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Characterizing electrical panel capacity, breaker space, and loads in U.S. single-family homes

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1. Introduction

Electrical panels distribute electricity to appliances, equipment, and other building loads and maintain safety by preventing overloads of branch circuits, feeders, and utility service wires connecting homes to the grid. Load calculations in the National Electrical Code (NEC) determine the capacity of installed electrical panels in the United States, which are rated in amps (A) [1,2]. Circuit breakers within electrical panels affect the magnitude and number of loads that panels can serve. In home retrofits and renovations, existing electrical panels may not accommodate new electrical loads, either due to insufficient electrical capacity or a lack of available breaker spaces. Homes with these panel constraints may need to replace existing panels with new panels that have greater capacity and breaker space.

Electrical panel replacements threaten the viability of adding new loads to homes by increasing project costs and extending project timelines [3]. The limited public data on electrical panel replacements suggest that costs commonly reach several thousand U.S. dollars, not including the cost of increasing electrical service from the utility [4,5]. Upgrades to electrical service levels that may accompany panel replacements can add significant additional costs, including the cost of electric distribution system infrastructure upgrades (e.g., a transformer) upstream of a building that enable higher service levels [6]. Service upgrades also can delay building retrofit timelines by weeks to months [4]. Depending on utility cost recovery practices, these costs may fall entirely on the upgrading utility customer or may be recovered (entirely or partially) from other utility customers through electricity bills [6]. Constrained electrical panels that require replacements, therefore, could lead to homeowners delaying or deferring improvements such as the installation of air conditioning equipment, hinder the increasing adoption of air-source heat pumps, and limit the number of homes that can support charging for the growing number of electric vehicles sold in the United States [7,8]. Panel replacements also could put upward pressure on electricity rates if the recovery of service upgrade costs occurs through electricity bills.

Currently, there is no publicly available or peer-reviewed nationwide data on the capacity and available breaker space of existing electrical panels in the United States or other countries. Public data sets that characterize the U.S. housing stock, namely the Residential Energy Consumption Survey, the U.S. Census, the American Housing Survey, and California's Residential Appliance Saturation Survey, do not include information on electrical panels [9–12]. A recent household survey conducted by the Electric Power Research Institute (EPRI) provided national estimates of panel capacity in U.S. residential buildings [13,14]. EPRI found that 27% of single-family detached homes have electrical panels with 100A or less of capacity and 56% have capacity of 151–200A.[1] The EPRI

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[1] In the EPRI report, the panel bin shares do not sum to 100% due to the inclusion of responses that lacked panel capacity values in the calculation of shares. We recalculated the panel bin shares without the null responses such that the sum of shares across the panel bins was 100%.

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study did not provide state-level estimates of panel capacity or breaker space.

Beyond the EPRI study, other sources of panel capacity data for the U.S. housing stock are state-specific studies that have small sample sizes, do not relate panel capacity or breaker space to multiple building characteristics, and are largely not peer-reviewed. Pecan Street reported panel capacity by building vintage and floor area for 263 homes, most of which are in Austin, Texas [15]. They found that 59% of panels are less than 200A and that panel capacity positively correlates with building area. A survey of single-family buildings in Massachusetts reported that about half of respondents have 100A panels and about half have 200A panels [16]. The only peer-reviewed paper on panel capacity that we found in the literature, Fournier et al., 2024, estimated that 39% and 32% of California single-family homes have 200A and 100A panels, respectively, and that 24% and 59% of California multifamily homes have 90A and 60A panels, respectively [17]. The authors also estimated that homes in disadvantaged communities had smaller panels than homes in non-disadvantaged communities.

A number of small non-peer-reviewed studies also have addressed panel capacity in California homes. An analysis of Home Energy Score data in California's San Francisco Bay Area indicated that the majority of panels are between 100A and 200A [18]. A study by the California Public Utilities Commission (CPUC) found that 53% of 395 single-family homes have 200A panels and that 21% and 46% of the 160 surveyed multifamily units have 100A and 125A panels, respectively [19]. Additional data on panel capacity in California multifamily dwellings and manufactured homes come from market characterization studies sponsored by the state's investor-owned electric utilities [20,21].

We identified one public study that characterized limitations in panel breaker space: a non-peer-reviewed survey commissioned by the CPUC. The survey found that 30% of panels in the studied California single-family homes have zero breaker space and 40% have five or more open slots. For multifamily dwellings, these values are 36% and 32%, respectively [19].

We also did not identify any peer-reviewed study in the literature that estimates the electrical loads served by existing panels across U.S. single-family homes. Two conference papers estimate building load using NEC load calculations. Quinn et al., 2024 uses section 220.83 of the NEC to estimate the panel capacity needed under a set of building upgrade packages on buildings in the Residential Energy Consumption Survey but does not provide estimates of existing load and remaining load [14]. Golino et al., 2024 uses both NEC sections relevant to residential single-family building retrofits, 220.83 and 220.87, to estimate existing load in 159 surveyed homes in Massachusetts [22]. Pergantis et al., 2025 measures the current draw from installed electrical equipment on the electrical panel in a test home during a field study of a control system that maintains current within an existing panel's rating [23].

In this paper, we estimate nationwide electrical panel capacity, breaker space, and existing loads in U.S. residential homes. We collected and standardized field data from multiple sources to develop predictive models of electrical panel capacity and available breaker space (Sections 2.1-2.2). We applied these models to a validated representation of the U.S. housing stock, ResStock™, to provide more detailed and geographically granular estimates of panel capacity and available breaker space than currently exist in the literature (Section 2.3) [24]. In particular, we estimated panel capacity by state, building floor area, building vintage, and percent of area median income (AMI), and we estimated available breaker space by panel capacity and state (Sections 4.1-4.2).

We then simulated NEC electrical service load calculations (sections 220.83 and 220.87) to estimate existing loads in U.S. single-family homes (Section 3). We compared the difference between the existing panel capacity from the predictive models and the estimated loads in both NEC sections to determine remaining capacity for adding electrical loads nationally, estimates that currently do not exist in the literature (Section 4.3). Taken together, our results provide a comprehensive summary of the state-of-play for electrical service panels in the U.S. single-family housing stock. We discuss the results in the context of the literature and address the limitations of our approach in Section 5.

Our results also address a need for research on the implications of adding new electric loads to buildings raised in the literature [25]. By characterizing existing electrical panels, we enable future research on the costs and grid impacts of adding new loads to single-family U.S. buildings.

Furthermore, the predictive modeling methods we present address the lack of characterizations of electrical panels outside the United States. While we use data from the United States, our predictive modeling approach, which relates panel capacity to building characteristics, could be applied to data from other countries to estimate existing panel capacity and breaker space. This approach may be of interest to European countries that have had recent increases in heat pump sales and, in particular, to Germany, which has policy support for heat pump adoption [26,27]. Our simulation of NEC load calculations also demonstrates an approach that researchers can follow in other countries with electrical code books specific to their locations [28,29].

2. Methods

We developed predictive models of electrical panel capacity and available breaker space based on field data from single-family homes (attached and detached). We applied these predictive models to building stock metadata from the ResStock tool to estimate panel capacity and breaker space for the U.S. single-family building stock. We also implemented NEC load calculations to estimate headroom for additional electrical loads in these buildings. Fig. 1 summarizes the key steps in developing the predictive models and performing the NEC load calculations.

2.1. Predicting existing electrical panel capacity

2.1.1. Panel capacity predictive model training data

We built a dataset of panel ratings and home characteristics from 34,098 homes for predictive model development [30]. Table 1 summarizes the size and vintage of each dataset and lists the key home characteristics and installed equipment used for model

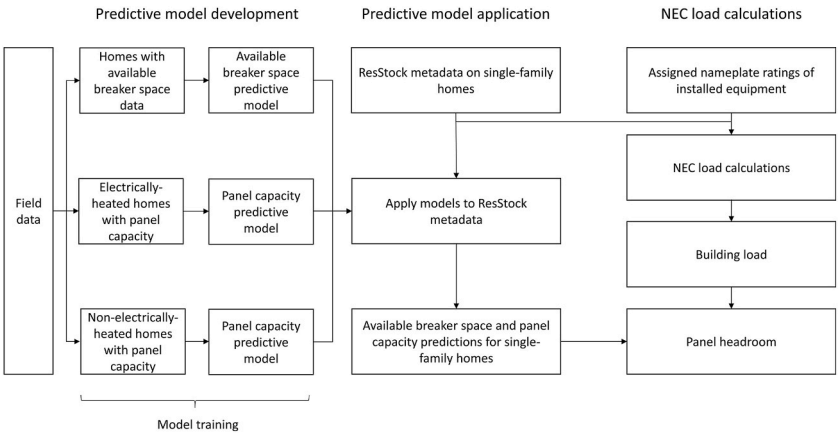


Fig. 1. Process for developing predictive models and NEC load calculations.

development. We standardized categorical field values in our dataset to account for variation in naming conventions across our datasets (e.g., 'heat pump' and 'HP') and binned building years of construction into decadal vintage bins to align with the structure of ResStock data. We screened out 79 homes with panel capacities that we suspected were data entry errors.[2] This screen applied to both the panel capacity and breaker space predictive models.

More than 97% of our observations are from homes in California and Minnesota, two states with very high shares of natural gas space heating. When combined, our datasets had higher levels of natural gas space heating (96% vs. 48%), water heating (90% vs. 47%), cooking (65% vs. 31%), and drying (34% vs. 18%) than national figures reported in the 2020 Residential Energy Consumption Survey [37–39]. Our dataset also included homes with a range of electric appliances, as well as some homes that had equipment with fuel oil and propane as primary fuels. For each end use, we combined natural gas, propane, and fuel oil into a single non-electric primary fuel category due to the relative lack of buildings with propane and fuel oil. This simplification is reasonable because the type of non-electric fuel likely does not affect the panel capacity utilized by each relevant end use.

We binned the reported panel ratings to separate the most common panel capacities observed in the data (100A, 125A, and 200A) from less frequent and more variable capacity values (Fig. 2). The bins are as follows: <100A, 100A, 101–124A, 125A, 126–199A, 200A, and 201+A. Fig. 2 shows the share of homes by panel capacity bin for each dataset and all datasets combined. Across these data sources, 100A and 200A are the most common panel ratings, each accounting for 41% of the homes. We also found a range of panel sizes less than 100A (e.g., 50A and 60A) and in between 100 and 200A (largely 125A, 150A, and 175A). 125A panels were the most common of these intermediary sizes (8% of panels in the data). Panels <100A were the least-common, accounting for 2% of homes in the sample. The low prevalence of these panels likely reflects the study's focus on single-family homes; Fournier et al., 2024's California-focused study finds similar levels of <100A panels in single-family homes (3%) but much higher levels in multifamily homes (93%) [17]. The homes in the field data also covered a wide range of floor areas and vintages (Fig. 2).

2.1.2. Panel capacity predictive model development

We developed machine learning models that predict the probabilities of the electrical panel capacity bins based on the home characteristics in Table 2. We separated model training by primary heating fuel (electric and non-electric) so that our predictions for electrically heated homes were dominated by the greater prevalence of fossil fuel-heated homes in our dataset.

Variation in the size, presence of key variables, and data completeness among the source datasets created a trade-off between sample size and the number of variables included in a model, with more variables leading to smaller sample size. We managed this tradeoff by comparing the performance of models that differed in sample size and the number of training variables. For both the homes with electric heat and those with non-electric heat, we trained nine models (18 total), which were the unique combination of three variable sets in Table 2, two treatments of a binary rooftop photovoltaic (PV) indicator, and two cooling technology variables. The total model count is nine and not 12 (the product of count of variable sets, PV indicator options, and cooling technology variables) because variable set 3 does not include the PV indicator or cooling type. Sample size increased as the number of training variables decreased from variable set 1 to 3. Notably, with variable set 3, we were able to include the large TECH and CEE datasets, increasing the sample size to nearly 30,000 for homes with non-electric heat.

The PV and cooling variable cases were slight adjustments to the variable sets intended to increase sample size. First, we considered models that dropped the binary indicator for the presence of PV from variable sets 1 and 2 to increase the samples from the NEEA

[2] We identified panel capacities as data entry errors if they were unique to the dataset, non-integer, not divisible by five, or unrealistic for the homes they were in. Given the size of our dataset, we determined that it was unlikely that any panel size reported once was real. We then excluded homes with panel capacities that were non-integer or not divisible by five, as they did not agree with our understanding of electrical panel sizing. Finally, we removed homes less than 1500 ft^2 that had 10,000A panels, which we considered unrealistic.

Table 1
Data sources and key variables for panel capacity predictive model.

Data source	Northwest Energy Efficiency Alliance Residential Building Stock Assessment (NEEA RBSA) [31]	Bay Area Renewable Energy Network (BayRen) [32]	Berkeley Lab Citizen Science panel capacity survey [33]	Home Energy Analytics (HEA) [34]	TECH Clean California [35]	Minnesota Center for Energy and the Environment (CEE) [36]
Dataset description	Survey	Home Energy Score audit	National survey	Residential pay-for-performance program provider	Building retrofit program	Assessment and home sale data collection
Year of data collection	2016–2017	2015–2022	2022–2023	2021–2023	2021–2023	2020–2022
Building count	668	6231	272	1570	18,892	6465
Geographic coverage	Washington, Oregon, Idaho, Montana	California (San Francisco Bay Area)	National	California (PG&E Service territory)	California	Minnesota (Minneapolis)
Electrical service panel capacity (A)	X	X	X	X	X	X
Floor area (ft^2)	X	X	X	X	X	X
Year of construction	X	X	X	X	X	X
Primary space heating fuel	X	X	X	X	X	X
Primary water heating fuel	X	X	X	X	X	
Primary cooling type	X	X	X		X	
Primary cooking fuel	X	X	X	X		
Primary dryer fuel	X	X	X	X		
Has rooftop photovoltaics	X	X	X	X	X	

Note: X indicates that source includes the referenced variable.

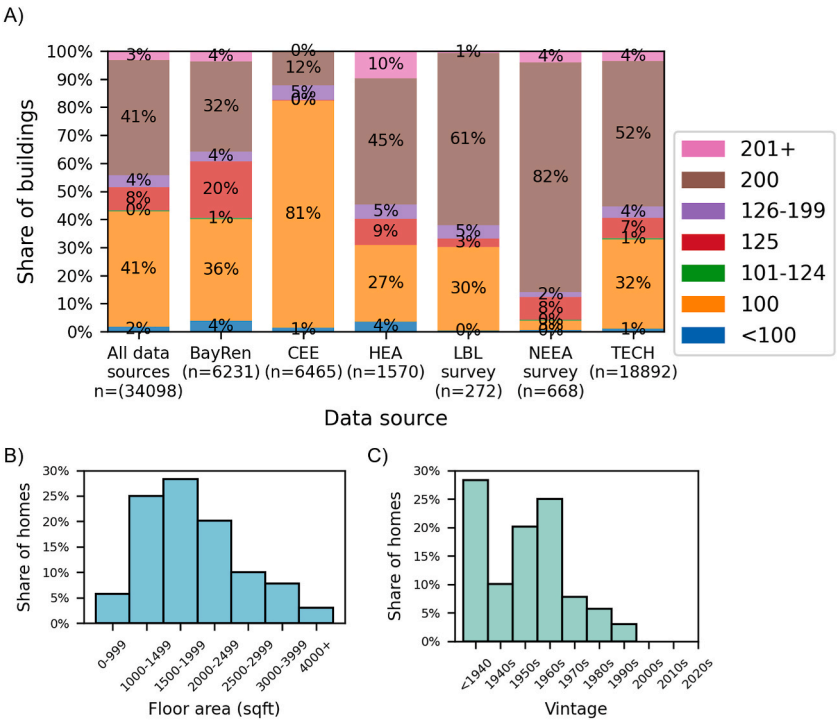


Fig. 2. A) Share of homes by electrical panel capacity bin (in amps) for each data source B) Share of homes by floor area bin C) Share of homes by vintage.
Note: There are homes in the 2000, 2010, and 2020 vintage bins but due to their small number relative to the other bins are not visible in the plot.

Table 2
Sets of home characteristics and installed equipment considered in machine learning model development.

	Variable set		
	1	2	3
Building type	X	X	
Building vintage	X	X	X
Floor area (ft^2)	X	X	X
Primary space heating fuel	X	X	X
Primary water heating fuel	X	X	
Cooling type	X	X	
Primary cooking fuel	X		
Primary drying fuel	X		
Has rooftop photovoltaics	X	X	
Sample size non-electric heat	5637	6035	29,223
Sample size electric heat	400	436	1060

dataset, which lacked PV information for about 20% of the homes. Second, we considered a binary variable for the presence of cooling in order to include the HEA data in our analysis, which lacked detail about the specific cooling technology installed.

2.1.2.1. Model selection. We trained XGBoost gradient-boosted decision trees using five-fold cross-validation on 80% of the data, leaving 20% for testing, for each of the models across a range of model parameter values [40]. We considered standard decision trees and random forest models as well, but selected XGBoost due to its performance in exploratory analyses and documentation of its high performance in many machine learning contexts, including classification problems [41]. We used XGBoost 2.0.1, scikit-learn 0.24.2, and a NumPy 1.26.1 random seed of 11 during this process. We trained these models separately for homes with electric and non-electric heating.

For each home in the training data, these models predicted the probability that the home's panel is within each panel capacity bin based on the home characteristics in Table 2. For example, the model may estimate that a home has a 15% chance of a 100A panel, a 25% chance of a 101–199A panel, a 50% chance of a 200A panel, and 5% chance each for <100A and 201+A panels. The model also returned a panel bin classification for each home that identified the bin with greatest predicted probability (e.g., the 200A panel in the

preceding example). During cross-validation, we measured model performance using the weighted F1 score, which is a standard machine learning scoring metric used for multilabel predictions [42]. This metric compares the actual panel capacity bins against the panel capacity bin classifications (the bin with the highest predicted probability).

We selected the best fit for each of the nine electric heat and nine non-electric heat models across the parameters summarized in Table 3. This parameter-tuning process helped avoid underfitting and overfitting. We then identified which of the nine models for electrically heated homes and which of the nine models for non-electrically heated homes had the highest weighted F1 scores. Table 3 also summarizes the parameters used in those best-fit models.

The best-fit model for the non-electrically heated homes used variable set 3. The best-fit model for the electrically heated homes used variable set 1, excluding rooftop PV and using the original cooling type variable. The best-fit model for the electrically heated homes leveraged a more geographically diverse set of homes than the best-fit model for the non-electrically heated homes. Homes from California, Washington, Oregon, and the South comprised 34%, 29%, 13%, and 13% of the homes in the best-fit model for electrically heated homes. In contrast, 77% and 22% of homes in best-fit model for the non-electrically heated homes were from California and Minnesota respectively.

2.1.2.2. Model performance and validation. Next, we analyzed the performance of the best-fit models using confusion matrices and validated the models by comparing the distributions of the actual and predicted panel capacity bins in the test data. We show the confusion matrices of the test data for the best-fit models in Table 4. The matrices summarize the performance of the model's panel capacity bin classifications (the bins with the highest predicted probability). Each row presents the percent of homes with an actual panel capacity that the model classifies into each capacity bin. These classifications indicate the panel capacity bin with the highest predicted probability. For example, the second row summarizes the predictions for homes that actually have 100A panels. The 73% in the second column and second row indicates that for 73% of those homes, the model predicts that 100A panels are most likely. In other words, the model makes a correct classification of panel capacity 73% of the time for actual 100A panels. The diagonal of the matrix (bolded) shows the share of panels correctly classified for each bin.

Overall, the matrix indicates that the best-fit models perform best at *classifying* 100A and 200A panels. In contrast, the models do not predict that any homes are most likely to have panels in the <100A, 101–124A, 126–199A, and >200A bins. Given the small sample sizes for these bins, we were not surprised that the model tends to predict 100A and 200A panels as most likely instead. However, these confusion matrices only summarize how the models performed at predicting the *most likely* panel capacity bin relative to the actual capacity bin. They obscure the distribution of the model's panel capacity bin predictions. For example, a model may predict that 0% of homes are most likely to have <100A panels but may predict that there is a 10% probability that each home has such a panel.

We validated that the model captures the observed distribution of panel capacity by summing the predicted probability of each panel capacity bin across the homes in the test dataset. This aggregation yielded the share of homes in each panel capacity bin that closely aligned with the distribution of panel capacity in the test data (Fig. 3). This alignment indicates that the model, while it performs best at predicting 100A and 200A as the most likely panel capacity, predicts each panel bin share very well in expectation. As described in Sections 2.1.2 and 2.3, our panel bin assignments draw from these distributions, not the classifications of the most likely panel bin that the confusion matrices summarize.

2.1.2.3. Variable importance. Fig. 4 summarizes the modeling parameters with the 10 highest importance values for the panel capacity predictive models for homes with non-electric and electric heat. These importance values reflect the degree to which a variable influences the construction of the decision trees in the model. They indicate that pre-1940s vintage and the presence of electric water heating were the most important variables for determining where the model made splits in the decision tree for the non-electric-heat and electric-heat models, respectively. Multiple vintage parameters and equipment fuels had substantial impacts on the models' structure. The variable importance quantifies which variables are significant for predicting panel capacity in our dataset. The absence of a variable from this summary (e.g., the presence of rooftop PV) does not mean that it is not a potential determinant of electrical panel

Table 3
XGBoost parameters in final panel capacity predictive models.

Parameter	Range considered in parameter-tuning process	Non-electric heat panel capacity model	Electric-heat panel capacity model
Maximum depth	2,3,4,5,6,7,9	4	7
Learning rate	0.5, 0.3, 0.5, 1, 1.25	1	1
Gamma (minimum loss for a leaf partition)	0.0, 0.1, 0.5, 1	0	0.1
Lambda (L2 regularization term on weights)	0.1, 0.5, 1, 5	0.5	0.1
Minimum child weight	1, 5, 10, 15	15	5
Number of estimators	25, 50, 100, 150, 200	25	150
Ratio of columns for each level of a tree	1	1	1
Ratio of columns to include in each tree	0.1, 1	1	0.1
Subsampling ratio of training instances	1	1	1
Stratified sampling	True, False	False	True
Objective function	Logistic	Logistic	Logistic

Table 4
Confusion matrix for top-performing model on test dataset for homes with electric and non-electric heat.

Predicted panel capacity (A)								
Actual panel capacity (A) – homes with non-electric heat (n=5845)		<100	100	101–124	125	126–199	200	>200
	<100 (n = 98)	**0%**	54%	0%	2%	0%	44%	0%
	100 (n = 2530)	0%	**73%**	0%	0%	0%	27%	0%
	101–124 (n = 26)	0%	58%	**0%**	0%	0%	42%	0%
	125 (n = 468)	0%	65%	0%	**0%**	0%	35%	0%
	126–199 (n = 253)	0%	52%	0%	1%	**0%**	47%	0%
	200 (n = 2295)	0%	41%	0%	0%	0%	**59%**	0%
	>200 (n = 175)	0%	45%	0%	0%	0%	55%	**0%**
Predicted panel capacity (A)								
Actual panel capacity (A) – homes with electric heat (n=86)		<100	100	101–124	125	126–199	200	>200
	<100 (n = 1)	**0%**	0%	0%	0%	0%	100%	0%
	100 (n = 13)	0%	**15%**	0%	15%	0%	69%	0%
	101–124 (n = 2)	0%	0%	**0%**	50%	0%	50%	0%
	125 (n = 9)	0%	22%	0%	**22%**	0%	56%	0%
	126–199 (n = 2)	0%	0%	0%	50%	**0%**	50%	0%
	200 (n = 56)	0%	9%	0%	0%	0%	**91%**	0%
	>200 (n = 3)	0%	0%	0%	0%	0%	100%	**0%**

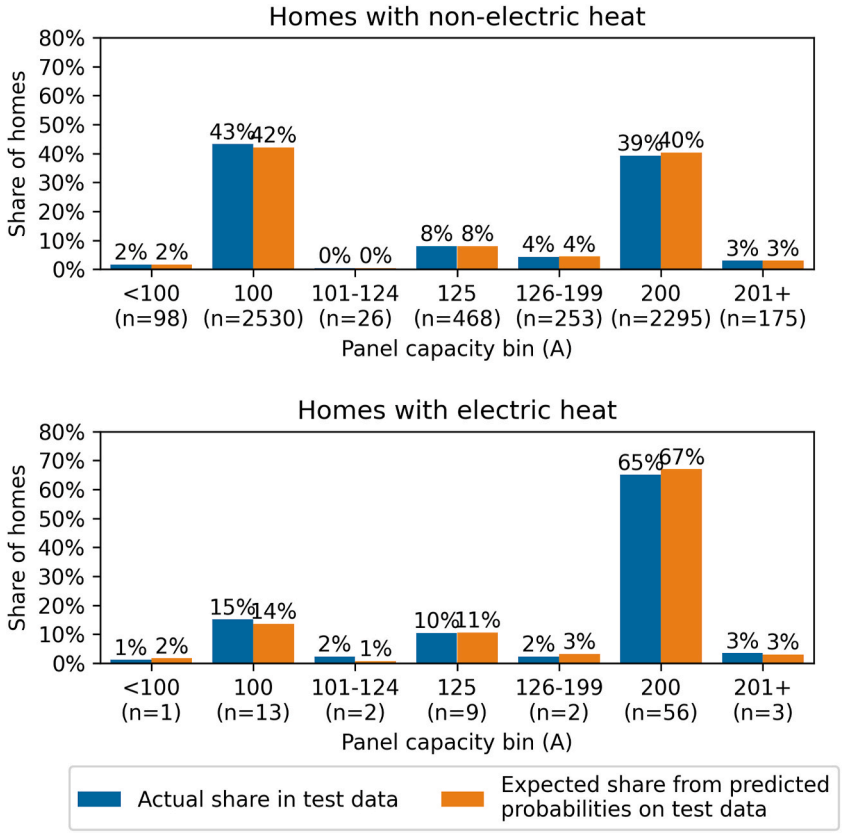


Fig. 3. Expected share of predictions from predicted panel probabilities by panel capacity bin.
Note: Some shares in the figure do not sum to 100% due to rounding.

capacity.

2.2. Available breaker space predictive model

We developed a predictive model of available breaker space in electrical panels using training data from 1066 single-family homes.

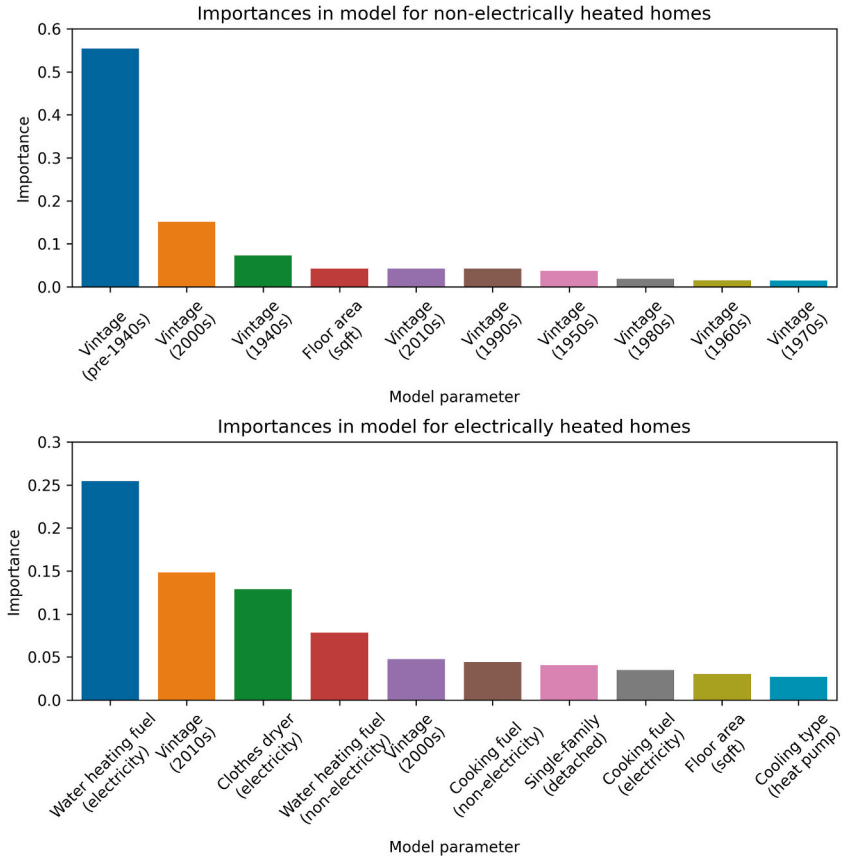


Fig. 4. Importance values of top 10 modeling parameters in the best-fit model for non-electrically and electrically heated homes.

These homes were from three data sources, two of which were part of the dataset used for the panel capacity model (BayRen and the Berkeley Lab Survey). The third source is CPUC data [19]. We excluded homes whose panels we screened out from the panel capacity predictive model. We also excluded three homes listed with 100 or more reported available breaker spaces, which we did not find basis for in market-available electrical panels.

We show the distribution of available breaker spaces observed in these homes in Fig. 5. Many of the homes in our dataset, irrespective of panel size, had zero available breaker spaces. Given the prevalence of zero values in this distribution, we specified a zero-inflated negative binomial regression with heteroskedasticity-robust standard errors to predict available breaker space [43].

Due to issues with complete separation of the data, which prevents solutions to regression models, we down-selected and simplified

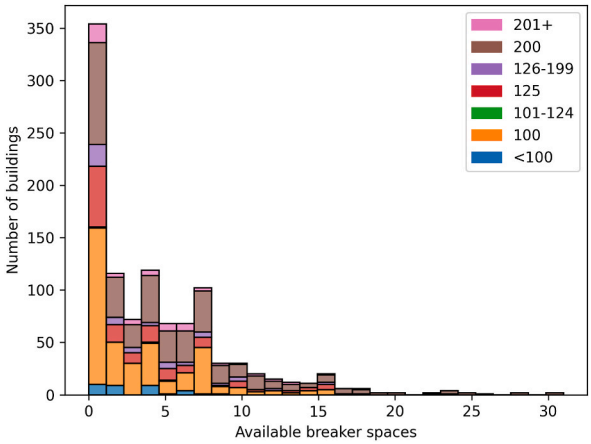


Fig. 5. Count of available breaker spaces by existing panel capacity bin (n = 1066).

the home characteristics that we used in the panel capacity model. We excluded home vintage and collapsed the 101–124A, 125A, and 126–199A bins into a single 101–199A bin. We used the count of major electrical end uses (space heating, space cooling, water heating, drying, cooking, rooftop PV, and electric vehicle (EV) charging) instead of binary indicators for the presence of each end use. When homes had heat pumps for heating and cooling, we counted only one major load for space heating and cooling. We recognize that the breaker spaces required for these loads may differ, but we accept estimating the average impact of a general 'major load' for the sake of a valid model. The final breaker space model (Formula 1) predicted available breaker space based on panel capacity, the count of major loads, and building floor area (in 1000 ft^2 [92.9 m^2]):

$$\textit{Available breaker space} \sim \beta_0 + \beta_1\, \textit{Panel capacity bin} + \beta_2 \textit{Count of major loads} + \beta_3 \textit{Floor area}$$

Formula 1. Available breaker space regression model.

In Table 5, we show the results of the zero-inflated negative binomial regression used to predict available breaker spaces. The regression has two components. The inflation model uses a logistic regression to estimate the probability that the number of breaker spaces will be zero instead of the count of breaker spaces predicted by the count models' negative binomial regression. Relative to the base panel capacity of 100A, the presence of larger panels increases the number of breaker spaces (positive coefficients in the count model). For a 200A panel, the negative coefficient in the inflation model indicates that the odds of having zero breaker spaces are lower relative to a 100A panel. The negative coefficient in the count model for the major electric end-use variable indicates that the number of available breaker spaces declines as the number of major electric end uses increases.

2.3. Applying predictive models to U.S. housing stock

We estimated the panel capacity and available breaker space in U.S. homes by applying our predictive models to the representative single-family homes in ResStock (attached and detached). Developed by the U.S. Department of Energy, ResStock is a building stock model of the U.S. residential sector designed to evaluate building upgrade scenarios and inform energy planning [24]. ResStock incorporates real weather patterns and calibrated, physics-based simulations in EnergyPlus to model subhourly end-use loads. ResStock models have been validated against U.S. Energy Information Administration (EIA) energy reporting, as well as smart meter and load research time series data from utility service providers, to ensure that they adequately capture both realistic energy use and end-use load profiles [44]. ResStock captures the locational variation in the U.S. building stock by using data from the Residential Energy Consumption Survey, American Community Survey, American Housing Survey, and American Time Use Survey to define approximately 331,000 representative homes. Each representative ResStock home has more than 100 housing characteristics, including location, floor area, vintage, end-use fuels, and income as percent of AMI [45]. We apply our predictive models to the building characteristics of these representative buildings to generate geographically sensitive estimates of panel capacity and breaker space.

For each representative ResStock home, the panel capacity model generated probabilities of each panel capacity bin. We then aggregated these probabilities across a range of the home characteristics in the ResStock metadata (e.g., floor area, vintage) to calculate expected counts and shares of homes with panels in each bin (see Section 4.1). We assigned each home a single panel capacity bin by randomly sampling from its predicted bin probabilities. We used this bin assignment in Section 4.3 to compare panel capacity to load in each ResStock home. We also used the panel bin assignment as an input in the available breaker space prediction. For each home, we predicted the probability that it has each available breaker space in the observed range of 0–31 breakers for a given count of major electrical loads and existing panel capacity. We then randomly sampled from this distribution to assign a single remaining

Table 5
Results of zero-inflated negative binomial regression on available breaker spaces.

	Variable	Coefficient
Inflation model	Intercept	−1.35942*** (0.29967)
	Major electric end use count	−0.09379 (0.07796)
	Panel capacity: <100A	−0.51301 (0.55906)
	Panel capacity: 101–199A	−0.04687 (0.27188)
	Panel capacity: 200A	−0.45283* (0.25224)
	Panel capacity: 201+A	−0.08688 (0.42006)
	Floor area (1000 ft^2)	0.16491 (0.14833)
Count model	Intercept	1.63561*** (0.09883)
	Major electric end use count	−0.05026** (0.02301)
	Panel capacity: <100A	−0.12448 (0.17164)
	Panel capacity: 101–199A	0.12942 (0.09032)
	Panel capacity: 200A	0.47378*** (0.07836)
	Panel capacity: 201+A	0.32819*** (0.12541)
	Floor area (1000 ft^2)	−0.03652 (0.05345)
	Alpha	0.50656*** (0.04674)
	Pseudo R^2	0.01016
	Note:	*p < 0.1; **p < 0.05; ***p < 0.01
		Values in parentheses are standard errors at 95% confidence interval
		The parameter alpha in the count model is there by default and measures overdispersion.

breaker space estimate for each home.

3. Simulating available panel capacity with NEC load calculations

We estimated the available panel capacity in the U.S. single-family housing stock under two compliance pathways in the 2023 NEC that determine whether panels can service new loads. Known as the Load Summing and Maximum Demand methods [1,2], the pathways differ in how they calculate the existing load in a home. Sections 3.2 and 3.3 provide an overview of these load calculations. Separately for each pathway, we calculated available panel capacity for each ResStock home by subtracting its estimated existing load from its predicted panel capacity. While the adopted NEC version can vary by state and municipality, the 2023 version represents current best practices.

3.1. Assigning discrete panel sizes to ResStock homes

In order to calculate available panel capacity, we needed to subtract the existing load from discrete values of panel capacity. For the homes with panels in the 100A, 125A, and 200A bins in Section 2.1, the bins were discrete values. For the homes with panels in <100A, 101–124A, 126–199A, and 201+A bins, we assigned the median discrete panel size in each bin from the training data, while considering variation in panel capacity with heating fuel for <100A panels and floor area for 201+A panels, respectively. We accounted for panel capacity variation for the <100A and 201+A bins due to observed variation in panel capacity with heating fuel and floor area respectively and the availability of data. We recognize that the capacity of panels in the 101–124A and 126–199A bins also may vary with building characteristics, but these bins lacked sufficient data for subsetting. The discrete assignments for 101–124A and 126–199A panels were 120A and 150A, respectively. For buildings with <100A panels, we assigned 90A if the building had electric heating and 60A if the building had non-electric heat. For buildings with 201+ panels, we assigned 250A, 300A, and 400A if the building's floor area was 0–2,999, 3000–3,999, or 4000+ square feet, respectively.

3.2. Simulating panel capacity requirements with the NEC Load Summing method

The Load Summing method corresponds to section 220.83 of the NEC [1]. This method tabulates existing and to-be-added loads associated with different end uses and then applies tiered demand factors to calculate the total load of the service. The tabulated loads are.

1) General lighting and receptacle loads at 3 VA/square foot, which we calculated based on the combined floor area of conditioned space and garage.
2) 1.5 kVA per branch circuit serving kitchen small appliances and laundry circuits. We assumed three branch circuits for each home (two per kitchen and one for laundry).

Table 6
Assigned power rating for standard size appliances.

End Use	Option	Power Rating (W or VA)
Clothes dryer	Electric	5760
	Electric ventless	2640
	Heat pump	860
	Heat pump, 120V	996
Dishwasher	Standard	1200
Electric vehicle supply equipment	Level 1	1650
	Level 2	7680
Garage door opener	½ HP	373
Garbage disposal	3/4 HP for post-1940 homes	559
Hot tub/spa	Electric	1000
Pool heater	Electric, 27 kW	27,000
Pool pump	Electric, 2 HP	1491
Range/oven	Electric	12,000
	Induction	12,000
	Electric, 120V, battery-assisted	1800
	Induction, 120V, battery-assisted	1800
Ventilation	Bathroom, 50 CFM	15
	Kitchen, 300 CFM	90
Water heater	Electric	4500
	Electric tankless, 1 bathroom	18,000
	Electric tankless, 2 bathrooms	24,000
	Electric tankless, 3+ bathrooms	36,000
	Heat pump	4500
	Heat pump, 120V, shared circuit	1000
Well pump	1 HP, 1–3 bedrooms	746
	1.5 HP, 4+ bedrooms	1119

3) Nameplate ratings of water heaters, cooking ranges/ovens, dryers not on the aforementioned laundry branch circuit, and all appliances fastened, permanently connected, or located on a particular circuit. We used nameplate ratings in ResStock (see nameplate rating assumptions in Table 6).

The Load Summing method then prescribes two ways to add these loads. 220.83(b) is specific to home retrofits that include the addition of air conditioning or electric heating, so we use 220.83(a), which can provide estimates of existing load only. 220.83(a) counts existing building loads at 100% for the first 8kVA and at 40% for the remaining tabulated loads.

We applied this calculation to the metadata of the approximately 331,000 ResStock simulated homes, which included nameplate ratings for space heating and cooling, water heating, laundry, cooking, and dishwashing technologies that are based on performance parameters and actual product labels.

For appliances other than heating, ventilation, and air conditioning (HVAC) and water heating, we assigned nameplate ratings to each technology (Table 6) based on a review of available market offerings. For electric tank water heaters, we used a single rating (4500 VA) because this is the maximum power regardless of tank size and efficiency. We assigned nameplate ratings to electric tankless water heaters based on the number of bathrooms they serve, assuming water demand of 3 gallons per minute (enough for a fixture and an appliance use simultaneously) for one bathroom and 6 gallons per minute (enough for whole house application) for more than one bathroom at a 40 °F rise.

We estimated power ratings through regression models of minimum circuit amperage on nominal capacity for direct expansion systems and electric and gas air handling units. ResStock sizes HVAC equipment in accordance with Manuals J and S of the Air Conditioning Contractors of America [46–48]. Using these manuals, all existing air-source heat pumps are sized to the cooling design load, with some oversizing allowed for larger heating design load based on factors that include climate, building envelope properties, heat transfer between occupants and appliances, and parameters of the heat pump. Additionally, ResStock sizes heat pump backup heating to cover 100% of the heating design load as emergency heat. The direct expansion systems included ducted and non-ducted heat pumps, central air conditioners, and room air conditioners that ranged from 0.5 to 10 tons in capacity. The air handling units served electric and gas furnaces ranging from 0.5 to 5 and 2.5–10 tons in capacity, respectively. We assumed that the results of the regression for air handlers serving gas furnaces applied to air handlers that supported other non-electric equipment as well. We then set minimum circuit amperage at 5A and 8A for electric and gas air handlers, respectively, to align with the observed data. We applied these regressions to ResStock equipment capacity values to estimate the amperage of the direct expansion and air handling units. We then calculated power ratings by multiplying direct expansion system amperage by 240V, electric furnace air handler amperage by 240V, and gas furnace air handler amperage by 120V. The results of the regression models can be found in the Supplementary Materials.

3.3. Simulating panel capacity requirements with the NEC Maximum Demand method

The Maximum Demand method corresponds to section 220.87 of the NEC [2]. This method calculates existing load by multiplying the maximum metered electricity demand (15-min or hourly) from the preceding 1-year period by 1.25. We implemented this method

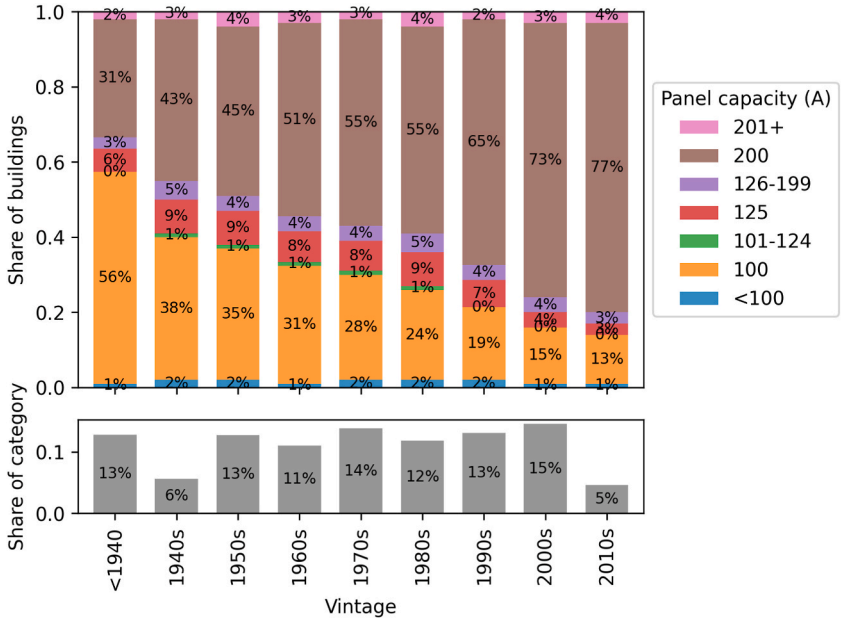


Fig. 6. Electrical panel capacity predictions by home vintage.

by finding the maximum 15-min demand for each ResStock home and multiplying it by 1.25.

4. Results

4.1. Existing electrical panel capacity estimates

We estimate that 58% of U.S. single-family homes have panels with capacity of 200A (55%) or more (3%). 100A panels (29%) are the most common panel size less than 200A, followed by 125A (7%), 126–199A (4%), <100A (2%), and 101–124A (1%). We also find that panel capacity varies by vintage, floor area bin, state, and percent of AMI.

200A panels are more common in new homes, and homes with panels of 100A or less are more common in older homes (Fig. 6). For example, in the most recent vintage of homes in ResStock (2010s), we estimate that 77% of homes have 200A panels and 13% have 100A panels. In contrast, we estimate that for homes built before 1940, 56% have 100A panels and 31% have 200A. While most older homes may have been originally constructed with 100A or smaller panels, the prevalence of 200A panels in our oldest vintage of homes suggests that many owners of these homes have replaced their panels to accommodate new loads (e.g., space cooling) or home retrofits (e.g., additions). ResStock does not characterize past remodeling, so we cannot directly assess these potential explanations with our data.

The share of single-family homes with 200A panels increases with floor area from 40% to 69% for homes with floor areas of 0–999 ft^2 (0–45 m^2) and 4000+ ft^2 (360+ m^2), respectively (Fig. 7). The share of 100A panels shows the opposite relationship with floor area, declining from 33% to 14% between the same floor area bins. Since larger homes generally contain more circuits and lighting and require larger space conditioning equipment, we would expect larger panels to be more prevalent in larger homes. The Load Summing NEC panel sizing calculation for home retrofits accounts for all of these features [1].

We examined the relationship between predicted panel capacity and the number of major electric end uses in a ResStock home, including heating, hot water, cooking, rooftop PV, and clothes drying. Fig. 8 shows that panel capacity increases monotonically as the number of major electric end uses in homes increases. With five or more major end uses, almost all homes have panels with 200A or more capacity. For homes that have no major electric end uses, less than 40% have a 200A or larger panel capacity.

We find significant state-level variation in panel capacity (Fig. 9). This variation reflects differences in the age of the building stock, home size, and fuel shares for space and water heating in each state. Notably, states in the South census region have the highest levels (70%) of larger panels (200A and above) and the lowest levels (21%) of smaller panels (100A and below), likely due to the higher prevalence of electric space heating (55% South; 18%–27% other regions) and water heating (67% South; 28%–36% other regions) [37,38,49,50]. Regions with the greatest prevalence of smaller panels (100A or less) include California and states in the Great Lakes area and Northeast. In these regions, the majority of space and water heating is done with fossil fuels, including natural gas, propane, and fuel oil [37,38,49,50]. These geographic trends are also consistent with our estimates of panel capacity by primary space- and water-heating fuel: homes with electric space or water heating are more likely to have 200A panels than homes with fossil-fired space or water heating (see Supplementary Materials for details).

Panel capacities increase with percent of AMI (Fig. 10). We estimate that for homes in the lowest percent of AMI bin (0%–30%) to the highest (150%+), the share with 200A panels increases from 48% to 60% and the share with 100A panels decreases from 33% to 25%. This relationship between panel capacity and percent of AMI is consistent across the country, with the share of 100A panels lower in southern states and higher in other regions for given percent of AMI bins. Notably, the panel capacity predictive model did not include any direct income variables. These estimated differences in panel capacity by percent of AMI bin likely reflect other features in the housing stock that are correlated with income[3] [51], along with the ability to pay for panel replacements and the home upgrades that require them.

The relationships between income variables and panel capacity in the TECH and NEEA datasets are consistent with the percent of AMI relationships shown above. Through a regression analysis (see Supplementary Materials for details), we find statistically significant results that the likelihood of panels 100A or smaller decreases as place-based (TECH) and household (NEEA) incomes increase while controlling for other relevant household characteristics. In single-family homes in the TECH dataset, a $25,000 increase in tract median income decreases the probability of a panel with capacity less than or equal to 100A by 1.4% in water and space heating projects. Single-family households in disadvantaged communities [52] that received heat pump installations for space-heating through the TECH program were 5% more likely to have a panel 100A or smaller than participating households that were not in disadvantaged communities. In the NEEA dataset, relative to a home with household income of $0–$50,000, homes with household incomes of $150,000–$200,000 and $200,000 and above are 31% and 32% less likely to have a 100A panel, respectively.

4.2. Available breaker spaces

We estimate that the number of available breaker spaces in existing electrical panels increases with panel capacity (Fig. 11). In particular, we estimate that panels 200A and above are more likely to have five or more available breaker spaces. This result accords with our expectation that larger panels, which contain more breaker spaces, would have more spaces available for new loads.

[3] In the 2020 Residential Energy Consumption Survey, the EIA reports that 56% of households with incomes below $60,000 lived in buildings built before 1980, as opposed to 47% of households with incomes above $60,000. Similarly, the EIA reports that 53% of households with incomes below $60,000 lived in buildings with five or fewer rooms, compared to the 26% of households with incomes $60,000 or above.

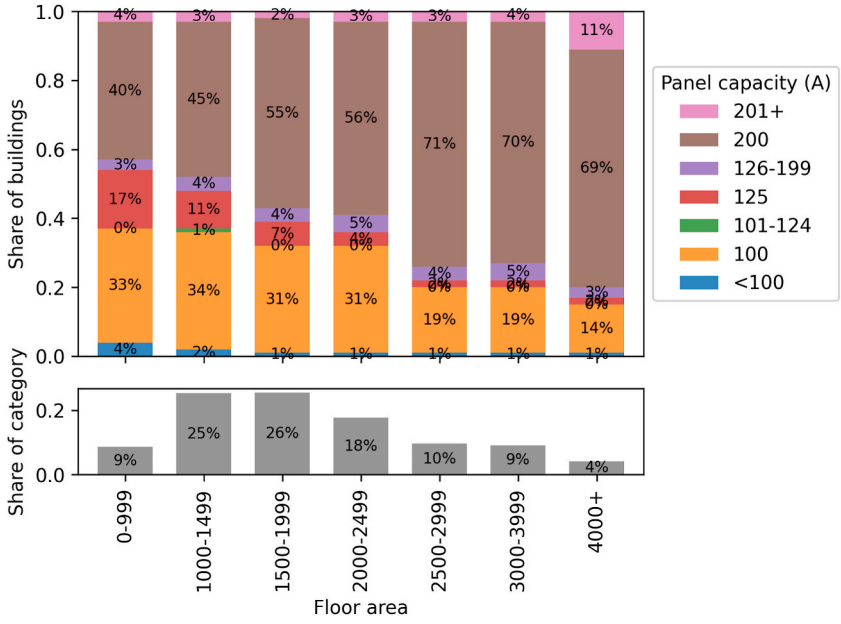


Fig. 7. Electrical panel capacity predictions by floor area.

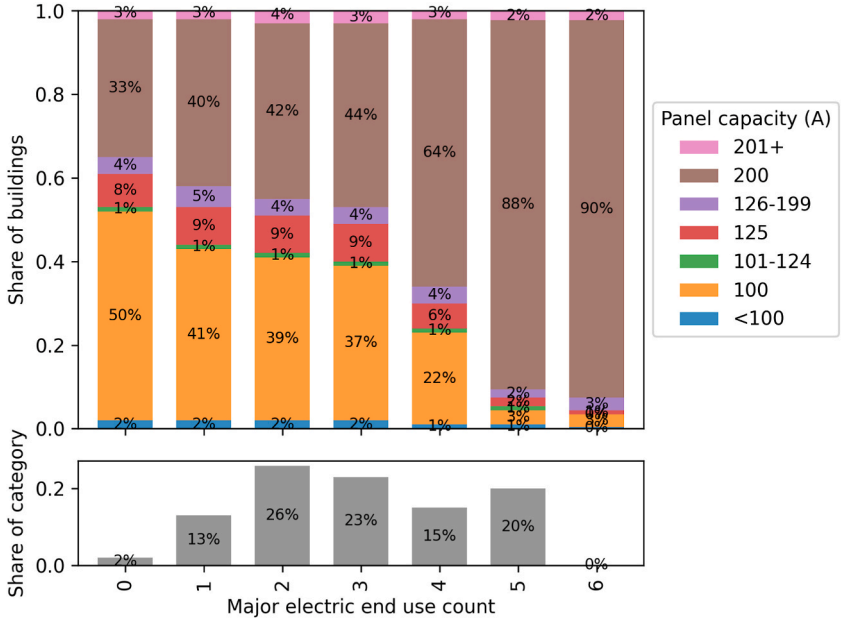


Fig. 8. Electrical panel capacity by number of major electric end uses.

However, we estimate cases of limited or no available breaker spaces across all panel sizes. For example, we estimate that 22% of all panels and 20% of 200A panels have zero breaker spaces remaining. The correlation between panel capacity and the number of major electric loads installed explains the limited breaker space in large panels. Of the homes in ResStock that we predict have 200A panels, 48% have five or more major electric end uses, compared to only 28% of homes predicted to have 100A panels. As the number of major electric end uses increases, the expected number of available breaker spaces declines. Contrary to the electrical panel capacity results, we find little geographic variation in homes with five or more available breaker spaces (Fig. 12). We attribute the lack of variation to countervailing impacts on available breaker space from panel capacity and the number of major electric end uses. Regions with smaller panels have fewer major electric end uses (as defined in Section 2.2) and regions with larger panels have more electric end uses (Figure S-3 in Supplementary Materials). For example, 21% of homes in the Midwest (where 36% of homes have 100A panels) have four or more major electric loads, much lower than the 59% of homes in the South (where 19% of homes have 100A panels).

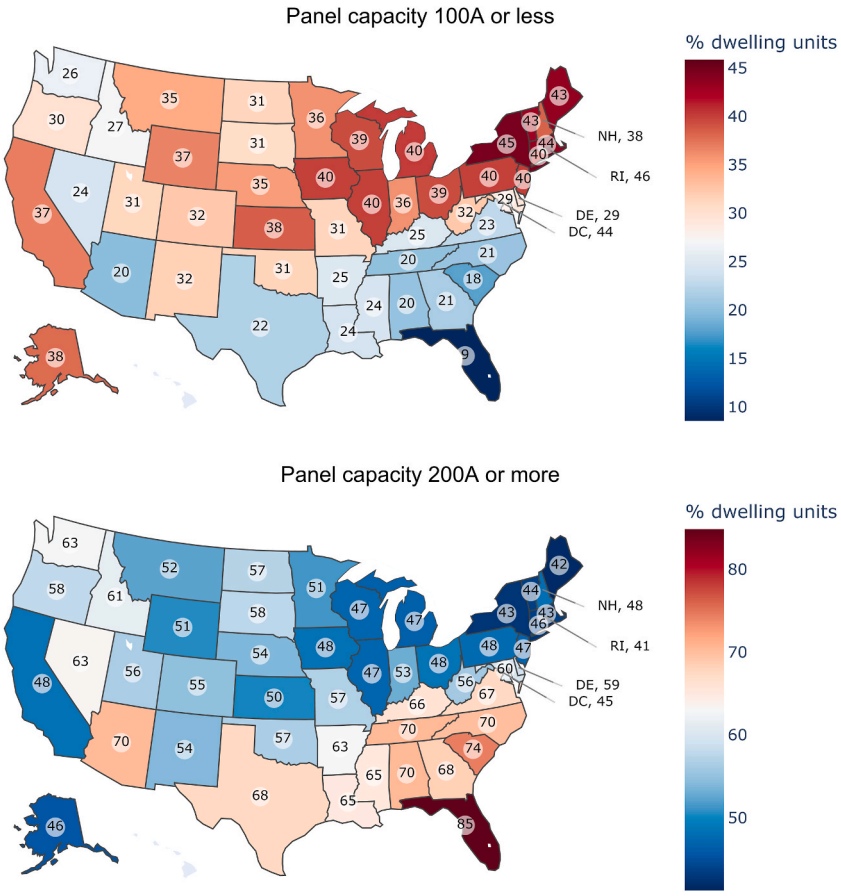


Fig. 9. Share of homes with predicted panel capacity 100A or less and 200A or more by state.

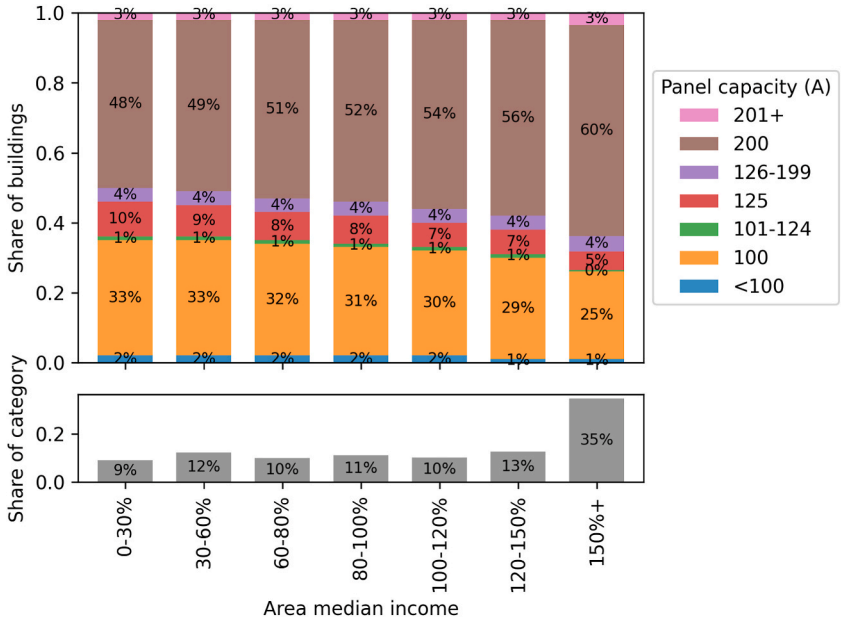


Fig. 10. Panel capacity by percent of AMI.

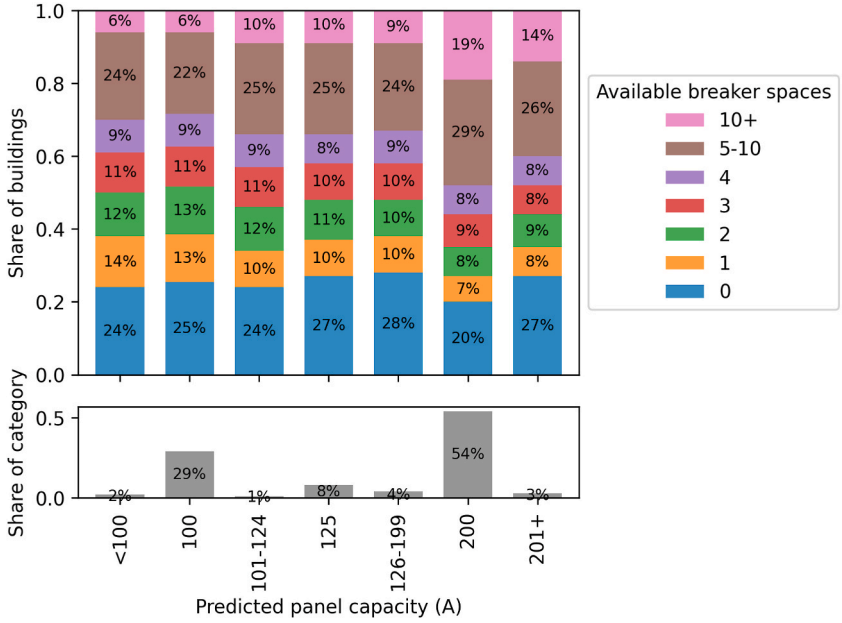


Fig. 11. Breaker space by panel capacity bin.

4.3. NEC load calculations

We estimate that electrical panels in most single-family homes have headroom for additional loads, based on a comparison of predicted panel ratings and NEC service load calculations for each ResStock building (Fig. 13 and Table 7). Predicted panel capacity exhibits a positive correlation with the loads estimated by the Load Summing Method (Pearson coefficient of 0.33) and Maximum Demand Method (Pearson coefficient of 0.27). NEC loads (in red in Fig. 13) increase as panel rating increases but do so at a lower rate than the panel rating. For example, with the Maximum Demand Method, load in the median home with a 200A panel (55A) is 45% higher than load in the median home with a 100A panel (38A) while the panel capacity is 100% higher. As a result, the panel utilization (the existing load as a percent of the panel rating) decreases as panel rating increases (Table 7).

The calculated loads (in red) and the amount of headroom available for new loads (in green) also depend on the NEC load calculation method. Existing loads estimated by the Maximum Demand Method are 40% lower than those estimated by the Load Summing Method for the median single-family home in ResStock (22%–52% interquartile range). The smaller load results in more headroom available for new loads across all panel ratings when using the Maximum Demand Method (Table 7). However, the additional headroom estimated by the Maximum Demand Method is not sensitive to panel capacity, with median additional headroom ranging from 27A to 30A between panels with <100A and more than 200A capacity. As a result, the absolute difference in panel utilization between the two methods declines as panel rating increases. For example, the median panel utilization is 30 percentage points lower with the Maximum Demand Method relative to the Load Summing Method for 100A panels but 16 percentage points lower for 200A panels (Table 7).

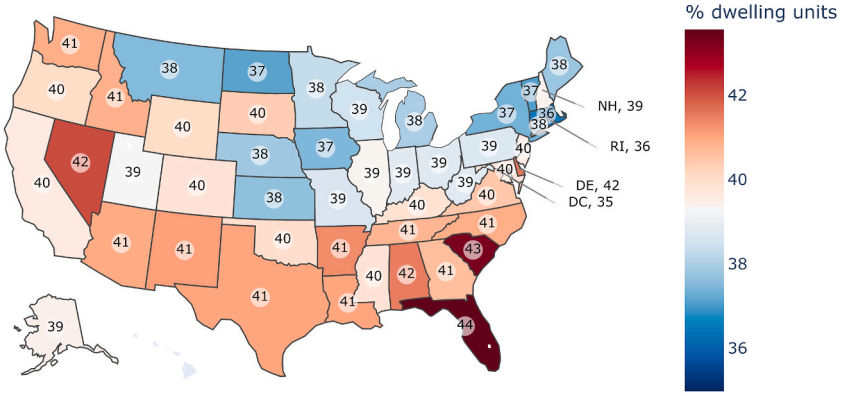


Fig. 12. Share of homes predicted to have five or more breaker spaces by state.

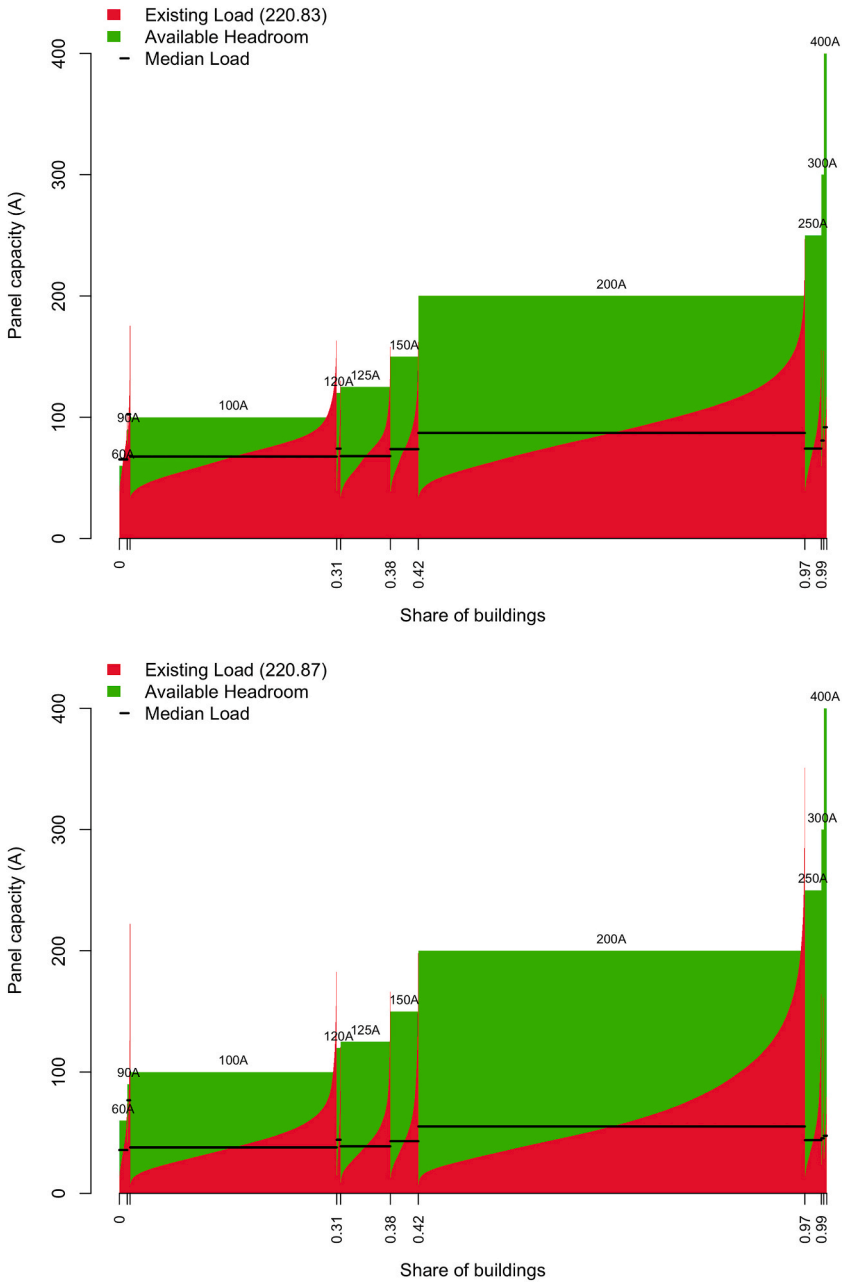


Fig. 13. Distribution of existing load and available headroom by predicted panel capacity bin using the Load Summing Method in NEC section 220.83 (top) and the Maximum Demand method in NEC section 220.87 (bottom).

Calculated loads exceed predicted panel capacity for a small share of homes in the Load Summing (2.7%) and Maximum Demand (1.5%) methods. Households whose assigned panel capacity is below their calculated load are more frequent for smaller panel sizes, especially the <100A panel bin. For example, the Load Summing Method predicts loads that exceed panel capacity in 63.6%, 5.1%, and 0.2% of homes with <100A, 100A, and 200A respectively. These results are most likely due to our probabilistic process for assigning panel size bins to households. As described in section 2.3, we drew a modeled home's panel capacity from a probability distribution of expected panel capacity bins based on the characteristics of that home. Panel sizes less than 100A, which are rare in each of the datasets we use, are low-probability predictions for all homes in our dataset. Therefore, every home that receives a <100A panel received an unlikely draw from the probability distribution. Our method cannot fully represent the correlation between load and panel size that we would observe in actual homes, in particular for homes with small panels. Since these homes account for a small share of our simulations, they do not affect our overall conclusions.

Table 7
Median NEC service loads, panel utilization, and panel headroom in the U.S. single-family housing stock by panel rating and NEC load calculation method.

Panel Rating (A)	Housing Stock Fraction (%)	Load Summing Method (220.83)			Maximum Demand Method (220.87)		
		NEC Load (A)	Panel Utilization	Panel Headroom (A)	NEC Load (A)	Panel Utilization	Panel Headroom (A)
60	1%	65	109%	−5	36	60%	24
90	0%	102	114%	−12	77	85%	13
100	29%	68	68%	32	38	38%	62
120	1%	74	62%	46	44	37%	76
125	7%	68	54%	57	39	31%	86
150	4%	74	49%	76	43	29%	107
200	55%	87	44%	113	55	28%	145
250	2%	74	30%	176	44	18%	206
300	0%	81	27%	219	45	15%	255
400	0%	92	23%	308	48	12%	352

5. Discussion

5.1. Results in the context of literature

Our panel capacity predictions align well with those reported by EPRI for single-family detached homes (Table 8) [13,14]. Nationally, we estimate similar shares of single-family homes with panel capacity less than or equal to 100A (31% in our estimates vs. 27% in EPRI's) and with 101–200A of panel capacity (66% vs. 70%, respectively). We estimate the same share of single-family homes have 201+A panels (3%). We also find a similarly high penetration of 101–200A panels in the South (76% vs. 79%) and higher levels of 100A panels in the Midwest relative to the South and West. In the Northeast, we estimate more homes have panel capacity less than or equal to 100A (42% vs. 32%) and fewer homes have panel capacity of 101–200A (55% vs. 65%). Our prediction that older homes have smaller-capacity panels is also consistent with the results of EPRI's survey [13,14]. The alignment of our results with EPRI's national survey suggests that our panel capacity predictive model has external validity and is able to relate panel capacity to homes in locations not represented in the training data.

We also predict levels of remaining breaker space very similar to those reported by EPRI (Table 8) [13]. Notably, we predict the same level of homes with one to two remaining breaker spaces (20%); our other predictions differ only by one to two percentage points. EPRI does not indicate whether the available breaker space is specific to single-family homes or includes responses from multifamily homes as well.

Relative to a survey of Massachusetts' single-family buildings, our model predicts fewer 100A (42% in our predictions vs. about 50% in the survey) and 200A panels (40% in our predictions vs. about 47.5% in the survey) [16] in Massachusetts. We do not know any other characteristics of the surveyed buildings, so we cannot determine whether differences in building floor area, vintage, or installed equipment explain the differences in our estimates. We estimate similar shares of California panels with a capacity of 200A or more (48%) and 100A or less (37%), as Fournier et al., 2024 does (51% 200A or more and 35% 100A or less). Our predictions of 200A panels in California single-family homes (45%) are lower than levels reported in the CPUC survey (53%) [19].

5.2. Limitations of data and methods

5.2.1. Predictive modeling data

Our machine learning model predicts electrical panel capacity based on home characteristics reported by surveys and building

Table 8
Comparison of predicted and reported panel capacity and remaining breaker space.

		Predictive model			EPRI survey		
Panel capacity (A)		≤100	101–200	201+	≤100	101–200	201+
	United States	31%	66%	3%	27%	70%	3%
	Midwest	38%	59%	3%	41%	58%	1%
	Northeast	42%	55%	3%	32%	65%	2%
	South	21%	76%	3%	17%	79%	4%
	West	32%	65%	3%	28%	70%	3%

		Predictive model	EPRI survey
Remaining breaker spaces	0	22%	24%
	1–2	20%	20%
	3–4	18%	17%
	5 or more	40%	39%

retrofit programs. However, our datasets lack detailed information on installed equipment. The datasets include fields for space and water heating fuels and the type of space cooling, but not the capacity of the installed equipment. Our model, therefore, cannot relate panel capacity to different equipment sizing in otherwise similar homes. Similarly, due to the lack of data from more states, our model cannot account for differences in equipment size that vary geographically due to climate or contractor practices and their impacts on panel capacity. We also do not have complete data on the equipment installed in the homes in our dataset. This gap in coverage means that we cannot directly relate panel capacity to miscellaneous plug loads and equipment (e.g., pool pumps). Our model does include floor area, which likely correlates with the number of plug loads and directly factors into the Load Summing method described in section 220.83 of the NEC. We also retain the diversity of panel capacity in similar homes by sampling from predicted probabilities of panel capacity. Additionally, our models' predictions in uncommon parts of the housing stock (e.g. the smallest floor area bins shown in Fig. 7) may be sensitive to the characteristics of a small number of homes in the training data. Finally, our model cannot account for geographic differences in panel sizing independent of NEC load calculations, such as a convention of using certain panel sizes (e.g. 125A) in place of other (e.g. 100A).

Our datasets do not have a shared socio-economic variable that our predictive model can use. Despite this limitation, the positive relationship between panel capacity and percent of AMI (as modeled by ResStock) that we estimate suggests that our model is able to leverage correlates of household income such as home vintage and floor area [51].

Self-selection of participants into the program and survey data used for model development also may affect our results, as their homes are likely not representative of the U.S. building stock. Additional data collection, including households from more states and non-single-family homes, as well as more detailed data on installed equipment in each household, could be used to create more detailed models in the future.

5.2.2. NEC load calculations

Our implementation of the 2023 NEC, which 18 states have adopted as of July 2025, may not reflect its use in all jurisdictions due to variation in the version of the NEC adopted [53]. We reviewed the 2020 NEC (adopted by 20 states as of July 2025) for substantive differences in sections 220.83 and 220.87 that would impact our results but did not find any. We believe our simulations are reasonable to apply nationally [53].

Our implementation of the 2023 NEC also may not reflect how some users interpret it. In particular, section 220.87 does not have an explicit requirement for metering frequency. We used 15-min peak demand instead of hourly. Recent research has shown that 15-min residential peak demand is 30% higher than hourly peak demand, which suggests that our estimates of load with section 220.87 are conservative relative to what estimates would have been with hourly data [54].

We also recognize limitations in ResStock's representation of the U.S. housing stock that may affect our load calculations. First, ResStock does not model electric vehicle charging nor have power ratings for appliances such as garbage compactors, over-the-range microwaves, on-demand hot water in sinks, and elevators, which results in underestimations of load for buildings that have these appliances. Since 1.1% of American homes charge an EV at home as of 2020 [55], the lack of EV charging in ResStock does not significantly affect our results. Second, ResStock models non-HVAC and non-water-heating loads as stochastic occupant schedule-based loads that meet Residential Energy Services Network (RESNET) 301 energy calculations, which introduces discrepancies between appliance load profiles and the nameplate ratings assigned in the Load-Summing calculation [56,57]. Third, ResStock's HVAC equipment sizing routine may differ from contractor practices. It provides continuous sizes instead of sizes determined by product offerings and assumes all heat pumps have back-up electric resistance heating in all climate zones, which may overstate capacity needs in those households. Fourth, ResStock's electric peak demand at the dwelling unit level is not fully validated with metered data, which introduces uncertainty into the Maximum Demand load calculation. However, the stochastic appliance occupant schedules do provide diversity in load shapes. Finally, the assigned power ratings are less diverse than what exists in the actual homes, which could lead to overestimated loads in some buildings and underestimated loads in others. Additional data on the size of equipment installed in U.S. households would address this gap and improve the accuracy of the load calculations.

5.3. Future research

Estimates of the electrical capacity and physical space constraints that existing electrical panels pose to building upgrades so far have been regional or have only considered electrical panel capacity [14,15,22]. Our estimate that 22% of homes nationally have no breaker space suggests that future studies should also consider breaker space constraints. Similarly, our simulations of NEC load calculations, which find generally lower load estimates with the Maximum Demand Method than the Load Summing Method, suggest that assessments of panel capacity constraints should consider both compliance pathways, as capacity constraints may result from one method but not the other. Finally, analyses of electrical panel constraints also could consider ways to mitigate constraints with: higher-efficiency and low-voltage equipment that reduces the incremental load a panel must serve; load control technologies such as circuit-sharing devices that can remove loads from NEC calculations [58]; control systems that keep home-wide electrical current below panel service ratings [23]; and tandem breakers and subpanels, which can resolve space constraints.

5.4. Conclusion and implications

We predict that 58% of U.S. homes have electrical panels 200A or larger and 31% have panels 100A or smaller. Our results suggest that 100A panels are more common in smaller and older homes and in homes with lower incomes (as measured by percent of AMI), which indicates potential affordability barriers to home upgrades. Our simulation of NEC load calculations indicates that most homes

have capacity to add new electric loads, with the amount of headroom depending on existing panel ratings and NEC load calculation methods.

Our results also indicate that available breaker space can constrain the addition of new loads in both small and large panels. We estimate that 25% of homes with 100A panels and 20% of homes with 200A panels have no available spaces for new branch circuits. However, many homes have three or more empty breaker spaces, and 48% of homes with 200A panels have five or more breaker spaces available.

Our state-level predictions suggest that the number of panel replacements and associated investment needed to support home upgrades will vary significantly across the United States. Homes in southern states will likely face fewer panel constraints, while California and states in the Midwest and Northeast will likely require more replacements or management of space and or capacity constraints. Finally, programs that support home upgrades may need to focus budgets on lower-income households, which are more likely to have 100A panels.

CRediT authorship contribution statement

Sean Murphy: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Lixi Liu:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Brennan Less:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Yingli Lou:** Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Jeff Deason:** Writing – review & editing, Methodology. **Iain Walker:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Xin Jin:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2026.115576.

Data availability

Data used for predictive modeling are available here: https://doi.org/10.5061/dryad.rv15dv4jw.

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Acronyms and abbreviations

A: Amperes or Amps
AMI: Area median income
BayRen: Bay Area Renewable Energy Network
CEE: Minnesota Center for Energy and the Environment
CPUC: California Public Utilities Commission
EIA: United States Energy Information Administration
EPRI: Electric Power Research Institute
EV: Electric vehicle

HEA: Home Energy Analytics
HVAC: Heating, ventilation, and air conditioning
NEC: National Electrical Code
NEEA RBSA: Northwest Energy Efficiency Alliance Residential Building Stock Assessment
PV: Photovoltaic
RESNET: Residential Energy Services Network