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RENEWABLE ENERGY

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

Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification

EXECUTIVE SUMMARY

March 2022

Disclaimer

This research was performed using computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory and Argonne National Laboratory.

Executive Summary

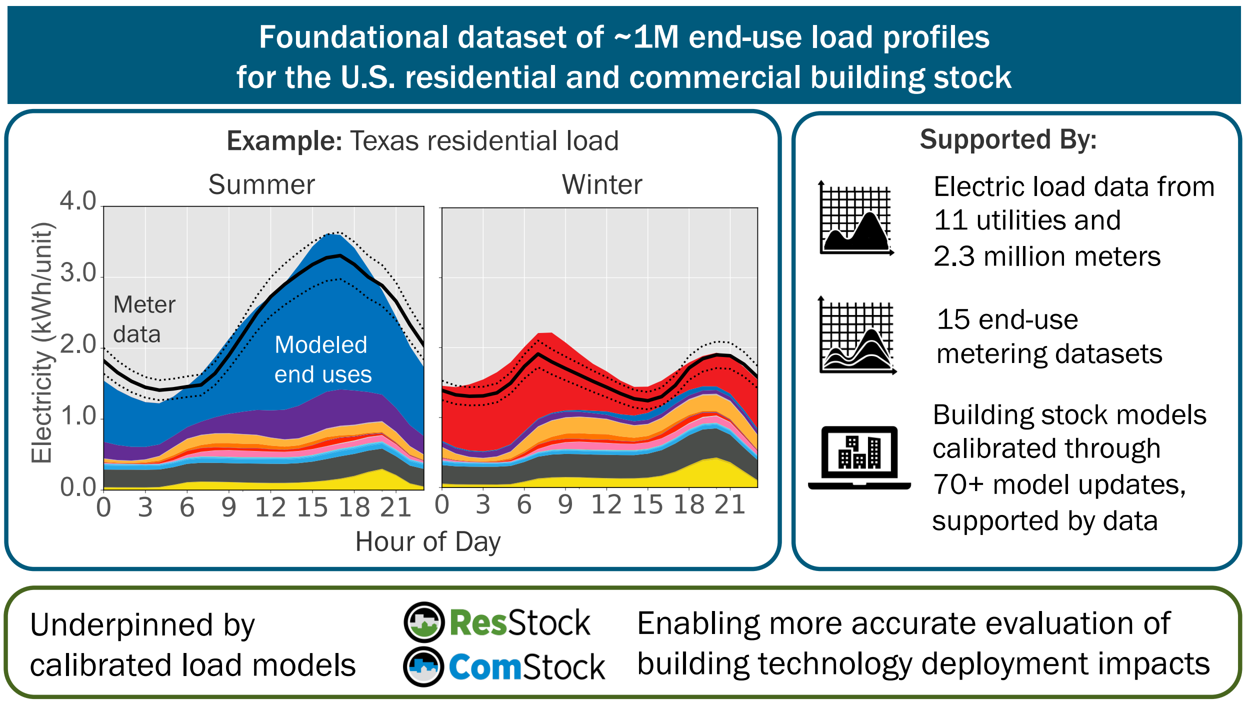

Figure ES-1. Graphical summary of the *End-Use Load Profiles* project

This Executive Summary is an excerpt from the full *Methodology and Results* report, which can be accessed at https://www.nrel.gov/docs/fy22osti/80889.pdf. The author list, acknowledgements, appendices, and sections referenced below can all be accessed in the full report.

Motivation and Background

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 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[1] 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* (Mims Frick et al. 2019).

The full *Methodology and Results* report provides detailed descriptions of how the dataset was developed, 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. A companion report, *End-Use Load Profiles for the U.S. Building Stock: Applications and Opportunities*, will be published subsequently and will describe example applications and considerations for using the dataset, intended for an audience of general dataset users.

[1] As of October 28, 2021, the dataset is available at https://www.nrel.gov/buildings/end-use-load-profiles.html

Project Team

The project team included researchers from the National Renewable Energy Laboratory (NREL), Lawrence Berkeley National Laboratory (LBNL), 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 A. 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).

Methodology

Historical and contemporary efforts to develop EULPs for particular regions have used direct submetering of a statistically representative sample of buildings. Applying such an approach to the contiguous United States would have cost an order of magnitude higher than the already significant budget for this project, would have likely been limited in coverage of building types and end uses, and would not have resulted in calibrated models that enable future what-if analyses of scenarios involving energy efficiency, electrification, demand flexibility, and changes in climate or behavior.

Our hybrid approach—using a wide range of empirical data to inform updates to detailed physics-simulation building stock models—produced EULPs covering all major commercial and residential building types and end uses, for all locations of the contiguous United States. More importantly, the calibrated building models enable what-if scenario analyses. Although a pure submetering approach was not feasible for the national DOE EULP effort, our approach would not have been possible without the foresight of organizations that have invested in regional end-use submetering load research. Our work was also made possible by the ratepayer- and taxpayer-funded investments in advanced metering infrastructure over the past decade. We have fully documented our hybrid approach methodology in Section 2 and model calibration updates in Section 3.

To implement our hybrid approach, we adopted a framework for calibration, validation, and uncertainty quantification (UQ) and defined quantities of interest (QOI) used to evaluate calibration progress, validation accuracy, and uncertainty (Section 2.1.1). As documented in Section 2.3, we reviewed the types of calibration relevant to building energy modeling—manual, automated, and output calibration—and the advantages and disadvantages of each. We summarized the few examples of load profile model calibration that existed prior to this project, which all informed our work to some degree, and established a calibration philosophy to guide the calibration for this project.

Empirical Data Sources

We worked with more than 30 data sharing partners to obtain the empirical data used for calibration and validation. This involved navigating privacy concerns and data transfer issues in order to obtain customer meter data and building metadata from about a dozen utilities (Sections 2.3.6 and 2.3.7). We developed an approach to process the meter data, associate it with building characteristics, and clean it for use in validation (Section 2.3.5). Whereas utility meter data enabled validation of whole-building and whole-sector load, we needed empirical timeseries data broken out by end use to calibrate our modeled end uses. There were a variety of residential end-use datasets available for use in this project (Section 2.3.6). In contrast, lack of commercial end-use data was a major data gap identified at the start of the project. Undertaking an end-use monitoring study would not have yielded data in time to use it for calibration, so we pursued a major outreach effort that resulted in procuring existing commercial end-use data from a range of unconventional sources (Section 2.3.5). In total, we used 33 empirical data sources for residential calibration and validation (Table 2) and 26 sources for commercial calibration and validation (Table 3).

We studied whether residential end-use data were transferable between regions, concluding that, with some exceptions, the *shapes* of most non-weather dependent end uses can be considered transferable between regions, though the magnitude of the end uses will vary depending on factors such as the saturation of end-use equipment in a given location (Section 2.3.9). Our project relies on physics-based simulations to model how end uses that depend on weather (cooling, space heating, and water heating) or location (lighting) vary from region to region. As such, historical weather data were another key aspect of empirical data for this project. We developed new capabilities to construct historical weather data files using ground-based measurements for most variables (temperature, humidity, wind speed/direction, and pressure) and satellite-derived solar radiation data (Section 2.4).

Calibration

To calibrate the EULP dataset, we made more than 70 improvements to the ResStock™ and ComStock™ models. To align with the phased timing of when we obtained empirical meter datasets, we divided the calibration effort into five residential and four commercial regional phases, each including comparisons to one or more utility meter datasets in a similar region. By design, calibration did *not* involve automated or manual tuning of inputs to minimize error, which often leads to "getting the right answer for the wrong reason." Instead, the objective of calibration was to make model improvements that reduce model error, but only when supported by data, such as weather, census, real estate, time use, EIA surveys, and submetering data (see Tables 2 and 3 for full lists of ResStock and ComStock data sources). The calibration process relied on both data science and buildings domain expertise.

We developed a novel approach to building stock model sensitivity analysis to evaluate which input parameters are more important for the improvements made for calibration (Section 3.1). Model improvements were typically in the form of increased accuracy, diversity, or resolution of input parameter distributions, as documented comprehensively in Section 3. To improve the realism of individual housing unit load profiles, we developed a novel approach to simulating stochastic occupant behavior schedules and integrated it into ResStock, as discussed in Section 3.2.1. As a final step in residential calibration, we developed an output correction model to reduce some of the remaining model error, as presented in Section 3.2.10.

Validation

A "validated" model does not mean that the outputs perfectly match the available empirical data; it means that model accuracy was evaluated for the quantities of interest and reported so that EULP data users know what level of confidence they should have when putting them to use. EULP data users should review the detailed validation results presented in Section 4, where, for each comparison, we provide discussion of accuracy and possible explanations for discrepancies. One finding from this research is that there can be a large degree of uncertainty in empirical load data, particularly for commercial buildings when disaggregating by building type or calculating energy use intensity, because of the metadata matching process (Section 4.2.2). Readers and data users may also be interested to understand how much accuracy improved as a result of the model input updates made for calibration; see examples in Figures ES-2 and ES-3 and discussion in Section 5.1.2.

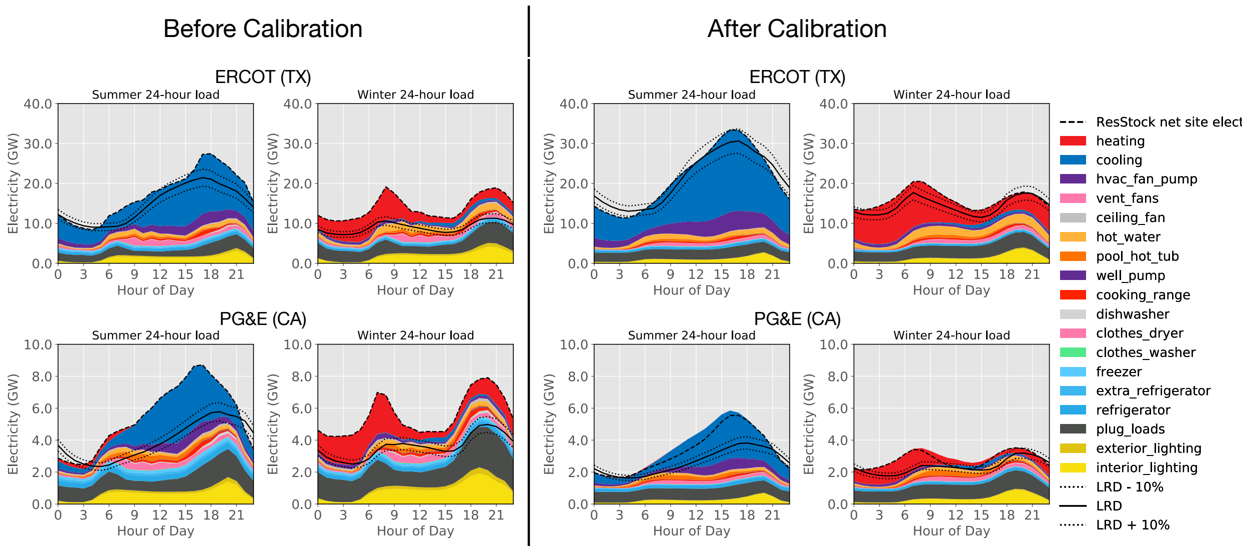

Figure ES-2. Before and after calibration example: ResStock comparisons to load research data (LRD) average daily profiles (note: before and after years are different). See Section 5.1.2 for a full discussion of how accuracy improved as a result of the model input updates made through calibration.

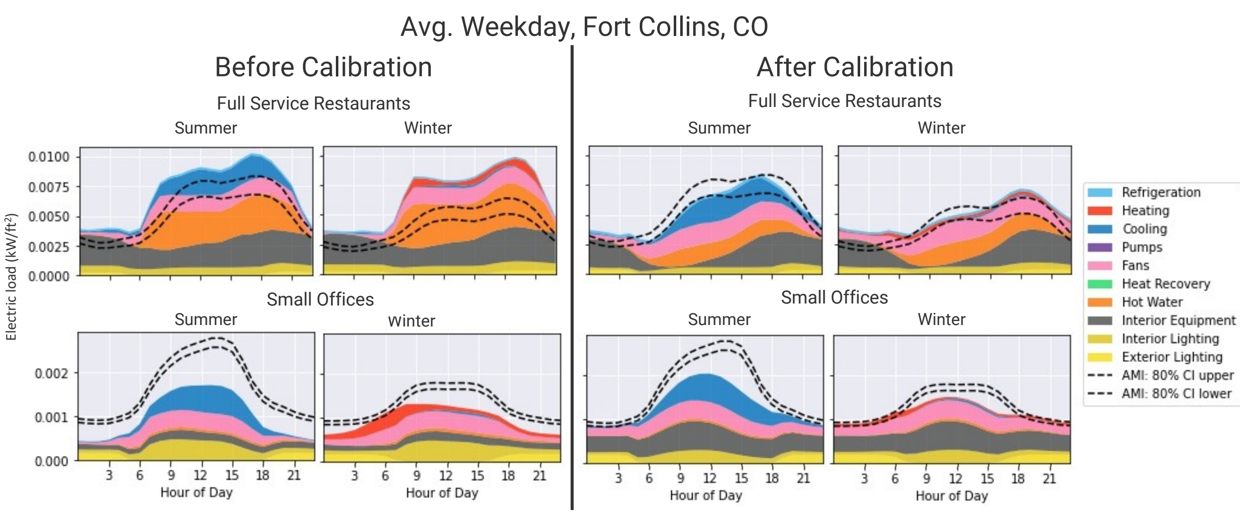

Figure ES-3. Before and after calibration example: ComStock comparisons to Fort Collins advanced metering infrastructure (AMI) average daily profiles. See Section 5.1.2 for a full discussion of how accuracy improved as a result of the model input updates made through calibration.

Uncertainty Quantification

Uncertainty in results is discussed at a high level in Section 5.1.3. We quantified the uncertainty ranges around model outputs by developing and applying a novel approach to building stock model uncertainty quantification that used trained timeseries surrogate models to evaluate millions of permutations of model inputs in order to propagate input uncertainty ranges through to outputs (Section 4.4). Results of this input uncertainty quantification indicate that the uncertainty in seasonal or top 10 day average peak magnitude is typically in the 3–9% range for ResStock and 4–11% for ComStock, depending on the season, building type, and region. The daily minimum base load magnitude has slightly lower uncertainty, with values in the 1–4% range for ResStock, and 3–6% for ComStock. Annual energy uncertainty is in the 3–6% range for ResStock and 3–8% for ComStock. Peak time uncertainty is typically 45–90 minutes for ResStock and 30–90 minutes for ComStock, depending on the season, building type, and region.

The other major source of model uncertainty is uncertainty from the use of insufficient numbers of ResStock or ComStock samples to estimate quantities of interest in particular locations or segments of the building stock (Section 5.1.3). This is an area of ongoing work, but our preliminary ResStock analysis showed that a sample of 1,000 dwelling units results in sample size uncertainty—that is, the error relative to the result with 1,000,000 samples—of less than 15% for all quantities of interest. With 10,000 samples, the uncertainty drops to less than 10% for all quantities of interest. Therefore, we recommend users ensure that there are at least 1,000 samples in a query of the data or in a downloaded aggregate data file. If there are less than 1,000 samples for a given query or aggregate, we recommend combining nearby geographies (e.g., counties) to increase the sample size.

Conclusion

The final product of this project is the first version (1.0) of an EULP dataset containing calibrated and validated 15-minute resolution load profiles for all major residential and commercial building types and end uses, for all locations of the contiguous United States. Although our hybrid approach was similar to some previous examples that used tens or hundreds of building energy models, the scale of our application was unprecedented, both in terms of empirical data gathered—2.3 million meters worth of hourly data from 11 utilities—and in terms of the granularity of building stock simulation—900,000 building energy models representing 58 billion ft^2 of commercial buildings and 133 million residential dwelling units.

The EULP dataset is available in three formats[2]—(1) via a web viewer, (2) as downloadable spreadsheet files, and (3) in a detailed format that can be queried with big data tools—to maximize accessibility for different types of users. The OpenStudio® model input files are also available for building energy modelers to use for their own analyses. Utility planners, consultants, regulators, state energy offices, researchers, and building owners are now able to use these resources, along with tools such as Berkeley Lab's forthcoming Time-Sensitive Value Calculator, to estimate the value of energy efficiency, demand response, and other distributed energy resources. Such analysis can be used to guide utility resource and distribution system planning, research and development prioritization, and state and local energy planning and regulation.

The EULP dataset can be updated over time by incorporating new input data (weather, census, real estate, time use, EIA surveys, and so on) into the models as they become available, giving the load models longevity beyond this calibration effort and beyond EULPs developed through a pure end-use submetering approach. Additionally, the calibrated models can be a foundation to develop *end-use savings shapes* that describe the difference in energy consumption between the current building stock and the building stock with an energy saving, electrification, flexibility, or other measure applied.

The EULP dataset and calibrated building stock models can play a key role by helping us understand, with more accuracy than ever before, how buildings and their occupants interact with the national electricity system, and the role that high-performing, energy-efficient, and demand-flexible buildings can play in an equitable transition to a decarbonized, affordable, and reliable energy system.

[2]All three methods for accessing the EULP dataset can be found on the dataset website: https://www.nrel.gov/buildings/end-use-load-profiles.html

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