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

Technical Advisory Group Meeting #7
May 26, 2020

NREL/PR-5500-79104

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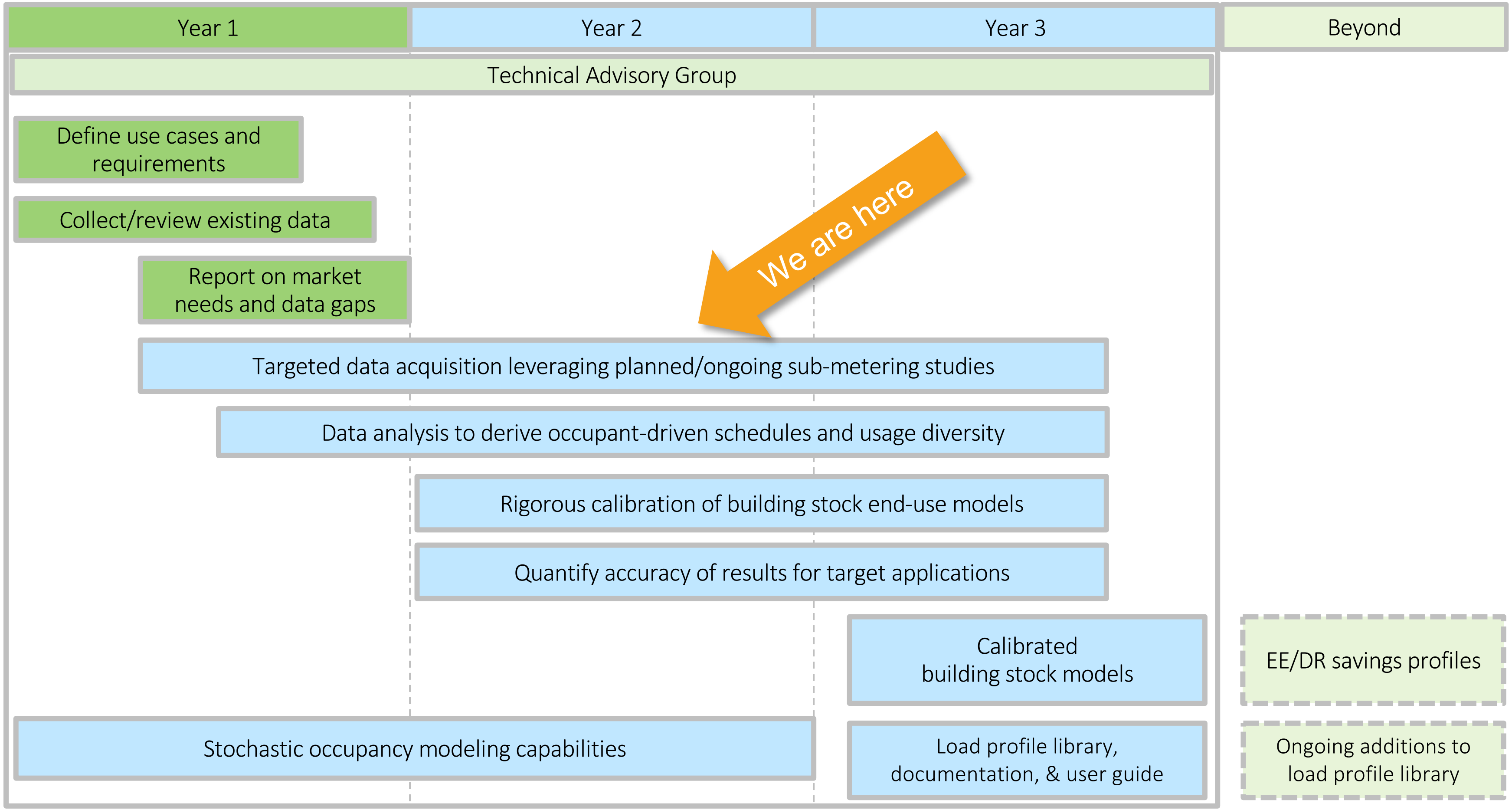
Logistics

- Welcome back!
- We are recording this presentation.
- Because of the large number of participants on the phone, everyone is in listen-only mode during presentations.
- Please use the chat box to send us clarifying questions during presentations. We will unmute lines after each topic for open dialogue.
- Slides and a recording will be available after the webinar.

Agenda

Welcome & Agenda Natalie Frick	Noon ET/9 am PT
Region 1 Calibration Results Presentation Anthony Fontanini	12:10 ET/9:10 PT
Region 1 Calibration Q&A Anthony Fontanini	12:40 ET/9:40 PT
Residential Stochastic Occupancy Results Presentation Eric Wilson	12:55 ET/9:55 PT
Residential Stochastic Occupancy Results Q&A Eric Wilson	1:10 ET/10:10 PT
Output Format Options and Demonstration Andrew Parker	1:25 ET/10:25 PT
Output Format Options and Demonstrations Q&A Andrew Parker	1:40 ET/10:40 PT
Break	2 ET/11 PT
Breakout Groups (today; more tomorrow)	2:30 ET/ 11:30 PT 3:15 ET/ 12:15 PT

Project Timeline



Residential Region 1 Calibration

EULP Technical Advisory Group Presentation
May 26, 2020

Anthony D. Fontanini, Ph.D.

1 Calibration strategy

2 Added capabilities

3 Baseload updates

4 HVAC updates

5 Residential stock end-use summary

6 Tracking quantities of interest

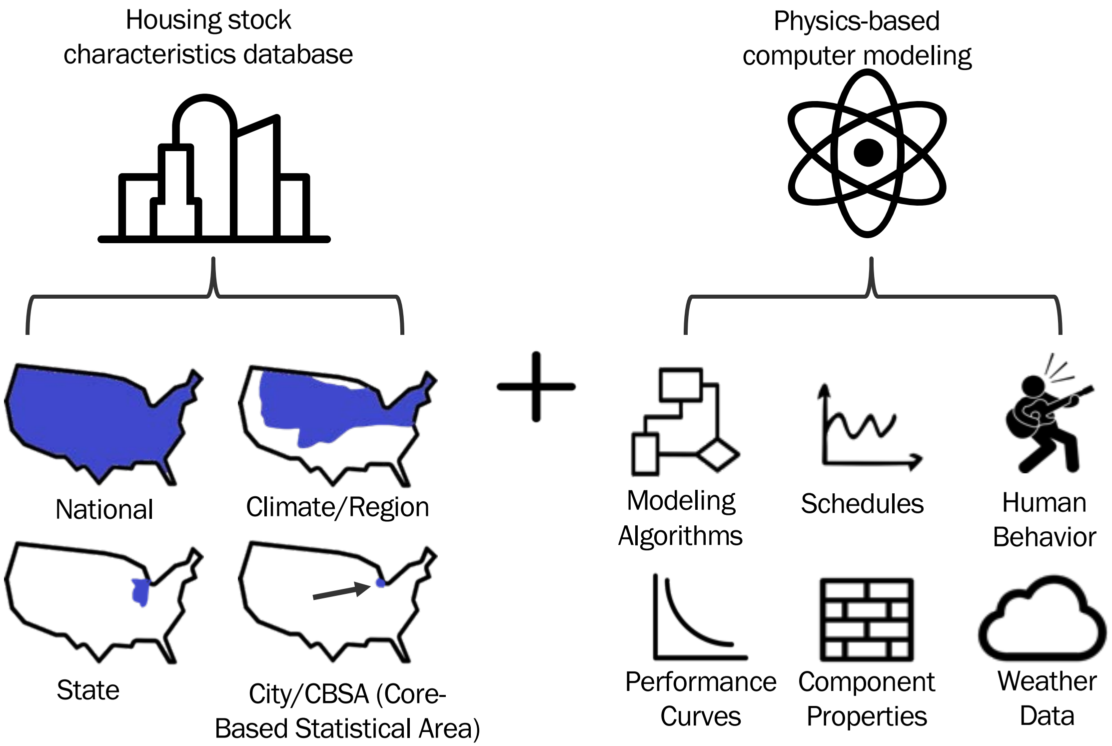
7 Current status of nationwide calibration

8 Areas for improvement

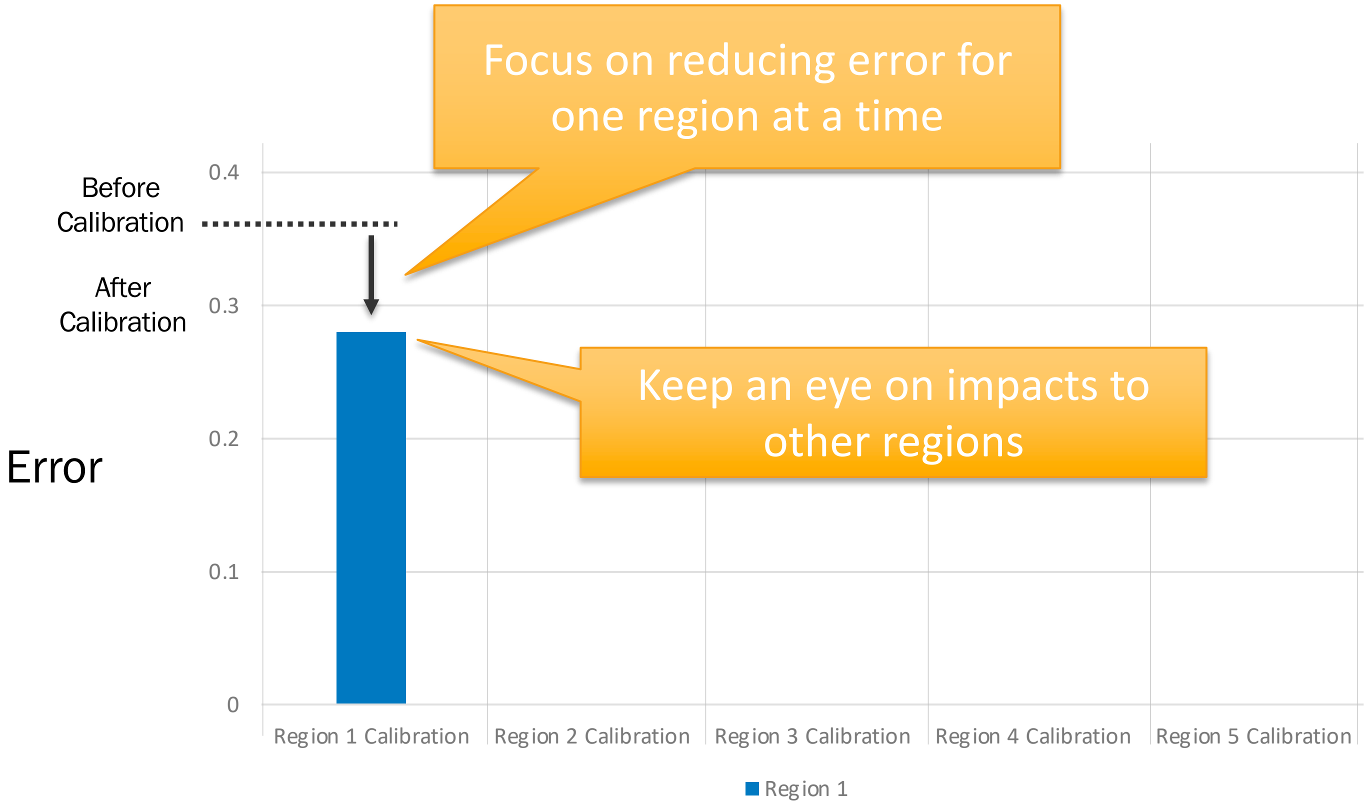
Calibration Strategy

Model Architecture

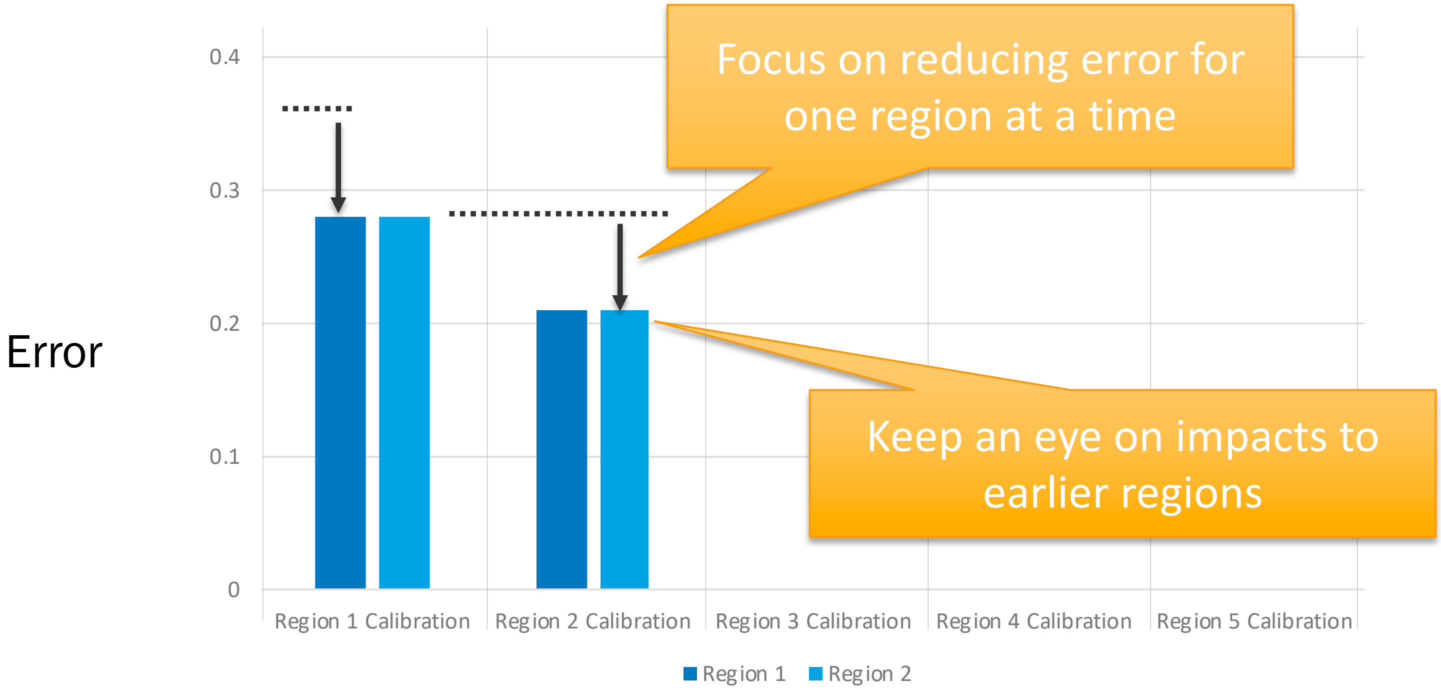
ResStock



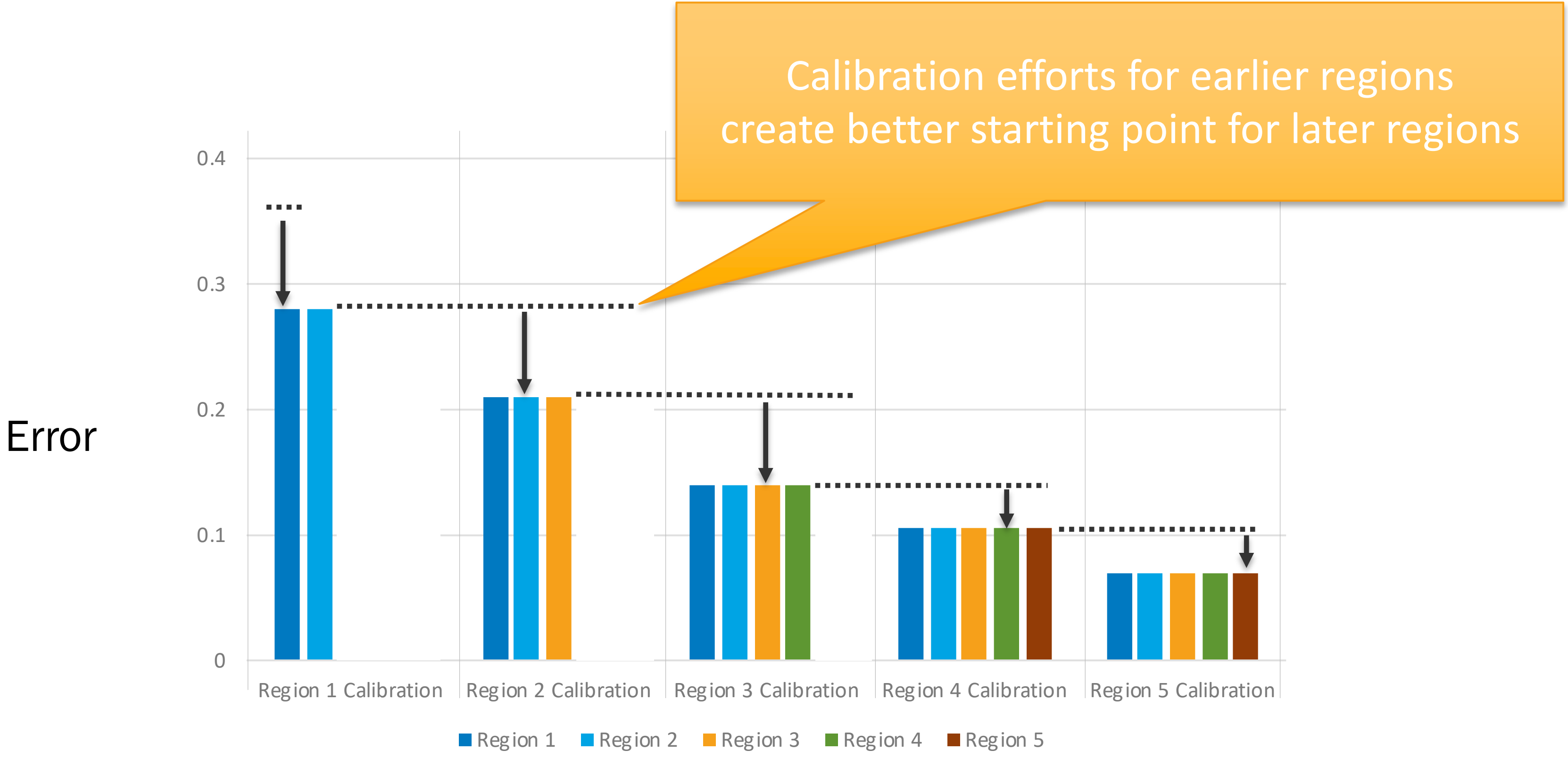
Calibration Process for One Region (i.e. ComEd)



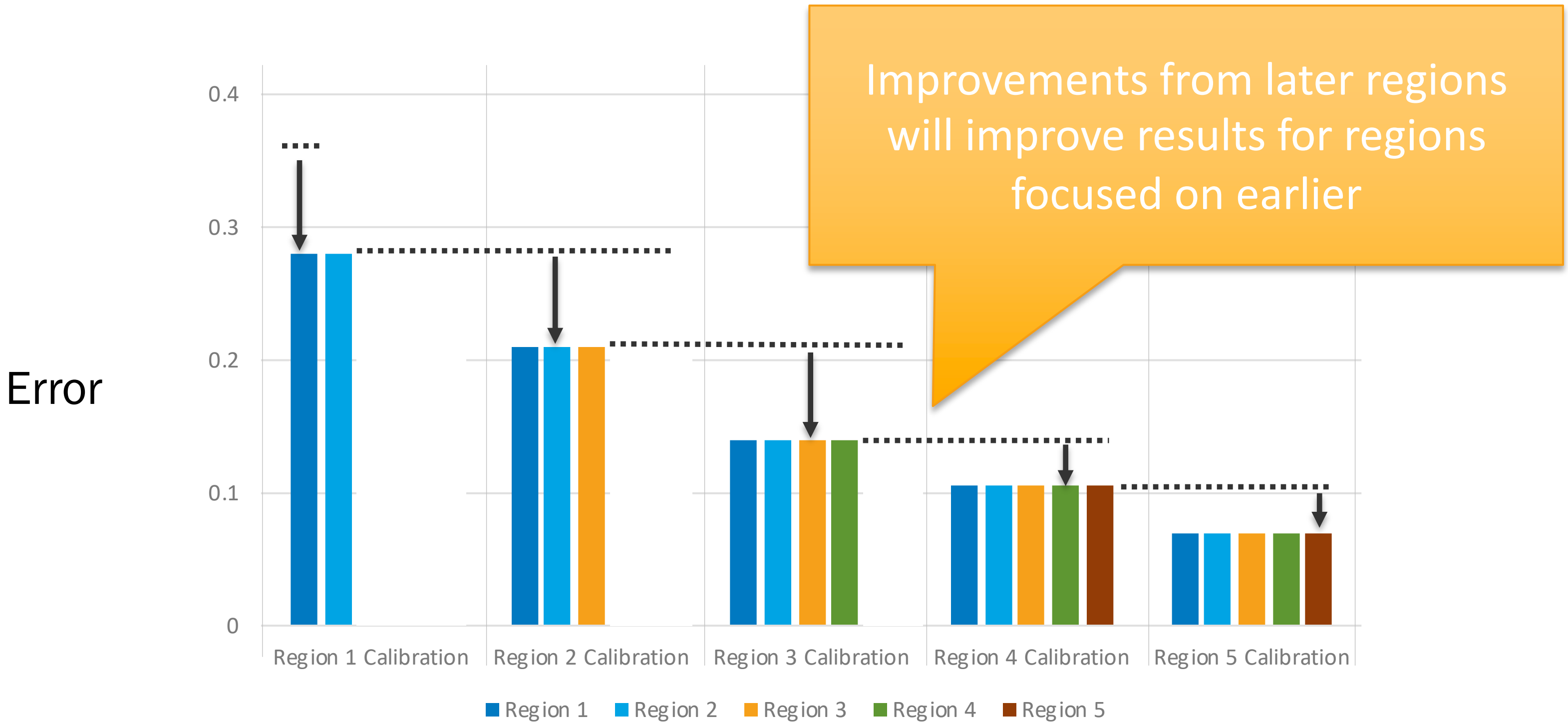
Calibration Process Over Time



Calibration Process Over Time

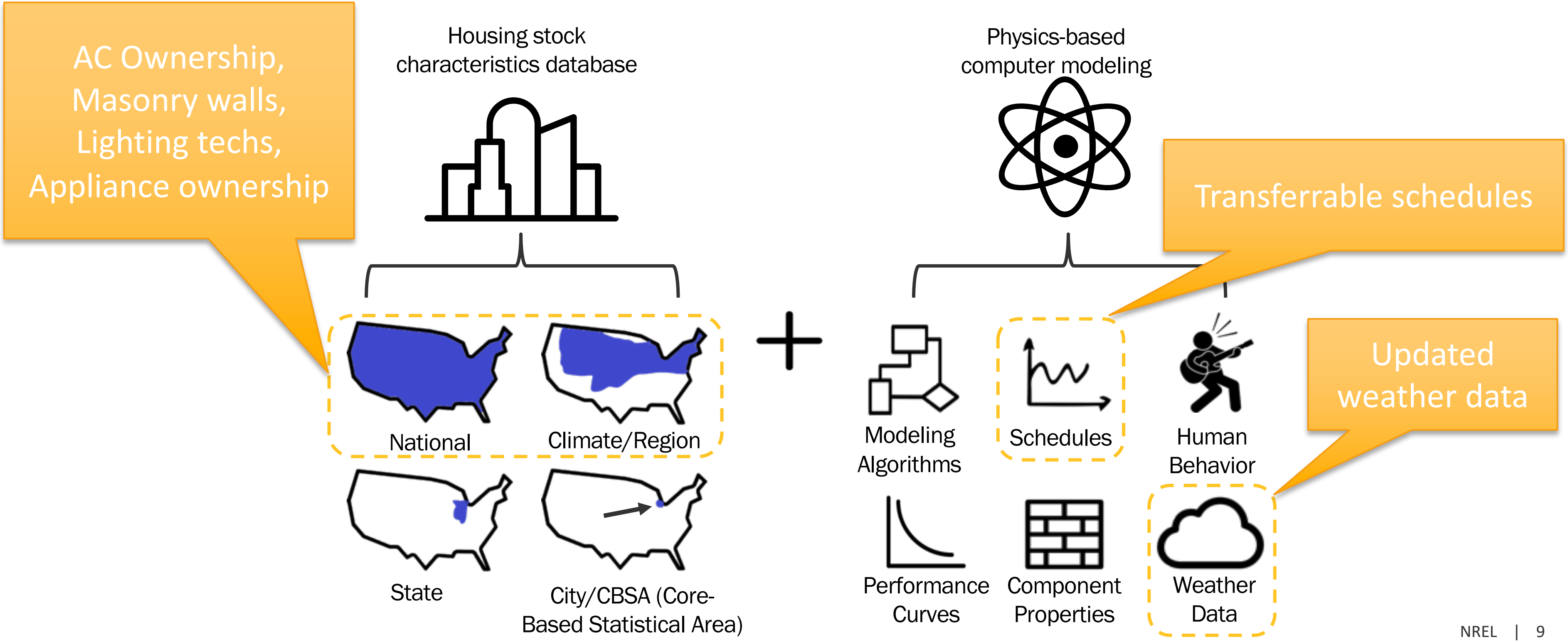


Calibration Process Over Time



Region 1 Focus: Nationally-Relevant Updates

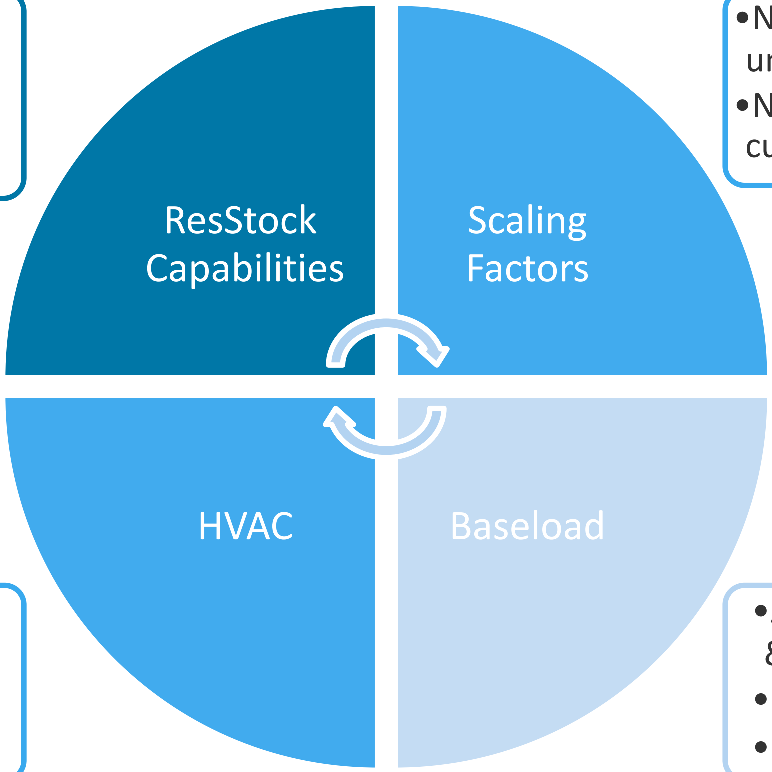
ResStock



Region 1 Calibration Strategy

- Geospatial resolution
- Multifamily high-rise
- Vacant units

- Number of dwelling units
- Number of residential customers

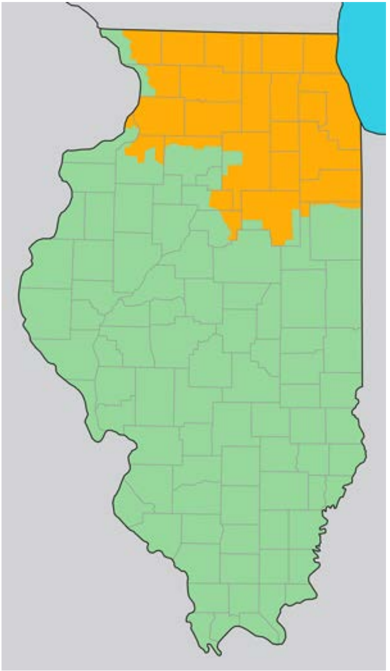


- System saturation & efficiency
- Setpoints
- Infiltration

- Appliance saturation & efficiency
- Plug loads
- Lighting

Region 1:ComEd Territory

- Region 1 calibration focused on ComEd service territory in Northern Illinois
- ComEd customer classes
  - Single-family gas heat (66.2%)
  - Multi-family gas heat (17.1%)
  - Single-family electric heat (8.5%)
  - Multi-family electric heat (8.2%)
- Primarily used data from 2016
- Will see some comparisons from 2012



List of updates

New capabilities

- Geospatial refactor to allow regional datasets
- Introduce national AMY weather data for the 215 weather stations

Baseload updates

- Fix pool pump saturation
- Update lighting technology saturations to 2015 U.S. Lighting Characterization Study
- Use exterior lighting schedule from T24 2016 Residential ACM
- Reduce saturation of major appliances for multifamily units
- Allow for studio plug load estimates
- Use RBSA plug load schedule
- Update refrigeration efficiencies
- Use more refined square footage bins

HVAC updates

- Introduction of masonry walls
- Improve estimates for window to wall ratio
- Investigate sensitivity to air mass capacitance multiplier
- Integrate LBLs ResDB for infiltration estimates
- Increase cooling saturation for CR04 (Great Lakes)
- Diversify heating and cooling setpoint setback schedules

Added Capabilities

Update: Geospatial Resolution

Established Geospatial Resolution

216 weather regions

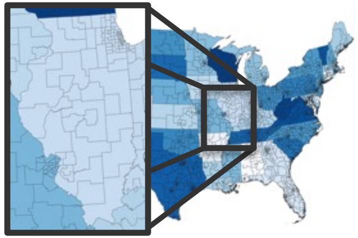
10 regions based on RECS

ResStock 0

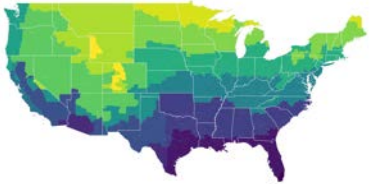
Added Geospatial Resolution

Set up ResStock for more regional datasets and reporting

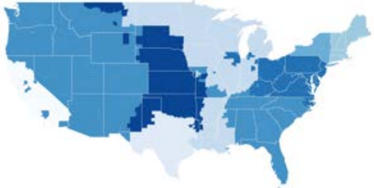
Public Use Microdata Area



Climate Zones



ISO and RTO boundaries



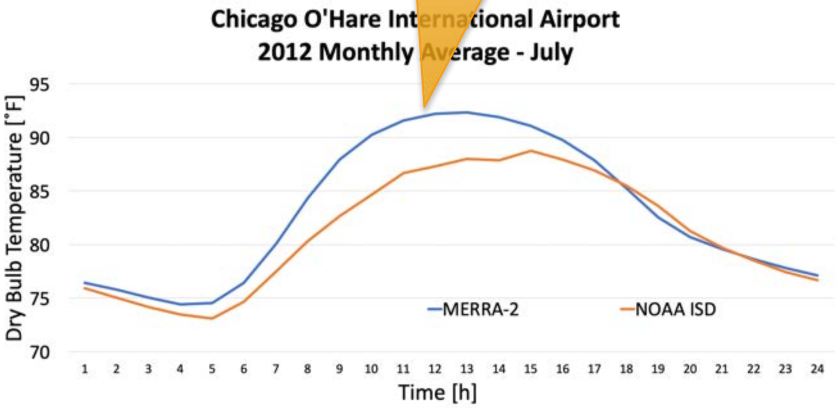
ResStock 1

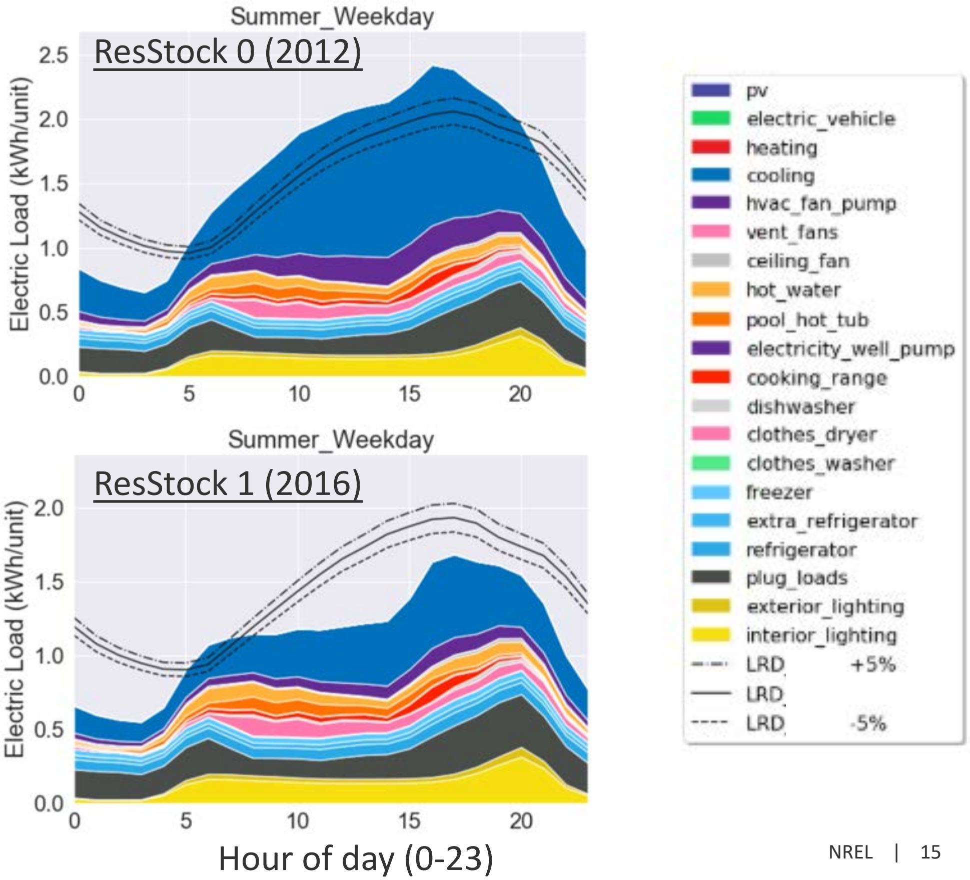
New Characteristics

- Census Region
- Census Division
- State
- Top 15 CBSAs
- County
- PUMA
- IECC Climate Zone 2004
- Building America Climate Zone
- ISO RTO Region

Update: Weather Data

1. Early peak seen in initial utility LRD comparison
2. Substantial overprediction of cooling





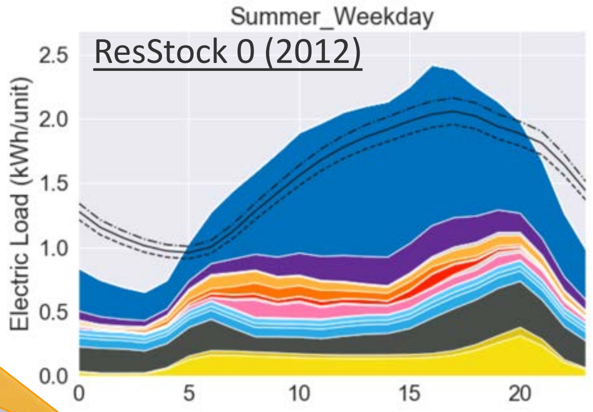
Weather Issue

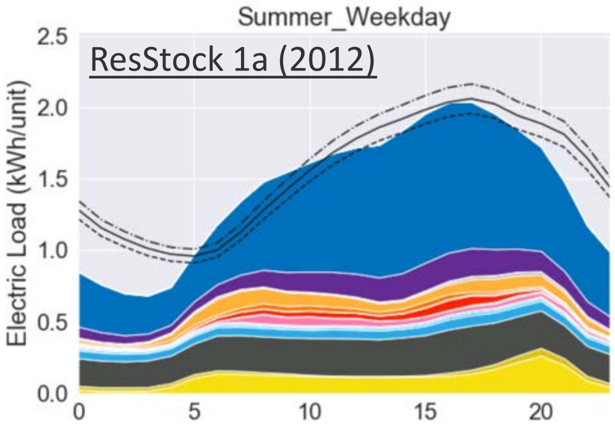
- Cause: use of wrong sentinel value for precipitation for E+ input
- Effect on inputs: ~4 inches of rain per hour all year
- Effect on outputs:
    - Substantial decrease of cooling load
    - Increase of heating loads

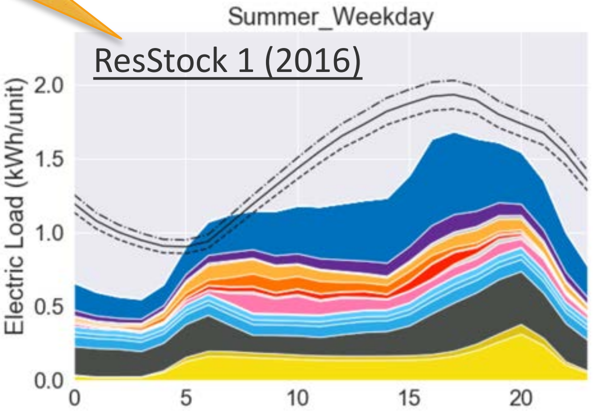
- Presenting difference of results:
    - ResStock 0 = Pre-calibration (simulation year 2016)
    - ResStock 1 = After calibration of region 1 (simulation year 2016)
    - ResStock 1a = After fix of precipitation (simulation year 2012)

Update: Weather Data

1. Missing realistic precipitation data
2. Wrong empty flag in E+ documentation
3. Simulating ~4 inches of rain every hour

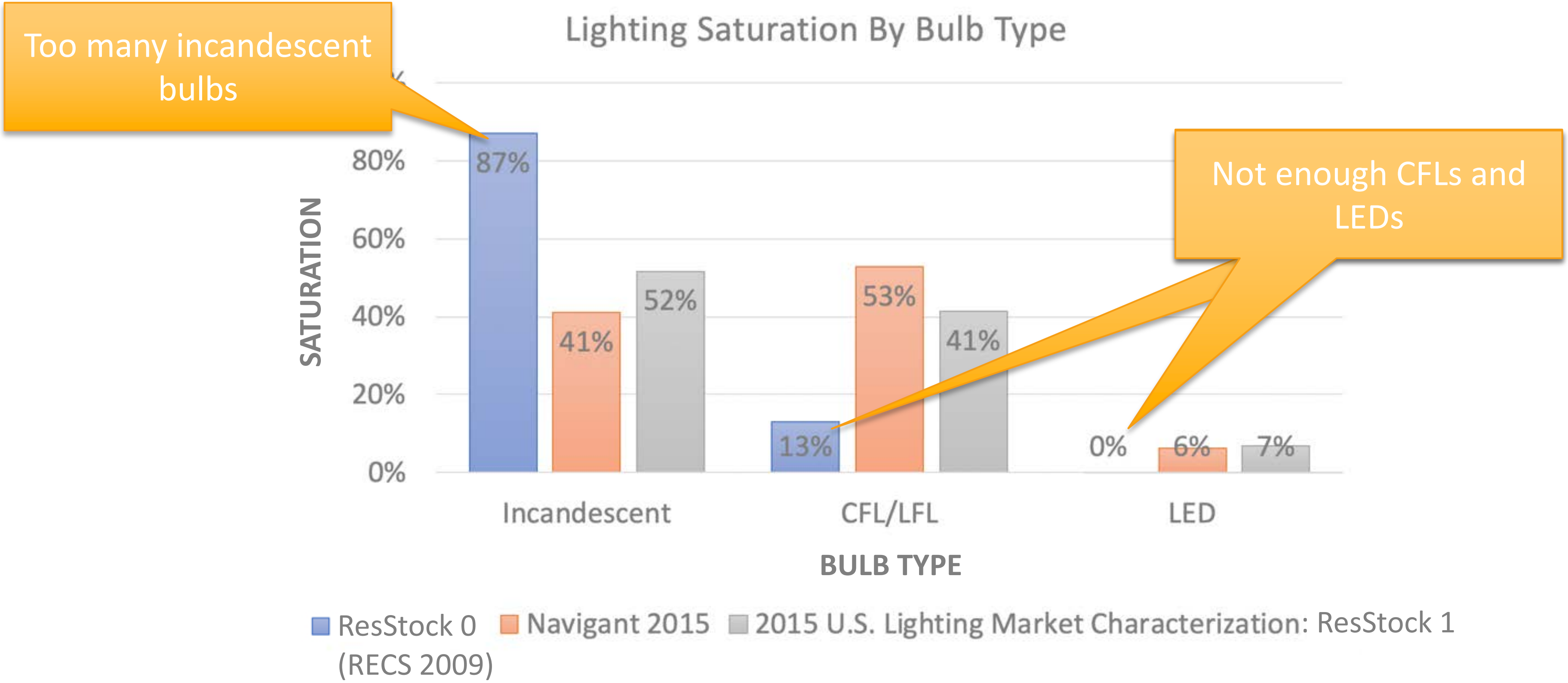




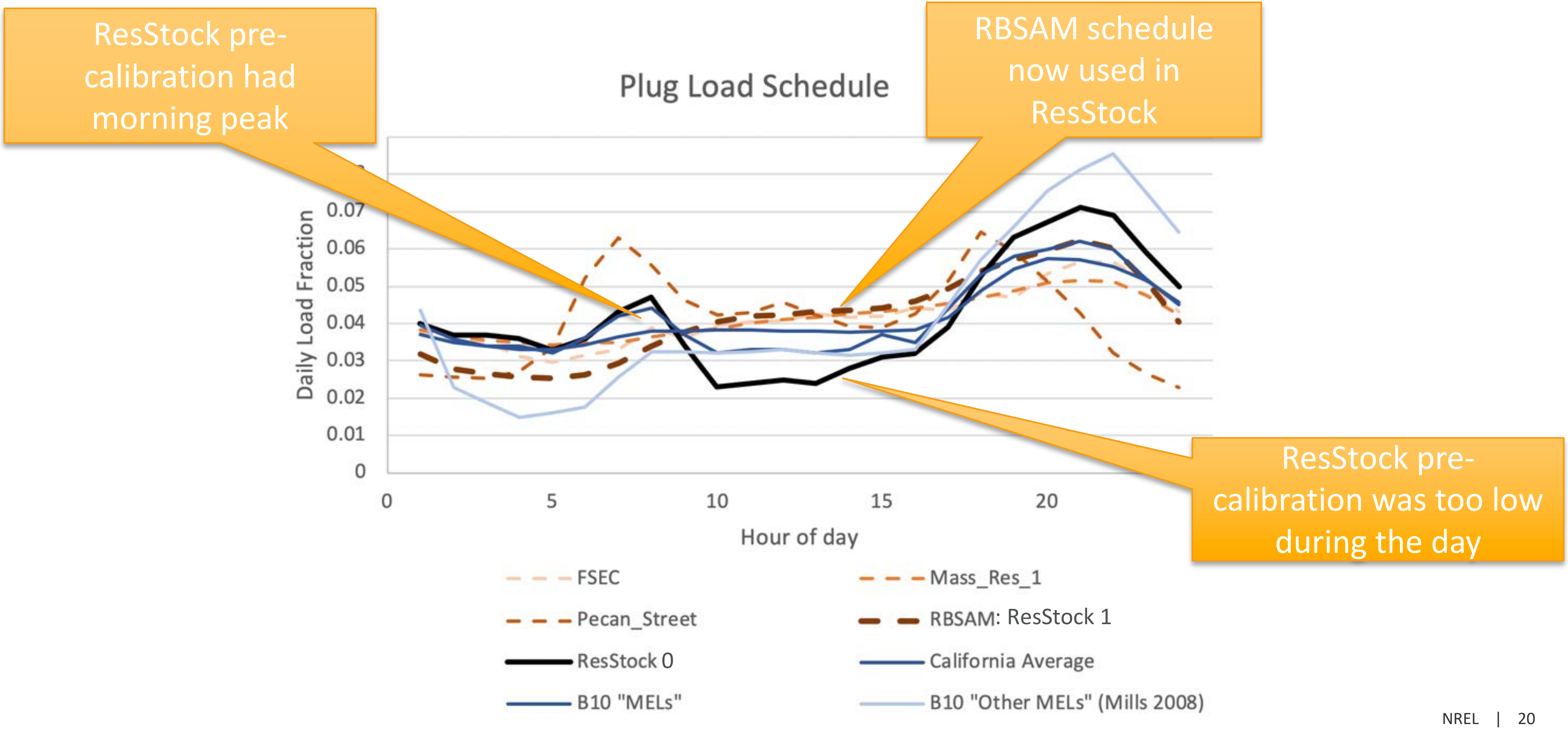


Baseload Updates

Update: Lighting Technology Saturation



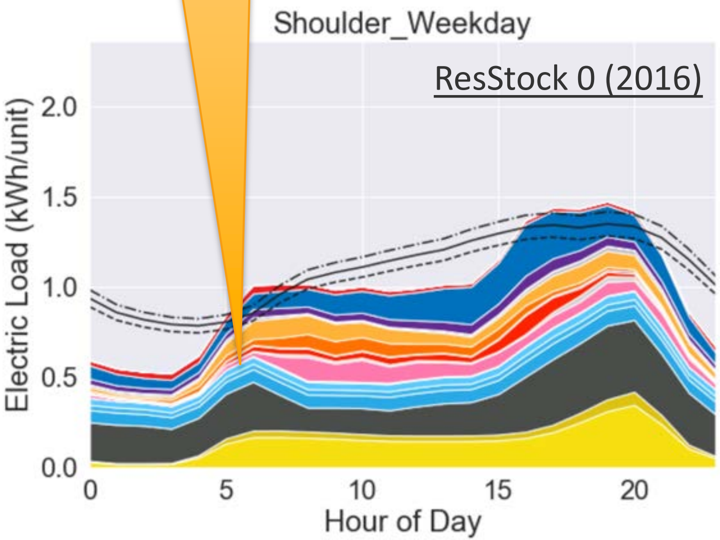
Update: Plug Load Schedule

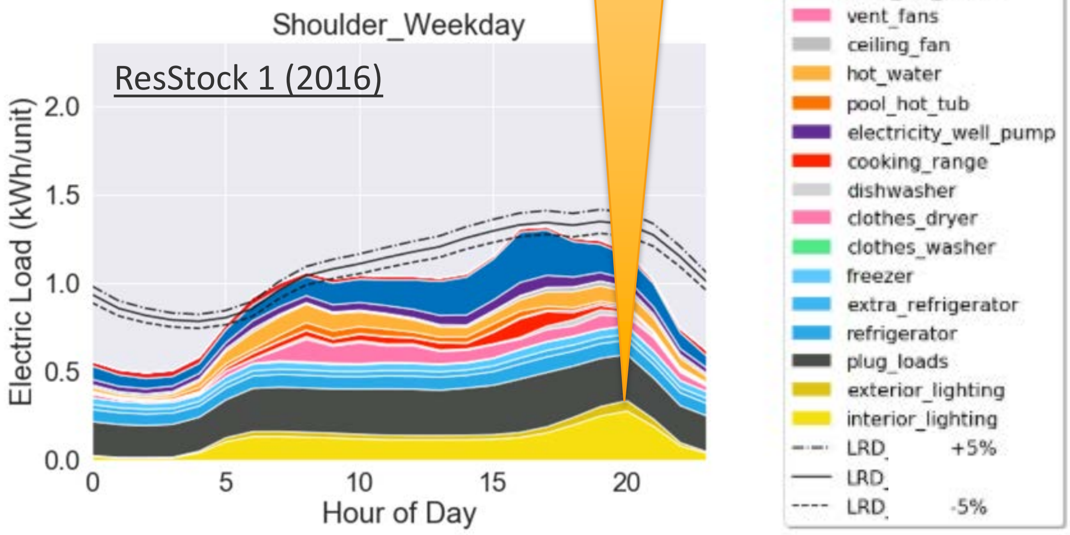


Impact: Lighting Saturation and Plug Load Schedule

Removed bump in plug loads

Small reduction in lighting load





Update: Increase Floor Area Bins

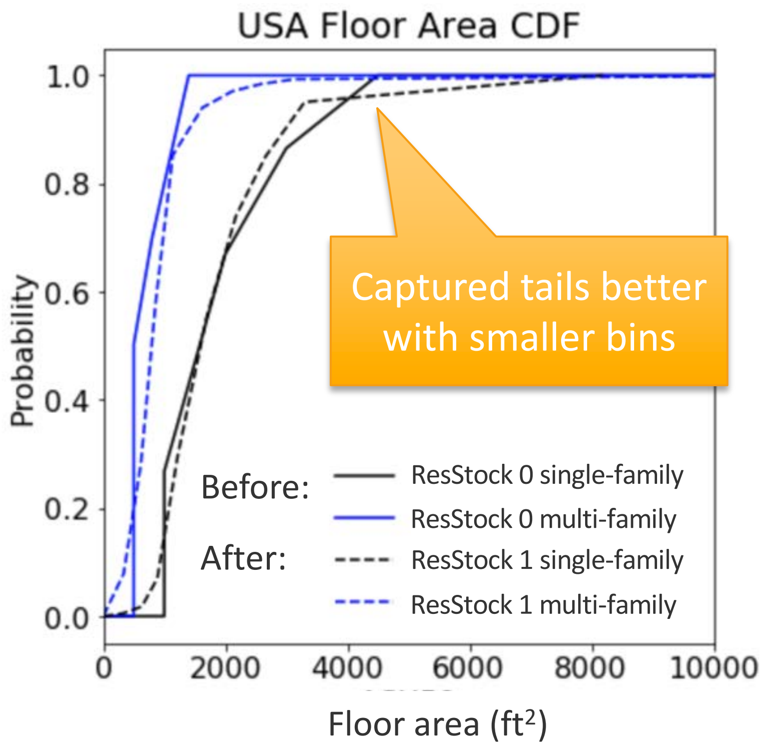
Floor Area (ft2)

ResStock 0	AHS 2017
0-1500	0-500
	500-750
	750-1000
	1000-1500
1500-2500	1500-2000
	2000-2500
2500-3500	2500-3000
	3000-4000
3500+	4000+

Take advantage of the American Housing Survey's larger sample size and higher geospatial resolution (CBSAs)

	ResStock 0	ResStock 1
	ft2	ft2
Single-Family Median	1578	1596
Multi-Family Median	500	793

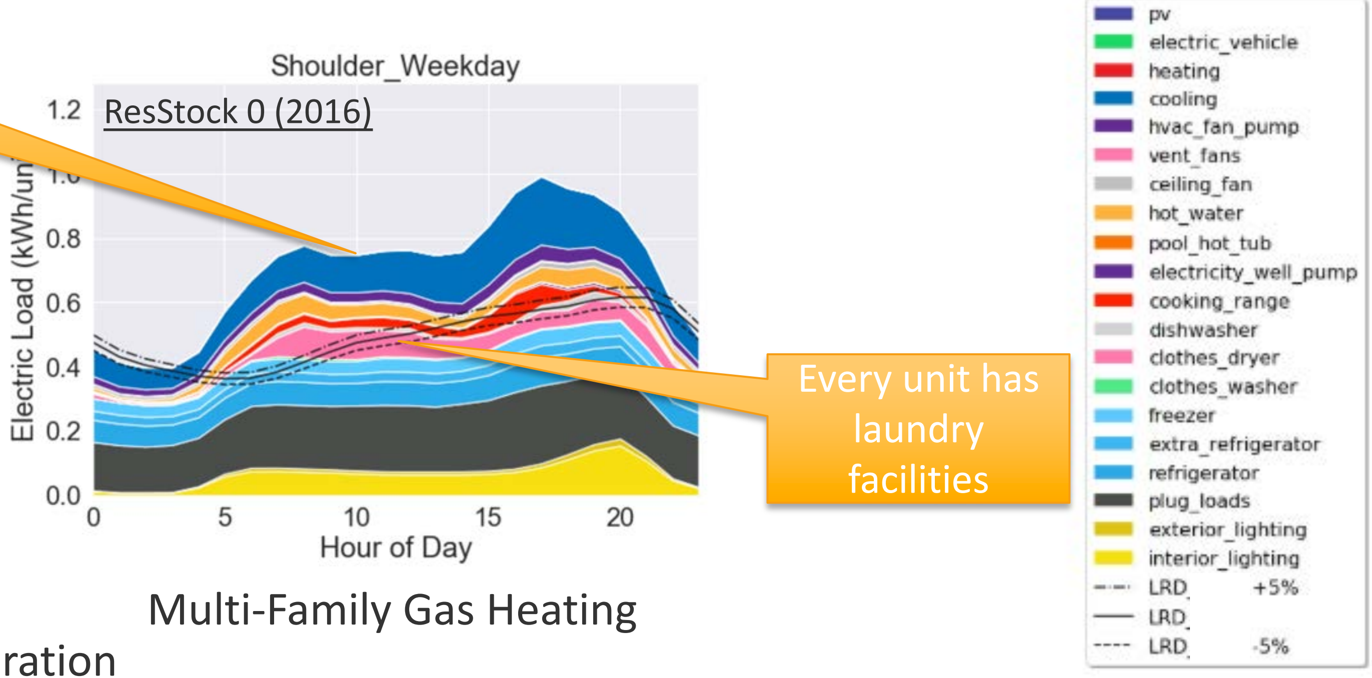
Multi-Family median significantly higher



Captured tails better with smaller bins

Update: Major Appliance Saturation

Load is too large for Multi-Family



Every unit has laundry facilities

Multi-Family Gas Heating

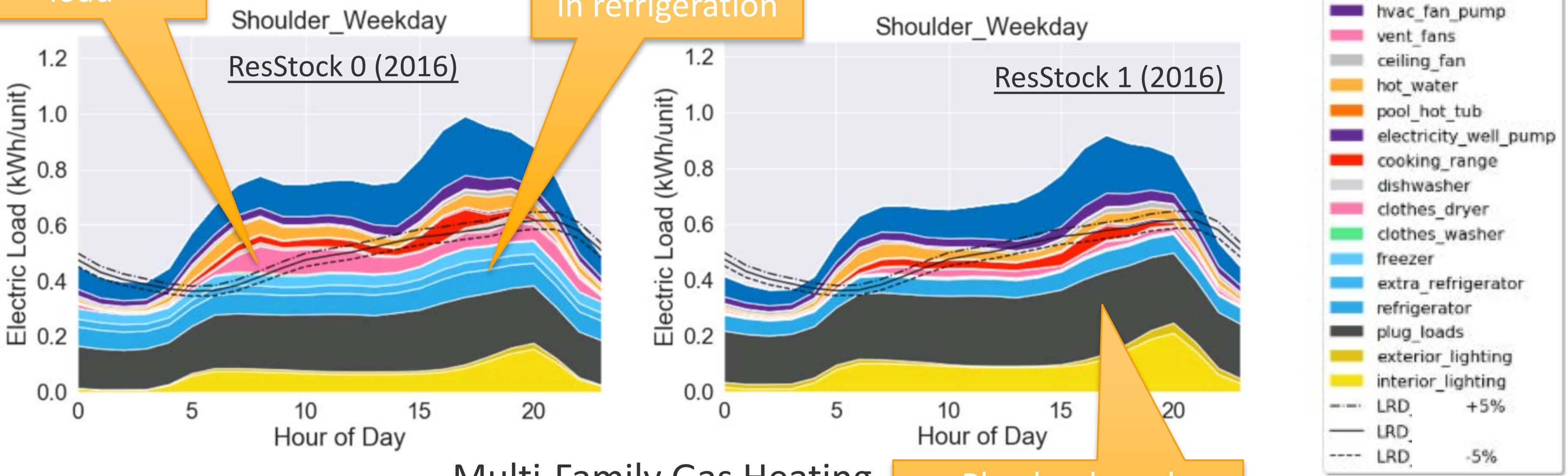
Updated:

- Clothes washer saturation
- Clothes dryer saturation
- Dishwasher saturation
- Refrigeration efficiencies
- Extra refrigerator and freezer saturation
- Specified for Top 15 CBSAs and Census Divisions
- Building type (e.g., multifamily) dependencies

Impact: Major Appliance Saturation and Floor Area

Reduced clothes dryer load

Reduction of load especially in refrigeration



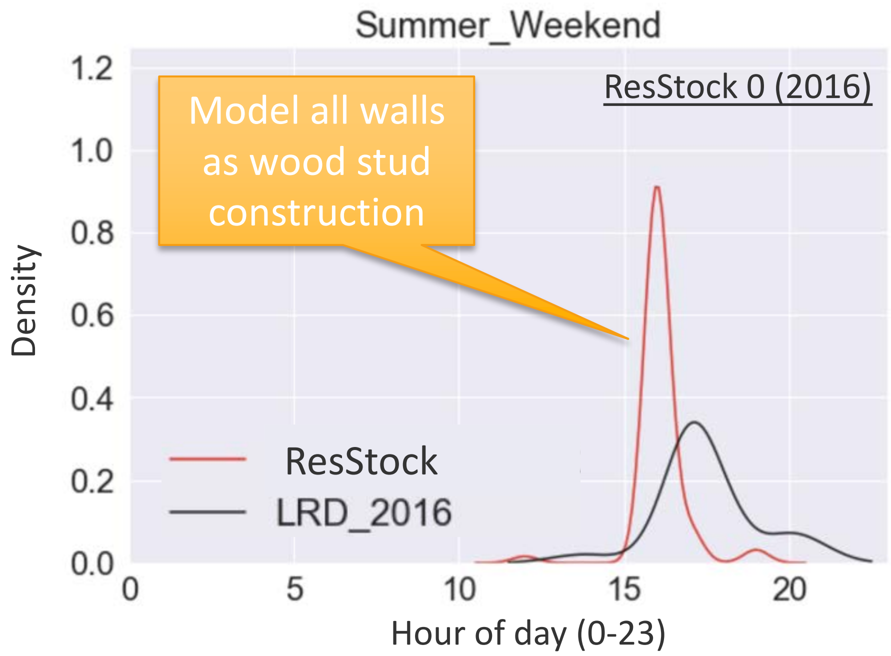
Multi-Family Gas Heating

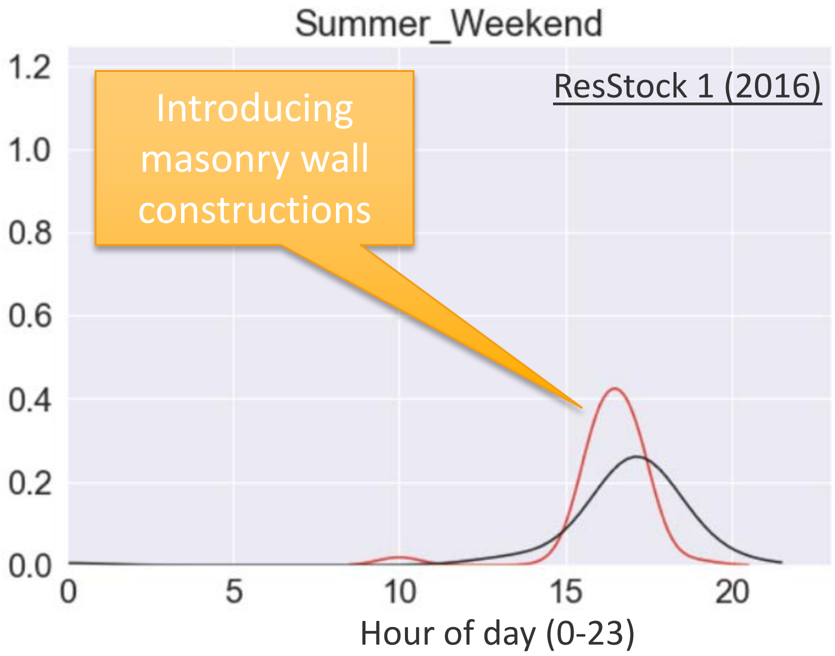
Plug loads and lighting increased because floor area increased

HVAC Updates

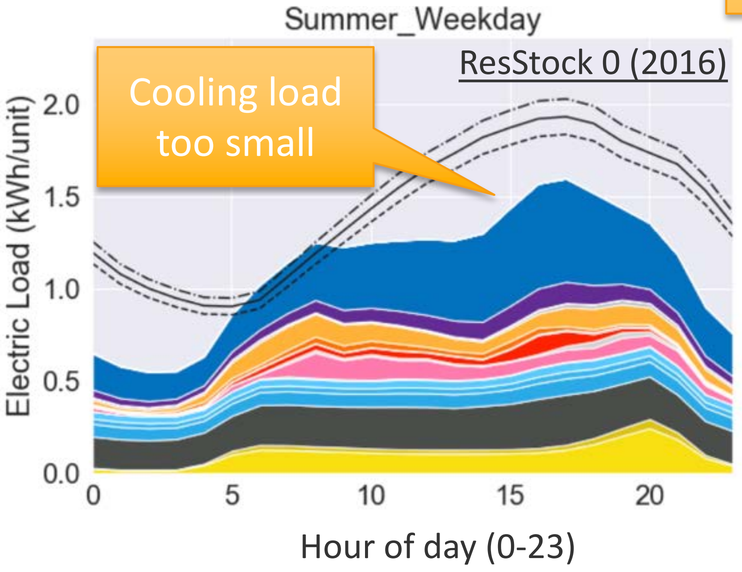
Update: Masonry Walls

Single-Family Gas Heating Summer Peak Time Distribution





Update: AC Ownership



AC ownership was too low

AC ownership for each customer class

	SF-G	SF-E	MF-G	MF-E
ResStock EFS SFD - CR04	88%	87%	-	-
ResStock EFS SFD - IL	88%	87%	-	-
RECS 2009 - CR04	87%	82%	78%	92%
RECS 2009 - IL	95%	78%	83%	83%
RECS 2015 - IECC 5A+ENC	91%	93%	86%	84%
AHS - Chicago CBSA	98%	99%	89%	96%

Precipitation Issue

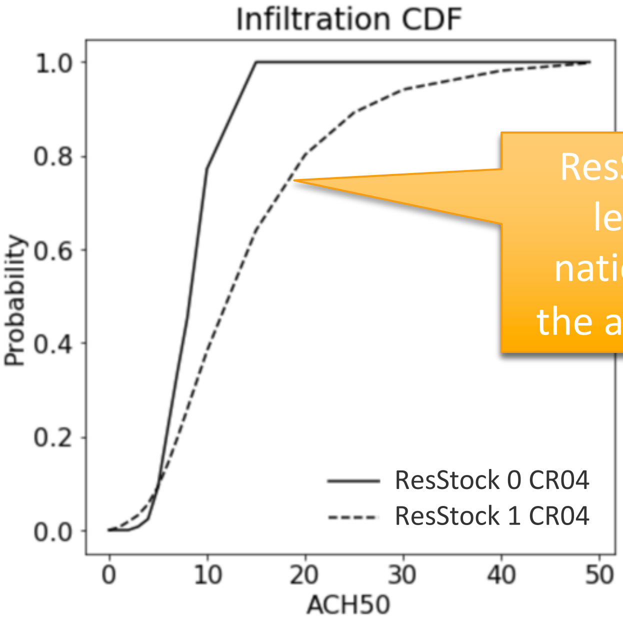
ResStock updated to 93% (using AHS data for the East North Central Census Division)

Update: Infiltration

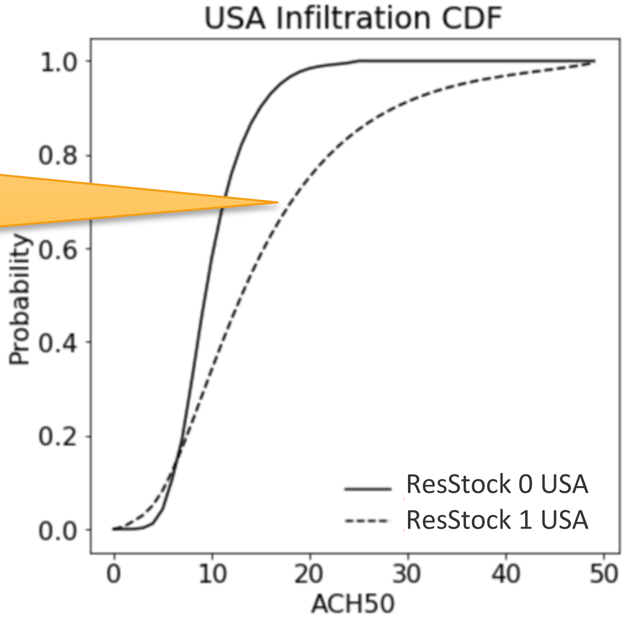
ResStock 0 (Chan et al.)
Median: 8.29 ACH50
ResStock 1 (with LBNL ResDB)
Median: 12.28 ACH50

Integrating LBL's ResDB into ResStock

ResStock 0 (Chan et al.)
Median: 8.84 ACH50
ResStock 1 (with LBNL ResDB)
Median: 13.07 ACH50



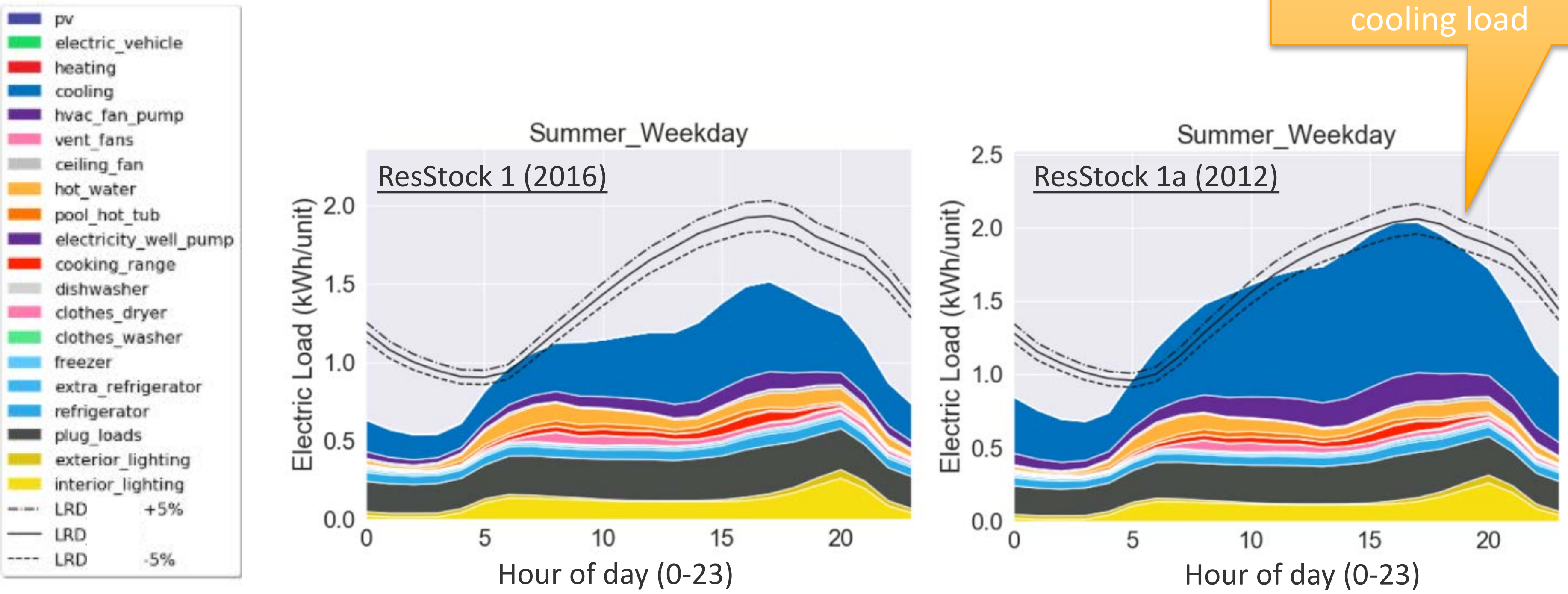
ResStock is now leakier both nationally and in the area of ComEd



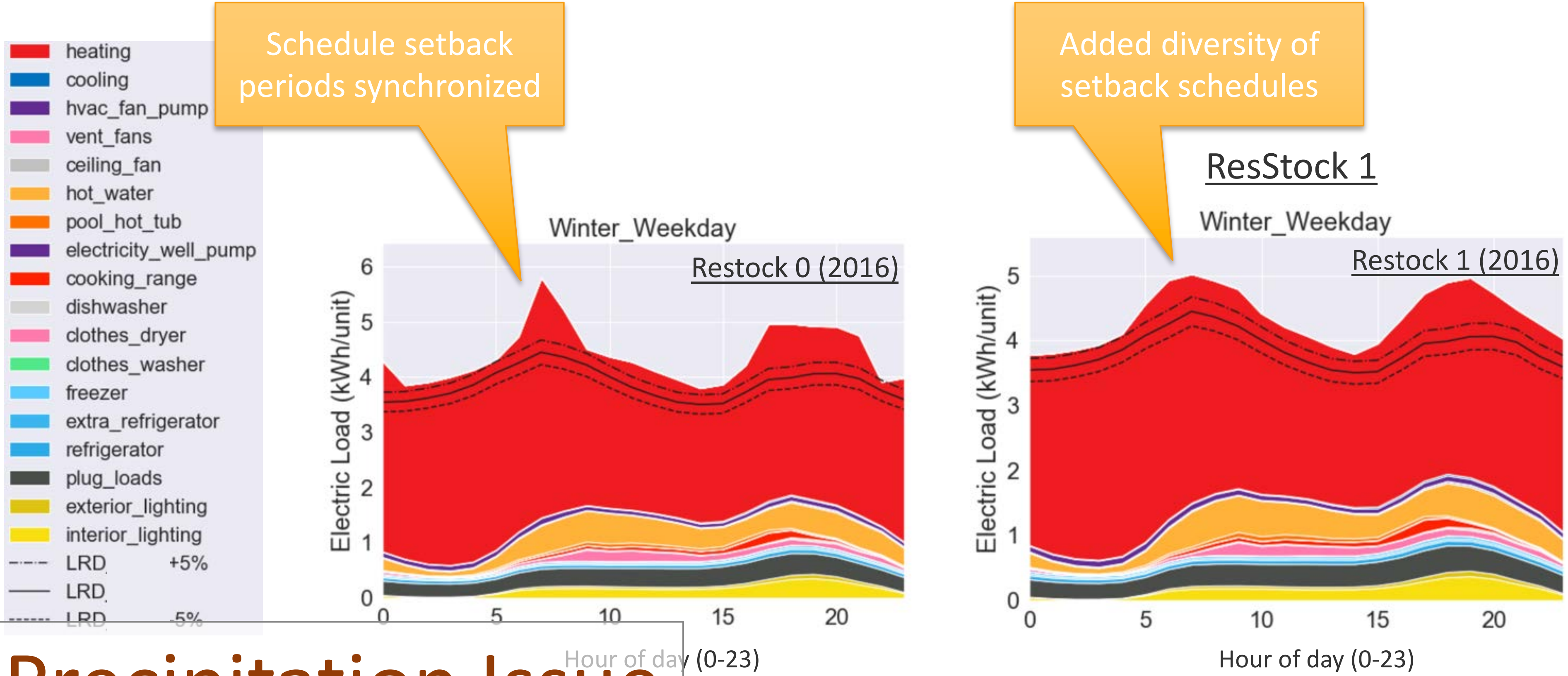
http://resdb.lbl.gov/

Impact: AC Ownership and Infiltration

Much improved cooling load



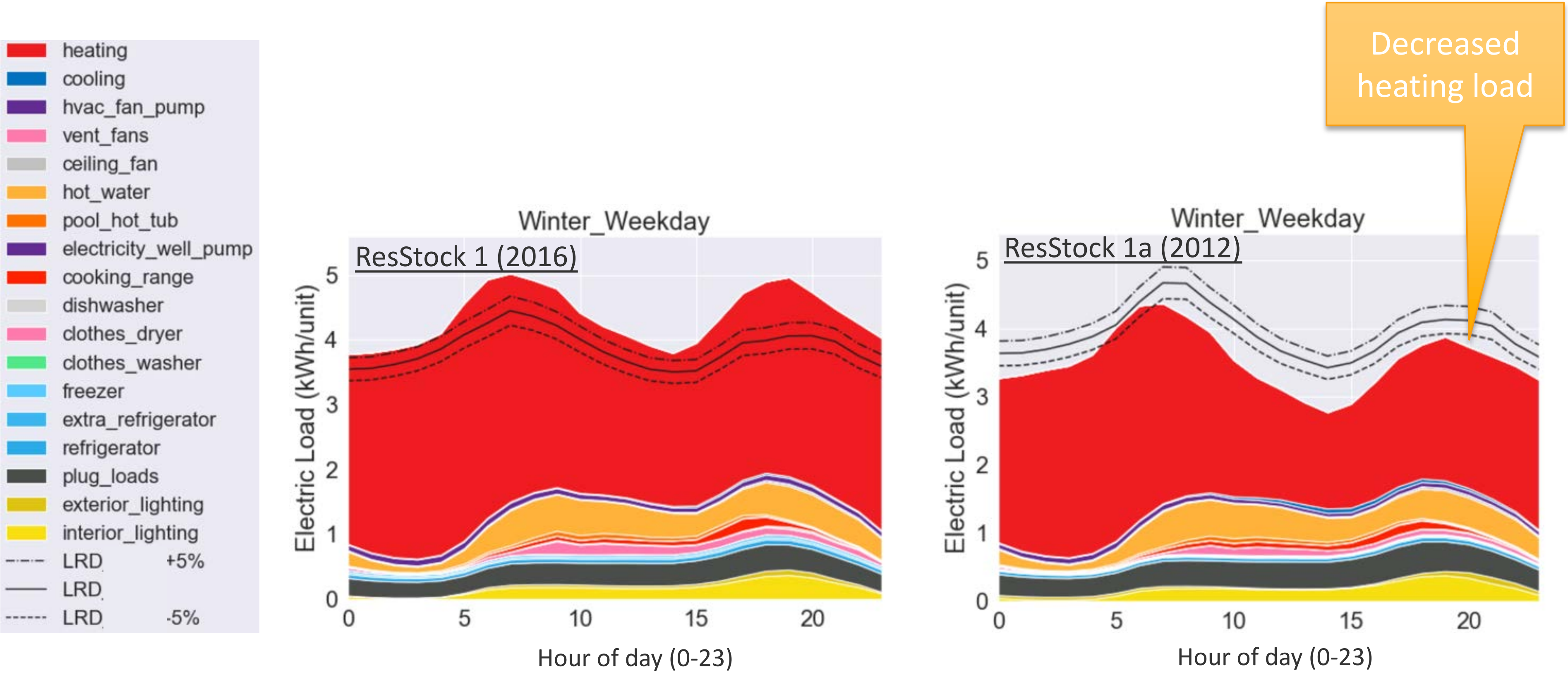
Update: HVAC Setpoint Schedule Diversity



Precipitation Issue

Single-Family Electric Heating

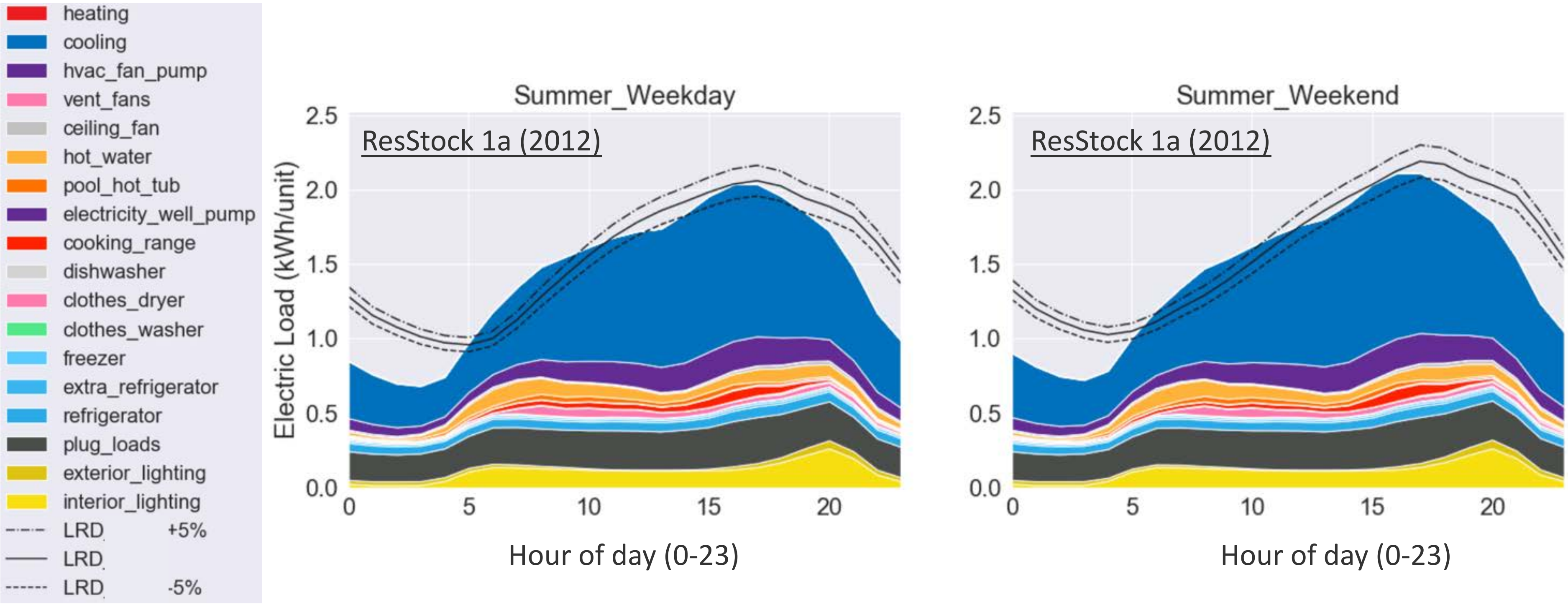
Update: HVAC Setpoint Schedule Diversity



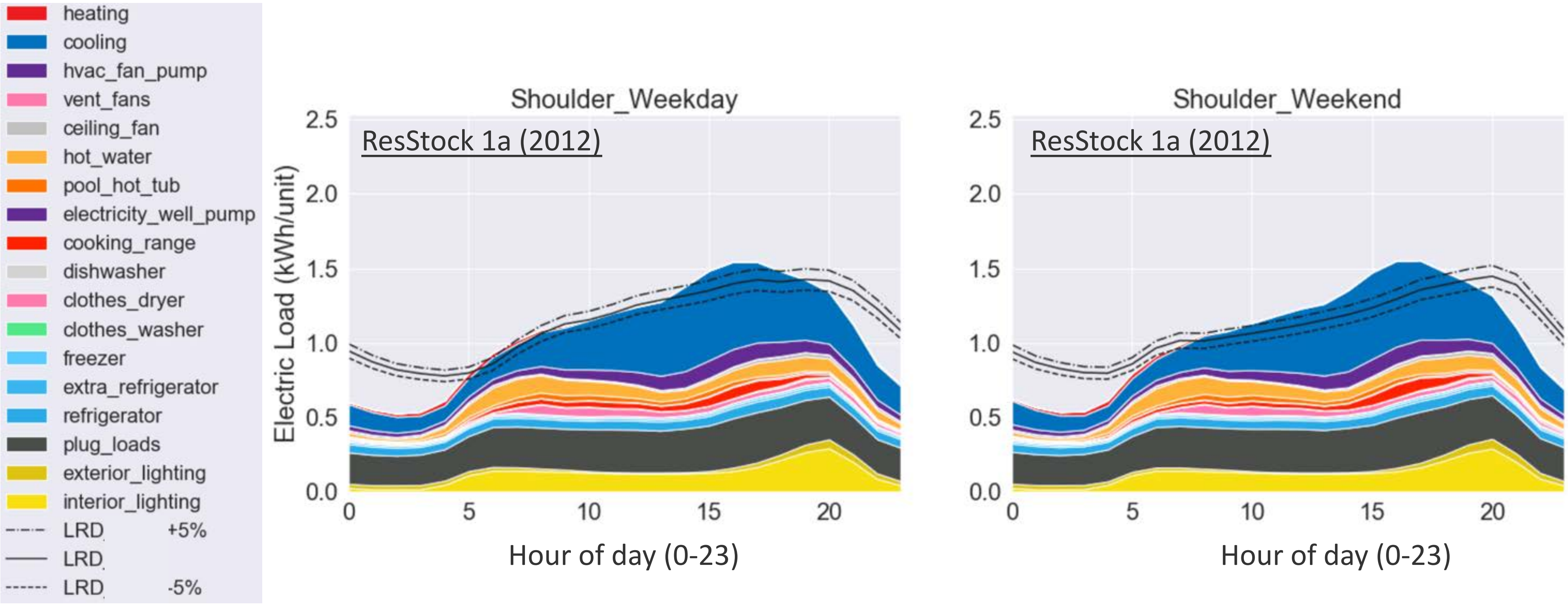
Single-Family Electric Heating

Residential stock end-use summary

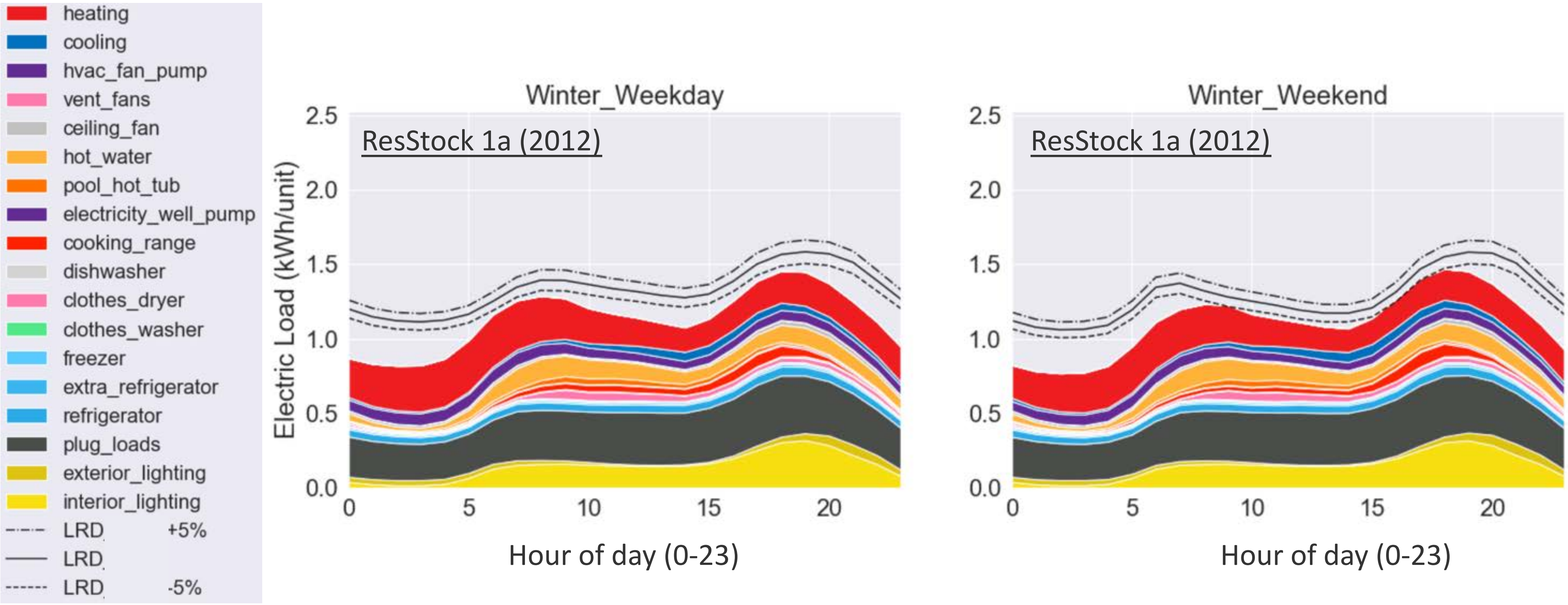
Seasonal end-use loads by day type



Seasonal end-use loads by day type

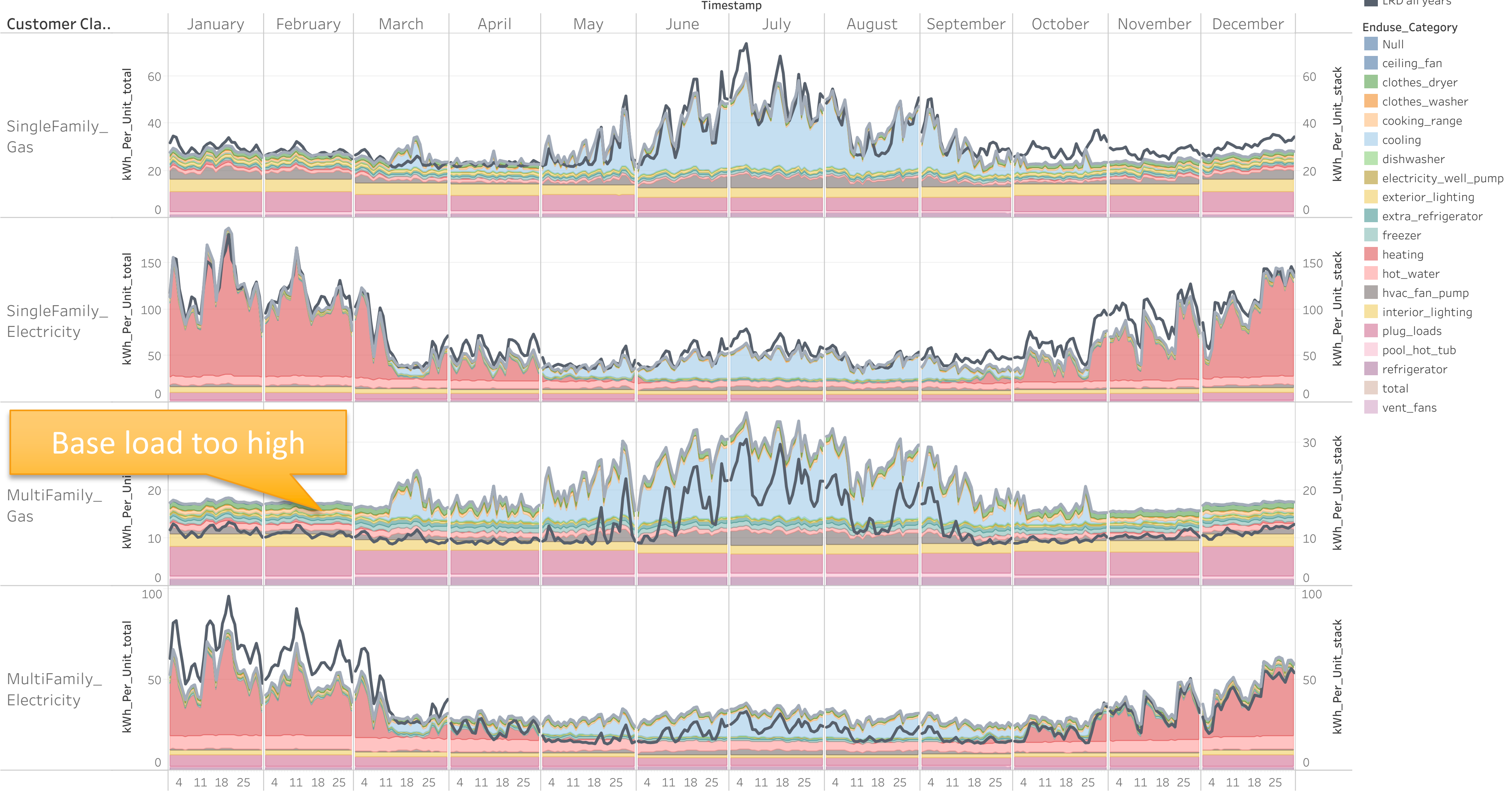


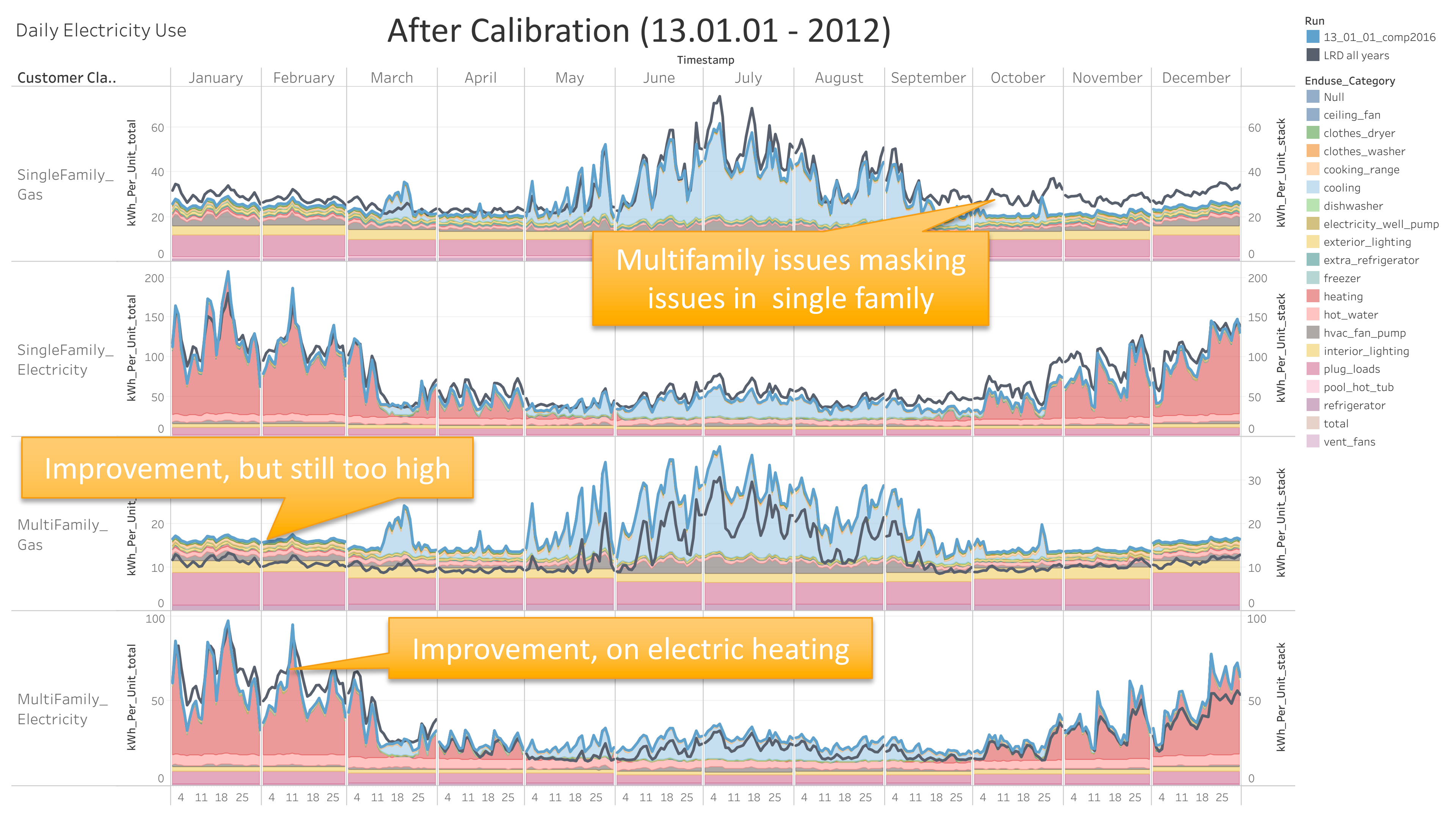
Seasonal end-use loads by day type

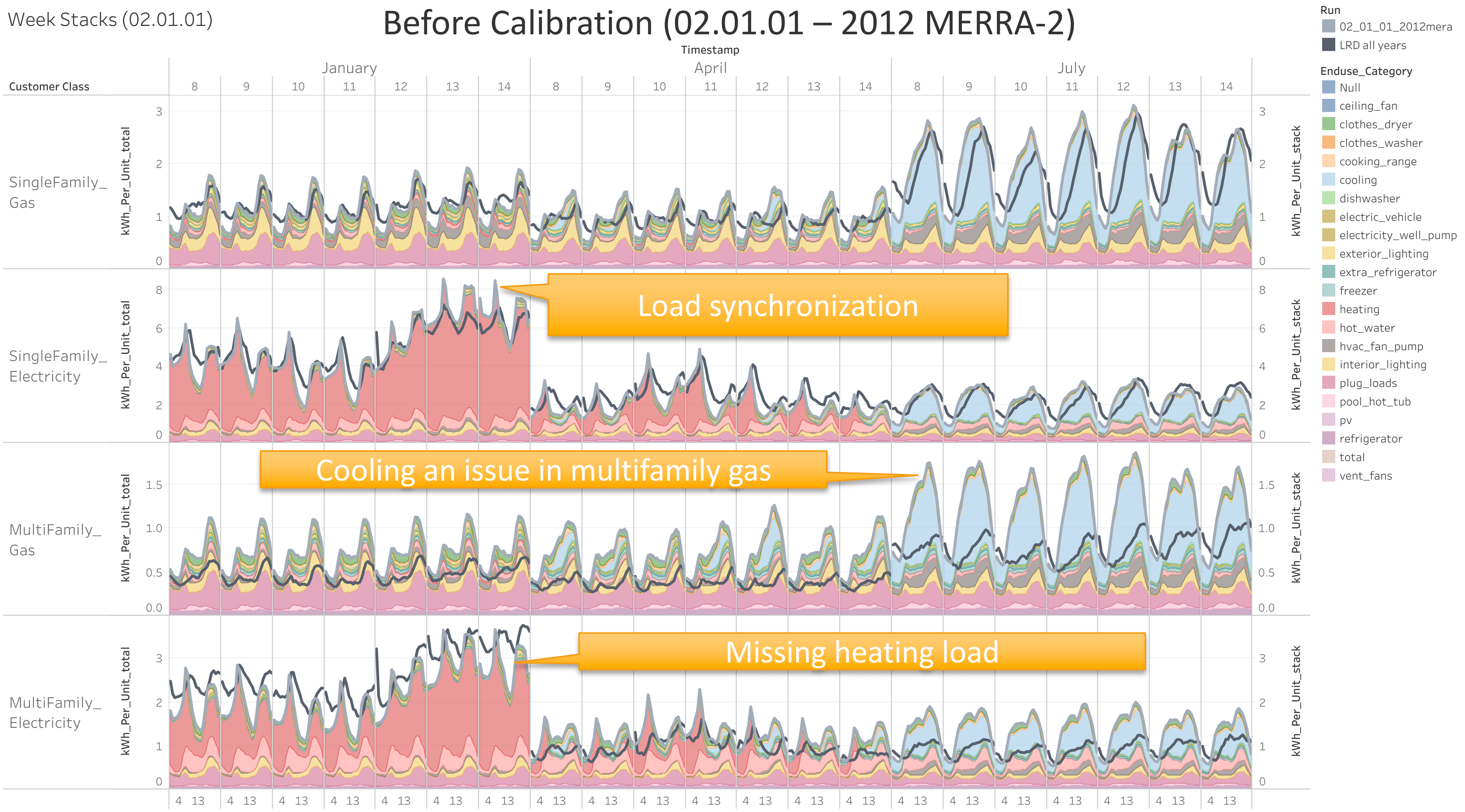


Daily Electricity Use (2)

Before Calibration (02.01.01 – 2012 MERRA-2)



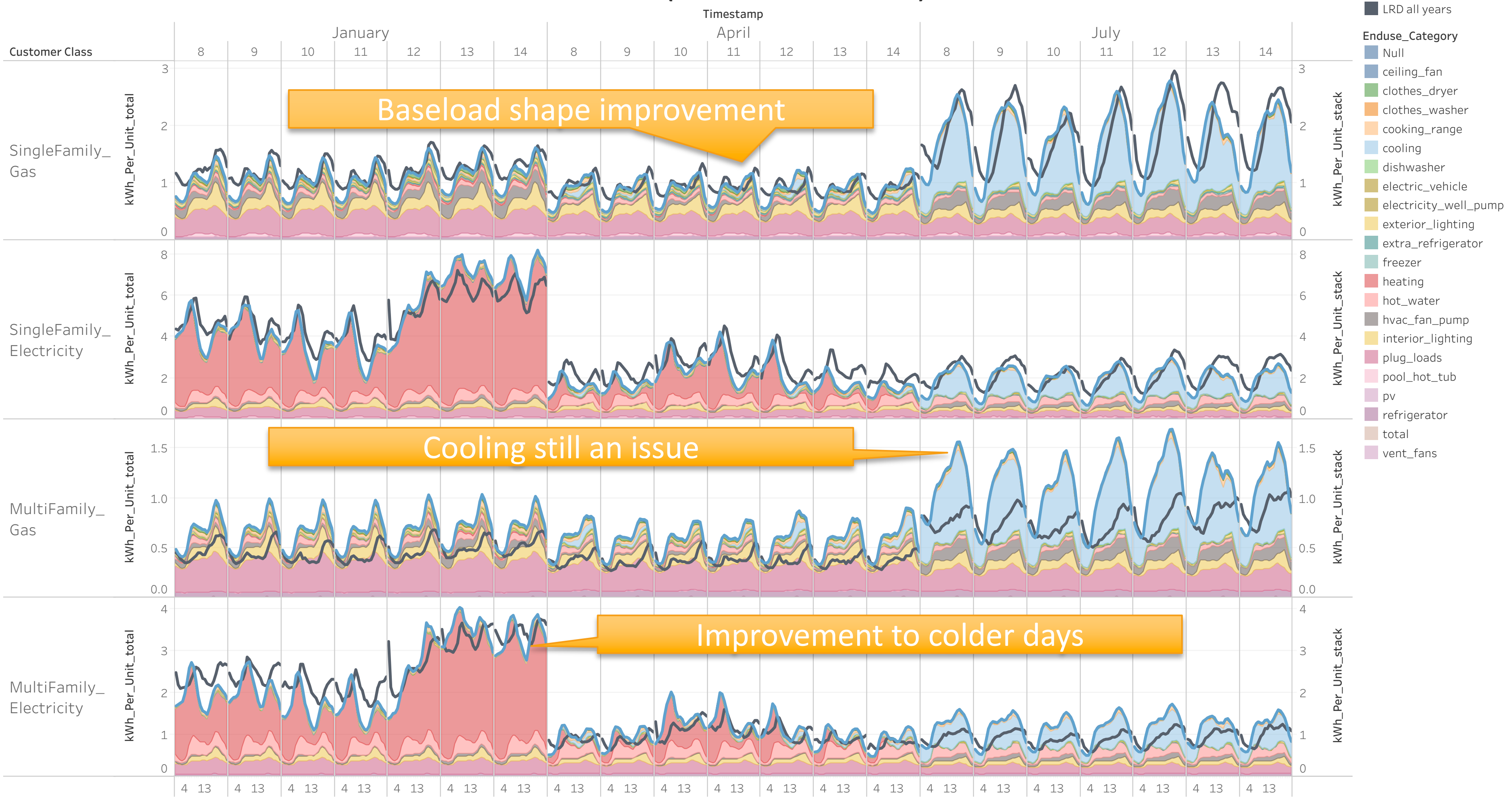

Daily Electricity Use
After Calibration (13.01.01 - 2012)
Timestamp
Customer Cla..
January
February
March
April
May
June
July
August
September
October
November
December
SingleFamily_Gas
SingleFamily_Electricity
MultiFamily_Gas
MultiFamily_Electricity
kWh_Per_Unit_total
kWh_Per_Unit_stack
4 11 18 25
Multifamily issues masking issues in single family
Improvement, but still too high
Improvement, on electric heating
Run
13_01_01_comp2016
LRD all years
Enduse_Category
Null
ceiling_fan
clothes_dryer
clothes_washer
cooking_range
cooling
dishwasher
electricity_well_pump
exterior_lighting
extra_refrigerator
freezer
heating
hot_water
hvac_fan_pump
interior_lighting
plug_loads
pool_hot_tub
refrigerator
total
vent_fans



Week Stacks (02.01.01)
Before Calibration (02.01.01 – 2012 MERRA-2)
Timestamp
January
April
July
Customer Class
SingleFamily_Gas
SingleFamily_Electricity
MultiFamily_Gas
MultiFamily_Electricity
kWh_Per_Unit_total
kWh_Per_Unit_stack
Load synchronization
Cooling an issue in multifamily gas
Missing heating load
Run
02_01_01_2012mera
LRD all years
Enduse_Category
Null
ceiling_fan
clothes_dryer
clothes_washer
cooking_range
cooling
dishwasher
electric_vehicle
electricity_well_pump
exterior_lighting
extra_refrigerator
freezer
heating
hot_water
hvac_fan_pump
interior_lighting
plug_loads
pool_hot_tub
pv
refrigerator
total
vent_fans

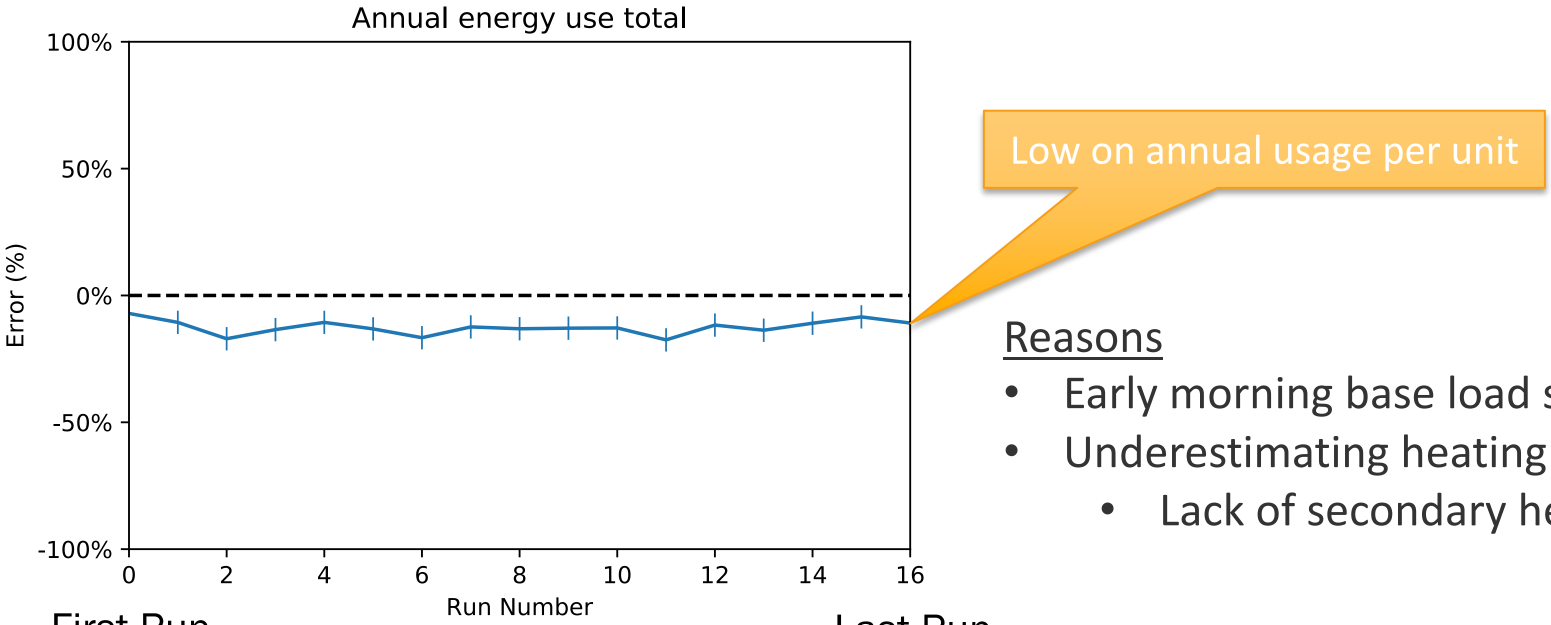
Week Stacks (12.01.01

After Calibration (13.01.01 - 2012)



Tracking Quantities of Interest

Region 1 Focus: Annual Error



First Run
ResStock 0

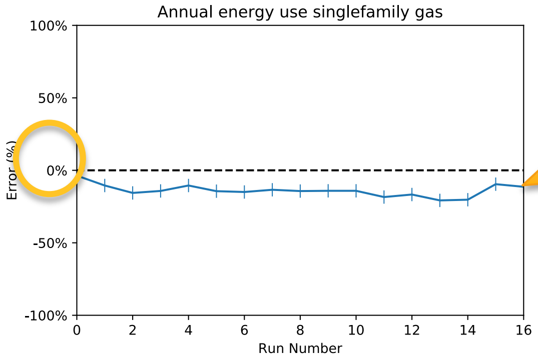
Last Run
ResStock 1a

Reasons

- Early morning base load still low
- Underestimating heating
    - Lack of secondary heating

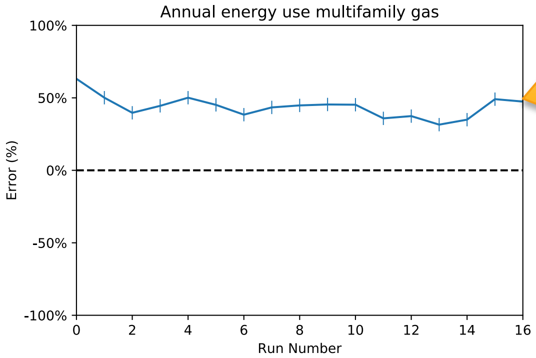
Region 1 Focus: Annual Electricity Error

Single-Family Gas Heating



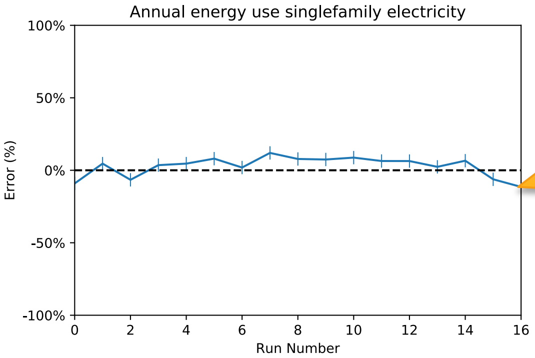
Balancing Multi-family and single-family improvements

Multi-Family Gas Heating



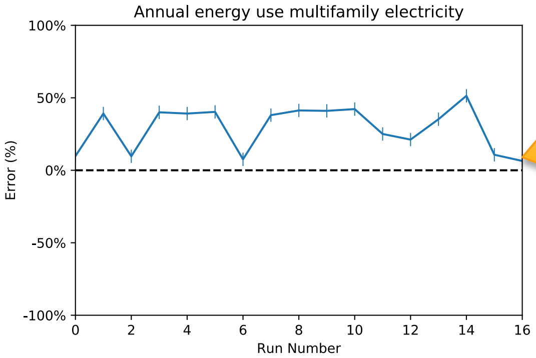
Address plug loads & lighting

Single-Family Electric Heating



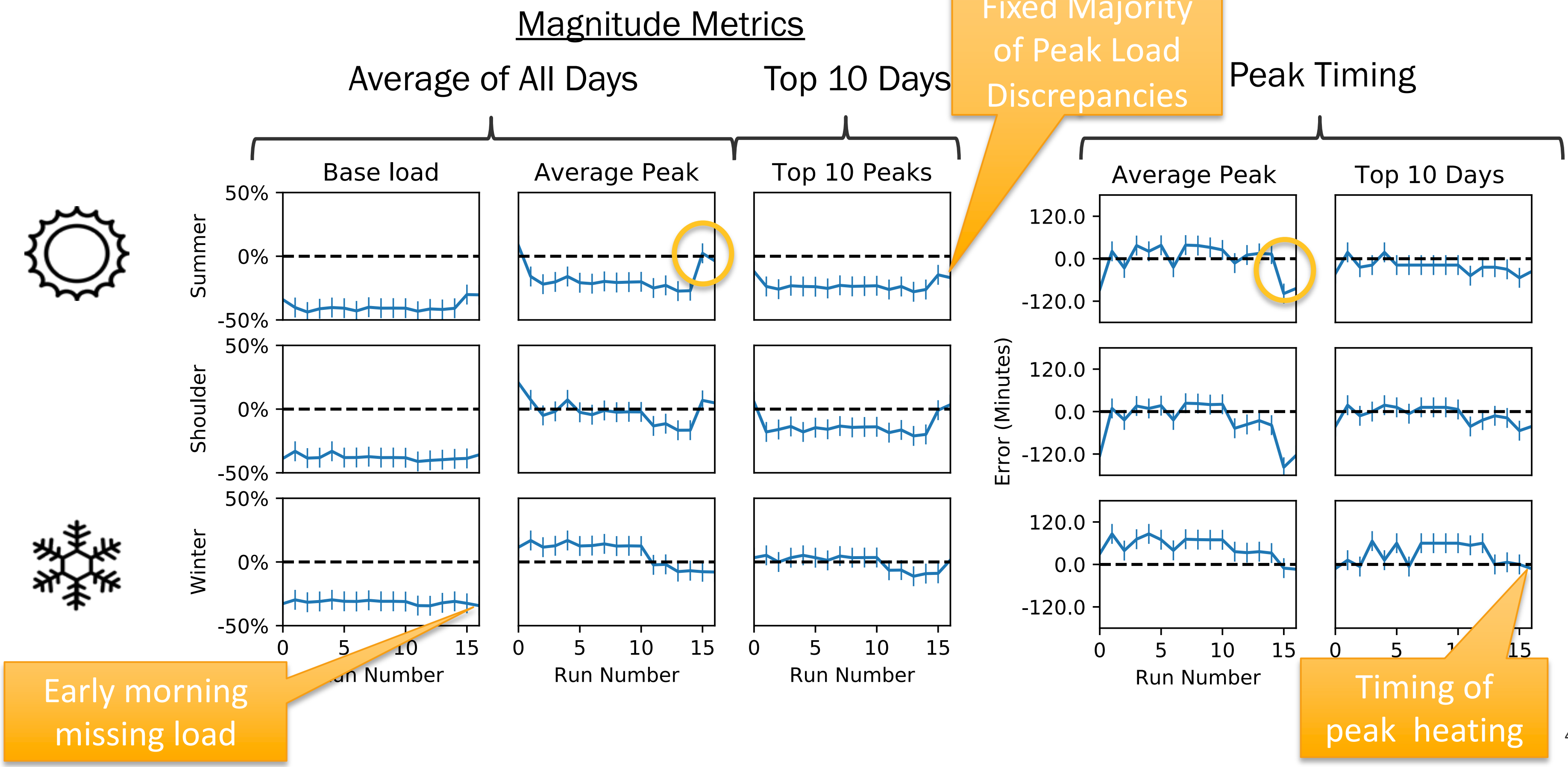
Precipitation issue masked slight under-heating issue

Multi-Family Electric Heating



Improved through calibration

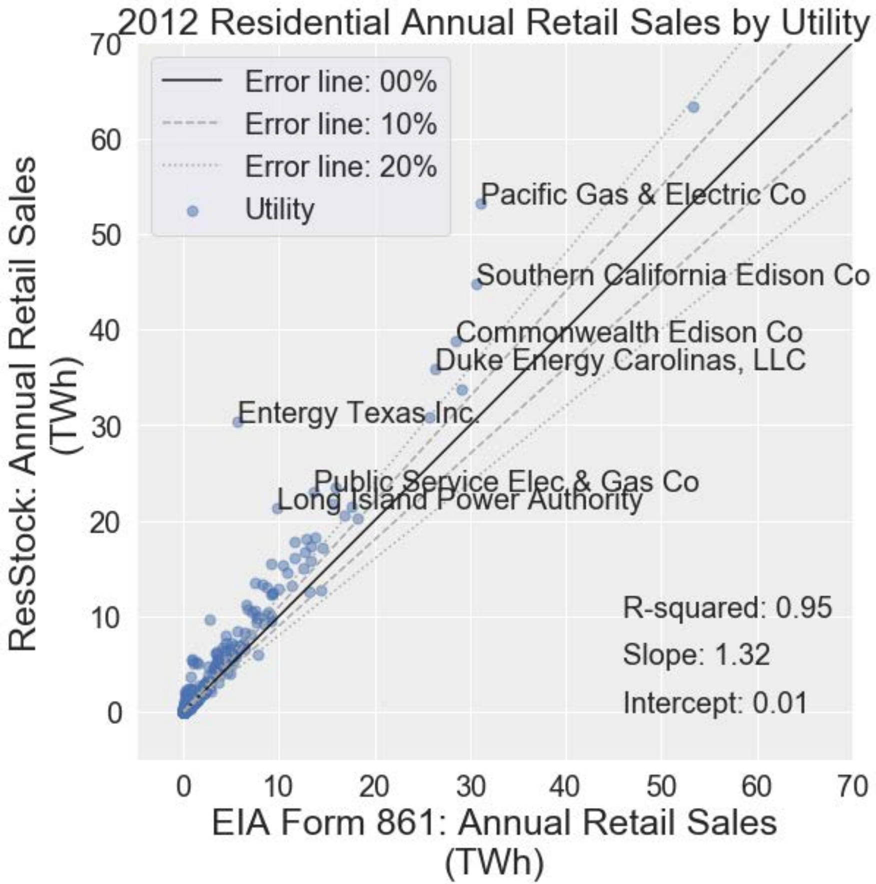
Region 1 Focus: Total Error Metrics



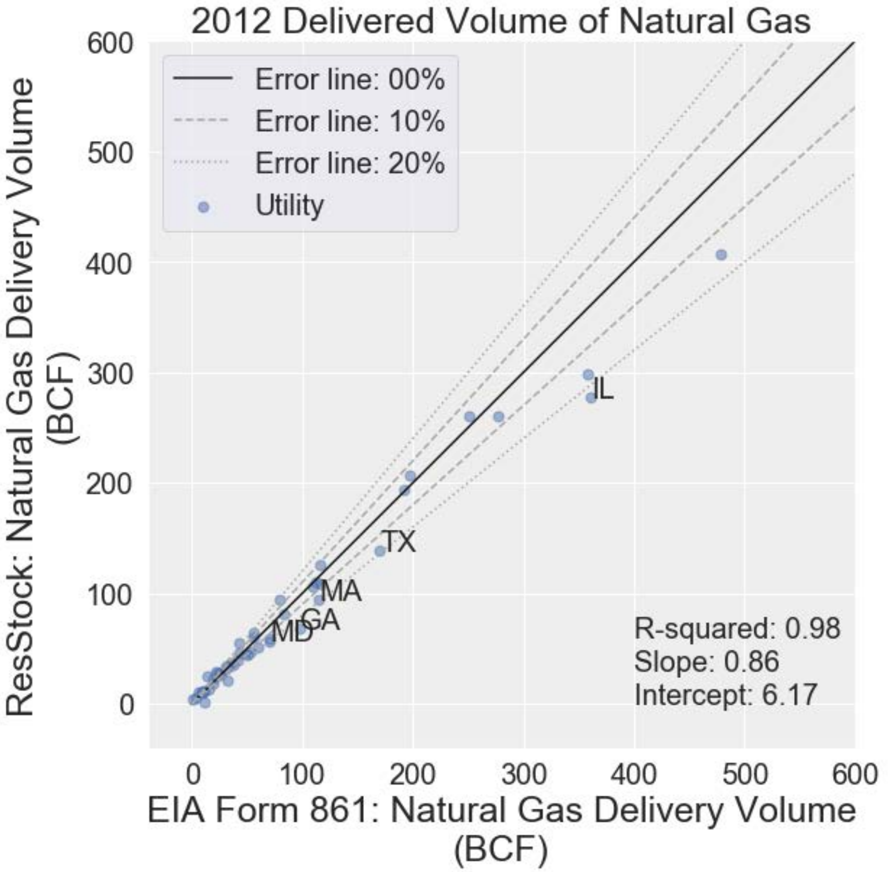
Current Status of Nationwide Calibration

Before Calibration (01.01.01 – 2012 MERRA-2)

Electricity

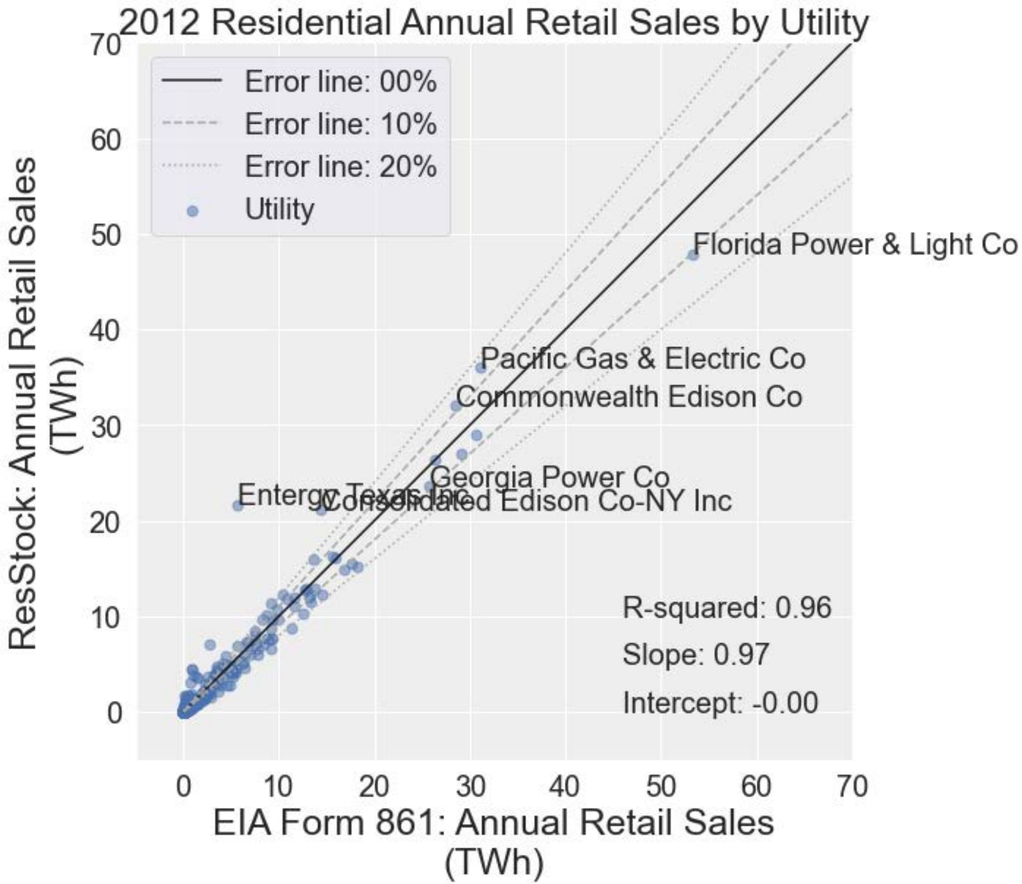


Natural Gas

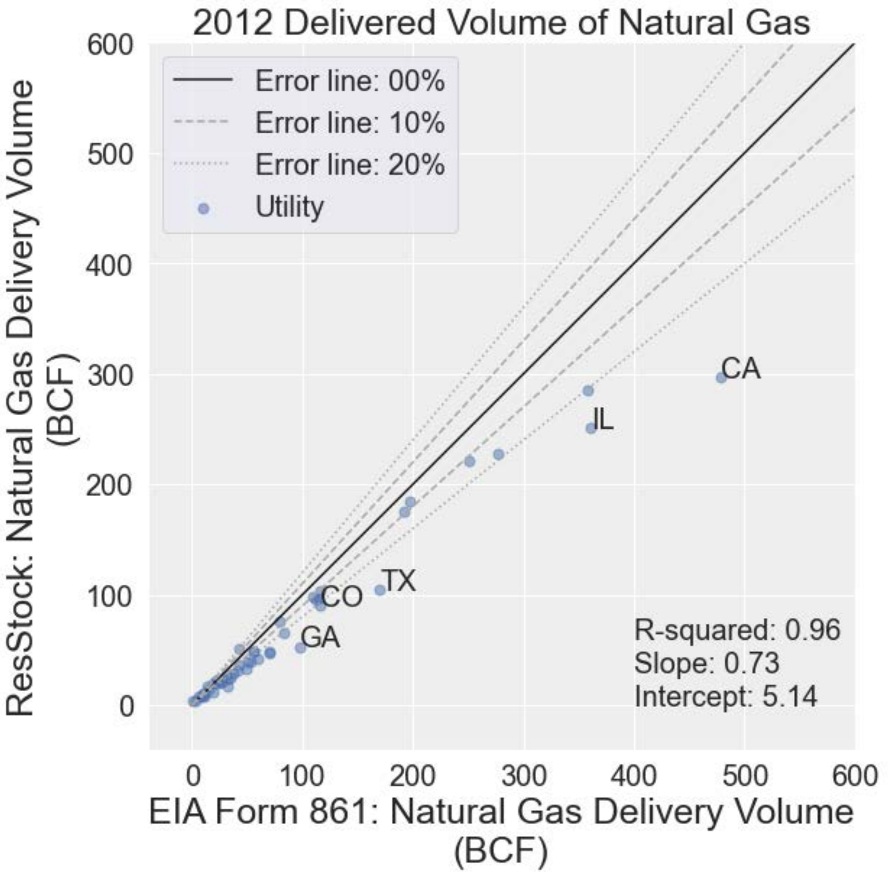


After Calibration (12.01.01 - 2012 MERRA-2)

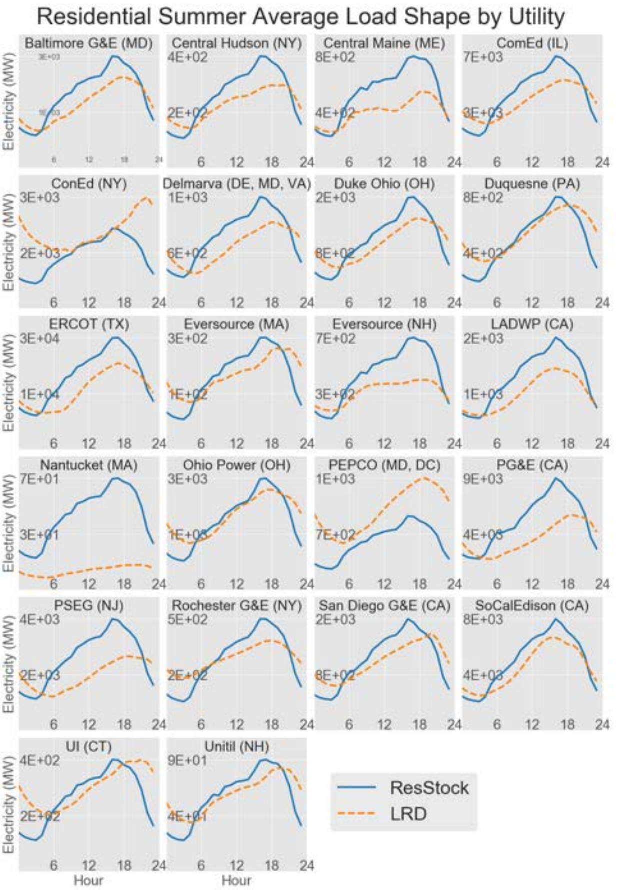
Electricity

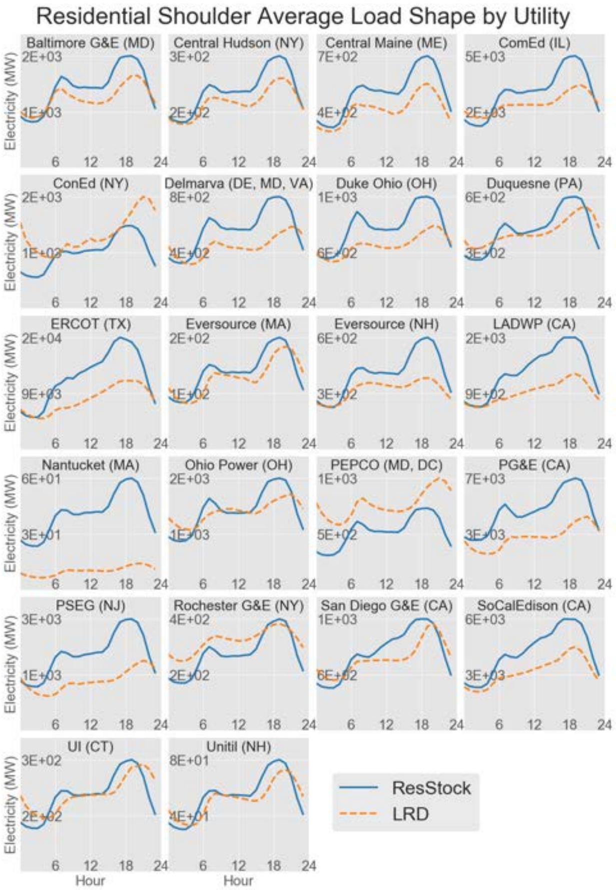


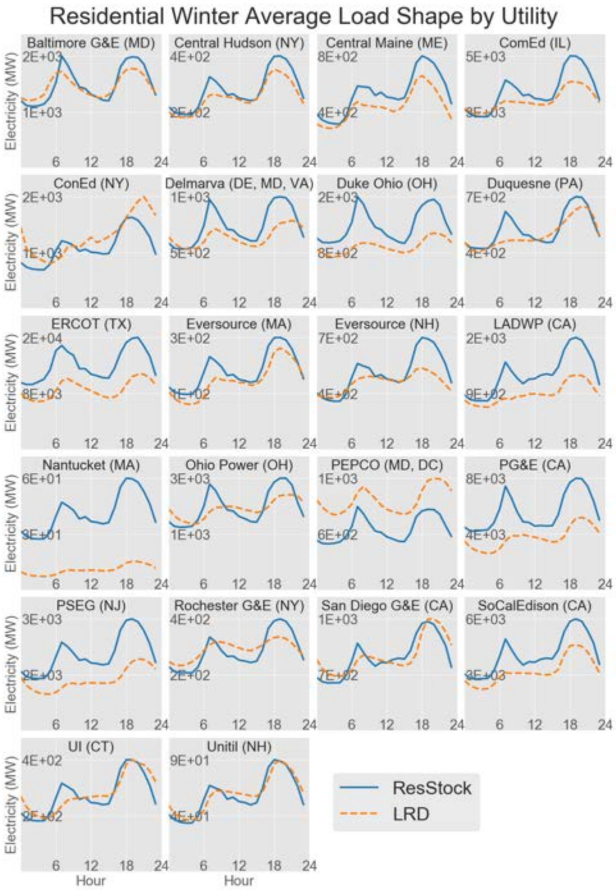
Natural Gas



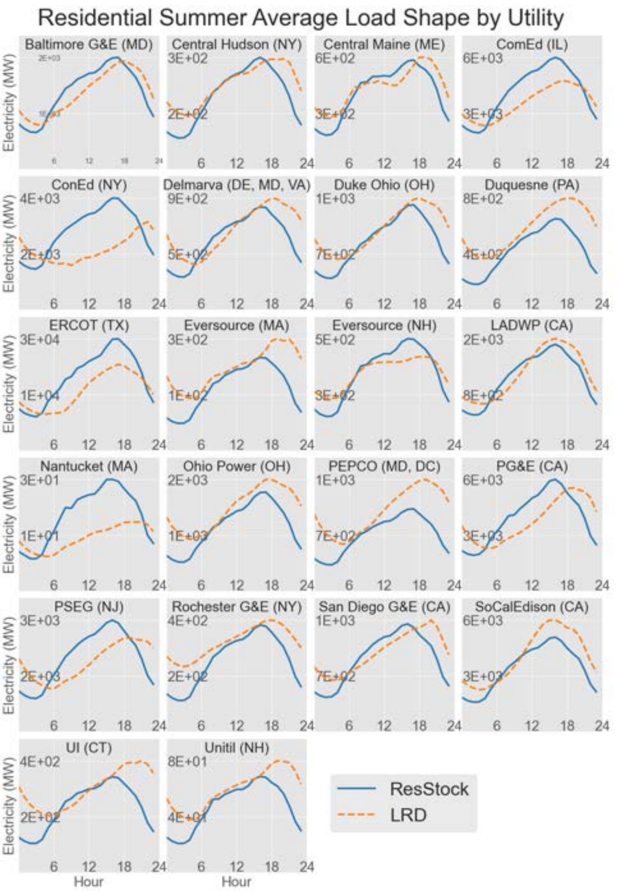
01.01.01 – 2012 MERRA-2

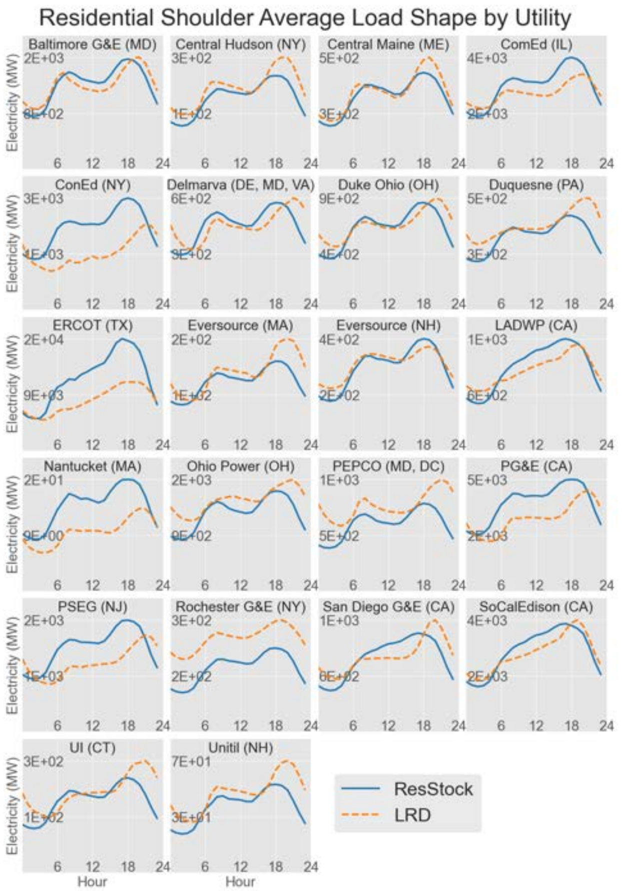


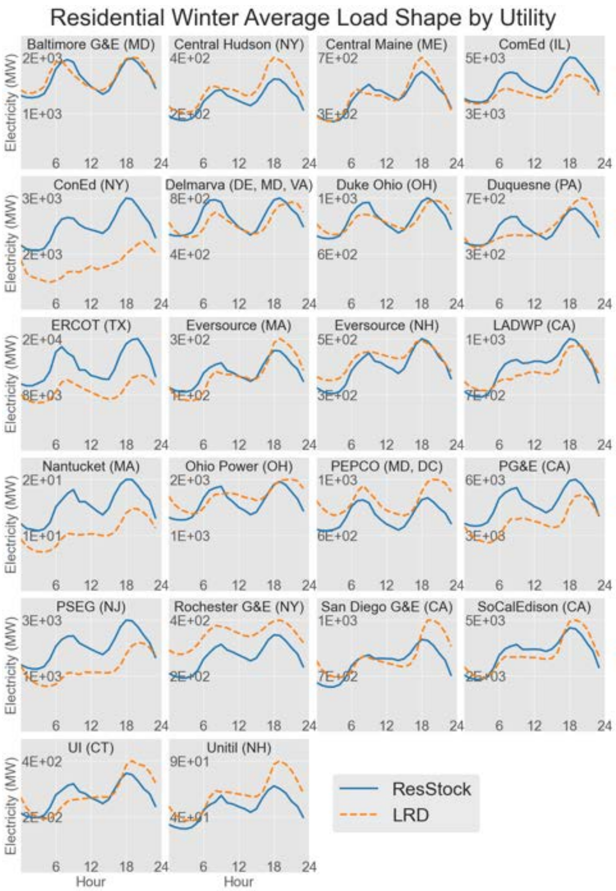




12.01.02 - 2012 MERRA-2

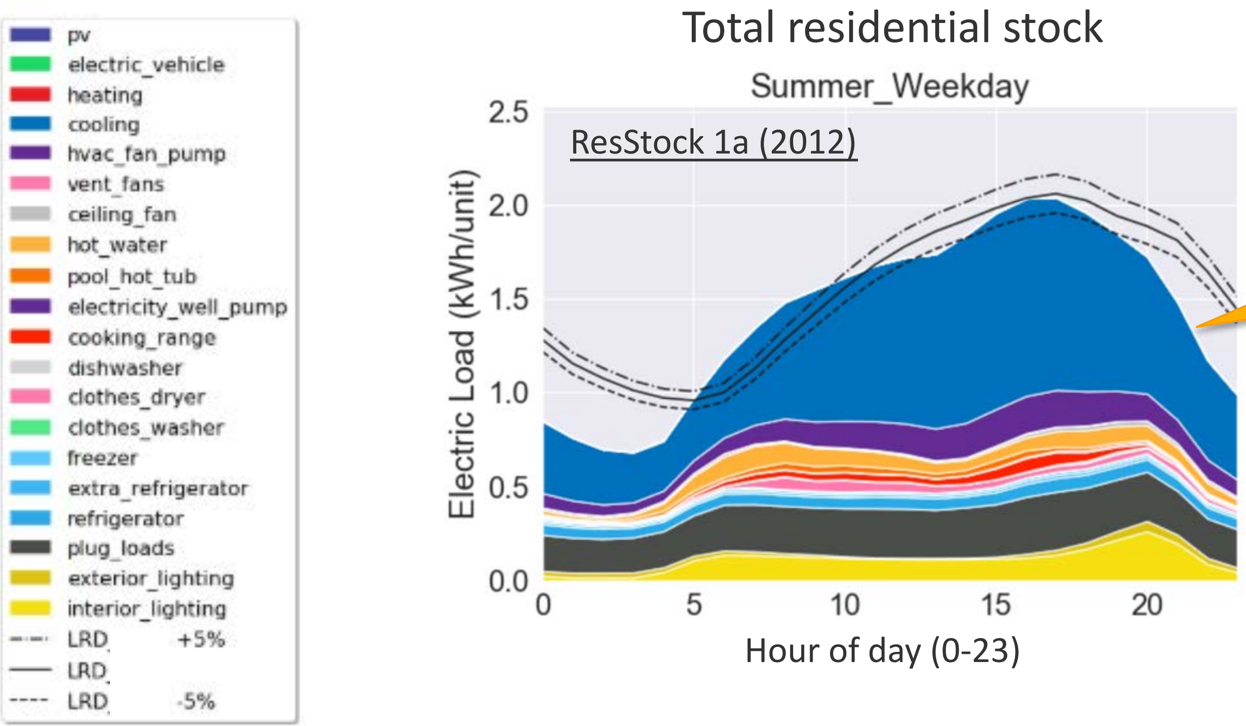






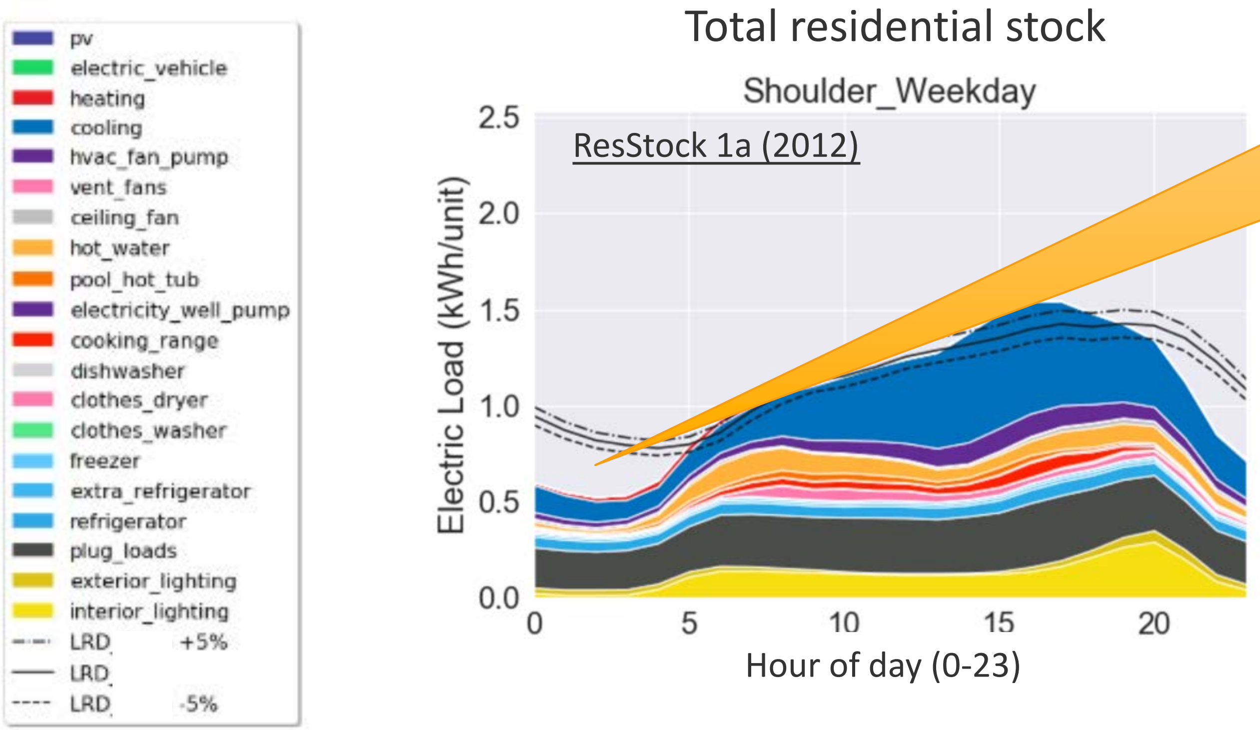
Areas for Improvement

Next Region: Likely Areas for Improvement



- Missing load at night
- Likely not a Chicago-specific problem

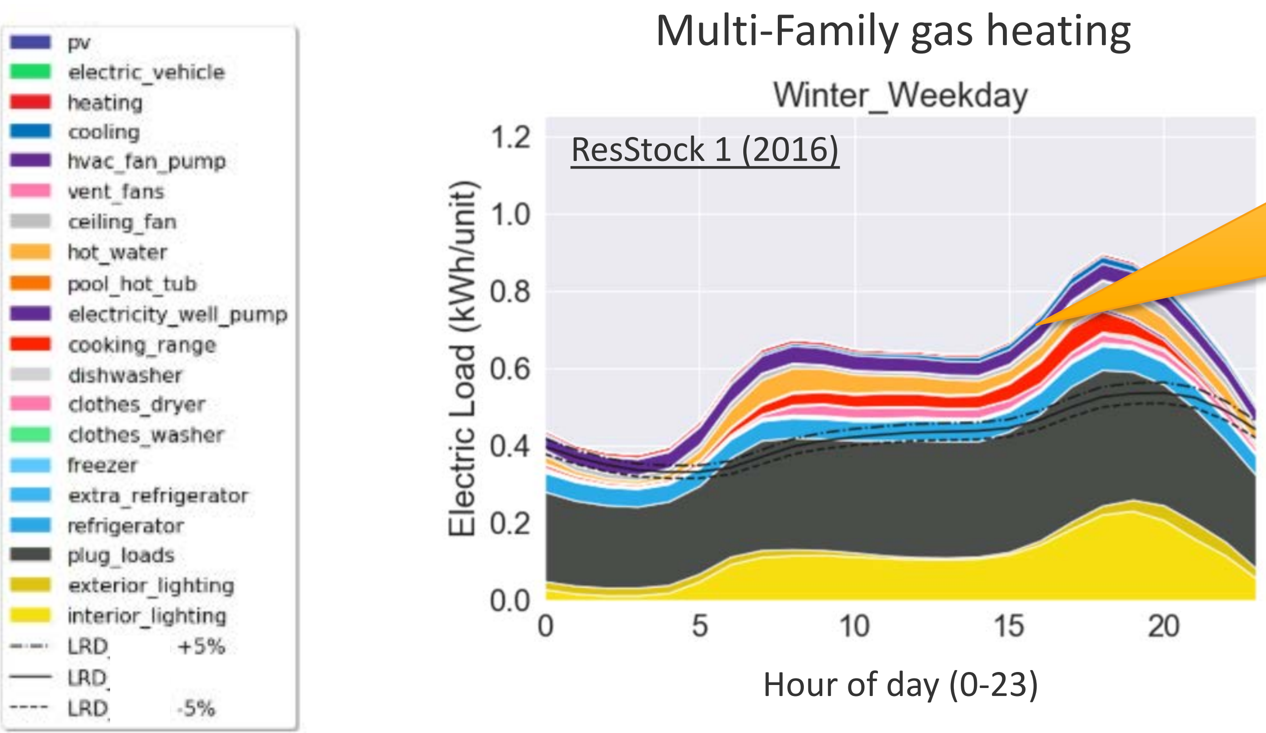
Next Region: Likely Areas for Improvement



Low at night:

- Secondary heating systems
- Missing cooling load
- Missing plug or appliance load

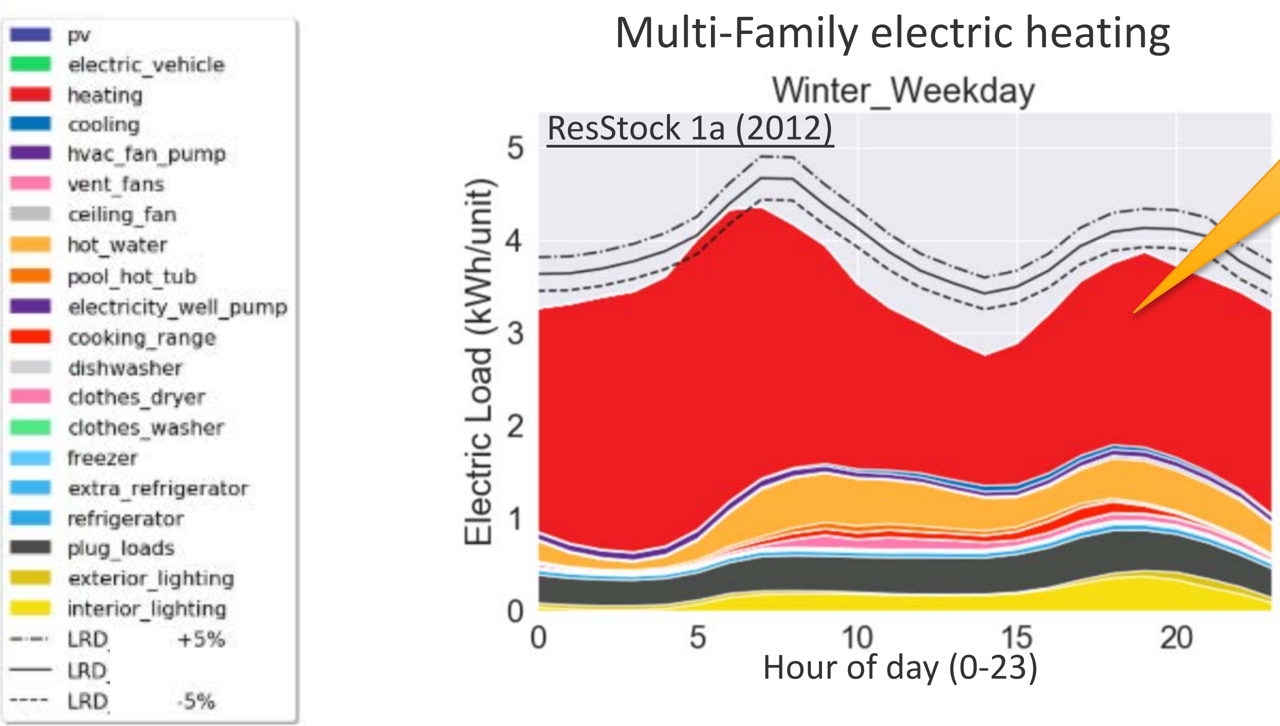
Next Region: Likely Areas for Improvement



Large load:

- Plug load magnitude
- Lighting density too high
- Vacant/limited use Multi-Family dwellings

Next Region: Likely Areas for Improvement



Low Load
- Electric heating saturation
- Electric heating efficiency

Conclusions

- Structural changes enabled incorporation of more granular datasets
  - Will benefit all regions moving forward
- Ran 14 iterations of ResStock incorporating 16 discrete changes
- Saw incremental improvements in our QOI metrics
- Improvements made not just to Region 1, but the entire U.S.
- Still seeing discrepancies in the following areas:
  - Cooling load
  - Night-time baseload
  - Multi-family baseload
  - Multi-family electric heating
- Have identified possible causes of discrepancies

Next Steps

- Will be moving on to Enhanced Region 2, but continue tracking:
  - Nationwide calibration data and utility load shapes
  - Region 1 metrics
- Enhanced Calibration Region 2:
  - Fort Collins, CO

Discussion Questions

- Were there any comparisons of data that you didn't understand or understand the reason for?
- Are there any other ways of looking at the data that you were surprised NOT to see in the way results were presented?
- This calibration focused on updating model inputs. Do you think there is a role for post-simulation calibration true-up factors, e.g., for scaling up or down daily cooling energy?

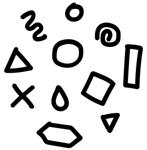
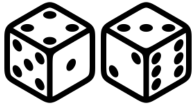
Stochastic Modeling of Residential Building Loads

EULP Technical Advisory Group Presentation
May 26, 2020

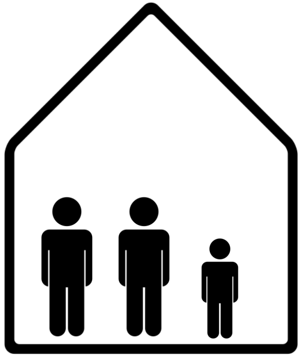
Eric Wilson

Motivation

To represent realistic load profiles and demand flexibility, we need to model

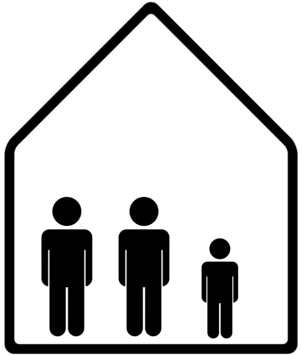
1. Heterogeneity 
2. Stochasticity 

Why does heterogeneity matter?

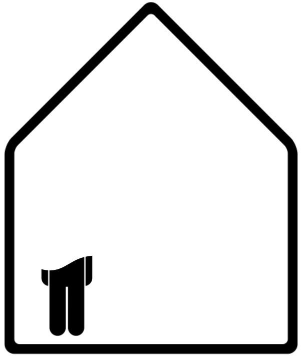


06:00
3 occupants

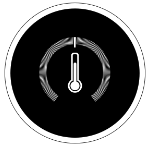
Why does heterogeneity matter?



06:00
3 occupants

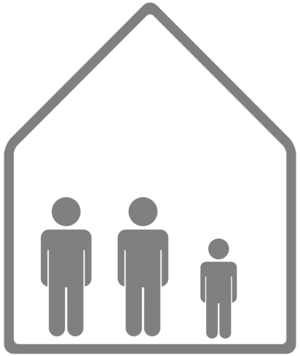


16:00
0.5 occupants

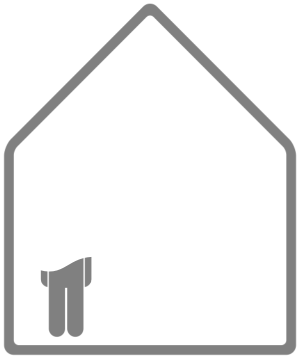


What is the demand flexibility of half of an occupant?

Why does heterogeneity matter?

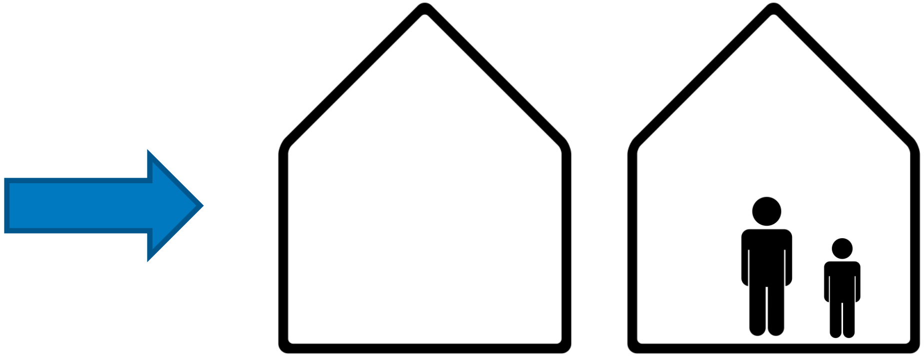


06:00
3 occupants



16:00
0.5 occupants

Diversity in occupancy level is needed to estimate demand flexibility



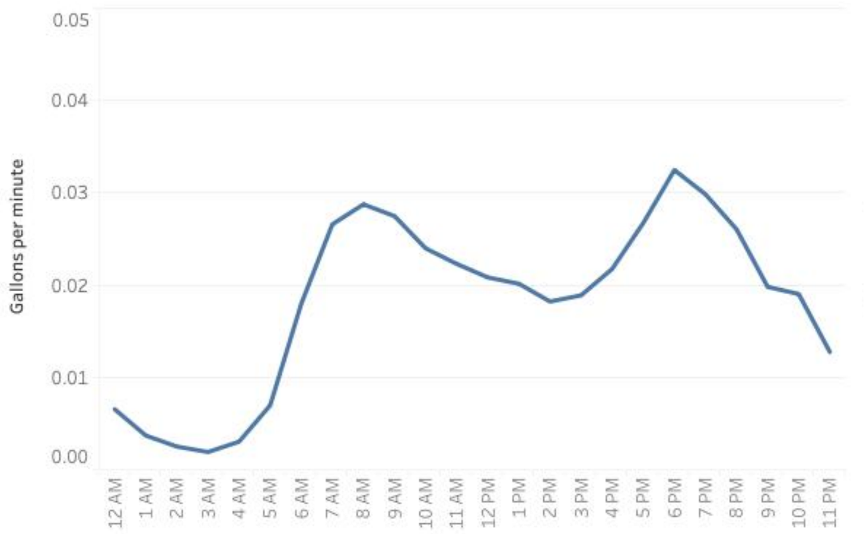
0 occupants
(flexible)

2 occupants
(not flexible)

Why does stochasticity matter?

Daily hot water draw profiles

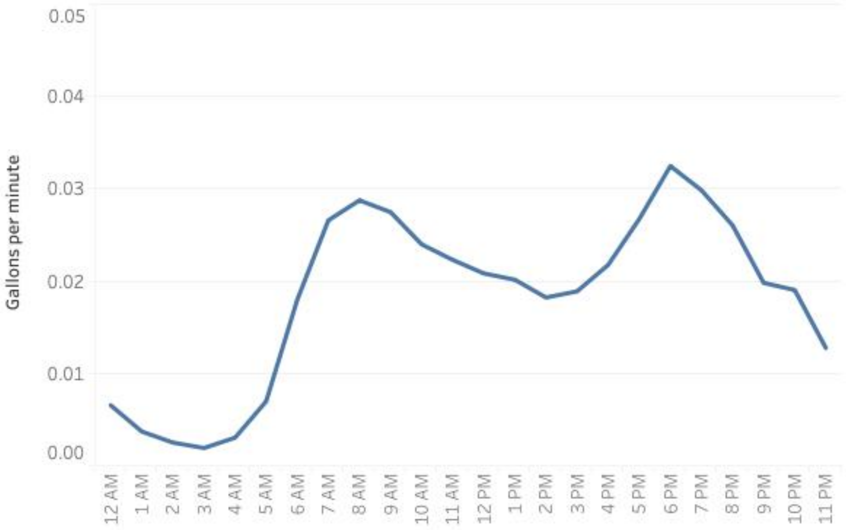
Blended average of all households



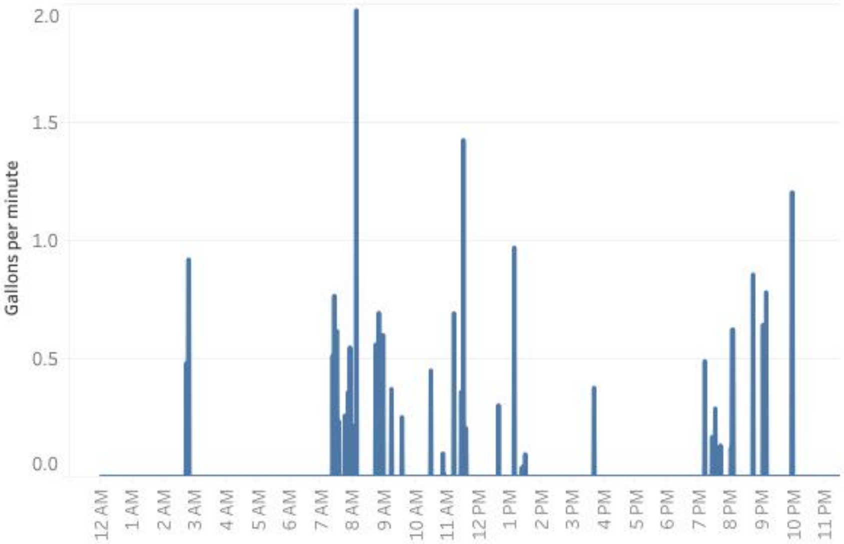
Why does stochasticity matter?

Daily hot water draw profiles

Blended average of all households



An individual household



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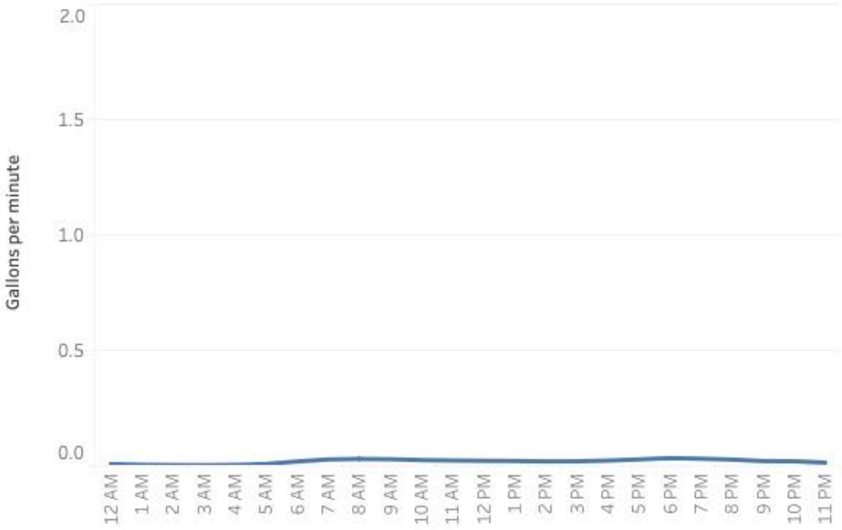
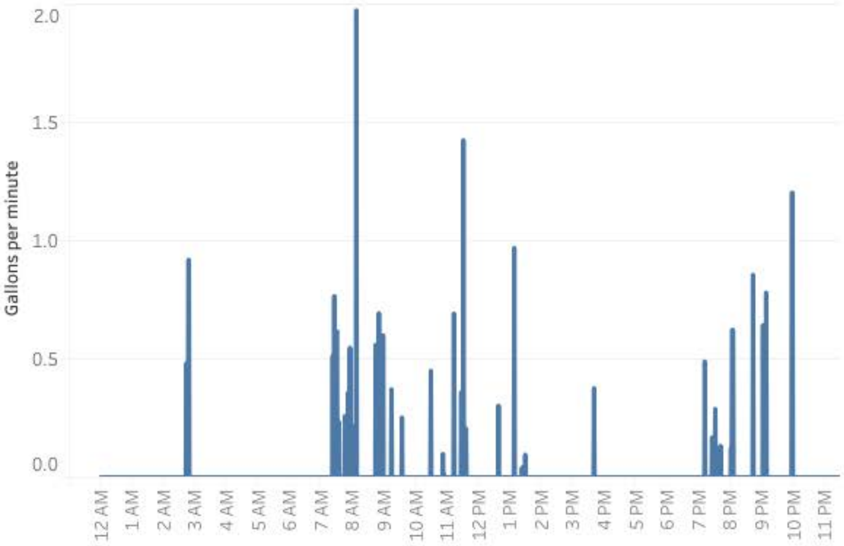
Daily hot water draw profiles

Blended average of all households

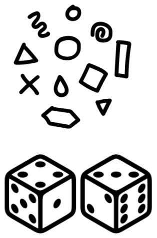


An individual household

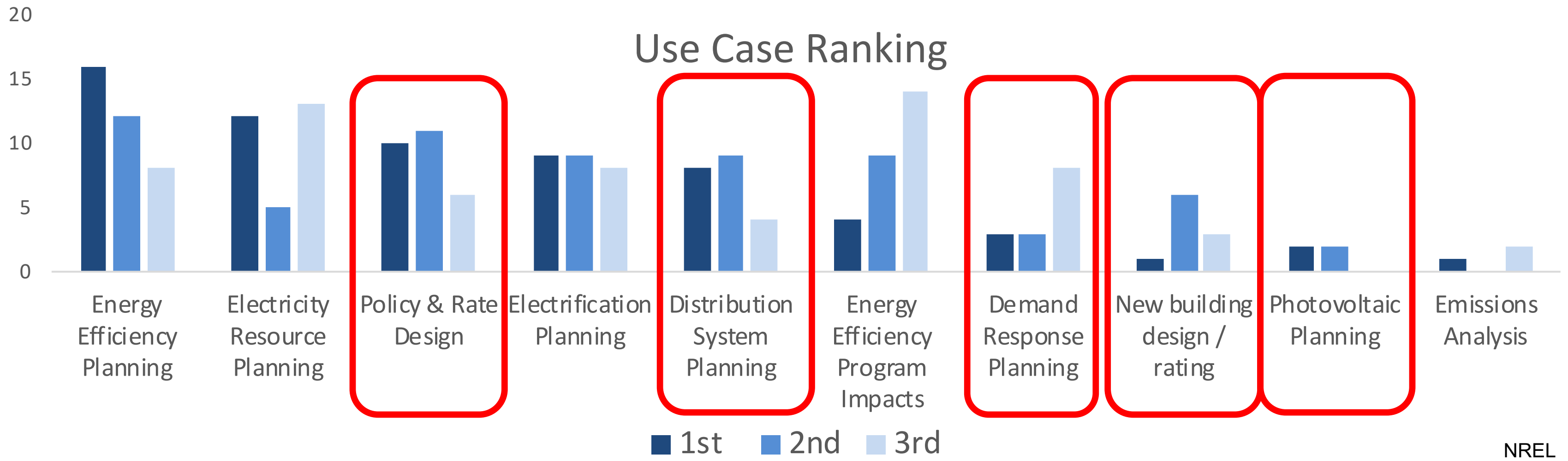


What is the demand flexibility?

Impact



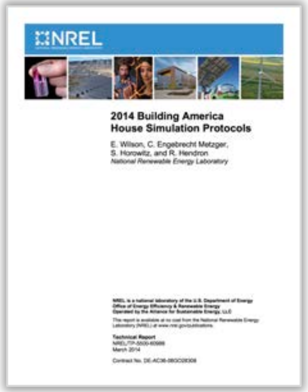
These more realistic heterogenous and stochastic load profiles are important for accurate analysis of use cases identified as important by the TAG



Current Progress

Historical Context

- **2004** – NREL has developed and maintained residential occupancy simulation protocols since 2004
- **2010** – “Tool for Generating Realistic Residential Hot Water Event Schedules” (Hendron et al. 2010)
  - Stochastic hot water draw generator based on data from 1200 homes
  - Developed initially for analysis of tankless and solar water heating systems
  - Later incorporated into NREL residential EnergyPlus simulation workflows and used for analysis of heat pump water heater performance.
- **2014** – ResStock inherits above residential occupancy simulation protocols and stochastic hot water draw profiles



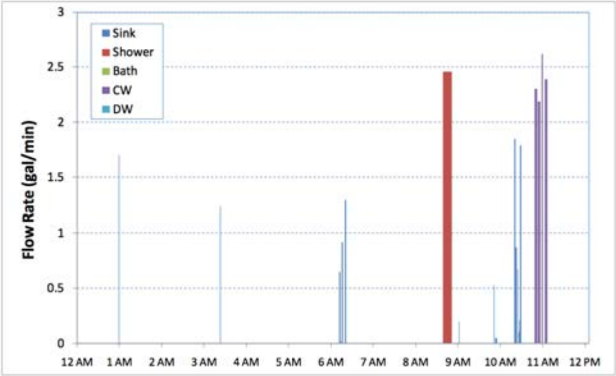


Figure 4 Example series of hot water events

ResStock

Historical Context

Activity	2019 Status Schedule Heterogeneity	 Schedule Stochasticity
Occupant (heat gain)	No	No
Sinks HW	Yes*	Yes*
Showers/Baths HW	Yes*	Yes*
Dishwasher HW	Yes*	Yes*
Dishwasher kW	Yes*	Yes*
Clothes Washer HW	Yes*	Yes*
Clothes Washer kW	Yes*	Yes*
Clothes Dryer kW	Yes*	Yes*
Cooking Range	No	No
Misc. Electric Loads	No	No
Lighting	No	No
Thermostat setpoints	No	No
Bath exhaust fan	No	No
Kitchen exhaust fan	No	No

* = Some degree of heterogeneity or stochasticity, but could be improved

Summary of Changes

Activity	2019 Status: Schedule Heterogeneity	2019 Status: Schedule Stochasticity	March 2020 Status: Schedule Heterogeneity	March 2020 Status: Schedule Stochasticity	Type: Occupants/ Household	Data sources: Start time	Data sources: Duration	Data sources: Magnitude (Power, Flow)
Occupant (heat gain)	No	No	Yes	Yes	Occupants	ATUS	ATUS	ATUS
Sinks HW	Yes*	Yes*	Yes	Yes	Household	DHWESG	DHWESG	DHWESG
Showers/Baths HW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	DHWESG	DHWESG
Dishwasher HW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	ATUS	DHWESG
Dishwasher kW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	ATUS	End-use datasets
Clothes Washer HW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	End-use datasets	DHWESG
Clothes Washer kW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	DHWESG	End-use datasets
Clothes Dryer kW	Yes*	Yes*	Yes	Yes	Occupants	ATUS	End-use datasets	End-use datasets
Cooking Range	No	No	Yes	Yes	Occupants	ATUS	ATUS	End-use datasets
Misc. Electric Loads	No	No	Yes	Yes*	Household	Modify avg. schedule based on occupancy		
Lighting	No	No	Yes	Yes*	Household	Modify avg. schedule based on occupancy		
Thermostat setpoints	No	No	Yes	No	Household	RECS, ecobee		
Bath exhaust fan	No	No	Yes	No	Household	Modify schedule based on occupancy		
Kitchen exhaust fan	No	No	Yes	No	Household	Modify schedule based on occupancy		

* = Some degree of heterogeneity or stochasticity, but could be improved

ATUS = American Time Use Survey

DHWESG = NREL Domestic Hot Water Event Schedule Generator (based on data from the American Water Works Association)

End-use datasets = Pecan St., RBSAM, FSEC, etc.

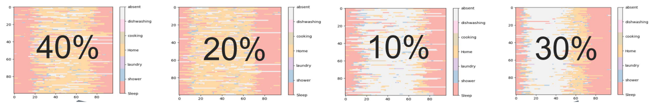
Completed Activities

- Literature Review of Methodologies and Selection of Approach (FY19)
- Occupancy data collection, cleaning, and processing
  - ATUS, RBSA, Pecan Street, etc.
- Implemented approach
  - Clustering algorithm to group similar ATUS occupancy patterns
  - Markov Chain simulations for occupancy status and major activities
  - Modification of lighting and misc. electric load schedules based on household occupancy
  - Integrated duration and flow rate sampling for hot water related activities
- Validated Markov Chain simulation outputs against input probability distributions
- Integrated approach into ResStock
  - Developed OpenStudio measure to generate schedule on the fly
  - Modified ResStock OpenStudio measures to use new schedules

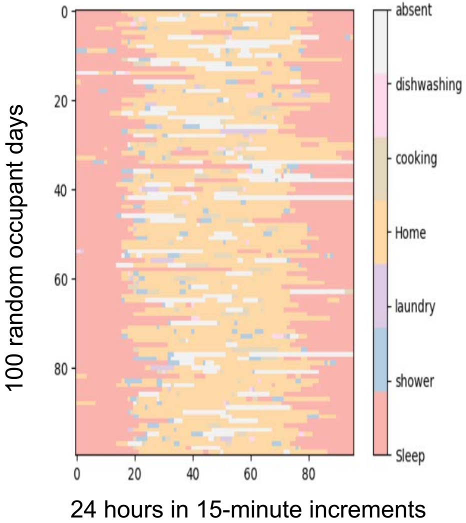
Overview of Approach

Overview of Approach

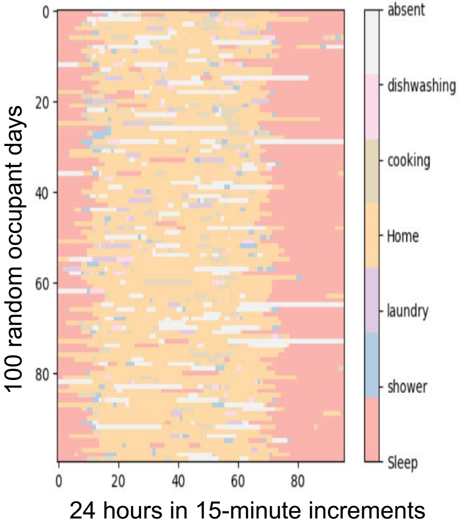
1. For a given household, randomly select occupant patterns for each member from available clusters (weekdays and weekends separately)



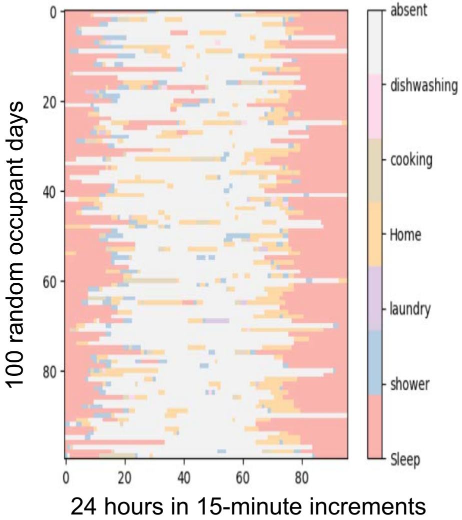
Pattern 1 – mostly at home



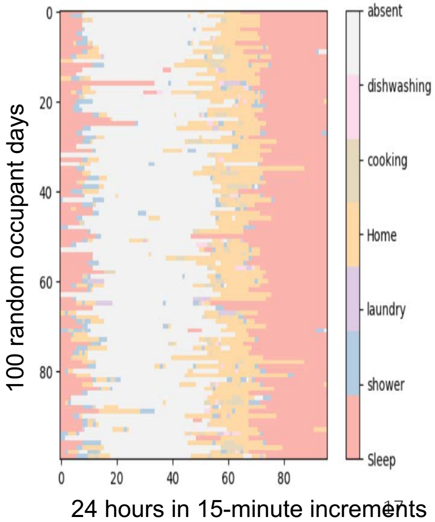
Pattern 2 – mostly at home, early wake-up



Pattern 3 – Mostly Away



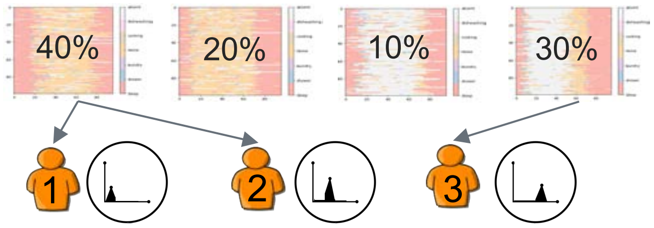
Pattern 4 – Daytime Worker



Overview of Approach

1. For a given household, randomly select occupant patterns for each member from available clusters (weekdays and weekends separately)

2. For each day, generate activity schedules for each occupant (occupant-level activities)



Overview of Approach

1. For a given household, randomly select occupant patterns for each member from available clusters (weekdays and weekends separately)

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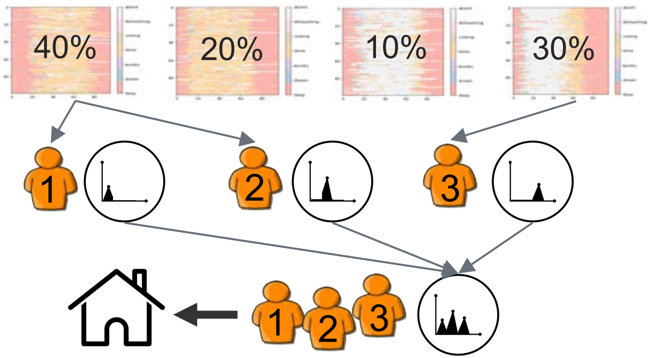
3. Merge activity patterns for occupants into household schedules



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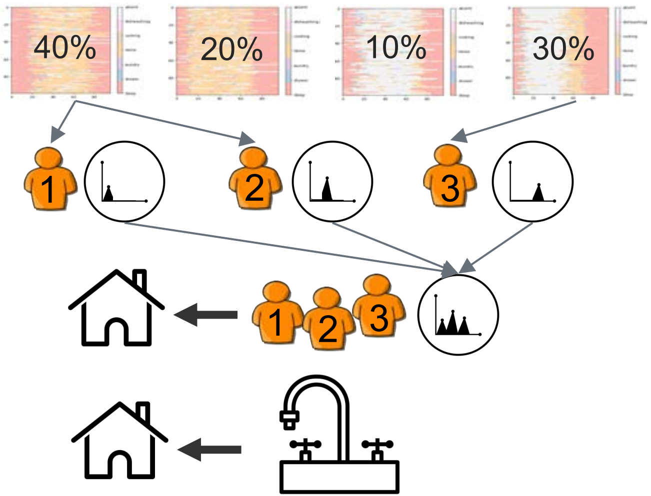
4. Generate schedules for household-level events (sink hot water draws)



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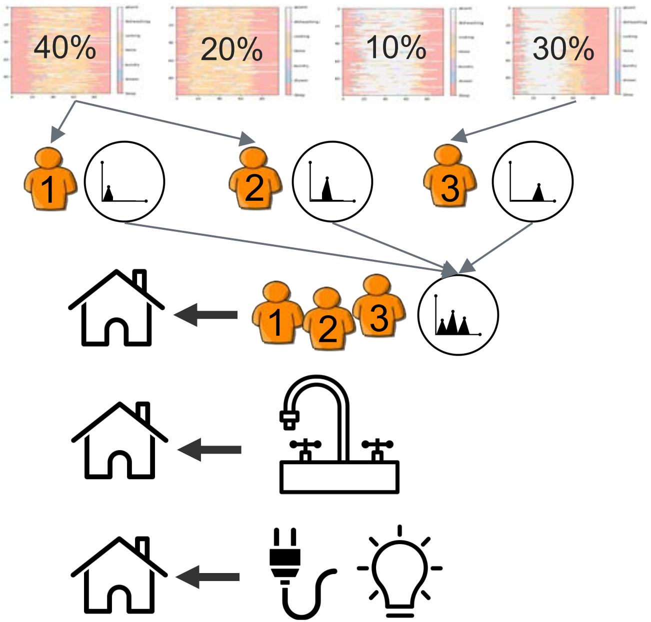
4. Generate schedules for household-level events (sink hot water draws)

5. Modify lighting and misc. plug load schedules to account for household-level occupancy status



Overview of Approach

1. For a given household, randomly select occupant patterns for each member from available clusters (weekdays and weekends separately)

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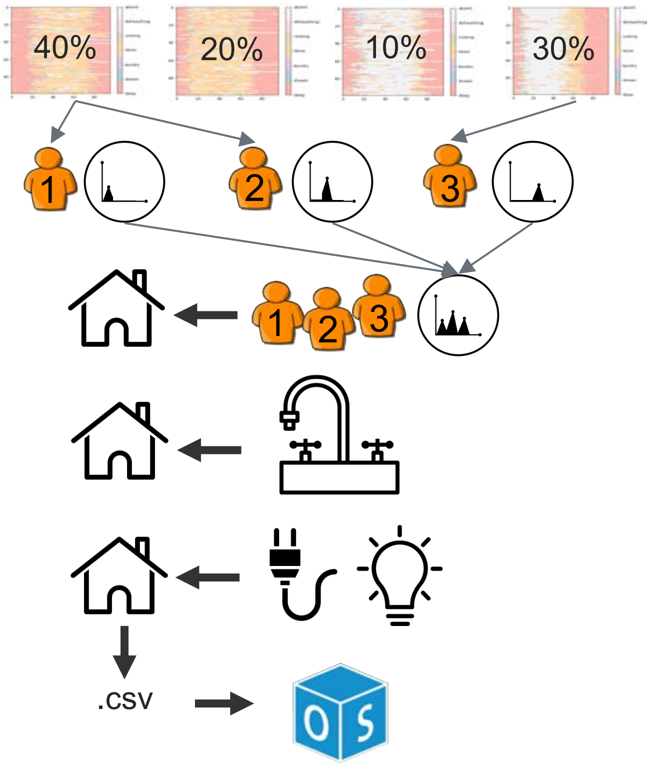
3. Merge activity patterns for occupants into household schedules

4. Generate schedules for household-level events (sink hot water draws)

5. Modify lighting and misc. plug load schedules to account for household-level occupancy status

6. Export all schedules to .csv file read by OpenStudio objects



Steps happen on-the-fly for each OpenStudio simulation

Sample Results

Sample Results

ResStock results demonstrating the new stochastic schedule generation approach are compared to previous results for:

- 1 example home
- 1000 homes aggregated
- Typical week (e.g., Jan 1 – Jan 7)
- Average week (average of all Sundays in a year, etc.)

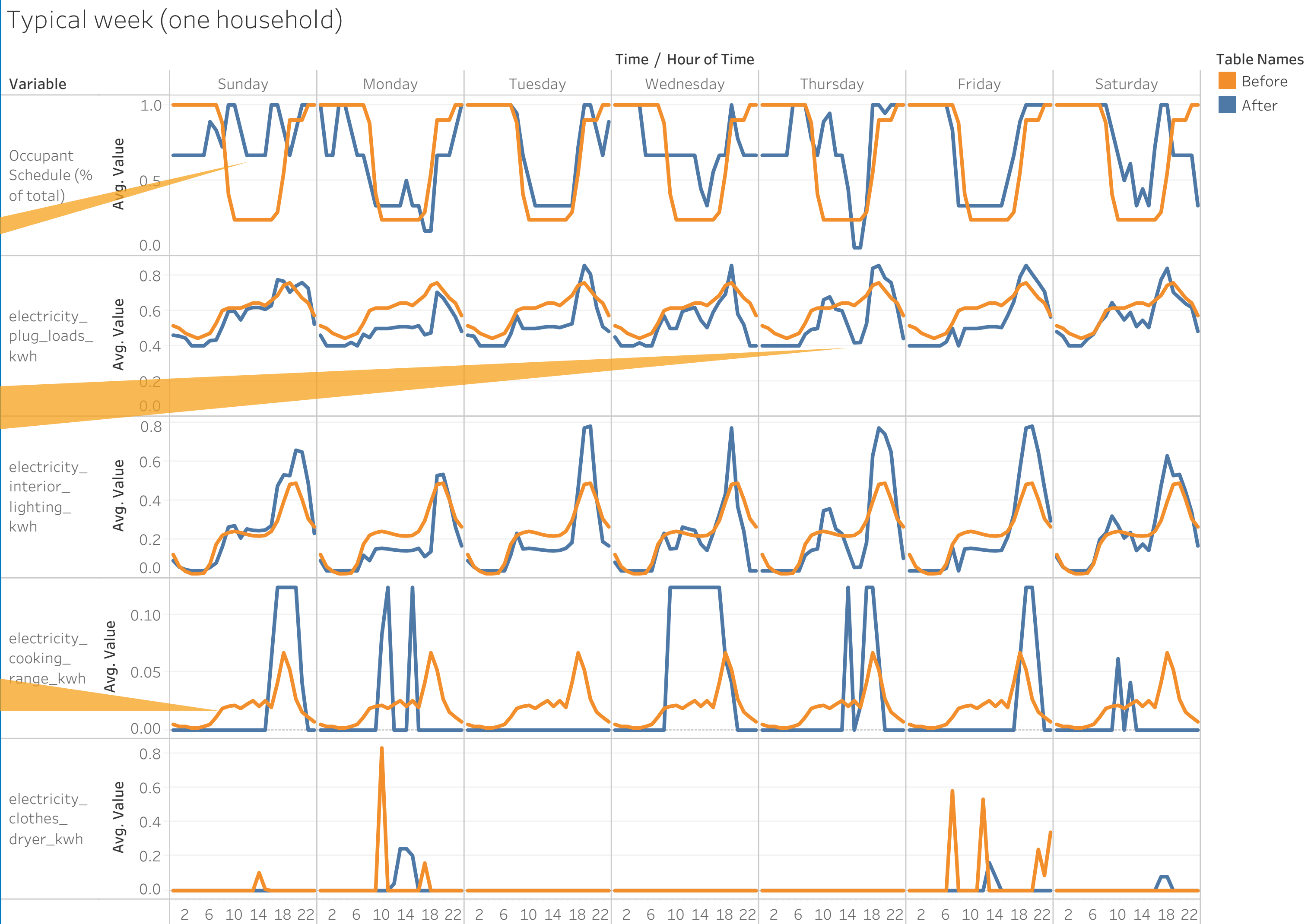
Example hot water schedules are also shown

1 home
Typical week

Occupancy now changes day to day

Plug loads and lighting are lowered to minimum value when occupants are away or sleeping

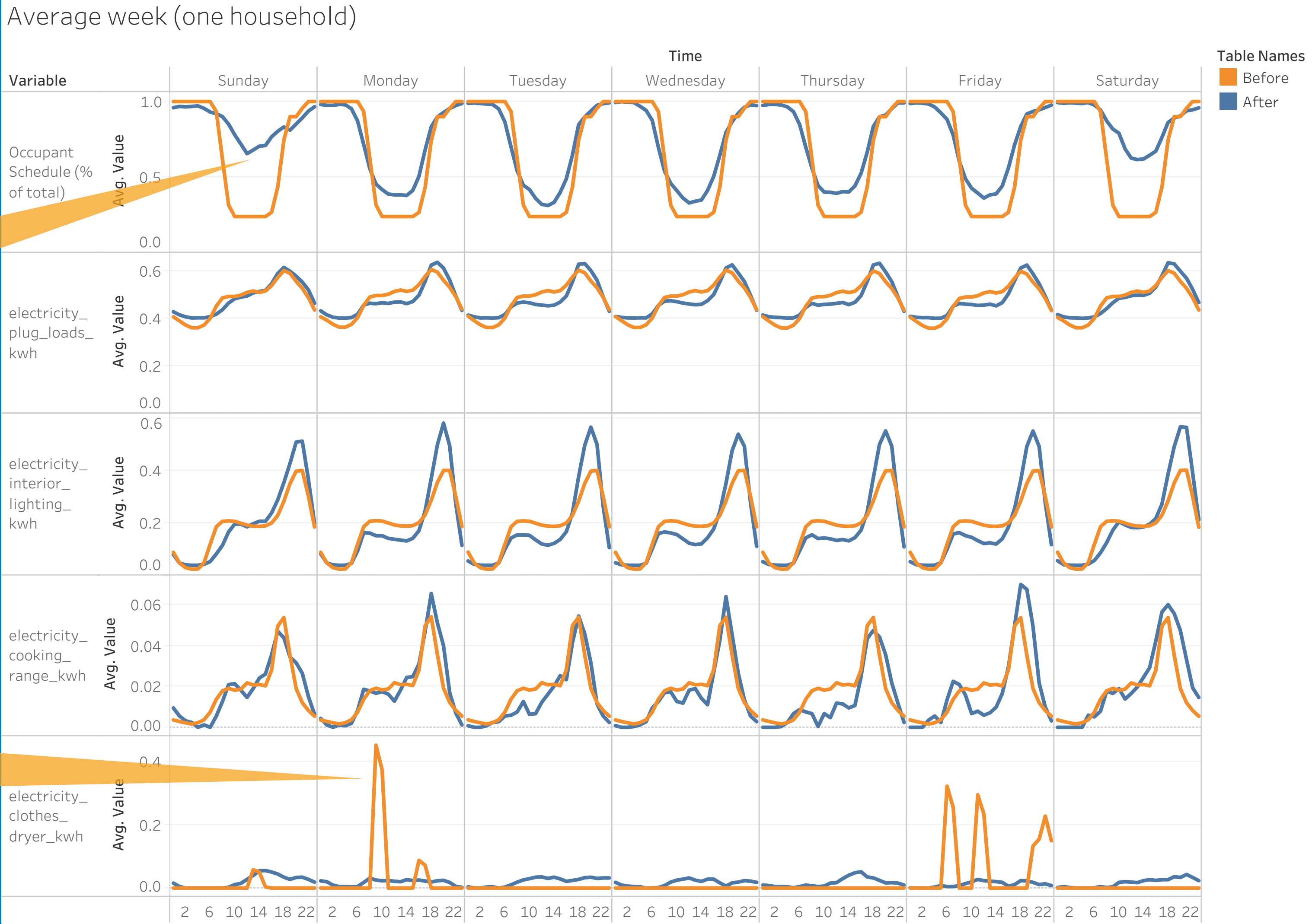
Previously, cooking range was identical day-to-day



1 home
Average week

Saturday and Sunday have higher % occupancy for this particular household

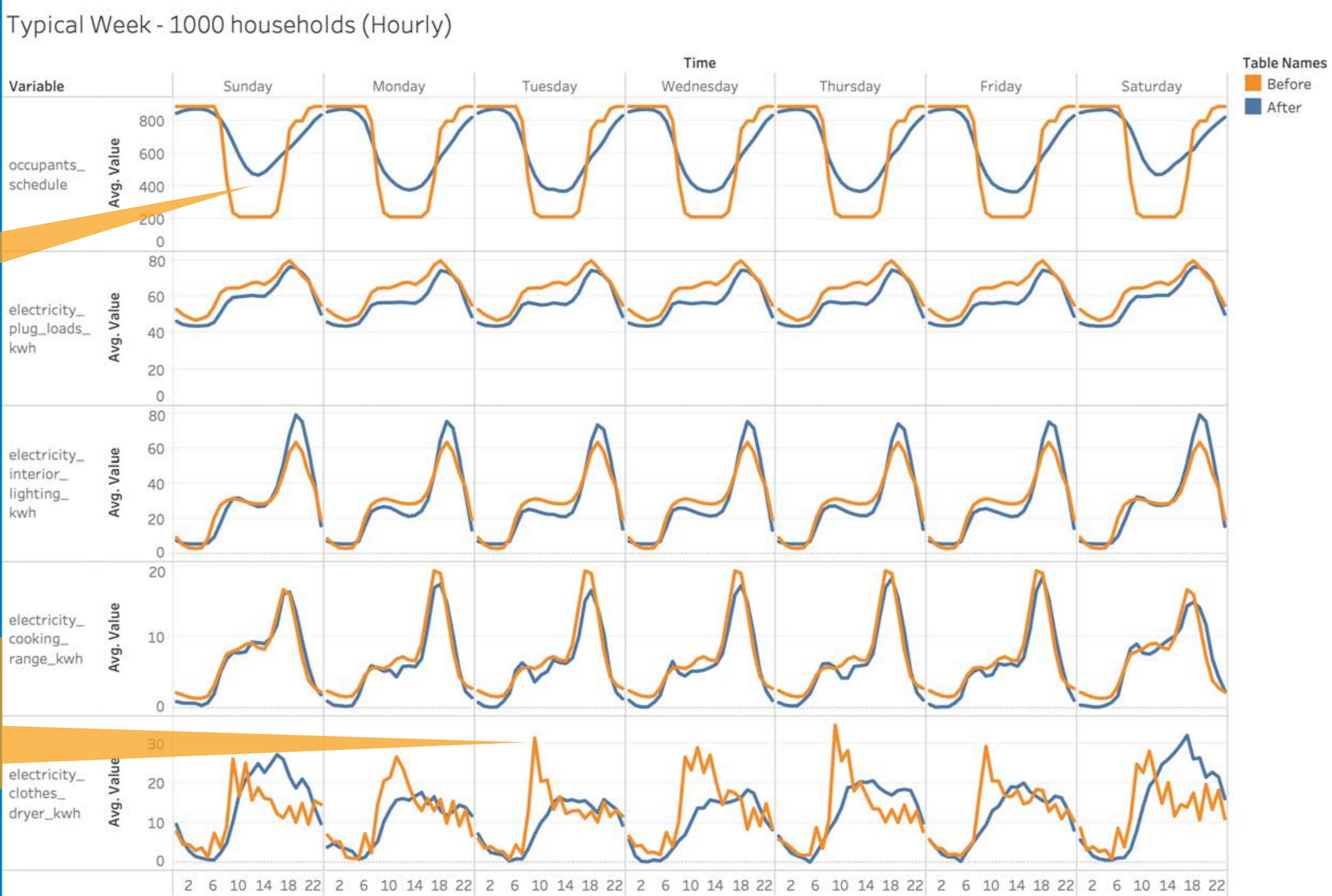
Previous clothes dryer schedule repeated each week



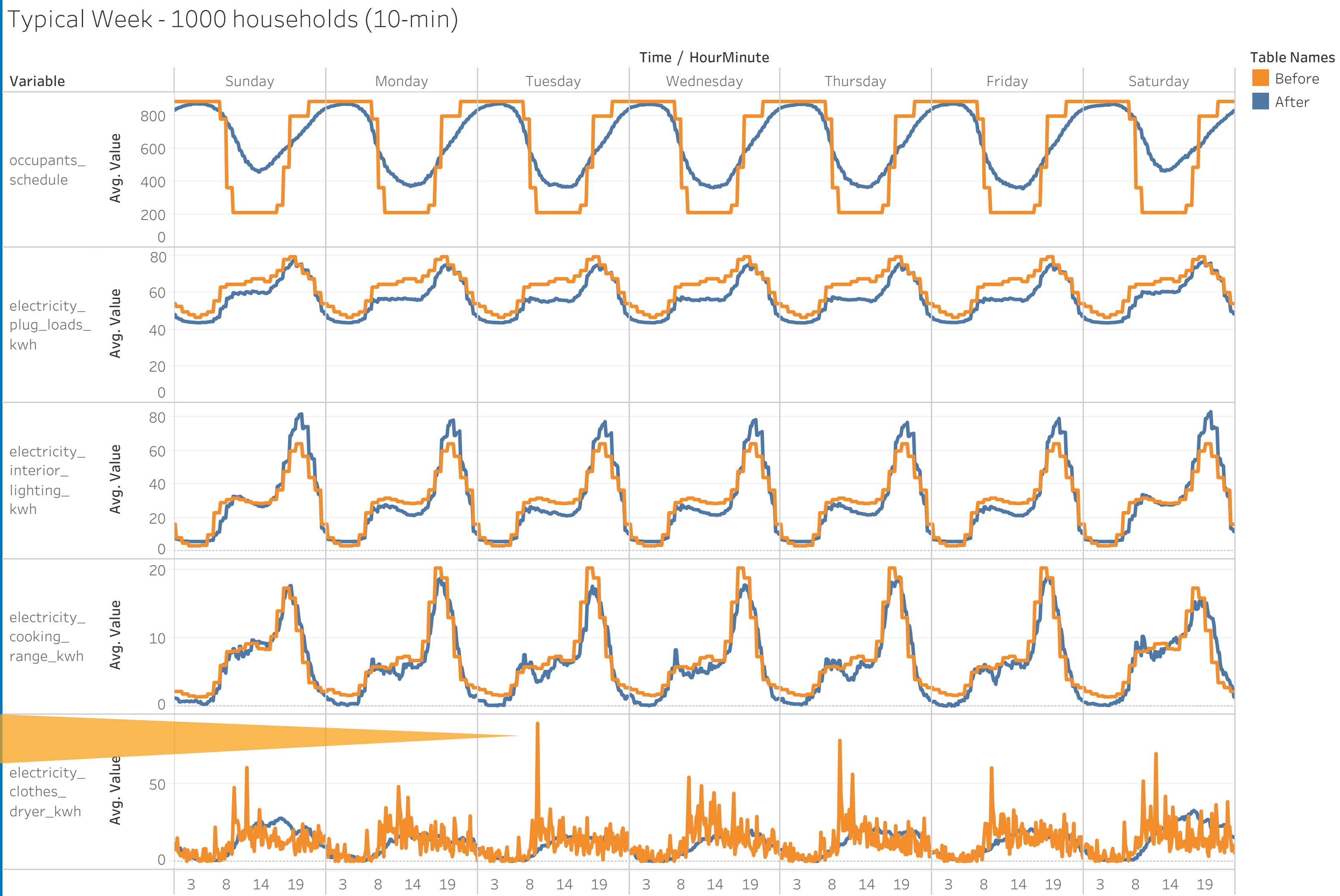
1000 homes Typical week

Greater diversity in occupancy patterns across 1000 homes

Spikiness indicates there was previously insufficient diversity to smooth out clothes dryer load



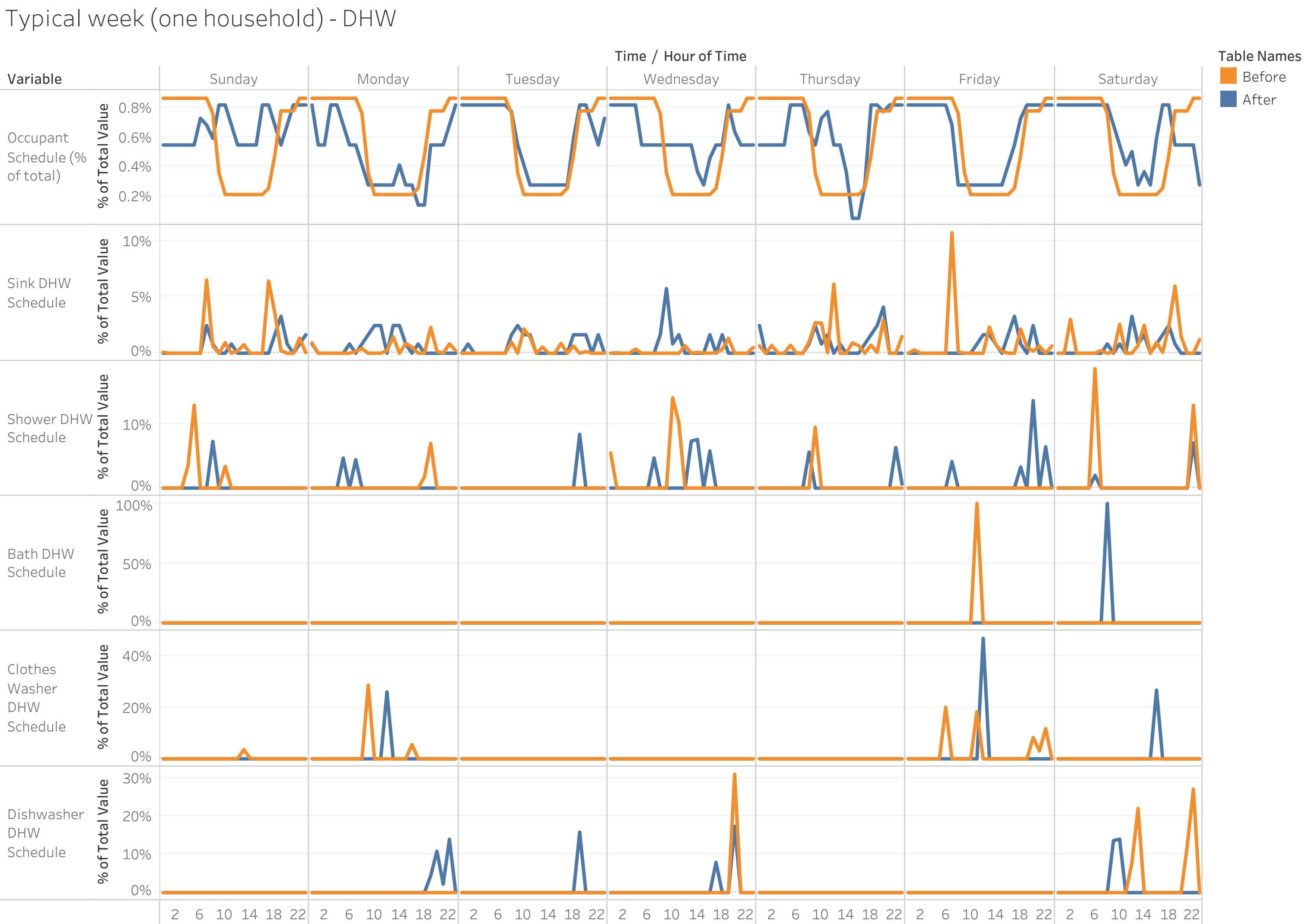
1000 homes Typical week 10-minute resolution



Previously, using subhourly resolution exacerbated spikiness dramatically, due to insufficient diversity

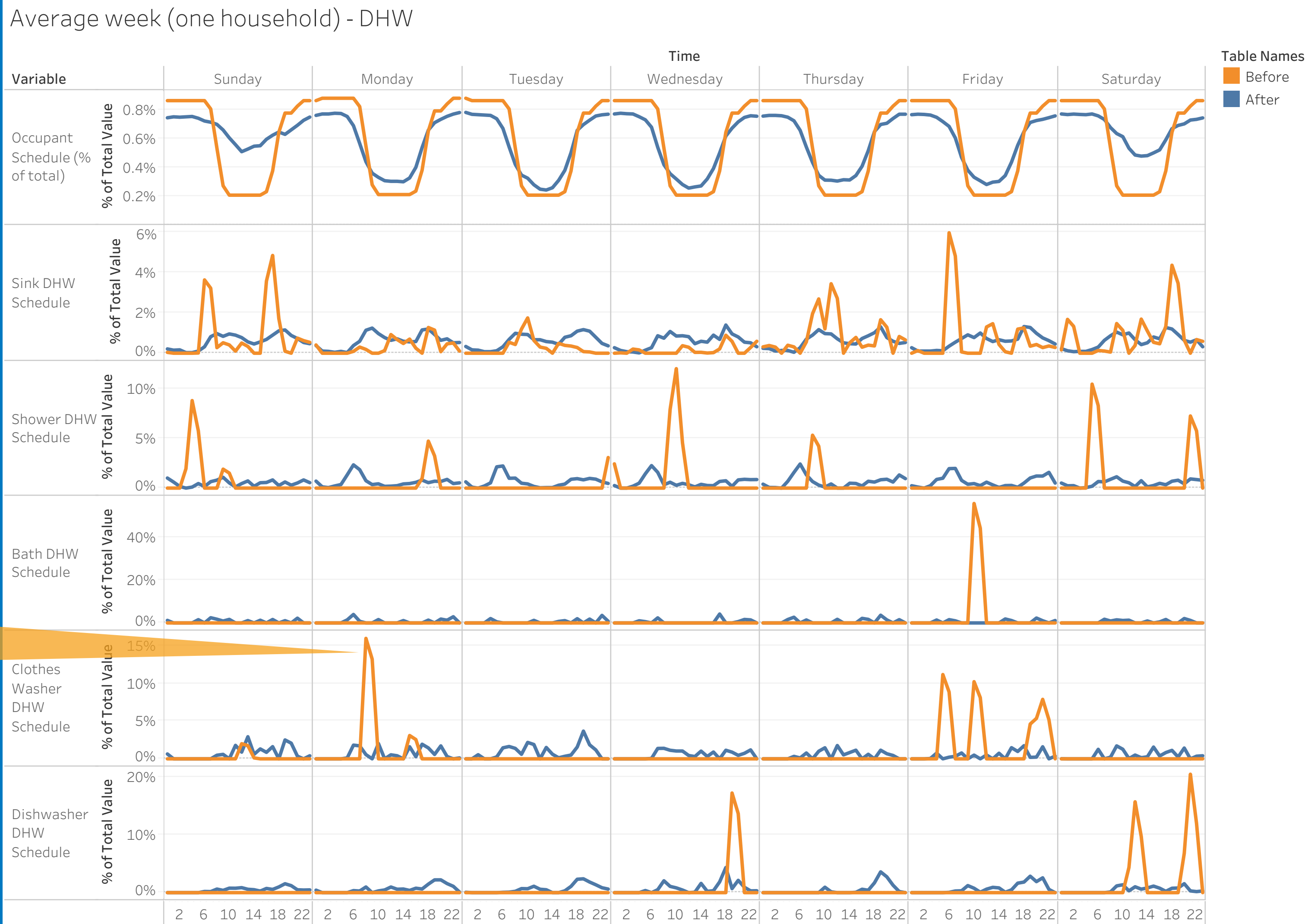
Hot water schedules

1 home
Typical week



Hot water schedules

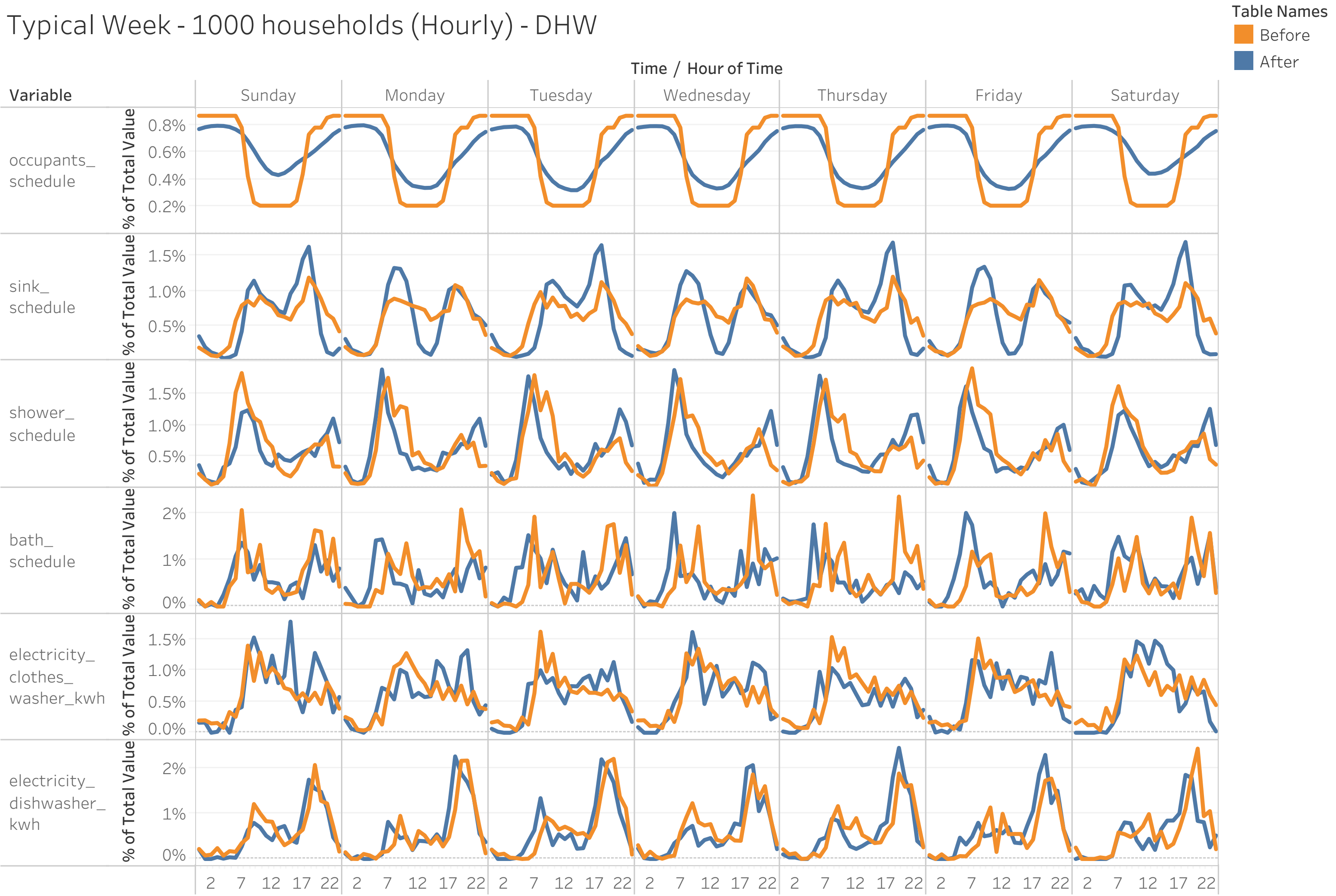
1 home
Average week



Previously, all hot water schedules repeated each week

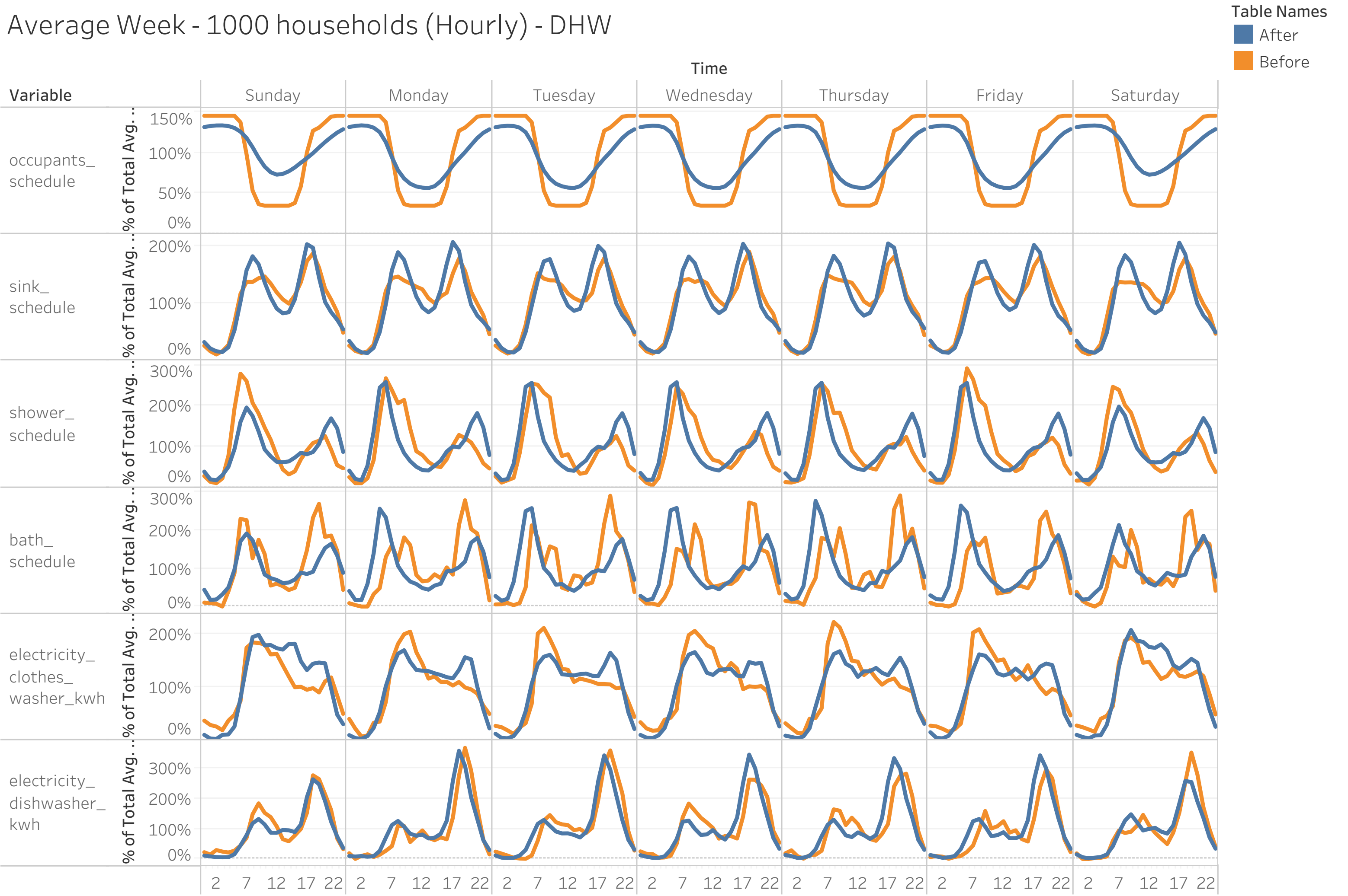
Hot water schedules

1000 homes Typical week



Hot water schedules

1000 homes Average week



Steps for ongoing improvement

- Continue to make improvements, such as:
  - Align thermostat schedules with occupancy
  - Incorporate demographic variables (age, employment status, etc.) for ATUS clustering
  - Refine clustering algorithm and number of clusters to achieve more realistic day-to-day variability

Breakout: Residential Stochastic Occupancy

Objective: Understand if the enhancements to modeling occupant-driven loads for individual households provide the needed level of fidelity for users' applications.

Breakout: Residential Stochastic Occupancy

- What additional information do you need to decide if the enhancements will meet your needs?
- Are there additional features that are necessary for your application of individual household load profiles?
- What time resolution do you think is necessary for your application?
- How important is it to have realistic day-to-day variation/repetition for individual household load profiles
- How important do you think it is to reflect variation in occupant energy use patterns from region to region?
- Do you think this variation can be accomplished by correlating behavior to demographic variables like employment status, age, education, income level?
- How important do you think it is to correlate occupant behavior to other housing characteristics that affect energy use like home floor area and vintage?

NREL
Transforming ENERGY

Load Profile Output Formats

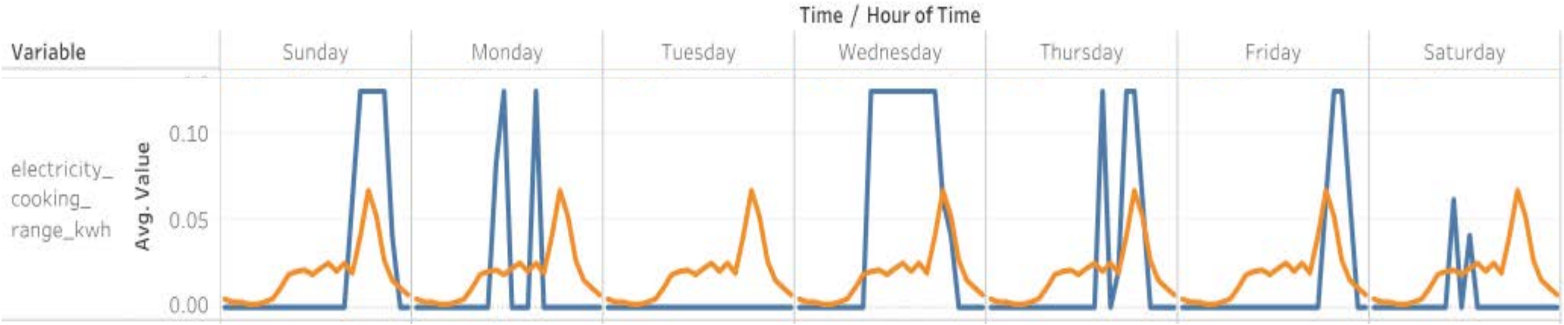
EULP Technical Advisory Group Presentation
May 26, 2020

Andrew Parker

End Use Load Profile Types

Individual building: one building; spiky and variable day-to-day

Aggregate: sum of many buildings; smooth, building-level variability disappears



What is the output of this project?

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

- Aggregate and individual building
- 15 minute time resolution for 1 year
- Calibrated
- Covers the whole U.S.

Working List of End Uses

Commercial

- HVAC
  - Heating
  - Cooling
  - Fans
  - Pumps
  - Heat rejection
  - Humidification
  - Heat recovery
- Service water heating
- Refrigeration
- Plug and process loads
- Lighting
  - Interior
  - Exterior

Residential

- HVAC
  - Heating
  - Cooling
  - Furnace/Air-conditioning
  - Boiler pumps
  - Ventilation fans
- Domestic water heating
- Major appliances
  - Refrigerator
  - Clothes washer
  - Clothes dryer
  - Dishwasher
  - Cooking range
  - Pool/spa pumps & heaters
- Miscellaneous plug loads
- Lighting
  - Interior
  - Exterior

Working List of Building Types

Commercial

- Small Office
- Medium Office
- Large Office
- Stand-alone Retail
- Strip Mall
- Primary School
- Secondary School
- Outpatient Healthcare
- Hospital
- Small Hotel
- Large Hotel
- Warehouse (non-ref.)
- Quick Service Restaurant
- Full Service Restaurant
- Supermarket
- Mid-rise Apartment
- High-rise Apartment

Residential

- Single-Family Detached
- Single-Family Attached
- Multifamily low-rise

Raw Data for One Building Model

Individual building: one building; spiky and variable day-to-day

1 residential model

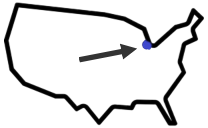
- 14 end-uses x 8,760 hrs/yr x 4 values/hr = 490,560 values
- ~7MB in optimized format

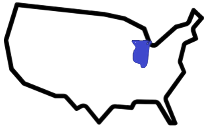
1 commercial model

- 13 end-uses x 8,760 hrs/yr x 4 values/hr = 455,520 values
- ~7MB in optimized format

Building Models per Geography

1 building model = x 1

City/CBSA*  = x ~1,000’s

State  = x ~10,000’s

Region  = x 800,000

*Core-Based Statistical Area

Raw Dataset: Individual Building Models for Nation

Individual building: one building; spiky and variable day-to-day

1 national-scale run of ResStock
- 450,000 dwelling units simulated
- 2.3 TB (timeseries data and separate tabular metadata file)

1 national-scale run of ComStock
- 350,000 buildings simulated
- 2 TB (timeseries data and separate tabular metadata file)

Pros: Aggregate any way you need to answer specific questions
Cons: Requires significant time, expertise, and computing to analyze

Representative Individual Building Profiles

Individual building: one building; spiky and variable day-to-day

For each region:

- Publish a smaller set of “representative” individual building load profiles
- Goal: enable realistic use of data on a personal computer using basic data analysis (Excel, python, etc.)
- How many models per region? 10, 100, 1000?

Pros: Can use like current profiles (from OpenEI, DOE Prototypes, etc.)
Cons: By definition, data is only a subset

Proposed Aggregations

Aggregate: sum of many buildings; smooth, building-level variability disappears

Publish most broadly useful pre-aggregated datasets

Sum of all buildings, split by

- Geography AND
- Building type AND
- Others? (building age, fuel type, floor area?)

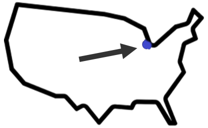
Pros: More splits = more analysis flexibility

Cons: Larger files, harder to use

Proposed Geographies

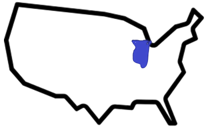
Rationale:

City/CBSA*



Cities are driving energy policy

State



Useful for national-level policy

Region

Useful for electrical planning.
Probably align w/ grid operations?

Others?

individual utility territories? Maybe for largest? - ill-defined

*Core-Based Statistical Area

Demo: VizStock web data viewer

Proposed Output – Aggregate Load Profiles

General use, quick understanding of aggregate profiles:

- Aggregate profile datasets for each geography published on web viewer – can sort/filter and download

Simplified analysis based on aggregate profiles:

- Downloadable in CSV format for ease of use in Excel.

Proposed Output – Individual Load Profiles

General use:

- Set of “representative” individual profiles for each region

Advanced analysis/research:

- Full individual building dataset available for download
- Likely a series of parquet files, expect multiple TB
- Requires advanced computing & big data skills to use

Building Energy Models – Useful to You?

Individual building: one building; spiky and variable day-to-day

1. Are building models (OpenStudio format) useful?

2. Would a subset of “typical” models be useful?

3. Would the full set of 800,000 models be useful?

Proposed Output – Energy Models

What-if scenario analysis:

- Publish a set of “typical” models for each region

Polling Question

Discussion Questions

Discussion Questions

1. Does the web viewer look like it will meet most of your needs?
2. Who would most likely be doing data analysis for you? Engineers, IT people, specialized data analysts, etc.?
3. What data analysis tools/processes do you typically use?
4. Do you have staff with big data experience?
5. Do you have a preference for file format (CSV, database, parquet, etc.)
6. Do you have experience dealing with datasets of 100's of GBs (bigger than a normal desktop/laptop can handle)
7. Are individual model (one building) level results useful to you?
8. Are the raw energy models (EnergyPlus IDF, OpenStudio OSM) files useful to you? The whole dataset will be 100's of thousands of models. If you had them, do you have the compute resources and skillsets necessary to run at that scale?

Discussion Questions

The full dataset of individual building/household end-use load profiles for ~1 million representative models will likely be larger than 1 TB (typical size of a laptop hard drive).

9. Would you find it useful to be able to download this these individual profiles as one large dataset? For individual weather station locations?

10. Would you find it useful to have the full dataset aggregated into diversified average profiles by building type and location? Would these average profiles be useful for any other parameters (building vintage, heating fuel type, floor area, etc.)?

11. Would you find it useful to have the full dataset filtered down to a reduced set of individual building/household profiles per building type and location? How many buildings/household would be desirable and manageable in this reduced set? 1, 3, 10 per building type and location?

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