

Occupant-Centric Grid- Interactive Buildings

1. Introduction & Overview

CE397
Spring 2024

Prof. Dr. Zoltan Nagy

The Plan for Today

- Me
- You
- Course Introduction
 - Motivation
 - Syllabus
 - Ground rules
- Example project
- Questions

Instructor

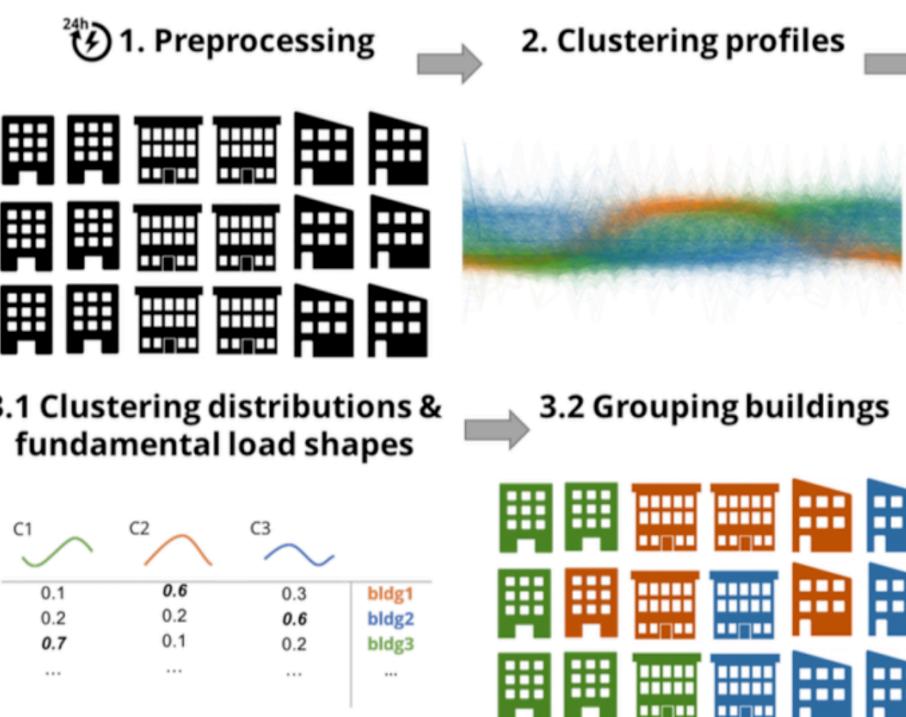
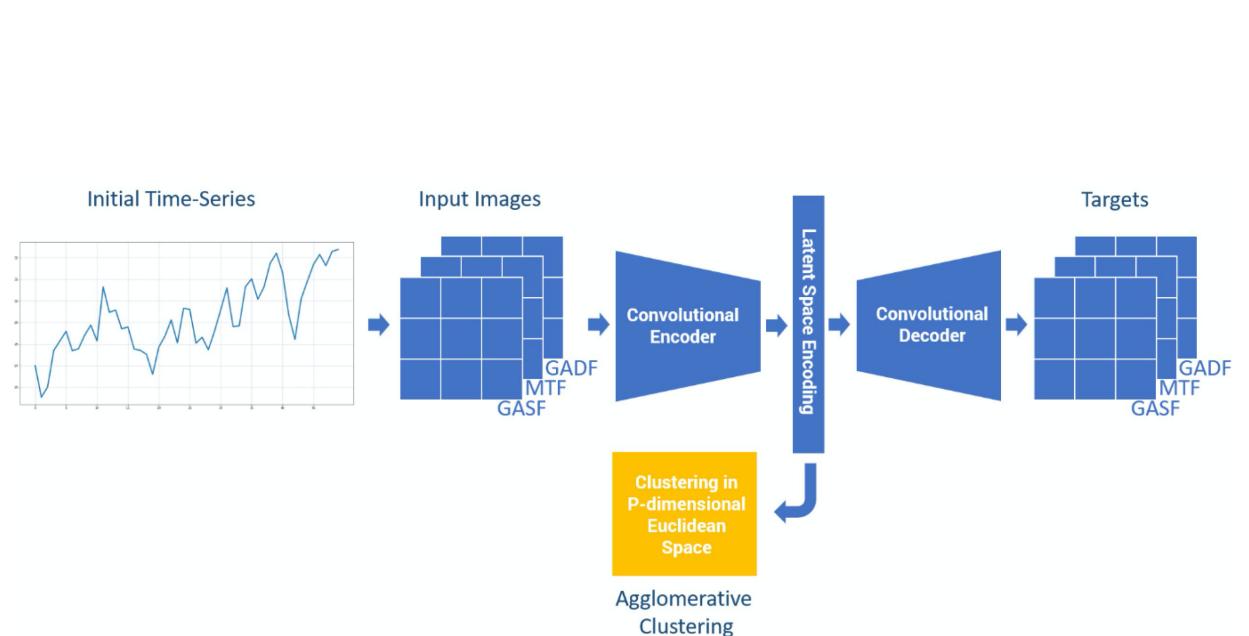
- Prof. Dr. Zoltan Nagy
ECJ 5.436
e-mail: nagy@utexas.edu
web: nagy.caee.utexas.edu
- Class times: W 9–12
- Office hours
By appointment

What about You?

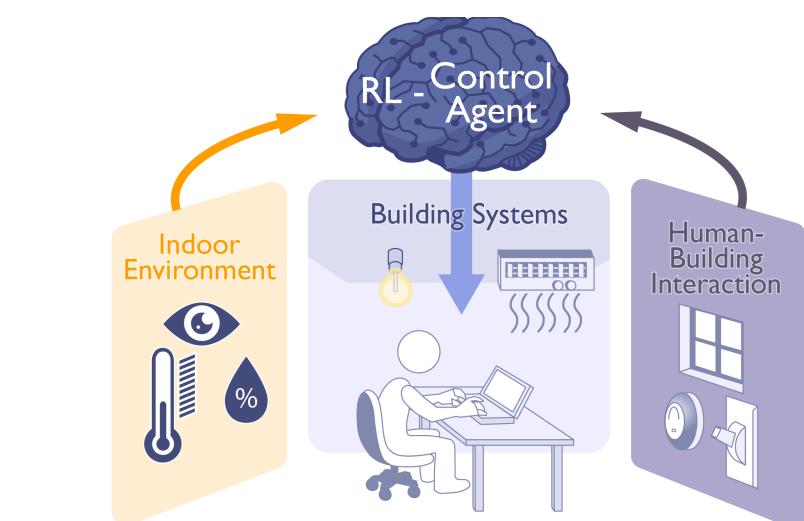
- Who are you?
 - Grad/Undergrad
 - Speciality
- Why are you here?
 - What are you excited about?
 - What are your expectations?
 - What are your concerns?

Research @ Intelligent Environments Lab

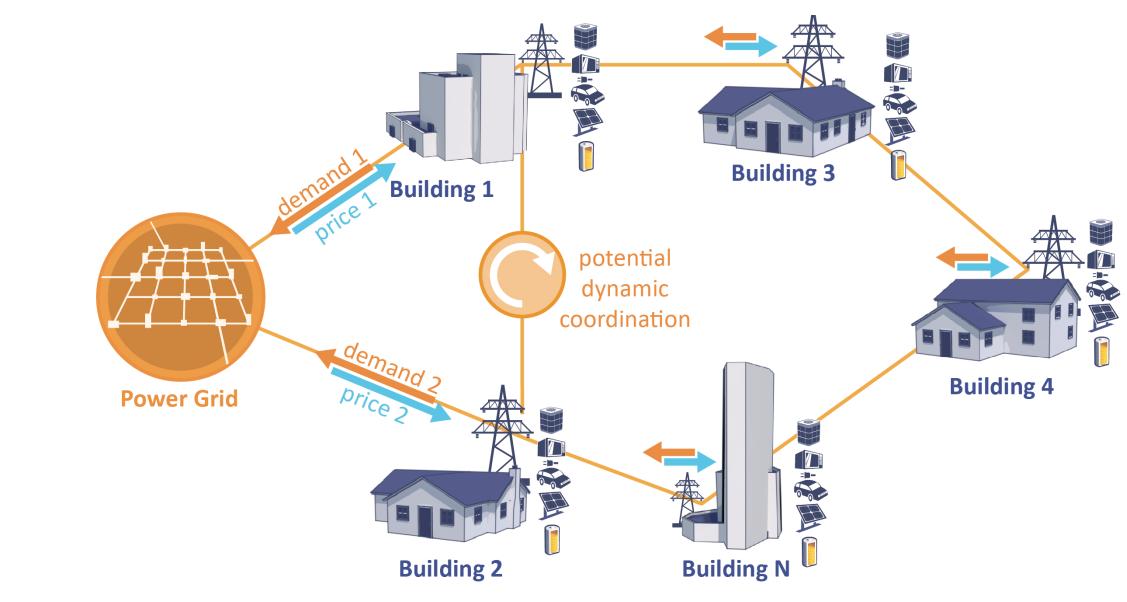
Unsupervised Learning



Reinforcement Learning



Green Electronics Council Award
 Finalist 2018

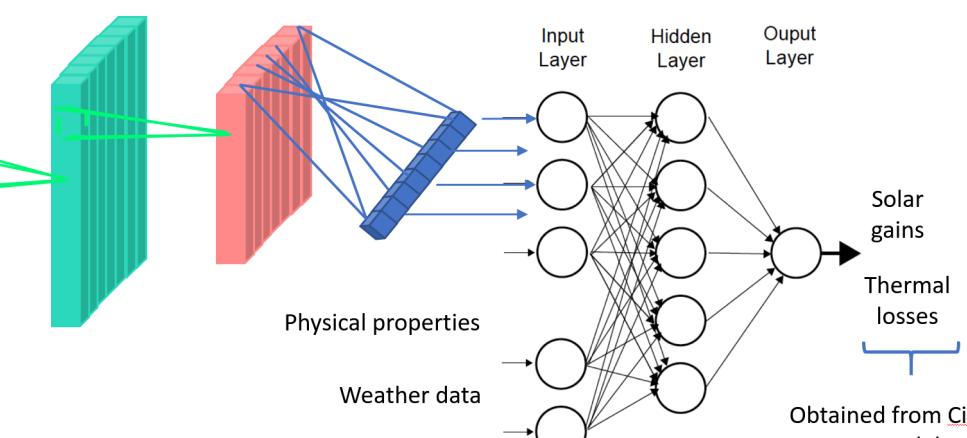


Editor's Choice (Applied Energy)
 Highly Cited Paper Award (Applied Energy)

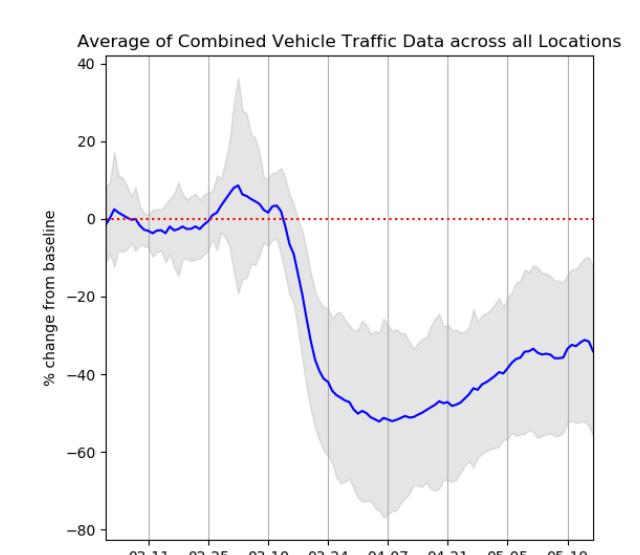
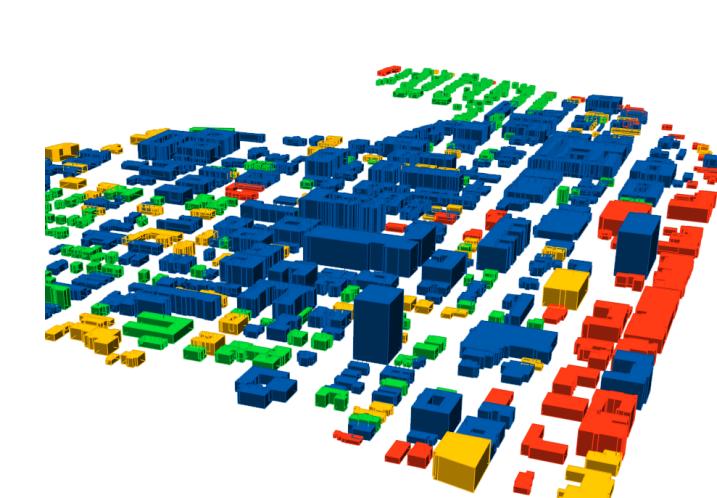
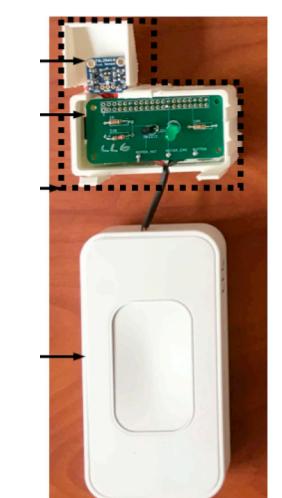
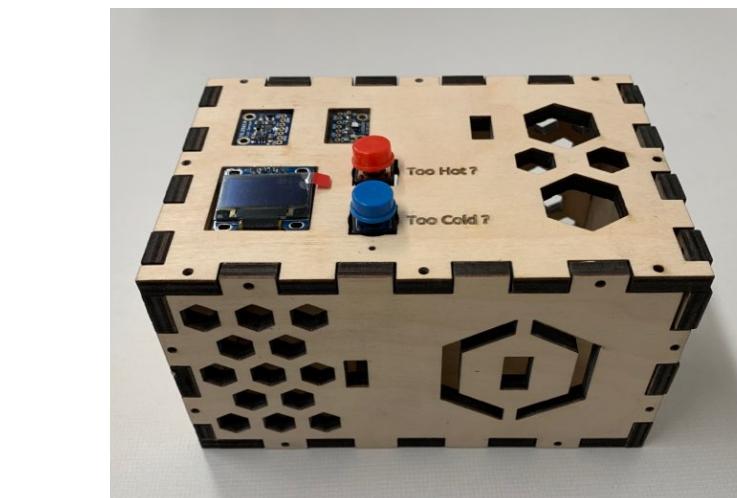
Supervised Learning



CityDNN: Silver Paper Award@CISBAT'19



IoT, Analytics & Systems Integration



What you will learn

1. **Understand** the and **describe** the most common machine learning algorithms
2. **Understand** and **model** the impact of occupants on building energy use
3. **Simulate** grid-interactive buildings
4. **Use** Python for data analysis applications

What I am NOT covering:

- Detailed mathematical proofs and derivations of the algorithms

Notes

- Open door policy & Office hours: Use them!
- Suggestion are welcome
 - Tell me what you like
 - Tell me what you don't like

Course Overview

- Communication via Canvas -> Overview
- Lectures streamed & recorded via **zoom**
- Lecture notes & files on **GitHub**
- Assignment/Quiz submission on Canvas

Hands-On Programming Course

- Machine learning and data analysis are a form of art that need to be mastered through doing it.
- Therefore, a large part of this course will focus on hands-on programming
- We will review Python programming basics first, and as the course evolves, we will move towards more free programming and application.

GPT-TA for programming and course

- Developed a GPT-TA trained on lecture notes and homework to act as your virtual TA
- <https://chat.openai.com/g/g-OFAttq2Or-gpta>
- Use it to ask questions about lectures, and programming tasks, and project.
- Report on its use (anonymously) on Canvas as weekly Quiz (required)
- We will need a name - make suggestions & vote !

Guest Lectures

- By industry experts, so far seven confirmed
- Typically 10.30-11.30
- Via zoom (different zoom link than class!)
- Lecture series advertised publicly as webinar

Project

- Final project related to applied grid-interactive buildings
- **Goal:** Use CityLearn to model and train residential home to reduce energy use, maintain comfort and resist power outages
- More details as we progress.
- Undergrads: work in groups of 2
- Grads: work alone
- Project replaces the final exam

Tentative Course Outline / Schedule

Week	Class	Topic	Guest Lecture
1	01/17	Introduction / Overview / Python	
2	01/24	Machine Learning I	
3	01/31	Machine Learning II	
4	02/07	Machine Learning III	Justin Hill (Southern)
5	02/14	Occupant Behavior Modeling	
6	02/21	Occupant Behavior Modeling	Tanya Barham (CEL)
7	02/28	Occupant Behavior Modeling	Jessica Granderson (LBNL)
8	03/06	Occupant Behavior Modeling	Hussain Kazmi (KU Leuven)
9	03/13	Spring Break	
10	03/20	Advanced Control & Calibration	Ankush Chakrabarty (MERL)
11	04/27	Calibration	Donghun Kim (LBNL)
12	04/03	Introduction to CityLearn	
13	04/10	Project Work	Siva Sankaranarayanan (EPRI)
14	04/17	Project work	
15	04/24	Project work	

Midterm Exam (take home)

- Midterm exam as take home
 - Hand out: 3/20 (after spring break)
 - Return: 3/27
- Covers the first two modules (Programming/ML & occupant behavior)

Grading

Homework assignments	30%
Project	30%
Mid-term exam	30%
Participation / Quiz / In-class Activity	10%

75%

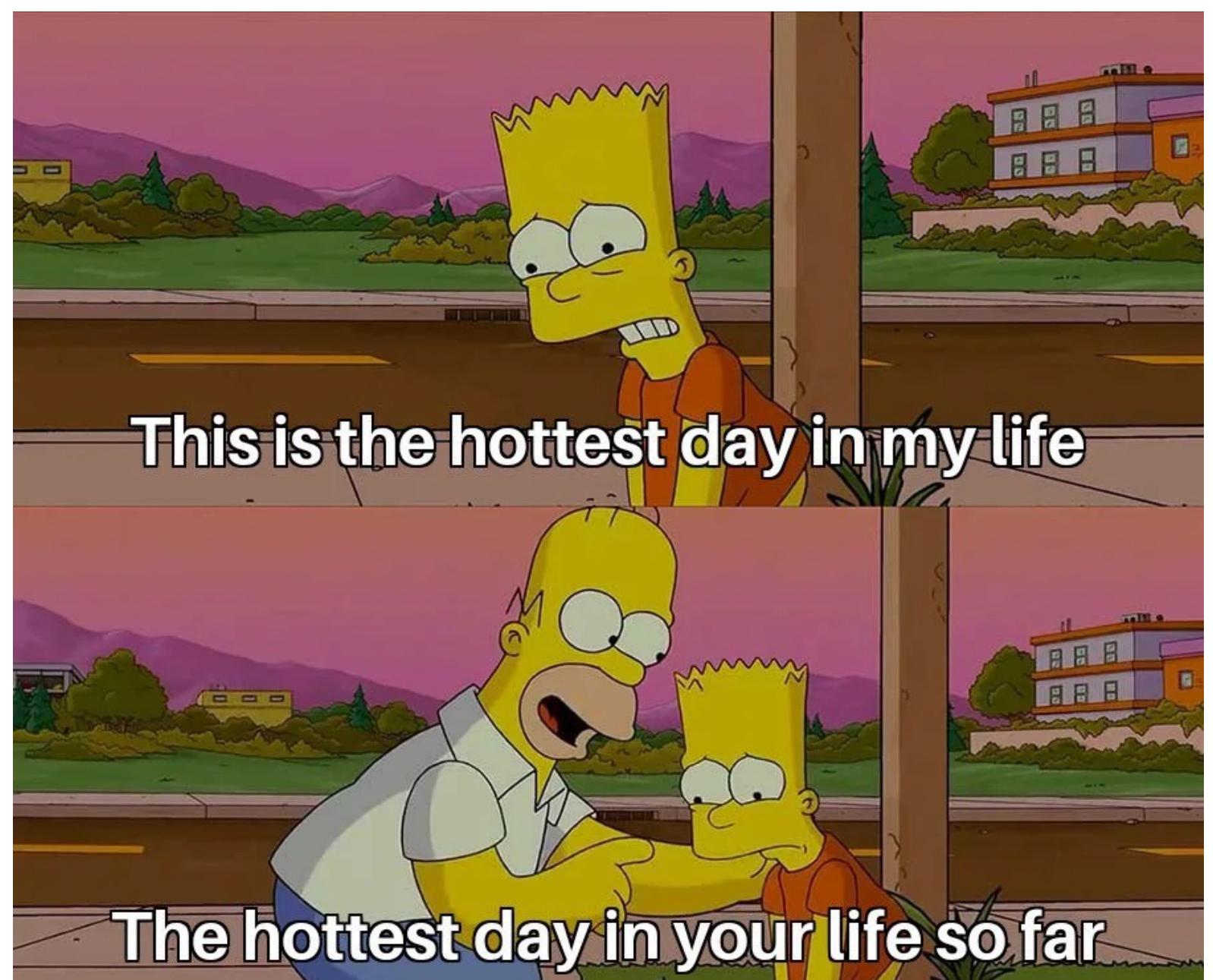
of all US electricity
is consumed within
buildings

US Energy Information
Administration, 2018

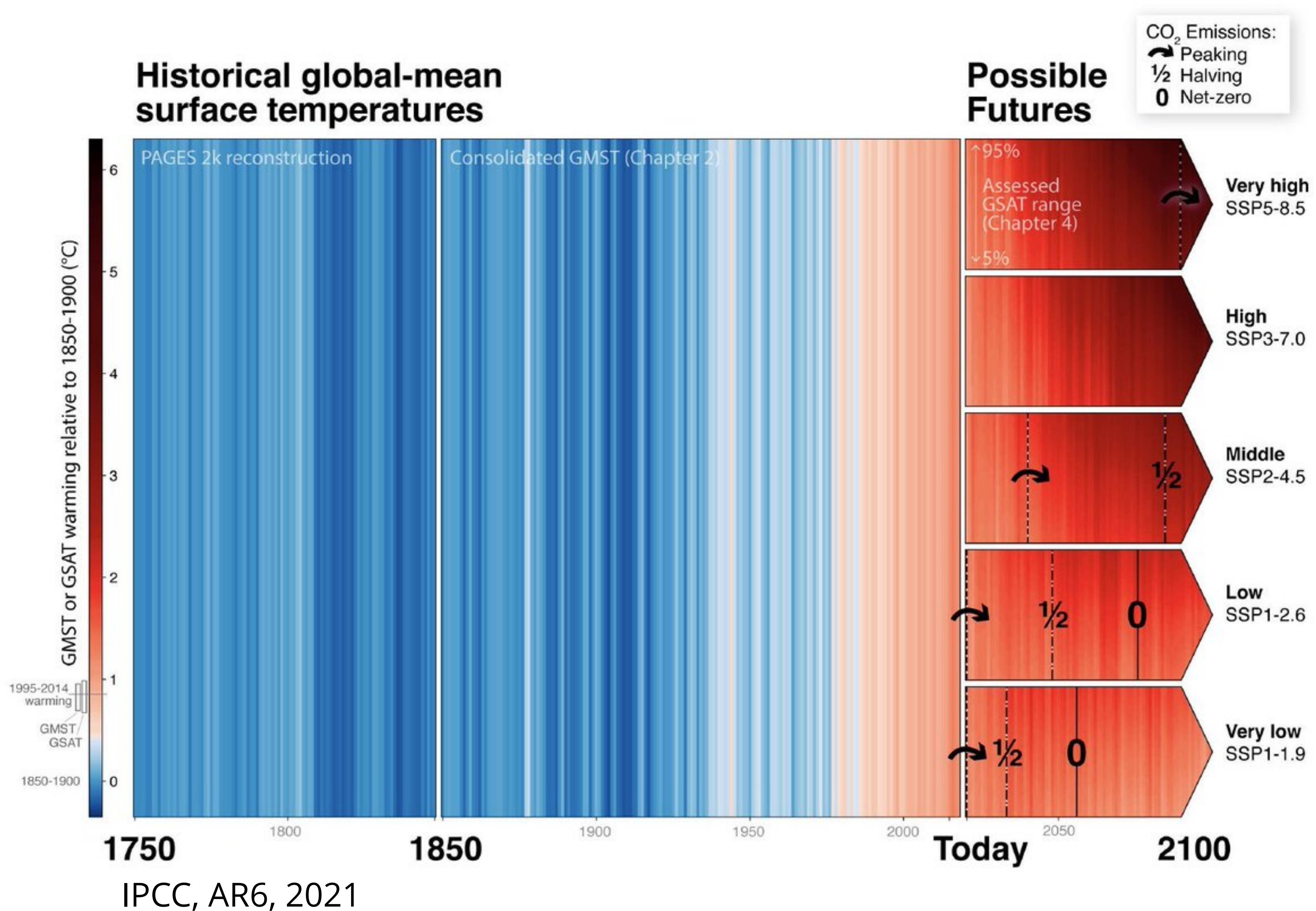
30%

of US greenhouse gas
emissions stem from
buildings

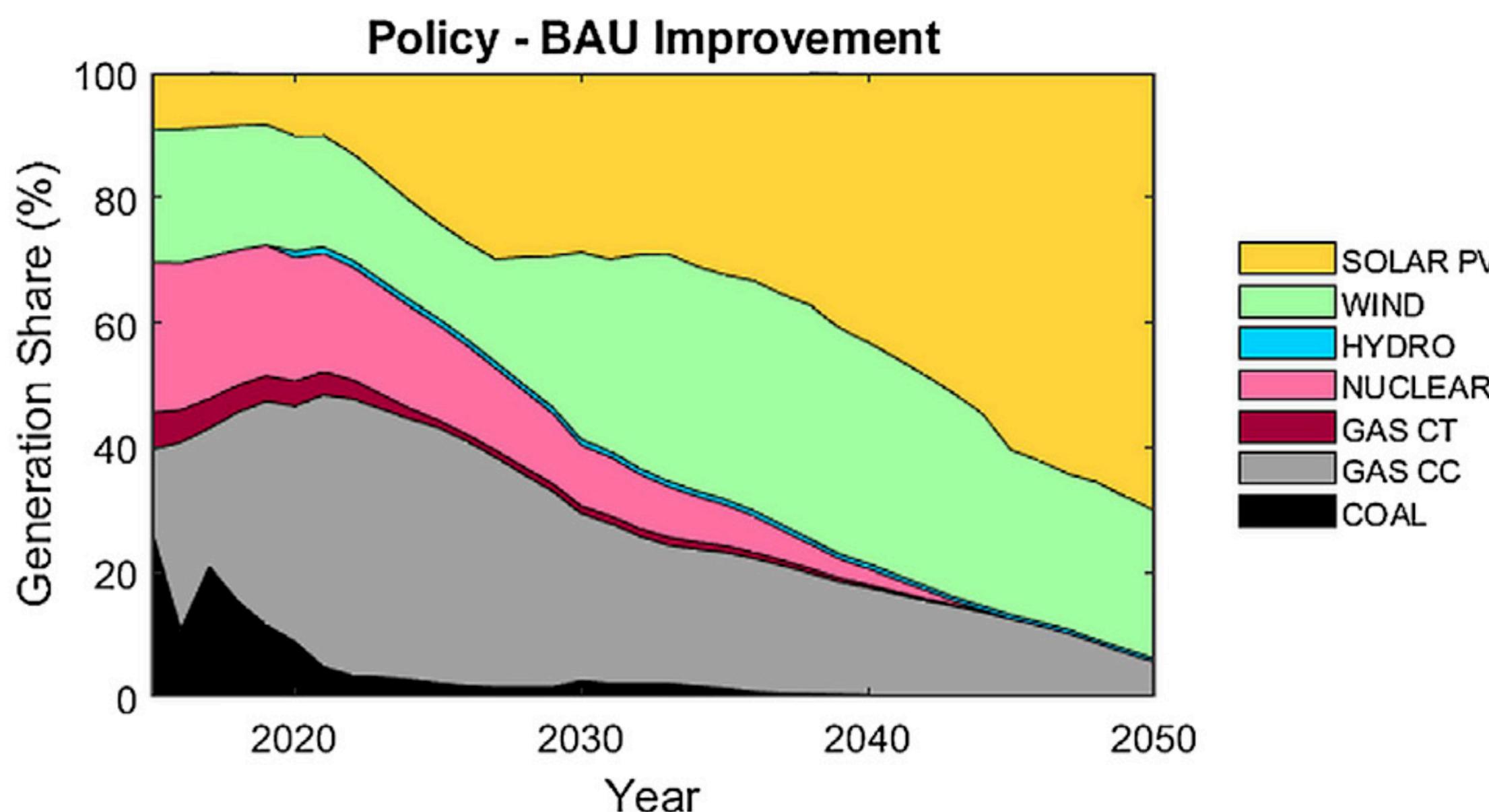
mostly for **heating** and
cooling



u/Restaurantmenu2

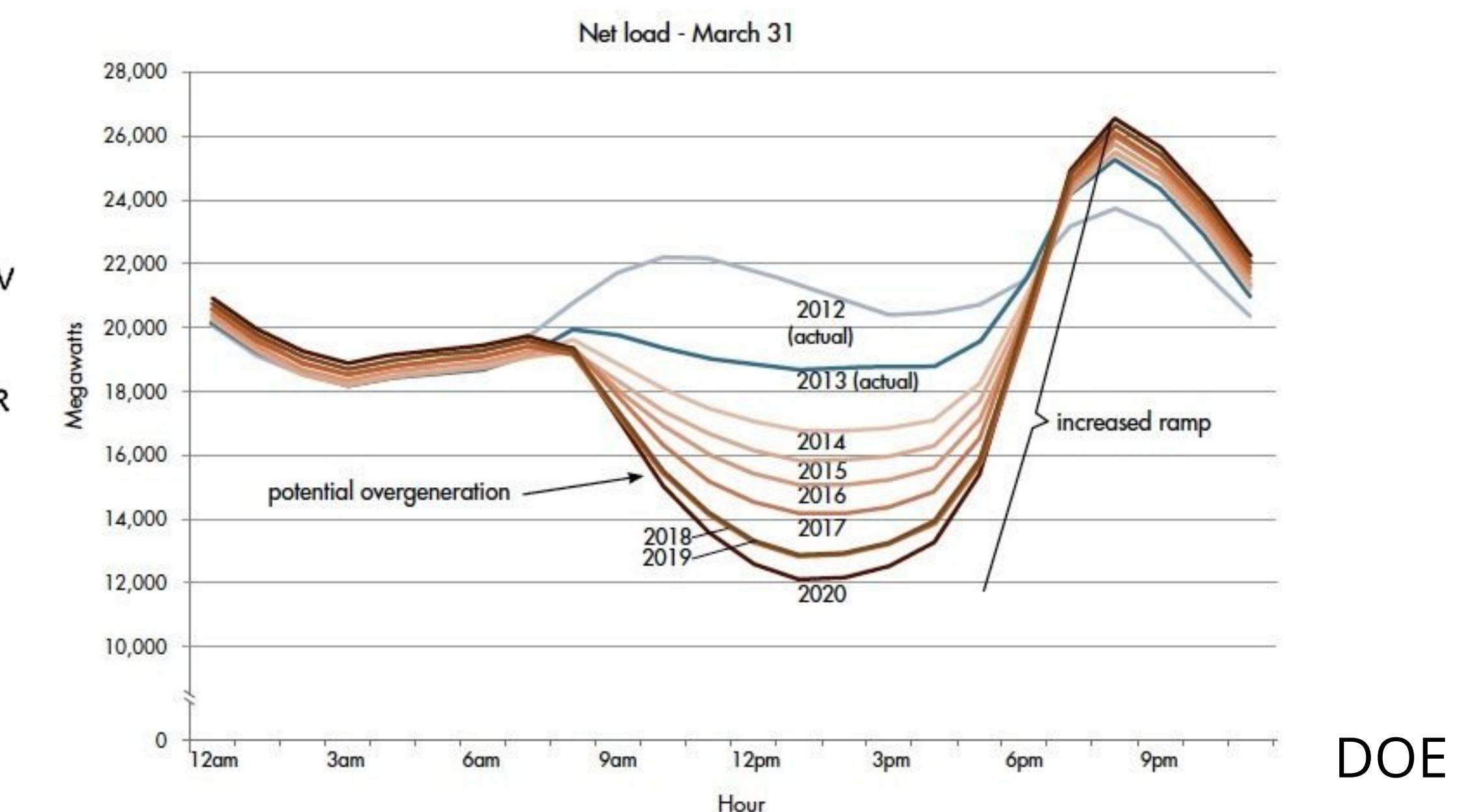
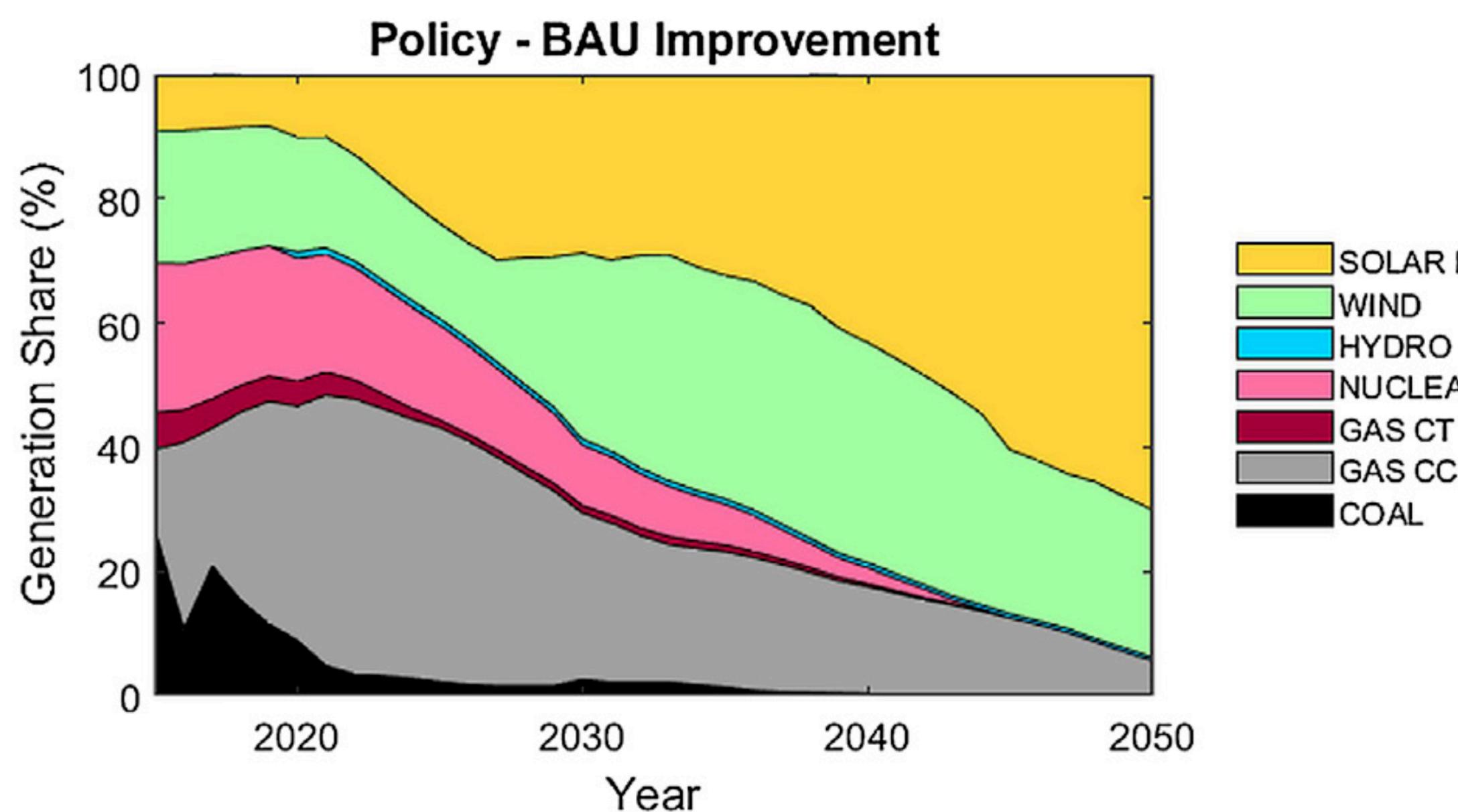


Emission reductions through electrifying of end use while decarbonizing the grid



Leibowicz et al, *Applied Energy*, 2018

Emission reductions through electrifying of end use while decarbonizing the grid



Energy flexibility needed to align supply with demand

Leibowicz et al, *Applied Energy*, 2018

70%

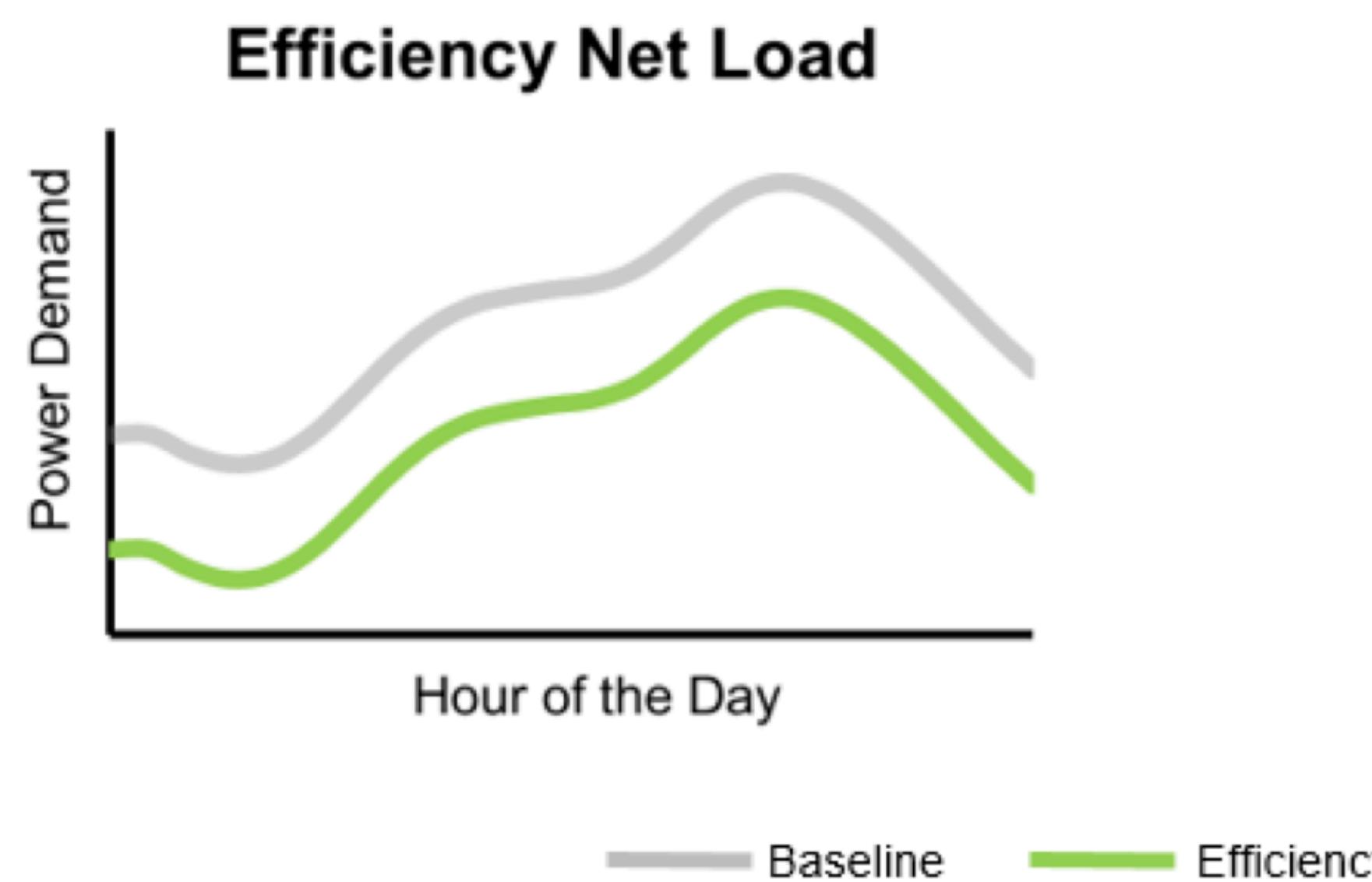
of US residential
buildings are **single
family homes**

70%

of US residential buildings are **single family homes**

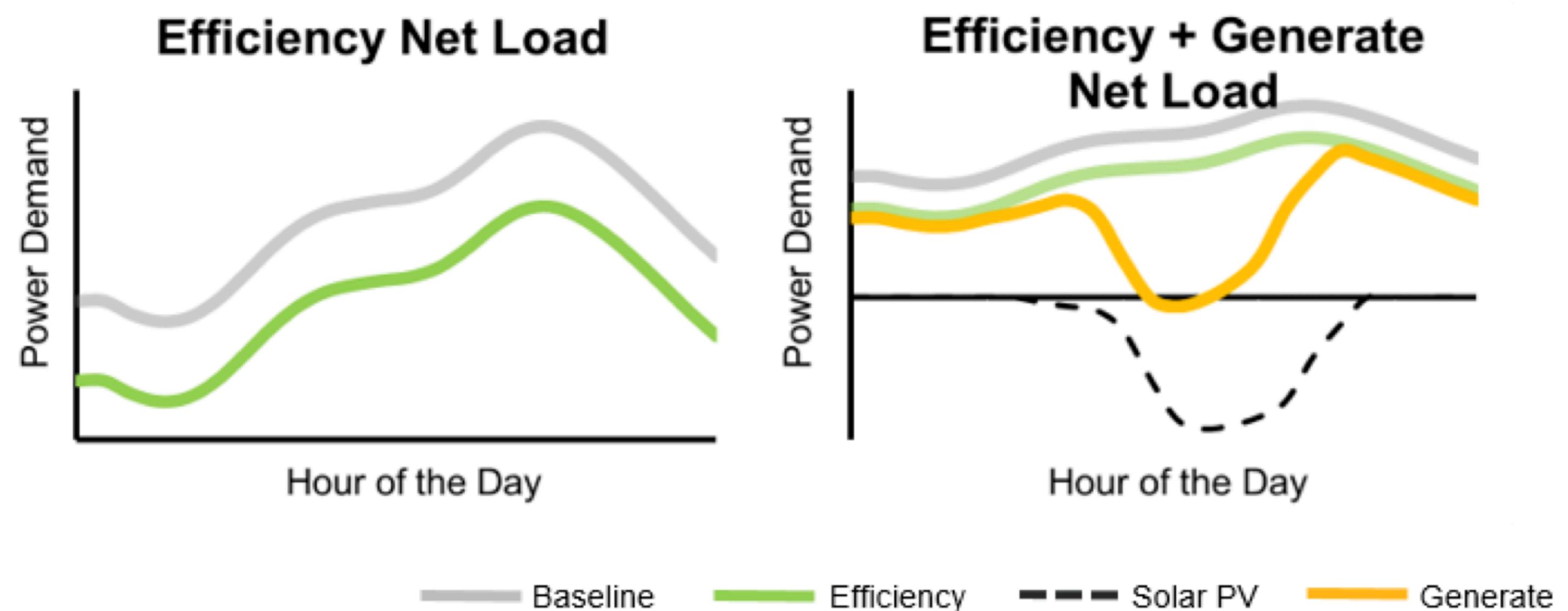
an **untapped potential** for energy flexibility

Grid-interactive communities can provide flexibility



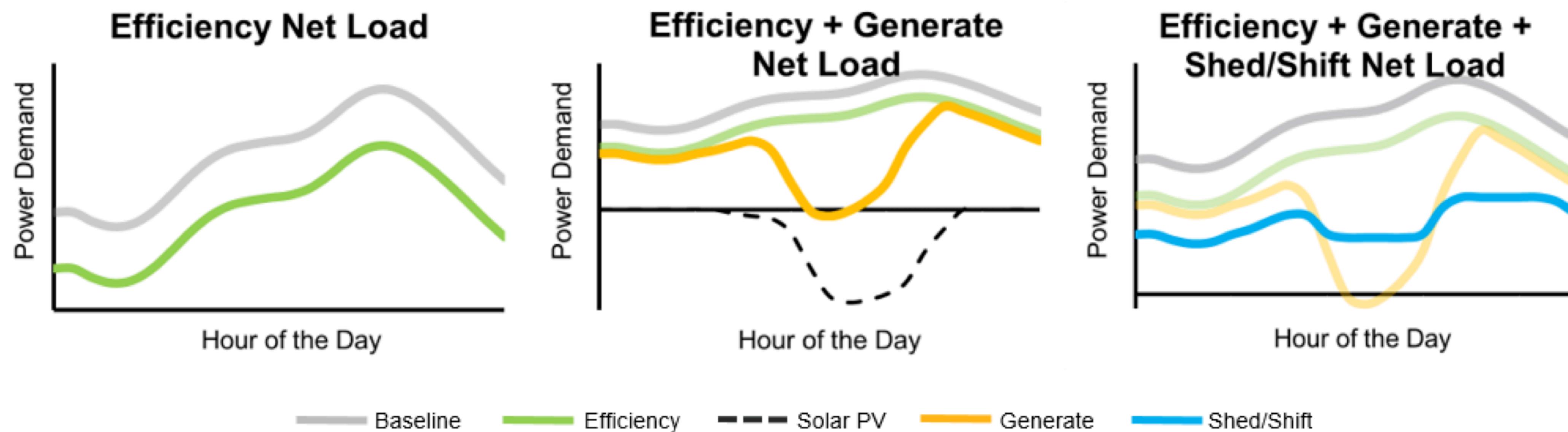
US Dept of Energy, 2019

Grid-interactive communities can provide flexibility



US Dept of Energy, 2019

Grid-interactive communities can provide flexibility

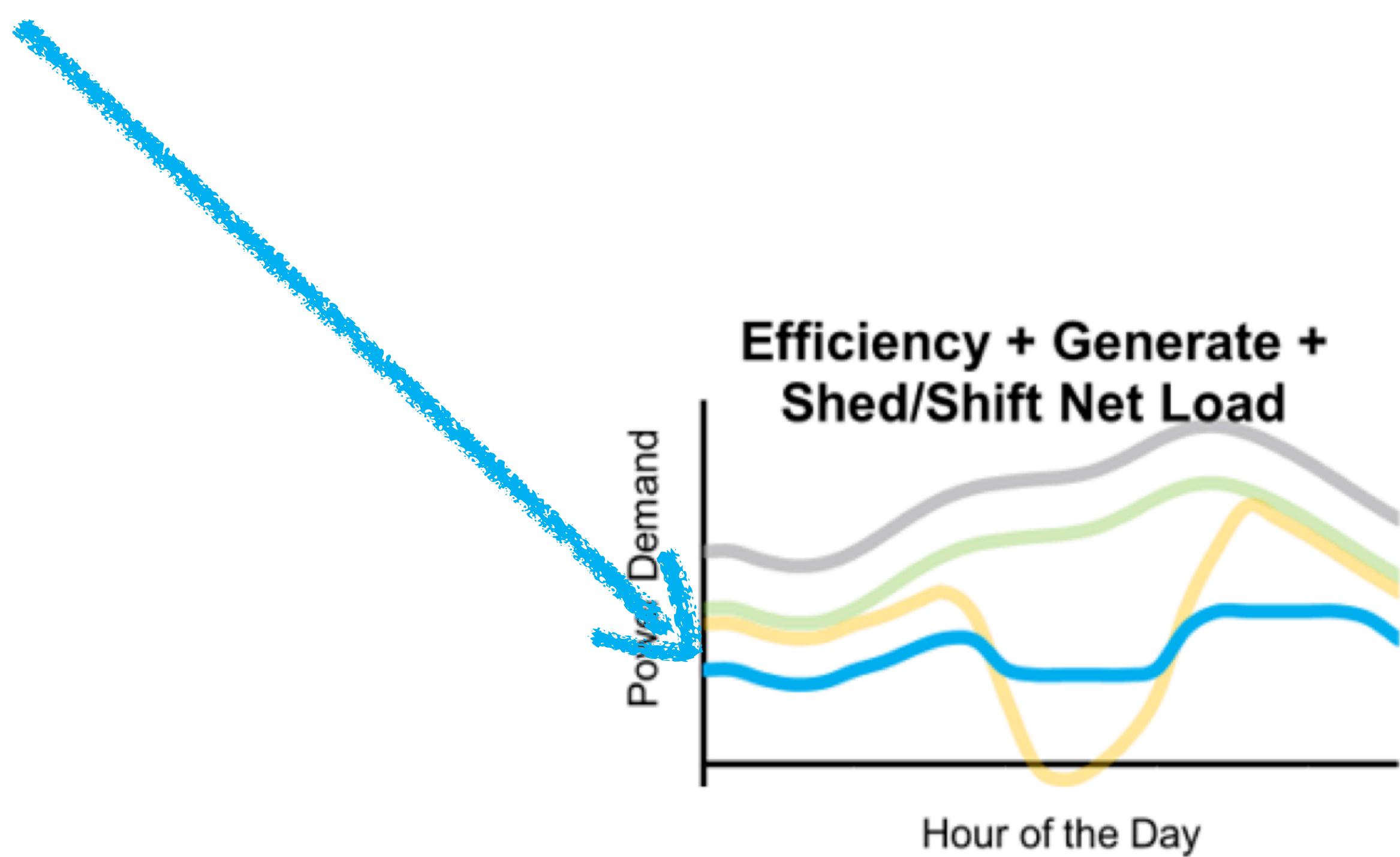


US Dept of Energy, 2019

How do we get to here?

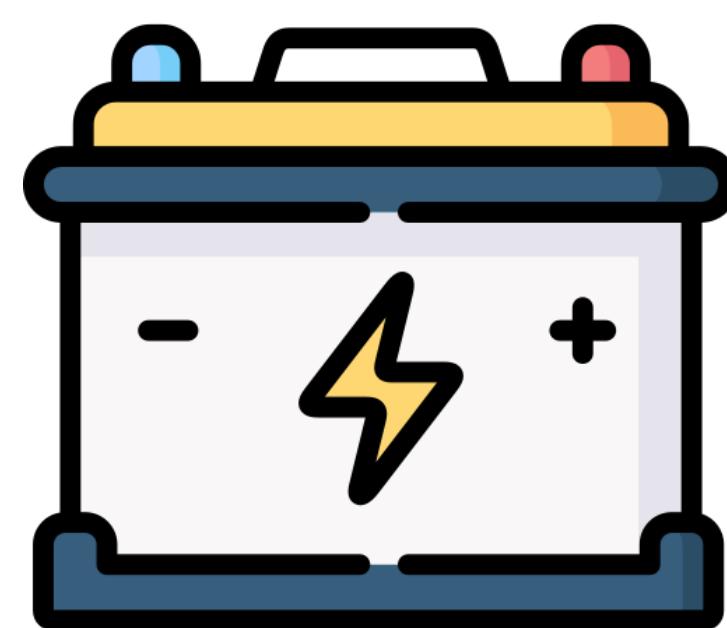


— Baseline — Efficiency - - - Solar PV — Generate — Shed/Shift

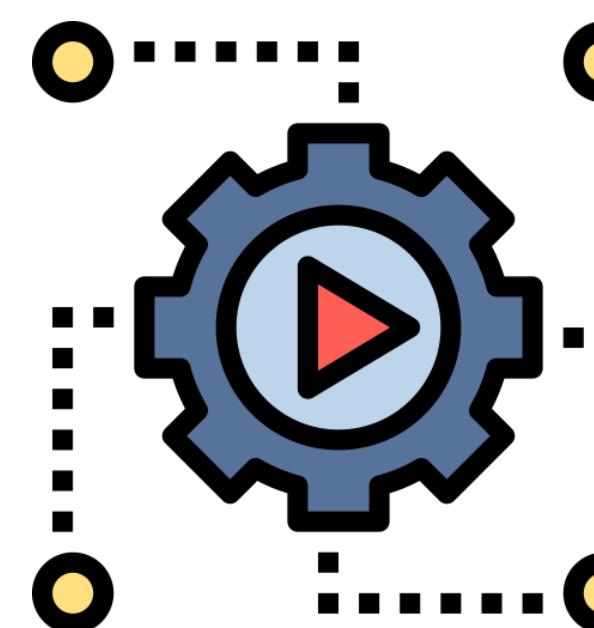


US Dept of Energy, 2019

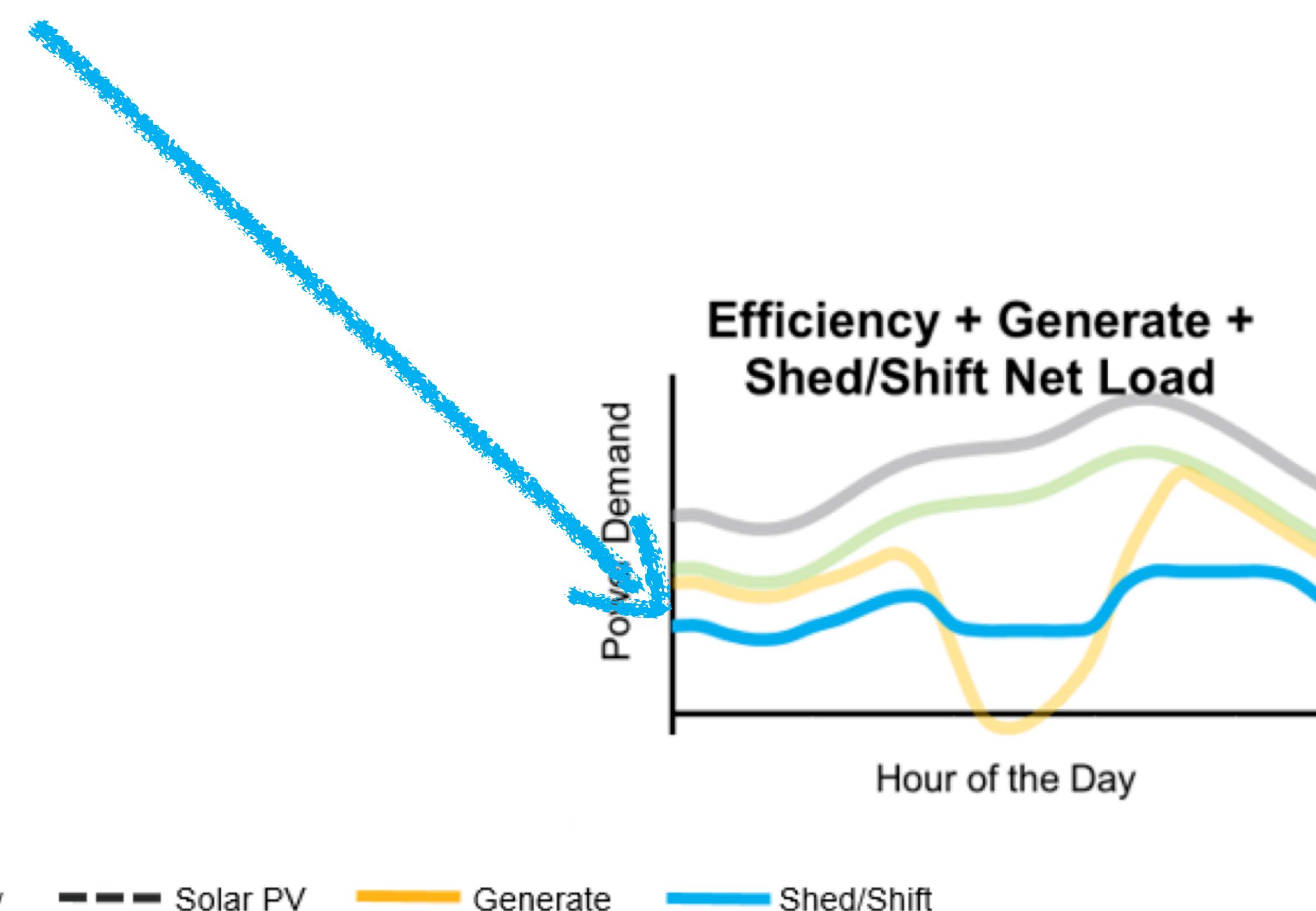
How do we get to here?



Storage



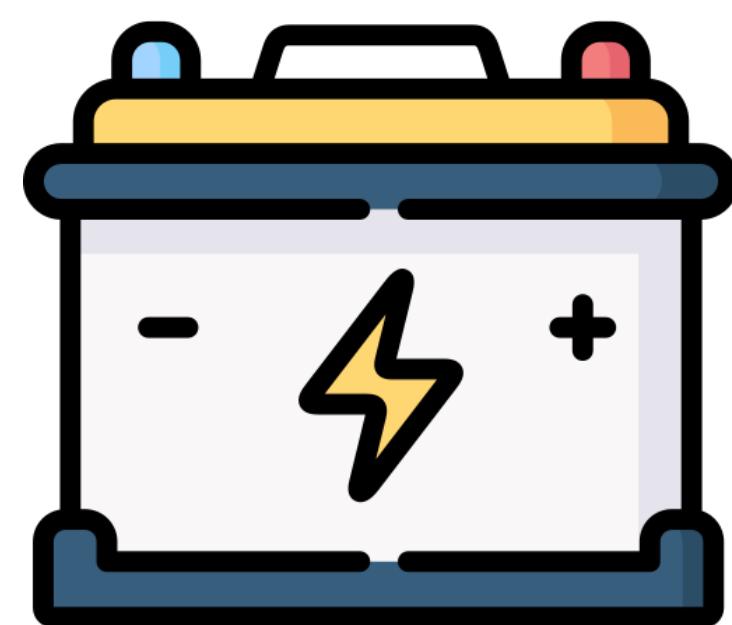
Control



US Dept of Energy, 2019

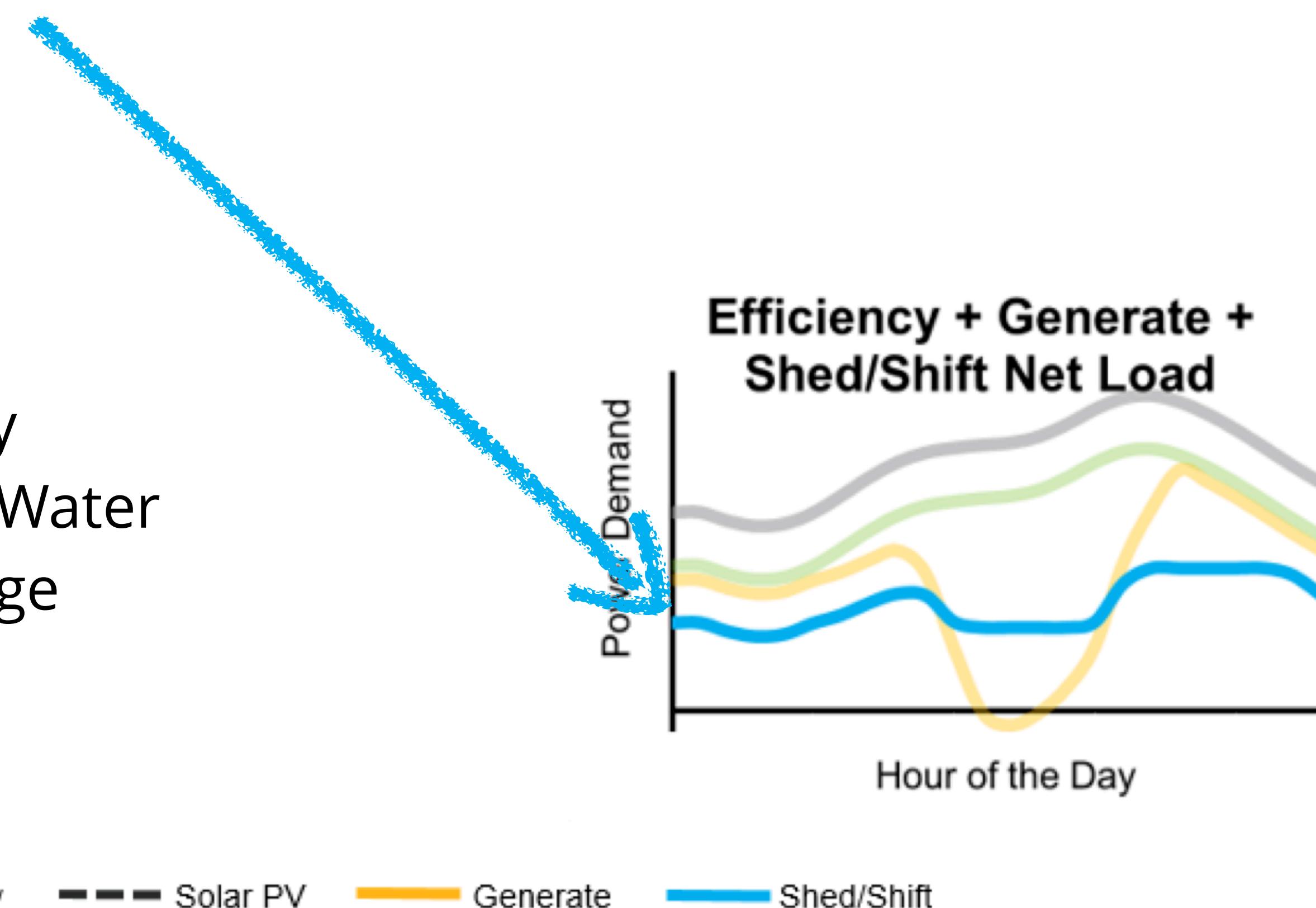
icons created by [noomtah](#) and [Freepik](#)

How do we get to here?



Storage

Electric Battery
Domestic Hot Water
Thermal Storage



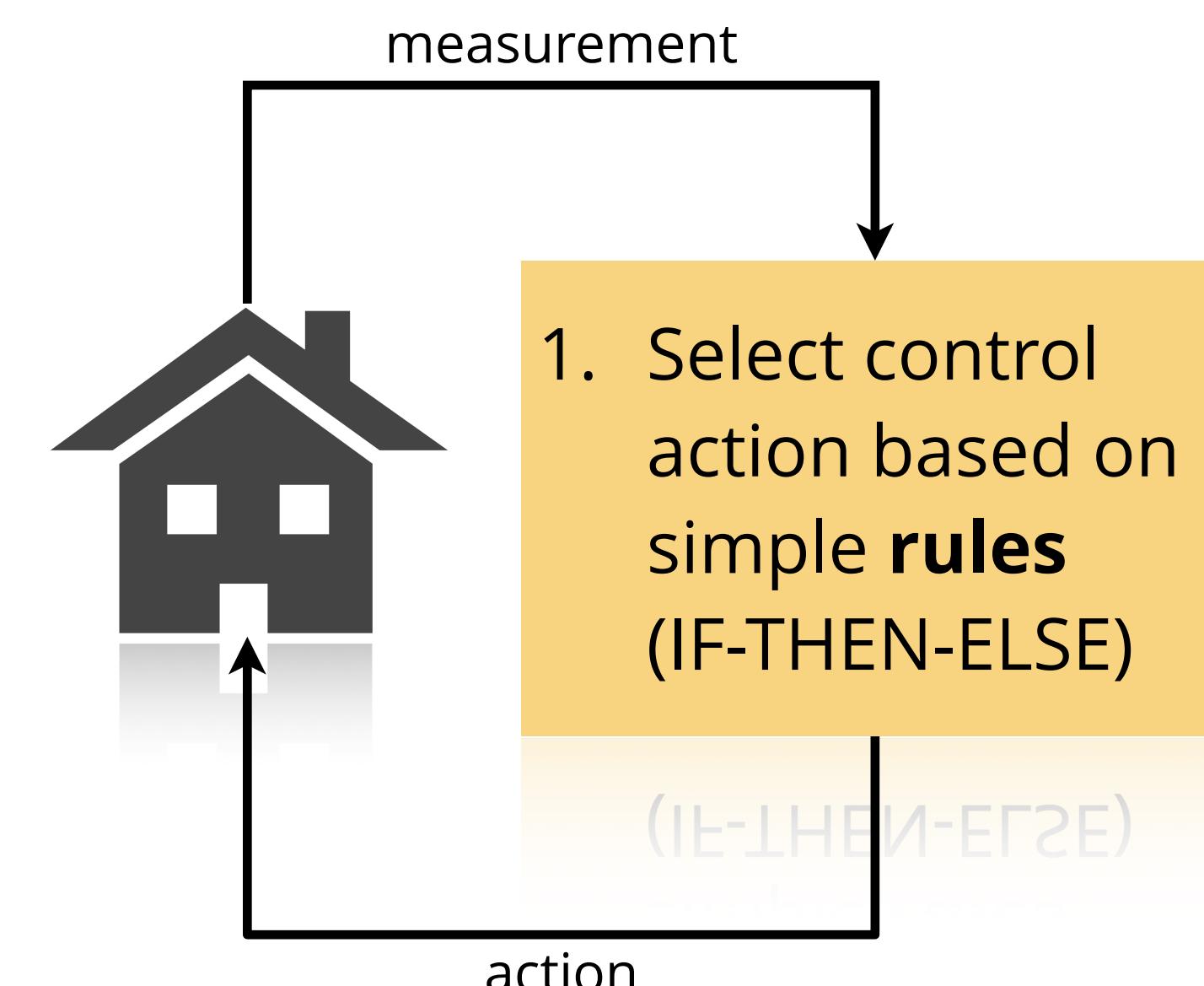
— Baseline — Efficiency - - - Solar PV — Generate — Shed/Shift

US Dept of Energy, 2019

icons created by [noomtah](#) and [Freepik](#)

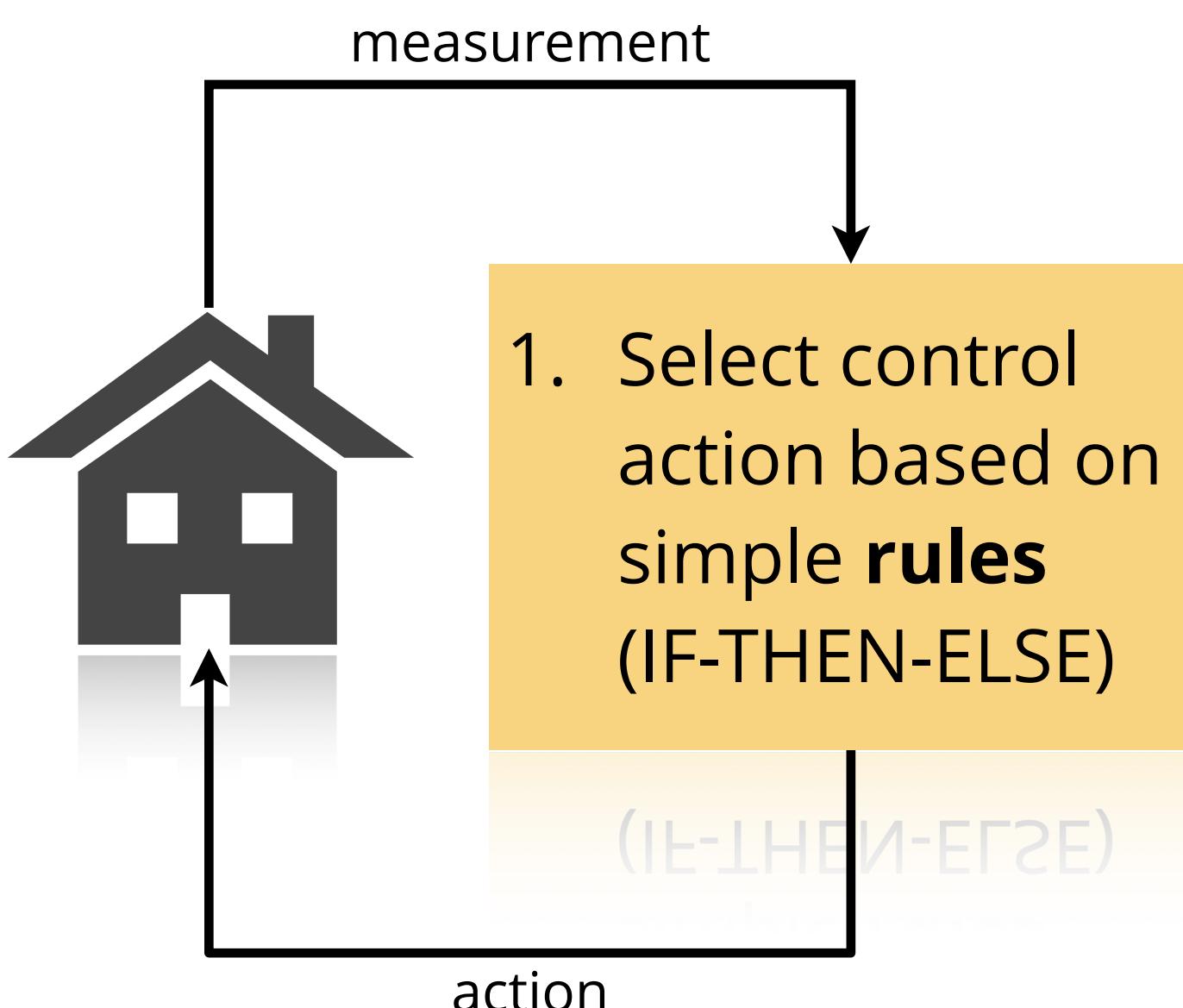
Control strategies for building energy management

Rule based control (RBC)

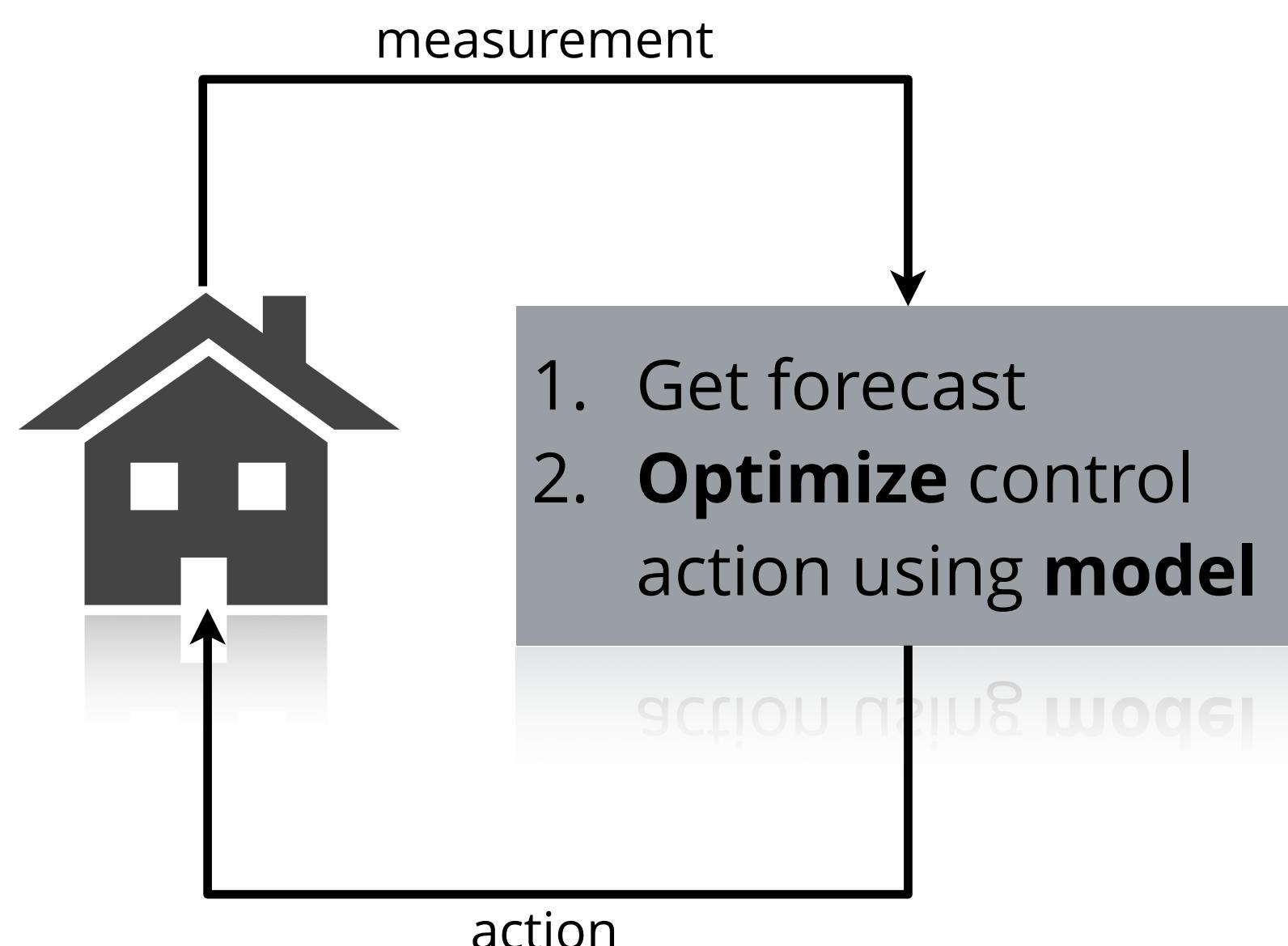


Control strategies for building energy management

Rule based control (RBC)

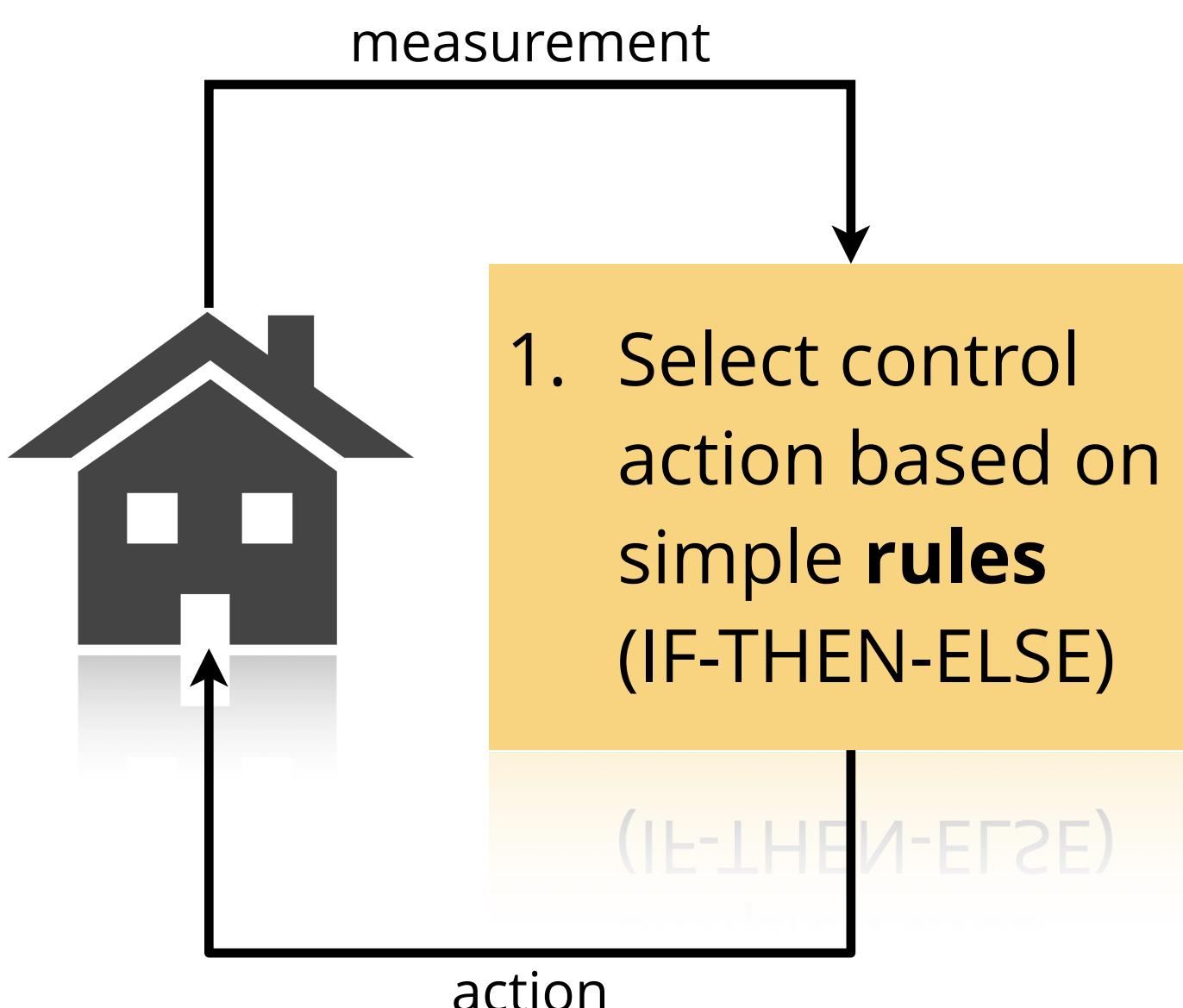


Model Predictive Control (MPC)

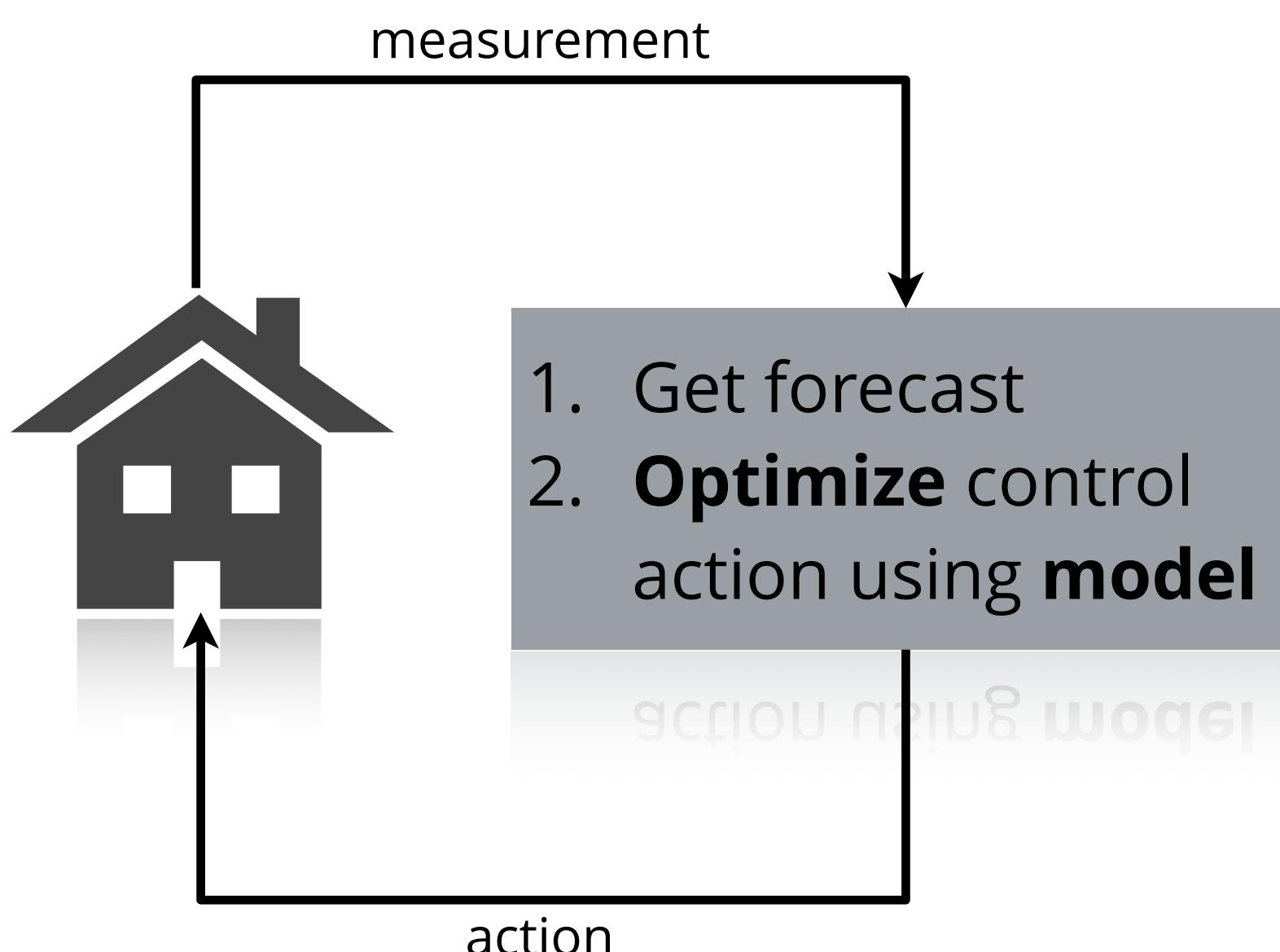


Control strategies for building energy management

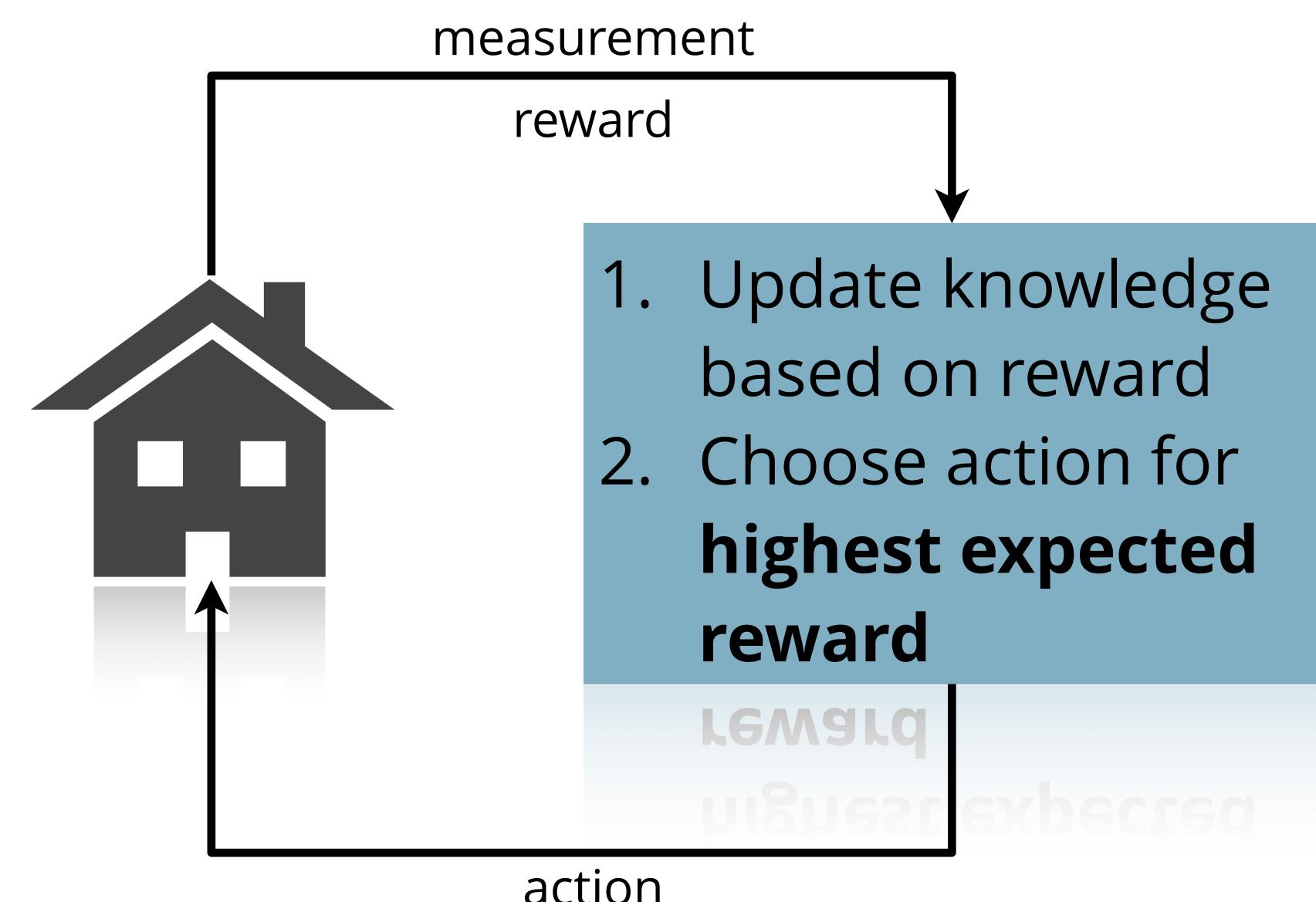
Rule based control (RBC)



Model Predictive Control (MPC)

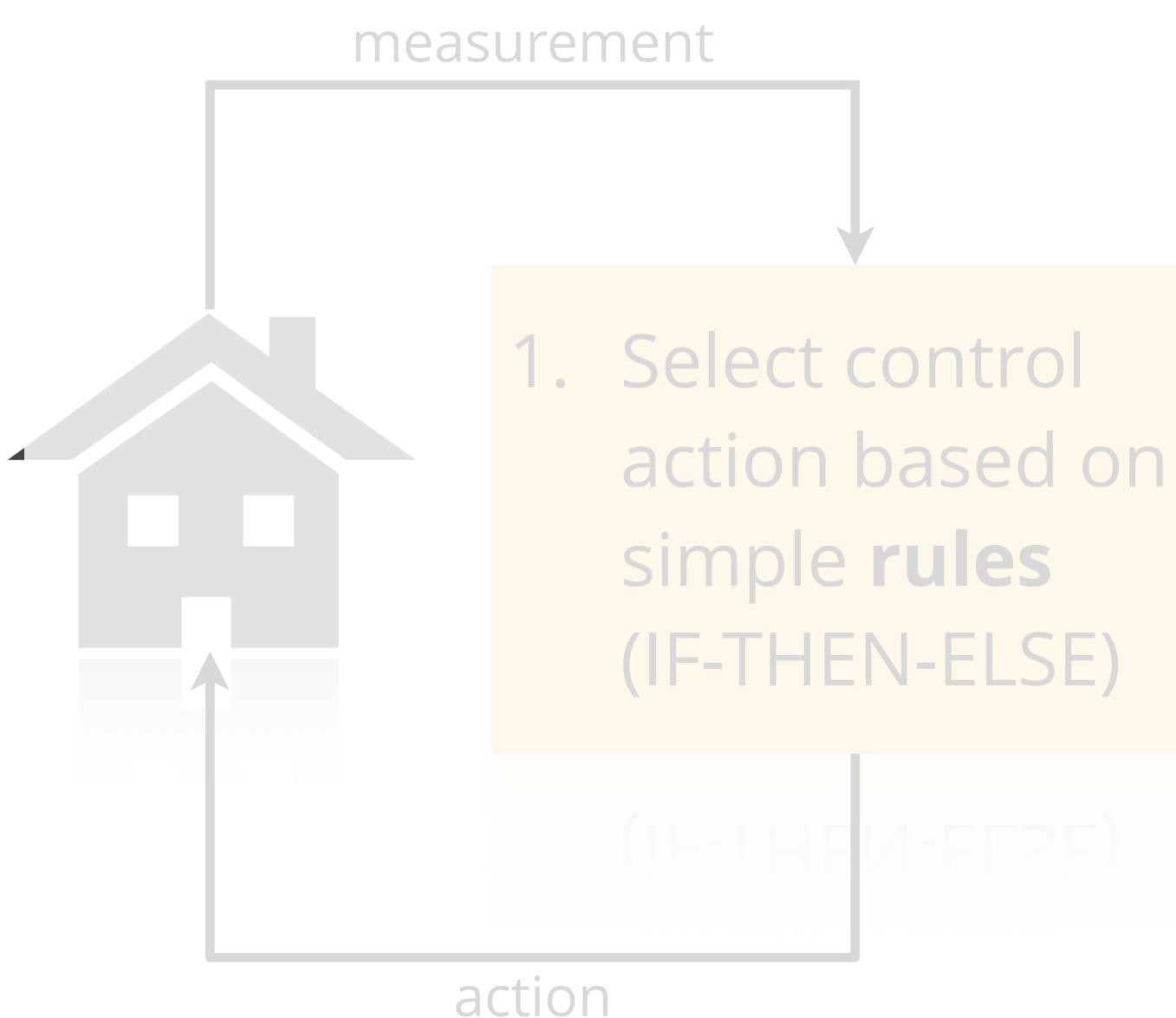


Reinforcement Learning Control (RLC)

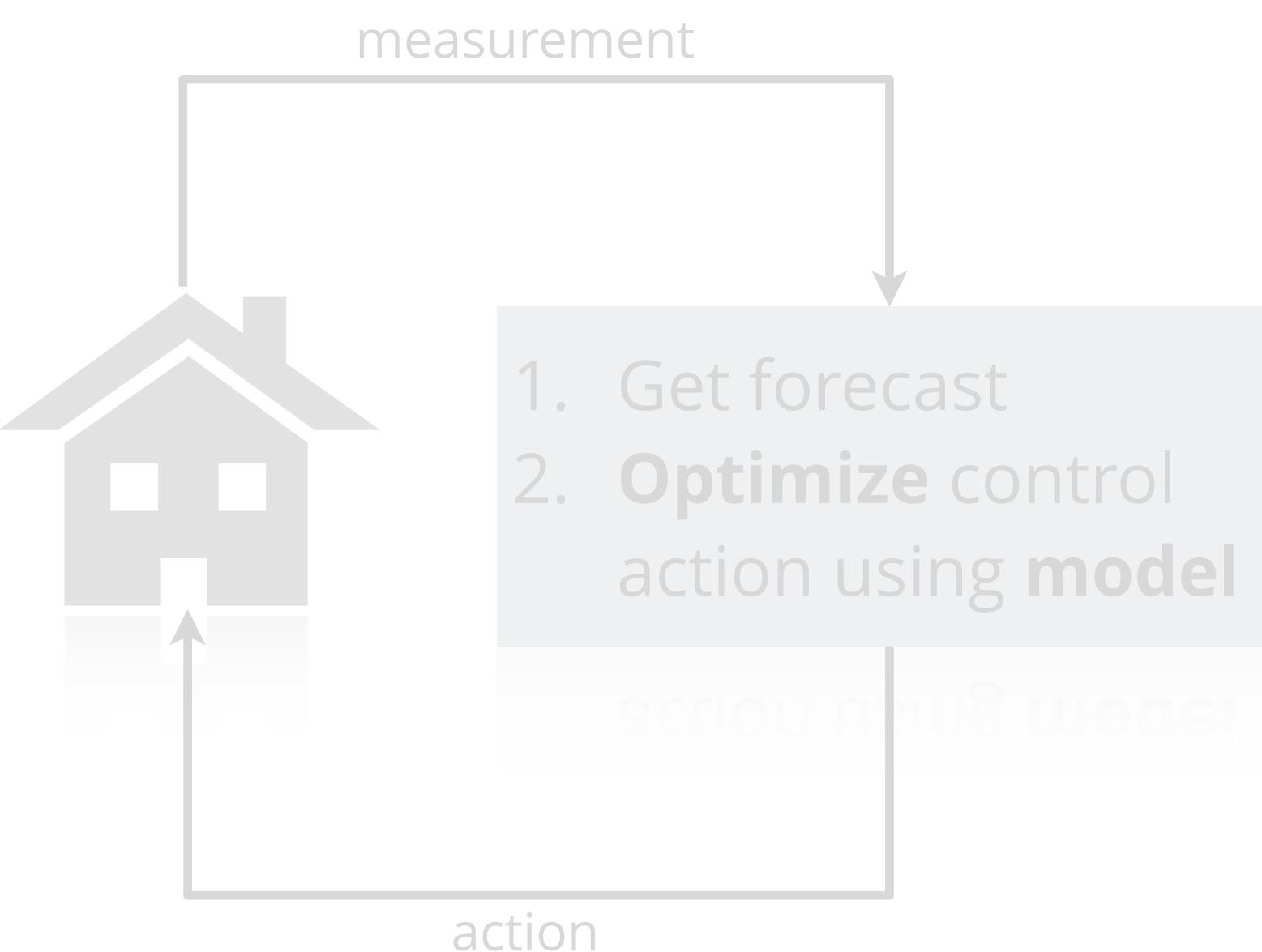


Control strategies for building energy management

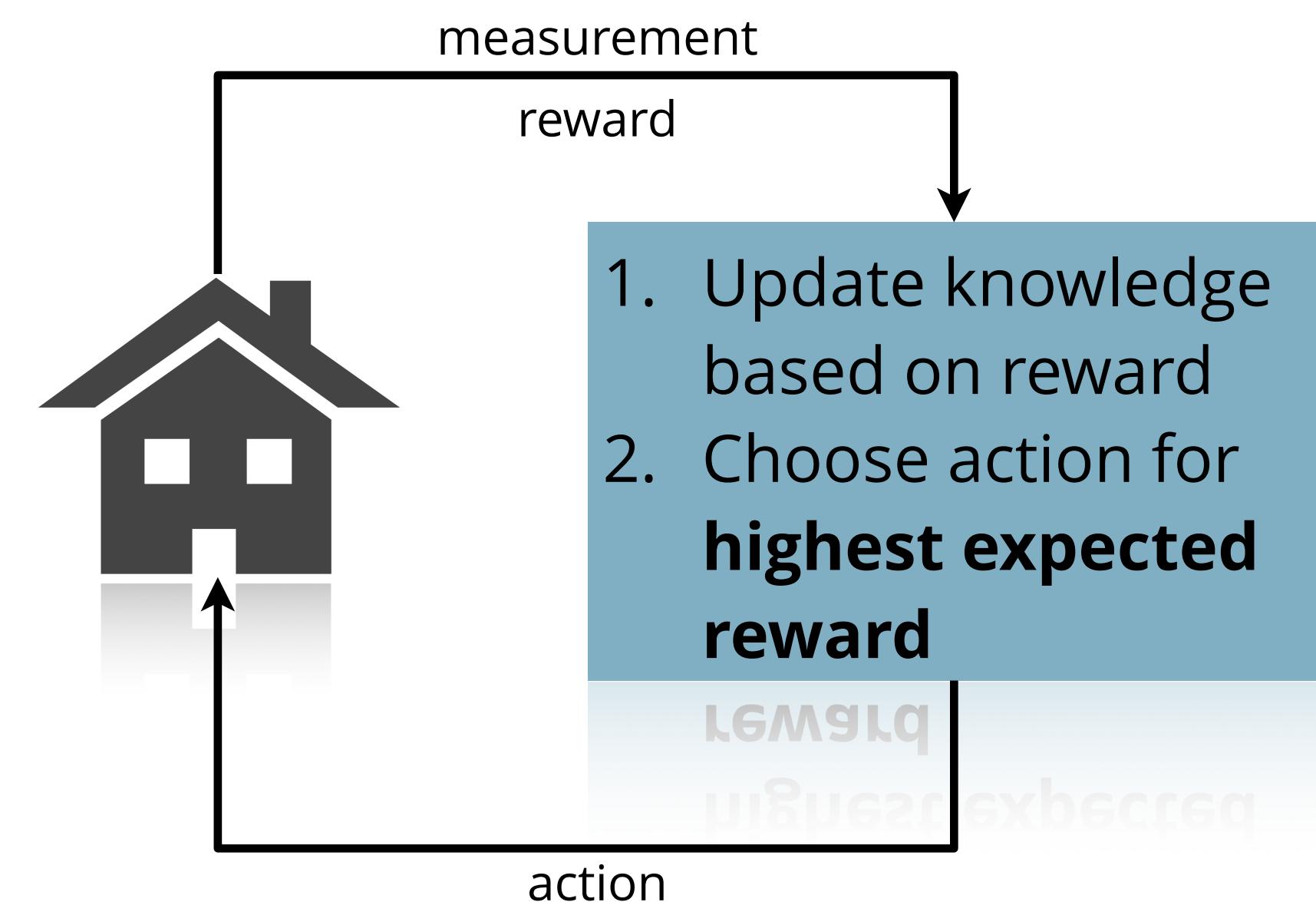
Rule based control (RBC)



Model Predictive Control (MPC)



Reinforcement Learning Control (RLC)



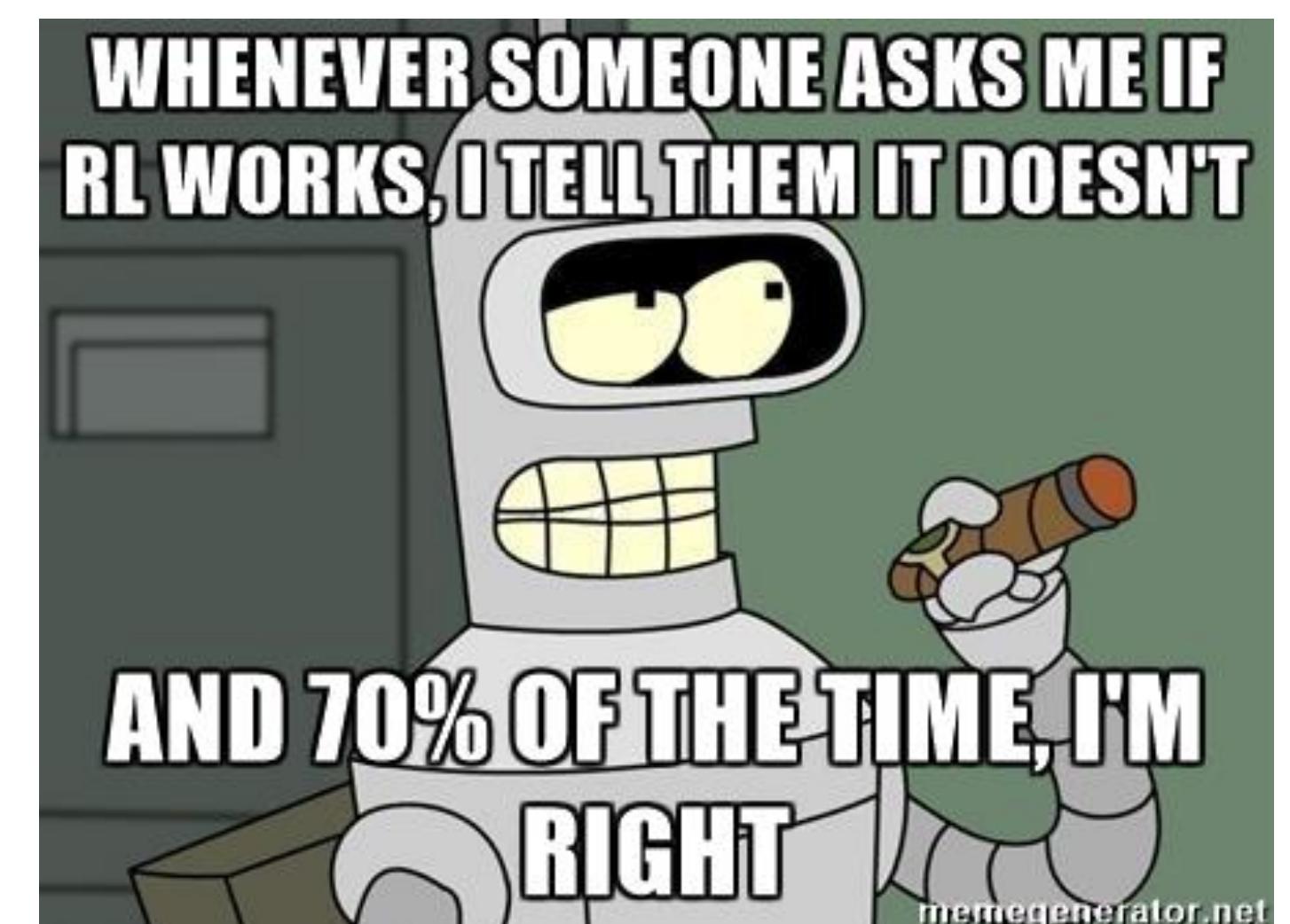
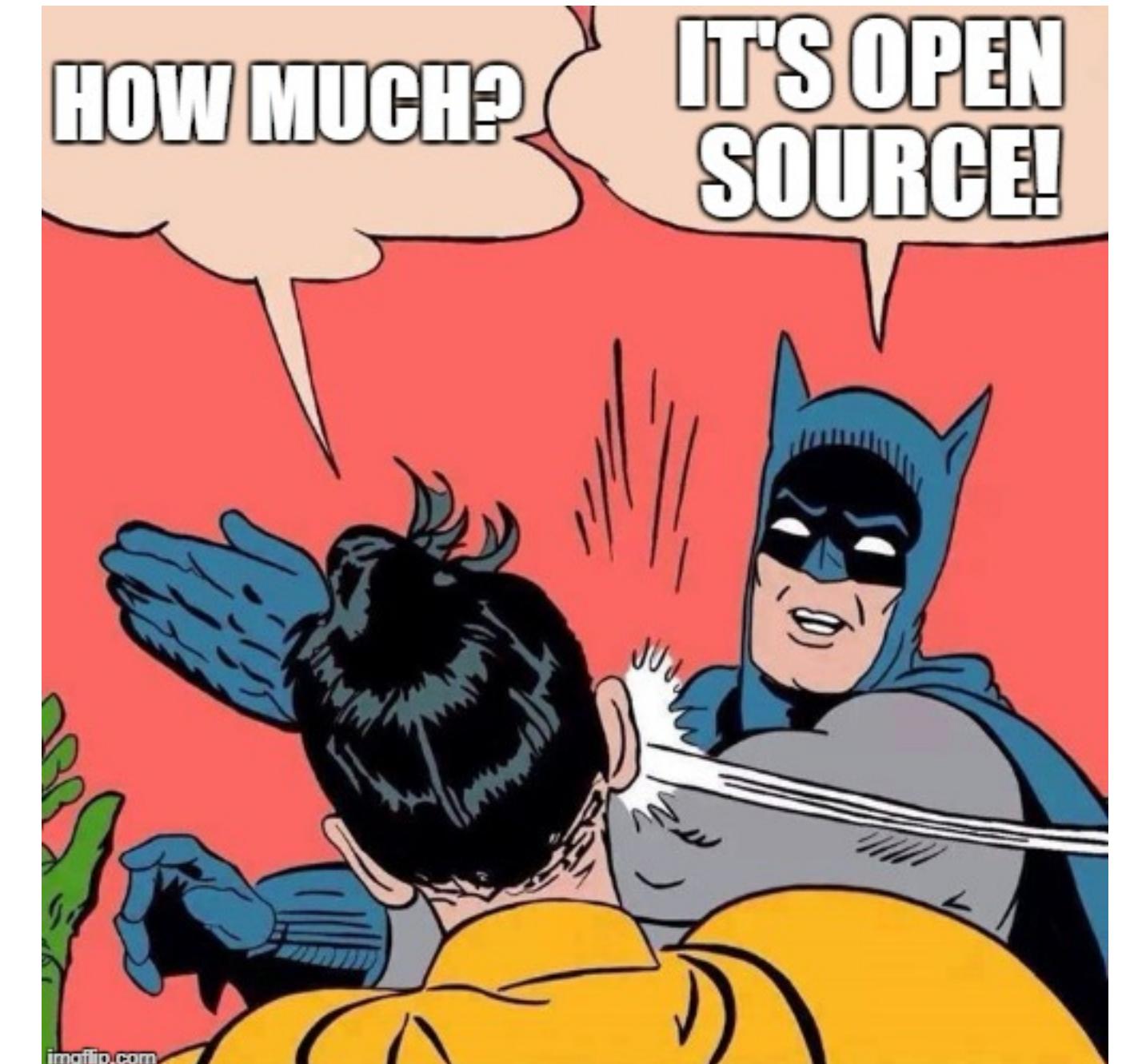
A formalized trial-and-error approach to map the actions to the states

CityLearn provides standardization

- Gym environment to study neighborhood/community scale
- Buildings & systems are abstracted out in the library
 - Availability and size of systems can be configured (PV, thermal, electric storage)
 - Own buildings can be imported/used*
- In V1 - demand is precomputed
 - Active energy storage control (load shifting)
 - Focus on control algorithms (RLC, MPC, RBC)
- Code & Docu accessible through www.citylearn.net

```
[ ]: pip install CityLearn
```

- Open source: can be extended/adapted to your needs

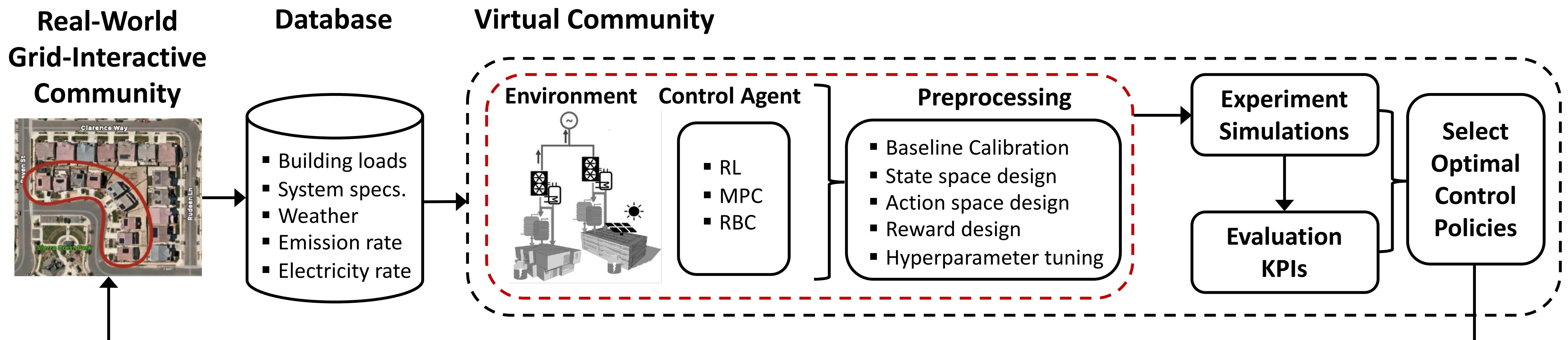


Can we learn from one building and deploy on another building? Can we learn to *flex*?

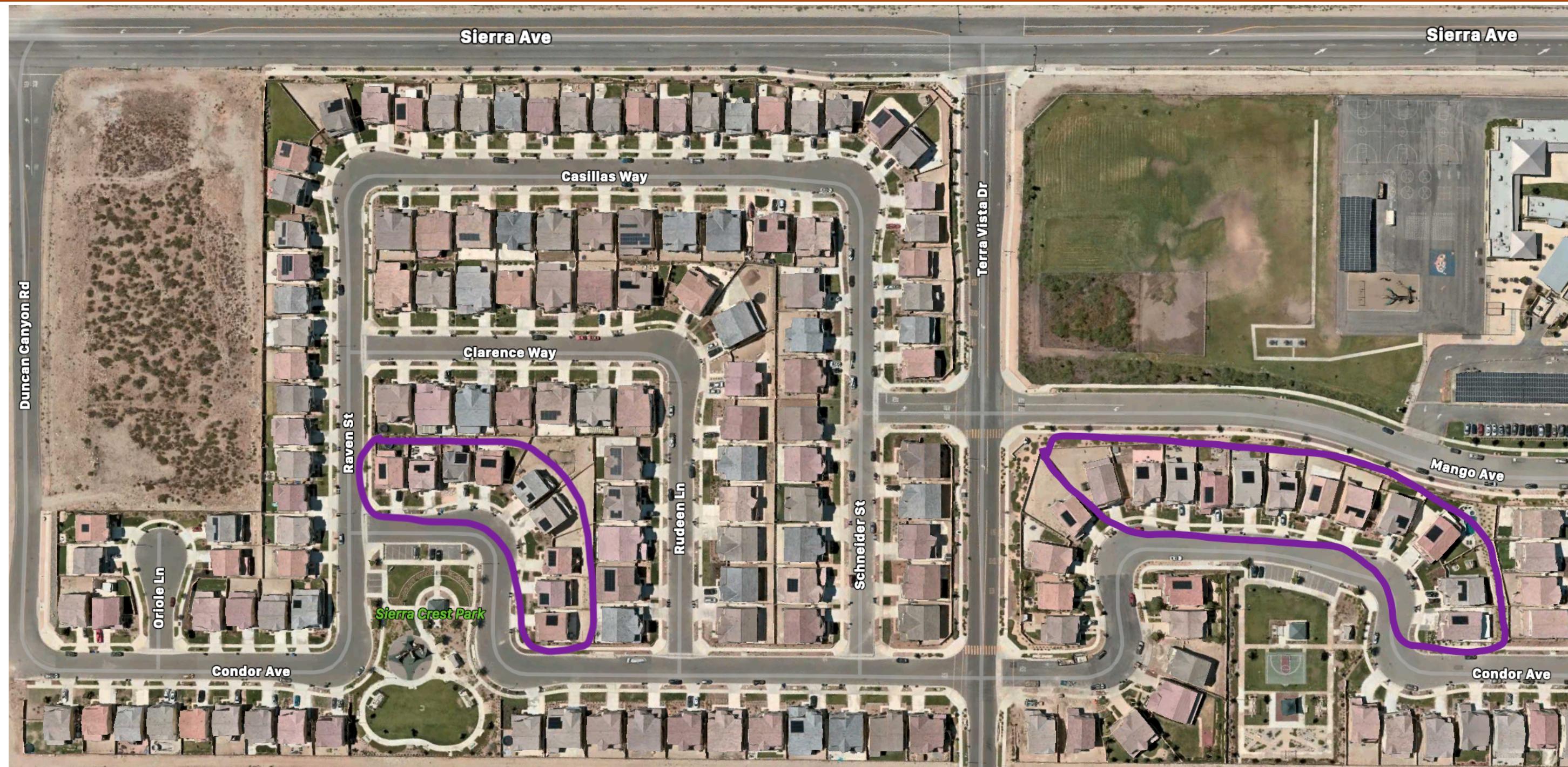
Can we learn from one building and deploy on another building? Can we learn to *flex*?

Yes, we can.

Can we learn from one building and deploy on another building? Can we learn to *flex*?



Nweye et al. "Multi-agent offline and transfer learning for occupant-centric operation of grid-interactive communities", Applied Energy (In Press), May. 2023, <https://arxiv.org/pdf/2301.01148.pdf>.

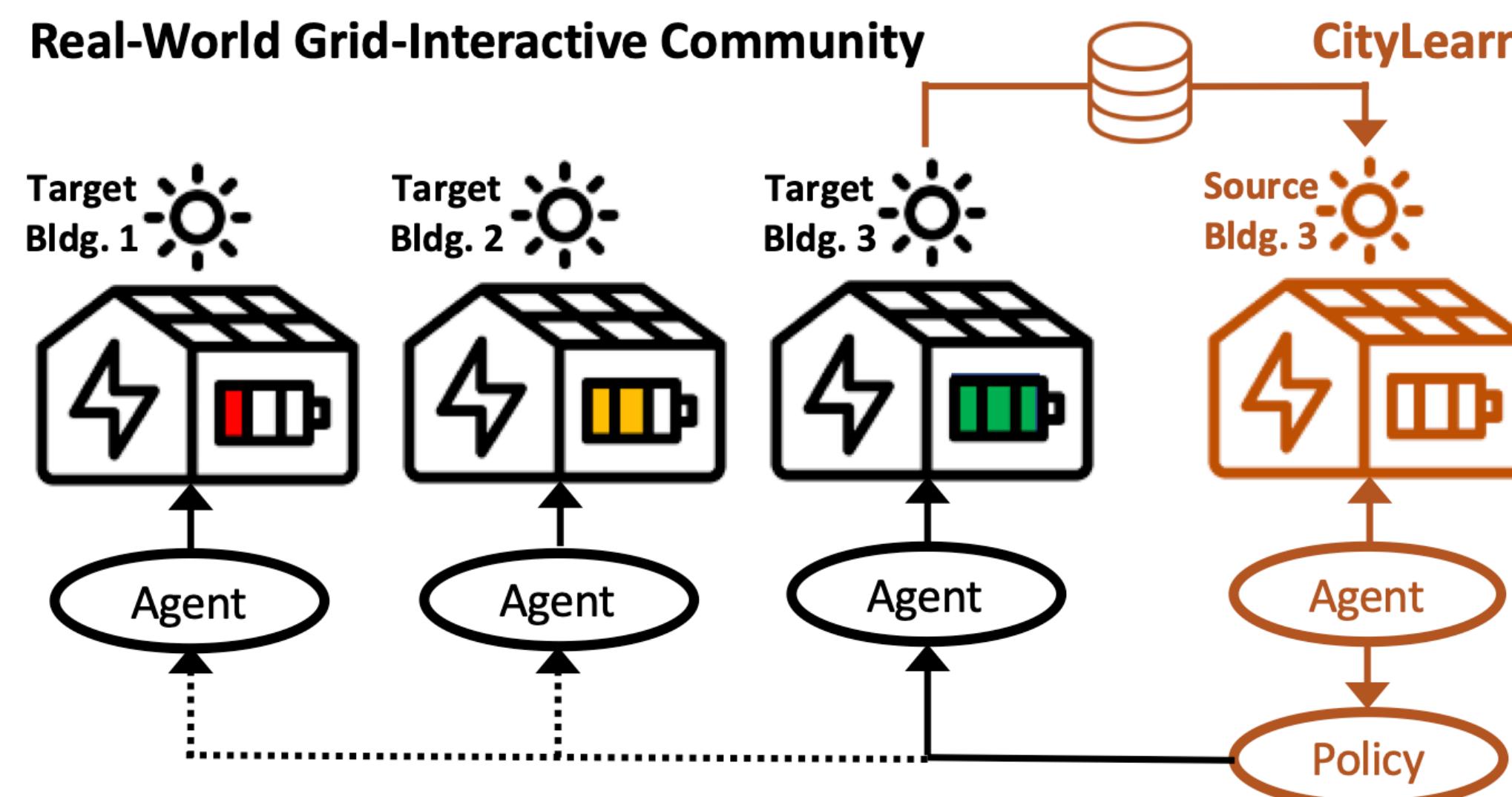


17 high efficiency SF homes in Fontana, Ca.
 All with Solar PV and electric battery storage

Control task is to charge/discharge battery

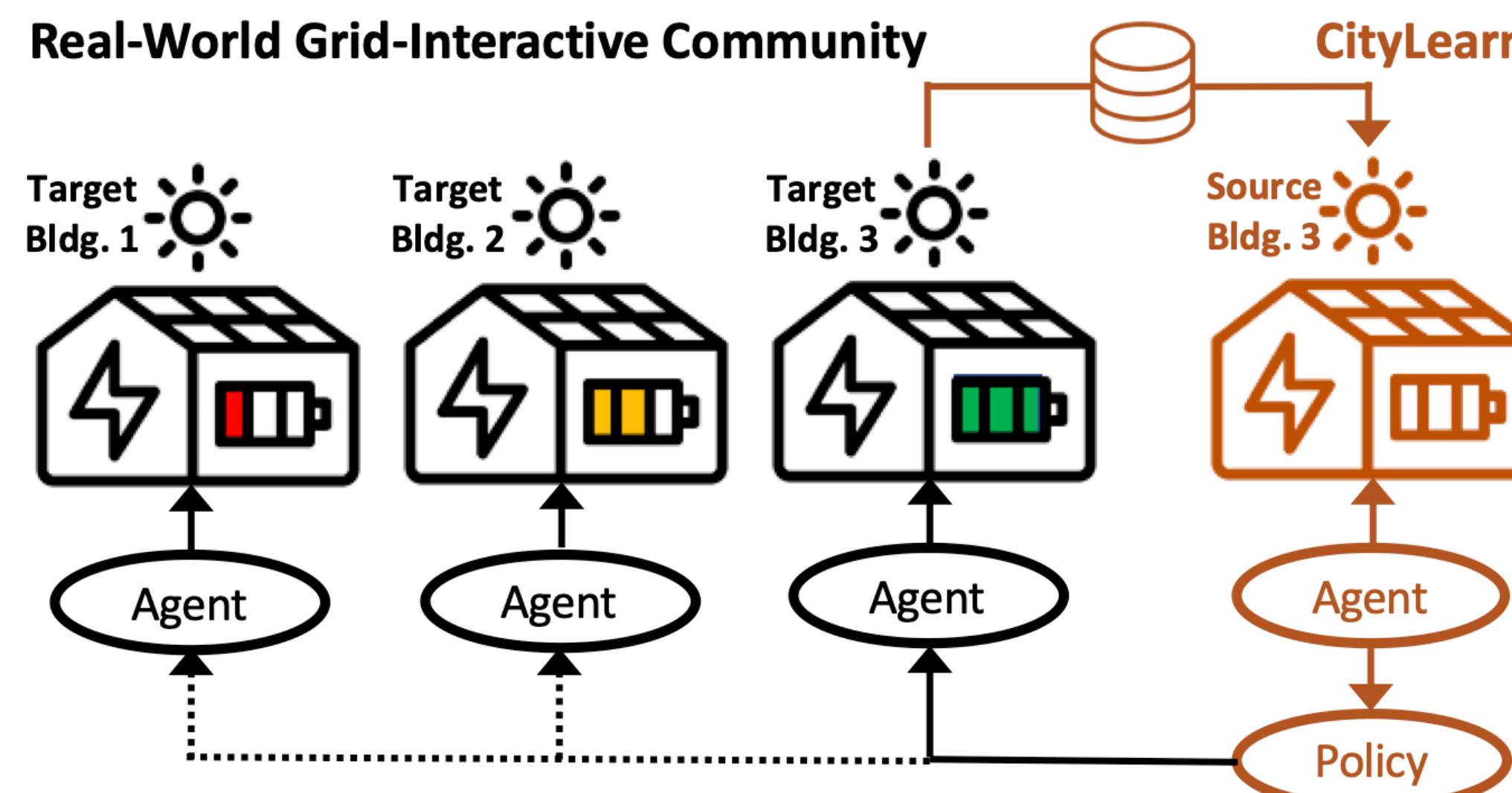
Electric Power Research Institute, *Grid integration of zero net energy communities*, 2017.
 URL: https://www.calmac.org/publications/CSIRDD_Sol4_EPRI_Grid-Integration-of-ZNE-Communities_FinalRpt_2017-01-27.pdf

Training & Deployment strategies



DS1: unique controller for each building
with 12 months data (**perfect knowledge**)

Training & Deployment strategies



DS1: unique controller for each building with 12 months data (perfect knowledge)

DS3: train for 5 months of one building transfer policy to all other buildings and deploy on unseen 7 months
(transfer learning)

Time of Use (RBC) & KPIs

Table 1

Time-Of-Use rate plan (\$/kWh) used as electricity rate in simulation environment.

Time	June-September		October-May	
	Weekday	Weekend	Weekday	Weekend
8 AM-4 PM	0.21	0.21	0.20	0.20
4 PM-9 PM	0.54	0.40	0.50	0.50
9 PM-8 AM	0.21	0.21	0.20	0.20

Reference RBC based on time-of-use tariff
(charge when cheap,
discharge when expensive)

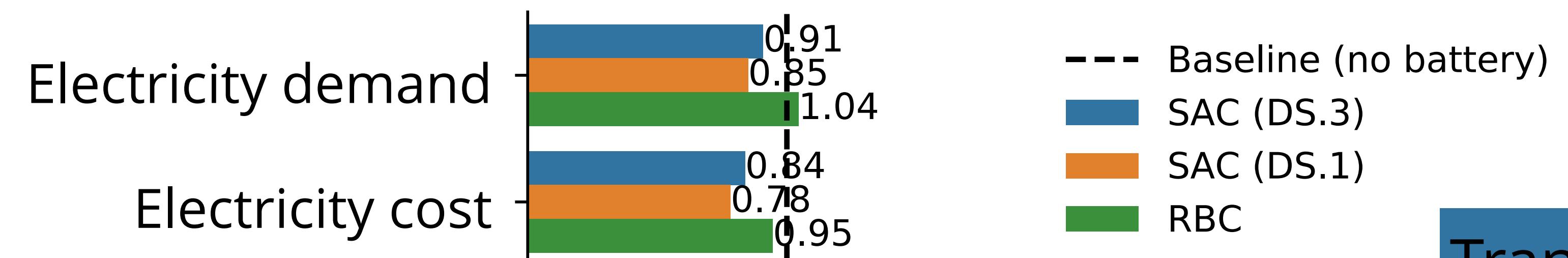
Building level KPIs:

- net electricity consumption
- electricity cost
- carbon emissions
- zero net energy

Additional district level KPIs:

- Average daily peak
- Ramping
- 1-Load Factor

Some results: DS1 better than DS3 better RBC



Transfer Learning

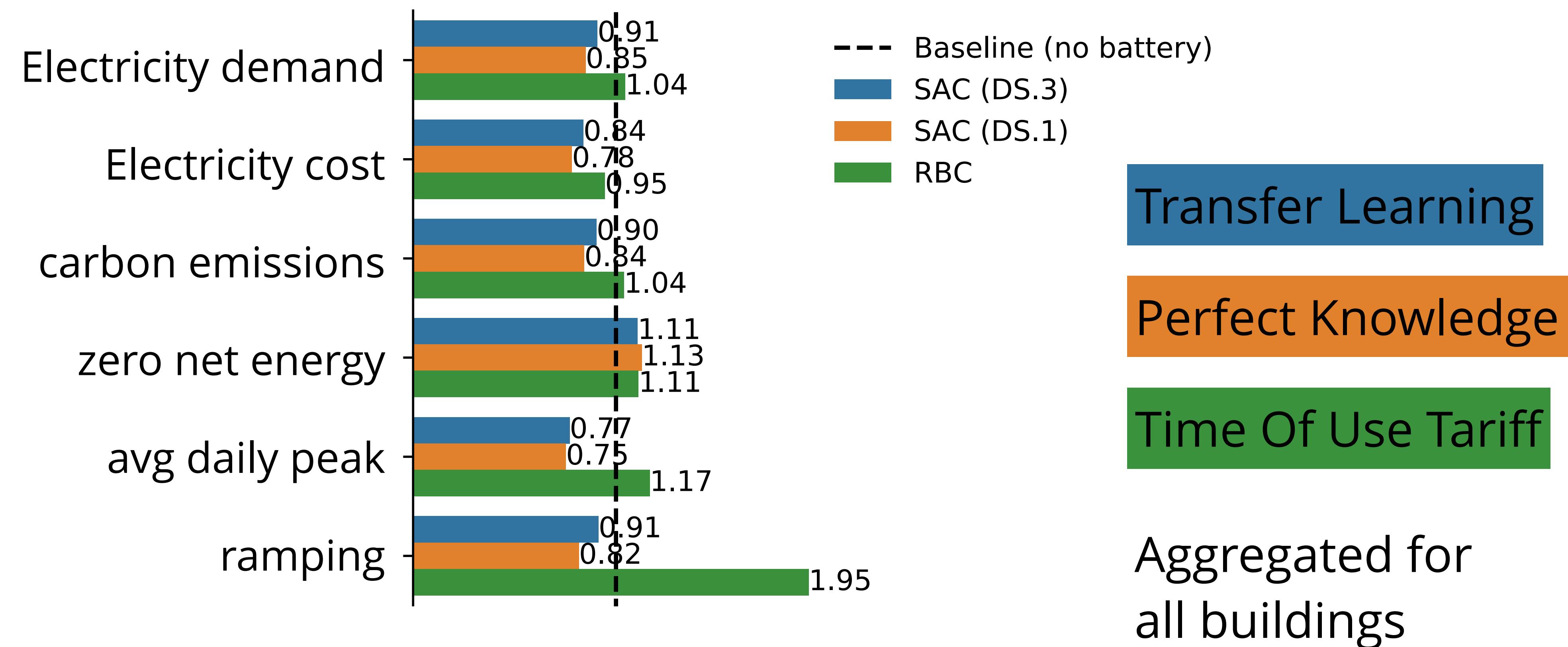
Perfect Knowledge

Time Of Use Tariff

Aggregated for
all buildings

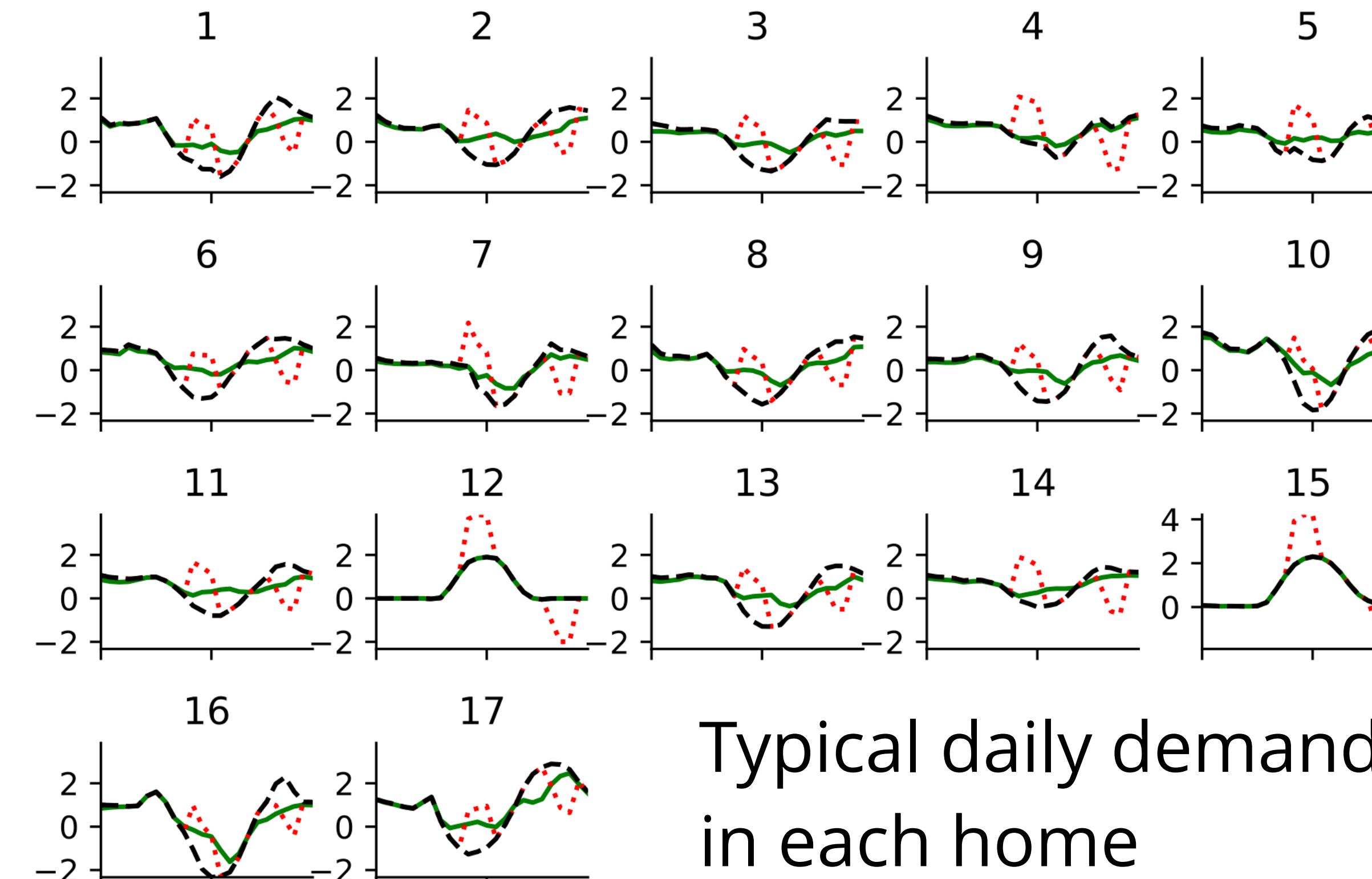
$$KPI = \frac{KPI_{control}}{KPI_{baseline \text{ (no battery)}}}$$

Some results: DS1 better than DS3 better RBC



$$KPI = \frac{KPI_{control}}{KPI_{baseline \text{ (no battery)}}}$$

TOU shifts peak but we can *learn to flex better*



(a) Building-level.

No Control

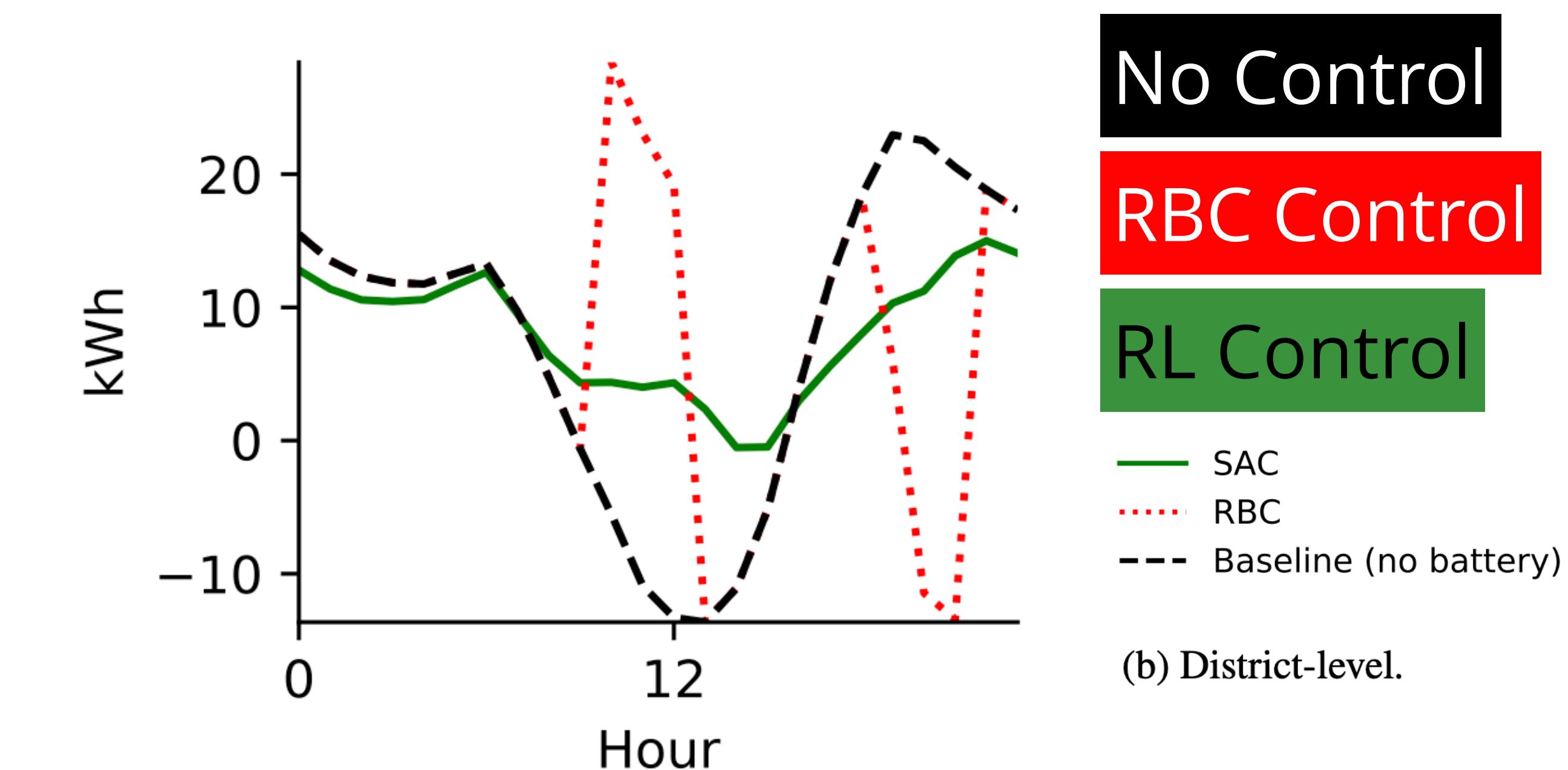
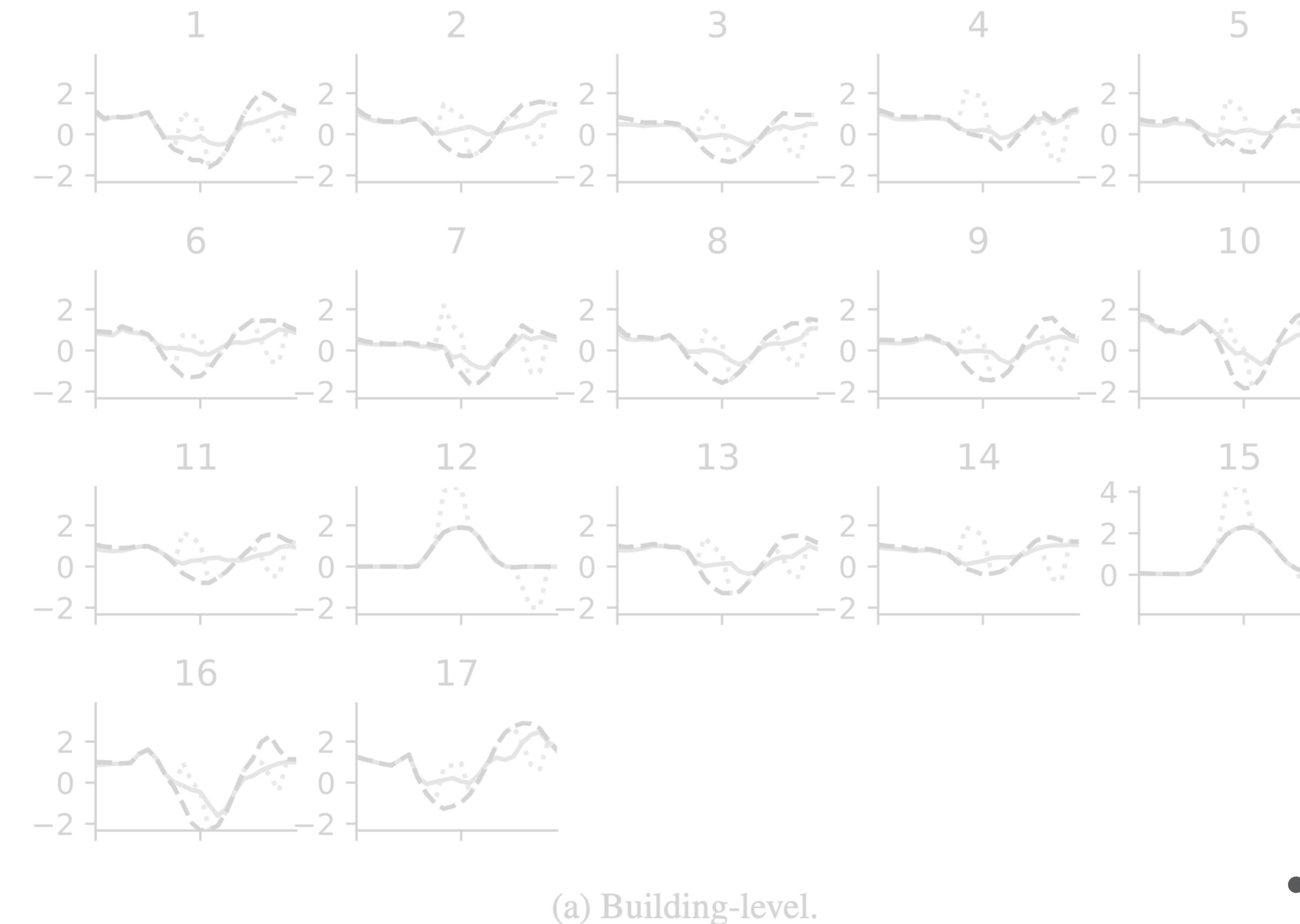
RBC Control

RL Control

SAC
RBC
Baseline (no battery)

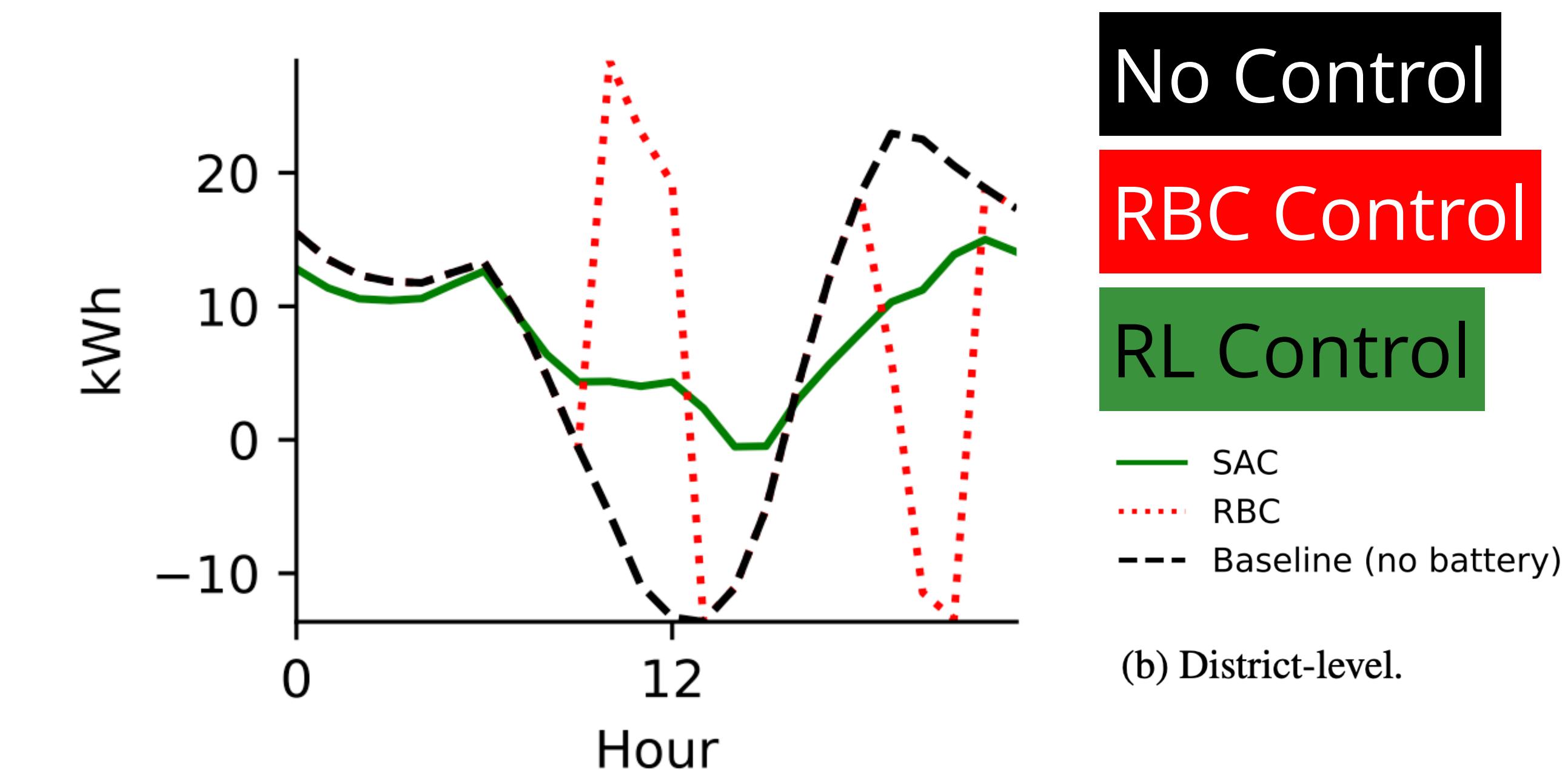
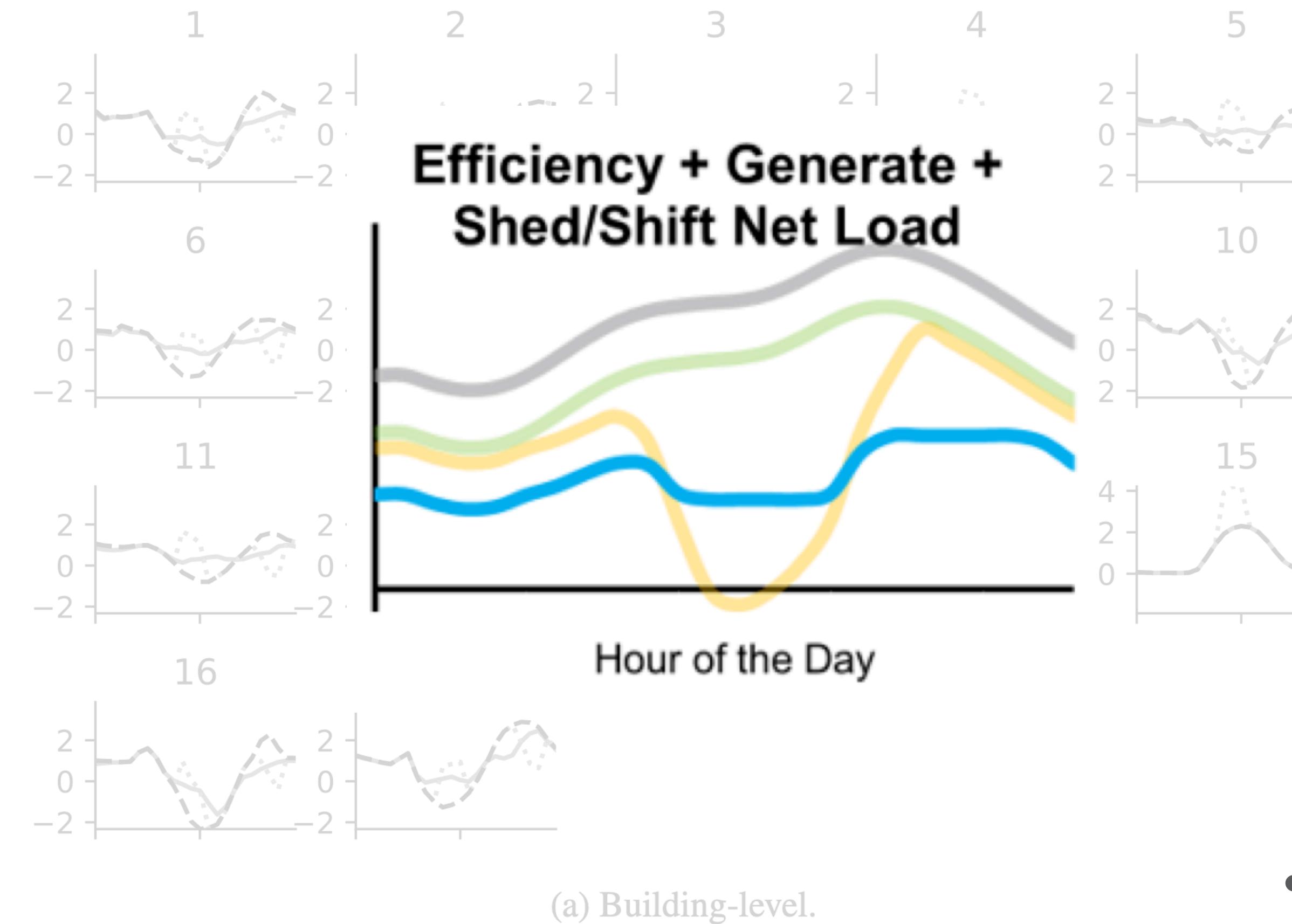
- Adapting to individual homes unlocks aggregated flexibility

TOU shifts peak but we can *learn to flex better*



- Building level control can unlock community level benefits
- Flex load smoother than TOU

TOU shifts peak but we can *learn to flex better*



- Building level control can unlock community level benefits
- Flex load smoother than TOU

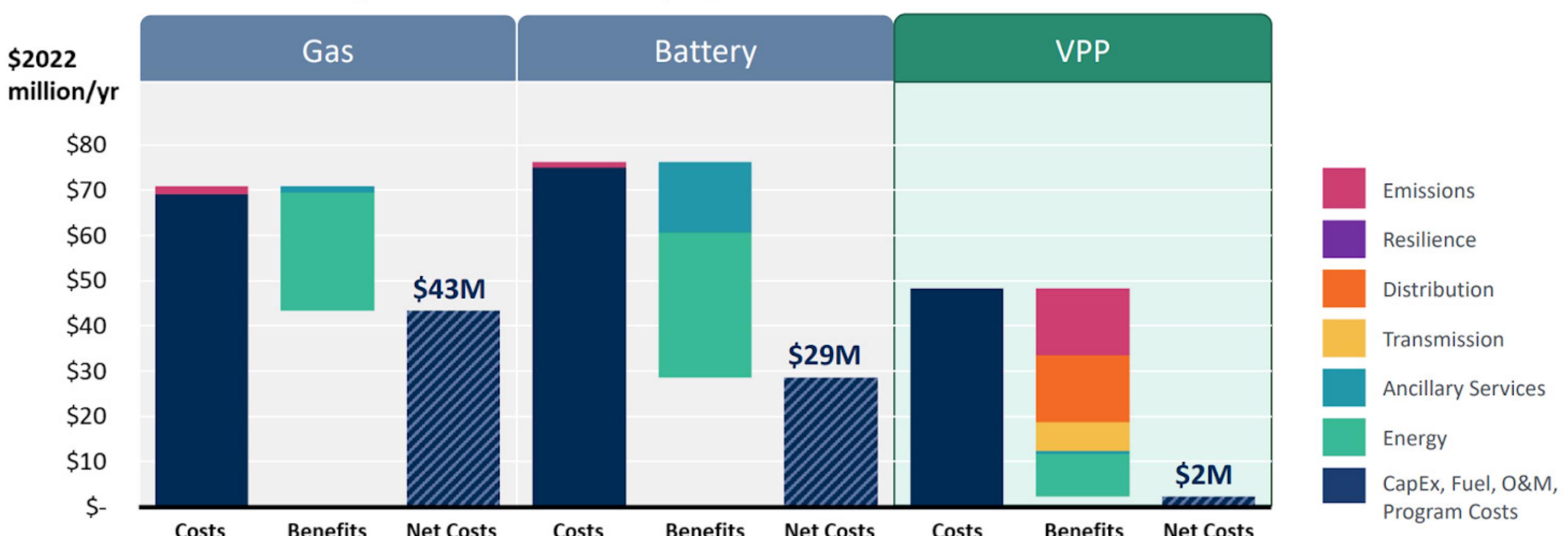
Flexing can avoid power plant & transmission costs

THE VALUE OF VPPS

Resource Adequacy... For Cheap

The VPP could provide the same resource adequacy at a significant cost discount relative to the alternatives.

Annualized Net Cost of Providing 400 MW of Resource Adequacy



Questions?

Introduction to Python

- Tutorial / Walkthrough
- Activity 1 - Getting Started
- Homework 1