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

Technical Advisory Group Meeting #9
January 28, 2021

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Logistics

• We are recording the webinar.

• Because of the large number of participants on the phone, please keep yourself muted during presentations.

• Please use the chat box to send us clarifying questions during presentations. You can chat or unmute yourself to ask a question during our designated discussion time.
Agenda

• Welcome back! (5 minutes)
  – Project overview, timeline, deliverables and resources
• Update on ComStock calibration: Commercial AMI Classification and discussion (40 minutes)
• Update on ResStock calibration: Residential Calibration on Region 3 and discussion (40 minutes)
• Next steps/wrap up (5 minutes)

Links to the slides are also in the chat box.
The novel approach delivers a nationally-comprehensive dataset at a fraction of the historical cost.

Hybrid approach combines best-available ground-truth data—
  • submetering studies,
  • whole-building interval meter data, and
  • other emerging data sources
— with the reach, cost-effectiveness, and granularity of physics-based and data-driven building stock modeling capabilities.
EE/DR savings profiles

Stochastic occupancy modeling capabilities

Technical Advisory Group

Rigorous calibration of building stock end-use models

Load profile library, documentation, & user guide

Data analysis to derive occupant-driven schedules and usage diversity

Calibrated building stock models

Ongoing additions to load profile library

You are here

Com: 1 of 5 planned regions complete
Res: 3 of 5 planned regions complete

Project Timeline

Year 1
Define use cases and requirements
Collect/review existing data
Report on market needs and data gaps

Year 2
Targeted data acquisition leveraging planned/ongoing sub-metering studies
Data analysis to derive occupant-driven schedules and usage diversity
Rigorous calibration of building stock end-use models
Quantify accuracy of results for target applications

Year 3

Beyond

Stochastic occupancy modeling capabilities

Year 1

Year 2

Year 3

Beyond

Com: 1 of 5 planned regions complete
Res: 3 of 5 planned regions complete

You are here

Defining use cases and requirements
Collecting/reviewing existing data
Reporting on market needs and data gaps

Targeting data acquisition leveraging planned/ongoing sub-metering studies
Data analysis to derive occupant-driven schedules and usage diversity
Rigorous calibration of building stock end-use models
Quantifying accuracy of results for target applications

Stochastic occupancy modeling capabilities

You are here

Com: 1 of 5 planned regions complete
Res: 3 of 5 planned regions complete
# Summary of FY21 Final Products for End-Use Load Profiles

## Public Datasets
- VizStock Web Interface
- Pre-aggregated Load Profiles
- Raw Individual Building Load Profiles
- Raw Individual Building Models

## Dataset Access Instructions
The project website will provide instructions on how to access and download the various dataset formats.

## Webinar
Conduct public outreach webinar to TAG and other stakeholders to present project outcomes.

## EERE or NREL report
*End-Use Load Profiles for the U.S. Building Stock: Methodology and Results of Model Calibration, Validation, and Uncertainty Quantification*
- Content: Detailed description of model improvements made for calibration; detailed explanation of validation and uncertainty of results
- Audience: Dataset and model users interested in technical details
- NREL lead; LBNL and ANL co-authors

## EERE or LBNL report
*End-Use Load Profiles for the U.S. Building Stock: Applications and Opportunities*
- Content: Example applications and opportunities for using the dataset
- Audience: General users of datasets
- LBNL lead; NREL co-authors

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* Dates may change
Resources

**Publications**

- Li et al. Characterizing Patterns and Variability of Building Electric Load Profiles in Time and Frequency Domain (forthcoming)
- Bianchi et al. 2020. Modeling occupancy-driven building loads for large and diversified building stocks through the use of parametric schedules
- Parker et al. 2020. Framework for Extracting and Characterizing Load Profile Variability Based on a Comparative Study of Different Wavelet Functions
- Present et al. 2020. Putting our Industry's Data to Work: A Case Study of Large Scale Data Aggregation
- N. Frick. 2019. End Use Load Profile Inventory

**Presentations and Slides**

- Technical Advisory Group slides
  - [LBNL](#) and [NREL](#) site
- E. Wilson. 2020. EFX webinar
- E. Wilson. 2019. Peer Review presentation

**Software**

- [OpenStudio Occupant Variability Gem](#) and [Non Routine Variability Gem](#) (more info at [IBPSA newsletter](#))

**Data**

- First year of 15-min NEEA HEMS data available: [https://neea.org/data/end-use-load-research/energy-metering-study-data](https://neea.org/data/end-use-load-research/energy-metering-study-data)
Recap & Motivation from Commercial Calibration Region 1
Building Classification

• Classification of AMI is critical for commercial building stock model calibration
  • Area and building type

• CoStar classifies based on real-estate needs
  • Some are clear: offices, outpatient, standalone retail
  • Some are ambiguous: strip malls, warehouses

• We care that the classifications also match from an energy standpoint
  • Otherwise, we are comparing modeled apples to AMI oranges
Investigated “Outliers” with Google Maps

- strip_mall (23 outliers)
  - 9 are convenience store/gas stations
  - 11 are restaurants (or primarily restaurants)
- warehouse (18 outliers)
  - 13 are manufacturing
  - 2 are autobody shops
- small_office (13 outliers)
  - 2 are manufacturing
  - 1 is a nursery/greenhouse
  - 1 is a multifamily condo w/ maybe office space on first floor?
  - The rest are just normal-looking offices
- retail (5 outliers)
  - 3 are nursery/greenhouses
- outpatient (4 outliers)
  - All appear to legitimately be outpatient... perhaps some specialties use much more energy?
- quick_service_restaurant (1 outlier)
  - Drive-through where service is not tied to floor area

Conclusion: Most “outliers” were actually misclassified buildings, not truly “outliers” of the target building type
Impact of Misclassification & Outliers

Misclassification & outliers: more impactful than any model changes we did in Region 1!

Identification methods
Misclassification Detection Study
Introducing a New Team Member

• Peter DeWitt, Ph.D.
  • Joint Appointee between NREL and the University of Colorado Anschutz Medical Campus
  • Ph.D. Biostatistics
    • University of Colorado Anschutz Medical Campus
  • M.S. Statistics
    • Colorado State University
  • B.S. and M.S. Mathematics & Computer Science
    • Colorado School of Mines

• Primary Role:
  • Inform study design and assessment from a statistician’s point of view
Xcel Energy has provided our project with **monthly energy billing data** for over 500,000 meters.

The scale of this dataset is ideal for testing outlier removal methods based on annual electric EUI (kWh/sf/yr), building area, and total electric usage, which can then be translated to our AMI dataset processing workflow.

For the context of this work, outliers could be defined as buildings that have inaccurate metadata (area and/or building type), or unrealistically high/low energy values.
Building Classification & Outliers

Goals:
1. Determine effective method for detecting/removing misclassified buildings based on energy consumption and building area
2. Retain a reasonable distribution of energy consumption, footprint, and energy use intensity

Approach:
1. Initial dataset of ~517k monthly meters from Xcel Energy
   • Covers 8 states
   • ~211k have CoStar matches (for building type & area metadata)
2. Sample the population, manually classify samples
3. Test different misclassification/outlier detection approaches
   • Only testing simple, non-timeseries-based approaches
Data Set Before/After Culling

Before: 8 States, 89k Buildings

After: 8 States, 57k Buildings

**Premise:** 1 Xcel location

**Meter:** 1 Xcel energy reading; can have multiple per premise

**Building:** 1+ Xcel meters/premises matched with 1+ CoStar entries
- 1 building with 1 meter
- 1 building with several meters
- 2 buildings of the same type on the same parcel with several meters
### Data Culling

Started with ~89k buildings

<table>
<thead>
<tr>
<th>Number removed</th>
<th>Reason</th>
</tr>
</thead>
<tbody>
<tr>
<td>805</td>
<td>Missing information about DOE building type</td>
</tr>
<tr>
<td>25</td>
<td>Remove billing credits (not actually energy consumption data)</td>
</tr>
<tr>
<td>11,224</td>
<td>Remove Xcel gas-only (keep buildings where Xcel provides electricity)</td>
</tr>
<tr>
<td>4</td>
<td>Restrict to billing from 2017-Dec-01 through 2019-Jan-01</td>
</tr>
<tr>
<td>6,376</td>
<td>Restrict to buildings with all meters observed for the full 2018 calendar year</td>
</tr>
<tr>
<td>311</td>
<td>Remove Zero energy use</td>
</tr>
<tr>
<td>72</td>
<td>Remove buildings with footprint &lt; 100 sf</td>
</tr>
<tr>
<td>13,296</td>
<td>Remove buildings where not all premise ids have complete billing data</td>
</tr>
</tbody>
</table>

Ended with ~57k buildings
Apply a filter to identify misclassified data, i.e., wrong building type.

Methods are based on
- Extremes of EUI (kWh / sqft / year) or
- Extremes of 2D density of consumption (kWh / year) and footprint (sqft)

Extreme values could indicate:
- Misclassified building, e.g., small office is really a hospital
- Uncharacteristic building, e.g., small office with a bitcoin mining setup
### Misclassification and Outlier Detection Methods Tested

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boxplot</td>
<td>• EUI&lt;br&gt;• $\log_{10} EUI$</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Multiple of the Median</td>
<td>• EUI&lt;br&gt;• $\log_{10} EUI$</td>
</tr>
<tr>
<td>Kernel Density (KD)</td>
<td>2D: kWh/year by square footage (both on $\log_{10}$ scale)</td>
</tr>
</tbody>
</table>

Outlier removal occurs per CoStar building type.

- **Outlier** removal occurs when values fall outside the $1.5 \times \text{IQR}$ range from Q1 or Q3.
- A value is considered an **Outlier** if it is below $Q1 - 1.5 \times \text{IQR}$ or above $Q3 + 1.5 \times \text{IQR}$.
- Values between $Q1 - 1.5 \times \text{IQR}$ and $Q3 + 1.5 \times \text{IQR}$ are considered **Not an outlier**.
- Values below or above the $100 - p$th percentile of the data are considered **Outlier**.

**Annual Energy**

- $\text{Annual Energy} = (100 - p)$th percentile data

**Area**

- $\text{Area} = \text{Outlier}$
- $\text{Area} = \text{Not an outlier}$
# Misclassification and Outlier Detection Methods Tested

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension(s)</th>
<th>Outlier Test</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boxplot</td>
<td>• EUI</td>
<td>$&lt; Q_1 - xIQR$</td>
<td>• Common</td>
<td>• Will not exclude low EUI if $Q_1 - xIQR &lt; 0$</td>
</tr>
<tr>
<td></td>
<td>• $\log_{10}$EUI</td>
<td>$&gt; Q_3 + xIQR$</td>
<td>• Easy to implement</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$x \in {1.5, 3}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multiple of the Median</td>
<td>• EUI</td>
<td>$&lt; \frac{1}{x} \tilde{m}$ or $&gt; x\tilde{m}$ where $\tilde{m}$ is the median $x \in {3, 4, 5}$</td>
<td>• Easy to implement</td>
<td>• Does not account for spread in the data</td>
</tr>
<tr>
<td></td>
<td>• $\log_{10}$EUI</td>
<td></td>
<td>• Can exclude low and high values</td>
<td>• Sensitive to magnitude of the median</td>
</tr>
<tr>
<td>Kernel Density (KD)</td>
<td>2D: kWh/year by square footage (both on $\log_{10}$ scale)</td>
<td>Based on percentile estimates; omit the lowest $p^{th}$ percentile</td>
<td>• Can id extremes in consumption and square footage even when EUI is “reasonable”</td>
<td>• Implementation for AMI is to be determined</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Implementation for AMI is to be determined</td>
<td>• May exclude “good data”</td>
</tr>
</tbody>
</table>
Verification and Evaluation of Methods

- Sampled ~300 buildings for human verification from lower 10\textsuperscript{th} percentile of kernel densities
  - Focus on buildings which were uncharacteristic of others with the same label
- Sensitivity = TP / (TP + FN)
- Specificity = TN / (TN + FP)

**High Sensitivity**
- Identify and remove misclassified data at the expense of omitting correctly classified data

- Sensitivity and Specificity are inversely related
- Selection of preferable methods is subjective

### Table: Verification and Evaluation

<table>
<thead>
<tr>
<th>Method</th>
<th>Truth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Misclassified</td>
<td>Correctly Classified</td>
</tr>
<tr>
<td>True Positive (TP)</td>
<td>False Positive (FP)</td>
</tr>
<tr>
<td>False Negative (FN)</td>
<td>True Negative (TN)</td>
</tr>
</tbody>
</table>

- **High Specificity**
  - Retain a lot of correctly classified data at the expense of retaining misclassified data
Manual Verification Procedure

1. Search the address in Google Maps
2. Check for building type match using exterior signage or business name
   • Can you make any reasonable argument that it is properly classified?
3. Check for building area match using Google measure tool (accounting for multiple stories)
   • Report as misclassified if error > 50%
4. Report building classification as accurate or inaccurate
   • **If both** building type and area are **correct**, the building is listed as “Verified Accurate”
   • **If at least one** of building type or area is **incorrect**, the building is listed as “Verified Inaccurate”
   • If the building is not available on Google Maps, the building is listed as “Not Verifiable”

Human verification error is possible when identifying building type and measuring area.
Verification Results

• 309 sites were verified – these sites are weighted towards the tails and are not representative

• Building Area Classification Results
  • Unverifiable: 27 (9%)
  • Correctly Classified: 248 (80%-all sites; 88%-removing unverifiable)
  • Incorrectly Classified: 33 (11%- all sites; 12%-removing unverifiable)

• CoStar Building Type Classification Results
  • Unverifiable: 31 (10%)
  • Correct: 211 (68%-all sites; 76%-removing unverifiable)
  • Incorrect: 67 (22%- all sites; 24%-removing unverifiable)

• Combined Classification Results (both building area and building type were correctly classified)
  • Unverifiable: 36 (12%)
  • Correct: 186 (60%-all sites; 68%-removing unverifiable)
  • Incorrect: 87 (11%- all sites; 12%-removing unverifiable)
Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: OFFICE
- Human
  - RETAIL_AUTO DEALERSHIP
Examples of Misclassified Buildings

• Provided Data Set
  • CoStar: INDUSTRIAL_TRUCK TERMINAL
• Human
  • OFFICE_SERVICE
Examples of Misclassified Buildings

• Provided Data Set:
  • CoStar: Flex Light Distribution

• Human:
  • Small Office
Examples of Misclassified Buildings

• Provided Data Set
  • CoStar: INDUSTRIAL_WAREHOUSE
• Human
  • Flea Market

kWh/sf/year value < 0.5 – ComStock does not attempt to model buildings of this type of irregularity
Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: FLEX
- Human
  - Camper/trailer retailer

kWh/sf/year value < 0.1 – ComStock does not attempt to model buildings of this type of irregularity
Examples of Misclassified Buildings

- Provided Data Set
  - CoStar: INDUSTRIAL_WAREHOUSE
- Human
  - Church maintenance equipment storage

\[
\text{kWh/sf/year value < 0.2 – ComStock does not attempt to model buildings of this type of irregularity}
\]
Sensitivity and Specificity

If **sensitivity** (identifying misclassified data) was priority, then the 3X Median or a higher-percentile Kernel Density method would be of interest.

If **specificity** (maintaining properly classified data) was priority, then the Boxplot methods or a lower-percentile Kernel Density method would be of interest.
Sensitivity and Specificity

- Verification bias accounted for via methods of Begg and Greenes (1983)
- Estimates for kernel density (KD) percentiles greater than 10 are the least reliable
  - Initial sampling did not account for interest in percentiles > 10
  - Expanding the method set includes buildings which were not considered to be at risk of being an outlier
  - Could extend the verification set so useful estimates of for KD with $p > 10$ can be made
Example: Outlier Removal Methods on CoStar Small Retail

Statistics on removed data can be provided for each calibration AMI dataset.
Notes on Reported Units and Scales

All reported energy values are for **electricity only**, and therefore exclude any potential gas heating or equipment. EUI values may seem lower than typical due to this exclusion.

All EUI values are reported in **kWh/sf/year**, not kBtu/sf/year. Multiply the reported values by ~3.41 if kBtu/sf/year is a more familiar metric to you.

**Log scales** are used on several plots – keep this in mind when assessing behavior at increased values.
Example: Outlier Removal Methods on CoStar Small Retail
Example: Outlier Removal Methods on CoStar Small Retail

Typical Verizon = 1,800 sf

CBECS Retail 10th percentile = 1,750 sf

Typical football field = 57,600 sf

Typical CVS = 13,000 sf
Example: Outlier Removal Methods on CoStar Small Retail

CBECs Retail 10th Percentile = 2.53 kWh/sf/year

Bullitt Center 2014 EUI = 2.93 kWh/sf/year

NREL RSF A-wing 2019 lighting only = 1.08 kWh/sf/year

CBECs Retail 90th Percentile = 25.35 kWh/sf/year
What We Do and Don’t Model

• We **do not** currently model buildings that are unconditioned or not adequately lit in accordance with commercial building standards (i.e., an unconditioned “warehouse” barn with minimal lighting)
  • All ComStock models include an HVAC system and regularly-used lighting

• We **do not** currently model buildings that experience irregular occupancy, including:
  • Buildings that are up for lease or sale with no active tenants
  • Buildings that experience unoccupancy due to renovations
  • Buildings that typically experience abnormally low, sporadic usage (e.g., a restaurant that only serves on Sundays, flea market, etc.)

• We **do** model buildings with varying occupied start and end times

• We **do** model buildings with typical low-occupancy periods (e.g., summer setbacks in schools)

• We **do** model buildings with varying schedules (e.g., lighting and plug loads) and operation behavior

• We **do** model buildings with varying HVAC system types, lighting power densities, vintages, insulation values, window properties, size, aspect ratio, etc.
Selecting Method(s)

• There is no clear statistical “winner”, as the most appropriate option is highly subjective to the application.

• The main goals of the EULP project are to calibrate our stock models to:
  1. realistic measured building energy data with reasonable and achievable energy behavior that we can represent with ComStock.
  2. datasets that cover the variety of occupied and operational buildings in the stock.

• The **gold standard** approach would be to manually verify every data point in every AMI dataset for calibration, but this is **unrealistic** due to both time and insufficient metadata.

• Must find a **balance** between keeping data that provides a **useful and representative variety**, while being sure to maximize the removal of **misclassified and unrealistic** data that could skew calibration.

• **Median 3X outlier** and **Kernel Density 25%** methods were chosen for further investigation by the project team as they appear to best meet the intent of the project goals.
Focus on Two Methods: CoStar Small Retail
Focus on Two Methods: CoStar Small Retail

Range: 804k; min: 5k; max: 809k

Range: 15.4mil; min: 3k; max: 15.5mil

3x median method keeps a 19x larger energy (kWh/yr) range
Focus on Two Methods: CoStar Small Retail

3x median method keeps a 18x larger square footage range

Range: 51k; min: 1280; max: 52k

Range: 898k; min: 256; max: 898k
Focus on Two Methods: CoStar Small Retail

KD 25% method keeps a 5x larger EUI (kWh/sf/yr) range

Range: 185; min: 1; max: 186

Range: 25; min: 4; max: 39
Focus on Two Methods: Summary

3x Median:
• Tends to maintain a larger range of building area and energy usage as this method filters by EUI only. This can leave uncommonly large or small buildings in the dataset.
• Usually results in a narrower range of EUIs as it filters specifically along this axis.

KD 25%:
• Tends to maintain a smaller range of building area and energy usage as this method removes outliers on both axis, resulting in an inclusion boundary that hugs the mass. This can remove buildings with uncommonly small and large area and energy usage relative to the dataset.
• Usually results in a wider range of EUIs as it does not filter specifically along this axis.

Next Steps:
• Test both outlier removal methods on AMI dataset to understand performance and stability on a calibration-region dataset, where dataset size is smaller.
• Determine if minimum and maximum EUI and square footage values would be appropriate in conjunction with either or both methods.
Key Takeaways

1. Confirmed finding from Region 1 using a multi-state dataset
   • Many buildings are misclassified
   • These must be removed before using data for calibration to avoid bad comparison

2. Evaluated 20 different approaches
   • No statistical “winner”
   • But several methods are reasonable given the project goals

3. Classification is a hard, even with manual human verification

4. Key factors moving forward are to be clear and transparent about the outlier removal methods being used when processing AMI datasets for calibration
   • Communicate the outlier detection method used
   • Report percentages of data being removed (square footage and energy) for each AMI dataset
Commercial AMI Classification
Poll Question
1. Based on the approaches presented today, which of the following are you more concerned about having a negative effect on commercial calibration efforts?

a. Misclassified buildings and bad data will remain in the calibration data set
b. Valid data will be removed from the calibration data set
Questions?
Appendix
### Summary Statistics For CoStar: SMALL RETAIL

<table>
<thead>
<tr>
<th></th>
<th>EUI (kWh/sf/yr)</th>
<th>Building Area</th>
<th>kWh / year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Median</td>
<td>Max</td>
</tr>
<tr>
<td>All Data</td>
<td>0.002</td>
<td>12.9</td>
<td>730.7</td>
</tr>
<tr>
<td>Median 3</td>
<td>4.300</td>
<td>13.7</td>
<td>38.7</td>
</tr>
<tr>
<td>KD25</td>
<td>0.964</td>
<td>14.3</td>
<td>185.7</td>
</tr>
</tbody>
</table>

**3x Median:**
- EUI – min value of 4.3 EUI seems reasonable; max value of 38.7 EUI seems reasonable.
- Building Area – max value of 900k sf seems uncommon but reasonable. Method does not filter specifically along area axis, which allows for a greater range.
- kWh/year – Method does not filter specifically along kWh/yr axis, which allows for a greater range.

**KD 25%:**
- EUI – min value of 0.964 EUI is very low; max value of 185.7 EUI seems high. Yields larger EUI range.
- Building Area – yields large decrease in maximum value, resulting in a decreased building area range.
- kWh/year – yields large decrease in maximum value, resulting in a decreased energy range.
## Summary Statistics For DOE: Warehouse

### EUI (kWh/sf/yr) | Building Area | kWh / year
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Min</strong></td>
<td><strong>Median</strong></td>
<td><strong>Max</strong></td>
</tr>
<tr>
<td>All Data</td>
<td>&lt;0.01</td>
<td>4.36</td>
</tr>
<tr>
<td>Median 3</td>
<td>1.45</td>
<td>4.49</td>
</tr>
<tr>
<td>KD25</td>
<td>0.71</td>
<td>4.51</td>
</tr>
</tbody>
</table>

### 3x Median:
- **EUI** – min value of 1.45 electric EUI seems low but reasonable for a low-occupancy storage warehouse.
- **Building Area** – min value of 347 sf seems low for a warehouse, but max value of 794k sf seems reasonable.
- **kWh/year** - Method does not filter specifically along kWh/yr axis, which allows for a greater range.

### KD 25%:
- **EUI** – min value of 0.71 EUI seems very low; max value of 24.6 EUI seems reasonable. Method yields larger EUI range.
- **Building Area** – minimum value seems reasonable, but maximum value seems low.
- **kWh/year** – yields large decrease in maximum value, resulting in a decreased energy range.
Focus on Two Methods: DOE Warehouse (n = 8,671)
Examples of Misclassified Building Types

• Provided Data Set:
  • DOE: small office
  • CoStar: Office
• Human:
  • Office Medical

• This is a potential issue – the data set might be correct, “support services” suggest that there are few, or no medical procedures done here.
• What is the difference between a “Office” and “Office Medical”
Examples of Misclassified Building Types

• Provided Data Set:
  • DOE: outpatient
  • CoStar: Health Care, Rehabilitation Center

• Human:
  • Specialty Religious Facility

• Facility was associated with a church, but upon further investigation it was determined that the facility is a rehabilitation center and was correctly classified in CoStar.
Residential Region 3 Calibration

Anthony D. Fontanini, Ph.D.
Eric Wilson
Technical Advisory Group
January 28, 2021
Calibration Strategy
Model Architecture

- Housing stock characteristics database
  - National
  - Climate/Region
  - State
  - City/CBSA (Core-Based Statistical Area)

- Physics-based computer modeling
  - Modeling Algorithms
  - Schedules
  - Human Behavior
  - Performance Curves
  - Component Properties
  - Weather Data
Calibration Process for One Region

Focus on reducing error for one region at a time

Keep an eye on impacts to other regions
Calibration Process Over Time

Focus on reducing error for one region at a time

Keep an eye on impacts to earlier regions

Error

Region 1 Calibration  Region 2 Calibration  Region 3 Calibration  Region 4 Calibration  Region 5 Calibration

Region 1  Region 2
Calibration Process Over Time

Calibration efforts for earlier regions create better starting point for later regions.
Calibration Process Over Time

Improvements from later regions will improve results for regions focused on earlier.
Region 3 Focus: Nationally-Relevant Updates

Housing stock characteristics database

Physics-based computer modeling

Monthly usage multipliers

More weather stations

Foundation types, roof material, lighting type, central DHW

Household size

National

Climate/Region

State

Public Use Microdata Area (PUMA)

Modeling Algorithms

Schedules

Human Behavior

Performance Curves

Component Properties

Weather Data
Region 3 Calibration Strategy

- HVAC
  - Roof material distributions
  - Update foundation type distributions
  - Cooling type IECC dependency fix
  - Cooling load/sizing bugfix

- Validation Comparisons
  - 2019 end-use data from 73 homes from ongoing NEEA HEMS
  - Monthly EIA electricity sales by state for residential sector
  - Monthly EIA natural gas sales by state for residential sector
  - Aggregates of AMI data from Seattle City Light

- Baseload
  - More geographic resolution in household size
  - Monthly appliance usage multipliers
  - Regional variation in lighting efficiency
  - Regional variation in plug load usage
  - Add Multifamily Central DHW differentiation
  - Water heater fuel type and efficiency dependencies

- ResStock Capabilities
  - More weather data locations
  - Faster multifamily modeling
Residential Calibration Dimensions

Calibration effort

- Annual electric sales of all utilities in U.S.
- Annual and monthly electricity and natural gas consumption by state, sector
- Annual end-use loads of occupied dwelling units
  - Building type
  - Climate zone
  - Fuel (electricity, natural gas, propane, fuel oil)
- Load duration curves and seasonal load shapes of >20 utilities around U.S.
- Sub-metered end-use load data power levels and load shapes

AMI data from future region 5
AMI data from future region 4
Aggregates of AMI data from Seattle City Light, WA
AMI data from Fort Collins municipal service territory (CO)
Advanced metering infrastructure (AMI) data from ComEd service territory (IL)
Residential Calibration Dimensions

- EIA Form 861 electricity, natural gas data
- RECS end-use scatterplots
- Utility load research data (LRD)
- Submeter end-use data
- Load duration curves and seasonal load shapes of >20 utilities around U.S.
- Annual end-use loads of occupied dwelling units
  - Building type
  - Climate zone
  - Fuel (electricity, natural gas, propane, fuel oil)

- Advanced metering infrastructure (AMI) data from ComEd service territory (IL)
- AMI data from Fort Collins municipal service territory (CO)
- AMI data (aggregated by building type) from Seattle City Light, WA
- AMI data from future region 4
- AMI data from future region 5

- New: monthly electric and gas comparisons
- New: NEEA HEMS 73 homes
Region 3 – Seattle, WA

- Seattle, WA (pop. ~745k) plus parts of adjacent suburbs
- Municipal utility
- Primarily used AMI data from 2019 (8% sample; aggregated by building type)
- Compared to previous regions:
  - Higher % multifamily
  - Higher % electric heating

### chars.geometry_building

<table>
<thead>
<tr>
<th>Type</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Family Detached</td>
<td>46.7%</td>
</tr>
<tr>
<td>Multi-Family with 5+ Units</td>
<td>41.4%</td>
</tr>
<tr>
<td>Multi-Family with 2 - 4 Units</td>
<td>6.2%</td>
</tr>
<tr>
<td>Single-Family Attached</td>
<td>4.7%</td>
</tr>
<tr>
<td>Mobile Home</td>
<td>0.9%</td>
</tr>
</tbody>
</table>

### chars.heating_fuel

<table>
<thead>
<tr>
<th>Fuel Type</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>54.7%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>38.0%</td>
</tr>
<tr>
<td>Fuel Oil</td>
<td>5.1%</td>
</tr>
<tr>
<td>None</td>
<td>0.9%</td>
</tr>
<tr>
<td>Other Fuel</td>
<td>0.8%</td>
</tr>
<tr>
<td>Propane</td>
<td>0.6%</td>
</tr>
</tbody>
</table>
List of updates

New validation comparisons
• 2019 end-use data from 73 homes from ongoing NEEA HEMS
• Monthly EIA electricity sales by state for residential sector
• Monthly EIA natural gas sales by state for residential sector
• Aggregates of AMI data sample from Seattle City Light

New capabilities
• More weather data locations
• Faster multifamily modeling

Baseload updates
• More geographic resolution in households size → Usage of DHW, appliances, and plug loads
• Monthly appliance usage multipliers
• Regional variation in lighting efficiency
• Regional variation in plug load usage
• Add Multifamily Central DHW differentiation
• Water heater fuel type and efficiency dependencies

HVAC updates
• Roof material distributions
• Update foundation type distributions
• Cooling type IECC dependency fix
• Cooling load/sizing bugfix
Where did we end up?

Calibration improvements and load shape status
Seattle City Light, WA: Annual Error

Relative error: annual electricity use per unit

- Single-Family Detached load too high
- Electric heating load too high

High on annual usage per unit
Seattle City Light, WA: Total Error Metrics

### Average of All Days
- **Baseline Load**
- **Average Peak**
- **Top 10 Peaks**

### Top 10 Days
- **Average Peak**
- **Top 10 Peaks**

### Peak Timing
- **Average Peak**
- **Top 10 Peaks**

**Significant improvement in cooling peak**

**Improved summer peak timing**

**Roughly equal morning/evening peaks cause timing issues**

**Baseload improvement**
Seasonal end-use loads by day type

Seattle City Light service territory, WA
Seasonal end-use loads by day type

Seattle City Light service territory, WA
Seasonal end-use loads by day type

Seattle City Light service territory, WA
New validation comparisons
NEEA Home Energy Metering Study (HEMS) Comparisons

Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - filtered to west of Cascades (BPA H1C1; N=36)
  - Single-family only
- RBSAM (2012-2013)
  - filtered to west of Cascades (BPA H1C1; N=57)
  - Single-family only

AMI is much lower on heating
AMI is lower on cooling
Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - filtered to WA, west of Cascades (BPA H1C1; N=24)
  - Single-family only
- RBSAM (2012-2013)
  - filtered to west of Cascades (BPA H1C1; N=57)
  - Single-family only

Filtering HEMS to WA (and not OR) west of the Cascades reduces cooling slightly and increases heating slightly
NEEA Home Energy Metering Study (HEMS) Comparisons

Monthly kW per home profiles

- Seattle 2019 AMI,
  - 8% sample
  - Aggregate for single-family only
- HEMS (2019),
  - filtered to WA, west of Cascades (BPA H1C1; N=24)
  - Single-family only
- RBSAM (2012-2013)
  - Seattle city limits (N=12)
  - Single-family only

Filtering RBSAM to Seattle reduces cooling and heating, improving match to AMI, but sample size is low and weather is 2012-2013
ResStock vs. HEMS vs. RBSAM
End Use Comparison (Single-Family Only)

ResStock, AML for Seattle

2019

ResStock, AMI for Seattle

HEMS for WA, west of Cascades (N=24)

2019

N=20 elec. (83%) (14 heat pumps)
N=4 gas heat

RBSAM, west of Cascades (N=57)

2012-13

N=27 elec. (47%) (18 heat pumps)
N=30 gas heat (53%)

Plug loads and lighting are not separately metered in HEMS (except for a few circuits)

Plug loads and lighting are not separately metered in RBSAM (except for a few circuits)

Misc. electric space heaters categorized as heating in HEMS and plug loads in RBSAM and ResStock

Heat pumps in shoulder months assumed to be in heating mode but may actually include cooling

Heat pumps in shoulder months assumed to be in heating mode but may actually include cooling
ResStock vs. HEMS vs. RBSAM
End Use Comparison (Single-Family Only)

ResStock, AMI for Seattle
2019

HEMS for WA, west of Cascades (N=24)
Corrected to 25% elec. heat
(70% of samples are heat pumps vs. 25-35% in the stock)

Plug loads and lighting are not separately metered in HEMS
(except for a few circuits)

RBSAM, west of Cascades (N=57)
Corrected to 25% elec. heat
(67% of samples are heat pumps vs. 25-35% in the stock)

Plug loads and lighting are not separately metered in RBSAM
(except for a few circuits)

Heat pumps in shoulder months assumed to be in heating mode
Monthly EIA electricity sales by state, sector

Region 1 and 2 calibration regions included comparison to annual EIA sales data:
We now compare monthly residential sector electricity and gas sales for every state.

Washington (Region 3)

- Overpredicting electric heating
- Underpredicting gas heating
We now compare monthly residential sector electricity and gas sales for every state.

**Colorado (Region 2)**

- **Underpredicting**
  - Cooling
  - Electric heating

- **Overpredicting**
  - Gas heating
Monthly EIA electricity, gas sales by state, sector

We now compare monthly residential sector electricity and gas sales for every state

**Illinois (Region 1)**

Cooling looks good

Overpredicting electric heating

Gas consumption looks good
Added Capabilities
Update: More weather data locations

- Increased number of weather station data regions from 215 to 941
- Weather data regions are the same for ResStock and ComStock
- Increases resolution in weather events (e.g., cold fronts rolling across grid) and sunrise/sunset times, which should increase weather response diversity in aggregate load profiles

**Before: 215 weather data regions**

**After: 941 weather data regions**
Impact: More weather data locations

Before: 215 weather data regions
Impact: More weather data locations

After: 941 weather data regions

Some utilities got worse (e.g., Fort Collins)

Noticeable improvement in CA gas use
• ResStock data sources are primarily defined in terms of dwelling units (and not multifamily buildings)
• Previous approach:
  – Model an entire multifamily building for each sampled dwelling unit
• New approach:
  – Model only a dwelling unit for each sampled dwelling unit
  – Shared walls are modeled as adiabatic
• Benefits:
  – Speed improvements: HPC usage reduced by about 80%
  – Aligns with HPXML and associated workflows (Home Energy Score, WAP, ERI)
• Drawbacks:
  – Some heat flows not captured
    • Heat transfer between shared walls
    • Minor shading differences
    • 0.20% effect across total energy, 2.46% effect for worst test building
  – Cannot explicitly model central HVAC systems serving multiple units; using ANSI/RESNET/ICC 301-2019 approach instead
Testing: Faster Multifamily Modeling

Test results for 10,000 MF buildings

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Total Site Energy Difference</td>
<td>0.11%</td>
</tr>
<tr>
<td>Maximum Total Site Energy Difference</td>
<td>3.80%</td>
</tr>
</tbody>
</table>
Impact: Faster Multifamily Modeling

Negligible change to multifamily in Seattle, which is expected

This change leveraged work from another project; it was motivated by runtime improvements and not by an observed error.
Baseload Updates
Update: More granular household sizes

*Before:* Number of occupants depends on building type and number of bedrooms

*After:* Number of occupants depends on building type and number of bedrooms and PUMS region ($N=2,335$)

- Number of occupants affects usage of domestic hot water, appliances, and plug loads
- Switch from RECS 2015 to PUMS 2017 allows PUMA level spatial granularity in the distributions and leverages more than 6 million samples.
Update: More granular household sizes

Before: Number of occupants depends on building type and number of bedrooms

After:  Number of occupants depends on building type and number of bedrooms and PUMS region (N=2,335)

- Number of occupants affects usage of domestic hot water, appliances, and plug loads
- Switch from RECS 2015 to PUMS 2017 allows PUMA level spatial granularity in the distributions and leverages more than 6 million samples.

PUMS shows fewer occupants on average, so baseload is reduced nationally
Impact: More granular household sizes

Modeling fewer occupants per household reduces baseload

Seattle, WA

− Before
− After
− AMI

Fort Collins, CO

ComEd, IL
The stochastic occupancy model incorporated for Region 2 eliminated monthly usage variation for four major appliances.

Now we re-introduce monthly usage variation for these appliances.

Uses an average of monthly variation patterns seen across 6 end-use datasets.

Implemented by slightly lengthening/shortening event durations to achieve correct monthly usage.
Update: Regional variation in lighting efficiency

*Before:* Lighting technology saturation is a national average distribution

*After:* Lighting technology saturation depends on building type and Census Division (N=10)

### Before:

<table>
<thead>
<tr>
<th>Option</th>
<th>Incandescent</th>
<th>100% CFL</th>
<th>100% LED</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>52%</td>
<td>41%</td>
<td>7%</td>
</tr>
</tbody>
</table>
Update: Regional variation in lighting efficiency

**Before:** Lighting technology saturation is a national average distribution

**After:** Lighting technology saturation depends on building type and RECS Census Division (N=10)

<table>
<thead>
<tr>
<th>Dependency=Census Division RECS</th>
<th>Dependency=Geometry Building Type RECS</th>
<th>Option=100% Incandescent</th>
<th>Option=100% CFL</th>
<th>Option=100% LED</th>
</tr>
</thead>
<tbody>
<tr>
<td>East North Central</td>
<td>Single-Family Detached</td>
<td>44%</td>
<td>46%</td>
<td>10%</td>
</tr>
<tr>
<td>East South Central</td>
<td>Single-Family Detached</td>
<td>49%</td>
<td>44%</td>
<td>7%</td>
</tr>
<tr>
<td>Middle Atlantic</td>
<td>Single-Family Detached</td>
<td>43%</td>
<td>44%</td>
<td>13%</td>
</tr>
<tr>
<td>Mountain North</td>
<td>Single-Family Detached</td>
<td>36%</td>
<td>51%</td>
<td>14%</td>
</tr>
<tr>
<td>Mountain South</td>
<td>Single-Family Detached</td>
<td>38%</td>
<td>52%</td>
<td>10%</td>
</tr>
<tr>
<td>New England</td>
<td>Single-Family Detached</td>
<td>41%</td>
<td>44%</td>
<td>15%</td>
</tr>
<tr>
<td>Pacific</td>
<td>Single-Family Detached</td>
<td>34%</td>
<td>50%</td>
<td>16%</td>
</tr>
<tr>
<td>South Atlantic</td>
<td>Single-Family Detached</td>
<td>48%</td>
<td>43%</td>
<td>9%</td>
</tr>
<tr>
<td>West North Central</td>
<td>Single-Family Detached</td>
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<td>11%</td>
</tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Pacific</td>
<td>Mobile Home</td>
<td>34%</td>
<td>50%</td>
<td>16%</td>
</tr>
<tr>
<td>Pacific</td>
<td>Multi-Family with 2 - 4 Units</td>
<td>39%</td>
<td>54%</td>
<td>8%</td>
</tr>
<tr>
<td>Pacific</td>
<td>Multi-Family with 5+ Units</td>
<td>39%</td>
<td>54%</td>
<td>8%</td>
</tr>
<tr>
<td>Pacific</td>
<td>Single-Family Attached</td>
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<td>50%</td>
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Update: Regional variation in lighting efficiency

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<td>Single-Family Detached</td>
<td>46%</td>
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</tr>
</tbody>
</table>

**Before:**

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>52%</td>
<td>41%</td>
<td>7%</td>
</tr>
</tbody>
</table>

**After:**

- Pacific region has most efficient lighting
- Single-family has more efficient lighting than multifamily
Update: Regional variation in lighting efficiency

*Before:* Lighting technology saturation is a national average distribution

*After:* Lighting technology saturation depends on building type and RECS Census Division (N=10)

Comparison of national average lighting saturation to previous ResStock data sources →

![Lighting Saturation By Bulb Type](chart.png)

- **Incandescent**
  - RECS 2009 (ResStock before EULP): 87%
  - 2015 DOE U.S. Lighting Market Characterization (ResStock before Region 3): 52%
  - RECS 2015 (ResStock now): 44%

- **CFL/LFL**
  - RECS 2009 (ResStock before EULP): 13%
  - 2015 DOE U.S. Lighting Market Characterization (ResStock before Region 3): 41%
  - RECS 2015 (ResStock now): 45%

- **LED**
  - RECS 2009 (ResStock before EULP): 0%
  - 2015 DOE U.S. Lighting Market Characterization (ResStock before Region 3): 7%
  - RECS 2015 (ResStock now): 11%
Update: Regional variation in plug load usage

Captures regional variation in plug loads that isn’t captured elsewhere (e.g., humidifiers, dehumidifiers, fans)

Misc. plug load kWh reported in RECS 2015 microdata relative to misc. plug load kWh calculated using regression equations derived from RECS 2015 →

\[ MELS_{SFD} = \alpha(1146.95 + 296.94 n_{\text{occ}} + 0.30 ffa) \]
\[ MELS_{SFA} = \alpha(1395.84 + 136.53 n_{\text{occ}} + 0.16 ffa) \]
\[ MELS_{MF} = \alpha(875.22 + 184.11 n_{\text{occ}} + 0.38 ffa) \]

\( n_{\text{occ}} \): Number of occupants
\( ffa \): Finished floor area
\( \alpha \): Plug load regional and building type multiplier

SFD: Single-Family Detached
SFA: Single-Family Attached
MF: Multi-Family

** MELS are defined by the following fields in RECS 2015: televisions, microwaves, humidifiers, and other devices not elsewhere classified
Impact: Base load updates
(lighting, appliances, plug loads)

- Before
- After
- AMI

Reduction in baseloads
Update: Water heater dependencies

**Before:** Water heating *fuel type* and *efficiency* depends on space heating fuel type and custom region (N=10)

**After:** Water heating *fuel type* depends on space heating fuel type, custom region (N=10), and building type

Water heating *efficiency* depends on water heater fuel type and custom region (N=10)

<table>
<thead>
<tr>
<th>Water Heater Fuel</th>
<th>Allows other data sources to be integrated</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Dependency=Geometry Building Type RECS</th>
<th>Dependency=Heating Fuel</th>
<th>Dependency=Location Region</th>
<th>Option=Electric</th>
<th>Option=Fuel Oil</th>
<th>Option=Gas</th>
<th>Option=Other Fuel</th>
<th>Option=Propane</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Home</td>
<td>Electricity</td>
<td>CR06</td>
<td>90%</td>
<td>0%</td>
<td>4%</td>
<td>0%</td>
<td>5%</td>
</tr>
<tr>
<td>Multi-Family with 2 - 4 Units</td>
<td>Electricity</td>
<td>CR06</td>
<td>93%</td>
<td>0%</td>
<td>7%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Multi-Family with 5+ Units</td>
<td>Electricity</td>
<td>CR06</td>
<td>93%</td>
<td>0%</td>
<td>7%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Attached</td>
<td>Electricity</td>
<td>CR06</td>
<td>87%</td>
<td>0%</td>
<td>13%</td>
<td>0%</td>
<td>0%</td>
</tr>
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<td>0%</td>
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<td>0%</td>
<td>5%</td>
</tr>
<tr>
<td>Mobile Home</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>25%</td>
<td>0%</td>
<td>75%</td>
<td>0%</td>
<td>0%</td>
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<td>Natural Gas</td>
<td>CR06</td>
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<td>Natural Gas</td>
<td>CR06</td>
<td>13%</td>
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<td>87%</td>
<td>0%</td>
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</tr>
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<td>Natural Gas</td>
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<td>25%</td>
<td>0%</td>
<td>75%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Water Heater Efficiency</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Dependency=Location Region</th>
<th>Dependency=Water Heater Fuel</th>
<th>Option=Electric Heat Pump, 80 gal</th>
<th>Option=Electric Standard</th>
<th>Option=Electric Tankless</th>
<th>Option=Oil Indirect</th>
<th>Option=Oil Premium</th>
<th>Option=Oil Standard</th>
<th>Option=Gas Standard</th>
<th>Option=Gas Tankless</th>
<th>Option=Other Fuel</th>
<th>Option=Propane Standard</th>
<th>Option=Propane Tankless</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR06</td>
<td>Electricity</td>
<td>3%</td>
<td>17%</td>
<td>79%</td>
<td>1%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>CR06</td>
<td>Fuel Oil</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>9%</td>
<td>15%</td>
<td>76%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>CR06</td>
<td>Gas</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>17%</td>
<td>83%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>CR06</td>
<td>Other Fuel</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>CR06</td>
<td>Propane</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>19%</td>
</tr>
</tbody>
</table>
Update: Higher efficiency water heaters

Before: Tank vs. Tankless from RECS; all tanks are “Standard Efficiency”

After: RECS water heater blanket field is used as a proxy for premium storage tank water heaters
Heat pump water heaters are added in (3% of electric stock in WA, OR per RBSA II; 0.5% elsewhere per Butzbaugh et al.)

Water Heater Fuel

<table>
<thead>
<tr>
<th>Building Type RECS</th>
<th>Heating Fuel</th>
<th>Location Region</th>
<th>Option=Electric</th>
<th>Option=Fuel Oil</th>
<th>Option=Gas</th>
<th>Option=Other Fuel</th>
<th>Option=Propane</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Home</td>
<td>Electricity</td>
<td>CR06</td>
<td>90%</td>
<td>0%</td>
<td>4%</td>
<td>0%</td>
<td>5%</td>
</tr>
<tr>
<td>Multi-Family with 2 - 4 Units</td>
<td>Electricity</td>
<td>CR06</td>
<td>93%</td>
<td>0%</td>
<td>7%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Multi-Family with 5+ Units</td>
<td>Electricity</td>
<td>CR06</td>
<td>93%</td>
<td>0%</td>
<td>7%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Attached</td>
<td>Electricity</td>
<td>CR06</td>
<td>87%</td>
<td>0%</td>
<td>13%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Detached</td>
<td>Electricity</td>
<td>CR06</td>
<td>90%</td>
<td>0%</td>
<td>4%</td>
<td>0%</td>
<td>5%</td>
</tr>
<tr>
<td>Mobile Home</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>25%</td>
<td>0%</td>
<td>75%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Multi-Family with 2 - 4 Units</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Multi-Family with 5+ Units</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Attached</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>13%</td>
<td>0%</td>
<td>87%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Detached</td>
<td>Natural Gas</td>
<td>CR06</td>
<td>25%</td>
<td>0%</td>
<td>75%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Now model Heat pump water heaters
Now model higher efficiency tank models

Water Heater Efficiency

| Location | Water Heater | Option=Electric Heat Pump, 80 gal | Option=Electric Tankless | Option=Electric Premium | Option=Electric Standard | Option=Fuel Tankless | Option=Fuel Premium | Option=Fuel Standard | Option=Gas Tankless | Option=Gas Premium | Option=Gas Standard | Option=Other Fuel Tankless | Option=Other Fuel Premium | Option=Other Fuel Standard | Option=Other Fuel Tankless | Option=Other Fuel Premium | Option=Other Fuel Standard | Option=Other Fuel Tankless | Option=Other Fuel Premium |
|----------|--------------|-----------------------------------|--------------------------|----------------------------|-------------------------|-----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|-------------------------|-----------------------------|-------------------------|-----------------------------|------------------------|------------------------|------------------------|
| CR06     | Electricity  | 3%                                | 17%                      | 79%                        | 1%                      | 0%                    | 0%                  | 0%                  | 0%                  | 0%                  | 0%                  | 0%                      | 0%                          | 0%                      | 0%                          | 0%                     | 0%                     | 0%                     |
| CR06     | Fuel Oil     | 0%                                | 0%                       | 0%                         | 0%                      | 9%                    | 15%                 | 76%                 | 0%                  | 0%                  | 0%                  | 0%                      | 0%                          | 0%                      | 0%                          | 0%                     | 0%                     | 0%                     |
| CR06     | Gas          | 0%                                | 0%                       | 0%                         | 0%                      | 17%                   | 83%                 | 0%                  | 0%                  | 0%                  | 0%                  | 100%                    | 0%                          | 0%                      | 0%                          | 0%                     | 0%                     | 0%                     |
| CR06     | Other Fuel   | 0%                                | 0%                       | 0%                         | 0%                      | 0%                    | 0%                  | 0%                  | 0%                  | 0%                  | 0%                  | 0%                      | 0%                          | 0%                      | 0%                          | 0%                     | 0%                     | 0%                     |
| CR06     | Propane      | 0%                                | 0%                       | 0%                         | 0%                      | 0%                    | 0%                  | 0%                  | 0%                  | 0%                  | 0%                  | 0%                      | 0%                          | 0%                      | 0%                          | 0%                     | 0%                     | 0%                     |
Impact: Water heater dependencies, Higher efficiency water heaters

Seattle, WA

- Before
- After
- AMI

Efficiency improvements are minimal
HVAC Updates
Before: the EULP project  
100% medium asphalt shingles

After: Calibration region 2  
Distribution based on RECS  
For example:

<table>
<thead>
<tr>
<th>Dependency= Geometry Building Type</th>
<th>Dependency= Location Region</th>
<th>Option= Asphalt, Medium</th>
<th>Option= Composition Shingles</th>
<th>Option= Metal, Dark Slate</th>
<th>Option= Tile, Clay or Ceramic</th>
<th>Option= Tile, Concrete</th>
<th>Option= Wood Shingles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Home</td>
<td>CR06 (WA, OR)</td>
<td>0%</td>
<td>49%</td>
<td>45%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Attached</td>
<td>CR06 (WA, OR)</td>
<td>0%</td>
<td>74%</td>
<td>0%</td>
<td>4%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Single-Family Detached</td>
<td>CR06 (WA, OR)</td>
<td>0%</td>
<td>84%</td>
<td>4%</td>
<td>0%</td>
<td>1%</td>
<td>0%</td>
</tr>
</tbody>
</table>

This change leveraged work from another project; it was not motivated by an observed error.
Impact: Roof material distributions

Negligible change (as was expected)

- Before
- After
- AMI
Update: Cooling type IECC dependency

The HVAC organization restructure completed during Region 2 accidentally removed a dependency on location

Cooling type (central AC, room AC, heat pump, none) depends on:

**Before:**
- building type,
- vintage,
- heating type (ducts or not, heat pump or not)

**After:**
- building type,
- vintage,
- heating type (ducts or not, heat pump or not),
- IECC Climate Zone

**Slicing RECS 2009 four ways requires careful binning of responses to ensure sufficient samples for all combinations:**
- Due to low sample sizes for some Heating Types, Heating Type data for Non-Ducted Heating and None is grouped.
- Due to low sample sizes for some Building Types, Building Type data are grouped into: 1) Single-Family Detached and Single-Family Attached, and 2) Multifamily 2-4 units and Multifamily 5+ units, and 3) Mobile Homes.
- Due to low sample sizes for some Vintages, Vintage ACS (20-year bins) is used instead of the typical 10-year bins used for RECS data.

**Other assumptions:**
- If a sample has both Central AC and Room AC, we assume it has Central AC only
- If a sample indicates using a heat pump for AC but does not indicate using a heat pump for heating, then we either assign it a heat pump for heating (if electric heating was indicated), or we assign it Central AC (if non-electric heating was indicated).
Update: HVAC Cooling Load/Sizing Fix

The stochastic occupancy feature added during Region 2 accidentally increased the magnitude of internal gains used for the design cooling load calculation for air conditioner sizing.

This did not significantly affect annual energy use, only peak demand (~1% of hours).

After this discovery, we implemented automated before/after checks on heating/cooling capacities and other output variables such as unmet hours for heating/cooling setpoints.
Impact: Cooling type IECC dependency, Cooling Load/Sizing Fix

Seattle, WA

Fort Collins, CO

ComEd, IL

- Before
- After
- AMI

Major improvement in cooling

* Also includes fix to air conditioner sizing bug introduced in Region 2 calibration (primarily affect peak days)

Not much change since cooling saturation in ComEd is closer to national average
Update: Foundation type distributions

Before:
Depends on state (1988 source)

After:
Depends on IECC Climate Zone, building type, and vintage

For example:

<table>
<thead>
<tr>
<th>Climate Zone</th>
<th>Dependency=Geometry</th>
<th>Option=Crawl</th>
<th>Option=Heated Bsmt</th>
<th>Option=Pier and Beam</th>
<th>Option=Slab</th>
<th>Option=Unheated Bsmt</th>
</tr>
</thead>
<tbody>
<tr>
<td>4C Single-Family Detached</td>
<td>1940</td>
<td>55%</td>
<td>15%</td>
<td>0%</td>
<td>17%</td>
<td>13%</td>
</tr>
<tr>
<td>4C Single-Family Detached</td>
<td>1940-59</td>
<td>39%</td>
<td>30%</td>
<td>0%</td>
<td>29%</td>
<td>2%</td>
</tr>
<tr>
<td>4C Single-Family Detached</td>
<td>1960-79</td>
<td>55%</td>
<td>6%</td>
<td>10%</td>
<td>28%</td>
<td>0%</td>
</tr>
<tr>
<td>4C Single-Family Detached</td>
<td>1980-99</td>
<td>68%</td>
<td>2%</td>
<td>3%</td>
<td>25%</td>
<td>2%</td>
</tr>
<tr>
<td>4C Single-Family Detached</td>
<td>2000-09</td>
<td>64%</td>
<td>3%</td>
<td>9%</td>
<td>25%</td>
<td>0%</td>
</tr>
<tr>
<td>4C Single-Family Detached</td>
<td>2010s</td>
<td>64%</td>
<td>3%</td>
<td>9%</td>
<td>25%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Assumptions:
- All mobile homes have Pier and Beam foundations.
- Multi-family buildings cannot have Pier and Beam and Heated Basements
- Single-family attached buildings cannot have Pier and Beam foundations
Impact: Foundation type distributions

- Seattle, WA
- Fort Collins, CO
- ComEd, IL

- Before
- After
- AMI

Minor increase in electric heating
Minor increase in cooling peak
Alternate Comparisons
The overprediction of electric heating in multifamily buildings led us to investigate whether building-level meters for centrally metered HVAC and domestic hot water (DHW) are included in the Seattle residential AMI data.

For Seattle:
• Individual units typically have a residential rate code
• Common areas and central metering are typically given a commercial rate code

We can remove central system HVAC and DHW from ResStock results for Seattle to see how this affects the comparison (see next slide).
• Uses data from RECS (entire U.S.) and RBSA (Pacific Northwest) on the prevalence of central HVAC and DHW

We have inquiries out to Fort Collins and EIA to better understand how much this affects other dataset comparisons.
• In ComEd, common meters are classified as residential
• This effect may show up in Region 4 Hot Humid, which has higher electric heat fractions.
Alternate Comparisons

**With and without central heating/cooling**

- **With** central heating/cooling
- **Without** central heating/cooling
- **AMI**

Seattle, WA – Multifamily Units

No significant difference because there is little to no central cooling

Significant improvement in winter load match

**With and without DHW**

Without central heating/cooling
- **With** central DHW
- **Without** central DHW
- **AMI**

Seattle, WA – Multifamily Units

Improvement in summer load match

Improvement in shoulder load match
ResStock Correction Model
Motivation for a correction model

• Cannot model everything
  – Ex: Cooling setpoints are lower in summer than shoulder
  – Ex: Mean radiant temperature causes setpoints to change during heat waves

• Best available data does not accurately capture all aspects in building stock
  – Ex: RECS does not capture monthly changes in setpoints
  – Ex: Best available data could over or underpredicts appliance saturations, age/efficiency, setpoints, etc.
Example: model discrepancies across timescales

City of Fort Collins Total Residential Stock
Average of Top 10 Load Days

Consistent under-prediction of cooling and over-prediction of heating across timescales and data sources

- ResStock
- AMI Data
Example approaches

Goal is to correct bulk errors but not overfit

Correction to EIA state and monthly data
1. Adjust all end-uses
2. Adjust only HVAC loads
3. ...

Approach will evolve until calibration is finished
• Example extension: County and daily factors based on HDD/CDD
Example model formulation

Planning on using multiplicative factors

- If use state and month factors, then calculate 588 (49x12) factors
- Model 1: all end-uses
- Model 2: only HVAC end-uses

\[
\tilde{e}_{sm}(t) = \alpha_{sm} e_{sm}(t)
\]

Corrected end-use energy
Simulated end-use energy

State and month correction factor

\[ s \in \{AL, AZ, AR, \ldots, WI, WY\} \]
\[ m \in \{Jan, \ldots, Dec\} \]

Do not model Alaska and Hawaii, but do model DC
Example impacts of the potential correction models

Fort Collins Total Residential Stock: Daily Electric Load

Significant improvement in heating season

Improvement in cooling season, but needs work
Example impacts of the potential correction models

Fort Collins Total Residential Stock

Average of top 10 load days

Hour of day

Model 2 slightly better load shape suggests errors are HVAC related

Overcorrection in summer suggests degree days may be important

Model 2 (HVAC only)

AMI Data
Residential stock end-use summary

Seattle, WA
Seasonal end-use loads by day type

Seattle City Light service territory, WA
Seasonal end-use loads by day type

Seattle City Light service territory, WA
Residential stock end-use summary

Fort Collins municipal utility, CO
Seasonal end-use loads by day type

Fort Collins municipal utility, CO

Hour of day (0-23)
Seasonal end-use loads by day type

Fort Collins municipal utility, CO

Hour of day (0-23)

Hour of day (0-23)
Seasonal end-use loads by day type

Fort Collins municipal utility, CO
Residential stock end-use summary

ComEd service territory, IL
Seasonal end-use loads by day type

ComEd service territory, IL
Seasonal end-use loads by day type

ComEd service territory, IL

- Heating
- Cooling
- HVAC fan pump
- Vent fans
- Ceiling fan
- Hot water
- Pool hot tub
- Electricity well pump
- Cooking range
- Dishwasher
- Clothes dryer
- Clothes washer
- Freezer
- Extra refrigerator
- Refrigerator
- Plug loads
- Exterior lighting
- Interior lighting

Electric Load (kWh/unit)

Hour of day (0-23)
Seasonal end-use loads by day type

ComEd service territory, IL
Tracking Quantities of Interest
Seattle City Light, WA: Annual Error

Relative error: annual electricity use per unit

- Single-Family Detached load too high
- Electric heating load too high
Fort Collins, CO: Annual Error

- Relative error: annual electricity use per unit

- High on annual usage per unit

- Reasons
  - Heating energy too high
ComEd, IL: Annual Error

Reasons
• Baseload is low in early morning

Only slightly low after corrections
Seattle City Light, WA: Total Error Metrics

Average of All Days

- Baseload improvement

Top 10 Days

- Significant improvement in cooling peak
- Roughly equal morning/evening peaks cause timing issues

Peak Timing

- Improved summer peak timing
Fort Collins, CO: Total Error Metrics

Average of All Days

Top 10 Days

Peak Timing

Higher winter load after weather update

Issue with winter timing

Average summer peak improvement
ComEd, IL: Total Error Metrics

Average of All Days

Peak Timing

Baseload still an issue

Timing of peak heating relatively accurate

Low on top peaks in summer

Error (min)
Areas for Improvement
Seattle, WA

Too much electric heating

→ Incorporate partial home heating with electric baseboard

→ Update vacant unit setpoint assumptions

Fort Collins, CO
Two regions provide additional insight into areas for improvement:

**Fort Collins, CO**
- Overpredicting cooling in Fort Collins, especially in the shoulder season.
- \(\Rightarrow\) Incorporate more seasonal usage of AC.

**ComEd, IL**
- Overpredicting cooling in ComEd in May, though not in remainder of summer.

Daily electric load graph.
Next Region: Likely Areas for Improvement

Two regions provide additional insight into areas for improvement.

Fort Collins, CO

Fort Collins still shows too much cooling, especially in the shoulder season.

→ Incorporate more seasonal usage of AC

ComEd, IL

ComEd peak magnitude is good, but still too low at night.

Lighting drops off too quickly?
Conclusions (1)

• Ran 10 iterations of ResStock incorporating 12 discrete changes
  • Saw general improvements in QOI metrics
  • Most of the improvements made will carry over to the entire U.S.
• Increased number of weather stations
  • Weather data regions are the same for ResStock and ComStock
  • Increases resolution in weather events
• Integrated single-unit modeling capability
  • Reduces computational cost for running ResStock
• New/Updated visualizations
  • EIA monthly state electric and natural gas sales
  • NEEA Home Energy Metering Study (HEMS) Comparisons
Conclusions (2)

• Summary of changes
  • Reduced baseload by adding geographic resolution to household size
  • Increases resolution in weather events by increasing number of weather stations
  • Added regional and building type variation in lighting and plug loads
  • Included monthly variation of baseloads with the stochastic occupant-driven load model
  • Added multifamily central DHW differentiation
  • Model higher efficiency tank and heat pump water heaters
  • More granular roof materials and updated foundation type distributions

• Priority areas for improvement for next region
  • Electric Heating
  • Regional behavior time shifts
  • Heating/cooling correction model

• Will be moving on to Regional Dataset 4 (Horry and EPB), but continue tracking metrics for the first three region datasets
Residential Calibration
Poll Questions
Residential Calibration Poll Question 1

1. Are we addressing the calibration issues you hoped we would address?
   a. Yes
   b. Some (please explain in chat)
   c. No (please explain in chat)
2. If the residential EULP calibration stopped today, would our results be more useful than existing load profile sources (e.g., Hourly Load Profiles for TMY3 Locations on OpenEI.org)?

   a. Yes, for all of my desired use cases
   b. Yes, for most of my desired use cases (please explain in chat)
   c. Yes, for some of my desired use cases (please explain in chat)
   d. No, for none of my desired use cases (please explain in chat)
3. If we have multiple regional data set options for the final residential region, which should we prioritize?

   a. Using a data set from a **new climate or geographic region**
   b. Using a **large dataset**, even if it is from a climate and geographic region that has already been covered
   c. Other (enter in chat)
Wrap-up
Next steps

• Next technical advisory group meeting via webinar in April/May 2021.
• Region 4 residential calibration (Hot-Humid/Southeast)
• Region 2 commercial calibration (Seattle, Portland)
• Begin working on our final year reports

Since we were unable to meet in person this year, we missed the opportunity for longer dialogue. If you have any ideas/critiques/concerns you think would be helpful to talk through on a smaller call, please indicate “yes” and we will reach out.

– Yes
– No