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End-Use Load Profiles for the U.S. Building Stock

Practical Guidance on Accessing and Using the Data

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List of Acronyms

AMY	Actual meteorological year
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
AVERT	AVoided Emissions and geneRation Tool
CBECS	Commercial Building Energy Consumption Survey
COP	Coefficient of performance
DSM	Demand-side management
DER	Distributed energy resource
ERCOT	Electric Reliability Council of Texas
EV	Electric vehicle
EULP	End-use load profile
EUSS	End-use savings shape
EPA	U.S. Environmental Protection Agency
GEB	Grid-interactive efficient building
IECC	International Energy Conservation Code
IRP	Integrated resource planning
NREL	National Renewable Energy Laboratory
NWA; NWS	Non-wires alternatives; Non-wires solutions
PUMA	Public Use Microdata Area
PV	Photovoltaic
RECS	Residential Energy Consumption Survey
TAG	Technical advisory group
TMY	Typical meteorological year
DOE	U.S. Department of Energy
WECC	Western Electricity Coordinating Council

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1 Introduction

End-use load profiles (EULP), which quantify how and when energy is used, are critically important to utilities, public utility commissions, state energy offices, and other stakeholders. Applications of EULPs focus on understanding how efficiency, demand response, and other distributed energy resources (DERs) are valued and used in R&D prioritization, utility resource and distribution system planning, and state and local energy planning and regulations. Consequently, high-quality EULPs are critical for widespread adoption of electrification, demand flexibility, and grid-interactive efficient buildings (GEBs). For example, EULPs can be used to forecast energy savings in buildings or to identify energy using activities that can be shifted to different times of the day.

Saving Shapes and ResStock™ and ComStock™ Data Releases[1]

Energy *savings shapes* describe the difference, at an hourly or sub-hourly resolution, between the use of electricity before and after the installation of an energy efficiency, electrification, or demand flexibility measure over the course of one year (Frick, Eckman and Goldman 2017). In some cases, such as replacing incandescent lamps with LED lamps, the consumption and savings shapes will have the same profile. In many cases, for example when replacing an electric resistance heater with a heat pump, the consumption and savings shapes will be different. NREL recently produced a national dataset of residential savings shapes to empower analysts to tackle a broad range of questions concerning the potential of building electrification measures and more.

As of December 2022, there have been two releases of ResStock EULPs and one release of ComStock EULPs. The initial release, in October 2021, included data for both residential and commercial buildings, and represents the baseline building stock as it was in 2018 as closely as possible with the best available data.

The September 2022 release includes updated residential EULPs for the 2018 baseline building stock, and also includes load profiles for 10 efficiency and electrification upgrade packages (Present et al. 2022a). Two of the packages are only envelope measures, four consider partial electrification, and four are complete electrification packages. Data from this release can be used to calculate residential savings shapes, so it can be referred to as the *end-use savings shape* (EUSS) data. The September 2022 ResStock release supersedes the October 2021 ResStock EULPs.

In this report, we refer to the data from either release as *EULPs.*

[1] See the project website to stay informed about these future dataset releases. https://www.nrel.gov/buildings/end-use-load-profiles.html

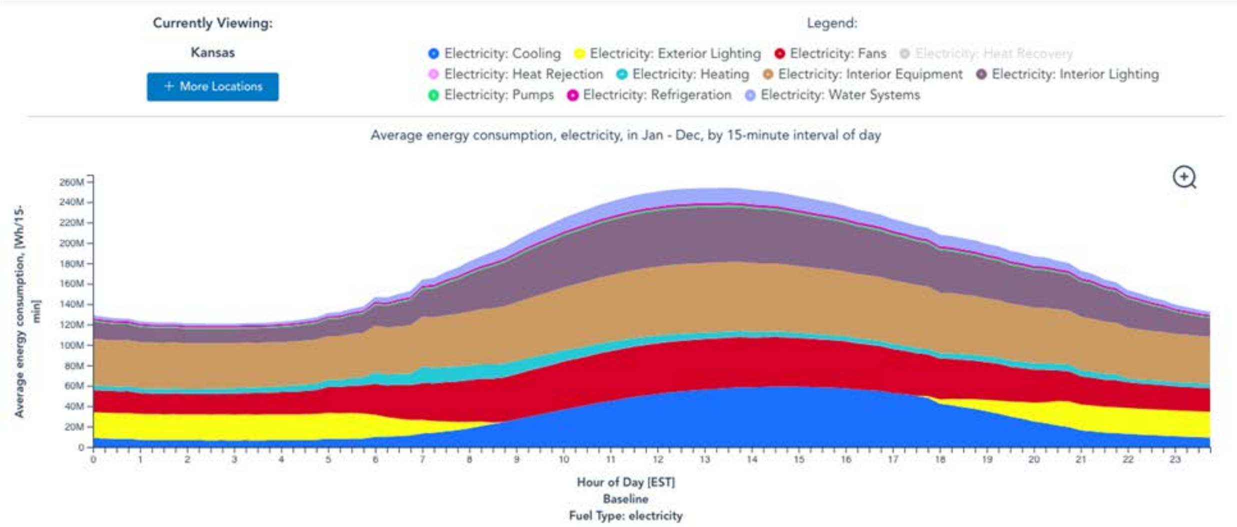

Figure 1. ComStock data viewer: average 15-minute commercial electricity consumption in Kansas

Source: *https://comstock.nrel.gov/datasets*

ResStock™ and ComStock™

ResStock and ComStock are physics-based simulation models developed by the National Renewable Energy Laboratory (NREL) to represent the energy use and energy saving potential of the U.S. residential and commercial building stocks with high granularity at national, regional, and local scales. They use a large number of representative building energy models[2]—10,000s or 100,000s, depending on the application—to represent the building stock with high fidelity. The building characteristics used in those energy models are statistically sampled from the full stock to create a set of buildings with a realistic diversity of building types, vintages, sizes, construction practices, installed equipment, appliances, occupant behavior, and climate zones.

The 15-minute end-use energy consumption of the individual building energy models are compiled into a database that can be filtered and aggregated. Figure 1 is an example of ComStock outputs as displayed in the online data viewer. See Accessing the End-Use Load Profiles for more details about the access options.

Previous, publicly available EULPs have limited applicability because of age and incomplete geographic representation. To help fill this gap, the U.S. Department of Energy (DOE) funded NREL to develop 15-minute temporally resolved electricity, natural gas, fuel oil, and propane EULPs for the residential and commercial building stock. The project focused primarily on calibrating and validating the outputs from ResStock and ComStock using a variety of empirical ground truth datasets, including anonymized utility meter data from more than 2.3 million customers, various end-use submetering datasets, and other public and private datasets related to energy use in buildings. The published EULPs represent the energy consumption of the U.S. building stock with approximately 900,000 physics-based building energy models.

[2] Each building energy model represents the *consumption* from a building or dwelling unit with one particular set of characteristics (e.g., wall insulation, heating system type and efficiency) and the *behavior* of one set of occupants (e.g., thermostat setpoints, occupancy hours, cooking schedule).

The ResStock and ComStock EULPs have three primary advantages compared to prior publicly available EULPs:

- **Building stock**: The building stock is described as it was in 2018, allowing analysts to consider a range of building characteristics instead of having to choose a small subset of "representative" buildings.
- **Geographic granularity**: The EULPs are presented at a very geographically granular level—by Census Public Use Microdata Area[3] (PUMA) or county—allowing analysts to use EULPs that represent a smaller, more discrete geographic area.
- **Behavioral diversity**: The EULPs are generated with building energy models that have a wide range of assumptions of how and when occupants use energy. This variety allows analysts to study the range and distribution of energy consumption of individual buildings, as well as an aggregate load shape that is not driven by any one assumption of when occupants use certain equipment.

[3] U.S. Census Bureau. Public Use Microdata Areas (PUMAs). https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html

2 Using this Report

Public utility commission staff, state energy offices, utilities, and others will be able to use the EULPs—together with tools such as Lawrence Berkeley National Laboratory's (Berkeley Lab's) Time-Sensitive Value Calculator (Frick, Carvallo and Pigman 2022)—to estimate the value of energy efficiency, demand response, and other DERs for a wide range of timescales. Such analysis can be used to guide utility resource and distribution system planning, research and development prioritization, as well as state and local energy planning and regulation. Additionally, the calibrated models behind the EULP dataset are the foundation to develop end-use savings shapes.

The report has two major sections. The first section provides practical guidance on **how to access the EULPs, and considerations and limitations for using them.** It will help users:

- Determine which data format and access method best meets their research goal: aggregate, web viewer, or individual model.
- Understand the information available from the online viewer: which is the easiest way to access the data.
- Identify buildings that are relevant to their research using the metadata and the online data viewer.
- Locate and use the building energy models that are the foundation of the EULPs.

The second section of the report **identifies and describes use cases** and specific examples of implementing the EULPs. The examples provide relevant information on seven common use cases for the EULPs (Table 1).

Table 1. Summary of End-Use Load Profiles Use Cases in this Report

Use Case	Application of End-Use Load Profiles
Integrated resource planning	Develop load forecast or energy efficiency supply curves
Long-term load forecasting	Analyze the impact of particular equipment adoption scenarios statewide, across a utility area, or a smaller geographic area; improve baseline building energy consumption assumptions
Transmission planning	Disaggregate the load into components that behave differently during and after a fault
Distribution system planning	Analyze the value of solar and wind as well as different types of energy efficiency based on the location and timing of the generation or savings
Electrification planning	Understand how electrification could affect annual electricity consumption and how the increase in consumption could be spread across hours of the year
Demand-side management	Use as an input to cost-benefit analysis to understand the time-value of energy efficiency; in potential assessments to understand the available amount and timing of energy efficiency (e.g., improving baseline building energy consumption assumptions); and in program design
Bill impacts and rate design	Estimate how electricity bills may increase or decrease with adoption of DERs or switching to a new time-based electricity rate for individual buildings with realistic load profiles, and aggregations of buildings

The Conclusion section of the report offers guidance that analysts can consider when using the EULPs. See Appendix A for additional information on project background, approach, data acquisition, occupant behavior model and model calibration and validation.

3 Accessing the End-Use Load Profiles and Savings Shapes

The EULPs are published in three formats: aggregates, web viewer, and individual load profiles. The data in the aggregates and web viewer are aggregations of results from building energy models with particular characteristics, while the individual load profiles are the results from a single building energy model. These three access methods are discussed below, and Table 2 provides a summary of their distinct characteristics.

Table 2. Summary of Characteristics of End-Use Load Profiles Publishing Methods

	Pre-aggregated Load Profiles	Data Viewers (Custom Aggregations)	Individual Building/Dwelling Unit Load Profiles
What is the data format?	.csv file with 15-minute energy consumption data by fuel and end use for one year	Bar charts, timeseries plots; option to download .csv file	.csv file with 15-minute energy consumption data by fuel and end use for one year
What characteristics are used to determine the aggregation?	Geography, building type	Customizable (e.g., geography, climate zone, building characteristics)	None
How many building energy models were used to create the aggregation?	Displayed in models_used column	Determined by filtering the metadata file	1 per profile
How much of the building stock is represented in the aggregation?	Displayed in units_represented (residential) or floor_area_represented (commercial) columns	Determined by filtering the metadata file	1 dwelling unit (residential) or building (commercial)
How is this data accessed?	OpenEI Data Lake[4]	ResStock and ComStock websites[5]	OpenEI Data Lake

3.1 Aggregates

Users can download 15-minute timeseries files for aggregations of each building type[6] in a particular geographic area from the OpenEI Data Lake. The aggregate files contain energy consumption broken

[4] The file README.md lays out the directory structure and provides a brief explanation of the information that can be found in each type of file. This file can be opened with a web browser, a text editor such as Notepad (Windows) or TextEdit (Mac), or a programming language such as Python.
[5] Require a free account that can be used for both.
[6] See Appendix C for a list of building types.

down by end use[7], as well as the number of building energy models used to develop the aggregate EULP and the total number of dwelling units or floor area they represent. These files are available for both typical meteorological year (TMY) and actual meteorological year (AMY) weather data at several levels of geographic aggregation:

- ASHRAE/IECC climate zone
- DOE Building America climate zone (DOE 2013)
- Independent System Operator (ISO) or Regional Transmission Operator (RTO) region[8]
- PUMA (2021 release only)
- County (2021 release only)
- State

For residential buildings, the files from the September 2022 release are available for the baseline building stock as well as 10 efficiency and electrification packages (i.e., savings shapes). They include carbon emissions for four of the scenarios in NREL's Cambium database[9] in addition to energy.

3.2 Data Viewers

ResStock and ComStock offer Data Viewer user interfaces for accessing the EULPs online. Each interface organizes data by (1) annual and timeseries energy and (2) building characteristics. This organization allows users to filter, visualize, and download results in custom ways.

3.2.1 Annual and Timeseries Energy

The *annual energy* and *timeseries energy* views allow users to explore energy consumption. The data viewer offers annual end-use bar charts, timeseries end-use charts, and annual energy histograms that users can explore further by filtering by location, fuels, and building characteristics.

The timeseries view displays energy consumption by end use for a day, month, or the entire year at 15-minute, hourly, or daily intervals. The data is aggregated in one of four ways. Two of the ways allow the user to select sum or average energy consumption:

- **Sum** of the energy consumption of the selected segment of the building stock during the selected timestep (e.g., 15-minute or hour interval) during the selected months.
- **Average** of the total consumption of the selected segment of the building stock during the selected timestep during the selected months.

In the other two cases, the data shown is determined by the daily peak energy consumption or maximum consumption during a 15-minute period of a day:

- The **peak day**[10] is the day with the highest daily peak (e.g., a hot day in a summer peaking region). The results are displayed as a 15-minute timeseries.

[7] See Appendix C for a list of end uses.
[8] FERC. RTOs and ISOs. https://www.ferc.gov/power-sales-and-markets/rtos-and-isos.
[9] NREL. Scenario Viewer: Data Downloader. cambium.nrel.gov/.
[10] Peak and minimum peak days are determined independently for ResStock and ComStock. To find the peak 15-minute period that includes both residential and commercial buildings, download the timeseries files, sum each time

- The **minimum (min) peak day** is the day with the lowest daily peak (e.g., a temperate spring day). The results are displayed as a 15-minute timeseries.

Users can export a .csv file of the data displayed in the chart or the full year of 15-minute timeseries data for the segment of the building stock selected with the custom filters.

Figure 2 is an example of the timeseries view from the ComStock Data Viewer. It shows the average electricity consumption of Kansas's commercial building stock, by end use, for each 15-minute period of a day. The top portion is the data viewer interface, which includes options for the fuel types and time periods to display and a button for adding filters.

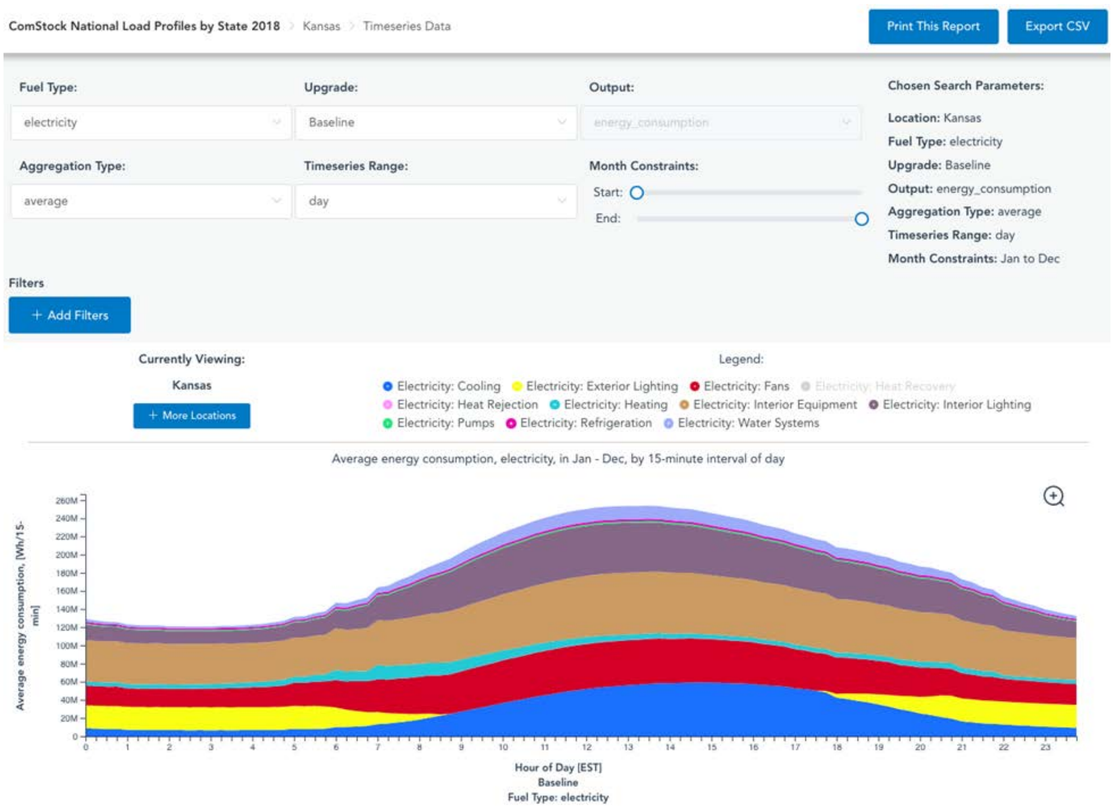

Figure 2. ComStock timeseries data view showing the average 15-minute commercial electricity consumption in Kansas

Source: https://comstock.nrel.gov/datasets

In ResStock, analysts have the option of only viewing the baseline EULPs, which represent the 2018 building stock, or comparing that baseline to one of the measure packages (which will create a savings shape). The comparison graphics show the EULPs for the baseline, the measure package, and the difference in total energy consumption between the scenarios (e.g., the savings shape). Figure 3 is an example from Illinois comparing average electricity load profiles for the baseline and the basic enclosure efficiency upgrade measure package.

stamp, and filter for the time with maximum consumption. As of December 2022, peak and minimum peak days are determined based on the consumption of all the fuels, not just electricity. To determine the peak solely with electricity consumption, download the timeseries files.

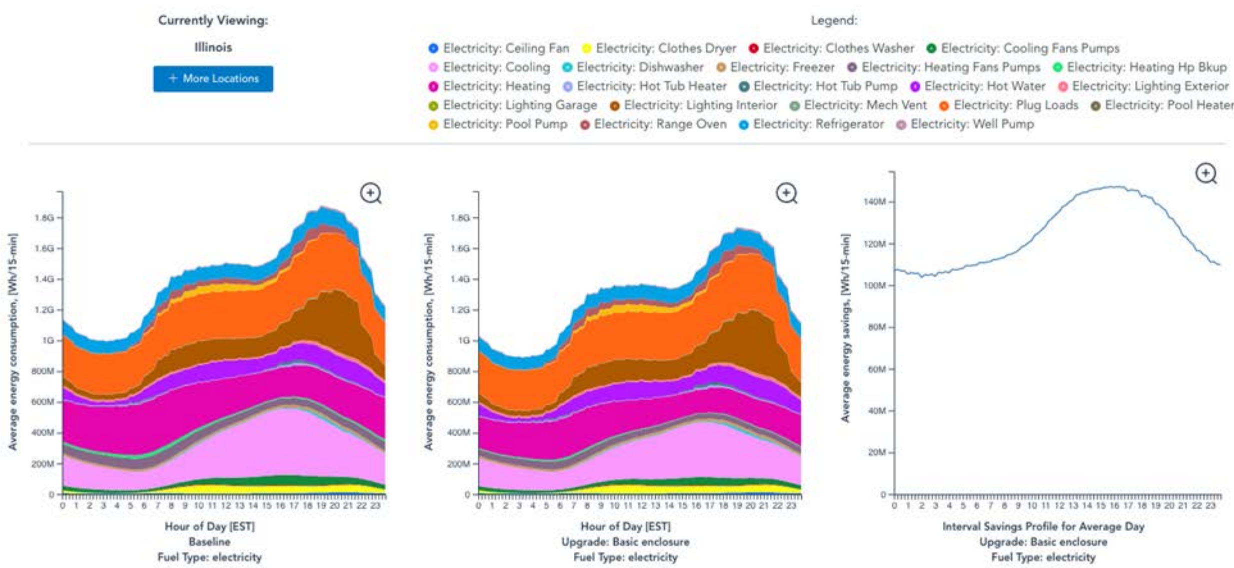

Figure 3. ResStock timeseries data view showing the average electricity savings from a basic enclosure upgrade to the residential building stock in Illinois

Source: https://resstock.nrel.gov/datasets

3.2.2 Building Characteristics

The *building characteristics* views allow users to explore the distribution of building types and characteristics in the selected geographic area. For example, Figure 4 shows the distribution of heating fuel with a filter for residential buildings with at least 10 dwelling units in the contiguous United States.[11] This is just one of many filters that can be applied. Users can export a .csv file of the data displayed in the chart in Figure 4.

[11] The sources of building characteristics data used in ComStock and ResStock to produce this dataset are listed in Tables 2 and 3 of Wilson et al. (2022). The ResStock probability distributions for each of these parameters are located at: https://github.com/NREL/resstock/tree/eulp_final/project_national/housing_characteristics (EULP dataset version) and https://github.com/NREL/resstock/tree/develop/project_national/housing_characteristics (latest developmental version). See the comments included at the bottom of each file for additional assumptions about how the probability distributions were derived. The ComStock probability distributions are not publicly available because some of the source datasets are proprietary.

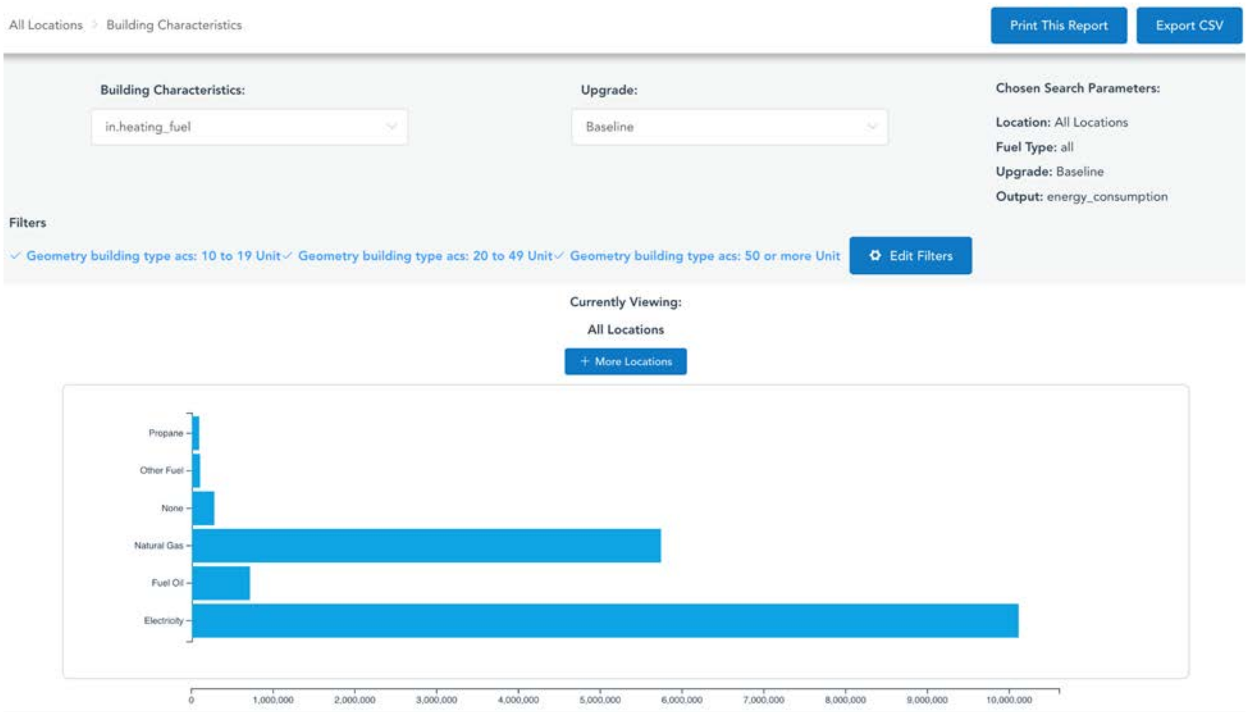

Figure 4. ResStock Building Characteristics view showing an example with heating fuel for multifamily buildings with at least 10 units

Source: https://resstock.nrel.gov/datasets

3.3 Individual Buildings[12]

The ResStock and ComStock EULPs use approximately 900,000 building energy models to describe the building stock. Each model represents the *consumption* from a building or dwelling unit with one particular set of characteristics (e.g., wall insulation, heating system type and efficiency) and the *behavior* of one set of occupants (e.g., thermostat setpoints, occupancy hours, cooking schedule). These differences affect all aspects of the consumption—annual energy consumption, end-use breakdown, and timing of consumption. The timeseries results and individual building energy models are available for download from the OpenEI Data Lake.

The residential and commercial metadata files[13] allow users to identify particular buildings or dwelling units with specific characteristics. The files contain one row for each energy model (residential dwelling unit or commercial building) and include data on the building type (e.g., single-family detached, small office), location (e.g., state, PUMA, weather station), building characteristics (e.g., floor area, HVAC system type), and annual energy consumption by end- use and fuel type. The metadata can be used to identify a set of building models or load profile results with specific characteristics to download, determine the number of building models included in a custom aggregation, and compile custom

[12] In this context, a "building" refers to an individual energy model. On the residential side, each model simulates a dwelling unit, so a multifamily structure would be composed of multiple "buildings." On the commercial side, each model simulates a building.

[13] Each dataset has the metadata available in two file formats. "timeseries_aggregates_metadata/metadata.tsv" is tsv format and can be opened in a spreadsheet program such as Excel. "metadata/metadata.parquet" contains identical data but is in parquet format and can be accessed programmatically.

aggregations programmatically using a scripting language such as Python.[14] The fields of the metadata files are described in the data_dictionary.tsv file provided with each dataset.

The building energy models corresponding to each individual building simulation results are also available for download.[15] The models can be re-run with other weather files, changed to represent a retrofit, or simply used as a starting point for other modeling efforts. The metadata files provide the characteristics of the models so that users can select those with the desired characteristics to download.

[14] In the future, additional resources on how to do this will be available at https://www.nrel.gov/buildings/end-use-load-profiles.html.

[15] The models for the 2021.1 release are in OpenStudio format. The models for the 2022.1 residential release are in Home Performance eXtensible Markup Language (HPXML) format.

4 Considerations and Limitations

A companion report, *End-Use Load Profiles: Methodology and Results* (Wilson et al. 2022), provides a robust discussion of the accuracy and uncertainty in the published EULPs. Here, we highlight seven considerations and limitations analysts should review prior to using the EULPs:

- Stock characteristics
- Weather files
- Time zones
- Individual buildings and aggregates
- Sample sizes
- Uncertainty

4.1 Stock Characteristics

The October 2021 ResStock and ComStock EULP releases represent a snapshot of the 2018 building stock—specifically in the distribution of building types and characteristics. ResStock covers all the residential building types reported in the Residential Energy Consumption Survey (RECS).[16] It does not include group quarters such as dormitories or military barracks. ComStock models 14 building types,[17] which together make up 66% of site energy consumption and 64% of floor area reported in the Commercial Building Energy Consumption Survey (CBECS)[18] (figures 5 and 6). ResStock covers the contiguous United States; ComStock also includes Alaska and Hawaii.

[16] EIA. RECS Terminology. https://www.eia.gov/consumption/residential/
[17] Small office, medium office, large office, retail, strip mall, warehouse, primary school, secondary school, full-service restaurant, quick-service restaurant, small hotel, large hotel, hospital, and outpatient.
[18] EIA. 2018 Commercial Buildings Energy Consumption Survey consumption and expenditures preliminary results. https://www.eia.gov/consumption/commercial/.

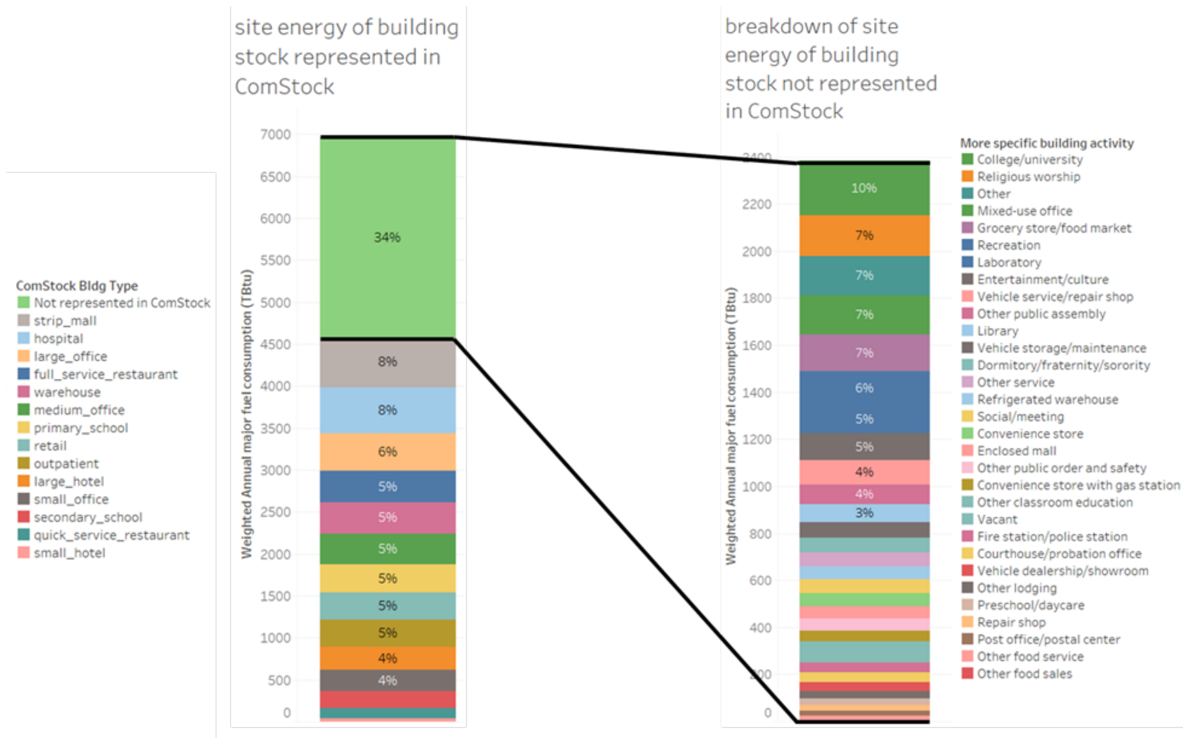

Figure 5. Annual energy consumption of commercial building types represented in ComStock compared to CBECS 2012

Source: NREL, pers. comm., 2022

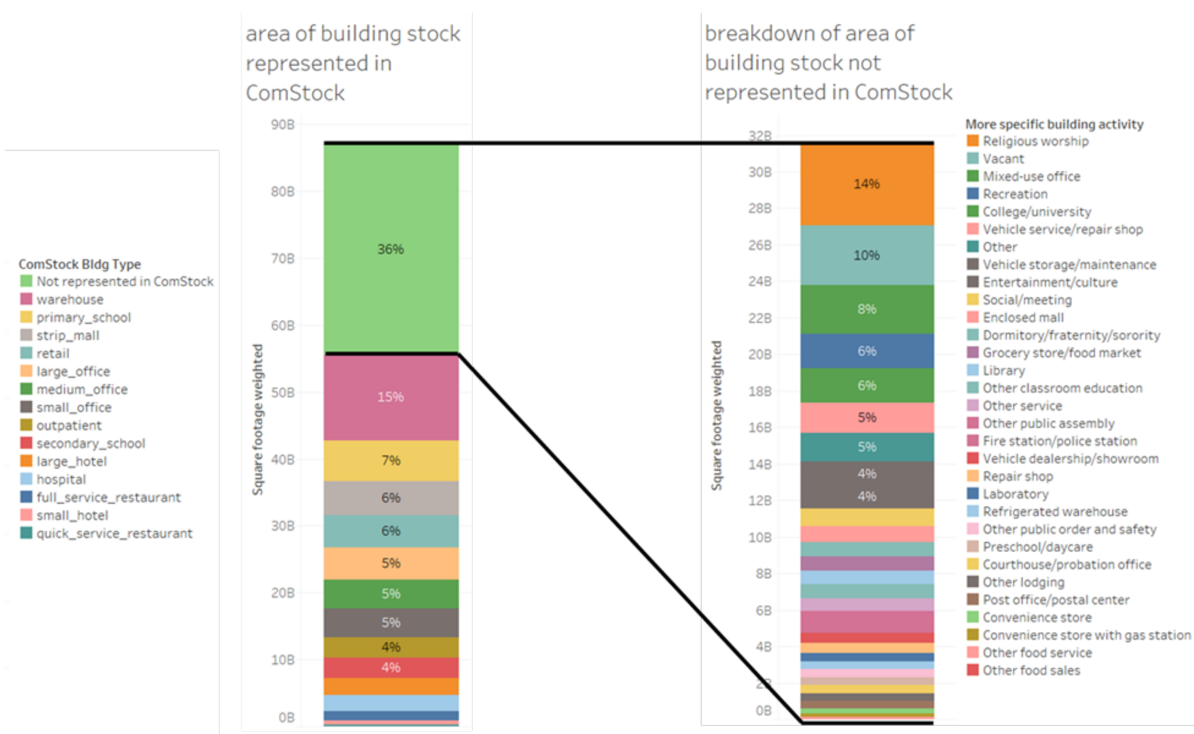

Figure 6. Floor area of commercial building types represented in ComStock compared to CBECS 2012

Source: NREL, pers. comm., 2022

Using ComStock to Represent the Full Commercial Load

Because ComStock does not represent all of the energy consumption or floor area covered in CBECS (figures 5 and 6), it must be scaled up for planning use cases that consider the complete commercial or system load. There are two approaches to scaling the ComStock data: analysts can (1) scale up the consumption from ComStock to match total known floor area, or (2) take a known total load, subtract the ComStock modeled load, and consider the remainder a static "gap model" that can be scaled or modified independently. The gap model represents both the unmodeled buildings and also non-building loads that are not metered, such as street lighting.

In both cases analysts would assume that the end-use breakdown and load shapes are the same in the unmodeled building types as they are in ComStock.

4.2 Weather Files

The ResStock and ComStock EULPs come with two weather options: typical meteorological year (TMY) and actual meteorological year (AMY).[19] Building energy modeling traditionally uses TMY files because they reflect long term patterns. However, TMY cannot be used for calibration to empirical data, so the project team developed 2018 AMY files and provides results for both types of weather (Wilson et al. 2022).

Table 3 summarizes the advantages and disadvantages of the two types of weather files.

Table 3. Advantages and Disadvantages of TMY and AMY Weather Files

	Advantages	Disadvantages
TMY	- Standard for building energy modeling - Based on 15-30 years of data - Publicly available at no cost[20]	- The climate is changing, so weather that was typical in 1976-2005 will not continue to be "typical" - Not synchronized across locations - Cannot be compared to empirical data
AMY	- Synchronized across locations - Can be compared to empirical data	- Based on a single year - Input files in EnergyPlus Weather (EPW) format for energy modeling are available for purchase but are not free.[21] However, .csv files with the major weather variables are available on the OpenEI Data Lake.

The primary advantages of TMY data are that it is based on many years of weather data—up to 30 years in many cases—and are publicly available for use in energy models. However, because the TMY data is based on weather data collected between 1976-2005, the weather that was typical during that period is not

[19] The initial October 2021 release of the EULPs only includes AMY data from 2018. The September 2022 release for ResStock adds AMY data from 2012.
[20] TMY3 weather files in EPW format are available at https://energyplus.net/weather. For convenience, a set of these files renamed to match ResStock and ComStock county IDs is available at https://data.nrel.gov/submissions/156.
[21] Vendors providing AMY weather in EPW format are listed at https://energyplus.net/weather/simulation.

representative of typical weather in the future because of climate change.[22] Also TMY data is not synchronized across files; one weather file may have a heat wave on the same day that a neighboring location using a different weather file does not (Wilcox and Marion 2008). Users should only aggregate data generated with the same TMY file (e.g., nearby PUMAs or counties) for applications that compare or aggregate *timeseries* results from the same day or hour (see the text box for more information). It is not problematic to aggregate data across multiple TMY weather files for applications only using *annual* energy results.

The primary advantages of AMY data are that it is only from a single year and therefore inherently synchronized, and that it can be compared against empirical data. The disadvantages are that it is based on a single year and that EPW weather files for modeling must either be purchased or constructed from multiple sources. Users should employ results created using AMY data to compare time-dependent consumption across multiple weather files (e.g., calculating aggregate peak demand across a state or regional grid). It also should be used in applications that compare or aggregate results from the same day or hour in locations assigned to different weather files.

Neither type of weather file takes the effects of climate change into account.

Aggregating Timeseries Results

Applications that compare or aggregate *timeseries* results from the same day or hour, such as calculating aggregate peak demand across a state or regional grid, require that the EULPs being used be synchronized.

Users performing timeseries analysis must verify that the TMY data was generated with the same TMY file, as indicated in the “in.weather_file_TMY3” field in the metadata. AMY data is inherently synchronized; it can always be used and may be used for analysis in regions that include multiple TMY files.

If the analysis covers a region with only a single weather file, users can compare the actual conditions in the TMY and AMY data to help inform their decision on which data to use. The metadata indicates the weather files used for each model,[23] allowing the analyst to compare applicable parameters of the TMY and AMY data for a particular location.[24] For example, analysts interested in a hot year may choose to use the TMY or AMY data with more cooling degree days in their location.

4.3 Time Zones

All of the EULPs are in Eastern Standard Time. When conducting an analysis in another time zone, or during a period that covers daylight saving time, users must shift the profiles accordingly. The weather files are given in local standard time.

[22] EPA. 2021. Climate Change Indicators: Heating and Cooling Degree Days. https://www.epa.gov/climate-indicators/climate-change-indicators-heating-and-cooling-degree-days.
[23] “in.weather_file_2018” and “in.weather_file_TMY3” columns
[24] While the full AMY weather files in EPW format that are used for running an energy model are not publicly available, the EULP dataset includes some key AMY weather information including dry bulb temperature and relative humidity.

4.4 Individual Buildings and Aggregates

Individual buildings have more variation in consumption than aggregate load profiles. Figure 7 illustrates 15-minute consumption for a peak day based on a range of numbers of models. The top left chart is based on two models and contains several spikes and steep ramps throughout the day during the specific times when the two sets of occupants cook or turn on their clothes dryers. As more models are added to the aggregation, the load shape smooths out and the peak gets lower because the aggregation includes characteristics, behavior, and usage patterns from a diverse set of buildings and occupants. See Sample Sizes, below, for a discussion of the implications of this.

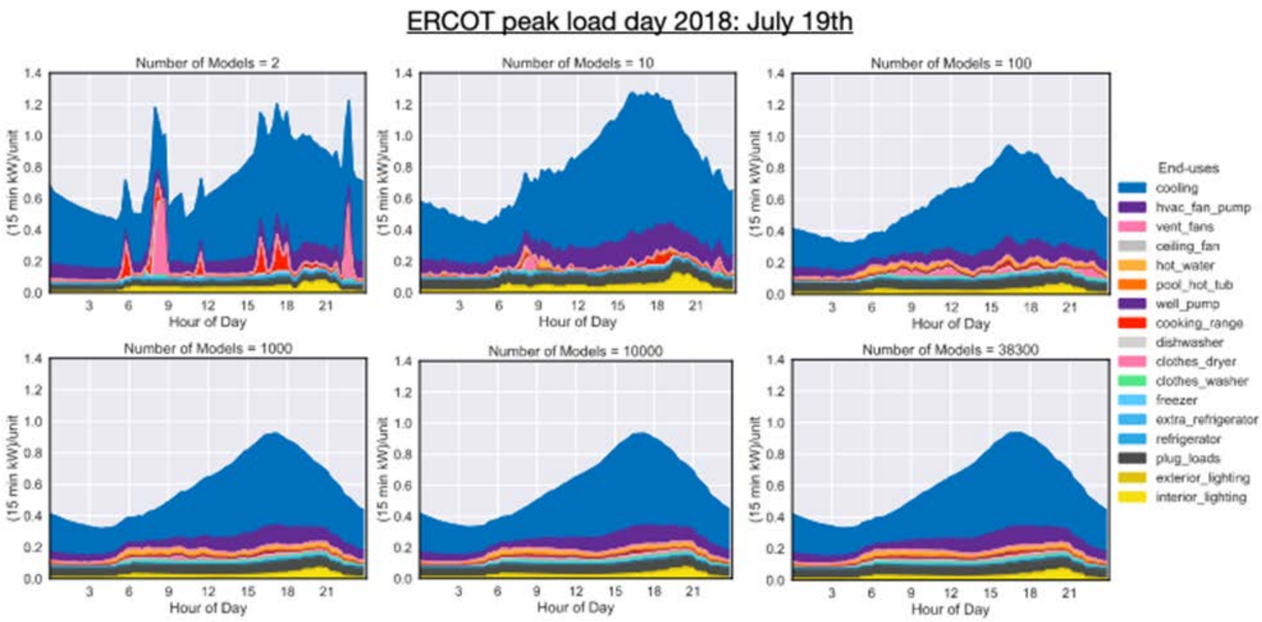

Figure 7. Visual convergence of ERCOT end-use loads by the number of models used to construct the end-use timeseries

Source: Wilson et al. 2022, Figure 368

Generally, it is most appropriate to use individual building load profiles when studying a distribution of possible outcomes. For example, as discussed in the Bill impacts use case, analysts can use individual building load profiles to understand the range of potential impacts a change in rate structure may have on a particular type of building. When studying the overall behavior or impact of the load, aggregate load profiles are the most appropriate because they reflect the building stock as a whole.

4.5 Sample Sizes

The ResStock and ComStock EULPs are provided at a very granular level, both in terms of geography and the ability to filter based on building characteristics. Users who create specific analysis criteria may produce results that are generated from very few building energy models (i.e., a small sample size). This will produce results that may be biased based on the characteristics of those few samples, and also may exhibit unrealistically spiky usage patterns (Figure 7).

There are two ways to determine the number of models included in an aggregation:

- Pre-aggregated data files: The pre-aggregated files downloaded from the Open EI Data Lake have a "models_used" column.
- Metadata: Custom aggregations from the Data Viewer or Building Characteristics tab require the metadata to determine the number of models. Applying the same filters in the metadata as the online interface will show the number of models that meet the criteria.

The residential project team recommends that an aggregation be based on at least 1,000 models (Wilson et al. 2022, Section 5.1.3). If the desired aggregation contains fewer models, users can relax geographic or other filters to increase the sample size. However the building stock may differ in the expanded geography, and it could be preferable to stay with the smaller sample or find other buildings of a similar vintage in another city. This is an area of ongoing research, so users are advised to try several options and compare their metrics of interest.

4.6 Uncertainty

Wilson et al. (2022) contains extensive comparisons of the electric ResStock and ComStock EULPs and the metered data used for calibration. Analysts can use these comparisons to assess their confidence in the ResStock or ComStock EULPs underlying a particular analysis. The comparisons include annual comparisons with data from EIA (e.g., Wilson et al. 2022, Figure 189), visual season average time-of-day comparisons to the calibration datasets (e.g., Wilson et al. 2022, Figure 220), and numeric summaries of particular quantities of interest (e.g., Wilson et al. 2022, Figure 186; included here as Figure 8). Because the data used for validation is also imperfect, differences between modeled and measured data are a combination of errors in both (Wilson et al. 2022, p. 342 Uncertainty in Empirical Data).

Figure 8 displays the percentage difference for several consumption metrics when comparing ResStock EULPs and calibration data. The negative (blue) numbers show that ResStock EULPs tend to underestimate residential electricity consumption in Horry County, South Carolina; the positive (red) numbers show that they tend to overestimate the peak consumption in Tallahassee, Florida.

	qoi_type	average_daily_base			average_daily_peak			top_10_average_daily_peak		
	season	shoulder	summer	winter	shoulder	summer	winter	shoulder	summer	winter
region	region_name									
region 1	ComEd, IL	-29%	-27%	-30%	-1%	7%	-11%	4%	1%	-18%
region 2	Fort Collins, CO	-7%	-9%	-2%	51%	36%	8%	47%	18%	20%
region 3	Seattle, WA	29%	35%	6%	46%	61%	8%	35%	57%	3%
region 4a	Chattanooga, TN	-11%	-4%	-16%	32%	26%	7%	47%	24%	19%
region 4b	Tallahassee, FL	-2%	-8%	7%	41%	24%	62%	81%	24%	128%
region 4c	Horry County, SC	-24%	-12%	-28%	-10%	-8%	-17%	1%	-8%	-14%
region 5a	Cherryland, MI	-34%	-35%	-26%	-3%	6%	-15%	22%	6%	-21%
region 5b	State of VT	-16%	-27%	-17%	20%	18%	-2%	22%	8%	-4%

Figure 8. Magnitude of discrepancies for the total residential building stock

Source: Wilson et al. 2022, Figure 186

Each comparison may result in different levels of discrepancy. For example, ResStock EULPs for winter electricity use in Florida are similar to EIA monthly retail sales for Florida (Wilson et al. 2022, Figure 161; included here as Figure 9. However, Figure 8 shows that winter peak consumption in Tallahassee is overestimated. This suggests that the discrepancy may be specific to Tallahassee.

The validation effort focused on electricity. For natural gas, comparisons between the ResStock and ComStock monthly and annual consumption and EIA survey data informed improvements in the models (see examples in Figure 9), but comparisons at a more granular timescale were outside the scope of this project. Although they are included in the modeled load profiles, the consumption of propane and fuel oil were not compared against outside data sources.

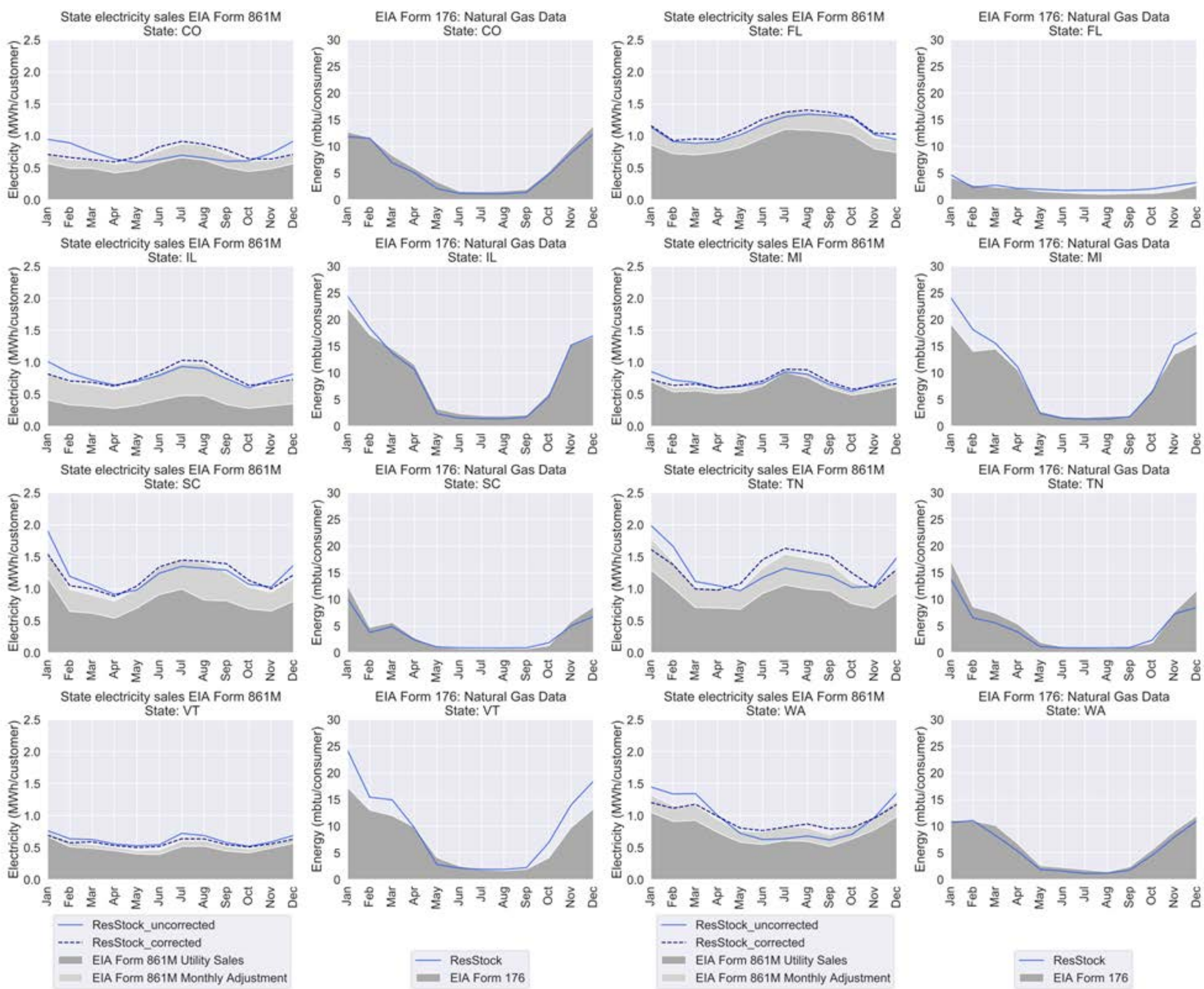

Figure 9. ResStock monthly electric (with and without correction) and natural gas energy compared to 2018 electric sales and natural gas data reported in EIA-861M and EIA-176, for the states that were part of the residential calibration regions. A complete set of state monthly comparisons to EIA-861M and EIA-176 is in Appendix F of Wilson et al. (2022).

Source: Wilson et al. 2022, Figure 161

4.6.1 Residential heating and cooling correction factors

The NREL team developed state-by-state daily correction factors for heating and cooling to account for weather-dependent error in the ResStock EULPs as compared to measured data.[25] The correction factors have not been applied to the EULPs in the October 2021 dataset but are available to download for the AMY 2018 dataset only.[26]

For additional information on using the EULPs and considerations and limitations of the data set, see Wilson et al. 2022.

[25] The methodology is described in Wilson et al. 2022, Section 3.2.10.
[26] If desired, multiply the space heating and cooling end uses by their corresponding factor for each day of the year and state.

5 Use Cases

The remainder of this report focuses on use cases for the ResStock and ComStock EULPs and savings shapes. We discuss seven use cases:

- Integrated Resource Planning
- Long-term load forecasting
- Transmission planning
- Distribution system planning
- Electrification Planning
- Demand-side management planning
- Bill impacts and rate design

This report is not intended to provide an exhaustive list of use cases for the EULPs and savings shapes, but to highlight some use cases the Technical Advisory Group identified as most important (Frick et al. 2019).

The ResStock and ComStock EULPs and building stock data can improve analysis for a variety of use cases. ResStock and ComStock EULPs have three key properties which add significant value to prior publicly available EULPs:

- **Stock characteristics:** Features such as the age of a building or the type of mechanical equipment used are examples of building stock characteristics, which impact how much energy a building consumes. Typically building energy analyses use a few “representative” buildings that have envelope characteristics, equipment types, and efficiencies that are common in an area. The ResStock and ComStock datasets represent the building stock as it was in 2018, which allows analysts to consider a more complete picture without choosing a small subset of building characteristics.
- **Geographic granularity:** Geographic granularity refers to the smallest geographic division for which data is available. For example, data that is aggregated to the state level is relatively coarse, whereas data that is aggregated to the city level is much more granular. Often building energy analyses are conducted at a relatively coarse geographic scale, such as the state or climate zone level, ignoring differences in weather and building stock within that region. The ResStock and ComStock datasets offer building stock characteristics and end-use load profiles down to the PUMA or county level, which allows analysts who are interested in a specific geography to use data from that geography instead of a larger region.[27]
- **Behavioral diversity:** To simulate the energy consumption of the building, a building energy modeler must specify the behavior of the building occupants; for example, when they turn on the lights, shower, leave, and return home, as well as the temperature setpoints. When the specified

[27] Several of the data sources underlying the building stock information provide data at a more geographically granular level, for example state or census division. Wilson et al. (2022) describes how the data sources were used to derive the stock characteristics at the PUMA or county level.

behavior of the occupants varies between buildings, the models can be said to include behavioral diversity. The ResStock and ComStock EULPs use approximately 900,000 building energy models to describe the building stock. Instead of choosing one "typical" schedule of behavior for each building type, ResStock and ComStock assign each model its own set of schedules representing different levels of energy consumption and timing of end uses. Taken granularly, this behavioral diversity allows analysts to study the range and distribution of impacts (e.g., Bill impacts and rate design). Taken at the stock level, the behavioral diversity creates a more realistic load shape that is not driven by any one assumption of when occupants use certain equipment.

The residential savings shapes can be used in all of the use cases discussed, although they currently cover 10 residential efficiency and electrification upgrades.

5.1 Integrated Resource Planning

Electricity resource planning—also referred to as *integrated resource planning* (IRP)—is the process of identifying short- to longer-term resource options to meet projected annual and peak load forecasts, electricity reliability requirements, and public policy goals at a reasonable cost. These processes typically provide a forum for regulators, electric utilities, and electricity industry stakeholders to evaluate the economic, environmental, and social benefits and costs of different investment options.

In IRPs, EULPs may be used in several ways. Typically, energy efficiency is a downward adjustment on the load forecast in an IRP (discussed in the load forecasting section below). When the quantity of efficiency that is cost-effective is determined outside of an optimization model, EULPs can improve assumptions about the timing of savings in an IRP. Using the EULPs, aggregate savings for the forecasted quantity of cost-effective energy efficiency can be spread across daily, weekly, or monthly load shapes. This can improve the accuracy of energy and capacity impact estimates.

A less common approach is to model energy efficiency as a selectable resource where it is included with all other resource options in an optimization model (Frick et al. 2021a). If this is the case, savings shapes, or end-use load profiles if the savings shapes are not available, can be used to help create energy efficiency supply curves. Energy efficiency supply curves are created as part of a market potential study, which is discussed in the DSM planning section below. The ResStock and ComStock building stock characteristics can be used to inform the load forecast and the development of energy efficiency potential, discussed in the load forecasting and DSM planning sections.

5.2 Long-term Load Forecasting

Electricity load forecasts predict electricity consumption (measured in kilowatt-hours, kWh) and peak load (measured in kilowatts, kW) over a variety of time scales. Short-term forecasting predicts consumption for hours or days to guide operational decisions, while long-term forecasting predicts consumption in future years (Anwar et al. 2018). Long-term load forecasts are used by electricity resource planners and ISOs/RTOs primarily as the basis for understanding future electricity needs and developing plans to ensure there are adequate resources to meet future demand, without incurring excess costs.

Typically, hourly EULPs have not played a significant role in informing electricity load forecasts because building energy consumption is often estimated using econometric forecasting models that do not rely on EULPs as inputs and because EULPs have been difficult to obtain. Econometric models rely on historical relationships between independent variables (e.g., population, employment, fuel prices) and their dependent variable—the demand for electricity. These models are less accurate when future public policies (e.g., electrification, codes and standards) or the availability of technologies (e.g., electric vehicles [EVs], solar photovoltaic [PV]) differs significantly from the historical period over which their statistical relationships were derived. Long-term forecasting models, which can better capture changes in public policies and technologies, generally are built up from representations of end use energy demands.

For example, the New York Independent System Operator (NYISO) began using the ResStock and ComStock EULPs in its long-term forecasting as part of its Comprehensive Reliability Plan, which creates 30-year energy and peak demand forecasts for the state. The forecast is for 11 geographic areas in the state that also overlap with 8 utility service territories. Prior to using an hourly forecast model (and the ResStock and ComStock EULPs), NYISO relied on total hourly loads in a geographic area from grid performance data, which represents overall customer class consumption.

They began exploring an hourly forecast model for a variety of reasons. These include increased adoption of new electric loads that are significantly different than existing hourly and peak loads, increased electrification of space heating and water heating, the impact of electric vehicles and energy storage technologies, and the resulting gradual forecast change over time from summer peaking to winter peaking system behavior. In their most recent Comprehensive Reliability Plan, NYISO used the ResStock and ComStock EULPs to consider very granular geographic data at the PUMA level.

NYISO also has used the ResStock and ComStock EULPs to understand the impact of electrification through close review of space heating and cooling end uses for electric and gas consumption. Currently in New York, a large fraction of space heating equipment in the state uses natural gas, fuel oil, or propane. NYISO was able to use the ResStock metadata to study buildings with electric versus natural gas heating and create representative electrified load profiles by PUMA to better understand the impact of declining fossil fuel usage and increased electricity usage. NYISO used this data to create representative annual and monthly energy consumption as well as hourly peaks, and to improve hourly load forecasting of new technologies.

Similarly, the EULP building metadata may be used to better reflect improvements in residential building stock characteristics. Analysts can filter the EULP dataset to provide load profiles for buildings constructed in the past 10 years for a specific geography. The aggregate shape of the building EULPs can be used to represent new construction instead of relying on the average consumption of the entire building stock.

5.3 Transmission Planning

The electric power *transmission* system moves "bulk energy products from where they are produced or generated to distribution lines that carry the energy products to consumers."[28] Transmission planners are responsible for developing long-term plans to maintain the reliability of the bulk power system in the area they oversee. As part of that process, planners simulate performance of the system at a few key times, typically the summer and winter peak hours as well as a spring light-load hour, to determine if infrastructure changes are needed. Planners use these simulations to assess whether the system will meet

[28] FERC Glossary. https://www.ferc.gov/industries-data/resources/public-reference-room/ferc-glossary

required performance thresholds after a fault or loss of a larger generator or transmission line (Faris et al. 2020).

The performance simulations rely on composite load models, which are timeseries data of electricity consumption decomposed into different load components (Faris et al. 2020; Liu et al. 2020).[29] These components do not map one-to-one to the building end uses considered in end-use planning. For example, single phase motors or three phase motors can both provide commercial space cooling, but the motors belong to two different load components because they respond to electric faults differently. Tables, named the *Rules of Association*, show how to map building end uses to the load components of composite load models.

To simplify the process of specifying composite load models for each load-serving transmission bus represented in a performance simulation, NERC has developed generic composite load models for four feeder prototypes that represent a suburban area, an urban downtown, a hybrid of the two, and a rural area. While the prototypes are adjusted for different climates, the underlying building models are generic, and the relative proportions and characteristics of the models are fixed for each prototype (Faris et al. 2020). Planners can use the ResStock and ComStock EULPs to select data from the particular geographic area they are analyzing instead of using the prototypes. The Western Electricity Coordinating Council (WECC) Modeling and Validation Subcommittee is hoping to use the ResStock and ComStock EULPs as the foundation for updating the WECC composite load model that is used by transmission planners across the western United States. The ResStock and ComStock EULPs may improve the current model because they were developed with a wider range of end-use consumption data, calibrated to overall load shapes, and include detailed building stock estimates at a high geographic resolution (Faris, pers. comm., 2022).

As part of a multi-lab study that will identify how Puerto Rico can achieve 100% renewable energy by 2050, one team is analyzing the impact that transitioning to renewable energy would have on the transmission infrastructure (e.g., increased capacity needs). The analysis requires residential and commercial EULPs, particularly the cooling shape, to construct the load composition model and understand building energy needs. However, there is not end-use data available for Puerto Rico, even at an annual level.[30] To fill the gap, a team at Berkeley Lab used the ResStock and ComStock EULPs for Miami to disaggregate Puerto Rico’s sector-level energy consumption into end uses. The results are being used as an input to the transmission analysis that is part of the larger study.

5.4 Distribution System Planning

Electricity distribution system planning is “focused on assessing needed physical and operational changes to the local grid to maintain safe, reliable, and affordable service” (Cooke et al 2017). Utilities have long conducted distribution system planning internally, but publicly available information and insight into distribution system planning is fairly nascent. Historically, the primary objective of distribution planning focused on meeting peak load capacity during a limited number of hours of the year.

[29] Typical components are: three phase motors, high inertia motors, low inertia motors, residential air conditioners and heat pumps, power electric loads (representative of variable frequency drives and computing), and static load (representative of lights, resistive space heating and water heating).
[30] As of fall 2022, LUMA Energy has a consultant under contract to conduct the first energy efficiency baseline and potential study in Puerto Rico to gather data to support their future planning.

Recently, there has been a shift towards more granular and publicly accessible distribution system planning due to a variety of factors, including increased adoption of DERs, quickly growing electric load from technologies such as electric vehicles and heat pumps, and policy requirements to assess PV hosting capacity[31] and consider non-wires alternatives (NWA) (also known as non-wires solutions) (Frick et al. 2021b).[32]

EULPs have not historically been used in distribution system planning. However future distribution planning tools will need to analyze hourly load patterns and inter-hour volatility to manage solar and EV charging and potentially discharging variability. Emerging examples of utilities using EULPs for forecasts and non-wires alternatives, and researchers using them for locational value analysis and advanced distribution system management, are discussed below.

Some utilities perform an NWA analysis as part of their distribution system planning. Typically, an NWA analysis compares DER solutions to traditional wired solutions to determine if it is cost-effective to defer or eliminate a distribution system upgrade. Utility value can be determined by using substation load profiles to allocate the value of planned utility investments to specific hours, based on historic peak load hours, to create hourly distribution costs. The hourly distribution costs are used to determine the cost-effectiveness of different solutions.

Using EULPs to categorize the substation load profile provides planners with a clearer picture of what measures can be used to reduce peak load. For example, if a distribution circuit overload is projected on hot summer days at midday, then solar generation should be expected to align well with the peak. Figure 10 shows how dispatching DERs, such as solar plus storage or direct load control of water heating and air-conditioning, prevents a reliability problem because the output profile of the DERs is aligned with the grid need by the hour of day and forecast year.

[31] *Hosting capacity* is the amount of DERs (e.g., solar PV) that can be interconnected to the distribution system without adversely impacting power quality or reliability under existing control and protection systems and without infrastructure upgrades (Frick et al. 2021; EPRI 2015; NREL n.d.).
[32] Non-wires alternatives are single or aggregated DERs considered as a resource option for meeting distribution system needs related to load growth, reliability, and resilience.

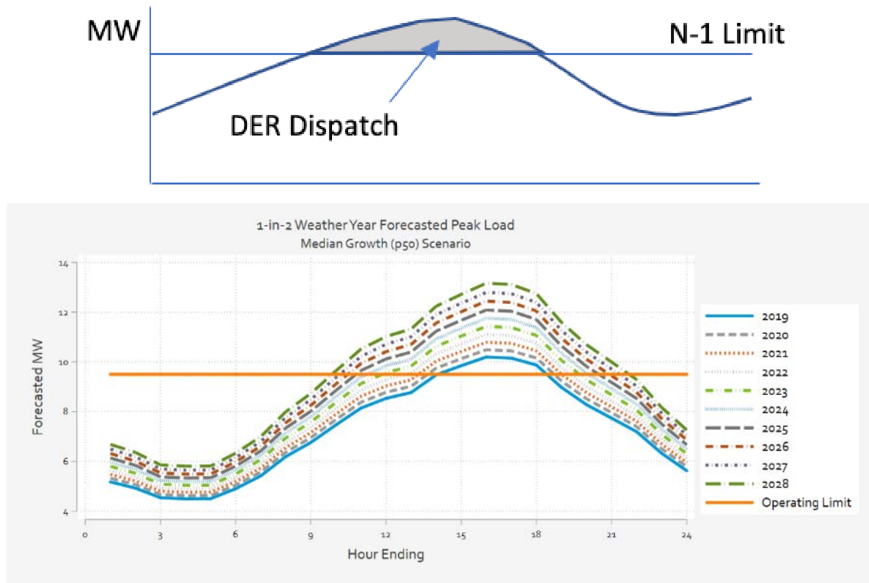

Figure 10. Timing of DER output profile must align with grid need

Source: Frick et al. 2021b

Researchers at NREL have used the EULPs to analyze locational value of solar and wind (Bowen et al. 2022). The project relied on the DOE 2013 OpenEI end-use load shapes[33] to develop the timing of building energy consumption (because the ResStock and ComStock EULPs were not yet available). Those load shapes were used as one input to determine the value of self-consumption (i.e., the avoided electricity consumption from the grid offset by generation from behind-the-meter load [BTM] systems). The results of the analysis are heavily dependent on BTM load assumptions, and more recent and accurate assumptions would have produced more robust results. A separate project at NREL created synthetic distribution network models and advanced tools for analysts to use to test, for example, advanced distribution system management capabilities.[34] Researchers used the ResStock and ComStock EULPs as a fundamental input into the distribution test systems. In addition to the annual timeseries of load, the end-use breakdowns allowed them to estimate reactive power that needs to be managed (Palmintier et al. 2021).

5.5 Electrification Planning

Electrification is the process of replacing equipment that directly burns fossil fuels such as natural gas, propane, and fuel oil with electric equipment. In buildings, the principal end uses powered by fossil fuels are space heating, water heating, cooking, and clothes drying.[35] A common electrification measure is replacing a gas furnace with an electric heat pump (Deason et al. 2018).

[33] OEDI. Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States. https://data.openei.org/submissions/153.
[34] Synthetic Models for Advanced, Realistic Testing: Distribution Systems and Scenarios, or SMART-DS.
[35] Transportation is a rapidly electrifying sector, and the extra demand from EVs is sometimes included in building loads. However EVs are not currently included in these EULPs.

Decarbonization is a key motivation for electrification. As more renewable energy is added to the electric grid, electricity becomes less carbon intensive and therefore can satisfy the end use requirements of buildings with lower emissions. Because it can be the least-cost pathway to decarbonizing buildings, policymakers are increasingly supporting electrification as a way of achieving climate goals (ACEEE 2020; Steinberg et al. 2017; Aas et al. 2020; MA EEAC 2020; DOE 2022). Electrification also can provide other benefits, such as grid support and ancillary services, increased load flexibility to respond to variable renewable energy generation, and improved air quality (Deason et al. 2018).

Various parties, such as grid system planners, policymakers, and researchers may want to understand how electrification could affect annual electricity consumption and how the increase in consumption is spread across the hours of the year. The ComStock and ResStock EULPs describe existing patterns of fossil fuel consumption in buildings and can be used to estimate the impacts of converting that consumption to electricity.

For example, a study conducted for the California Air Resources Board on the technical feasibility of zero carbon communities in California calculated the carbon emissions from operating buildings using individual prototype building energy models with default schedules (CREC 2021). The ResStock and ComStock EULPs allow an alternate approach with load shapes containing behavioral diversity and a more sophisticated representation of the residential and commercial building stock.

As part of a study on net zero emissions for Oregon buildings, Synapse Energy Economics used the ResStock and ComStock EULPs to analyze the impact of electrification on the electric system, particularly on peak demand (Takahashi et al. 2022). They normalized the end-use load shapes, scaled them up or down depending on their projections of annual energy consumption, and then recombined them to find the future overall and seasonal system peaks.

With the release of the load shapes of the residential electrification packages that can be used to derive savings shapes, analysts could use a similar approach and would be able to understand the differences in load shapes between electric resistance and heat pumps to get a more accurate estimate of peak load. As they note, this would likely result in a higher estimate of peak demand since heat pumps revert to electric resistance heating when it is sufficiently cold.

Modeling Heat Pump Conversions

For residential buildings, the 2022 data release includes packages with heat pumps for space heating, water heating, or both. These can be used directly for electrification planning.

For commercial buildings, results from electrification packages are not yet available. It is not recommended that analysts use baseline ComStock building models with heat pumps for space and water heating to represent future loads as part of electrification planning for two reasons.

First, CBECS 2012 was used to determine HVAC system types, and they show that there are relatively few heat pumps in cold climates. This means that heat pumps are assigned to a small fraction of ComStock samples in cold climates. As described in the *Sample sizes* section above, with fewer samples, there will be higher uncertainty in how well those samples represent the stock overall. For example, in a given cold-climate state or county, buildings with heat pumps could be coincidentally correlated with very poor or very good thermal insulation, resulting in biased results for the filtered subset of buildings with heat pumps. This is less of a problem in warm climates, where heat pumps are more prevalent in the existing stock.

Second, the heat pumps used in the baseline models were assumed to be of relatively low efficiency based on the data available describing the stock. In the future, heat pumps will likely be more efficient, particularly in cold climates.

The September 2022 release of ResStock data includes ten upgrade packages, of which four are whole-home electrification scenarios and four are partial electrification scenarios. The EULPs of the upgrades, or the difference between the upgraded and baseline EULPs (savings shapes) can be used directly in electrification planning. Figure 11 is a screenshot of the ResStock Data Viewer comparison between the baseline and high efficiency whole home electrification and enhanced enclosure upgrade package for Maine.

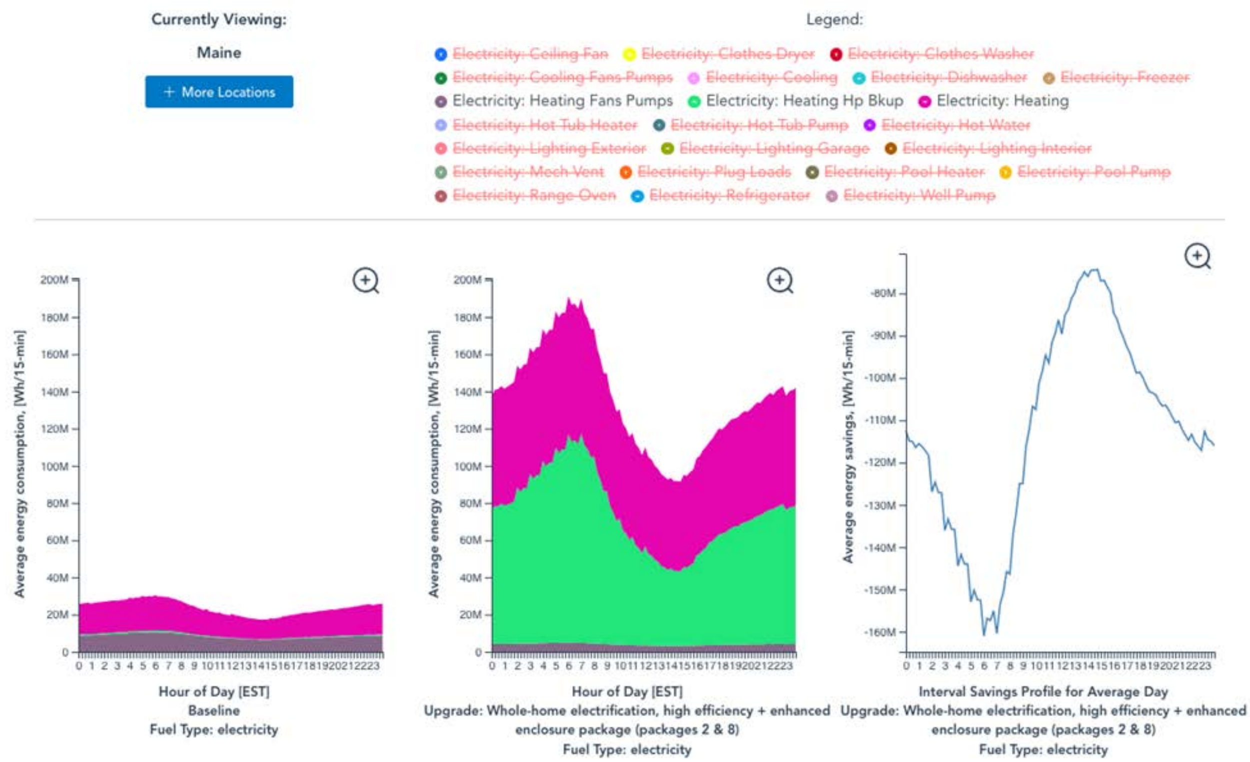

Figure 11. Residential electric heating in Maine: baseline and high efficiency whole home electrification and enhanced enclosure upgrade package

Source: https://resstock.nrel.gov/datasets

In the absence of electrification savings shapes for commercial buildings, a stopgap process can be employed to estimate the increase in electricity consumption due to installation of heat pumps. First, divide the hourly energy consumption of the appliance that will be replaced by a heat pump by its efficiency to calculate the heat demand.[36] Next, convert the heating demand into electricity consumption using an hourly heat pump efficiency. Because efficiency varies with outdoor temperature, temperature-dependent efficiency curves and the weather file associated with the particular EULPs should be used.[37] This process is called a "bin method" because efficiency values are assigned to temperatures based on the temperature bin in which each interval falls. Although this method neglects details of heat pump

[36] Average heating efficiencies can be found in the commercial metadata. Because calibration of fossil fuel consumption was not a focus of the EULP calibration process, whenever possible, use known fossil consumption data to scale the modeled fossil consumption load profiles to account for differences between modeled and observed heating demand. If measured data is not available, check the annual and monthly validation comparisons for EIA natural gas use provided in Sections 4.1.1 and 4.2.1 of the Methodology and Results report, to determine the level of confidence to have when using the fuel use profiles.

[37] The Cold Climate Housing Research Center's (CCHR) Air Source Heat Pump Calculator (https://heatpump.cf/) and the Northeast Energy Efficiency Partnerships' (NEEP) Cold Climate Air Source Heat Pump List (https://ashp.neep.org/) are two sources of heat pump efficiency curves. When constructing coefficient of performance (COP) curves, it may be important to include a cutoff temperature below which the system needs to use electric resistance heating. The CCHR efficiency curves are based off of measured data and implicitly contain such a cutoff. The NEEP database includes capacity maintenance values that can inform how reliance on supplemental electric resistance relates to outdoor temperatures.

performance that will affect annual and peak electricity use,[38] it allows analysts to generate estimated hourly electrified profiles that take temperature-dependent COPs into account.

Figure 12 shows an example of the added electricity demand in January from Houston, Texas, of replacing the packaged single zone units that have gas coils (PSZ-AC gas) with heat pumps. To estimate the heating demand for buildings with this type of heating, we used the ComStock Data Viewer to filter the state-level TMY dataset to samples in Houston, Texas, with PSZ-AC gas and downloaded the timeseries data. The metadata file shows that the average gas coil efficiency for these units is 0.79, so we divided each timestep of the gas heating load by 0.79. Using the hourly dry bulb temperature from the Houston TMY3 weather file and a heat pump efficiency curve from the equipment library in OpenStudio, we assigned a coefficient of performance (COP) to each interval of ComStock's hourly data. For outdoor temperatures below freezing, we assumed that the heat pump is using supplemental electric resistance heat and that the COP is 1. We then calculated the heat pump electricity consumption by dividing the heating demand by the COP.

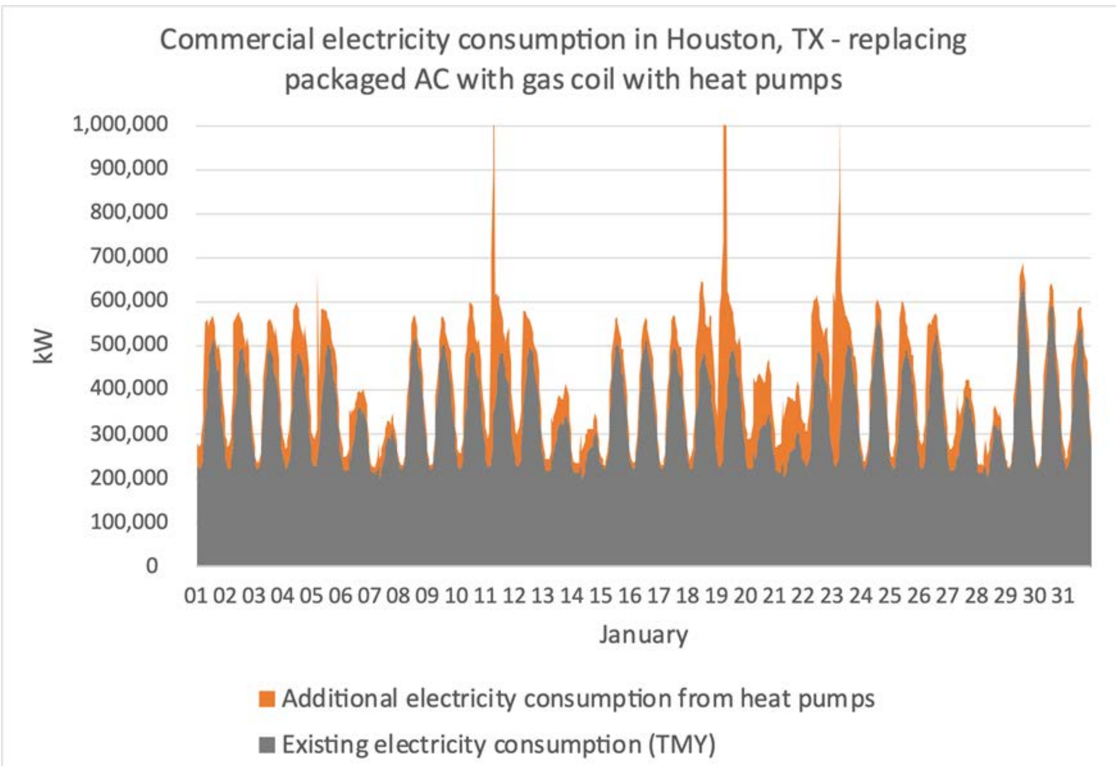

Figure 12. Hourly commercial electricity consumption in January in Houston, Texas, after replacing packaged single zone AC with gas coil with heat pumps (TMY weather)

[38] For example, the relationship between COP and compressor speed in variable-speed systems, defrost energy use, heat pump sizing, capacity vs. outdoor temperature and the relationship between sizing, capacity retention, and supplemental heat use (Williamson and Aldrich 2015; Schoenbauer et al. 2017).

Carbon Emissions

Various sources, including NREL's Cambium and the Environmental Protection Agency's Avoided Emissions and geneRation Tool (AVERT) provide data for calculation carbon emissions from hourly electricity consumption. The September 2022 ResStock data release includes annual and timeseries carbon emissions using long run marginal emissions factors for four Cambium scenarios. See Present et al. 2022b for a discussion of different types of carbon emissions factors and which are most appropriate for particular applications.

5.6 Demand-side Management Planning

This section discusses using EULPs in three aspects of demand-side management (DSM) planning: benefit-cost analysis, potential assessments, and program design.

5.6.1 Benefit-cost Analysis

Energy efficiency benefit-cost analysis compares the relative benefits and costs of efficiency from different perspectives. A benefit-cost ratio above one means the measure or program has positive net benefits. A benefit-cost ratio of less than one means the cost exceeds the benefits. If lifecycle benefits exceed costs, the measure or program is considered cost-effective. As with all modeling, improved accuracy of the model inputs (i.e., energy efficiency cost and benefit data) creates more robust results.

Energy efficiency benefit-cost analysis is very widely used, as it is required in all but one U.S. state (Kushler 2021). Utilities and program administrators use it in program planning and evaluation, and it is used by utilities and regulators to determine the level of investment in efficiency that a utility will make. Energy efficiency program administrators use it when designing and planning their energy efficiency programs (e.g., adding and removing energy efficiency measures from a program to increase or decrease the portfolio or program cost-effectiveness).

Some utilities employ annual hourly energy efficiency data, from EULPs or savings shapes, to determine when savings occur, and the financial value associated with the savings. For example, the California Public Utilities Commission (CPUC) created the Avoided Cost Model, a publicly available tool that forecasts the long-term marginal costs used to evaluate the cost-effectiveness of DERs, including efficiency.

Specifically, the Avoided Cost Model uses annual hourly (8,760) data to forecast both the long-term costs and components of avoided costs in California. Figure 13 provides an example output, showing the average monthly value of energy in California climate zone 12 in 2030.

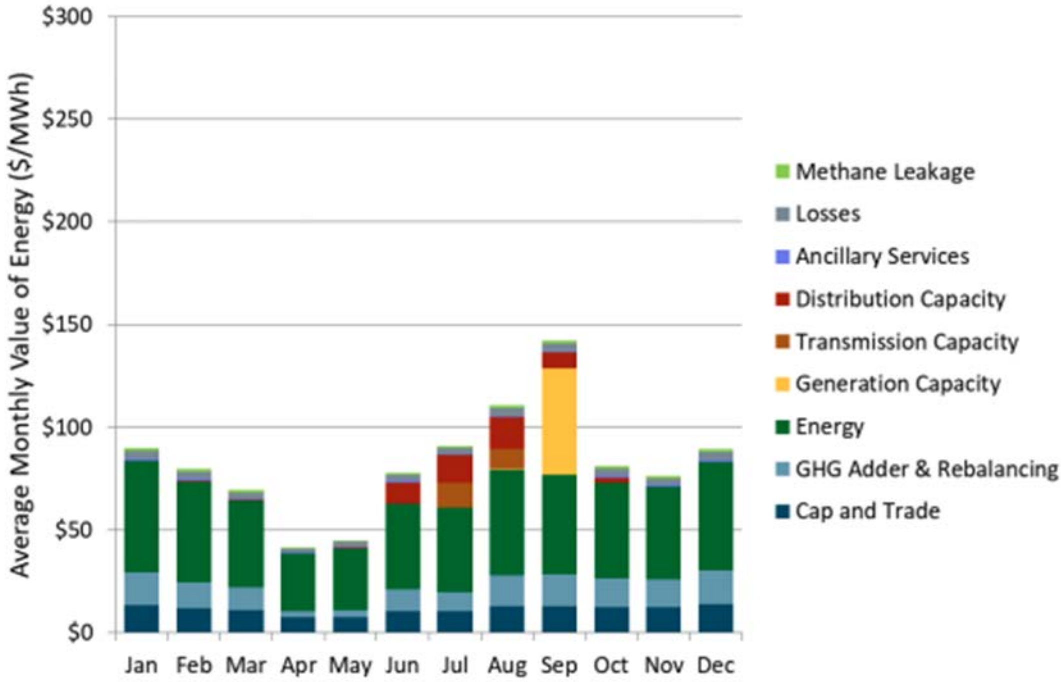

Figure 13. California avoided cost model output for California climate zone 12 in 2030

Source: E3 2021

Utilities that do not have access to their own savings shapes can make use of the ResStock savings shapes and ComStock EULPs to determine the value of efficiency savings (assuming that the savings occur in the same hours as consumption for measures that are not included in the 10 upgrade packages in the September 2022 release of ResStock data).[39] Often when estimating the benefits and cost, utilities do not use hourly savings shapes or base the savings shapes off of a small number of building models that do not include a diversity of load shapes (Frick, Eckman, and Goldman 2017). This approach does not always adequately capture the diversity of occupant behavior and building characteristics and can overstate the peak demands for the total building stock or end uses. The ResStock and ComStock EULPs alleviate this problem by including a diversity of occupant behavior and the distribution of building stock characteristics.

[39] A follow-on project is currently underway at NREL to develop savings shapes for additional residential and commercial energy efficiency and electrification measures and packages.

Time-Sensitive Value Calculator

Berkeley Lab recently released a tool that allows users to determine the value of a measure's savings (or generation)—the Time-Sensitive Value Calculator (Frick, Carvallo and Pigman 2022). The Calculator takes hourly profiles of up to six measures at a time and monetizes their value for six value streams, producing outputs in tabular and graphical formats. It was designed for public utility commissions, state energy offices, utilities, and stakeholders to estimate the value of energy efficiency and DER measures under various future electricity system scenarios.

The user manual provides detailed instructions on how analysts can use the ResStock and ComStock EULPs to determine the value of efficiency savings. For more information on the tool and user guide see https://emp.lbl.gov/publications/time-sensitive-value-calculator.

5.6.2 Potential Assessments

Potential assessments identify the cost, availability, and performance characteristics of energy efficiency resources. The objective of the assessment is to provide accurate and reliable information regarding the amount, end-use or savings load profile, availability, and cost of acquiring or developing the energy efficiency resources. For reference, see Mosenthal and Loiter (2007) and Neubauer (2014). Common uses of the assessments include informing energy efficiency program design; serving as inputs to IRP, including the development of supply curves for use in capacity expansion models where energy efficiency resources compete with other electricity system resources on the basis of cost, reliability, economic risk, and other factors such as environmental impacts; or to inform state energy efficiency goals.

Several types of energy efficiency potential can be calculated and are discussed in Appendix D.

It is common practice to use EULPs, savings shapes, or both in efficiency potential assessments. The ResStock and ComStock EULPs provide analysts with updated building stock characteristics and end-use shapes that will improve the accuracy and fidelity of efficiency potential assessments through improved estimates of baseline energy consumption.

5.6.2.1 Energy Efficiency Supply Curves

As mentioned in the Integrated Resource Planning and Load forecasting sections of this paper, traditionally, future electricity consumption and peak demand are represented in a load forecast. This results in "before" and "after" load forecasts, without and with reductions that will be achieved by efficiency. The "after" reflects lower projected levels of electricity use and serves to define the generation resource planning target.

However, an alternative approach is to model energy efficiency as a selectable resource where it is included with all other resource options in an optimization model (Frick et al. 2019). The essential idea of treating efficiency as a selectable resource is that its economically optimal level and timing are determined endogenously; that is, efficiency becomes a decision variable directly comparable to amounts and timing of natural gas or renewable generation.[40] When this approach is applied, EULPs inform the process of creating energy efficiency supply curves (in the absence of savings shapes).

[40] As with any modeling exercise, analysts can produce suboptimal results if they model efficiency as a selectable resource. See Takahashi 2015 for examples.

Energy efficiency supply curves are created with inputs that are often identified in a market potential study. The efficiency supply curves represent the timing and type of efficiency that can be obtained at a range of costs. These curves enable the economic comparison of efficiency and new generation investments. Each supply curve represents the aggregate savings of a bundle of individual energy efficiency measures with unique characteristics. Multiple supply curves are necessary to account for end-use load shape, development limits, and cost of the resource acquisition. Figure 14 is an example of an efficiency supply curve from the Northwest Power and Conservation Council's 2021 Power Plan.

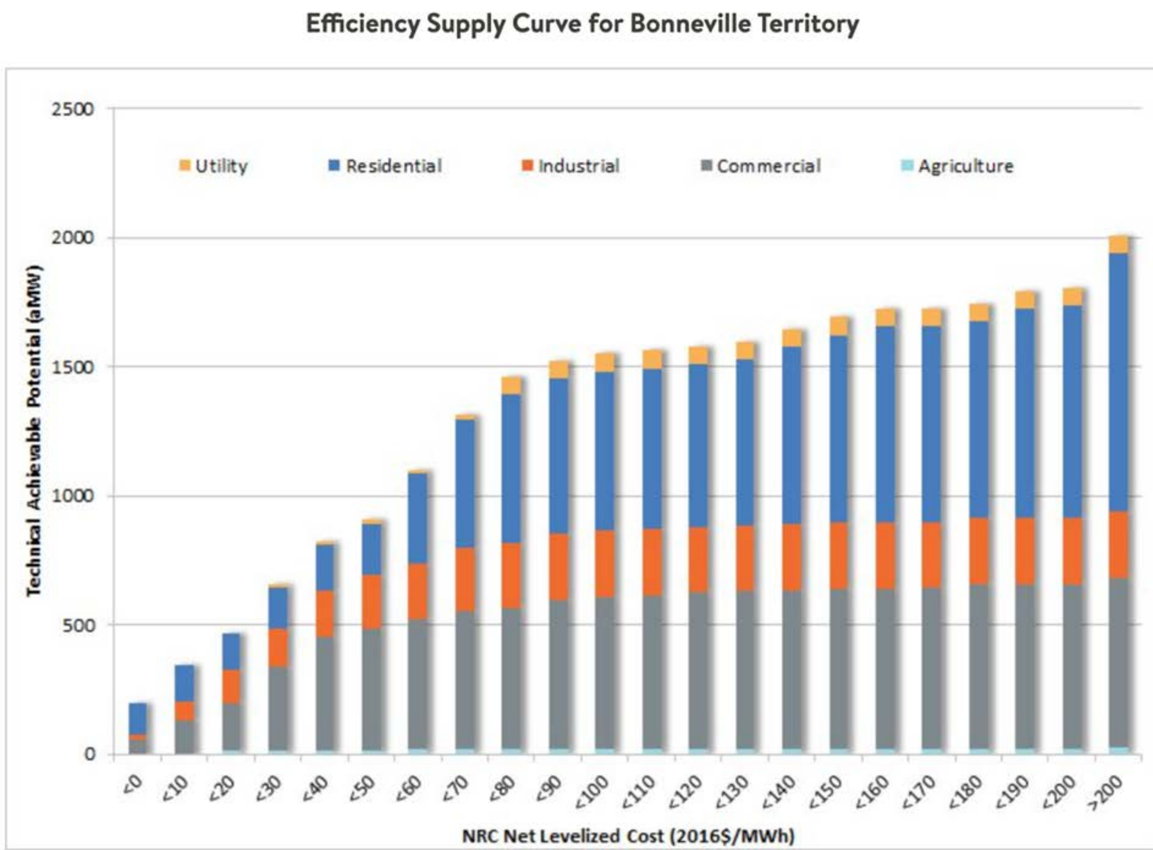

Figure 14. Efficiency supply curve for Bonneville Territory

Source: Northwest Power and Conservation Council (2021)

Currently, most utilities consider efficiency as a load forecast decrement and do not create efficiency supply curves. However, there are examples from several utilities in many states (e.g., Georgia, Hawaii, Indiana, Missouri, Oregon, and Washington) that have used or are considering adopting this approach.

5.6.3 Program Design

This section focuses on utility customer funded energy efficiency programs. These are programs that customers fund and the utility or program administrator implements to directly support the uptake of cost-effective energy efficiency measures. There are many types of energy efficiency programs, including rebate, direct install, upstream or midstream incentive, commissioning, and new construction programs. There also are several objectives that energy efficiency programs may seek to achieve, such as resource acquisition, market transformation, or education and training.

Given the variety of program types and objectives, energy efficiency program design must consider many components, including program cost-effectiveness, energy and demand savings, the amount of the incentive payment to the customer (if applicable), whether the incentive payment will be upstream or midstream of the customer, how to market the program, and how to verify program savings.

As with the other energy efficiency program planning efforts (e.g., benefit-cost analysis), use of EULPs can help program administrators prioritize measures or programs that save energy during high or low demand periods. It also can inform new program design—or existing program and measure incentive or rebate levels—to achieve efficiency portfolio goals at least cost.

For example, in Massachusetts, eight program administrators are sponsoring long-term research to better understand residential load profiles for all major residential electric end uses in the state (Guidehouse 2020). The purpose of the research is to help inform energy and peak demand savings calculations for program evaluation and design, as well as to help program administrators identify the future savings potential of existing homes. The first phase of the research, published in July 2018, made several program recommendations based on the time-sensitive demand and energy value of efficiency, including the following:

- Early retirement for central air conditioning and heat pumps can increase peak demand savings and energy savings.
- Residential end-use loads vary widely during peak times. Electric clothes dryers, dehumidifiers, electric water heaters, and pool pumps may all be opportunities for peak demand savings with low impact on occupant comfort.
- Electrification of water heating presents opportunities for ongoing peak demand and energy reduction. Heat pump water heaters offer both peak demand and energy savings.
- Residential lighting is the biggest contributor to winter peak load. Early retirement programs—removing inefficient products from service when they are still operating and replacing them with more efficient products—could reduce peak load and produce energy savings.

The national EULP dataset can help inform similar program decisions in states that do not have the same degree of load profile research. For example, Figure 15 compares the hourly end use consumption for a peak day in Massachusetts between the metered load profile study and the EULPs from ResStock with broadly similar results.

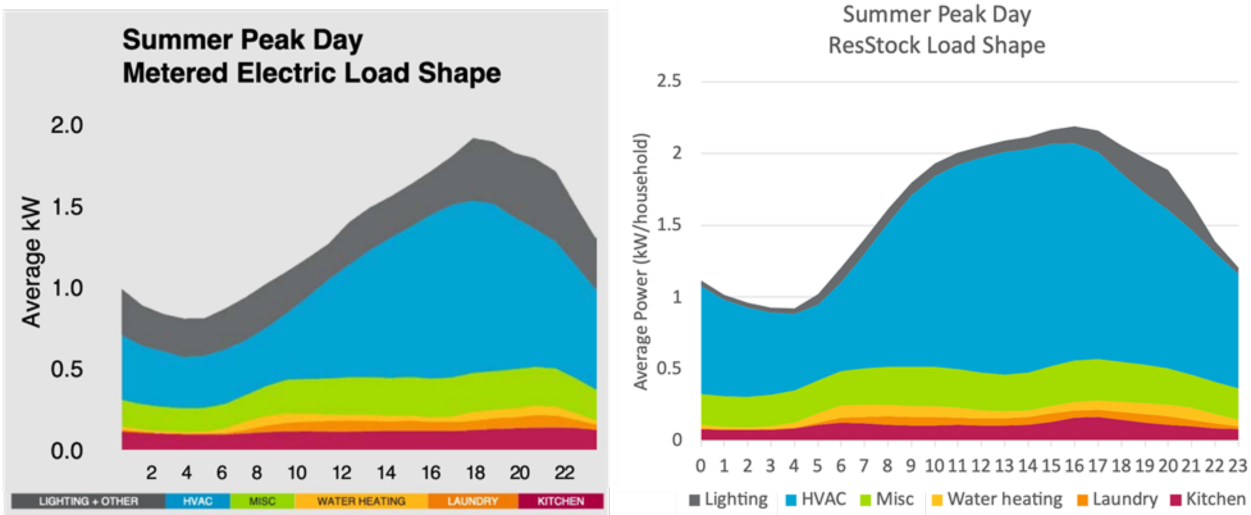

Figure 15. Massachusetts residential end use consumption on a peak summer day—metered study vs. ResStock

Sources: Guidehouse 2020 (left); ResStock (right)[41]

5.7 Bill Impacts and Rate Design

Analysis to estimate how electricity bills increase or decrease with the installation of DERs or a switch to a new time-based electricity rate provides useful information to consumers seeking to reduce their electricity bills, as well as to utility planners trying to align consumption with grid needs. Bill impact analysis relies on the energy consumption patterns of a building or building load shape. This is often derived from a building energy model that uses average, standardized behavioral patterns and “typical” building characteristics. Instead of relying on standardized and typical inputs, an analyst could take advantage of the behavioral diversity and the distribution of building stock characteristics included in the ResStock and ComStock EULPs.

For example, a PV and storage company interested in targeting a particular building type in a specific region could use the ResStock and ComStock EULPs to identify the range of bill impacts from different PV+storage system sizes.[42] The analyst could choose a number of models with the desired characteristics, overlay the electricity consumption with the electricity rate to estimate monthly and annual electric bills, and identify solar PV and energy storage system sizes that achieve the customer’s project goal (e.g., demand charge reduction). This method would show more realistic peaks for demand charges and represent the distribution of performance that comes from variations in behavior and building characteristics. PV+storage companies sometimes obtain utility bills or advanced meter interval (AMI) data for prospective customers, but this is often a slow process that does not facilitate quick customer identification and targeting.

[41] The end uses cannot be disaggregated in exactly the same way in these two datasets. For Guidehouse 2020, "miscellaneous” includes TVs, primary desktop computers, pool pumps, and dehumidifiers; other plug loads are included in “lighting + other.” In the ResStock chart, “miscellaneous” includes all the plug loads, pool pumps and heaters, hot tub pumps and heaters, and well pumps.

[42] This method could also be used for a PV+storage system with a different objective such as maximizing self generation or minimizing greenhouse gas emissions.

Residential Batteries and Resilience

A report from a team at Berkeley Lab, *Evaluating the Capabilities of Behind-the-Meter Solar-plus-Storage for Providing Backup Power during Long-Duration Power Interruptions* (Gorman et al. 2022), used the EULPs to study how batteries can impact resilience across the country. They are using building characteristic data to select “typical” load profiles for a variety of different building types in each county and modeling the effect of adding solar and battery storage to generate a distribution of possible resilience outcomes for a range of systems sizes and outage types. They are also using end use breakdowns to compare resilience outcomes of whole buildings to selected critical loads. This work is part of a larger three-year study evaluating the capabilities of behind-the-meter solar-plus-storage for providing backup power during long-duration power interruptions.

Similarly, the ResStock and ComStock EULPs can be used to estimate the potential bill impact of time-based rate structures. A comparison of ComEd’s time-based rate structure with a flat rate found that 97% of customers in the sample would have saved money on the time-based rate even without changing their behavior (Figure 16) (Elevate Energy 2015). The analysis used AMI data, but a similar analysis could be performed with individual building EULPs in places where AMI data is not available. Using individual building profiles instead of a stock-level aggregation provides a distribution of possible outcomes and the realistic spikiness of individual dwelling unit or building loads for rates with demand charges. One advantage of using ResStock and ComStock instead of AMI data for this application is that the characteristics of the buildings used to generate the EULPs are included in the ResStock and ComStock data, so analysts can identify characteristics of the buildings with small or negative bill savings. This could help target and prioritize buildings for efficiency upgrades.

Figure 16. Distribution of savings for residential customers switching from a fixed-price rate to a time-based rate

Source: Elevate Energy. 2015. ComEd Hourly Pricing Performance vs. Fixed-Price Rate During 2013

6 Conclusion

EULPs, which quantify how and when energy is used, are critically important to utilities, public utility commissions, state energy offices, and other stakeholders. Applications of EULPs focus on understanding how efficiency, demand response, and other DERs are valued and used in R&D prioritization, utility resource and distribution system planning, and state and local energy planning and regulations. Consequently, high-quality EULPs are critical for widespread adoption of electrification, demand flexibility, and GEBs.

This report provides practical guidance on accessing the ResStock and ComStock EULPs, and discusses opportunities to use the data in a variety of use cases, summarized in Table 4.

Table 4. Summary of End-Use Load Profiles Use Cases in this Report

Use Case	Application of End-Use Load Profiles
Integrated resource planning	Develop load forecast or energy efficiency supply curves
Long-term load forecasting	Analyze the impact of particular equipment adoption scenarios statewide, across a utility area, or a smaller geographic area; improve baseline building energy consumption assumptions
Transmission planning	Disaggregate the load into components that behave differently during and after a fault
Distribution system planning	Analyze the value of solar and wind as well as different types of energy efficiency based on the location and timing of the generation or savings
Electrification planning	Understand how electrification could affect annual electricity consumption and how the increase in consumption could be spread across hours of the year
Demand-side management	Use as an input to cost-benefit analysis to understand the time-value of energy efficiency; in potential assessments to understand the available amount and timing of energy efficiency (e.g., improving baseline building energy consumption assumptions); and in program design
Bill impacts and rate design	Estimate how electricity bills may increase or decrease with adoption of DERs or switching to a new time-based electricity rate for individual buildings with realistic load profiles, and aggregations of buildings

As analysts consider using the 2021 and 2022 ResStock and ComStock EULP data releases, we offer the following guidance:

- ResStock and ComStock EULPs, as compared to prior publicly available EULPs, offer **greater granularity**. Analysts can identify and use a discrete subset of representative buildings, target a specific geographic area and consider behavioral diversity (e.g., study the range and distribution of energy consumption of individual buildings, as well as an aggregate load shape that is not driven by any one assumption of when occupants use certain equipment) in their research.
- Using narrow criteria to select subsets of buildings may produce EULPs that are represented by a small number of building energy models. **Small sample size may produce results that are**

biased based on the characteristics of those few samples, and also may exhibit unrealistically spiky usage patterns. Guidance on an appropriate sample size and approaches for dealing with small sample sizes are areas of ongoing research.

- Wilson et al. (2022) includes extensive comparisons of the electric ResStock and ComStock EULPs and the metered data used for calibration. Analysts can use these comparisons **to assess their confidence** in the ResStock or ComStock EULPs underlying a particular analysis.
- **Approaches that will produce more robust results** include using a larger sample size, using data from areas that contributed to calibration, and focusing on electricity data.
- ComStock contains EULPs for natural gas and electricity. The **focus of the calibration and validation effort was on electricity,** not fossil fuels. Guidance on the practical implications of validation results is an area of ongoing research.
- Several **residential savings shapes** can be derived by comparing the ResStock 2022 data release baseline EULPs to the measure package EULPs.
- The EULPs are published with results using TMY weather and one or two years of AMY weather, depending on the release. Analysts who wish to study other weather years, including **projections based on climate change models and extreme weather**, can run a subset the calibrated models with alternate weather files.[43] To look at building energy performance during extreme weather periods, analysts can also use the provided TMY and AMY weather files to identify periods with extreme temperatures.
- Public utility commission staff, state energy offices, or others that lack experience using the EULPs may benefit from **collaborating with the national labs** or working with consultants when using the datasets.
- Examples provided in this report are **illustrative of emerging uses of the EULPs**, and many of them are forward looking. They are not intended to be comprehensive. For example, there are many uses for the building energy models that are the foundation of the EULPs that are not discussed in this report. We welcome information from additional examples.

Follow-on projects are underway at NREL to develop savings shapes for additional residential and commercial energy efficiency and electrification measures and packages. See the project website for current data releases.[44]

[43] See Brown and Rajkovich 2020 for an overview of types of future-looking weather files for building energy simulation.

[44] NREL. End-Use Load Profiles for the U.S. Building Stock. https://www.nrel.gov/buildings/end-use-load-profiles.html.

Glossary

Behavioral diversity represents the variation of occupant behavior in a building (e.g. thermostat setpoints and setpoint schedules, timing of hot water use).

Calibration is "the process of using empirical data to inform changes in a model" (Wilson et al. 2022).

Demand-side management (DSM) is a **"**utility action that reduces or curtails end-use equipment or processes. DSM is often used in order to reduce customer load during peak demand and/or in times of supply constraint. DSM includes programs that are focused, deep, and immediate such as the brief curtailment of energy-intensive processes used by a utility's most demanding industrial customers, and programs that are broad, shallow, and less immediate such as the promotion of energy-efficient equipment in residential and commercial sectors" (EIA Glossary).

Distributed energy resource (DER) is **"**a resource sited close to customers that can provide all or some of their immediate power needs and/or can be used by the utility system to either reduce demand or provide supply to satisfy the energy, capacity, or ancillary service needs of the grid" (SEE Action 2020).

Distribution system is the "portion of the electric system composed of medium voltage (69 kV to 4 kV) sub-transmission lines, substations, feeders, and related equipment that transport the electricity commodity to and from customer homes and businesses and link customers to the high-voltage transmission system. The distribution system includes all the components of the cyber-physical distribution grid including the information, telecommunication, and operational technologies and transformers, wires, switches, and other apparatus" (Homer et al. 2017).

Electrification is "the substitution of electricity for direct combustion of non-electricity-based fuels used to provide similar servicesThe process of replacing equipment that directly burns fossil fuels such as natural gas, propane, and fuel oil with electric equipment" (Zhou and Mai 2021).

End-use load profiles (EULP)s quantify hourly or sub-hourly consumption of an end use (e.g., residential lighting, commercial HVAC) over the course of one year.

Integrated resource planning (IRP) "refers to a utility plan for meeting peak demand and energy needs over a planning period, using a combination of supply-side and demand-side resources that represents the least cost resource mix, accounting for risk and uncertainty" (Homer et al. 2017).

Long-term load forecasts are estimates of electricity consumption and peak demand over time horizons of one or two decades. They are a key element in electric utilities providing reliable and affordable electricity supply to customers while comply with energy and environmental regulations.

Non-wires alternatives "are non-traditional investments or market operations that may defer, mitigate, or eliminate the need for traditional transmission and distribution investments" (Homer et al. 2017).

Savings shapes are "the hourly or sub-hourly difference between the use of electricity in the baseline condition and post-installation of the energy efficiency measure (e.g., the difference between the hourly consumption of an electric resistance water heater and a heat pump water heater, or the difference between the hourly lighting use in a commercial building pre- and post-installation of daylighting controls or occupancy sensors) over the course of one year (Frick, Eckman and Goldman 2017)."

Supply curves represent the timing and type of a resource that can be obtained at a range of costs. Typically the resource is an electricity generator, but supply curves can also be created for energy efficiency.

Transmission system (electric) is "an interconnected group of electric transmission lines and associated equipment for moving or transferring electric energy in bulk between points of supply and points at which it is transformed for delivery over the distribution system lines to consumers or is delivered to other electric systems” (EIA Glossary).

Validation is “the process of evaluating how accurately a model represents the real world” (Wilson et al. 2022).

References

Aas, D., A. Mahone, Z. Subin, M. Mac Kinnon, B. Lane, and S. Price. 2020. The Challenge of Retail Gas in California's Low-Carbon Future: Technology Options, Customer Costs and Public Health Benefits of Reducing Natural Gas Use. CEC-500-2019-055-F. Prepared for: California Energy Commission. https://www.ethree.com/wp-content/uploads/2021/06/CEC-500-2019-055-F.pdf.

American Council for an Energy-Efficient Economy (ACEEE). 2020. *State Policies and Rules to Enable Beneficial Electrification in Buildings through Fuel Switching*. https://www.aceee.org/sites/default/files/pdfs/fuel_switch_revised_5-14-20.pdf.

Anwar, T., B. Sharma, K. Chakraborty, and H. Sirohia. 2018. "Introduction to Load Forecasting." *International Journal of Pure and Applied Mathematics* 119 (15): 1527-1538.

Bowen, T., S. Koebrich, K. McCabe, and B. Sigrin. 2022. "The Locational Value of Distributed Energy Resources: A Parcel-Level Evaluation of Solar and Wind Potential in New York State." *Energy Policy* 166. https://doi.org/10.1016/j.enpol.2021.112744.

Brown, C. and N. Rajkovich. 2020. *Assessment of Future Typical Meteorological Year Data Files*. 21-01. Prepared for: NYSERDA. https://www.nyserda.ny.gov/About/Publications/Energy-Analysis-Technical-Reports-and-Studies/Transportation-Reports.

The Center for Resource Efficient Communities (CREC). 2021. *Zero-Carbon Buildings in California: A Feasibility Study.* Prepared for: California Air Resource Board and California Environmental Protection Agency. https://crec.berkeley.edu/uploads/16RD004_CREC_ZCB_Final_Report_w__Appendices_(1).pdf.

Deason, J., M. Wei, G. Leventis, S. J. Smith, and L. C. Schwartz. 2018. *Electrification of Buildings and Industry in the United States: Drivers, Barriers, Prospects, and Policy Approaches*. Berkeley, CA: Lawrence Berkeley National Laboratory. https://eta-publications.lbl.gov/sites/default/files/electrification_of_buildings_and_industry_final_0.pdf.

Department of Energy (DOE). 2013. "Building Science-Based Climate Maps." https://www1.eere.energy.gov/buildings/publications/pdfs/building_america/4_3a_ba_innov_buildingscienceclimatemaps_011713.pdf.

DOE. 2022. *The Inflation Reduction Act Drives Significant Emissions Reductions and Positions America to Reach Our Climate Goals*. DOE/OP-0018. https://www.energy.gov/sites/default/files/2022-08/8.18%20InflationReductionAct_Factsheet_Final.pdf.

Electric Power Research Institute (EPRI). 2015. *Distribution Feeder Hosting Capacity: What Matters When Planning for DER?* https://www.epri.com/research/products/000000003002004777.

Elevate Energy. 2015. *ComEd Hourly Pricing Performance vs. Fixed-Price Rate During 2013.* https://www.elevatenp.org/wp-content/uploads/HourlyvsFlatPrice-2015-09-25-FINAL-1.pdf

Energy Information Administration (EIA). "Glossary". https://www.eia.gov/tools/glossary/index.php.

Environment, Energy and Economics, Inc (E3). 2021. *Distributed Energy Resources Avoided Cost Calculator Documentation.* Prepared for: California Public Utilities Commission. https://willdan.box.com/v/2021CPUCAvoidedCosts.

Faris, A., D. Kosterev, J. H. Eto, and D. Chassin. 2020. *Load Composition Analysis in Support of the NERC Load Modeling Task Force 2019-2020 Field Test of the Composite Load Model*. Berkeley, CA: Lawrence Berkeley National Laboratory. https://doi.org/10.2172/1644285.

Frick, N. M., T. Eckman, and C. Goldman. 2017. *Time-Varying Value of Electric Energy Efficiency*. Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/time-varying-value-electric-energy.

Frick, N. M., and L. Schwartz. 2019. *Time-Sensitive Value of Efficiency: Use Cases in Electricity Sector Planning and Programs.* Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/time-sensitive-value-efficiency-use.

Frick, N. M., E. Wilson, J. Reyna, A. Parker, E. Present, J. Kim, T. Hong, H. Li, and T. Eckman. 2019. *End-Use Load Profiles for the U.S. Building Stock: Market Needs, Use Cases, and Data Gaps.* Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/end-use-load-profiles-us-building.

Frick, N. M., T. Eckman, G. Leventis, and A. Sanstad. 2021a. *Methods to Incorporate Energy Efficiency in Electricity System Planning and Markets*. Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/methods-incorporate-energy-efficiency.

Frick, N. M., S. Price, L. Schwartz, N. Hanus, and B. Shapiro. 2021b. *Locational Value of Distributed Energy Resources*. Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/locational-value-distributed-energy.

Frick, N. M., J. P. Carvallo, and M. Pigman. 2022.*Time-Sensitive Value Calculator.* Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/time-sensitive-value-calculator.

Gorman, W., G. L. Barbose, J. P. Carvallo, S. Baik, C. Miller, P. White, and M. Prapost. 2022. Evaluating the Capabilities of Behind-the-Meter Solar-plus-Storage for Providing Backup Power during Long-Duration Power Interruptions. Berkeley, CA: Lawrence Berkeley National Laboratory. https://emp.lbl.gov/publications/evaluating-capabilities-behind-meter.

Guidehouse. 2020. *Massachusetts Residential Baseline Study*. Prepared for: The Electric and Gas Program Administrators of Massachusetts. https://ma-eeac.org/wp-content/uploads/RES-1-Residential-Baseline-Study-Ph4-Comprehensive-Report-2020-04-02.pdf.

Homer, J., A. Cooke, L. Schwartz, G. Leventis, F. Flores-Espino, and M. Coddington. 2017. *State Engagement in Electric Distribution System Planning.* Richland, WA: Pacific Northwest National Laboratory. PNNL-27066. https://eta-publications.lbl.gov/sites/default/files/state_engagement_in_dsp_final_rev2.pdf.

Kushler, M. 2021. "Cost-Effectiveness Testing for Energy Efficiency Programs: Background, Current Status and Recommendations for Best Practices Going Forward." Presented at: Better Buildings Residential Network Peer Exchange Call Series. https://www.energy.gov/sites/default/files/2021/03/f83/bbrn-peer-test-021121.pdf.

Liu, Y., P. Etingov, S. Kundu, Z. Hou, Q. Huang, H. Zhou, M. Ghosal, D.James, J.Zhang, Y. Xie, P. Cappers, A. Blick, Y. Zhang, Y. Tang, Z. Chu, D. Chassin, and I. Chakraborty. 2020. *Open-Source High-Fidelity Aggregate Composite Load Models of Emerging Load Behaviors for Large-Sale Analysis*.

Richland, WA: Pacific Northwest National Laboratory. PNNL-29592. https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-29592.pdf.

Massachusetts Executive Office of Energy and Environmental Affairs (EEA). 2020. *MA Decarbonization Roadmap*. https://www.mass.gov/info-details/ma-decarbonization-roadmap.

Mosenthal, P. and J. Loiter. 2007. *Guide for Conducting Energy Efficiency Potential Studies*. National Action Plan for Energy Efficiency. Bristol, VT. https://www.epa.gov/sites/default/files/2015-08/documents/potential_guide_0.pdf.

National Renewable Energy Laboratory (NREL). "Advanced Hosting Capacity Analysis." https://www.nrel.gov/solar/market-research-analysis/advanced-hosting-capacity-analysis.html. Accessed August 29, 2022.

Neubauer, M. 2014. *Cracking the TEAPOT: Technical, Economic, and Achievable Energy Efficiency Potential Studies.* ACEEE. U1407. https://www.in.gov/iurc/files/ACEEE_Attachment_A_Cracking_the_TEAPot.pdf.

Northwest Energy Efficiency Alliance (NEEA). 2021a. *Northwest End Use Load Research Project - Commercial Energy Metering Study*. https://neea.org/data/nw-end-use-load-research-project/.

NEEA. 2021b. *Northwest End Use Load Research Project - Home Energy Metering Study*. https://neea.org/data/nw-end-use-load-research-project/.

Northwest Power and Conservation Council. 2021. "Conservation in the Plan Scenarios". *2021 Power Plan*. https://www.nwcouncil.org/2021powerplan_scenarios_conservation/.

Palmintier, B., T. Elgindy, C. Mateo, F. Postigo, T. Gómez, F. de Cuadra, and P. D. Martinez. 2021. "Experiences Developing Large-Scale Synthetic U.S.-Style Distribution Test Systems." *Electric Power Systems Research* 190, 106665. https://doi.org/10.1016/j.epsr.2020.106665.

Present, E., P. White, R. Adhikari, N. Merket, E. Wilson, and A. Fontanini. 2022a. *End-Use Savings Shapes: Public Dataset Release for Residential Round 1*. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/buildings/assets/pdfs/euss-resround1-webinar.pdf.

Present, E., P. Gagnon, E. Wilson, N. Merket, P. White, and S. Horowitz. 2022b. "Choosing the Best Carbon Factor for the Job: Exploring Available Carbon Emissions Factors and the Impact of Factor Selection." NREL/CP-5500-82241. Presented at: ACEEE Summer Study on Efficiency in Buildings. Pacific Grove, CA. https://aceee2022.conferencespot.org/event-data/pdf/catalyst_activity_32485/catalyst_activity_paper_20220810190542996_ca9a88a9_04f7_48dc_88c1_2ba530e44474

Schoenbauer, B., N. Kessler, A. Haynor, and D. Bohac. 2017. *Cold Climate Air Source Heat Pump*. Prepared for: Minnesota Department of Commerce, Division of Energy Resources. https://www.mncee.org/sites/default/files/report-files/86417-Cold-Climate-Air-Source-Heat-Pump-%28CARD-Final-Report-2018%29.pdf.

State and Local Energy Efficiency Action Network (SEE Action). 2020. *Grid-Interactive Efficient Buildings: An Introduction for State and Local Governments.* Prepared by: Lisa Schwartz and Greg Leventis, Lawrence Berkeley National Laboratory. https://eta-publications.lbl.gov/sites/default/files/bto-see-action-gebs-intro-20200415.pdf.

Steinberg, D., D. Bielen, J. Eichman, K. Eurek, J. Logan, T. Mai, C. McMillan, A. Parker, L. Vimmerstedt, and E. Wilson. 2017. Electrification & Decarbonization: Exploring U.S. Energy Use and Greenhouse Gas Emissions in Scenarios with Widespread Electrification and Power Sector Decarbonization. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-68214. https://www.nrel.gov/docs/fy17osti/68214.pdf.

Takahashi, K. 2015. "Searching for Best Practices for Modeling Energy Efficiency in Integrated Resource Planning." Presented at: ACEEE National Conference on Energy Efficiency as a Resource. https://www.synapse-energy.com/sites/default/files/Modeling-EE-in-IRP.pdf.

Takahashi, K., S. Kwok, J. Tabernero, and J. Frost. 2022. *Toward Net Zero Emissions from Oregon Buildings: Emissions and Cost Analysis of Efficient Electrification Scenarios*. Prepared for: Sierra Club. https://www.synapse-energy.com/net-zero-emissions-oregon-buildings.

Titus, E., and C. McChalicher. 2021. *NEEP Regional End Use Load Profile Data Inventory and Needs Assessment*. Northeast Energy Efficiency Partnerships (NEEP). https://neep.org/sites/default/files/media-files/regional_data_inventory_and_needs_assessment_-_formatted.pdf.

Wilcox, S., and W. Marion. 2008. *Users Manual for TMY3 Data Sets (Revised)*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-581-43156. https://www.nrel.gov/docs/fy08osti/43156.pdf.

Williamson, J. and R. Aldrich. 2015. *Field Performance of Inverter-Driven Heat Pumps in Cold Climates.* Prepared for: DOE Building America Program. http://www.nrel.gov/docs/fy15osti/63913.pdf.

Wilson, E., et al. 2022. End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy22osti/80889.pdf.

Zhou, E. and T. Mai. 2021. Electrification Futures Study: Operational Analysis of U.S. Power Systems with Increased Electrification and Demand-Side Flexibility. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-79094. https://www.nrel.gov/docs/fy21osti/79094.pdf.

Appendix A. Project Background[45]

The United States is embarking on an ambitious transition to a 100% clean energy economy by 2050, which will require improving the flexibility of electric grids. One way to achieve grid flexibility is to shed or shift demand to align with changing grid needs. To facilitate this, it is critical to understand how and when energy is used. High quality end-use load profiles (EULPs) provide this information, and can help cities, states, and utilities understand the time-sensitive value of energy efficiency, demand response, and distributed energy resources.

Publicly available EULPs have traditionally had limited application because of age and incomplete geographic representation (Frick, Eckman, and Goldman 2017; Frick and Schwartz 2019). To help fill this gap, the U.S. Department of Energy (DOE) funded a three-year project—End-Use Load Profiles for the U.S. Building Stock—that culminated in the release of a publicly available dataset of simulated EULPs representing residential and commercial buildings across the contiguous United States. The motivation for this work is further detailed in a November 2019 report: Market Needs, Use Cases, and Data Gaps (Frick et al. 2019).

This report describes example applications and considerations for using end-use load profile outputs from the ResStock™ and ComStock™ models, intended for an audience of general dataset users. A companion report, *End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification*, provides detailed descriptions of how the dataset was developed. It is intended for an audience of dataset and model users interested in the technical details. These details include descriptions of all of the model improvements made for calibration and the final comparisons to empirical data sources (Wilson et al. 2022).

Project Team

The project team included researchers from the National Renewable Energy Laboratory (NREL), Lawrence Berkeley National Laboratory (Berkeley Lab), and Argonne National Laboratory (ANL). The project was guided by an extensive technical advisory group (TAG) of 92 individuals representing 61 organizations, including stakeholders from electric utilities, independent system operators (ISOs) and regional transmission organizations (RTOs), public utility commissions, state and local governments, consulting firms, software companies, academic institutions, nongovernmental organizations representing utilities and regional efficiency groups, and DOE. A full list of TAG members is included in Appendix B. As a project partner, the Electric Power Research Institute assisted the project team with utility data outreach. Northeast Energy Efficiency Partnerships received funding from the New York State Energy Research and Development Authority and the Massachusetts Clean Energy Center to engage with stakeholders in the Northeast, assist with data gathering and outreach, and develop a data inventory and needs assessment for the Northeast (Titus and McChalicher 2021).

Project Approach and Components

The primary focus of the End-Use Load Profiles for the U.S. Building Stock project was calibrating and validating the EULP outputs from models of the U.S. residential and commercial building stocks—ResStock and ComStock. A variety of empirical ground truth datasets, including anonymized utility meter

[45] This appendix is an excerpt from Wilson et al. 2022 with minor edits.

data from more than 2.3 million customers, various end-use submetering datasets, and other public and private datasets related to energy use in buildings, were used in the calibration and validation effort. The major components of the project are summarized in Figure A-1.

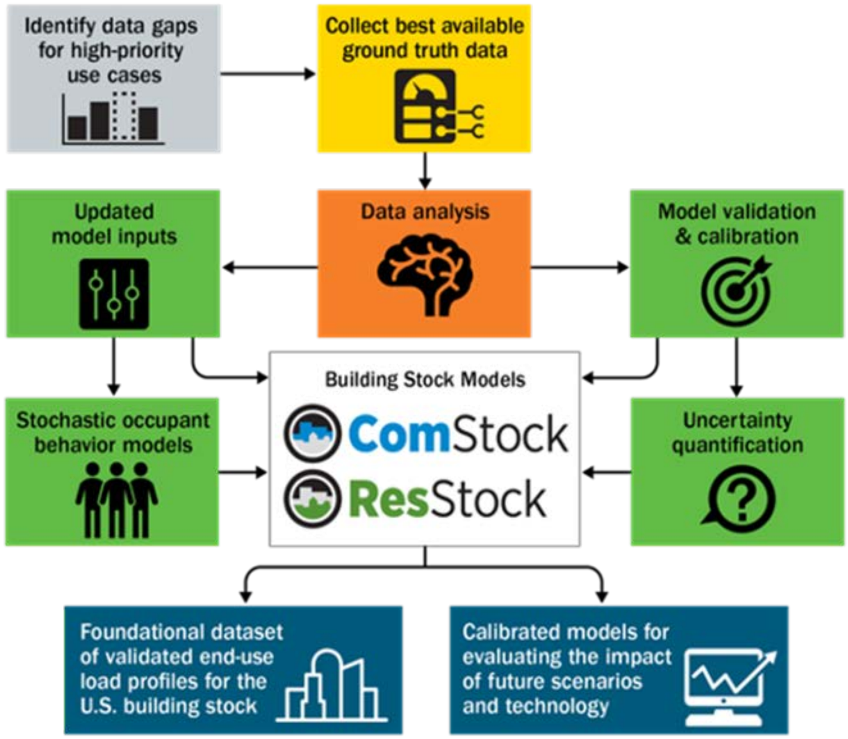

Figure A-1. Major components of the end-use load profiles for the U.S. building stock project

One important question to address is: "why didn't this project use direct submetering of a statistically representative sample of residential and commercial buildings to develop EULPs for the whole United States?" The first reason is that the costs were estimated to be an order of magnitude higher than the already significant available budget. These cost estimates were an extrapolation of the budget and scope of the competitively bid Northwest End Use Load Research Project recently commissioned by the Northwest Energy Efficiency Alliance (NEEA 2021b; NEEA 2021a). The second reason is that by using the selected approach, in addition to generating EULPs that represent the existing building stock, we are generating calibrated models of the building stock. These models are valuable because they can later be used to perform what-if analyses to estimate the impacts of various potential changes to the building stock to inform public- and private-sector decision-making.

Market Needs, Use Cases, and Data Gaps

The first year of the project was focused on identifying and prioritizing use cases for EULPs, defining EULP data requirements for those use cases, defining the data needed for model calibration/validation, and identifying major data gaps. The results of the project's first year are published in *End-Use Load Profiles for the U.S. Building Stock: Market Needs, Use Cases, and Data Gaps* (Frick et al. 2019).

Acquisition of Data for Calibration/Validation

The next major component of the project—spanning all three years—was acquiring empirical data for calibration and validation of the ResStock and ComStock models. We obtained access to a range of measured data, including utility meter data from more than 2.3 million customers, utility meter metadata, various end-use submetering datasets, and other public and private datasets related to energy use in buildings.

New Residential Stochastic Occupant Behavior Model

The goal of this project was to produce EULPs at both the aggregate and individual building scales. Aggregate profiles represent the total profile for an end use in one or more customer segments in a utility territory or other region. Individual profiles represent individual building or housing unit patterns, complete with the normal spikes and variability present in individual buildings and housing units. This is particularly important at the housing unit level. In large commercial and multifamily buildings, loads driven by stochastic occupant behavior are smoothed out to some degree, because of the larger number of occupants and the lesser degree of control that occupants have over end-use loads. To improve the realism of individual housing unit load profiles, we developed a new stochastic occupant behavior simulator and integrated it into ResStock. On the commercial side, we explored ways to improve the representation of occupant behavior in commercial buildings, but ultimately did not have sufficient data to implement any improved methods. We did derive commercial building operation variability from advanced metering infrastructure (AMI) data and integrated this variability into ComStock.

Model Calibration, Validation, and Uncertainty Quantification

The remainder of the project, spanning years two and three, was focused on ResStock and ComStock calibration, validation, and uncertainty quantification. These topics are the main subject of an accompanying report that includes an overview of the ResStock and ComStock approach to building stock modeling; the methodology used for calibration, validation, and uncertainty quantification; the changes made to ResStock and ComStock model inputs over the course of the calibration process; and the final results of model validation (Wilson et al. 2022).

Appendix B. List of Technical Advisory Group Members and Organizations

Name	Organization	Name	Organization
Charles Alonge	NYISO	Jim Leverette	Southern Company
Ayad Al-Shaikh	CalTF	Jessica Lin	Oracle
Jen Amann	ACEEE	Angela Long	PGE
Kausar Ashraf	Onatrio ISO	Kimberly Lukasiak	NV Energy
Jamie Barber	GA PSC	Ross Macwhinney	City of New York
Cyrus Bhedwar	SEEA	Cecily McChalicher	NEEP
Mark Bielecki	Center for Sustainable Energy	Bill McNary	EIA
Stephen Bird	Clarkson University	Pasi Miettinen	Sagewell
Michael Bishop	SolarReviews	Erik Miller	AES Indiana
Danielle Bond	C Power	Katherine Mitchell	Autodesk
Brad Borum	IURC	Claire Miziolek	Energy Solutions
Ali Bozorgi	ICF	Sarah Mullkoff	MI PSC
Kristen Brown	Electron	Mike Myser	Energy Platforms
Chris Burgess	MEEA	Paulomi (Lucy) Nandy	MEEA
Dave Chassin	SLAC	Shinvani Nathoo	ISO Ontario
Rebecca Chen	Ontario ISO	Chris Neme	Energy Futures Group
David Clement	NEEA	Clay Nesler	WRI
Sue Coakley	NEEP	Laura Ortega	CPS Energy
Barry Coflan	NEEP	Abhijeet Pande	TRC Solutions
Erin Cosgrove	NEEP	Dave Parsons	HI PUC
Timothy Costa	ISO New England	Bob Pauley	IURC
Matt Cox	Greenlink Analytics	David Podorson	Xcel Energy
Ron Domitrovic	EPRI	Susan Powers	Clarkson University
Paul Donohoo-Vallett	DOE	Curt Puckett	DNV
Tom Eckman	LBNL	Bob Ramirez	DNV
Tony Faris	BPA	Barbara Richards	Southern Company
Jamie Fine	Environmental Defense Fund	Rachel Scheu	Elevate Energy
Michael Fink	VEIC	Scott Schuetter	Slipstream

Ellen Franconi	PNNL	Prasenjit Shil	Ameren
Adam Gerza	Energy Toolbase	Rodney Sobin	NASEO
Krish Gomatom	EPRI	Justin Spencer	Apex Analytics
Benjamin Griffiths	Massachusetts	Robert Stephenson	VEIC
Mike Hamilton	Seattle City Light	Kenji Takahashi	Synapse
Alex Hofmann	APPA	Greg Thomas	PSD Consulting
Chris Holmes	EPRI	Elizabeth Titus	NEEP
Meg Howard	MA Clean Energy Center	JJ Vandette	VEIC
David Jacobson	Jacobs Energy	Puja Vohra	Slipstream
Bryan Jungers	E Source	Valerie von Schramm	CPS Energy
Steven Keates	ADM (now Truckee Donner PUD)	Dave Walker	MI PSC
Phillip Kelsven	BPA	Robert Weber	BPA
Sami Khawaja	Cadmus	Adam Wehmann	VEIC
Ben King	DOE (now Rhodium Group)	Bob Willen	Ameren
Kurtis Kolnowski	AEG	Cody Williams	Xcel Energy
Peter Langbein	PJM	Dan Williams	Measurable
Will Lange	WaterFurnace International	Craig Williamson	DNV
Greg Lawson	EIA	Dan York	ACEEE
Tuan Le	CPS	Henry Yoshimura	ISO New England

Appendix C. End-Use Load Profile Building Types, Inputs, and Outputs

Table C-1. Building Types

Residential	Commercial
• Single-Family Attached • Single-Family Detached • 2 Unit • 3 or 4 Unit • 5 to 9 Unit • 10 to 19 Unit • 20 to 49 Unit • 50 or more Unit • Mobile Home	• Health Care - Outpatient • Health Care - Hospital • Hotel - Small • Hotel - Large • Office - Small • Office - Medium • Office - Large • Restaurant - Full Service • Restaurant - Quick Service • Retail - Standalone • Retail - Strip Mall • School - Primary • School - Secondary • Warehouse

Table C-2. Fuels

Residential	Commercial
• Electricity • Fuel oil • Natural gas • Propane • Wood	• District cooling • District heating • Electricity • Natural gas • Other

Table C-3. End Uses

Residential	Commercial
• Bath Fan • Ceiling Fan • Clothes Dryer • Clothes Washer • Cooking Range • Cooling • Dishwasher • Ext Holiday Light • Exterior Lighting • Extra Refrigerator • Fans Cooling • Fans Heating • Fireplace • Freezer • Garage Lighting • Grill • Heating • Heating Supplement • Hot Tub Heater • Hot Tub Pump • House Fan • Interior Lighting • Plug Loads • Pool Heater • Pool Pump • Pumps Cooling • Pumps Heating • PV • Range Fan • Recirc Pump • Refrigerator • Vehicle • Water Systems • Well Pump	• Cooling • Exterior Lighting • Fans • Heating • Heat Recovery • Heat Rejection • Heating • Interior Equipment • Interior Lighting • Pumps • Refrigeration • Water Systems

Appendix D. Resource Potential Assessments

Reasonably accurate and reliable information about the amount, savings load shape, availability, and cost of energy efficiency resources are important inputs for electricity resource planning. This information is typically obtained by conducting energy efficiency (or conservation) potential studies. Potential studies can serve two important objectives: (1) provide data on the amount, timing, and cost of available energy efficiency, and (2) provide critical input for the design of energy efficiency programs. Potential studies are often performed at the end-use and customer-sector levels, and the results can be aggregated to different geographic levels, such as a utility, state, or region.

Energy efficiency potential analysis typically begins by identifying end uses of electricity (e.g., lighting, heating, and cooling) where energy efficiency measures exist, and the savings and potential number of installations associated with the measures. This produces the ***technical potential,*** an estimate of energy savings based on the assumption that all existing equipment or measures will be replaced with the most efficient equipment or measure that is both available and technically feasible over a defined time horizon, without regard to cost or market acceptance.

Economic potential is determined using one of two analytical processes. The most common applies a cost-effectiveness limit to all measures that comprise the technical potential in a jurisdiction. Such limits can be as simple as a maximum cost per kilowatt-hour or involve a more complex evaluation of a measure's energy savings, peak demand reduction benefits, or other power and non-power system benefits. The second approach competes energy efficiency resources directly against supply-side resources to assess whether developing more energy efficiency at varying cost levels increases or decreases the total electricity system cost.

Achievable potential is the portion of technical potential that can be realized after considering *non-financial barriers* (e.g., lack of knowledge, renter versus owner, product availability) that may prevent consumers from adopting energy efficiency measures and practices. Depending on the jurisdiction, it may be an estimate of the amount of savings that can be expected to occur within a specified time frame under the assumption that all available mechanisms (e.g., utility programs, codes, standards and market transformation) are deployed, or it may only consider the quantity of savings that can occur from utility customer-funded efficiency programs.

The relationship among the various types of energy efficiency potential (Figure D-1) varies by jurisdiction and the objectives of the potential study. When energy efficiency is treated as a resource, the determination of economic potential occurs following the assessment of achievable potential. In contrast, in the more typical process, technical potential is first reduced by the subjecting efficiency measures to a predetermined cost-effectiveness screening criteria. The resulting economic potential is then reduced to a level deemed achievable.

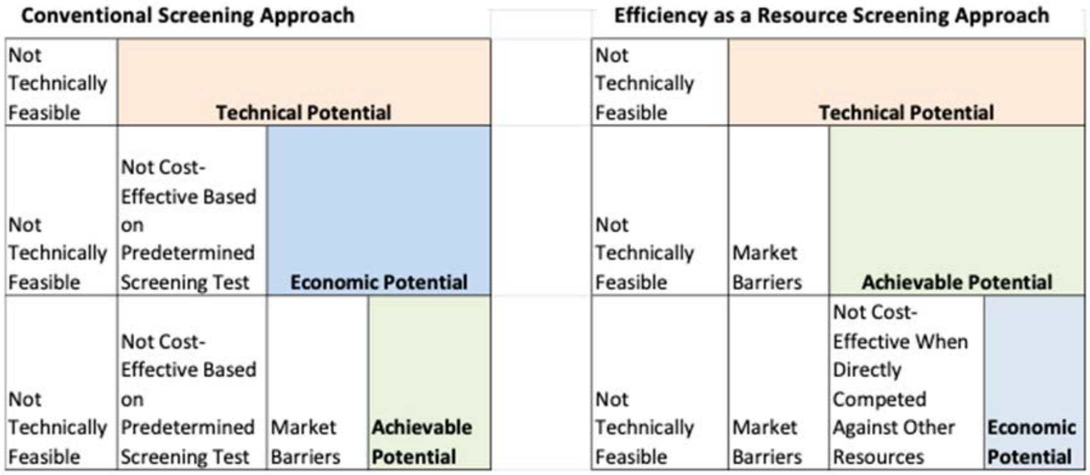

Figure D-1. Pathways to identifying energy efficiency potential

Estimating Technical Potential

Energy efficiency measures can reduce energy and peak demand by reducing the wattage needed to accomplish a given task (e.g., use of light-emitting diode [LED] lamps that require 12 watts to produce the same lumen output as 75 watt incandescent lamps); reducing the hours of operation (e.g., use of occupancy sensors to switch off lights in unoccupied spaces); or a combination of both wattage reduction and reduced hours of operation (e.g., use of daylighting controls to reduce wattage and to switch off lighting when natural lighting is adequate).

Broadly speaking, assessing technical potential entails creating an estimate of savings that could be achieved by any of these three approaches, assuming that every physically feasible end-use efficiency measure will be installed over some period of time, usually 10 to 20 years. Total technical potential generally falls into two resource categories: retrofit or lost-opportunity.

- *Retrofit* or instantaneous technical potential represents savings that could be achieved *at any time* through immediate energy efficiency actions that affect energy-use behavior. For example, the lighting system in an existing building can be retrofitted at any time.
- *Lost-opportunity* potential savings can only be captured during a specific window of opportunity, such as when a new home is being constructed or a new appliance is purchased. Failure to influence the efficiency of energy use during this time means that the opportunity to improve efficiency is generally lost for the life of the measure. The time period covered by the potential assessment is critical because it constrains the number of lost-opportunity energy efficiency measures to those that occur within that time frame.

Development of the technical potential savings can be derived from standard engineering calculations or energy efficiency program evaluations, or based on deemed savings from technical reference manuals. When treating energy efficiency as a resource, these assessments must be quite granular, identifying levelized cost and savings by measure, load profile, building type, sector, and vintage for each year of the planning period.

The most widely used method for estimating technical potential, commonly referred to as a *bottom-up approach,* starts with estimating savings for each individual efficiency measure, then multiplying those savings by the maximum market saturation of the measure. The main advantage of this approach is that through thorough characterization of specific energy efficiency measures and practices, it provides detailed information that informs energy efficiency planning and program design. The bottom-up approach requires users to compile information on a large, comprehensive number of energy efficiency measures and practices, their costs, potential savings impacts, and how they interact with energy systems and each other. Computation of technical potential savings using this method is mathematically straightforward: technical potential = savings per unit × the number of technically feasible units.

When assessing technical potential, it is important to account for the impact of codes and standards, as well as interactions between efficiency measures. Improvements in energy codes and standards affect the baseline assumptions regarding end-use energy intensity and therefore affect energy efficiency measure savings. To avoid overstating or double counting the savings from codes and standards, the analysis of technical potential must factor in the anticipated impact of approved codes and standards that take effect in the future.

As discussed in Frick et al. (2021a), when considering efficiency as a resource, the savings from known codes and standards should be embedded in the load forecast. Naturally occurring savings such as efficiency improvements resulting from appliance and equipment stock turnover (i.e., replacements) also should be included in the load forecast. To avoid double counting these savings, the efficiency level used as the basis for determining remaining potential should use the levels required by codes and standards, unless current practice efficiency levels are higher. The “better of codes, standards, or practice” rule ensures that the forecast loads and energy efficiency potential assessment use internally consistent assumptions.

The calculation of technical potential may also account for three types of interactions that affect the level of electricity savings. First are the interactions between equipment and facility improvements. For example, savings from the installation measures such as improvements to the building shell or building heating, ventilation, and air conditioning (HVAC) equipment may be affected by the installation of high-efficiency electric lighting.

Second, two or more energy efficiency measures may be applicable for the same end use. For example, a SEER 15 or SEER 16 air conditioner could be installed in a home, thus they have overlapping potential. To avoid double counting the technical savings potential at the end-use level, these interactions can be accounted for by either assigning each competing measure a “share” of the applicable end use or by assessing their incremental impacts. Continuing with the air conditioning example, the incremental savings from a baseline efficiency air conditioner to a SEER 15 can be multiplied by the number of air conditioners available to upgrade. The additional savings (and cost) for the SEER 16 air conditioner might then be calculated using the SEER 15 system as the baseline. Alternatively, some fraction of air conditioners available to upgrade could be assigned to the SEER 15 and the rest assigned to the SEER 16.

Finally, certain energy efficiency measures affect an end use indirectly and can result in overstating or understating savings potential. For example, installing more efficient lighting may increase heating loads while lowering cooling loads, and installing high-efficiency clothes washers can reduce the time required for drying clothes.

All of these interactive effects are typically dealt with by systematically stacking their effects so only incremental savings are used to estimate technical potential. The order in which certain energy efficiency measures are entered into the calculation of technical potential affects a measure's savings. Generally, there are two options for stacking an efficiency measure's effects. An analyst can make reasonable assumptions about the order in which the various measures might be installed; for example, according to their relative cost-effectiveness. The second option is to establish a rolling, declining baseline electricity use for each affected end use and apply it iteratively to measures, based on their order in the stack.

Estimating Economic Potential

The first step in estimating economic potential is to establish the cost-benefit analysis inputs. Cost-benefit analysis is intended to determine whether the benefits of an investment outweigh its costs. Cost-benefit analysis (e.g., total resource cost test, resource value test) is used to understand energy efficiency cost-effectiveness, and is typically established through local regulatory or legislative mandates. Consistent with the principles discussed in Frick et al. (2021a), cost-benefit analysis for energy efficiency should be comparable to that used for other resources.

As described previously, two general approaches are used to conduct cost-benefit analysis on technical potential. The difference between the two approaches is how the avoided costs are determined. In the first approach, analysts use predetermined avoided costs as an input in energy efficiency cost-benefit analysis. This is the most common method used today. In this approach, the avoided cost of additional electricity resources serves as the fundamental basis of comparison for determining the quantity of efficiency that is economic. In the second approach, energy efficiency competes directly with other resources in the capacity expansion modeling process. This approach allows the model to determine the impact of energy efficiency on system load growth and load shape. Thus, it impacts the type, amount, and timing of conventional resource development.

Estimating Achievable Potential

The objective of an achievable potential assessment is to determine the level of energy efficiency that can be reliably developed through programs, policies, and regulations that are specifically designed to overcome barriers that limit adoption of energy efficiency measures. Estimating achievable potential is subjective because it involves making assumptions about consumer behavior and decision-making processes.

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For more information, visit:

https://www.nrel.gov/buildings/end-use-load-profiles.html

https://emp.lbl.gov/publications/end-use-load-profiles-us-building-0

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