



# DOE/BPA Load Composition Analysis

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DOE Dynamic Load Modeling  
Workshop

23 March 2020

David Chassin (SLAC), Tony Faris (BPA),  
and Joe Eto (LBNL)

## Overview

1. Update on data, methods, and preparation of CLM feeder models
2. Summary of next steps in support of NERC LMTF and WECC MVS





# Load Composition Analysis

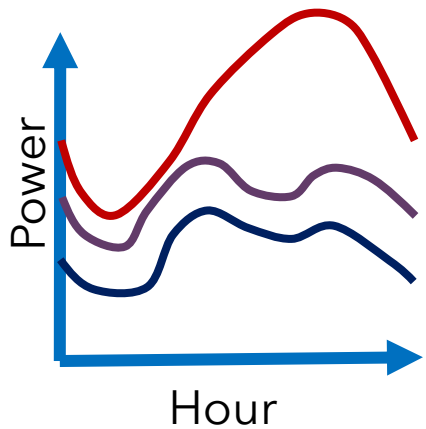
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## Support NERC LMTF

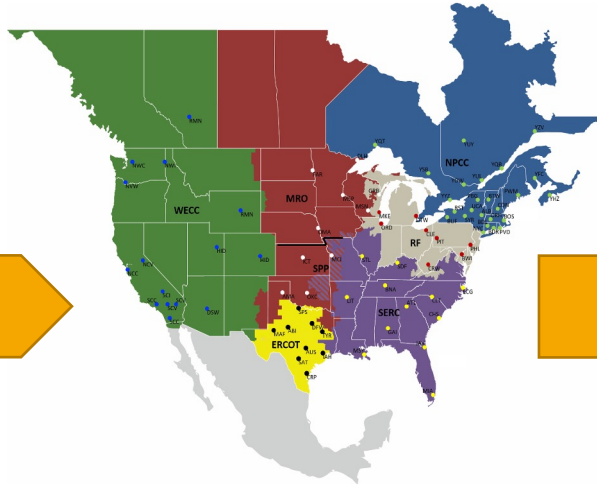
- Fields tests of Composite Load Model (CLM)
- Collaboration to prepare non-industrial feeder models
- Focus on Eastern Interconnection and Texas

# Load Composition Analysis: 4-step process

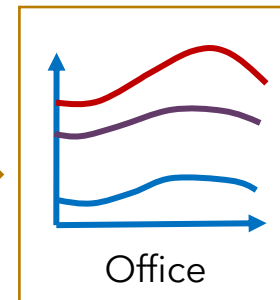
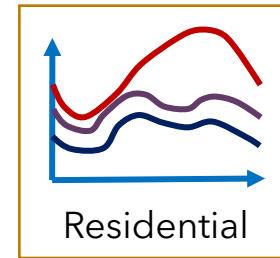
(1)  
**End-use Load Data**



(2)  
**Regional Loadshapes**



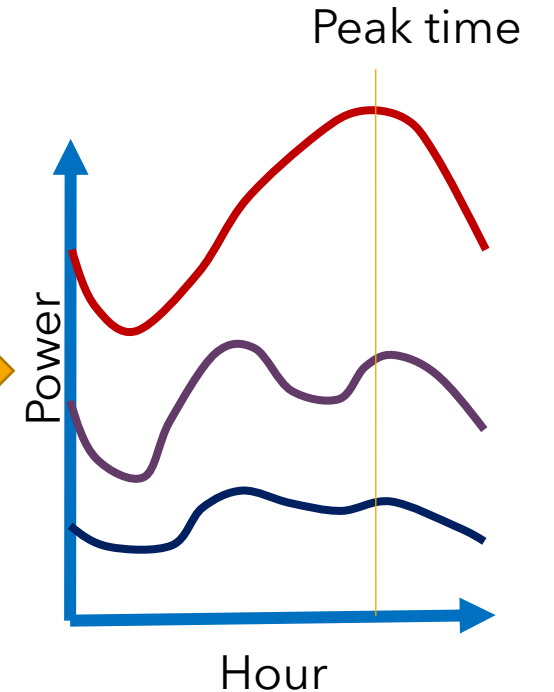
(3)  
**Economic Loadshapes**



⋮

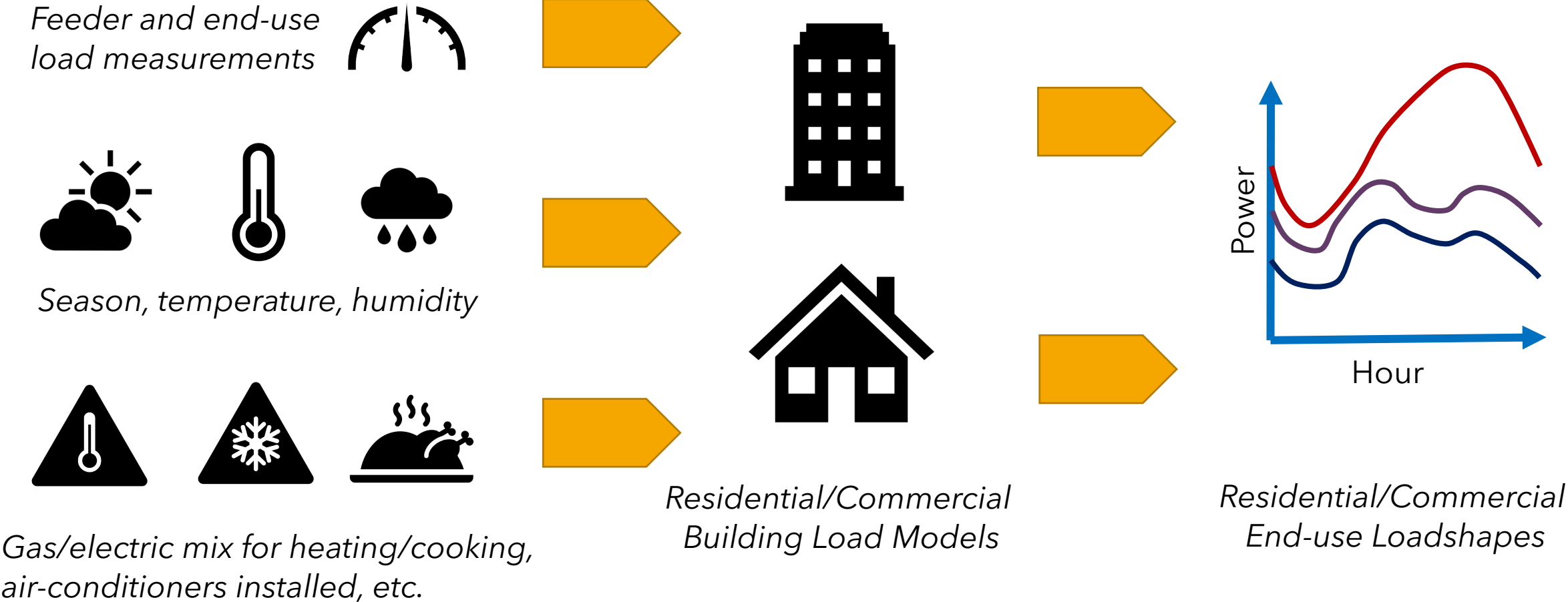


(4)  
**Load Components**



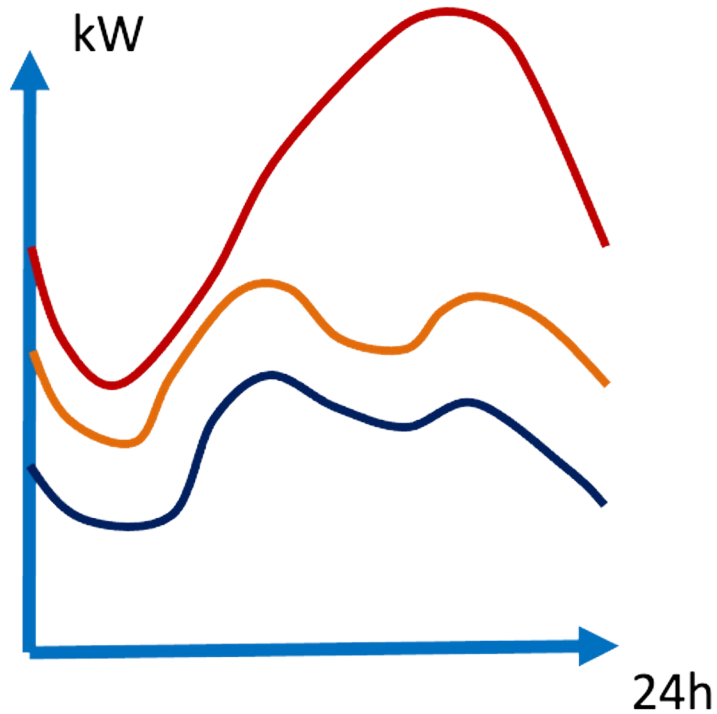
# Load Composition Analysis Step 1

## Identify end-use loadshapes for common building types

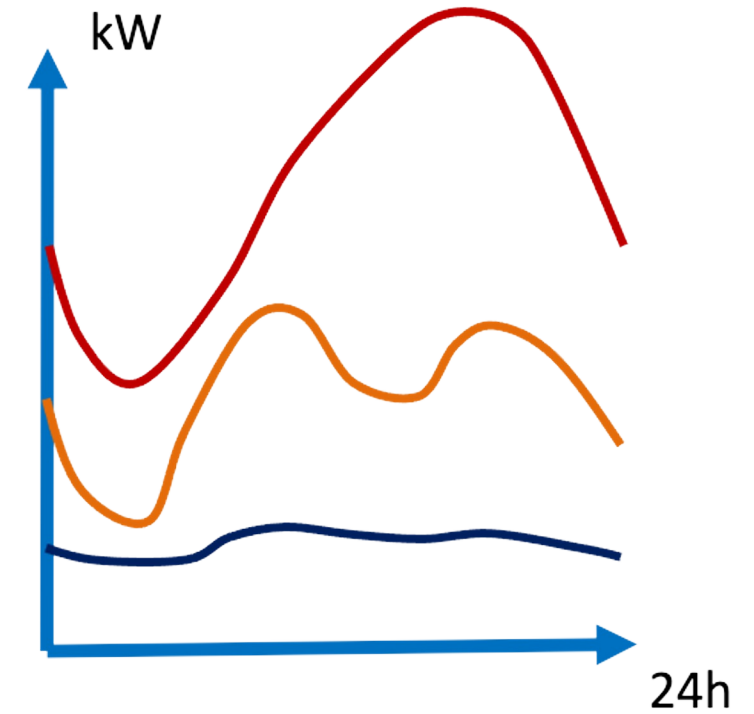
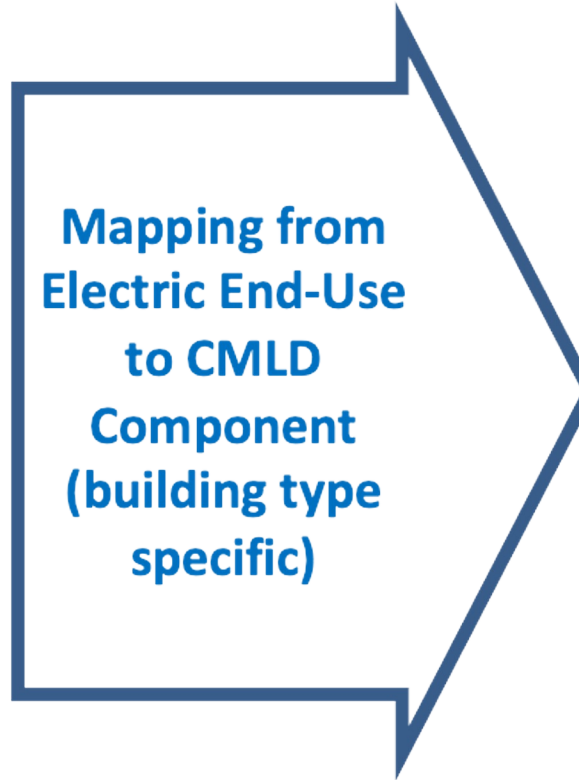




# Load Composition Analysis Step 3

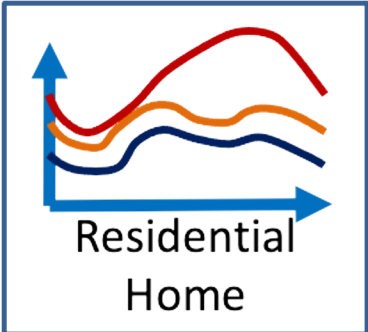


Load Shapes in Terms of End-Uses  
(Air-Conditioning, Water Heating, Refrigeration, ...)



Load Shapes in Terms of CMLD Components  
(Motor A, Motor B, ..., Power Electronic )

# Load Composition Analysis Step 4



*X % Residential*

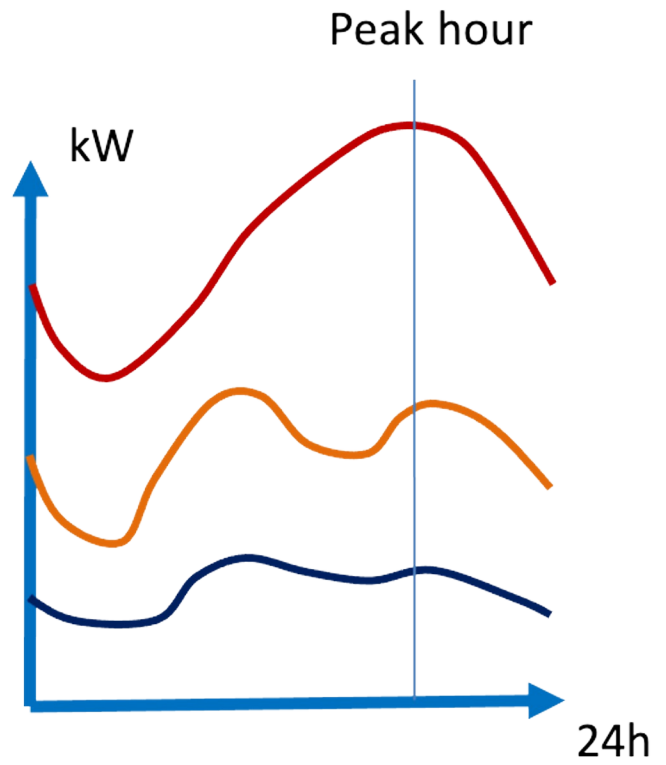


*X % Grocery*

...



*X % Office*



# Four Standard "Economic" Feeder Types

RES - suburban



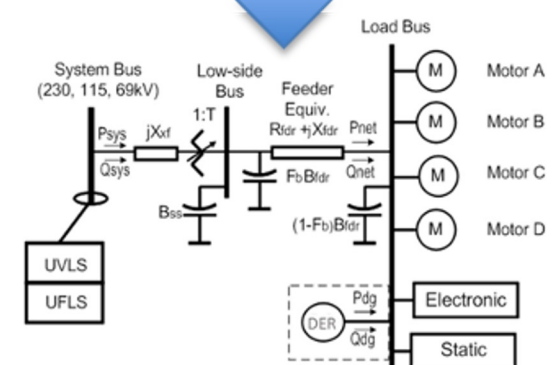
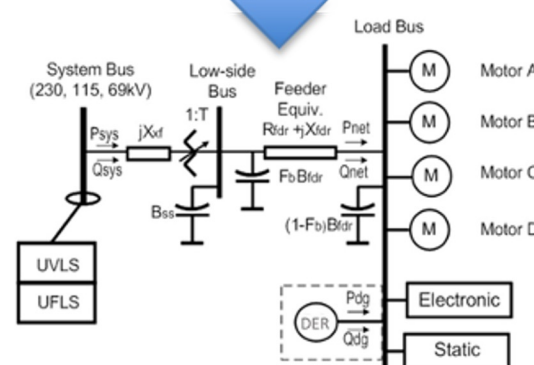
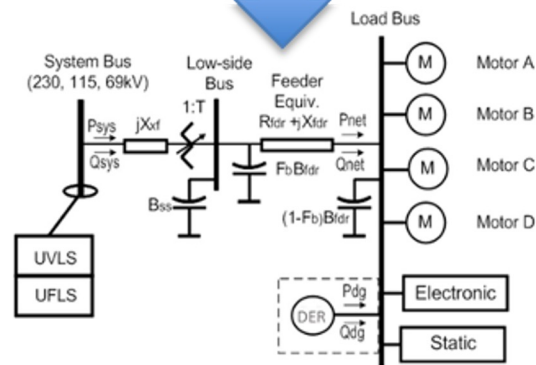
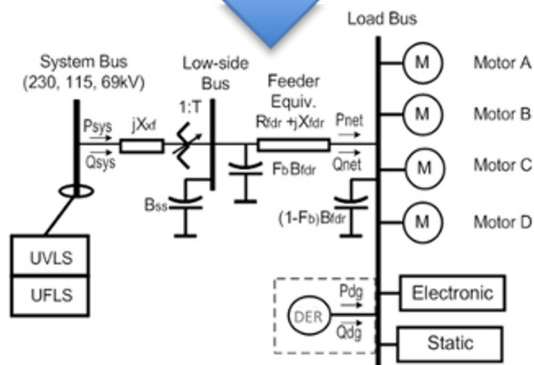
COM - urban



MIX



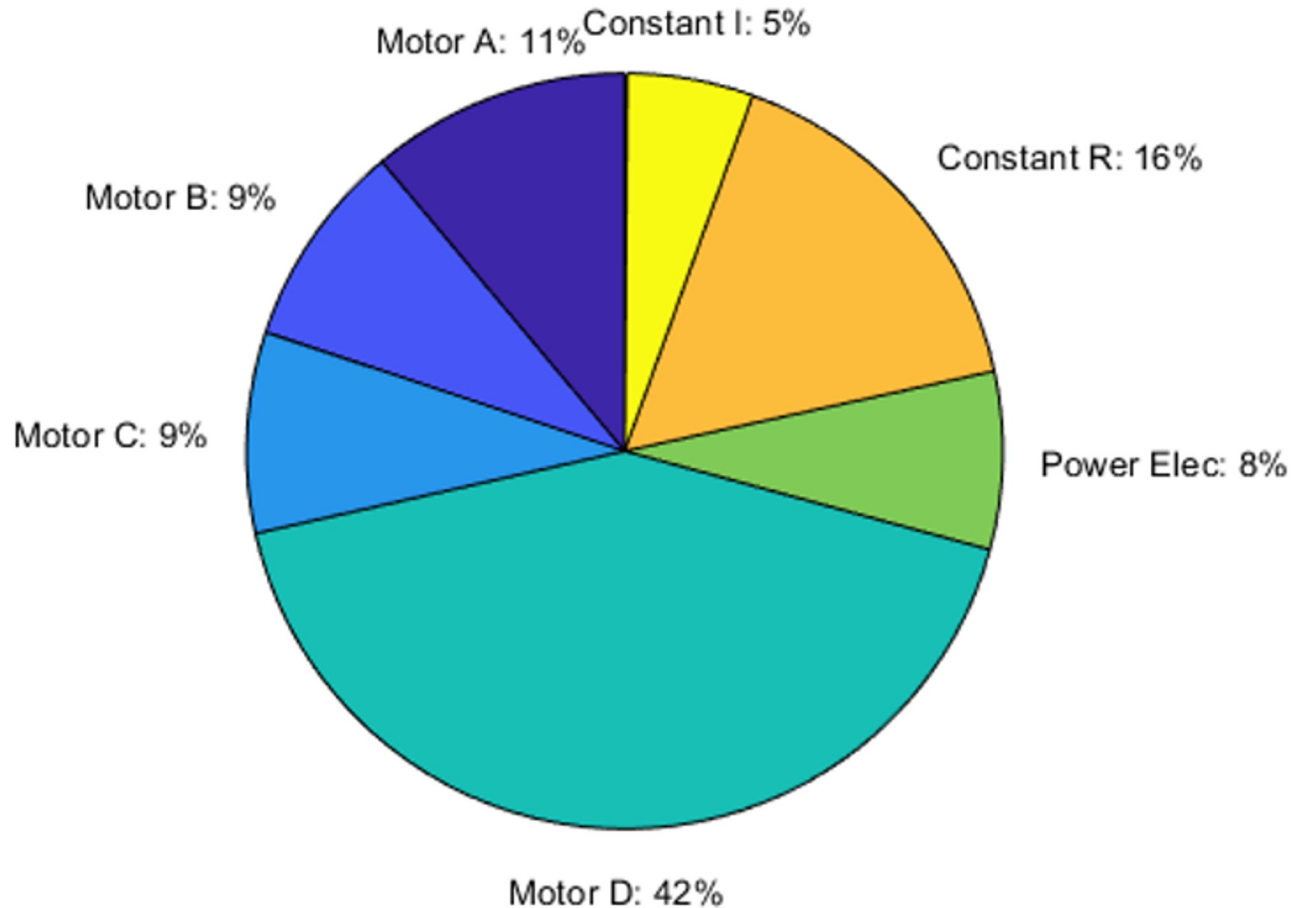
RAG - rural



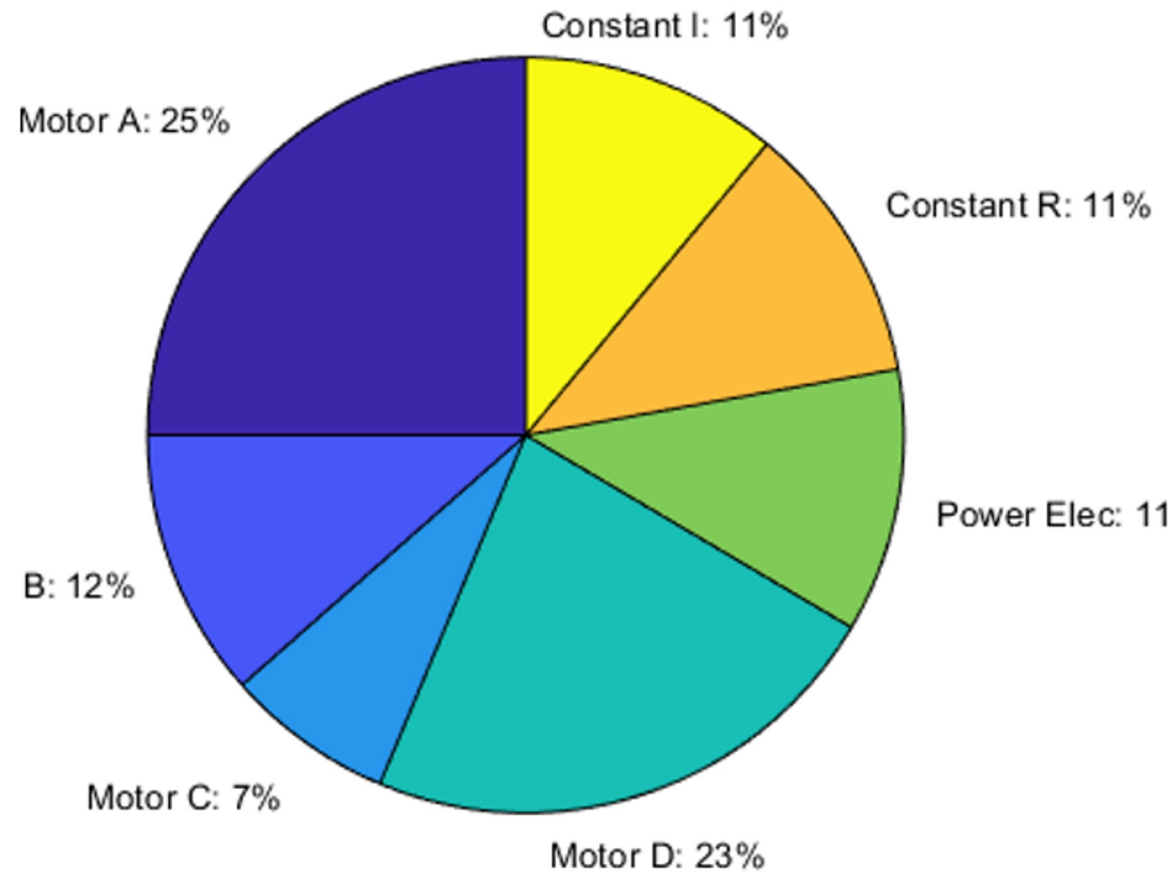


# Example Result - Phoenix AZ Summer Peak CLM

Load Composition: PHX\_RES - Summer 4:00 pm



Load Composition: PHX\_MIX - Summer 4:00 pm



# Technical Documentation

## Provide technical support information

- Load composition analysis role in CLM
- Technical details on 4-step process
- Representative results of analysis



Electricity Markets & Policy  
Energy Analysis & Environmental Impacts Division  
Lawrence Berkeley National Laboratory

## Load Composition Analysis in Support of the NERC Load Modeling Task Force 2019-2020 Field Test of the Composite Load Model

Anthony Faris and Dmitry Kosterev<sup>1</sup>, Joseph H. Eto<sup>2</sup>, and Dave Chassin<sup>3</sup>

<sup>1</sup>Bonneville Power Administration

<sup>2</sup>Lawrence Berkeley National Laboratory

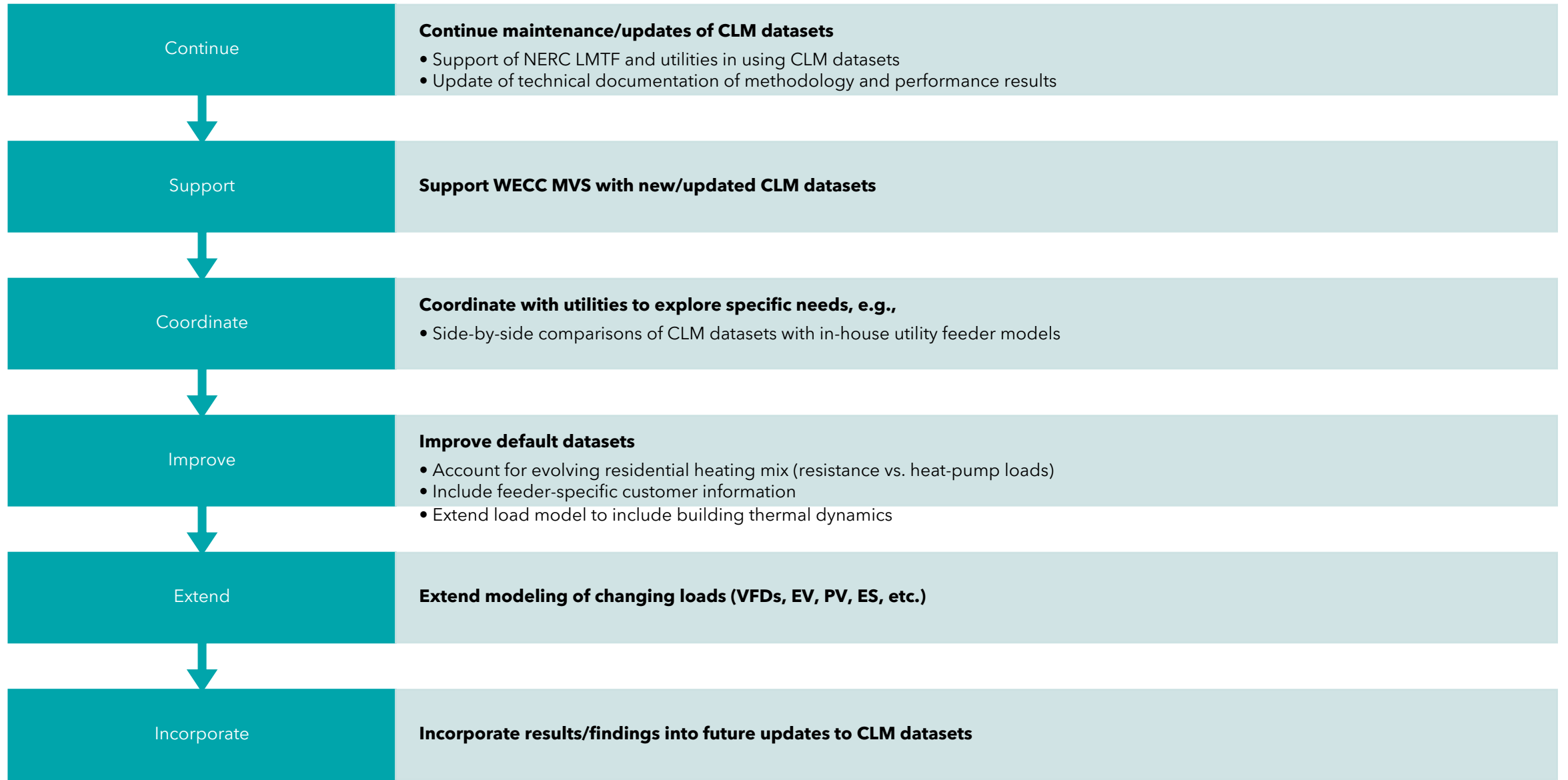
<sup>3</sup>Stanford Linear Accelerator Center

June 2020

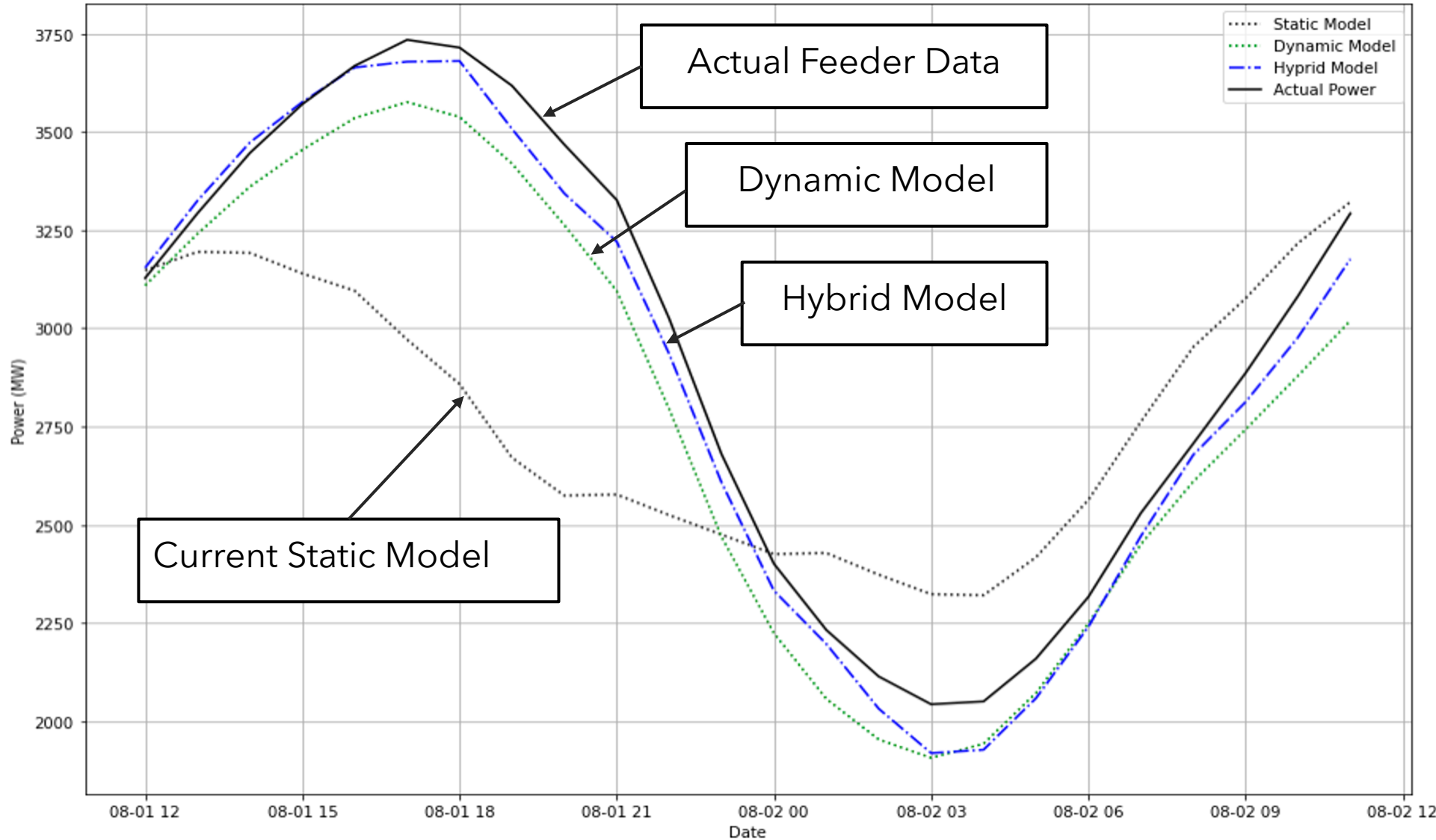


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# Next steps for Load Composition Team



# Enhanced load model: Capture salient building dynamics





# Thank you

Contact us:

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David Chassin ([dchassin@slac.stanford.edu](mailto:dchassin@slac.stanford.edu))

Tony Faris ([ajfaris@bpa.gov](mailto:ajfaris@bpa.gov))

Joe Eto ([jheto@lbl.gov](mailto:jheto@lbl.gov))

# Data-driven Building Load Modeling Methodology

**Problem: Predict load based on date, time, and weather based on historical feeder data**

Three approaches considered:

1. Static model (predict load based on current weather only)

$$\text{power} = F(\text{heat\_index}[0], \text{solar}[0])$$

2. Dynamic model (predict load based on recent weather and load)

$$\text{power} = G(\text{power}[1:N], \text{heat\_index}[0:N], \text{solar}[0:N])$$

3. Hybrid model (static model + dynamic residual model)

$$\text{power} = F(\text{heat\_index}[0], \text{solar}[0]) + G(\text{power}[1:N] - F(\text{heat\_index}[0], \text{solar}[0]), \text{heat\_index}[0:N], \text{solar}[0:N])$$

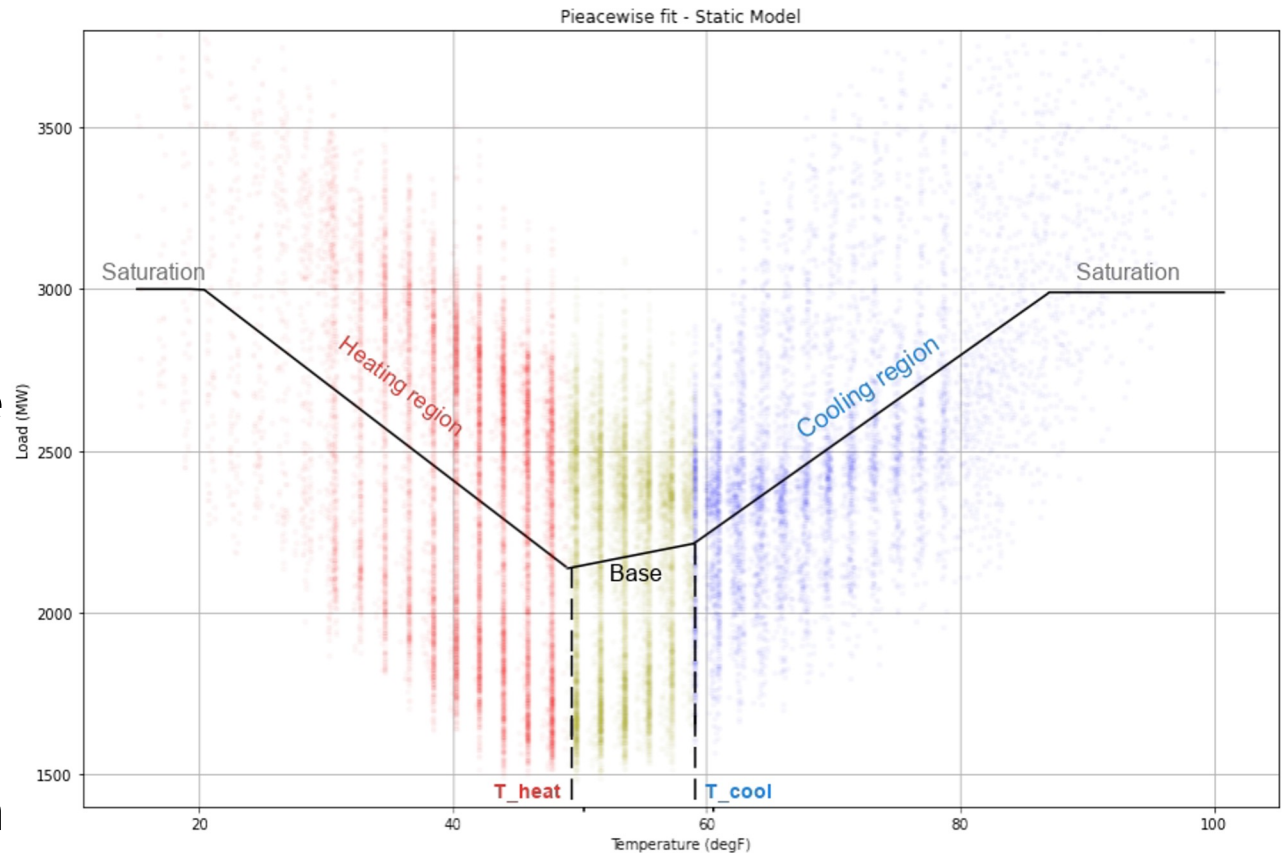
# Static Load Model

## Piecewise linear fit

- $F = \text{PWLF}(\text{heat\_index}, \text{power})$
- Five regimes
- Function of indoor temperature (heating, mixed, cooling)

## Temperature bins must be chosen

- Minimize slope of mixed region
- Temperature difference of 10 °F



# Dynamic Load Model

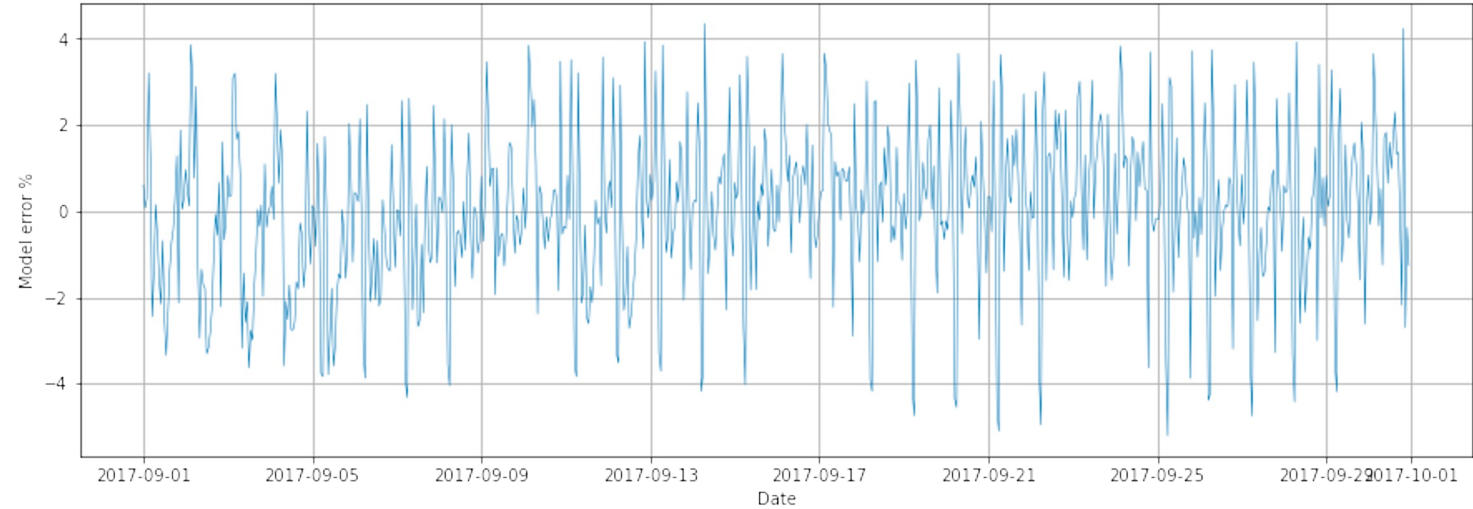
Discrete LTI transfer function

- $G = \text{LTIF}(\text{heat\_index}, \text{power})$
- Optionally add solar
- Features: hour, day, month

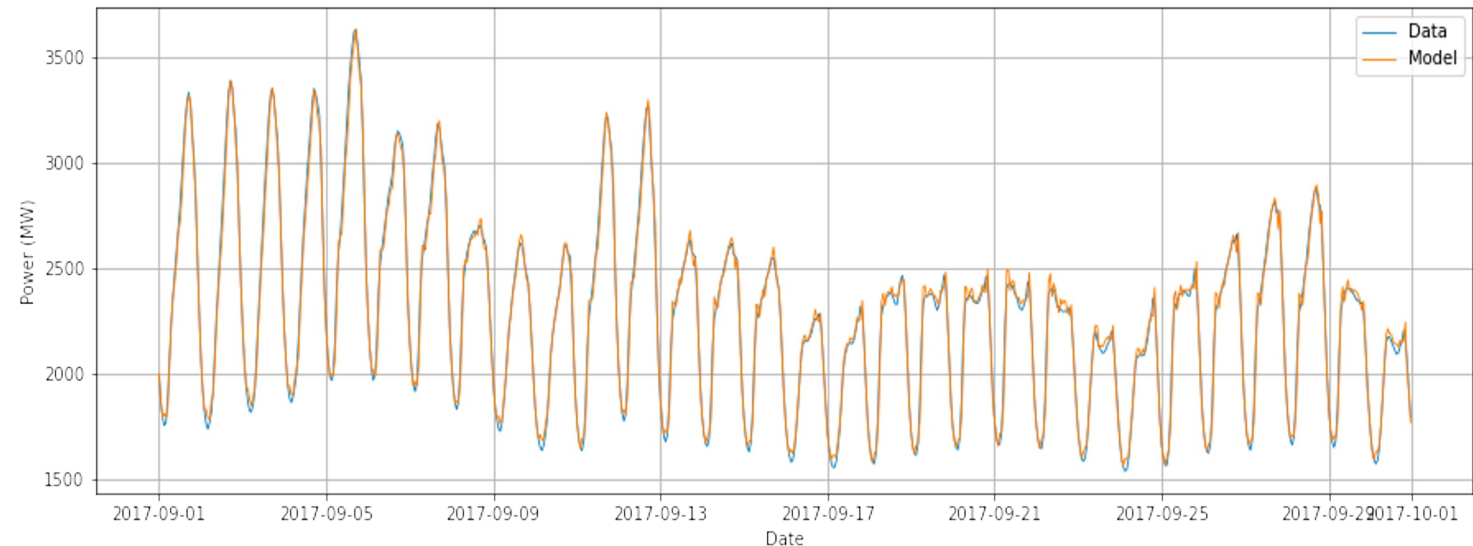
Model order N

- Minimizes RMSE
- Usually  $N \sim 24\text{h}$

Error plot (Dynamic Model)  
Mean of error = 1.3884%  
Stdev of error = 1.18



Power (Model vs Data)





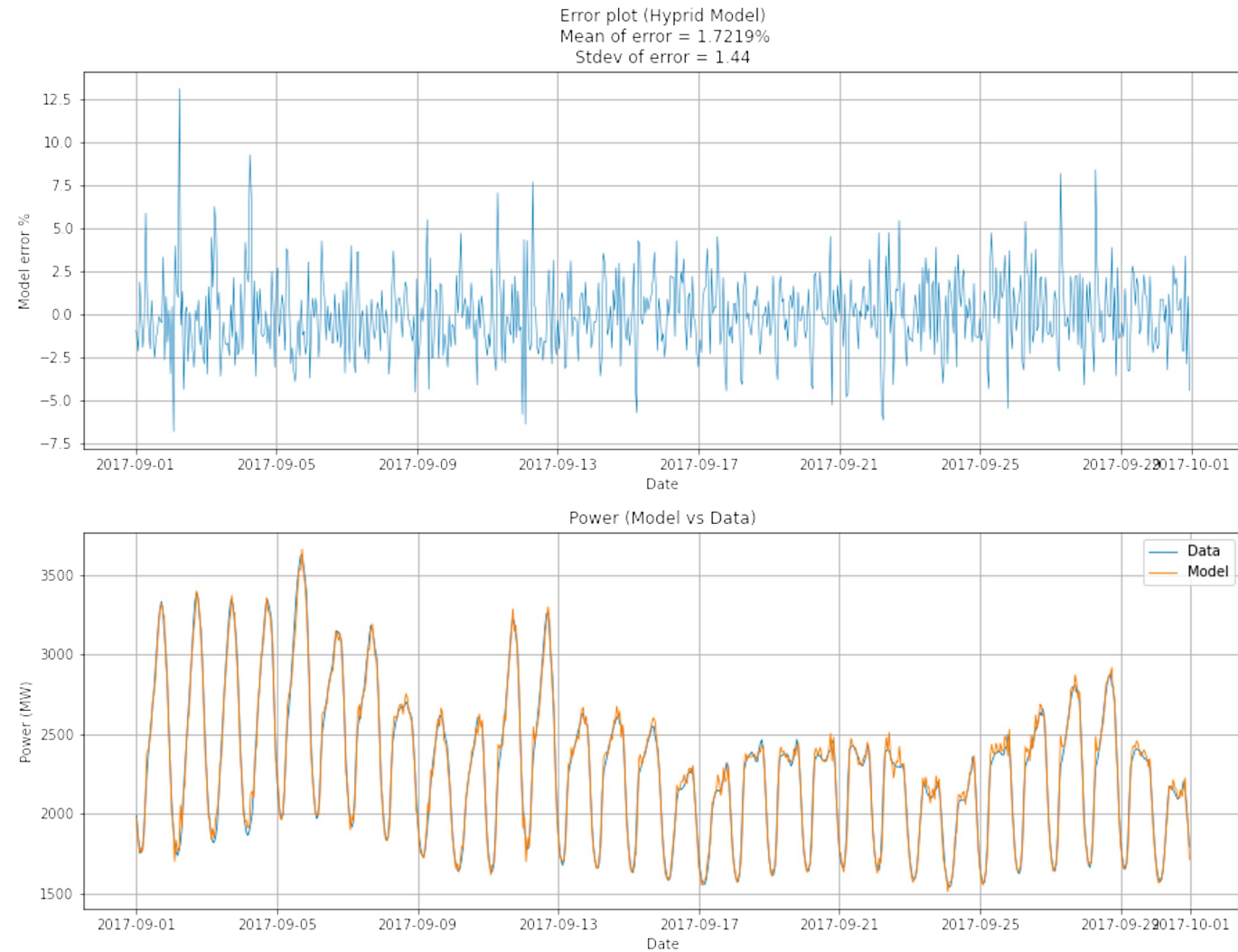
# Hybrid Load Model

Mix static and dynamic models

- Fit static model first
- Remove static load
- Fit dynamic model to residual

Static model aligns to climate regions

Dynamic model aligns to building-mix

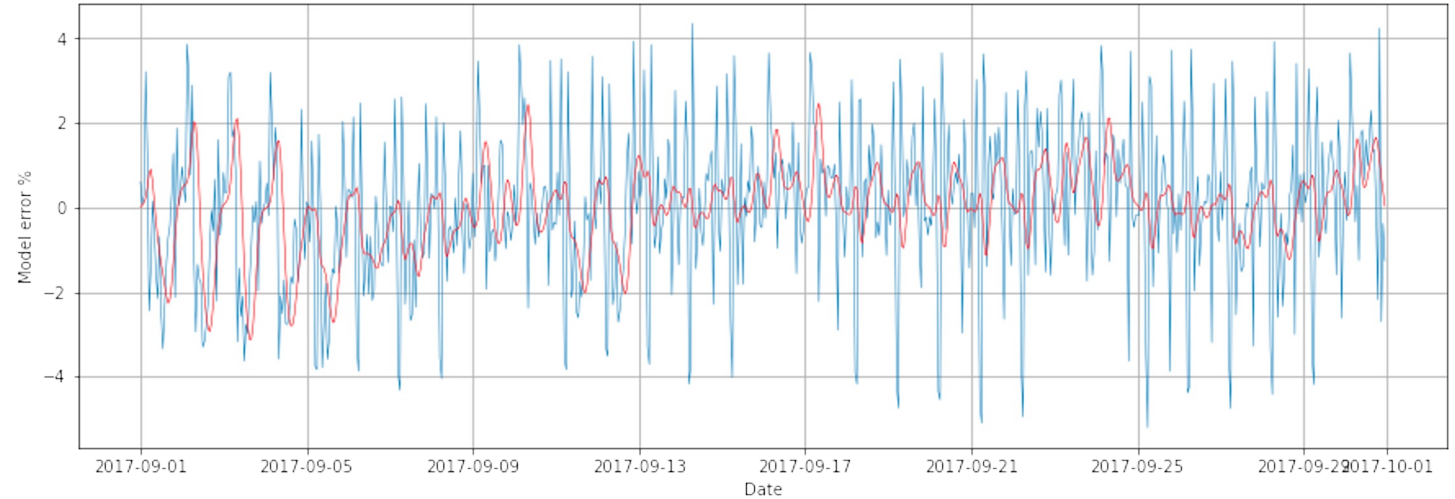


# Low pass filter

Remove high-freq. responses

- Removes overshoot
- Reduces error by 50-75%
- Best result on hybrid model

Error plot (Dynamic Model)  
Mean of error = 1.3884%  
Stdev of error = 1.18%  
Mean of filtered error = 0.6820%  
Stdev of filtered error = 0.62%



Error plot (Hybrid Model)  
Mean of error = 1.7219%  
Stdev of error = 1.44%  
Mean of filtered error = 0.6725%  
Stdev of filtered error = 0.59%

