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ResStock Measure Documentation: Electric Vehicle Adoption With Level 2 Charging

Philip White, Andrew Speake, Rajendra Adhikari, and Anthony Fontanini

National Laboratory of the Rockies

The National Laboratory of the Rockies is a national laboratory of the U.S. Department of Energy, Office of Critical Minerals and Energy Innovation, operated under Contract No. DE-AC36-08GO28308.

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May 2026

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Executive Summary

This report documents the development and simulation of the Electric Vehicle (EV) Adoption with Level 2 (L2) Charging measure within ResStock™. ResStock is a physics-based, bottom-up modeling tool designed to represent the diversity of the U.S. housing stock and estimate building energy use and bills for scenarios at both regional and national scales.

The EV Adoption with L2 Charging measure adds one EV and one L2 charger to every occupied dwelling unit. This approach models a future scenario to capture the effects of widespread EV adoption and L2 charging on the residential energy sector. Results show that full adoption increases national residential site energy use by approximately 7.2%, driven entirely by additional EV charging demand. The broad applicability of the measure allows users to combine results with the baseline and other EV scenarios to simulate different levels of adoption and participation. These custom scenarios can be designed to model EV technology penetration and behavior, and leverage ResStock granularity to construct adoption scenarios based on housing attributes or occupant demographics.

This measure provides a method for analyzing the interactions between residential energy demand and transportation electrification. By aligning charging behavior with other occupant-driven loads, users can evaluate strategies to balance household energy needs with grid reliability. The results highlight the growing influence of EV adoption on residential energy consumption and the importance of planning for increased electricity demand as the transportation sector electrifies. As EV adoption expands and charging technologies advance, this work supports data-driven decisions that promote a more efficient, resilient, and affordable energy future.

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List of Acronyms

EV	electric vehicle
FPL	federal poverty level
HVAC	heating, ventilating, and air conditioning
L1	level 1
L2	level 2
RECS	Residential Energy Consumption Survey
SOC	state of charge
VMT	vehicle miles traveled

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1 Introduction

Accessing Results

This documentation covers the "Electric Vehicle (EV) Adoption With Level 2 (L2) Charging" measure methodology and briefly discusses key results from a national-scale ResStock™ simulation. All results can be accessed on the ResStock Open Energy Data Initiative End-Use Load Profiles for the U.S. Building Stock Data Lake and on the data viewer at resstock.nlr.gov.

Measure Summary

Measure Title	EV Adoption With L2 Charging
Measure Definition	This measure adds one EV to each occupied dwelling unit. With each EV, an L2 charger is also added.
Applicability	This measure applies to all occupied dwelling units.
Not Applicable	This measure does not apply to vacant units.

Measure Motivation

Utilities, auto manufacturers, charging providers, and EV supply equipment manufacturers are working together to develop technologies (such as smart chargers) and services (such as time-of use 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. Without such coordination, increases in peak demand may require costly grid upgrades, increase electricity prices, and increase the risk of outages or degraded service.

This ResStock™ (Reyna et al. 2025) measure assigns one EV and an L2 charger to each occupied dwelling unit model in the baseline scenario. All existing units with level 1 (L1) chargers are upgraded to L2. By modeling widespread adoption of EVs and chargers, ResStock users can combine models from both the baseline and the measure to create their own unique EV saturation scenarios. This allows nuanced scenarios in which only segments of households adopt EVs or shift their charging load. Such a method can be used to model EV and charger adoption scenarios and examine the resulting energy and power impacts on the residential building sector. The simultaneous charging of EVs at multiple dwelling units in this measure can also quantify the potential stress that a local electric grid may incur during peak charging hours.

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2 Technology Summary

2.1 Introduction to Electric Vehicles in ResStock

EVs are an increasingly important component of residential energy demand, with charging behavior often correlated with other household loads due to shared occupancy and behavioral patterns. The current ResStock baseline reflects 2023 EV saturation levels, which corresponds to a small number of representative dwelling unit models with EVs (1.05% of all datapoints). For each EV-owning dwelling unit, ResStock assigns specific vehicle properties, driving behavior, and charging behavior dependent on location, demographics (income and tenure), or occupancy – factors that also influence other household load profiles. While the baseline includes a limited number of EVs, ResStock's EV measures enable scenario analysis of future adoption and charging patterns.

This measure comprises two components: adoption of an EV and adoption of an L2 charger. EV charging power in ResStock depends on the vehicle charger type, while EV charging demand depends on characteristics of the EV and driver behavior. When an EV is assigned to a dwelling unit in ResStock, the characteristics of the vehicle, driving behavior, and charging behavior are predetermined in the sampling routine, using distributions sourced from the 2020 Residential Energy Consumption Survey (RECS) and other datasets (Speake et al. 2025).

ResStock leverages physics-based modeling, where high-level EV and driving behavior ResStock inputs are translated to EnergyPlus inputs to model the charging energy demand of an individual dwelling unit, as shown in Figure 1. The ResStock baseline is consistent with EV saturations from 2023, which corresponds to a small number of representative models with EVs. The ResStock EV characteristics that inform the energy model and influence the charging energy demand include the (1) EV battery/vehicle type, (2) annual vehicle miles traveled (VMT), and (3) at-home charging fraction. The battery/vehicle type determines EV efficiency and battery capacity, while VMT influences the time spent driving, which in turn determines charging demand. The at-home charging fraction describes the share of the vehicle's electricity demand met by the residential charger. These inputs are assigned to all households in the ResStock baseline regardless of whether the EV is modeled. The charger type is not predetermined for all dwelling units and is instead explicitly defined in a measure. The EV charger power is assumed constant; however, the timing and duration of charging events are highly variable across models due to varying vehicle parameters, driving behaviors, and occupancy patterns. The underlying EV model accounts for charging and discharging losses by scaling the driving power with ambient temperature.

Figure 1. Steps to transform ResStock inputs into final building energy models

OS = OpenStudio

Baseline EV charging availability schedules indicate when a vehicle is plugged in and available to charge. These schedules are determined by the dwelling unit's occupancy schedule, whereas the periods of active charging are dependent on the availability schedule and the EV's state of

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charge (SOC). EV charging availability schedules in ResStock are generated stochastically based on the presence of an individual occupant assigned as the driver. During an "away period" for the driver, the vehicle is assumed to be driven immediately after the occupant leaves and just before they return home. While the baseline charging availability schedule is dependent only upon the driver's occupancy status, the duration and magnitude of charging energy depend on the VMT, the charger power, vehicle properties, and fraction charged at home, as discussed further in Section 4.1. The driving schedules are dependent on stochastic occupant behavior, but do not explicitly capture seasonal variations in travel.

More detailed information regarding baseline EV modeling and scheduling in ResStock can be found in Speake et al. (2025), which provides further details on EV stock characterization, model input generation, battery modeling, and analysis of baseline results.

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3 Applicability

The “EV Adoption With Level 2 Charging” measure applies to all occupied dwelling units without an L2 charger in the baseline scenario. This logic corresponds to 87.9% of the existing housing stock. Units with existing EVs are upgraded to an L2 charger, if applicable, but all driving behavior remains the same. Only a single EV is adopted per dwelling unit, as modeling multiple vehicles is not currently supported. This measure design allows flexibility when analyzing scenarios of adoption. For example, a user can select a percentage of a specific segment to adopt this measure while using the results from the baseline simulation for the remaining models. Units in multi-family buildings are included in the measure. Although multi-family households may not own the charging infrastructure or see its impact on their utility bills in practice, we model them consistently with other housing types, treating EV energy as a direct household energy cost. We also assume that multi-family chargers are always available, which may not be true in practice, and therefore the charging event durations may not reflect actual events.

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4 Modeling Approach

4.1 Methodology

To model baseline residential EV charging demand in ResStock, our approach: (1) characterizes regional inputs that affect EV battery parameters, driving behavior, and charger characteristics; (2) assigns these inputs as arguments to individual dwelling unit models; (3) generates occupancy-driven charging and discharging schedules; and (4) simulates building energy models with integrated EVs. We associate each EV with an at-home charger, and report only the charging energy of the dwelling unit, as charging energy away from home is not modeled. No vehicle-to-building energy exchange is considered in ResStock. To apply this measure to the baseline, we repeat Steps 2–4 using updated inputs to assign EV ownership and charger.

More detailed information regarding baseline EV modeling and scheduling in ResStock can be found in Speake et al. (2025), which describes the EV stock characterization, model input generation, battery modeling, and analysis of baseline results.

Electric Vehicle Stock Characterization

Included in the baseline ResStock inputs are probability distributions that describe the likelihood of EV-related attributes being assigned to dwelling units. These EV-related inputs are part of ResStock's broader stock characterization process, which defines detailed building, occupant, and technology characteristics for the U.S. residential building stock (see Section 3 Reyna et al. [2025] for more detail). EV input distributions are sampled to produce EV ownership profiles for each building model. The baseline of ResStock assigns each dwelling unit a value for EV ownership, the at-home charging fraction, the vehicle type that provides the battery capacity and efficiency, and the VMT per year. If a dwelling unit has an EV, an EV charger is applied, and its power draw is determined based on the charger level. Plug-in hybrid electric vehicles are not currently modeled in ResStock.

The ResStock EV implementation draws data from the TEMPO™ model (Muratori et al. 2021), EIA RECS 2020 (U.S. EIA 2020), the National Household Travel Survey (Federal Highway Administration 2022), vehicle registration data from Experian[1], the No Place Like Home study (Ge et al. 2021), and the Autonomie model[2]. The distributions of these options reflect 2023 saturation levels of EV technology and operation in the United States, ensuring that EV-related measures capture expected diversity[3]. All dwelling units are sampled with percentage of vehicle charge at home, a vehicle type, and a VMT. These options are only relevant in the baseline for dwelling units with an EV but are used to define vehicle and driving characteristics for dwelling units that adopt an EV in this measure. Table 1 describes the ResStock characteristics, or dependencies, that influence the distribution of EV-related options. The dependencies shown directly influence the EV inputs, but the dependencies themselves also have upstream inputs, which have an indirect influence on EV characteristics.

[1] For more information, visit https://www.experian.com/automotive/auto-vehicle-data.
[2] For more information, visit https://www.anl.gov/taps/autonomie-vehicle-system-simulation-tool.
[3] More information can be found in Section 3 of Speake et al. (2025)

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Table 1. Baseline EV ResStock Input Distribution Files and the Dependencies That Inform Option Distributions

ResStock Input File	Dependencies
Electric Vehicle Ownership	Public Use Microdata Area, federal poverty level (FPL), building type, tenure
Electric Vehicle Charger	EV ownership, FPL, building type, tenure
Electric Vehicle Battery	None
Annual Miles Driven	None
Home Charging Fraction	FPL, building type

Upstream dependencies are important for accurately reflecting the probabilities of EV ownership and operation across households. Figure 2 illustrates how these dependencies shape the baseline distributions for "EV Ownership," highlighting the significant variation that can occur across regions, housing characteristics, and demographics. California has a relatively high rate of EV adoption and diversity in housing characteristics and demographics, which makes underlying trends easier to observe and interpret. We see a strong correlation between higher EV ownership rates and urban areas, home ownership, and single-family detached housing.

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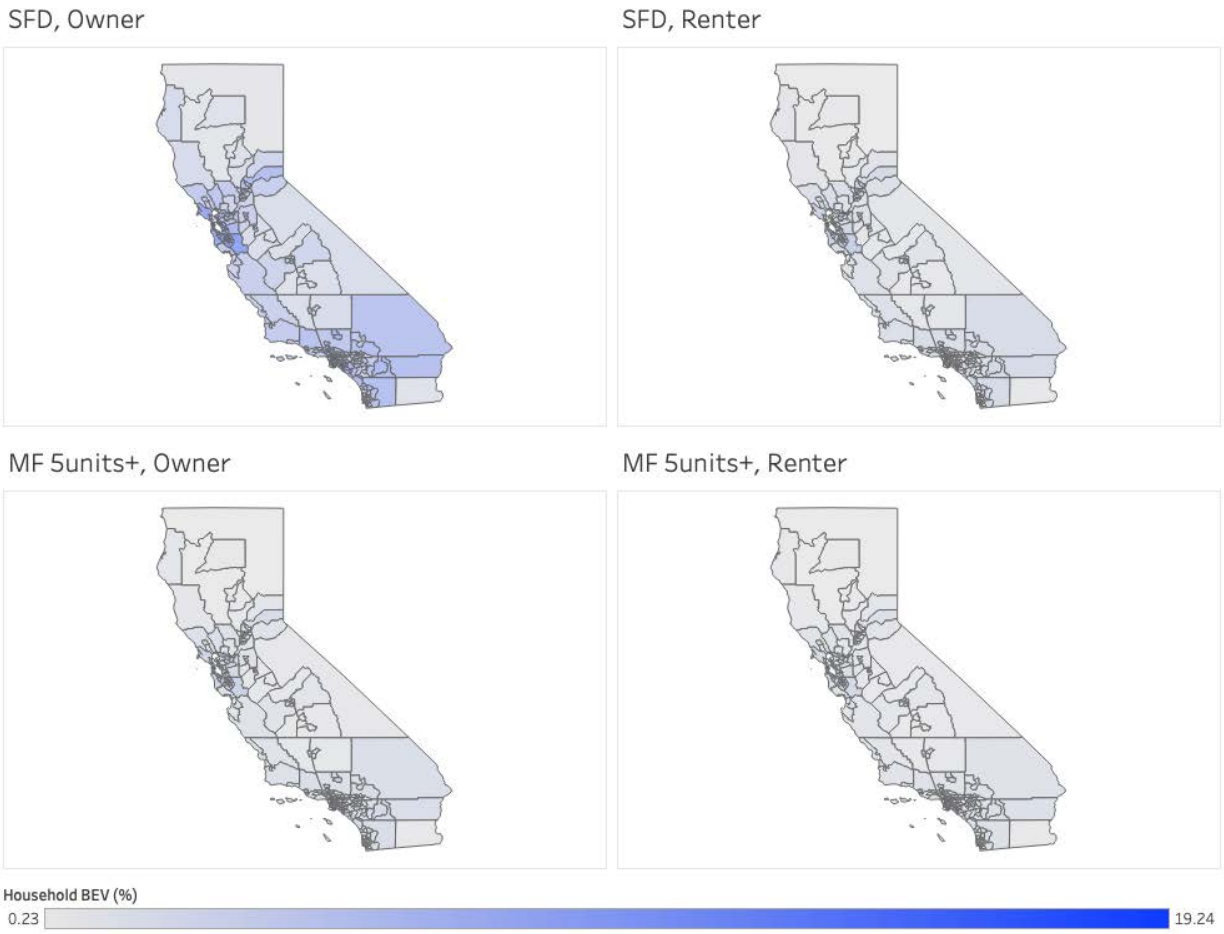

Figure 2. The percentage of EV ownership among households at the 400% FPL for different building types and tenures. Maps are disaggregated by Public Use Microdata Areas in California.

SFD = single-family detached; MF 5units+ = multi-family 5+ units; BEV = battery electric vehicle

Model Input Assignment

We synthesize data from the external sources to characterize EV ownership, driving behavior, and charging behavior in ResStock, which ultimately influences the at-home charging energy as described in Sections 3 and 4 of Speake et al. (2025). Table 2 summarizes the ResStock input files used to characterize EV energy use and driving behavior. The ResStock input files are distributions of parameters assigned in the baseline simulation but also represent parameters that can be adjusted in a measure. ResStock leverages the OpenStudio-HPXML workflow to model individual dwelling units as OpenStudio® models, with each ResStock option assigned one or more arguments in OpenStudio-HPXML to directly inform the energy model inputs.

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Table 2. Mapping of ResStock Input Files to ResStock and OpenStudio-HPXML Arguments[4]

ResStock Input File	ResStock Arguments	OpenStudio-HPXML Arguments	Description
Electric Vehicle Ownership	Yes, No	*ev_present* [bool]	Turns on/off the battery EV model.
Electric Vehicle Charger	L1, L2, None	*ev_charger_present* [bool] *ev_charger_power* (watts, or W) [float]	Describes presence and charging power of the EV charger.
Electric Vehicle Battery	Compact, Midsize, Pickup, and SUV with 200- and 300-mile ranges	*ev_battery_usable_capacity* (kilowatt-hours, or kWh) [float] *ev_energy_efficiency* (kWh/mile) [float] *ev_average_mph* (miles per hour, or mph) [float]	Physical description of the battery that ultimately informs charging demand; average speed used to calculate hours driven.
Annual Miles Driven	14 values ranging from 1,000 to 22,500 miles	*ev_miles_per_year* [integer] *ev_hours_per_week* [float] (calculated internally from *ev_miles_per_year* using an assumed default average speed)	Total miles driven per year; an assumed default average speed is used to calculate *ev_hours_per_week*, which informs the hourly driving schedules.
Home Charging Fraction	6 bins, 0-19%, 20-39%, 40-59%, 60-79%, 80-99%, 100%	*ev_fraction_charged_home* [float]	Describes what fraction of energy is provided by an at-home charger; informs the effective annual miles traveled for the generation of schedules.

Vehicle Schedules

We generate two EV schedules as inputs to the vehicle battery model, (1) a charging availability schedule, which indicates when a vehicle is plugged in and available to charge, and (2) a driving schedule, during which the EV battery is discharging energy. Both schedules are derived from the dwelling unit's occupancy schedule, and the driving schedule also depends on the assigned *ev_hours_per_week* argument. The durations of charging energy events are dependent on the charging availability schedule and the SOC. Figure 3 shows a snapshot of relevant schedules for a single EV driver. The schedules values represent the fraction of each 15-minute timestep during which the event occurs, and values less than one correspond to events shorter than 15 minutes.

[4] See Section 3 of Speake et al. (2025) for more detailed information on EV stock characterization in ResStock

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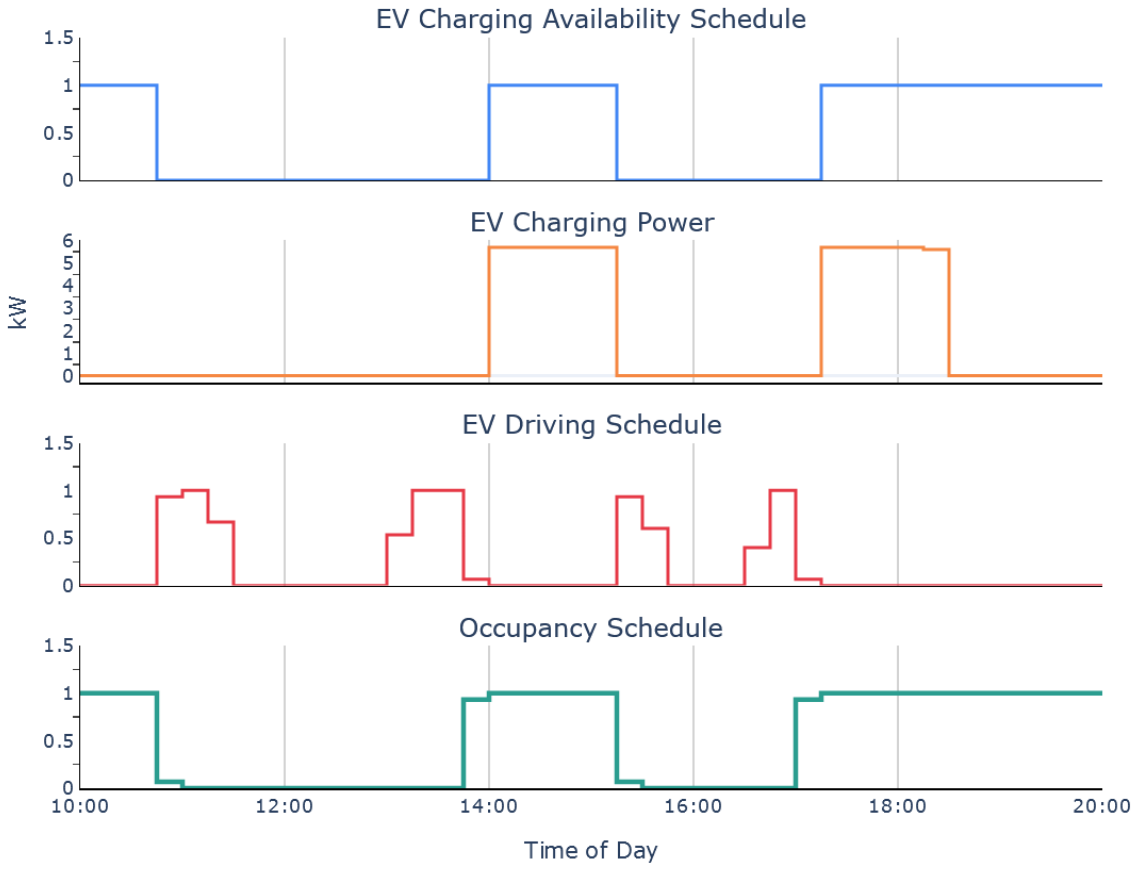

Figure 3. Illustration of a ResStock EV plugged-in schedule, charging power, driving schedule, and driver occupancy schedule

The durations of driving periods scale with the occupant's weekly driving hours and are proportionally adjusted with the duration of the away period. On average, higher-mileage drivers have shorter away periods in which they are not driving. We assume a constant driving speed but scale the discharge power based on the ambient temperature, as discussed in the following subsection. The charging schedule is similarly based on occupancy, where the baseline behavior assumes that the vehicle is plugged in when the occupant arrives home. In the figure, the charging availability schedule overlaps the occupancy schedule except for the time step where occupancy is partial (between 0 and 1). A partial occupancy time step, in which the occupant is home for only part of the 15-minute time step, would ideally reflect both charging and discharging. However, ResStock models these events entirely as discharging, as the underlying EnergyPlus® battery model can only be charged or discharged in a time step. This limitation may cut short or delay charging by up to 15 minutes; however, that is preferable to underestimating discharging, where events are shorter and changes in the duration would have a much larger impact on the total discharge energy—and, consequently, the charging energy.

The charging availability schedule shown in the figure indicates when the vehicle is plugged in and eligible to be charged, whereas the actual charging, i.e., energy consumption, is handled by the battery model. Once charging begins, the only parameters that influence the timing and the magnitude of energy use are the charger power and the battery SOC. When charging availability schedule has a value of 1, the EV will charge at a constant power (5.69 kilowatts [Pavuluri 2024]

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for L2 charger) until the maximum SOC is reached, at which point no further charging load occurs, regardless of the schedule. The behavior can be observed in Figure 3 prior to 10:30 and after 18:30 where charging power consumption remains zero despite charging availability schedule being 1. It can also be seen that the charging power remains constant at 5.69 kW when the vehicle is being charged – the slight depression during the second event where the charging power is below 5.69 kW is because in the underlying model charging doesn't occur for the full 15 minutes before charging stops after reaching the maximum SOC.

Electric Vehicle Modeling

The charging availability and driving schedules are aligned with the stochastic occupancy model (based on American Time Use Survey data) in OpenStudio-HPXML. We calculate the total hours driven per week using the *ev_average_mph* (calculated from Federal Highway Administration [2022]) and *ev_miles_per_year* arguments from the "Electric Vehicle Battery" and "Annual Miles Driven" input files, respectively, which inform the charging and discharging schedule generation. The battery model takes care of the actual power draw during the charging and discharging periods. An example of what these schedules look like is presented in Figure 3. The charging schedule algorithm assumes that the occupant plugs in their vehicle as soon as they arrive home and keeps it plugged in until they leave. Thus, the charging availability schedule is identical to the occupancy schedule of the driver, but the schedule of actual charging typically differs. This scenario makes the battery eligible to be charged anytime the EV is at home if the SOC is below the maximum level. Whether the charging happens and at what power level is managed by the battery and charger modeling. Additionally, not all EV owners are modeled as charging exclusively at home. The 2020 RECS included a question about what fraction of charging is done at home, with the options being 100%, 80% to 99%, 60% to 79%, etc., which was translated to a ResStock input file and sampled to assign the "Home Charging Fraction" input. This input scales the average energy consumption rate of the battery model, ensuring that the resulting charging energy reflects only the portion of charging that occurs at home. The charging power remains fixed regardless of the at-home charging fraction, and only the vehicle discharge power is affected. The underlying assumption in using this approach is that 2020 RECS respondents implement the fraction of their charging in terms of energy, as opposed to time.

EV charging and discharging energy are modeled within OpenStudio-HPXML, which leverages a lithium-ion battery model in EnergyPlus®. The "Electric Vehicle Charger" input directly influences charging power draw, which is assigned a constant value dependent on the charger level. The L2 charger type in this measure has a power draw of 5.69 kilowatts, which reflects the average EV charging power output of a 240-volt outlet. The other ResStock inputs in Table 2 influence the average EV energy consumption rate as well as the duration of driving events, which will reflect in the duration and energy demand of charging events. The "Home Charging Fraction" input adjusts for the actual charging energy provided by the at-home charger, however, we do not directly alter the number charging events but instead scale the average EV energy consumption rate.

The average EV energy consumption rate can be considered the average driving power output under design conditions. For each household, this output is calculated by:

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

Although we do not include all time-dependent variables impacting discharge events, we do incorporate a model that adjusts the average EV energy consumption based on the dwelling unit site ambient temperature at each time step. Ambient temperature plays a large role in EV energy usage, attributed primarily to the climate control systems of the vehicle cabin and battery. We deploy a curve of the discharge power versus ambient temperature[5] in the EnergyPlus Energy Management System[6] to capture the higher energy demand associated with cold-weather operation relative to mild or hot weather.

The "EV Adoption With L2 Charging" measure assigns the "Electric Vehicle Ownership" parameter to "Yes" and the "Electric Vehicle Charger" as "Level 2", while the remaining EV-related inputs are assigned during the baseline sampling routine, as described in this section and detailed further in Speake et al. (2025). This approach preserves both the diversity and the expected dependencies that influence vehicle type and operation.

4.2 Modeling Limitations

The modeled EV charging energy may not always align with the driving demand, as it is constrained by the charging schedule and charger type. Different combinations of EV-related inputs can thus lead to a discrepancy between charging demand and charging availability. This approach can result in reduced charging energy, which is quantified with a custom output variable "unmet driving hours", in which the EV is scheduled to be in use but does not have the required SOC to complete its driving hours. Unmet driving hours are seen in larger proportions in dwelling units with L1 chargers that lack the higher power input of L2 chargers, and charge mostly at home. Section 5 includes figures of the prominence of unmet driving hours in this measure. Unmet driving hours can be an important metric when designing vehicle and charger adoption scenarios. Input combinations with a higher number of unmet driving hours may be less realistic and, as a result, may be given less weight in scenario design.

We assume a direct relationship between home occupancy and driving/charging events, which results in similar daily schedules throughout the year, with distinct patterns for weekdays and weekends. While this simplifies modeling, it may underpredict or overpredict individual charging or discharging events, as real-world behavior is more variable. Similarly, we apply the "fraction charged at home" input directly to the discharging power, reducing charging loads evenly across the year. While this might be realistic for some drivers who split their charging between home and other locations, others may instead scale their number of at-home charging events, where only certain days are used to charge at home. In this case, our approach captures the annual demand but may underestimate the magnitude or duration of individual charging

[5] 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 Motors and secondarily informed by laboratory test results from AAA and Argonne National Laboratory.
[6] More information can be found in BTO (2022).

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events. This simplification may also lead to underestimation or overestimation of unmet driving hours, which in practice depend on alignment between charging locations and at-home hours.

This measure assumes a distribution of energy consumption rates and capacities that align with the current baseline EV stock, as set by the "EV Battery" input. This measure may potentially overpredict the energy demand if EV technology makes advancements in efficiency and capacity over a certain adoption period. This current snapshot of battery efficiency and capacity may also overpredict unmet driving hours compared to future EV technologies with higher efficiencies. Additionally, ResStock limits dwelling units to a single EV, which is reasonable for capturing aggregate trends but may underestimate peak charging power in households with multiple EVs. As EV adoption scales, capturing these dynamics will be increasingly important for accurately modeling demand spikes and infrastructure needs.

The inclusion of multi-family households introduces a modeling simplification. While residents in these units may not have ownership of charging infrastructure or see its impact on their utility bills, this approach treats EV charging as a household load, consistent with other building types.

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5 Results

This section provides an overview of results from the "EV Adoption With L2 Charging" measure package and the baseline scenario. The results are presented to illustrate the measure's performance and ensure confidence in its implementation, not to reflect a realistic scenario on its own. The measure is designed to offer the users flexibility when combined with the baseline or other measures. As such, results presented here should be interpreted with caution.

Although this section presents the energy and unmet driving hour impacts of the measure, the full set of outputs available in the dataset includes annual and time series charging energy, charging emissions, utility bills, and EV schedules. Section 5.1 shows the overall stock energy consumption, Section 5.2 displays the unmet driving hours, and Section 5.3 shows samples of time series data.

5.1 Annual Stock Energy Consumption

Figure 4 presents the distributions of annual ResStock energy usage for the baseline and the measure at the national level. With broad adoption of EVs and L2 chargers (87.9% of the housing stock), the national site energy usage increases by 7.2%, which is entirely driven by increases in EV charging electricity demand. Figure 5 shows annual stock energy consumption by Building America climate zone. Stock energy consumption expectedly increases with the "EV Adoption With L2 Charging" measure package in all climate zones. While EV charging loads are influenced by outdoor temperatures, the effect is much smaller compared to heating, ventilation, and air conditioning (HVAC) loads. As a result, the measure's percentage of change in total energy usage is mostly driven by the proportion of baseline HVAC energy usage, where milder climates will exhibit a higher percentage energy increase from EV adoption. Increases in total consumption range from 5.4% in the "Very Cold" climate zone to 10.6% in the "Hot-Dry" climate zone.

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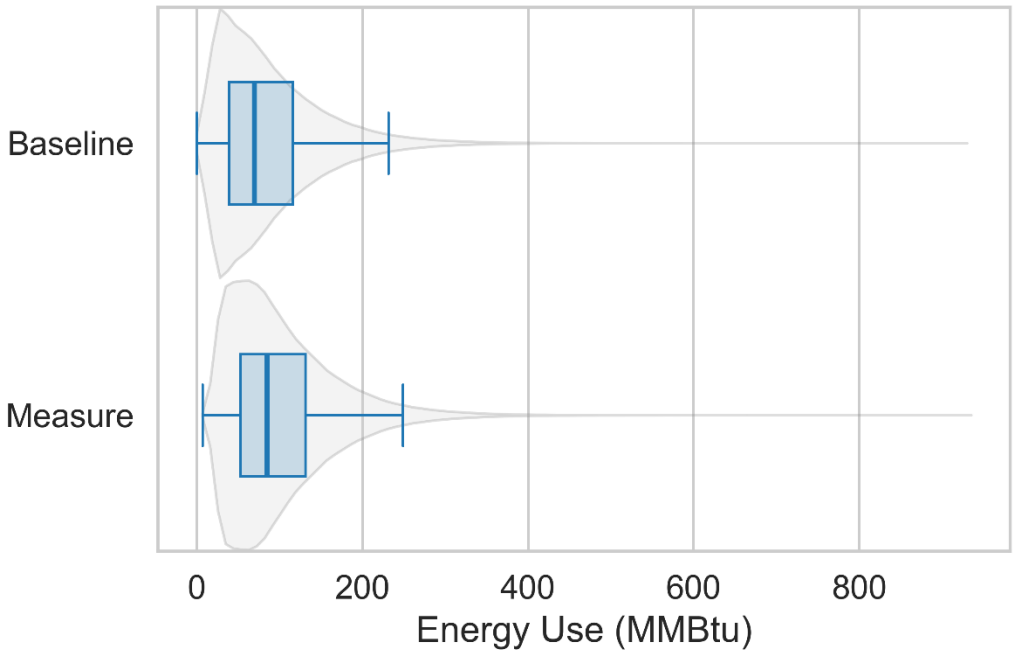

Figure 4. Distributions of total energy consumption the baseline and "EV Adoption With L2 Charging" measure

MMBtu = million British thermal unit

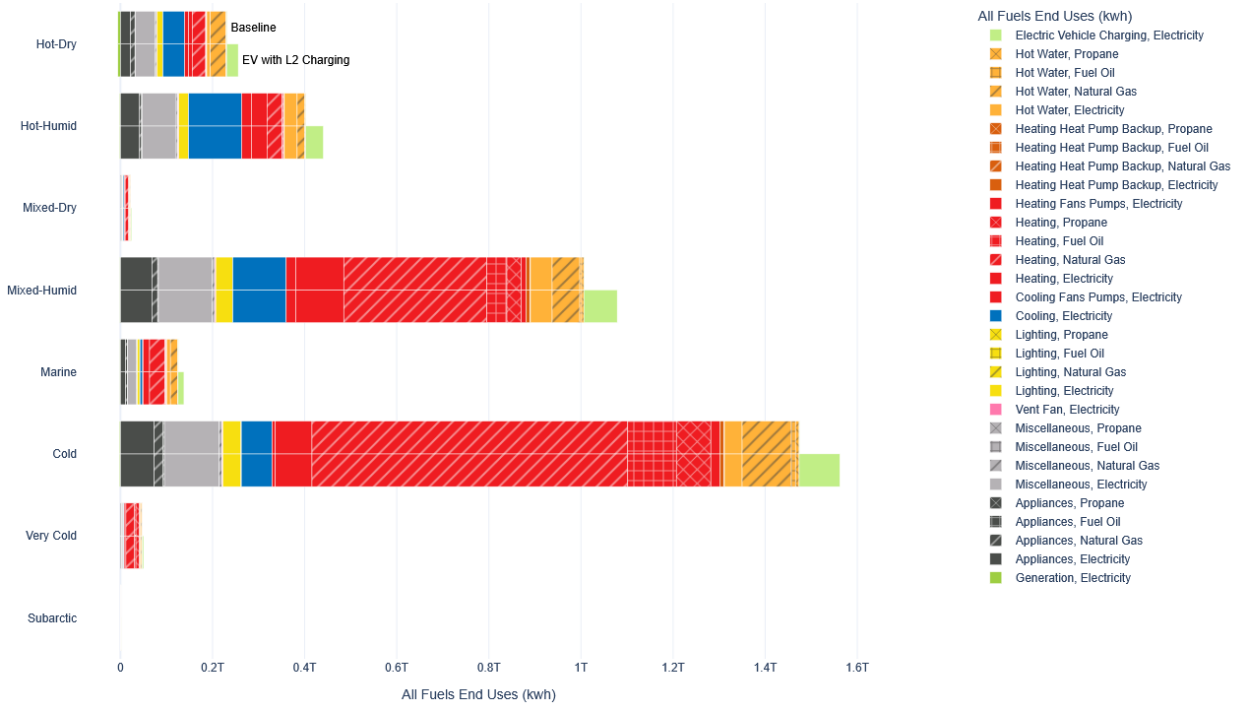

Figure 5. Total energy consumption by end use, separated into Building America climate zones for the baseline scenario and the "EV Adoption With L2 Charging" measure

kwh = kilowatt-hour

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5.2 Average Unmet Driving Hours

Figure 6 displays the average unmet driving hours for each VMT value and percentage charged at home. Unmet driving hours occur when battery charging is not sufficient for the EV's energy demand and are primarily a result of modeling limitations. The most important factors determining unmet driving hours are charger level, VMT, and percent charged at home. Charger level influences the rate of charging possible, while VMT and percent charged at home determine the amount of charging needed. Figure 6 highlights this trend, where only vehicles with high VMT and a high rate of home charging incur unmet driving hours. The decrease in this measure is due to the larger fraction of homes with L2 chargers, which are more likely to meet the vehicle's energy demand compared to L1 chargers. Vehicles with high VMT are relatively uncommon, and most vehicles in the stock experience no unmet driving hours. Across the entire stock, this measure results in an average of 0.35 unmet driving hours, affecting 2.17% of homes.

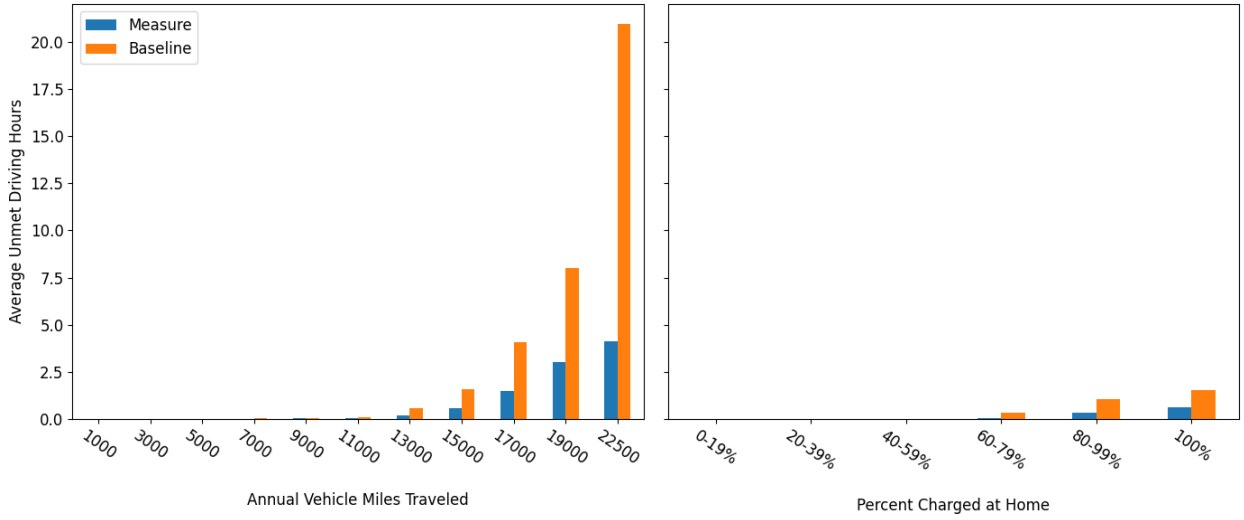

Figure 6. Unmet driving hours per EV per year by the EV characteristics "Annual VMT" and "Percent Charged at Home" for the baseline scenario and the "EV Adoption with L2 Charging" measure. Unmet driving hours occur when battery charging is not sufficient for the EV's energy demand.

5.3 Peak Considerations

Figure 7 shows the electricity demand for the state of Colorado over 3 days in the winter (left) and 3 days in the summer (right). The dashed line is the demand from the baseline scenario. This measure results in new electricity peaks coinciding with the average time an occupant returns home and aligns closely with the timing of the baseline daily peaks in both seasons. Note that this measure is not meant to reflect a realistic scenario on its own. Rather, it is designed to offer the users flexibility when combined with the baseline or other measures. As such, results should be interpreted with caution and not assumed to reflect real-world outcomes.

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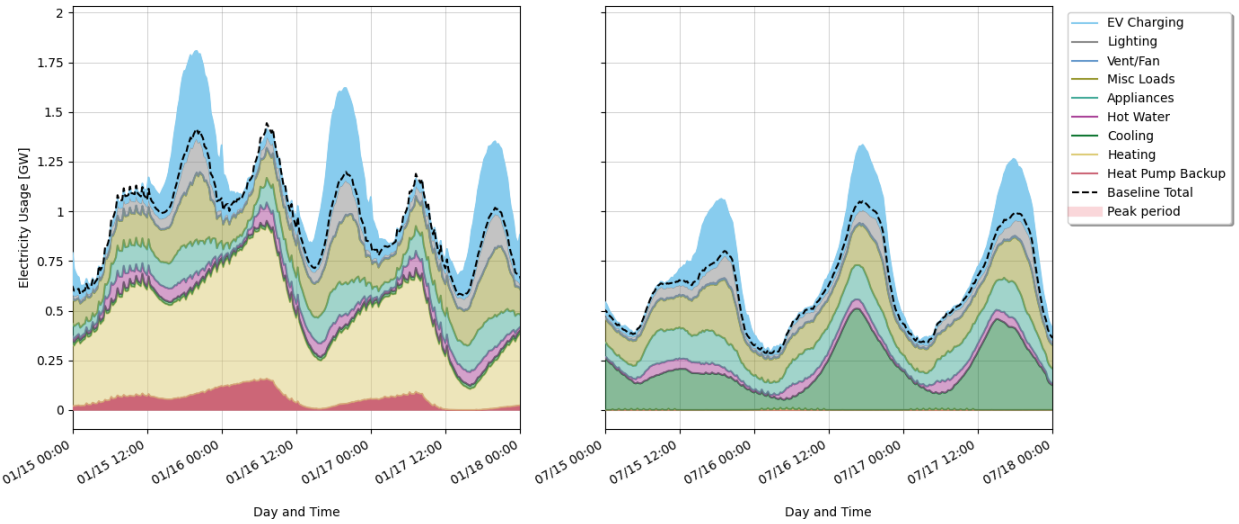

Figure 7. Electricity demand in Colorado for the measure over 3 days in the winter (left) and 3 days in the summer (right).

GW = gigawatt

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