Strategic Decarbonization Utilizing Building Stock Datasets

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ABSTRACT

Trends towards electrifying building thermal loads without commensurate energy efficiency measures means areas of the U.S. grid could see far higher demand growth in the next few decades than it has previously, in addition to shifting demand curves and peak periods. Combined with a progressively interactive grid featuring intermittent renewable resources and demand response capabilities, it will become increasingly important to understand the hourly impacts of building energy efficiency and electrification as granularly as possible. Building stock energy modeling offers a powerful tool to inform and optimize utility electrification strategies, understand how buildings might electrify, and inform the manner by which electrification might shape the demand for electricity. This paper describes the development and application of a load forecasting tool using publicly available building stock model datasets for an independent system operator (ISO). Using the tool, the ISO investigated the energy and demand impacts of heating electrification in their region. The conceptual approach could be used by other ISOs or utilities. In this paper, we present the development of the forecasting tool: building stock characterization, development of electrification pathways, adoption forecasting, and hourly demand modeling. We discuss how the specificity of the location, demographics, and building characteristics in the building stock datasets allow for detailed forecasts. These analysis methods can be translated to other organizations to prioritize high-value or -priority areas for electrification or other efficiency actions. We discuss potential ways to utilize these building stock datasets to create value for decarbonization initiatives run by various stakeholders.

Introduction

Commercial and residential buildings accounted for 35% of U.S. emissions in 2022 (EIA 2023), underscoring their pivotal role in achieving climate and decarbonization goals. Building electrification presents a pathway to decarbonization, with a growing number of buildings and homes embracing this shift. The proportion of U.S. households heated by electricity has grown from 1% to 40% between 1950 and 2020 (Davis 2022). While electrification can lower emissions by utilizing renewable energy sources, it also imposes higher demands on the grid. Simultaneously, the grid is experiencing rising demands for electric vehicle (EV) charging, driven by the increasing popularity of EVs in the U.S. market. Hybrid, plug-in hybrid, and battery electric vehicles accounted for 13% of new light-duty vehicle sales in 2022, rising to over 16% in 2023 (EIA 2024). Moreover, renewable energy sources are intermittent, and the grid is evolving toward greater interactivity. As utilities manage both rising electricity demand and variable supply, it will be increasingly important to understand and forecast the hourly effects of building energy efficiency and electrification.

Building stock energy modeling, the practice of developing a collection of building models to be representative of an overall building stock, is a valuable tool for informing and optimizing utility electrification strategies. It offers insights into how buildings might electrify, and how this impacts the demand for electricity. This paper presents the development of a load forecasting tool using the U.S. Department of Energy's (DOE) ResStock™ and ComStock™ datasets. We describe the general methodology of the load forecasting tool, present high-level results of the tool for an independent system operator (ISO) application and provide an overview of other potential applications for these datasets by stakeholders.

Comparison of Building Stock Dataset to Traditional Energy Information Resources

The U.S. Energy Information Administration's (EIA) residential energy consumption survey (RECS) (EIA 2022) and commercial building energy consumption survey (CBECS) (EIA 2021) are national-scale building energy characteristic and consumption surveys that have been conducted since 1979. The California Energy Commission's residential appliance saturation study (RASS) (CEC 2022) and commercial end-use survey (CEUS) (CEC 2019) are California surveys which have been conducted since the mid-2000's. The Northwest Energy Efficiency Alliance's residential building stock assessment (RBSA) (NEEA 2022) and commercial building stock assessment (CBSA) (NEEA 2019) are Pacific Norwest surveys which have been conducted since 2012 (RBSA) and 2001 (CBSA). These traditional surveys use a combination of self-reporting and onsite visits to collect data on building stock characteristics and use utility bills to describe energy consumption. They typically use engineering models to break whole-building energy consumption down into end uses and use standard error metrics to describe the survey results' reliability.

While these surveys contain a wealth of information on the building stock, the geographic granularity is low because of data collection costs and the need to protect privacy. For example, CBECS surveys about 6,000 buildings to represent the nearly 6 million commercial buildings in the country.

Building Stock Models, such as the U.S. DOE's ResStock (NREL 2024b) and ComStock (Parker et al. 2023) tools, developed by the National Renewable Energy Laboratory (NREL), combine RECS and CBECS with higher geographic resolution datasets such as the Census' American Communities Survey (ACS) (Census Bureau 2022) and the CoStar commercial real-estate database (CoStar 2024) to create hundreds of thousands of building descriptions. These building descriptions are converted into whole-building energy models using OpenStudio (Alliance for Sustainable Energy, LLC 2023), and the hourly energy consumption of each building by end-use is estimated using the EnergyPlus (NREL 2021) simulation engine coupled with local weather data. The result is more geographically, temporally, and end-use specific than the traditional surveys.

ResStock and ComStock are complimentary to, not duplicative of, traditional surveys. In some aspects, such as the distributions of buildings by vintage, size, and type, they are much more granular than traditional surveys. However, because ResStock and ComStock are not surveys, they do not have standard error metrics to describe how well their estimates describe the stock or energy consumption. Instead, their estimates are compared to a range of other data sources to present users with an idea of how well they represent reality. For some building types, fuels, etc. the fit between other data and these models is close; for others it is further. The models are periodically refined to improve this fit or incorporate new data. Users of ResStock and

ComStock data must be aware of, and account for, differences between model results and known data which have higher certainty. One method of doing this is described in this paper.

Deep Dive: Electrification Load Forecasting Tool Development

The development of the load forecasting tool for an ISO included five major tasks: (1) Characterizing the building stock using ResStock and ComStock; (2) Developing electrification pathways; (3) Forecasting adoption of the pathways; (4) Modeling hourly demand impacts of the pathways; (5) Pulling the resulting outputs into a final load forecast.

Building Stock Characterization

The initial phase involved analyzing over 40,000 individual building models from the ResStock and ComStock data in the study region. The characteristics were aggregated into technologically similar space heating, space cooling, and water heating systems, resulting in approximately 24,500 building characteristic combinations for modeling electrification pathways. This allowed us to group similar buildings into adoption groups based on key building characteristics.

Next, ResStock and ComStock model data were combined with 2020 ACS Census data for housing characteristics across the entire building stock in the study region. This information helped determine total square footage for each residential adoption group. To ensure comprehensive coverage, the resulting square footage was compared to EIA's CBECS and RECS data. Discrepancies were addressed by identifying 26 building types not modeled by NREL, leading to an underestimation of total square footage by 42%. To rectify this, the square footage associated with each unmodeled building type was added to the modeled building type with the closest energy use intensity (EUI).

Following the aggregation of space and water heating building characteristic square footage data into the adoption groups, we determined the average EUI on a kWh per square foot basis for each end use affected by electrification pathways. These EUI metrics serve as inputs for return-on-investment calculations in Task 2. Recognizing an underestimation in regional gas consumption by NREL's End-Use Load Profiles Results and Calibration Uncertainty report (Wilson et al. 2022), we scaled natural gas usage by 3.5x to align ComStock's estimate of with CBECs estimate of consumption for the same region. At the time of the study, the root causes of the underestimation were unknown, so we chose to scale space and water heating identically. Since this study was performed, the ComStock team has identified and accounted for some of the causes of this overestimation, which included things such as heating setpoints in warehouses, infiltration rates, and kitchen equipment power. Changes to the ComStock model are documented in release notes (NREL 2024a).

For the industrial sector, because the focus of the load forecast was on building electrification, we only modeled parts of the building load (heating, cooling, fans, lighting, etc.) and not the industrial process loads in those industrial buildings. Given sparse data, we utilized ACS 2017 data for Manufacturing Industries in the region to identify establishments. This information, refined for specific NAICS codes also present in EIA's Manufacturing Energy Consumer Survey (MECS) dataset, allowed us to estimate total square footage for the industrial sector in the region. Results were then scaled for each state based on their regional share. We modeled the industrial square footage as 10% medium office, 90% warehouse, based on the resemblance of warehouse facilities to manufacturing floors and the typical presence of adjoining office space in industrial facilities. The final output data for this task included total building square footage, average HVAC, and domestic hot water (DHW) and EUI, organized by building type, geographic location, and system characteristics. This data is integral for estimating energy impacts and return on investment from electrification measures in the subsequent electrification pathways development step, as well for the adoption modeling.

Developing Electrification Pathways

The first step in developing the electrification pathways was the identification of the key electrification technologies to analyze. After an extensive literature review, we selected the nine technologies shown in table 1.

Table 1. Electrification Pathways

Technology	Brief Synopsis	Reference Equipment
Ductless Air Source Heat Pump	Non-ducted split-system suitable for retrofits in smaller, non-ducted spaces. Can fully displace or partially supplement existing heating equipment.	Mitsubishi M-Series – MSZ-FS12NA & MUZ-FS12NAH (Mitsubishi 2021)
Ducted Air Source Heat Pump	Ducted split-system suitable for retrofits in small-scale ducted systems. Can fully displace or partially supplement existing heating equipment.	Lennox Central Heat Pump (Lennox 2020)
Variable Refrigerant Flow Systems (VRF)	Ductless heat pumps with higher capacities and variable-speed compressors. Can provide simultaneous heating and cooling; assumed as air-source equipment for full displacements.	Lack of direct performance data – used Mitsubishi M-Series as basis
Heat Pump Rooftop Units (RTU)	Compact, packaged heat pumps installed on rooftops. Suitable for full or partial displacements based on existing heating systems.	Rheem Renaissance Package Heat Pump (Rheem 2019)

Technology	Brief Synopsis	Reference Equipment
Dual Fuel Heat Pump Rooftop Units	Rooftop heat pump systems with integrated gas heating. Considered partial displacements due to some supplemental gas use.	Same as above.
Air-to-Water Heat Pumps	Air-source heat pumps producing chilled or heated water. Assumed suitable for hydronic systems as full displacements.	Trane ACX (Trane 2022)
Ground Source Heta Pumps (GSHP)	Use the ground as a heat source/sink via an underground fluid loop. Adoption driven by corporate sustainability goals; modeled as part of certain pathways.	We modeled a COP of 4.05 based on Energy Star rated models (EnergyStar 2024)
Heat Pump Water Heaters	Move heat to service hot water; recommended for modest water heating needs. Larger systems with storage for higher volume needs uncommon.	We modeled a COP of 4.05 based on Energy Star rated models (EnergyStar 2024)
Heat Pump Water Heater with Booster	Includes an electric booster heater for higher service water temperatures. Assumed for specific building types.	We assumed a blend of 15% electric resistance usage with above heat pump. This resulted in an average COP of 3.29.

After identifying the technologies, we modeled each to estimate performance data and anticipated customer economics. As a first step in this modeling, we established capacity and COP curves tailored to each pathway. The COP of a heat pump diminishes with lower outdoor temperatures and higher operating capacities, creating a compound effect. Since COP determines both the electric impacts on the gird and the operating costs, both outdoor temperature and operating profile will have a significant impact on the grid impacts and cost-effectiveness of electrification. As a further complication, sizing practices significantly impact the capacity at which a heat pump operates. For instance, an oversized heat pump at 30 degrees Fahrenheit may operate below its rated capacity, while a smaller one for partial heating replacement may function at full load. To address these complexities, we established parameters to fully define COP for each technology pathway. These parameters include:

- COP at various outdoor temperatures and capacities
- Percentage of heating load at design temperature handled by the heat pump
- Minimum operating temperature of the compressor

- Whether the pathway involves full or partial replacement of the existing fossil fuel heating system.

We obtained these values from equipment submittal sheets for the reference equipment used in the pathway characterization, as well as assumptions about how heat pumps will typically be sized and operated. This information also determines whether any unhandled heat load is managed by electric resistance heat with a COP of 1.0 or by the existing fossil fuel system.

Next, we created a Python function to compute the seasonal COP for a heat pump, considering electrification pathway, building type, and weather profile. The process involves determining the heating design temperature and maximum load around it, setting the heat pump sizing temperature, finding the maximum load near the sizing temperature, and sizing the heat pump based on load and the percentage of design load. The capacity and COP of a given temperature are determined by referencing all published performance data and linearly interpolating between known values. For example, if the temperature is 10 degrees and COP/capacity values are available for 5 degrees and 17 degrees, the 10-degree values are based on the linear interpolation between those two known values. Table 2 shows the parameters utilized for the Residential pathways.

Table 2. Residential Pathway COP/Capacity Details

Pathway	COP Curve (°F, COP)	Capacity Curve (°F, % of Max Cap)	% of load at design Temp	Minimum Operating Temp	Full or Partial
Ductless Heat Pump - Full	(47, 6.05), (17, 3.515), (5, 2.42)	(47, 1), (17, 1), (5, 1)	100%	-13	Full
Ductless Heat Pump - Part	(47, 4.93), (17, 2.47), (5, 2.01)	(47, 1), (17, 0.79), (5, 0.63)	60%	5	Partial
Central Heat Pump - Full	(47, 4.0), (17, 2.6), (5, 1.76)	(47, 1), (17, 0.76), (5, 0.72)	80%	5	Full
Central Heat Pump - Part	(47, 4.0), (17, 2.6), (5, 1.76)	(47, 1), (17, 0.76), (5, 0.72)	55%	5	Part
Ground Source Heat Pump - Full	4.05 COP at all temperatures	100% at all temperatures	100%	-20	Full

Pathway	COP Curve (°F, COP)	Capacity Curve (°F, % of Max Cap)	% of load at design Temp	Minimum Operating Temp	Full or Partial
Air to Water HP – Full	(47, 4.54), (17, 1.82), (5, 1.93)	(47,1), (17, 0.8), (5, 0.71),	80%	-5	Full
PTHP – Full	(47, 3.91), (17, 2.49), (5, 1.98)	(47, 1), (17, 0.65), (5, 0.58)	90%	5	Full
PTHP - Part	(47, 3.91), (17, 2.49), (5, 1.98)	(47, 1), (17, 0.65), (5, 0.58)	55%	5	Full

After electrification technologies were identified and modeled, they had to be matched to baseline conditions based on feasibility to determine what upgrades were valid for what baseline conditions. Feasible electrification pathways are dependent on multiple building characteristics such as building type, operating schedule, and existing space heating and water heating systems. For the purposes of this analysis, we have simplified the space heating analysis to consider only the existing HVAC systems by state and building type, as modeled in ResStock and ComStock, to determine the appropriate pathway. This assumes that the existing systems were designed and installed to satisfy application requirements for zoning, thermal loads, and other considerations, so if the selected electrification equipment can effectively replace the functionality of the existing equipment, the consideration of other issues will be inherently addressed. Up to three pathways were modeled for each baseline system type to reflect the potential variability in the electrification solutions implemented for a given baseline system. The resulting competition among the different pathways is described in the adoption modeling methodology.

Once electrification pathways and their mapping to baseline conditions was determined, a set of key parameters were established for each pathway to create accurate estimations of operating economics and return on investment for use in the adoption modeling. These parameters were the type of displacement, the amount of load served, the heating COP and temperature pairs, installed capacity costs, fossil fuel heating efficiency, implementation barriers, incentive support, and 2022 penetrations. Table 3 below gives an overview of what each of these parameters represent.

Table 3. Key Pathway Parameters

Parameter	Explanation
Type of Displacement	Each electrification technology was characterized as a full displacement of the existing fossil fuel heating loads (“Full”), a partial displacement of existing fossil fuel heating loads (“Partial”), or both

Parameter	Explanation
Heat Pump Load/Supplemental Load	A quantification of the portion of the thermal loads served by either the heat pump (inclusive of electric resistance supplemental heat, if applicable) or fossil fuel-fired supplemental heat (i.e., the existing heating system or the gas-fired section of a dual fuel heat pump)
Heating COP and Temperature Pairs	COP/Temperature pairs taken from reference equipment submittal sheet. Typically, 47f & 17f, with some units providing additional data points such as 5f or -13f. This paired with a simple bin analysis of typical weather data results in annual average kWh per MMBtu heat delivered.
Installed Capacity Cost	Installed capital costs, inclusive of equipment costs and installation labor, were estimated on a per-ft2 basis for space heating equipment and on a per-kBtu/h output for water heating equipment for C&I and on a per-housing unit basis for residential. Given the range in costs from the literature, we attempted to pull from a limited number of consistent sources for multiple categories of equipment costs where possible.
Fussil-Fuel Fired Supplemental Heating Efficiency	An efficiency of 80% was assumed for all fossil-fuel fired supplemental heating (inclusive of new and existing equipment)
Implementation Barriers	Barriers to implementation were created for each of the pathway/building type combinations to represent the technical difficulty of the installation of the pathway relative to current conditions These values were based on professional judgement of severity of retrofit needed.
Incentive Support	Incentives were determined for each state by looking at both current/planned offerings through state/utility energy efficiency programs and at federal incentives such as the those through the Inflation Reduction Act. Incentives were assumed to not stack between state and federal options, excepting tax incentives, so the higher of the two was chosen.

Parameter	Explanation
2022 Penetrations	Initial penetrations of heat pumps systems, required as an input to the adoption modeling, were estimated by reviewing baseline study data and leveraging ResStock & ComStock metadata.

Additional parameters were needed for the baseline conditions to aid in developing adoption figures for retrofit applications. These included an assumed failure condition that could trigger a replacement event, installed capital costs, and a deferred replacement credit for retrofit applications. Table 4 below has a summary of each of these parameters.

Table 4. Key Baseline Parameters

Parameter	Explanation
Assumed Replace-on-Failure Trigger Condition	We assumed that failure of either the existing heating or cooling equipment (if not a single package) will be the triggering event spurring a replacement with a heat pump system.
Installed Capital Costs	Installed capital costs for baseline systems were estimated on a per-square-foot basis for space heating equipment and on a per-kBtu/h output for water heating equipment for C&I and on a per housing unit basis for residential.
Deferred Replacement Credit	For the early retirement retrofit market, we assume a present value “credit” to reflect the value of the equipment cost a participant would have otherwise incurred had they not replaced their baseline system before the end of its useful life.

Once all parameters were developed, retail rates for fuels and electricity were collected for each state in the study region. Rates were taken from the most recent EIA statewide average at the time from the State Energy Data System. These rates, coupled with the above parameters were used to create return on investment metrics for use in the adoption forecast process. For both the retrofit and market driven pathways, the return on investment (ROI) calculation is simply the annual energy cost savings/impact divided by the net installed cost to the consumer.

Adoption Forecasting

The adoption forecasting methodology relies on the well-established Bass Diffusion Model, which was introduced in 1969 and has been widely employed for estimating the adoption patterns of various products (Bass 1969). This model employs a differential equation to depict cumulative market adoption as an "S" curve, encompassing a phase of slow initial adoption, a subsequent period of rapid market share increase, and a final phase of leveling off. The distinctive shape and speed of this curve are primarily determined by two key factors: the coefficient of innovation (P) and the coefficient of imitation (Q). The former influences the speed of adoption in the early stages after product release, while the latter describes how quickly a product is adopted through mechanisms such as word-of-mouth.

In adapting the Bass Diffusion Model for electrification measures, the maximum adoption level is adjusted based on assigned barrier levels, specifically focusing on technical challenges independent of financial considerations. The maximum adoption level is then derated by the ROI of the electrification pathway. State-level policies are considered as significant influencers of the coefficient of imitation, reflecting the pace at which a given electrification technology transitions from early adoption by innovators to widespread use.

To account for uncertainties surrounding changes in ROI and policy support over the study horizon until 2050, a Monte Carlo Simulation is employed. This simulation allows for a probabilistic forecast of variations in these key parameters, providing a more robust understanding of potential scenarios. The core variables of the forecasting model, in this case ROI, policy level, and barrier, are then correlated with the parameters of the Bass Diffusion Model.

The adoption forecast is further nuanced by considering the competitive landscape among multiple electrification technologies. In cases where mutually exclusive technologies are vying for adoption within a specific building segment, the assumption is made that the maximum adoption level is determined by the pathway with the highest ROI. The actual adoption percentages for each pathway are then scaled based on their respective shares in the Monte Carlo Simulation. Figure 1 is the resulting incremental adoption of residential heat pumps by building segment. Notably it shows a large acceleration in annual adoption out to the mid-2030s after which new conversions begin to slow down once the bulk of the housing stock has already been converted.

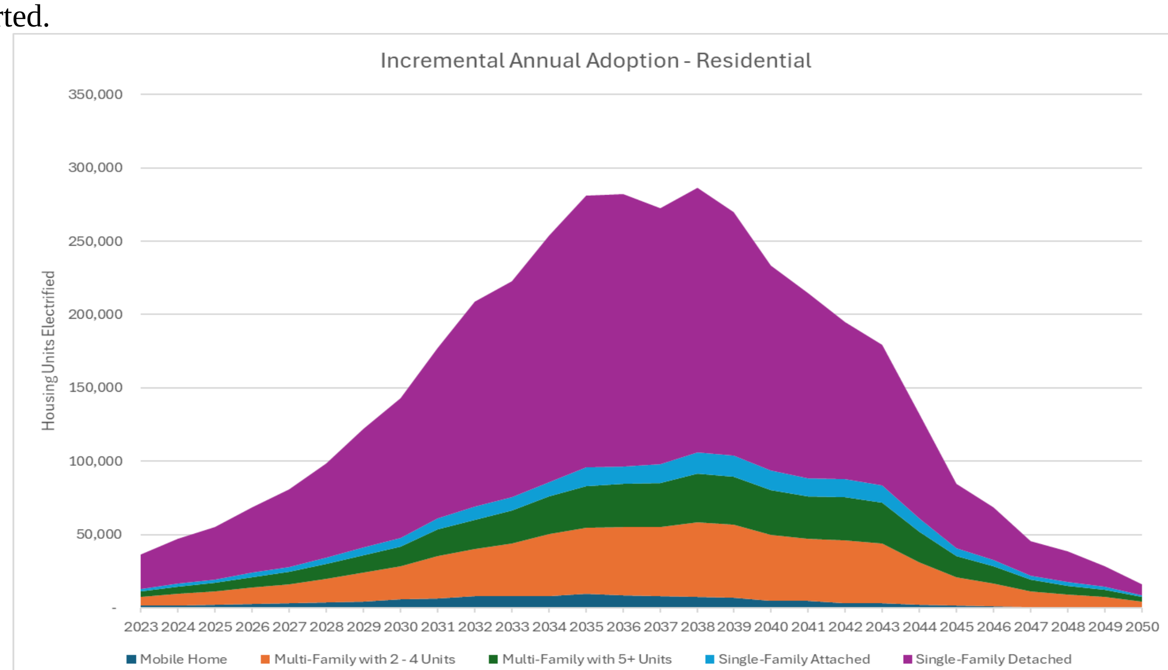

Figure 1. Residential electrification adoption by building segment.

Hourly Demand Modeling

In order facilitate estimates of grid impact, we created a set of regressions that would predict electric impact based on electrification pathway, building type, outdoor air temperature, hour of day, and weekday/weekend.

As a first step, we created aggregate weather data, using the weighted average of county-level weather files used by individual building models in ResStock and ComStock. Separate weather files are generated by building type and sector, factoring in the varying weightings in ResStock and ComStock. We paired this weather data with the end use profiles from the building stock modeling, allowing us to determine heating load at each hour and outdoor air temperature (assuming an 80% efficient existing heating system). Also, as discussed above, we applied a factor to increase heating load estimates to account for the underestimation in ComStock.

Next, for each hour in the year, the function extrapolates the COP of the heat pump at the given temperature based on equipment submittal sheets and the performance curves described above. If the temperature is below the minimum operating temperature, the heating load is addressed by the existing fossil fuel system for partial replacement or electric resistance heat for full replacement (note that minimum operating temperature was selected based on manufacturer data, and for some electrification pathways was low enough that supplemental heat was not needed). If the heating load exceeds the heat pump capacity, a mix of heat pump and backup heat is used.

Figure 2 is an illustrative graph that shows relative heating load on the y-axis (1.0 represents the maximum hourly load) and outdoor temperatures on the x-axis. The red vertical line indicates the minimum operating temperature, and the light red diagonal line depicts capacity increase as the temperature rises. Green dots signify hours with only the heat pump, pink dots denote hours with only electric resistance heat, and an orange dot represents hours with both electric resistance and heat pump heat.

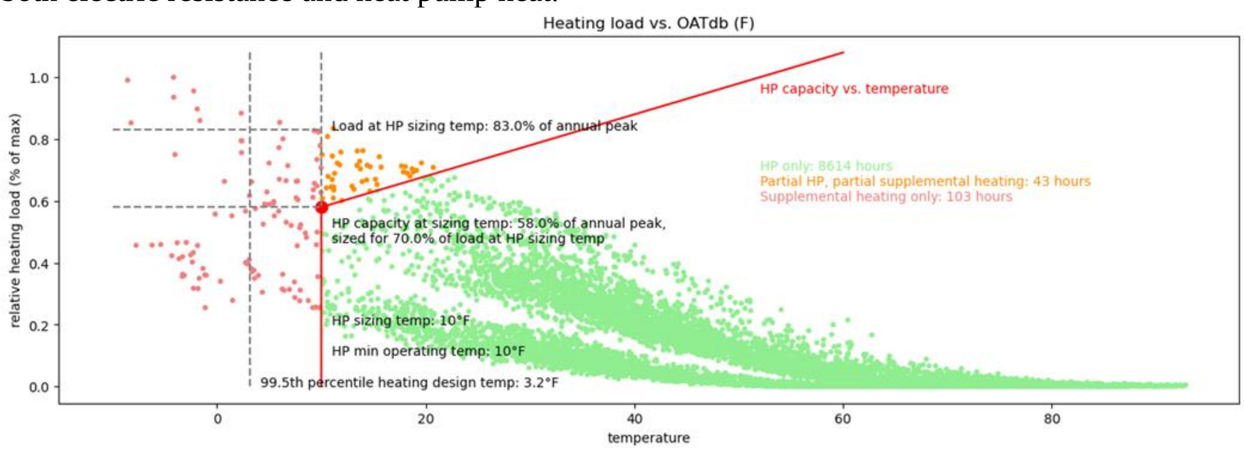

Figure 2. Illustrative heat pump hourly modeling results.

The electric load by building type, determined in the initial step, is converted to electric impact based on the temperature and heating system operation. During hours with green dots, the COP is determined using the heat pump alone. In hours with orange dots, a weighted average of the heat pump COP and electric resistance backup is used. Hours with red dots employ a COP of 1.0, representing electric resistance heat. For partial heating applications, there is no electric impact during hours with red dots, while hours with orange dots use the COP from the heat pump but on a portion of the total load.

To model electric impacts based on temperature and building type, a regression approach is adopted. The heating load from the previous step is converted to electric impacts using COP curves. The 8760 hourly data is categorized into day types (weekday/weekend) and hours. Scatter plots are generated for each day type and hour, plotting heating load against temperature. Regression equations are developed to determine electric impact as a function of pathway, building type, day type, and hour.

For full replacements, an exponential formula is used as the best fit regression line. However, for extremely low temperatures, where the exponential regression resulted in unreasonably high electric impacts, a maximum electric draw is defined at the 99.5% percentile load. This adjustment addresses the curve's steepness at very low temperatures, ensuring the electric draw does not exceed practical limits.

Final Forecast and Results

The final demand forecast is crafted through the amalgamation of the adoption forecast and the intricate details derived from hourly demand modeling. This forecast is not only comprehensive but also operates at both geographic and temporal resolutions, facilitating a nuanced and detailed analysis. Its adaptability stands out, as the analysis can be easily refreshed over time with the incorporation of updated heat pump characterizations, current adoption statistics, or refined demand modeling approaches, ensuring that the forecast remains accurate and reflective of the latest developments. Furthermore, its easy integration with existing demand forecast processes empowers it to offer valuable insights into the regional implications of building electrification.

The results of our analysis showed a very significant increase in electric demand, during cold winter days. This demand increase would result in a dual peaking system instead of summer peaking by the mid-2030s. Figure 3 is an example output, showing residential heating electrification driven demand in the year 2035. It is differentiated by full and partial displacement strategies, with extreme spikes from cold weather events. In this case the instantaneous demand increase over a baseline scenario of no heating electrification peaks at over 7 GW.

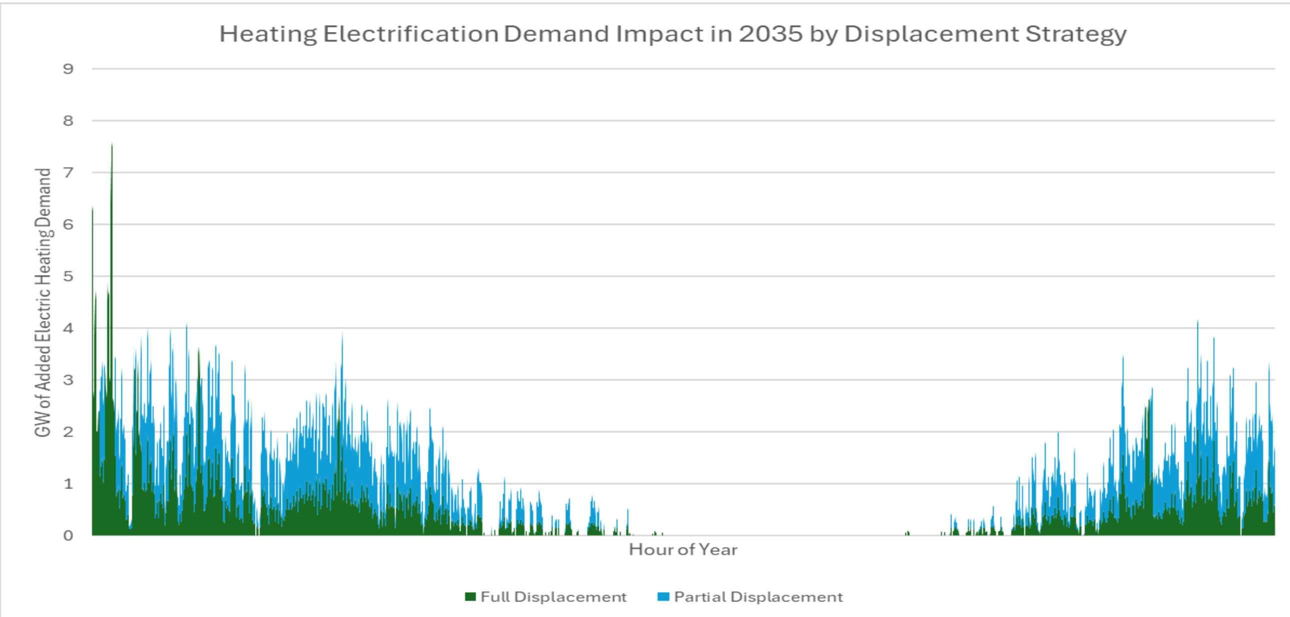

Figure 3. Residential electrification demand impacts modeled in 2035.

Discussion and Improvements

This methodology proved to be a powerful and flexible methodology for exploring various sensitivities in expended load growth due to heating electrification. However, given the complexity of the inputs and the detailed approach to modeling, many simplifications needed to be made and there is a lot of room for future improvements to the methodology. This section of the paper will highlight a few higher priority areas for improvement.

. As described, the methodology was designed to calculate impacts for each hour, building type, and weekday/weekend. However, this level of granularity severely limited the number of temperature samples for each hour/day combination curve. A fix to this would be to analyze each building model in ResStock/ComStock separately, instead of creating aggregated sets. However, this was computationally prohibitive at the time. Another solution would be to aggregate more building types or hours. However, this would decrease the impact of building occupancy schedules on the resulting impacts.

A second issue in the forecast is the lack of ability for a partial displacement to later convert to a full displacement. To address this, a more robust adoption model would need to be considered, with a significantly more complex market interaction scheme to account for the various competitive pressures.

A third area for improvement of the model would be to change the underlying characteristics of the heating electrification pathways over time. Improvements in efficiencies and decreasing capital costs could greatly alter the adoption and demand forecasts, however assuming improvements for the entire study horizon quickly becomes speculative.

Finally, the analysis involved significant assumptions on the sizing practices of heat pump installation and the COP performance curves. These parameters can be updated as more studies are performed looking at metered heat pump performance and typical sizing practices. The parameters in the adoption can likewise be updated, as more is understood about past adoption of heat pumps for heating.

Other Potential Use Cases

The additional analytical resolution provided by building stock models, both geographically and in building level analysis, presents an opportunity to enhance utility centric analyses. The demand forecast for electrification as discussed above is a clear example of how the building stock model provides a higher level of detail that could prove valuable in long-term planning efforts. This section of the paper will briefly speculate on where this style of analysis might provide additional value over standard industry practices.

Sensitivity Analyses for Decarbonization Programs

Decarbonization programs represent a fundamental shift in purpose and design from the traditional utility run energy efficiency program. Incentive strategies and their impact on installation practices can have drastic impacts on installed capacity and resulting grid impacts. For example, an incentive structure that is based on capacity may result in larger heat pumps than an incentive structure that is based on the number of compressors. The methodology above could be used to estimate the grid and budget impacts of one incentive strategy vs. another. This could similarly apply to general sizing strategies – what would be the difference in grid and financial impacts of sizing a heat pump at 100% of the design load, vs. 90% and using electric resistance back up. This could give greater insight into how program strategies and contractor standard practice might impact grid operations.

Potential Studies

Potential studies stand to gain a great deal of information and clarity from the inclusion of geographically oriented building stock models. While contemporary potential studies give face service to geographic resolution by focusing on utility or state service territories, bringing in more granular data can add significant value to potential studies, particularly for utilizes with diverse and distinct operating territories.

Baseline studies can be costly and difficult to obtain, and building stock models, if appropriately supported, can enable underfunded jurisdictions to utilize the more granular data a baseline study affords. Using regional comparisons, updates to building stock models based on a jurisdiction’s evaluation efforts can support another, greatly helping lesser funded and supported programs.

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