ownership	string	Initializes **Vehicle/VehicleType/ BatteryElectricVehicle** object	Assigns a BEV and flags the battery model for simulation

[13] For more information, visit https://github.com/NREL/OpenStudio-HPXML.

OpenStudio-HPXML Argument	ResStock Input File(s)	Data Type	HPXML Element[a]	Description
Vehicle: EV Battery Nominal Battery Capacity	Electric Vehicle Battery	double	NominalCapacity	Design capacity of the EV battery, not directly assigned but derived from the UsableCapacity
Vehicle: EV Battery Usable Capacity	Electric Vehicle Battery	double	UsableCapacity	Max usable capacity of the EV battery in kilowatt-hours
Vehicle: Combined Fuel Economy	Electric Vehicle Battery	double	FuelEconomyCombined/ Value	EV battery efficiency
Vehicle: Combined Fuel Economy Units	Electric Vehicle Battery	string	FuelEconomyCombined/ Units	EV battery efficiency units, set to kilowatt-hours per mile
Vehicle: Miles Driven Per Year	Annual Vehicle Miles Traveled	int	MilesDrivenPerYear	Total annual miles the EV is driven
Vehicle: Hours Driven Per Week	Annual Vehicle Miles Traveled	double	HoursDrivenPerWeek	Defaulted using a constant driving speed and the annual miles traveled
Vehicle: Fraction Charged at Home	Home Charging Fraction	double	FractionChargedLocation Location and Value	Sets the fraction charged location to home with a value between 0 and 1
Electric Vehicle Charger: Present	Electric Vehicle Charger	bool	Initializes **ElectricVehicleCharger** object	Applies an EV charger connected to the EV, if applicable
Electric Vehicle Charger: Charging Level	Electric Vehicle Charger	int	ChargingLevel	Sets the charger level to 1 or 2
Electric Vehicle Charger: Rated Charging Power	Electric Vehicle Charger	double	ChargingPower	Sets the charger power draw
Electric Vehicle Charger: Location	N/A	string	Location	Defaults to the garage if one is present, otherwise outside

[a]This column shows only the lower-level fields, which are nested within the Vehicle attribute (first eight rows) or the ElectricVehicleCharger attribute (last four rows).

4.2 HPXML Schema Updates

We introduced several new attributes to the HPXML schema to enable EV load modeling. HPXML is a standalone data standard used in the home performance industry and is the basis for describing building models in ResStock. The HPXML schema ensures consistency across tools while providing flexibility in describing residential buildings, including information for the site, building geometry, construction and energy efficiency, appliances and other loads, and operations. Although many new fields were introduced to HPXML, the "HPXML Element" column in Table 10 describes those used in our modeling approach. Additions to the schema not directly used in our modeling included manufacturing details, additional battery specifications, and support for vehicle types other than BEVs.

The process of deciding HPXML schema updates was layered. Initial proposals hinged on the requirements to model EVs in ResStock. This motivated the implementation of fields related to EV energy usage directly, such as miles traveled, battery efficiency, charger level, and percentage charged at home. We identified these inputs iteratively with the assessment of the controllable elements of the EnergyPlus lithium-ion battery model, as discussed in Section 5.1, and the potential for defining these inputs in ResStock, as discussed in Section 3. We further refined the proposed schema through interactions with users of HPXML, ensuring that our updates could be applied to other use cases. This step helped identify several other fields for EVs and vehicles more generally, such as other vehicle types, manufacturer information, primary vehicle location, and more general ways of describing fuel economy.

The new attributes are contained within a *Vehicles* attribute and an *ElectricVehicleChargers* attribute. *Vehicles* allow for any number of *Vehicle* attributes, which describe the vehicle type, various manufacturer information, driving behavior such as miles driven per year and hours driven per week, and fuel economy. Further, *VehicleType* encompasses several vehicle types, and a *Battery* object is associated with BEV and plug-in hybrid EV vehicle types. *ElectricVehicleChargers* encompasses all *ElectricVehicleCharger* attributes, which include connections to EVs, the charger location, and the charging power. Figure 14 presents a snapshot of an HPXML file generated in ResStock. The populated fields are limited to those necessary to model BEV charging and only populated if a BEV is present; other fields are ignored. Further diversity not realized until simulation includes the schedules dependent on the occupancy of the driver and the average EV energy consumption rate based on the dry-bulb temperature. Appendix A includes visualizations of the schema for the *Vehicle* and *VehicleType/BatteryElectricVehicle* attributes.

```xml
<Vehicles>
  <Vehicle>
    <SystemIdentifier id='Vehicle1'/>
    <VehicleType>
      <BatteryElectricVehicle>
        <Battery>
          <NominalCapacity>
            <Units>kWh</Units>
            <Value>100.0</Value>
          </NominalCapacity>
          <UsableCapacity>
            <Units>kWh</Units>
            <Value>80.0</Value>
          </UsableCapacity>
        </Battery>
        <FractionChargedLocation>
          <Location>Home</Location>
          <Percentage>1.0</Percentage>
        </FractionChargedLocation>
        <ConnectedCharger idref='EVCharger1'/>
      </BatteryElectricVehicle>
    </VehicleType>
    <MilesDrivenPerYear>10000.0</MilesDrivenPerYear>
    <HoursDrivenPerWeek>23.0</HoursDrivenPerWeek>
  </Vehicle>
</Vehicles>
```

Figure 14. A snippet of an HPXML file describing an EV and an EV charger for ResStock.

4.3 Intersection of TEMPO and ResStock Model Data

We leveraged the input and output data from the TEMPO and ResStock models in several areas and summarized all instances of data intersection in Table 11. Note that only data that are used by both tools are included in this table; other required data specific to ResStock are discussed primarily in Section 3. Data are grouped into two categories based on their usage:

ResStock Inputs: Several high-level ResStock input files use TEMPO data, which are shown in green. These data are used to characterize the baseline attributes relating to EVs, such as ownership or charging level.

EV Model Arguments: ResStock inputs are associated with specific arguments used to define the behavior of individual battery models; those inputs are shown in orange in the table. These arguments are used in the OpenStudio-HPXML workflow to define schedules, battery parameters, and charger parameters.

Table 11. Summary of Model Data Used To Integrate TEMPO and ResStock

ResStock input file	OpenStudio-HPXML input

Data	Source	Destination	Use	Notes
EV Ownership	TEMPO (Experian[14])	ResStock (input file)	Informs the geographic resolution for the "EV Ownership.tsv" input file; combined with data from the 2020 RECS	Direct TEMPO input for household vehicle stock, version 2022 Standard input available in every TEMPO release and also available for future scenarios of EV adoption
EV Type	TEMPO (Experian and NHTS[15])	ResStock (input file)	Provides a distribution of EV vehicle classes and battery mileage ranges to generate the "EV Type.tsv" input file	Direct TEMPO input for household vehicle stock, version 2022 Standard input available in every TEMPO release and also available for future scenarios of EV adoption
Annual VMT	NHTS	ResStock (input file and direct OpenStudio-HPXML argument)	Converted to hours driven via the "Average Speed" argument to inform the hourly driving schedule Hours driven is combined with the "Vehicle Energy Efficiency" argument to inform the average EV energy consumption rate	Derived from distribution of 2017 NHTS BESTMILE variable
Outlet Access	2020 RECS and Ge et al (2021)	ResStock (input file)	To be used in adoption modeling scenarios and results from the upgrade measures	Distributions from 2020 RECS and multi-family from Ge et al. (2021) study
Vehicle Energy Efficiency	TEMPO (Autonomie[16])	ResStock (OpenStudio-HPXML argument via EV type)	Contributes to the calculation of the average EV energy consumption rate	Autonomie release, 2022

[14] For more information, visit https://www.experian.com/automotive/auto-vehicle-data.
[15] (Federal Highway Administration 2022)
[16] For more information, visit https://www.anl.gov/taps/autonomie-vehicle-system-simulation-tool.

Data	Source	Destination	Use	Notes
Average Speed	NHTS	ResStock (OpenStudio-HPMXL argument via EV type)	Contributes to the calculation of the driving schedules and the average EV energy consumption rate	Derived from all NHTS household vehicle trips
Battery Capacity	TEMPO (Autonomie)	ResStock (OpenStudio-HPMXL argument via EV type)	Direct input to the EV battery model	Autonomie release, 2022
EV Discharge Power Curve	TEMPO	ResStock (battery model)	Scales the average EV energy consumption rate based on the ambient temperature	Sourced from empirical data[17]
Level-2 Charging Power	EV-WATTS	ResStock (OpenStudio-HPXML argument via EV charger)	Informs the constant charging power for level-2 chargers	EV-WATTS data collected between 2019 and 2023 (Pavuluri 2024)

[17] Updated data originally reported in Section 2.4 of Yip et al. (2023) were used. The updated temperature-energy relationship is primarily based on real-world performance data from Geotab and Recurrent Auto and secondarily informed by laboratory test results from AAA and Argonne National Laboratory.

5 Electric Vehicle Modeling

The core components of modeling baseline residential EV charging exist across two efforts: 1) the development of the EV battery model and 2) the schedule generation algorithm—both within OpenStudio-HPXML. OpenStudio-HPXML enables the generation of an HPXML file describing a residential building model and simulates it using OpenStudio and EnergyPlus. As discussed in Section 4.1, we translate ResStock characteristics to more specific building-level arguments in OpenStudio-HPXML, a process that occurs for every building model in the sampled ResStock baseline. This section describes how those arguments influence the EV model (Section 5.1) and the charging and discharging schedules (Section 5.2)

5.1 Baseline Electric Vehicle Model

EnergyPlus, the simulation engine upon which ResStock is built, provides a lithium-ion battery model through NREL's System Advisor Model[18] software package. This model has been incorporated into OpenStudio-HPXML and therefore has the potential to be utilized in ResStock. Although the existing implementation is intended for home battery systems, we leverage the detailed battery model to represent the charging and discharging energy of EVs using the *ElectricLoadCenter:Distribution* and *ElectricLoadCenter:Storage* EnergyPlus objects. The initial step toward applying this model is to understand the available model inputs, the intermediate and controllable model parameters, and the outputs. This step is necessary to properly configure the model within the context of an EV but also to feed back information to the EV stock characterization and HPXML schema update tasks. EnergyPlus is the lowest level of the modeling workflow (Figure 13), and therefore these inputs directly influence energy usage of the EV battery. Table 12 summarizes the most relevant arguments, parameters, and outputs of the EnergyPlus model and how they were adjusted in OpenStudio-HPXML.

Table 12. Summary of Relevant Fields in the EnergyPlus Battery Model

Outputs listed are not exhaustive but a selection that may be relevant to ResStock simulations

Field	Field Type	Description	OpenStudio-HPXML Implementation
Charge Power Fraction Schedule	Argument	Fractional time step schedule to specify charging periods, ranges from 0 to 1	Determined during schedule generation
Discharge Power Fraction Schedule	Argument	Fractional time step schedule to specify discharging periods, ranges from 0 to 1	Determined during schedule generation
Design Charge Power (Watts)	Argument	Maximum electric power for charging	N/A
Design Discharge Power (Watts)	Argument	Maximum electric power for discharging	N/A
DC to DC Charging Efficiency	Argument	Charging loss coefficient	Defaulted to 1.0; losses are captured during calculation of

[18] For more information, visit https://sam.nrel.gov/.

Field	Field Type	Description	OpenStudio-HPXML Implementation
			the time-dependent EV energy consumption rate
Fully Charged Cell Capacity	Argument	Alter the battery chemistry at the individual cell	Defaulted to 3.2 ampere-hours
Physical Battery Size (Number of Cells, Number of Strings in Parallel, Mass, and Surface Area)	Arguments	Define physical battery configuration	Defaulted based on inputted battery capacity[19]
Minimum and Maximum State of Charge	Arguments	Fraction of storage capacity used as the lower and upper limits for controlling charging	¾ of the unusable capacity fraction (usable capacity/ nominal capacity) is the minimum SoC and ¼ of the unusable capacity fraction is the maximum SoC
Zone Name	Argument	Location of battery; influences internal heat gains/losses and battery temperature	Set as garage if present, otherwise outside
Lifetime Model	Argument	The lifetime model used to model degradation	Defaults to none
Power Draw Rate (Watts)	Parameter (Actuator)	Optional control of the discharging power rate during simulation	Dynamically assigned at every time step dependent on ambient temperature and vehicle parameters
Power Charge Rate (Watts)	Parameter (Actuator)	Optional control of the charging power rate during simulation	Fixed input based on charger level
Charge Fraction	Output	Battery states of charge	N/A
Charge Energy (Joules)	Output	Battery charging energy	N/A
Discharge Energy (Joules)	Output	Battery discharging (driving) energy	N/A
Charge Power (Watts)	Output	Battery charging power	N/A
Discharge Power (Watts)	Output	Battery discharging (driving) power	N/A
Thermal Loss Energy (Joules)	Output	Energy lost for both charging and discharging	N/A
Battery Temperature (°C)	Output	Battery temperature	N/A

[19] For more information on EV battery defaults, visit https://openstudio-hpxml.readthedocs.io/en/latest/workflow_inputs.html#hpxml-vehicles

Whereas some of the arguments in Table 12 are directly exposed in OpenStudio-HPXML, others are abstracted or use new HPXML fields to assign. One abstracted argument is a single capacity value from which physical battery size inputs are derived, which helps simplify the connection to RECS and TEMPO inputs. Battery capacity is first determined by sampling the "Electric Vehicle Battery" ResStock input file and subsequently assigned in the HPXML file, which is then translated to the physical battery size arguments in EnergyPlus. Other more nuanced input translations include the charging and discharging schedules and the power draw rate, which are discussed in the following subsections.

Calculating Average EV Energy Consumption Rate

The parameters in Table 12 represent runtime variables that can optionally be altered at each time step of a simulation, also known as "actuators" in EnergyPlus. The power charge rate is assigned a fixed value at all time steps based on the charger level prior to simulation. The power draw rate, however, is calculated on the fly because 1) we do not have available data to explicitly describe the EV energy consumption rate a priori and 2) we can adjust the consumption rate based on ambient temperature using a curve derived from empirical data. The average EV energy consumption rate is dependent on many factors such as the driving behavior, vehicle type, temperature, battery control systems, and battery age. Due to the complexity in estimating, we elected to calculate a baseline average EV energy consumption rate at runtime and then scale this based on the ambient temperature at each time step.

To first calculate the baseline average EV energy consumption rate, we:

1. Determine the expected annual discharge energy (kilowatt-hours) by multiplying the EV energy efficiency (kilowatt-hours per mile) by the annual miles (miles)
2. Calculate the average EV energy consumption rate by dividing the annual discharge energy (kilowatt-hours) by the hours driven per year.

Although the current implementation does not include all time-dependent variables impacting discharge events, we do incorporate a model that adjusts power based on the ambient temperature. Ambient temperature plays a large role in EV energy usage, attributed primarily to climate control systems of the vehicle cabin and battery. We align with the approach used in TEMPO by deploying a curve of EV energy consumption versus ambient temperature[20] in the EnergyPlus Energy Management System (EMS)[21]. Figure 15 visualizes the scaling factor curve applied to the discharge power actuator. The scaling factors encompass losses for driving and charging but are applied entirely to driving in the OpenStudio-HPXML implementation due to requirements of the discharge curve. For temperatures outside the range shown in the plot (below 0˚F or above 100˚F), the scaling factor at the nearest bound is applied.

[20] Updated data originally reported in Section 2.4 of Yip et al. (2023) were used. The updated temperature-energy relationship is primarily based on real-world performance data from Geotab and Recurrent Auto and secondarily informed by laboratory test results from AAA and Argonne National Laboratory.

[21] More information can be found in BTO (2022).

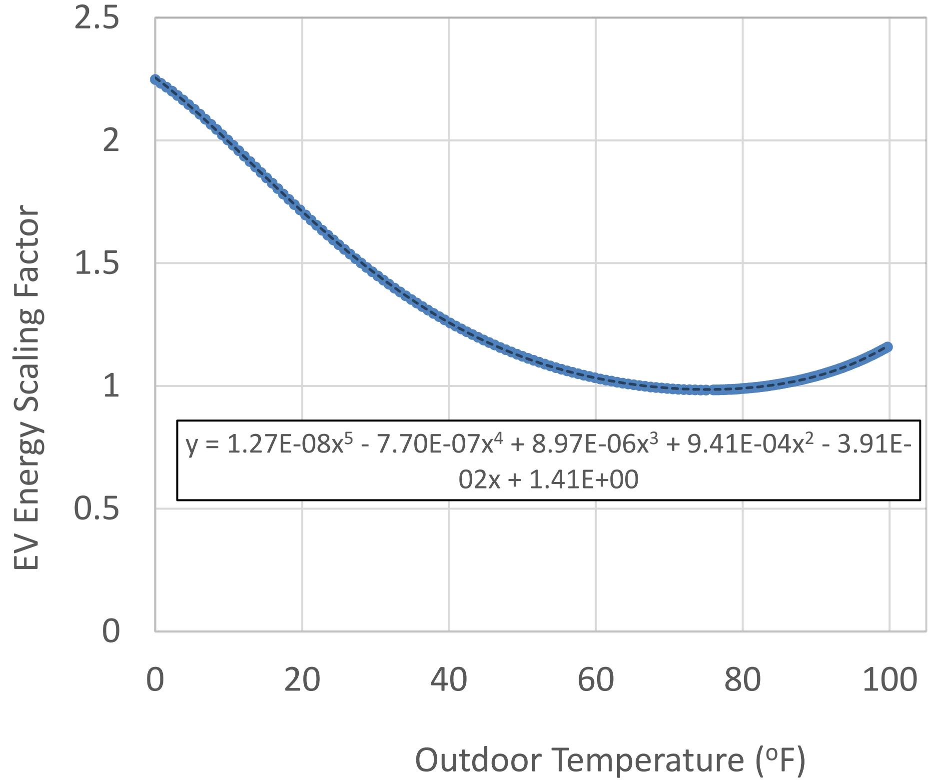

Figure 15. Curve of the EV energy scaling factors as a function of the outdoor temperature, and the resulting equation fit to the data

Figure 16 illustrates how the temperature curve influences the EV outputs. During a week in January, the ambient temperature ranges from approximately 4˚F to 60˚F, leading to maximum average EV energy consumption rates ranging from 2.9 kilowatts (kW) to 4.9 kW across 14 discharge events. The most efficient temperature range for EV operation occurs between 60˚F and 80˚F, whereas the poorest performance is seen at colder temperatures. As a result, discharge events at colder temperatures correspond with much higher power draws. The empirical data used to model temperature dependence incorporate all losses but are only applied to the discharging power, meaning the charging power remains constant during each charging event. However, temperature still directly affects charging, as colder temperatures correspond to longer charging periods and higher energy consumption per event.

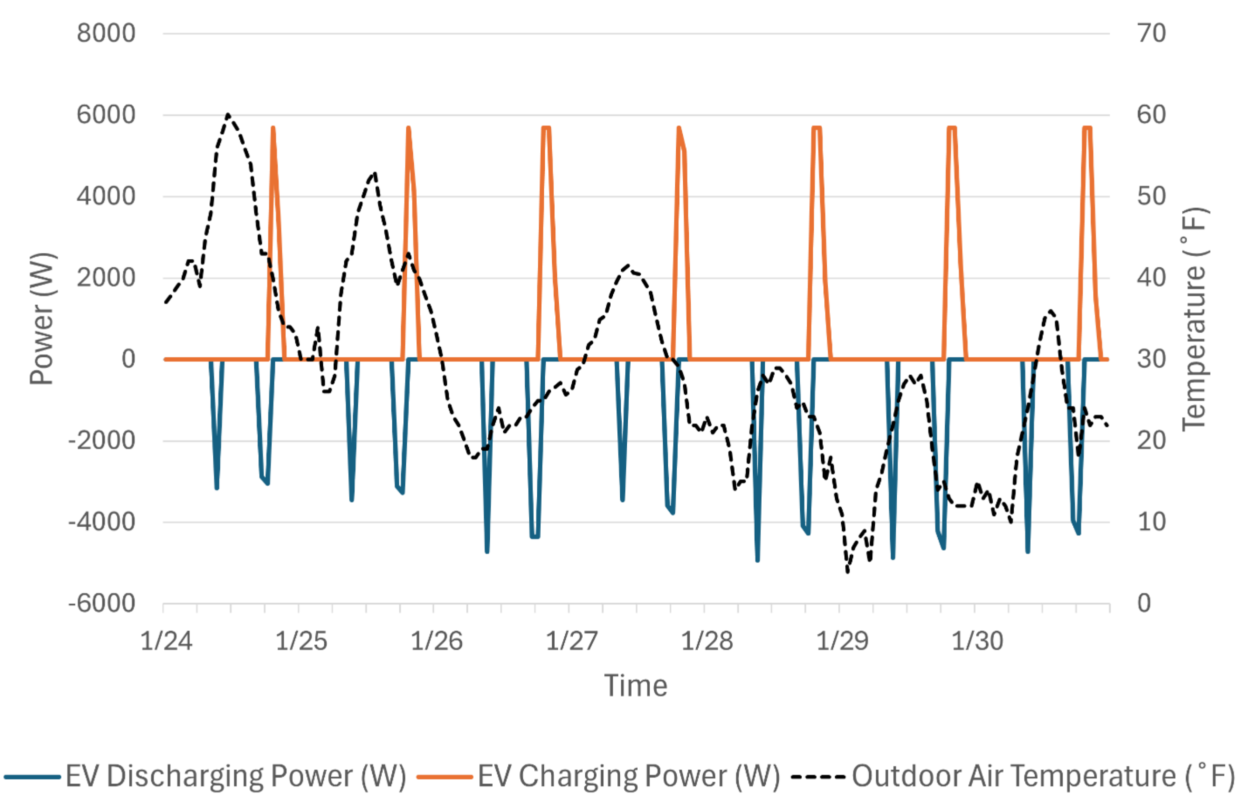

Figure 16. Snapshot of charging power, discharging power, and ambient temperature for a 7-day period in January

W = watts

Calculating Electric Vehicle Battery Capacity Limitations

Given the breadth of available inputs, it is not guaranteed that an EV battery will have sufficient capacity to meet the specified driving demand, as this depends on factors such as battery size, charger level, driving behavior, and climate. To assess this, we introduced unmet driving hours as a metric to quantify instances where the battery cannot support the driving needs. The unmet driving hours variable describes the hours intended to be spent driving but were not possible due to a lack of available capacity. This situation is uncommon, as a driver is likely to change their behavior by delaying a trip or charging elsewhere to meet demand. However, we elected to keep inputs constant during the simulation and instead quantify the prevalence of unmet driving demand. Although this is not common in the baseline ResStock workflow, it can be an important metric for applications that leverage managed charging of EV batteries. Our approach extends the existing EnergyPlus EMS[22] program written to adjust the discharge power at each time step. With each time step, the state of charge (SoC) is compared to the minimum SoC, and if they are equal during a discharge period, then the timestep is accumulated in the unmet driving hours variable. This variable can then be written as an annual or a time series variable to understand the driving impacts of various operational decisions of EVs. One example of where this could be

[22] More information can be found in BTO (2022).

helpful is understanding the trade-off between the energy or cost benefits of load shedding and the drawback of reduced driving time. Figure 17 shows an example of this, where we simulate a day with three discharging events and no charging events. During the second charging event, the SoC reaches the minimum SoC, and the remainder of that event and the following event are considered a period of unmet driving. This metric can ultimately be estimated as a required kilowatt-hour value or miles not met using the vehicle efficiency and average driving speed, which may be helpful given the use case.

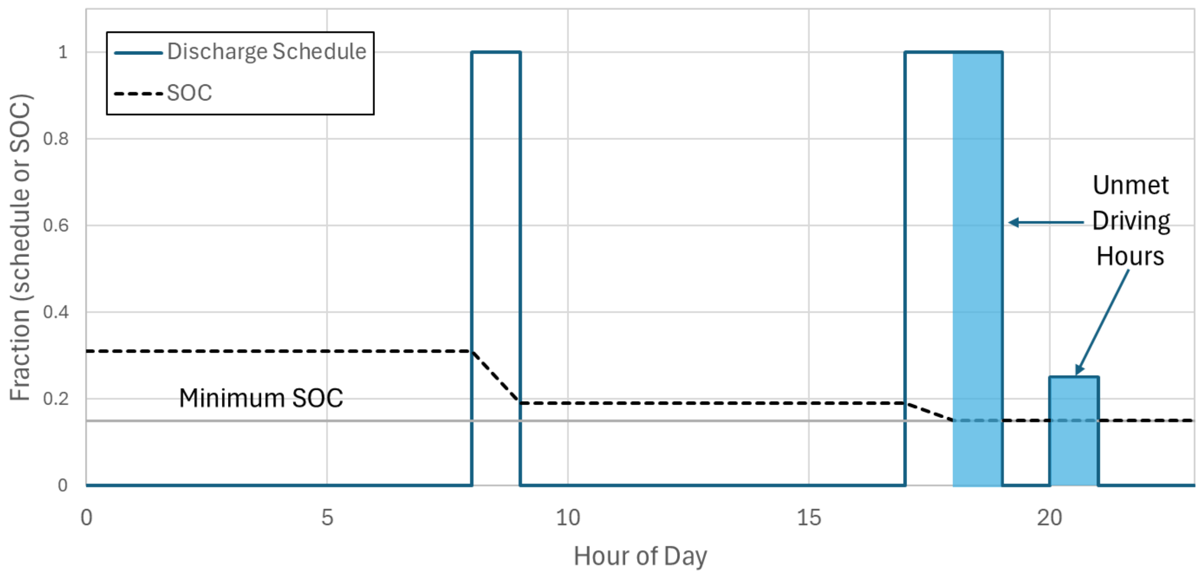

Figure 17. Example of how unmet driving hours are determined

5.2 Charging and Discharging Schedule Generation

We leverage the existing American Time Use Survey (ATUS)-guided stochastic occupancy generator in OpenStudio-HPXML to generate the EV battery charging and discharging schedule. The schedule generator takes the total hours driven per week (converted to hours driven per year) as an input to the EV schedule generator and produces the charging and discharging schedule. The battery model takes care of the actual power draw during the charging and discharging period. An example of what these schedules look like is presented in Figure 18. This schedule shows that during an "away period" for the occupant, the vehicle is discharged after the occupant leaves the home. Then, later in the day, the vehicle is discharged again while the occupant travels home.

The guiding theme for the discharge schedule is the assumption that the EV is owned by/associated with just one occupant in the dwelling unit. If there are multiple occupants in the unit, we randomly pick one of the eligible occupants. Individual occupant demographics are not tracked, so the only criterion for selecting an eligible occupant is that 80% of their away hours exceed the required annual EV driving hours. If there are no eligible occupants, then we pick the occupant with the highest away hours. Once the occupant is chosen, we assume that the EV battery discharge will start immediately after they leave the home and immediately before they arrive, simulating the scenario in which they left the home driving the EV, stayed somewhere for a while, and then returned home. Following that assumption, we sum the total away duration for the occupant and proportionally assign the driving hours to each away period. The driving hours assigned to each away period are distributed symmetrically at the start and end, always making sure to leave the center 20% as idle to allow for some idle duration at the destination away from home. Although this is a rare occurrence in ResStock modeling, if the chosen occupant does not have enough away hours to accommodate the needed driving hours, we truncate the driving hours and simulate only the amount that can be accommodated. Accounting for this rare truncation, ResStock can generate the schedule for 98.5% of the driving hours needed to model the input characteristics.

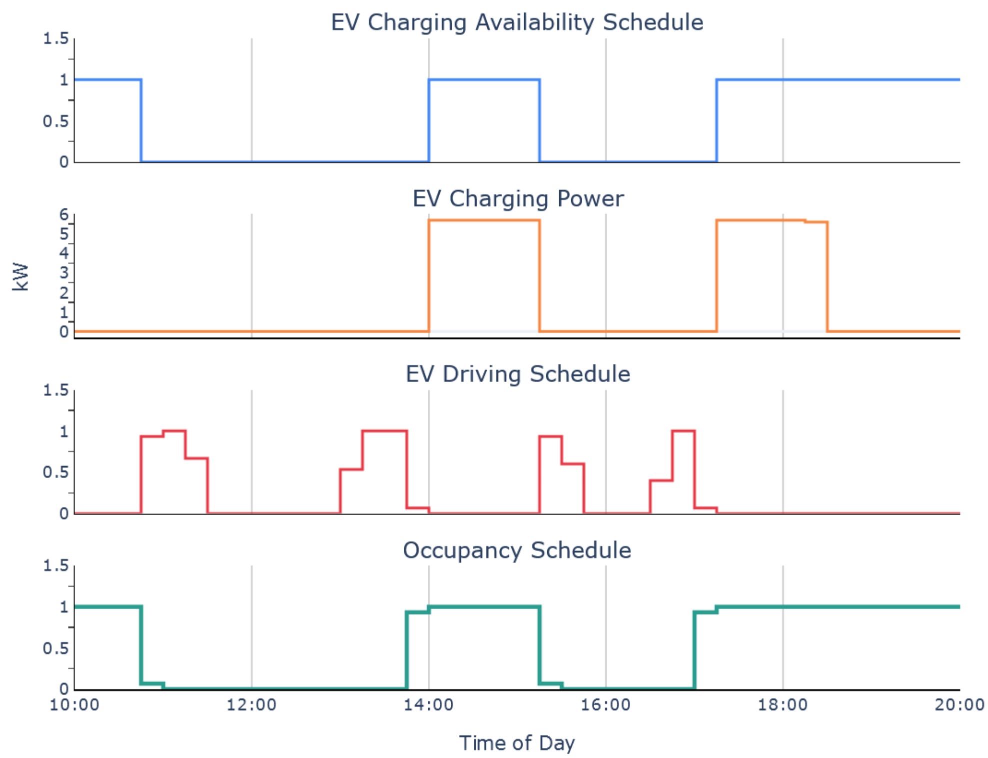

Figure 18. Illustrations of EV battery plugged in schedule, charging power, EV discharge schedule, and driver occupancy.

For charging schedule generation, a simple algorithm is used where we assume that the occupant plugs in their vehicle as soon as they are home and keeps it plugged in until they leave. Hence, the charging schedule is identical to the occupancy schedule of the EV-owning occupant. This makes the battery eligible to be charged anytime the EV is at home if the SoC is below the maximum level. Whether or not the charging happens and at what power level are managed by the battery and charger models. The TEMPO model makes similar assumptions in its "immediate" or "ASAP" charging strategy, as described in Yip et al. (2023). Charging strategies were of high interest to the stakeholders interviewed for this project. Our approach uses time-step-level schedules, so other charging strategies could be implemented based on time series inputs other than occupancy. Some examples of charging strategies that could be included are waiting a few hours after returning home to start charging, only charging when the vehicle battery SoC drops below a certain percentage, avoiding regional peak periods, or responding to time-of-use rate structures.

Not all EV owners charge exclusively at home. The 2020 RECS includes a question about what fraction of charging is done at home, with options such as 100%, 80% to 99%, and 60% to 79%. The battery model handles this scenario by proportionally reducing the average EV energy consumption rate. The underlying assumption in using this approach is that respondents answered the fraction of their charging in terms of energy, as opposed to time.

We made several assumptions in the baseline charging and discharging schedule generation algorithms:

- The EV is associated with a single occupant, and therefore we do not model scenarios where multiple occupants share the same EV.
- The EV driver drives every time they leave home, and therefore we do not model long periods in which the EV is parked. This assumption is a function of the current stochastic occupancy model, which does not have long periods of time when people do not leave home.
- The EV is driven proportional to the time the occupant is away.
- Because the underlying occupancy model does not have seasonality, the EV driving pattern also lacks seasonality. As such, we do not model things like long trips during the summer.
- The EV is plugged in anytime it is at home and begins charging as soon as the driver returns.
- The fraction charged at home is assumed to apply to every trip. For example, 80% charged at home is modeled as every trip consuming 80% of the energy instead of 20% of the trips requiring no charging at home.

These assumptions apply only to the baseline generation of schedules, whereas analysis scenarios include the ability to shift charging, which is out of scope for this report.

5.3 Model Outputs

The EnergyPlus battery model offers the ability to report several output variables, a selection of which are provided in Table 12. The only default output is Charge Energy, which is reported in annual and time series reports and is treated the same as any other building end use. This variable is also included on the electricity meter of the building and therefore influences energy bills and peak loads. Like other end uses in OpenStudio-HPXML, the EV charging energy can also be used to calculate and output as annual or time series emissions calculated using one or more existing emissions scenario options (Reyna et al. 2025). Further, given the alignment between occupant behavior and charging schedules, EV charging energy can be used to evaluate the EV baseline consumption and scenario-based energy impacts with respect to other concurrent household loads.

We utilize a battery model that is designed to model a home battery system, and therefore the existing workflow also reported Discharge Energy. We exclude this variable from being reported by default and from impacting the electricity meter, as it encompasses energy used for driving and is not considered a building load. However, annual and time series discharge energy can still be optionally reported to offer more details about the operation of the vehicle. Other optional time series outputs include charging and discharging power, the battery SoC, unmet driving hours, and the EV schedules, which may be helpful in analyses related to EVs.

6 Results

6.1 National Baseline Simulation Analysis

We explored various scenarios to understand and qualitatively assess the ResStock baseline EV outputs. These trends are driven by assumptions in the EV stock characterization, such as ownership, miles driven, and charger level, as well as the mechanics of the battery model in different climates. This exercise allowed us to check against expected behavior and address model assumptions as needed. We performed internal checks of estimated kilowatt-hour consumption, charging energy consumption, EV battery peak power, average power consumption, and time series energy outputs across segments including EV type, VMT, fraction charged at home, and charger level. Simulation results are from a national-scale ResStock run of 550,000 buildings, filtered down to 5,777 building models with EVs that reflect the baseline saturation of EV ownership.

Figure 19 and Figure 20 show the percentage difference between the estimated annual EV charging energy under design conditions and the actual modeled EV charging energy grouped by the household's Building America climate zone[23] and VMT, respectively. The annual EV charging energy under design conditions is the expected energy usage independent of ambient temperature and unmet driving hours. This value is calculated using ResStock inputs, where the product of the VMT (miles), the battery's efficiency (kilowatt-hours per mile), and the fraction that the battery is charged at the dwelling provides an estimate of the energy usage, assuming sufficient SoC throughout the year and constant efficiency. The percentage difference is calculated using the modeled outputs minus the predetermined estimation, so positive values indicate that modeled values are higher than the estimation. This analysis helps to validate the battery model to ensure that the final energy is reasonable relative to expectations. In general, modeled charging consumption is higher than the estimation, primarily driven by the influence of ambient temperature on the average EV energy consumption rate, which is encoded into the model simulation. Figure 19 shows this relationship, more mild climates tend to align better with the expected behavior under design conditions, whereas climate zones with colder extremes will require more charging energy. Outliers in Figure 19 can be explained with Figure 20, where higher mileages correspond with lower modeled charging energy compared to the estimated value—this is driven by "unmet miles," where the inputs describe a certain mileage for the year but the battery during simulation is constrained by its capacity and is fully depleted throughout the daily discharging and charging cycles.

[23] For more information, visit https://www.energy.gov/eere/buildings/building-america-climate-specific-guidance

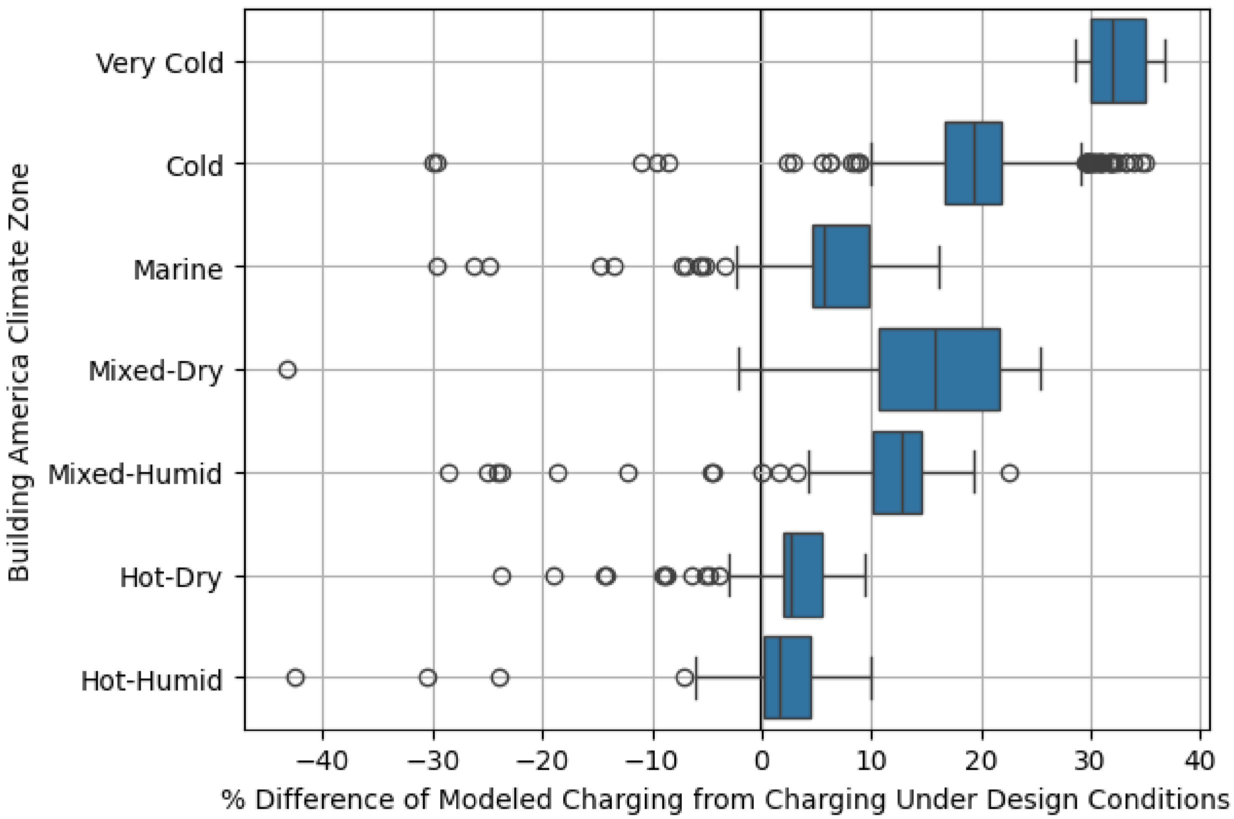

Figure 19. Percentage difference between modeled charging consumption and charging consumption under design conditions grouped by Building America climate zone

Negative values indicate a lower modeled value compared to the estimated one; positive values indicate a higher modeled value

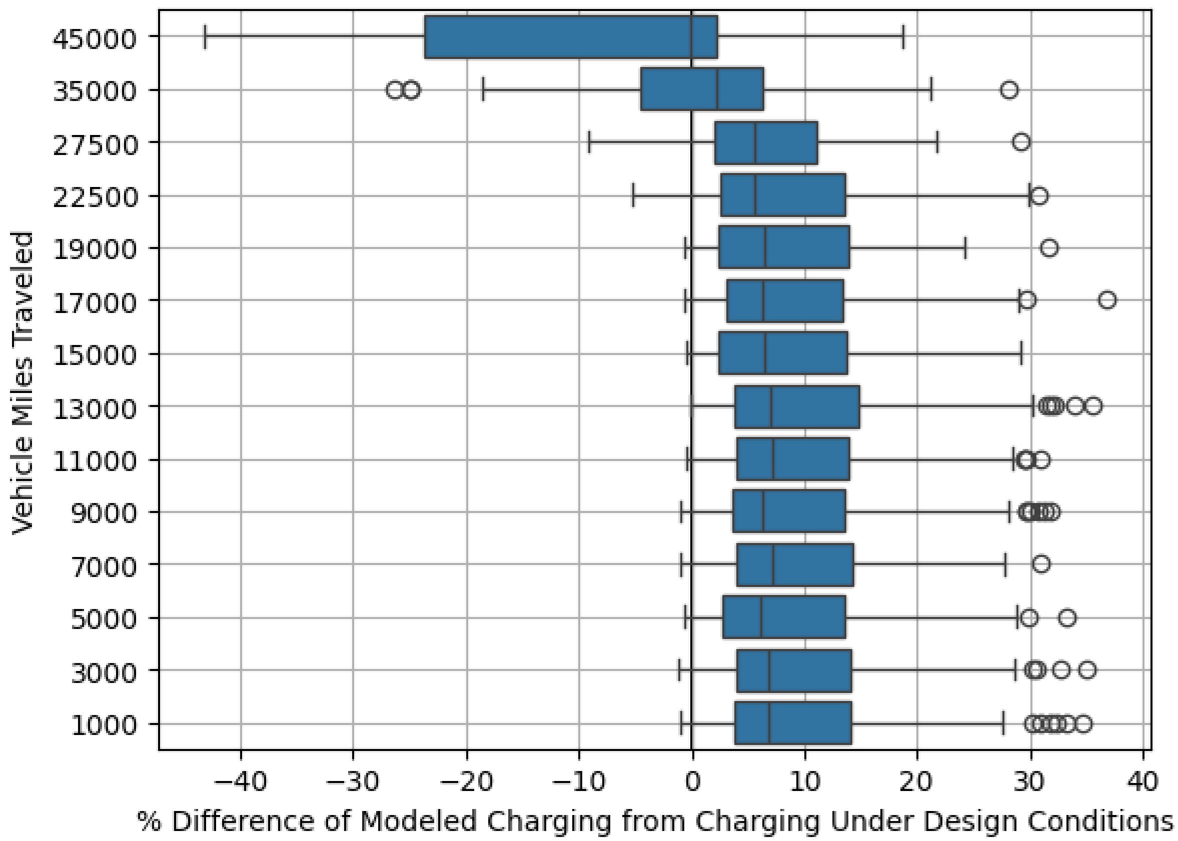

Figure 20. Percentage difference between modeled charging consumption and charging consumption under design conditions grouped by VMT

Negative values indicate a lower modeled value compared to the estimated one; positive values indicate a higher modeled value

Next, we analyzed trends in the modeled data by visualizing the charging consumption per EV grouped by various household characteristics—climate zone, building type, and EV type. Although each of these figures provides insights into EV charging energy trends, some variability is to be expected due to the small number of EVs, as uncertainty increases as the number of buildings within a housing segment decreases. These figures show the charging energy for residential charging only, excluding any potential charging away from the home. Figure 21 shows the effects of ambient air temperature on EV charging. We model the discharge energy as the driving demand that is met by the residential charger, and thus the charging consumption reported refers only to the at-home EV charger. Discharge energy is mostly a function of vehicle type, VMT, fraction charged at home, and ambient temperature during vehicle operation. Because the vehicle type, miles traveled, and fraction charged at home are independent of climate zone and the results are normalized by the number of EVs, Figure 21 demonstrates the effects of ambient temperature only. We incorporate a curve of the EV energy consumption rate versus ambient temperature that is also used in TEMPO to adjust for the variable demands of battery and space conditioning at each time step. In general, the lower the ambient temperature, the higher the average EV energy consumption rate, leading to lower states of charge on average and higher EV charging energy demand.

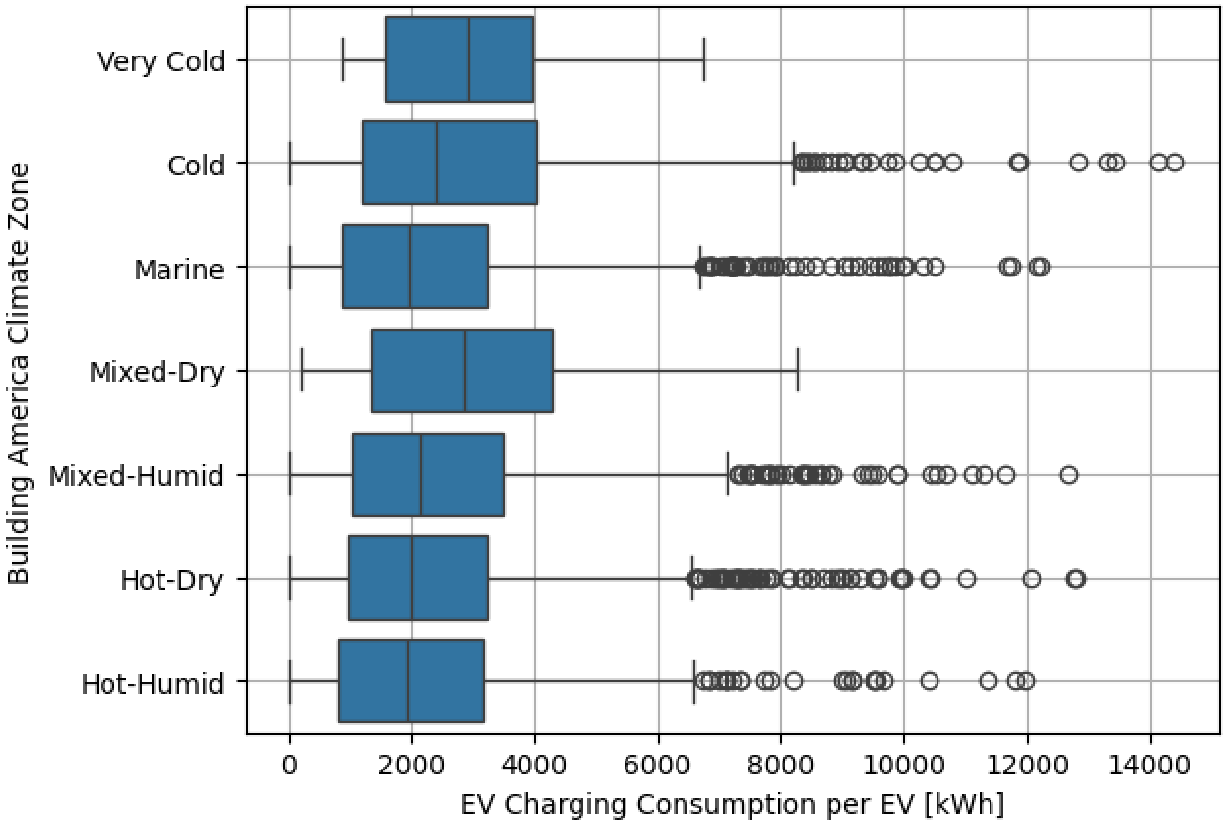

Figure 21. EV charging consumption per EV grouped by Building America climate zone

kWh = kilowatt-hour

Figure 22 shows the EV charging consumption per EV, grouped by the annual miles driven. As expected, EVs with higher VMT yield higher charging consumption values. Additionally, higher mileage corresponds to wider ranges of EV energy consumption. This observation may be a result of the scaling for fraction charged at home and fully discharged vehicles. Whereas the VMT refers to the total miles driven by a vehicle in a year, the actual energy is scaled by the percentage of charging done at home, which ranges from 10% to 100%. This scaling will proportionately impact EVs with higher VMTs and directly impact the final energy consumption. Additionally, the home charging fraction causes a subset of vehicles within each VMT category to have very low home charging demand.

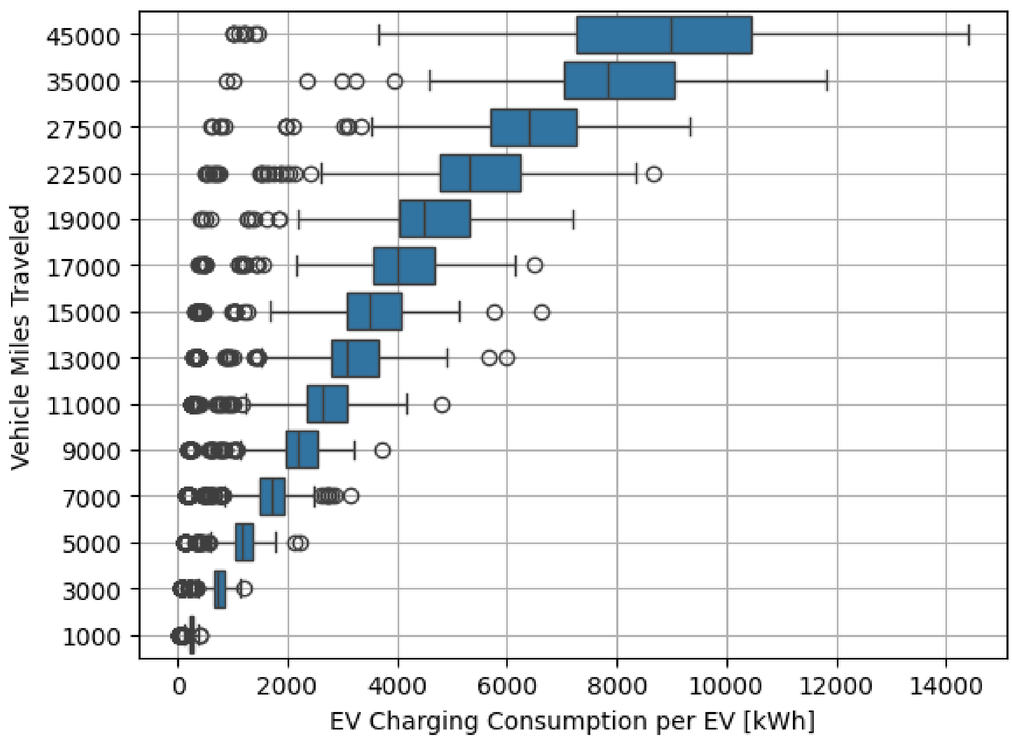

Figure 22. EV charging consumption per EV grouped by VMT

kWh = kilowatt-hour

Figure 23 displays the EV charging consumption per EV grouped by vehicle type. This ResStock input influences OpenStudio-HPXML battery model parameters, namely, the energy efficiency and the capacity. The trend of EV charging energy by battery type is primarily driven by the energy efficiency, where the most efficient options are "Compact, Battery Electric Vehicle, 200-mile range" and "Midsize, Battery Electric Vehicle, 200-mile range" and the least efficient option is "Pickup, Battery Electric Vehicle, 300-mile range." Although battery capacity can also influence the final energy usage, its impact is smaller, as it applies only to vehicles with unmet driving hours. Capacity will be most important in measures that shift or shed load, where it is more likely that a higher percentage of the battery capacity is used. These results are particularly sensitive to sample counts, specifically the "Pickup, Battery Electric Vehicle, 300-mile range," which has a low saturation (less than 1% of the EV stock).

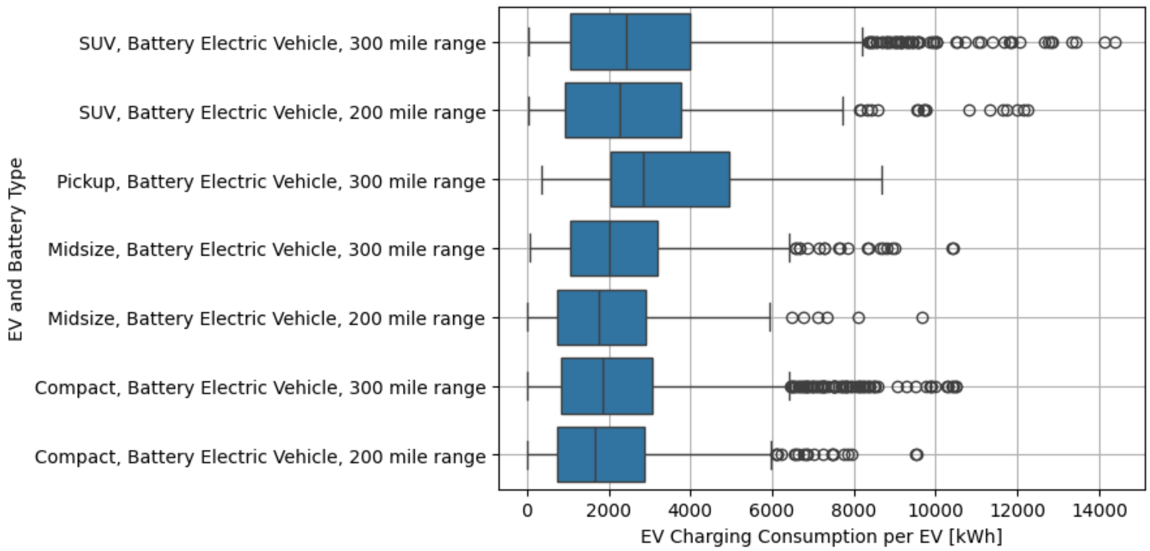

Figure 23. EV charging consumption per EV grouped by EV and battery type

kWh = kilowatt-hour

Because EV energy use is based on a physics-based battery model, it is important to understand the instances in which the battery is unable to meet the EV's required load. This can be accomplished using the "unmet driving hours" output, which quantifies the number of driving hours not simulated due to insufficient EV capacity. Drivers are unlikely to fully deplete a battery regularly; instead, they may change their behavior by skipping or delaying trips. However, rather than retroactively changing inputs, we quantify this as unmet driving time. Unmet driving is influenced by the vehicle's efficiency and capacity, the annual miles driven, the percentage charged at home, the charger level, and the outdoor air temperature. However, efficiency and capacity play a smaller role due to their relatively narrow range of possible values. Approximately 91% of dwellings with an EV in the ResStock baseline do not have any unmet driving hours. The remaining 9% of dwellings are shown in Figure 24, binned by the number of unmet driving hours.

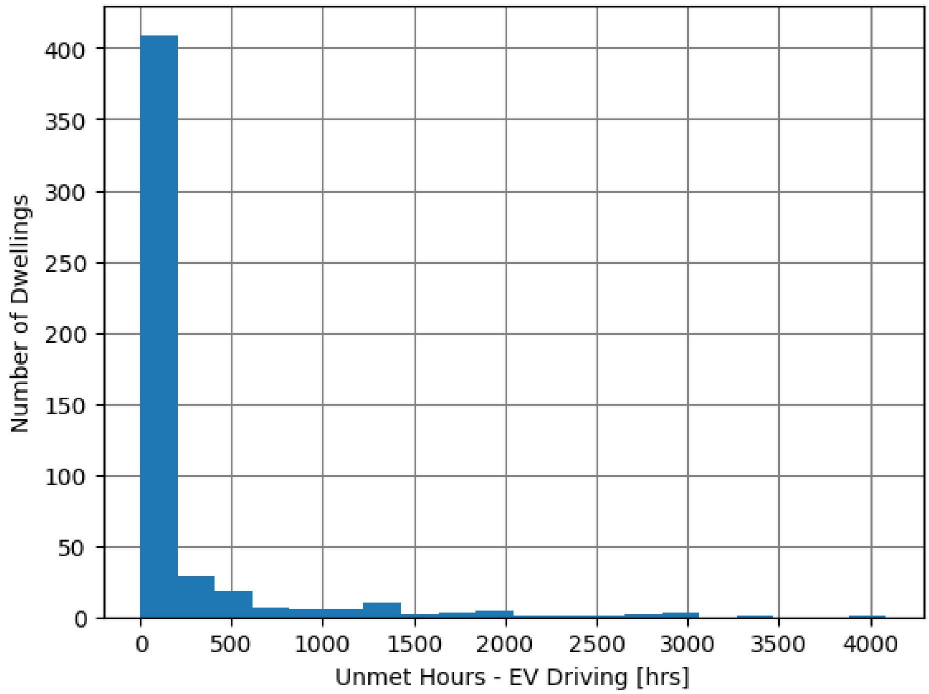

Figure 24. Unmet driving hours for dwellings in the ResStock baseline with a nonzero amount of unmet driving hours

Note that 9% of dwellings in the ResStock baseline with EV ownership have unmet driving hours

Unmet driving hours are not common for modeled vehicles, and values are generally low when they do occur. Only under certain combinations of EV characteristics do we see significant unmet driving hours. Data points with the highest risk for unmet driving hours generally have a level-1 charger, have high VMT, and charge mostly at home. Figure 25 shows the relationship between total unmet driving hours and these three inputs. We expect unmet driving hours to be rare in practice, which can mean that the combinations of these inputs in ResStock may not always reflect reality. For example, there are no dependencies on the VMT input, but it may not be likely that someone with high annual miles also has a level-1 charger or charges primarily at home. A possible improvement would be to further refine these inputs to reduce the prevalence of unmet driving hours. Beyond these three parameters, unmet driving hours will further increase if the EV has low efficiency, if the driver has limited at-home charging opportunities, or if the vehicle is operated in cold weather.

Section 3.4 shows that the two highest VMT saturations are not common within the baseline stock of ResStock and that an even smaller fraction will have level-1 chargers and a high charge-at-home percentage. However, because these segments show a high level of unmet driving hours, the VMT definition has been revised since this analysis to better reflect EV-specific driving behavior rather than of all vehicle types. Of the 5,777 dwellings with EVs that are modeled in the baseline, an estimated 597.3 megawatt-hours of charging energy is not realized due to unmet driving hours, which is ~4.1% of the total EV charging across the entire stock.

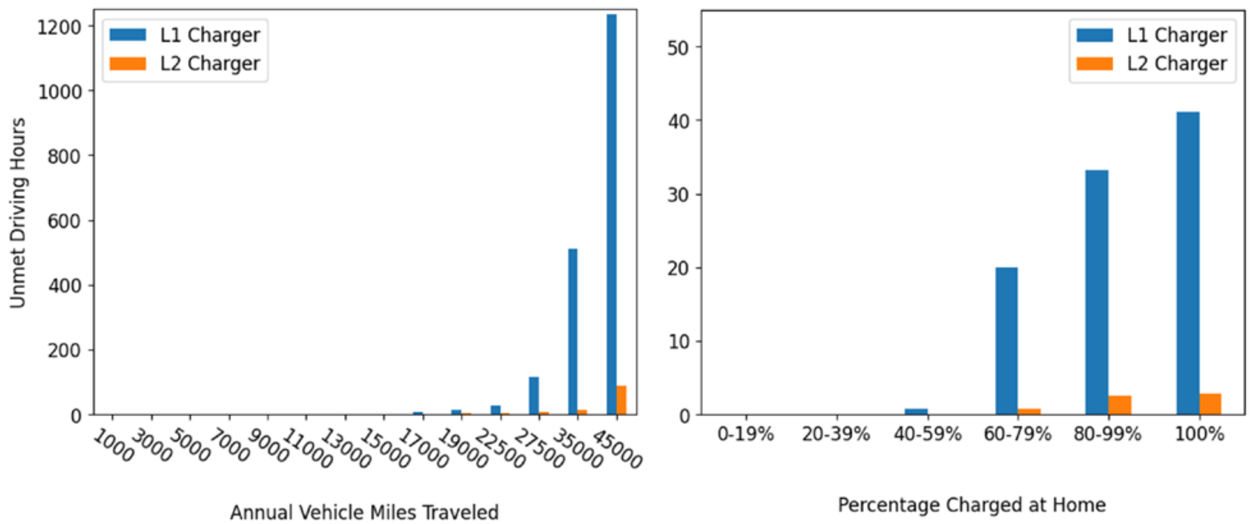

Figure 25. Average unmet driving hours for level-1 (L1) and level-2 (L2) charger types by VMT (left) and percentage charged at home (right)

We also explored time-dependent outputs of the EV charging energy. Each household with an EV is assigned one of two types of EV charger—level 1 or level 2. We specify a power draw of 1.6 kW for EV owners with level-1 chargers and 5.69 kW for those with level-2 chargers, determined using the EV-WATTS dataset (Pavuluri 2024), which includes characterization of EV supply equipment in the U.S. from 2019 through 2022. Because there is no other factor influencing charging power outside of this input, an initial check confirmed that the peak charging power for each household aligned exactly with the inputs of their respective charger type.

Figure 26 shows the average peak charging consumption for each building type. These data are driven by the proportions of level-1 and level-2 chargers that are present in building types—higher average peak charging consumption correlates with a larger portion of level-2 chargers in the sample of dwellings. Single-family detached homes have the largest share of level-2 chargers, at nearly 50% of homes that own EVs, whereas multi-family and single-family attached homes range from 29%–36% level-2 chargers. Although it is a small sample size, 40% of mobile homes with EVs have level-2 chargers. The peak charging values are bound by the charging power of level-1 and level-2 chargers—1.6 kW and 5.69 kW, respectively.

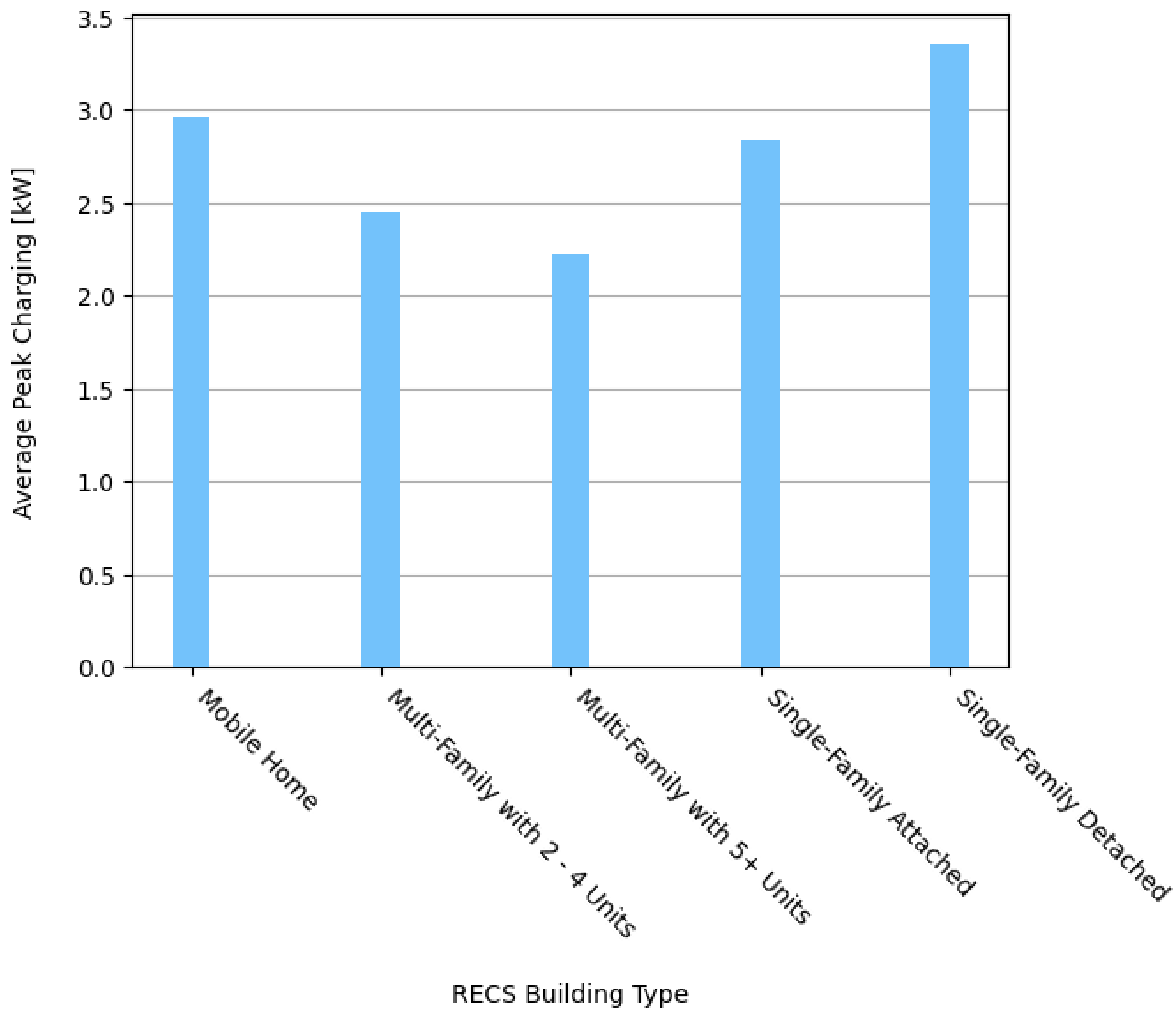

Figure 26. Average peak charging for each building type

Finally, we examined the aggregate time series energy usage for all EVs modeled. Figure 27 shows the shape of the curves for the average charging consumption in a day for different charger types. EV charging or, more precisely, the plugged-in schedule is generated using the stochastic occupancy schedules developed using the ATUS data. Most occupants plug in their vehicle in the evening and only unplug before their commute in the morning, and no managed charging is assumed. However, charging mostly completes overnight, resulting in an evening peak and no morning peak. The charger level plays an important role in the EV charging load shape. Level-2 chargers show a larger and earlier evening peak compared to level-1 chargers because the higher charging power of level-2 chargers enables them to finish charging the battery earlier. As EV adoption grows, understanding these charging patterns will be crucial for predicting and managing the peak grid impacts.

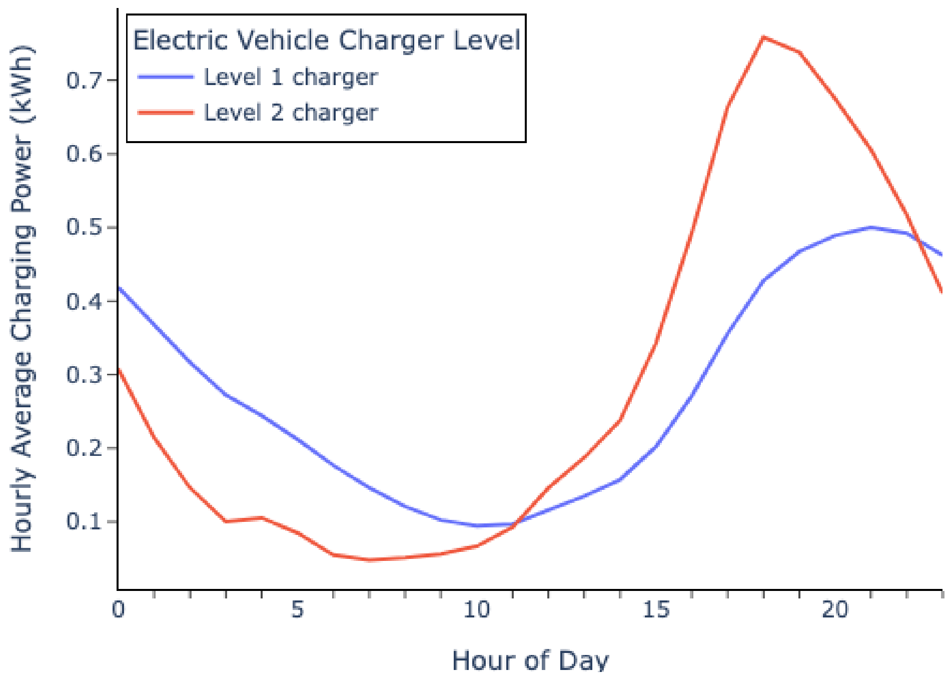

Figure 27. National average charging energy consumption

kWh = kilowatt-hour

6.2 Baseline Comparison to External Datasets

We performed a comparison of the baseline ResStock results to data from 2020 RECS, 2022 NHTS, EIA, and TEMPO results. One source of possible discrepancy between ResStock and TEMPO is the differences in the underlying schedule data, which are derived from the ATUS and NHTS, respectively. Figure 28 shows the national average charging and discharging schedules for EVs modeled in ResStock compared to the percentage of vehicles at home at any given time of the day in the NHTS. The shape of the charging schedule curve matches that of the EV-at-home curve from the NHTS relatively well, which indicates that, on the aggregate, NHTS schedules align with the occupancy profiles in ResStock, from which the charging schedules are sourced. Note that the charging schedule in Figure 28 captures only when the EV is "eligible" to charge or when it is plugged in. Charging does not always happen when the vehicle is plugged in—it will usually taper off at the end or stop altogether after the battery is fully charged, as indicated in Figure 27Figure 27. Differences between the ResStock charging schedule and NHTS data are primarily driven by misalignment between ATUS occupancy and NHTS vehicle location. We assume that a vehicle can be plugged in only when the driver is present at home, excluding cases where another occupant drives or the driver leaves their home in a different vehicle or use another mode of transportation. In addition to the charging schedule, Figure 28 presents the discharging schedule, which shows two distinctive humps at the morning and evening, reflecting the beginning and end, respectively, of daily commutes.

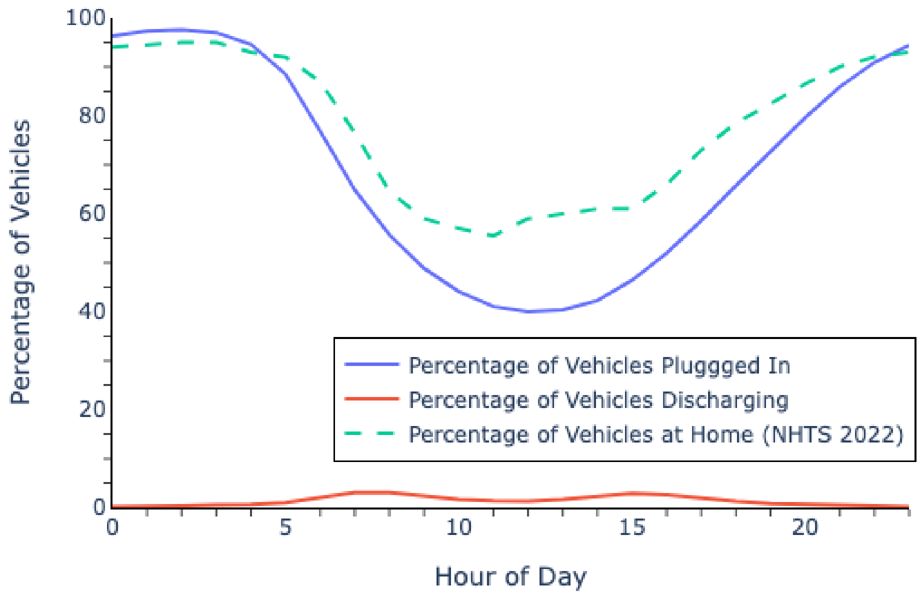

Figure 28. National percentages of ResStock EVs plugged in and discharging, compared to the national average of vehicles at home in the 2022 NHTS

We derived EV ownership rates from a combination of Experian registration data[24] and 2020 RECS data[25]. Experian determines the overall saturation at the county level, whereas the RECS fine-tunes the conditional probability on tenure, FPL, and building type. To validate both the process for joining datasets and the impact of the sampling routine in ResStock, we compared EV saturation levels of a sampled ResStock input file with 550,000 data points to the raw 2020 RECS microdata and the raw Experian registration data EV saturation levels, as shown in Figure 29. In general, the ResStock samples slightly underestimate the saturation level of EVs compared to the 2020 RECS and Experian data. Nationwide, the ownership rate of occupied homes for the 2020 RECS is 1.48%, for Experian is 1.65%, and for the sampled ResStock is 1.21%.

[24] For more information, visit https://www.experian.com/automotive/auto-vehicle-data.
[25] For more information, visit https://www.eia.gov/consumption/residential/data/2020/index.php?view=microdata.

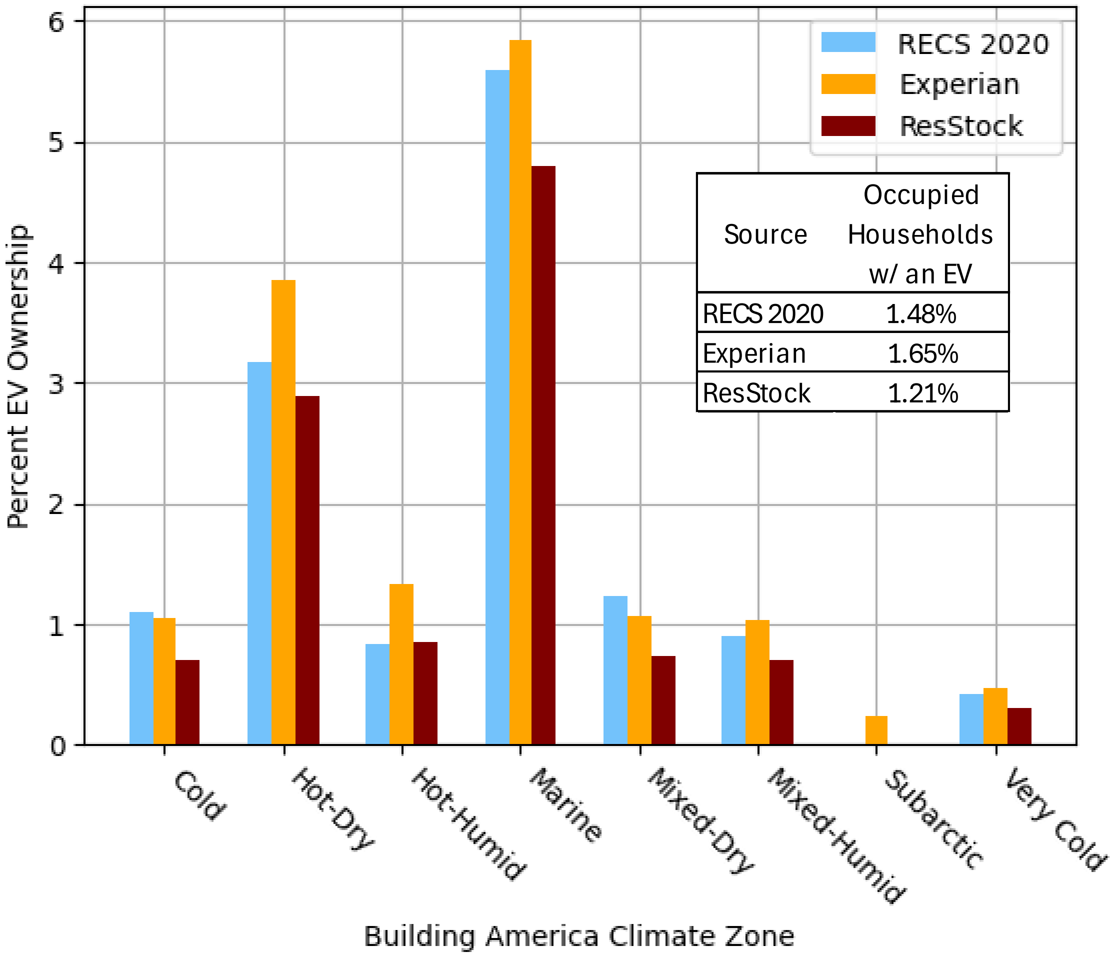

Figure 29. Comparison of EV ownership rates for occupied homes in the 2020 RECS dataset, Experian dataset, and a ResStock sample with 550,000 datapoints

The inset table describes the nationwide saturation level percentiles across occupied homes. Experian data have been uniformly adjusted by the ResStock national occupancy rate to account for only occupied dwellings.

The lower saturation in ResStock compared to Experian is not due to an incorrect probability distribution but is an artifact of quota sampling and relatively low EV penetration. The differences compared to the RECS are similarly influenced by the sampling routine but also the underlying differences between the Experian registration data and RECS survey methods. The probability distribution matches the saturation in the Experian data, as shown in Table 13. Further, although the ownership probabilities differ, the marginal distribution of EV ownership by tenure in Figure 30 shows that tenure correlation from the RECS is captured well.

Table 13. Options Saturation Showing the EV Ownership Percentages of Buildings in the National Stock for the ResStock .tsv Input, Experian, and RECS

EV Ownership	ResStock .tsv input (all units)	Experian (all units)	RECS (all units)	RECS (occupied only)
Yes	0.0145	0.0145	0.0130	0.0148
No	0.9855	0.9855	0.9870	0.9852

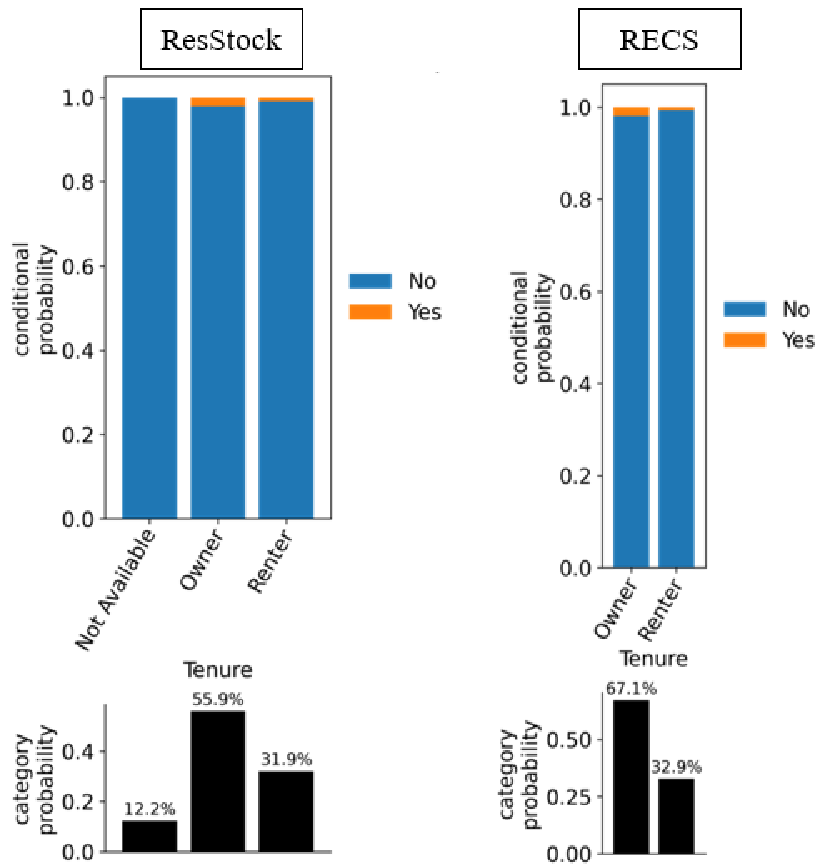

Figure 30. ResStock versus RECS marginal probability distribution comparison based on tenure. "Not Available" indicates vacant units.

Note that the RECS has only occupied units; hence, for unoccupied units, we assume that no EV is present, which slightly reduces our overall saturation compared to the RECS.

The reason the saturation in the sampled ResStock data is lower than the options saturation in the input file is that EV ownership has many dependencies—income, building type, PUMA, and tenure. These dependencies divide the national stock into 246,855 slices, some of which are very small. The EV saturation is quite small to begin with, so many of these slices end up getting assigned less than 1 EV (0.1 EVs, 0.3 EVs, etc.), which all get rounded to 0 EV during quota sampling, lowering the overall saturation. Although reducing the number of dependencies and increasing the size of the slices would counteract this problem, we have decided to retain these dependencies to capture important correlations. The discrepancy between the number of EVs modeled and the actual number of EVs can always be corrected through scaling in postprocessing, but capturing correlation is not possible in that fashion.

Finally, we compared baseline ResStock EV charging energy to modeled TEMPO and EIA annual charging energy. Table 14 shows comparisons of total and average charging energy for each of these models, as well as assumed BEV stock and VMTs. EIA does not publish EV stock numbers, and so we assume the same BEV count as TEMPO to calculate the average energy.

There are several underlying differences between ResStock and TEMPO. While TEMPO and EIA estimate all BEV charging, ResStock is limited only to residential charging. Therefore, the ResStock charging energy underestimates the total light-duty EV charging demand compared to the other sources. TEMPO and ResStock use the same vehicle registration data, but the BEV count for ResStock reflects the number modeled after the sampling routine and therefore differs slightly from TEMPO. Finally, ResStock assumes a higher annual VMT than TEMPO. ResStock assumes that the distribution of VMTs is nearly identical to internal combustion engine vehicles. As discussed in Section 3.4 and Section 6.1, this assumption may not match the driving patterns for EV owners and can lead to unrealistic unmet driving hours. As further discussed in the following section, by limiting the maximum VMTs in ResStock, we can better align with TEMPO and reduce the unmet driving demand. We can estimate how this change might influence the comparisons in Table 14. The average at-home charging demand is 2,503.7 kWh in ResStock. Assuming 80% of total charging occurs at home, we can estimate the total EV charging as 3,129.6 kWh per vehicle. If the average VMT were adjusted to align with TEMPO, which is 24.3% lower, total charging demand would likewise decrease by 24.3%, resulting in an estimated average charging energy of 2,367.2 kWh per vehicle. In general, differences in the underlying assumptions between models contribute to variations in their output results.

Table 14. Summary of annual data from the ResStock, TEMPO, and EIA.

Data	**BEV Stock Count**	**Annual Charging Energy (GWh)**	**Annual Charging Energy/EV (kWh)**	**Average VMT (miles)**
ResStock	1,467,358	3,673.8	2,503.7	10,895
TEMPO[a]	1,442,882	3,476.3	2,409.3	8,241
EIA[bc]	1,442,882	3,594.4	2,491.1	-

[a] 2022 baseline data including all battery-electric LDVs and charging energy from at-home and away chargers.

[b] Reporting 2022 estimated light-duty electric vehicle consumption data from the *Monthly Energy Review* (EIA 2025).

[c] EIA does not publish their BEV counts, assuming the same as TEMPO for the “BEV Stock Count”.

7 Conclusions

This report describes the methodology used to introduce data and assumptions from TEMPO into ResStock to model EV charging in line with whole-home building energy models. We have shown how national-scale datasets can be used to generate the necessary parameters for modeling EV charging and discharging and applied to physics-based models of individual residential buildings. An initial stakeholder consultation helped to prioritize elements of the implementation to ensure that users can draw meaningful insights from the resulting datasets and that the model remains extensible for future use cases. From the core findings identified in the stakeholder engagement (Section 2.2), our methodology can help answer questions on energy, cost, and emissions related to the load profile impacts of EVs and forecasting, charging infrastructure and strategies, utility bills and rate design, and home infrastructure. The remaining use cases, i.e., demand response/flexibility and resilience, can be achieved through extension of the battery model implementation, as the controllable elements and the necessary battery physics are already available.

The baseline EV stock characterization step laid the foundation for all downstream modeling inputs by merging datasets to describe the probabilities of EV-related parameters in the United States. This step was central to aligning ResStock with TEMPO's data and assumptions. We ensured that the nationwide distributions for EV ownership and miles traveled aligned with TEMPO, as well as the specific arguments mapped from the "Electric Vehicle Charger" and "Electric Vehicle Battery" input files. Additionally, we detailed the methodology for modeling EV charging at home, using options from the ResStock input files. Key requirements for modeling EV charging included the application of a lithium-ion battery model for EVs and the generation of occupant-driven charging and discharging schedules. By linking EV schedules to occupant behavior, EV loads are matched with home loads, which is particularly valuable for analyzing peak impacts or investigating demand flexibility strategies. Alongside energy, costs, and emissions, we provide additional flexibility in analyzing EV impacts by capturing the potential for unmet driving hours, or times when the vehicle's SoC cannot meet driving demand. Although this scenario is rare in the baseline, the results suggest that there are certain combinations of inputs that result in significant unmet driving hours and are unlikely to reflect reality. Prior to the final publication of the ResStock dataset, the maximum annual vehicle miles inputs will be capped to reduce the occurrence of these input combinations. When analyzing future scenarios, unmet driving hours can be an important metric to understand the trade-offs in demand flexibility or resilience.

Although not described in this report, the baseline capabilities allow modeling scenarios of EV adoption, charging, and driving behavior. More specifically, each EV-related argument we introduced can be adjusted in a ResStock simulation to model, for example, increased adoption of EVs and chargers, different EV efficiency levels, and changes in annual mileage or driving speed. The results of these upgrades can be analyzed along with the existing ResStock features to target specific housing segments or locations, providing a more nuanced look at populations, such as low-income households, specific building types, or climate zones. Further work is planned to expand the modeling options and to apply demand flexibility scenarios.

7.1 Accessing Data

The ResStock simulation data, which reflect baseline EV charging will soon be available in a public dataset release[26]. The dataset will include the baseline EV usage described in this report, as well as scenarios for EV adoption and demand shifting.

7.2 Broader Impacts of This Research

Although the main objective of this research was to integrate the ResStock and TEMPO models, other lasting benefits of this research have been realized. There are two outcomes that will benefit other research in this area and future DOE-funded research projects.

1. **EIA 2020 RECS released EV survey question data:** EIA's RECS is a national survey that collects detailed data on energy use, housing characteristics, and household energy behaviors in U.S. homes. As part of this research, the team leveraged their relationships with EIA and the RECS team to get previously unreleased EV survey responses into the public EIA 2020 RECS data. These new data will help policymakers, businesses, and the public make informed decisions about energy strategies and market forecasts of EVs and their interactions with households in the future.
2. **HPXML includes vehicles in the schema:** HPXML is a standardized data format used to exchange information about the energy performance of residential buildings. It facilitates communication between software tools, energy programs, and contractors by ensuring consistency in how data are shared and interpreted. HPXML is important because it streamlines processes in home energy assessments, improves data accuracy, and supports large-scale energy efficiency initiatives across the housing sector[27]. Adding vehicle characterization into the HPXML schema will benefit research by providing a more comprehensive view of a household's energy consumption, including both home and transportation energy use, whether from EVs or other vehicle types. This integration will enable researchers to better analyze the total energy footprint of households, helping identify more effective energy efficiency strategies. Additionally, it could improve policy development by aligning residential and transportation energy efficiency programs, offering more holistic solutions for energy conservation.

[26] Anticipated September 2025, data is hosted at https://data.openei.org/submissions/4520
[27] For more information, visit https://www.hpxmlonline.com/overview/

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Appendix A. HPXML Input Schema

HPXML schema diagrams for the *Vehicle* and *VehicleBattery* elements. The latest HPXML vehicle input information can be found at https://openstudio-hpxml.readthedocs.io/en/latest/workflow_inputs.html#hpxml-vehicles.

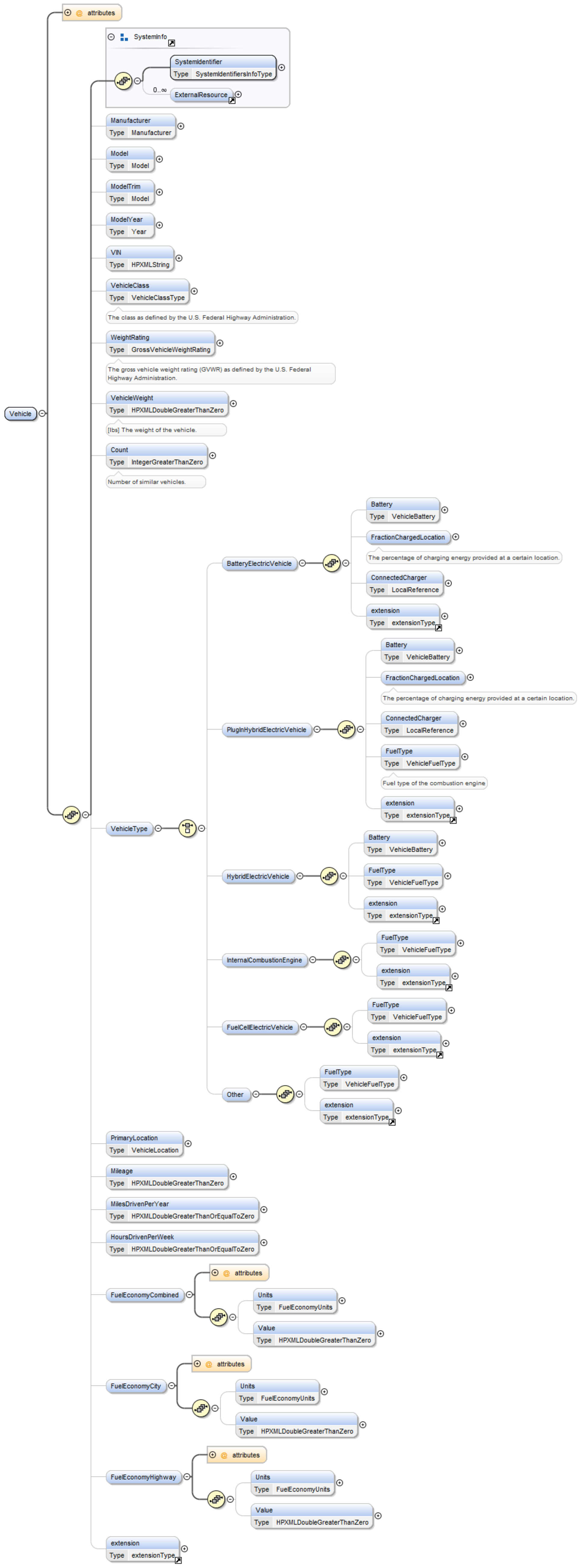

Figure A-1. A graphical representation of the *Vehicle* element developed in the HPXML schema

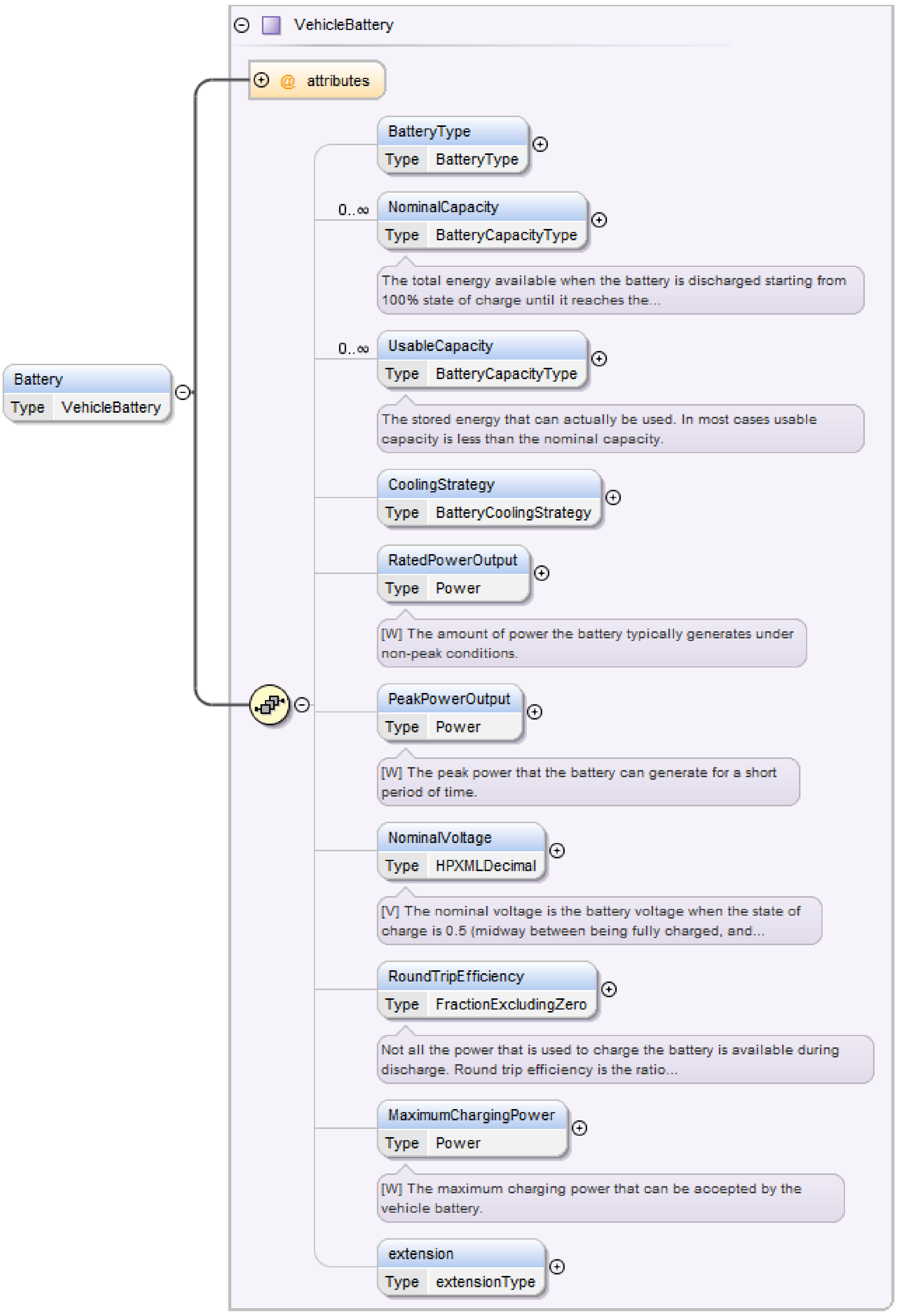

Figure A-2. A graphical representation of the *VehicleBattery* element developed for the HPXML schema, which applies to BEVs, plug-in hybrid EVs, and hybrid EVs