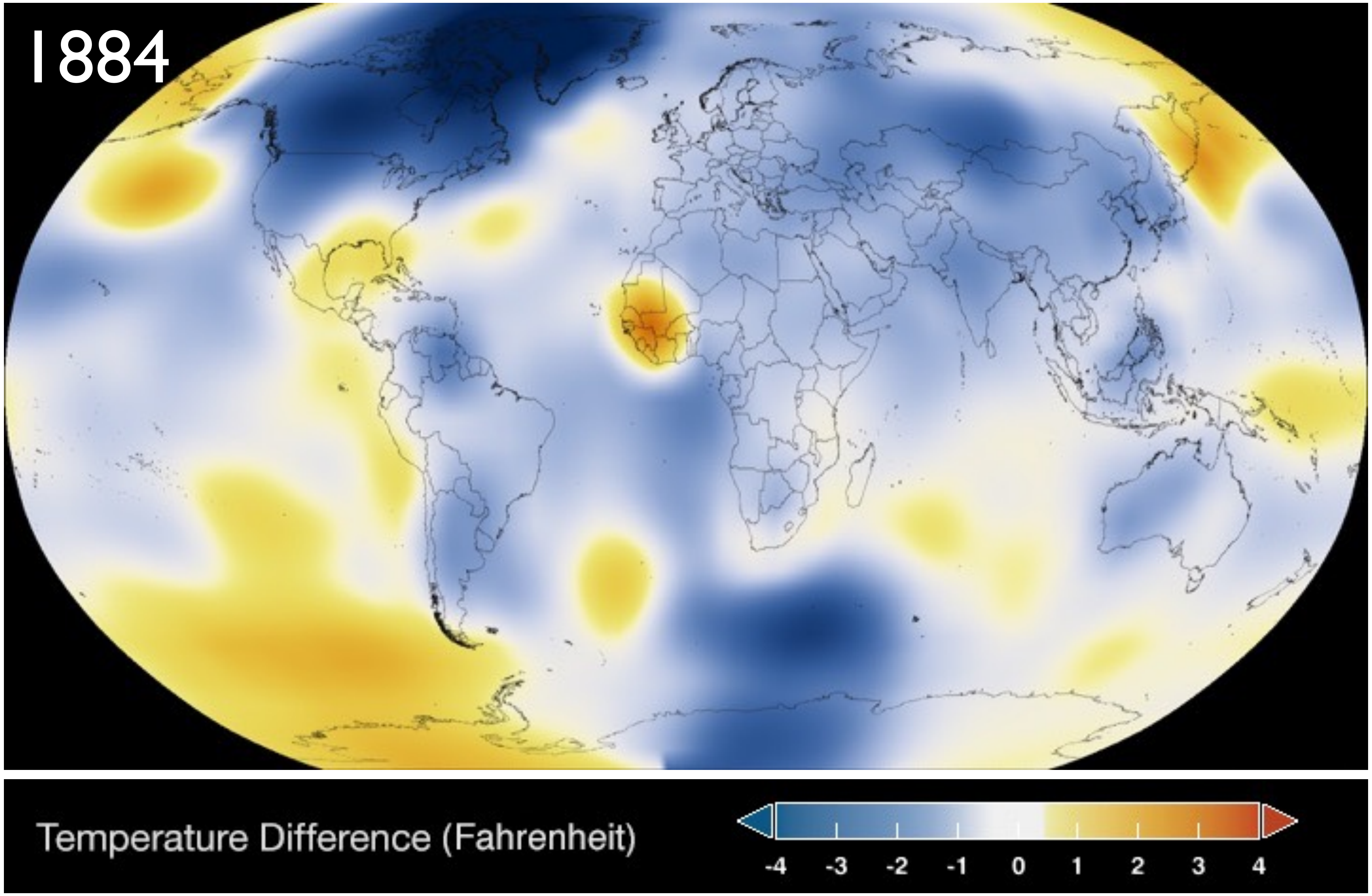
Building Smarter Energy Systems

and the path towards a sustainable future

Omid Ardakanian
University of British Columbia

University of Toronto
27 March 2017

Global Warming is Unequivocal



Data source: NASA/GISS
Credit: NASA Scientific Visualization Studio

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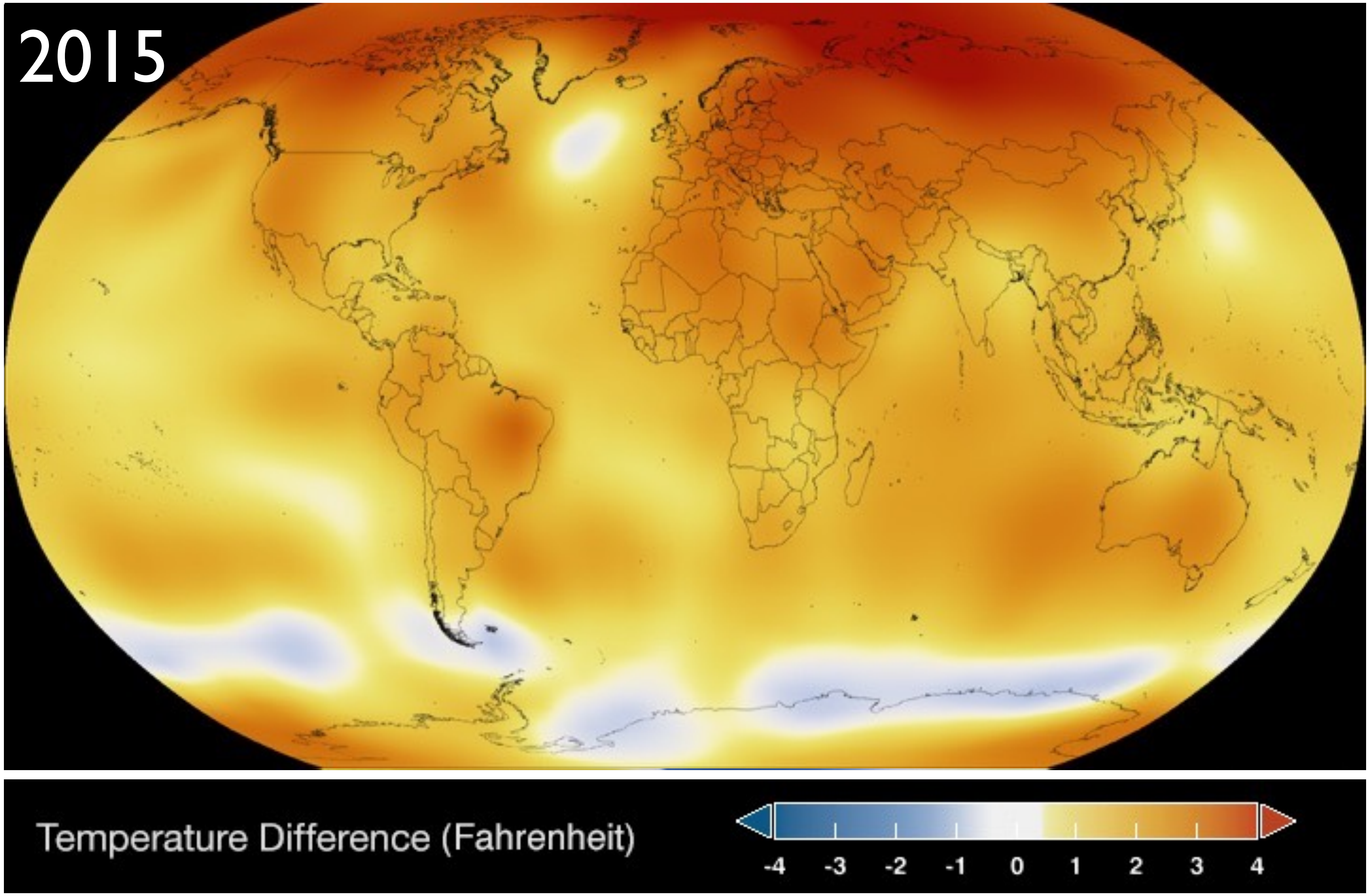

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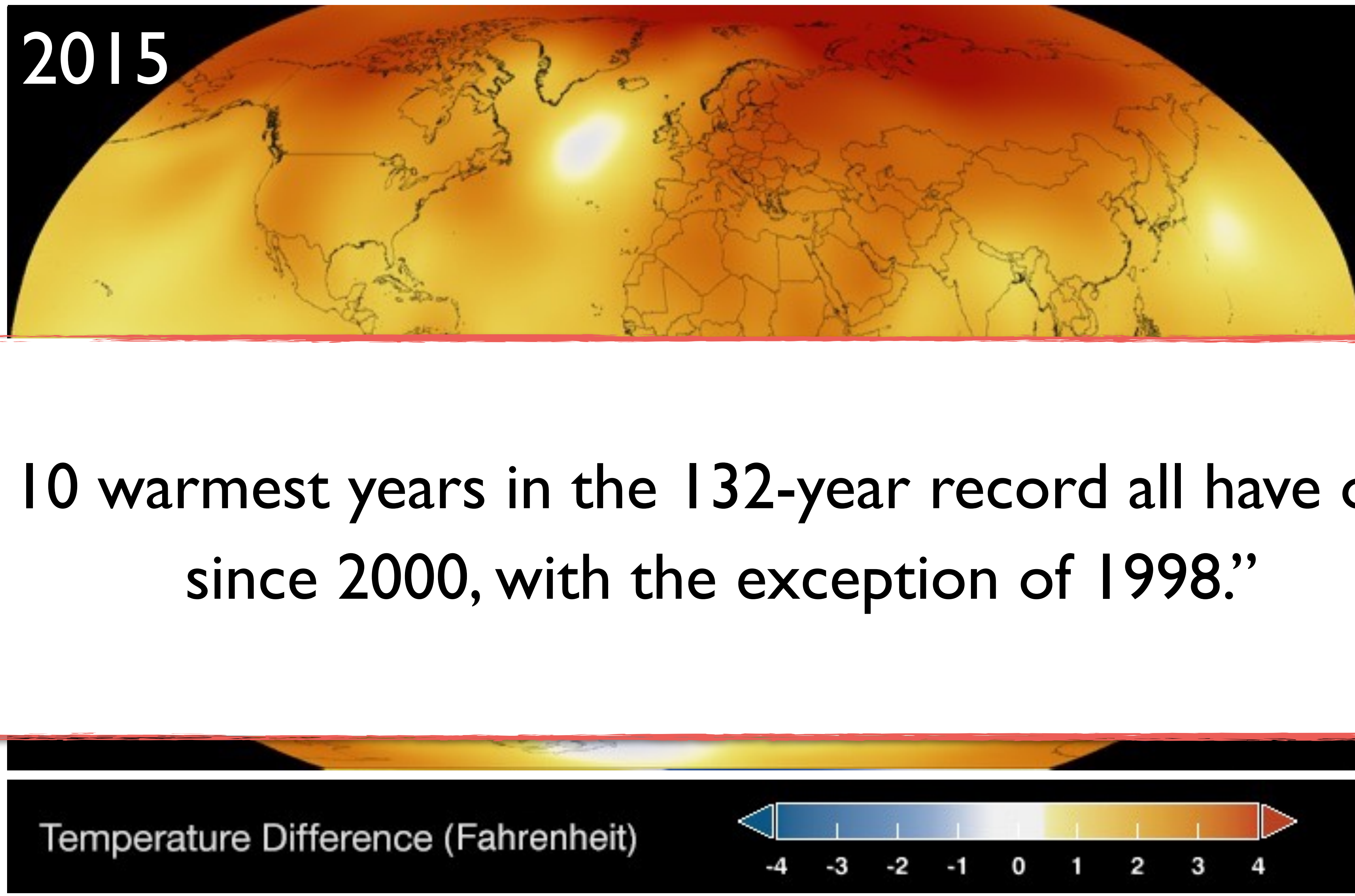
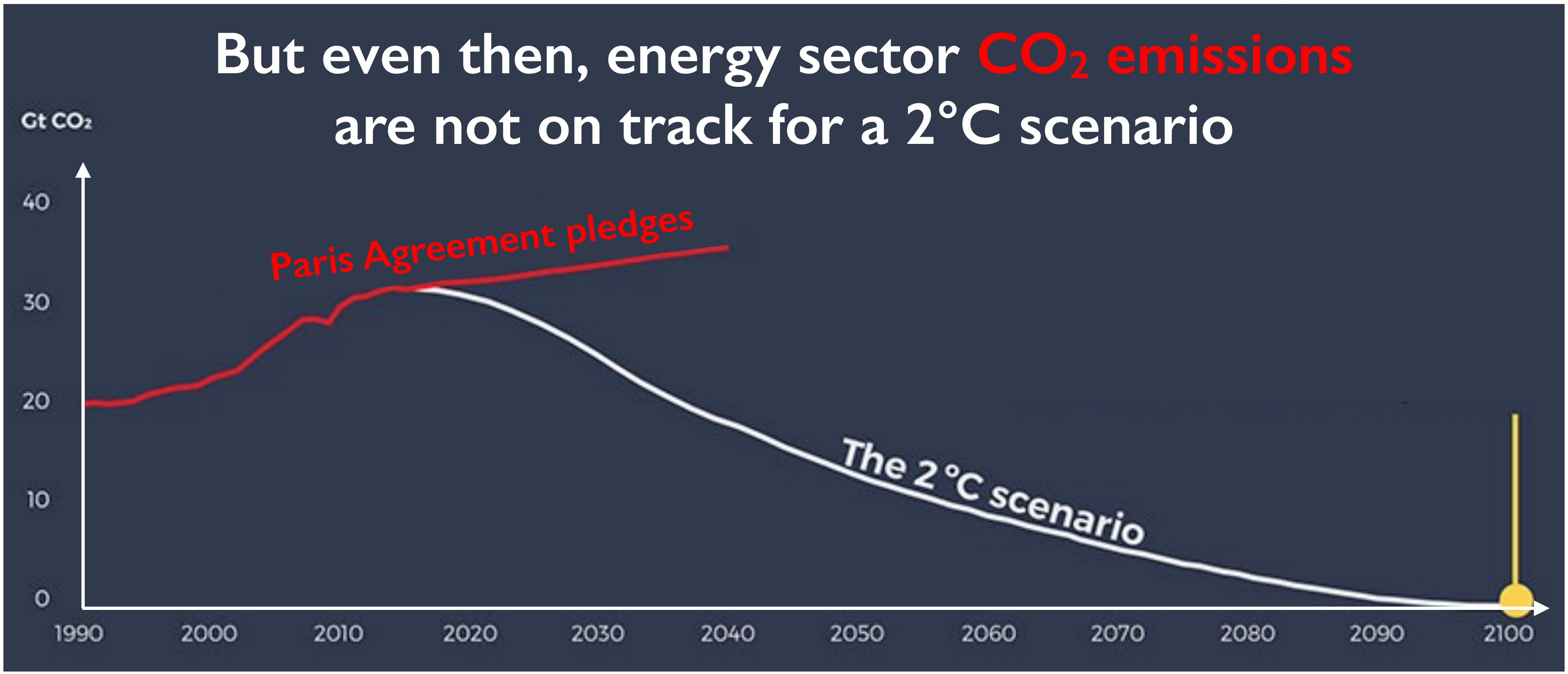


“The 10 warmest years in the 132-year record all have occurred since 2000, with the exception of 1998.”

Data source: NASA/GISS
Credit: NASA Scientific Visualization Studio

Global Efforts to Combat Climate Change



Source: IEA World Energy Outlook 2016

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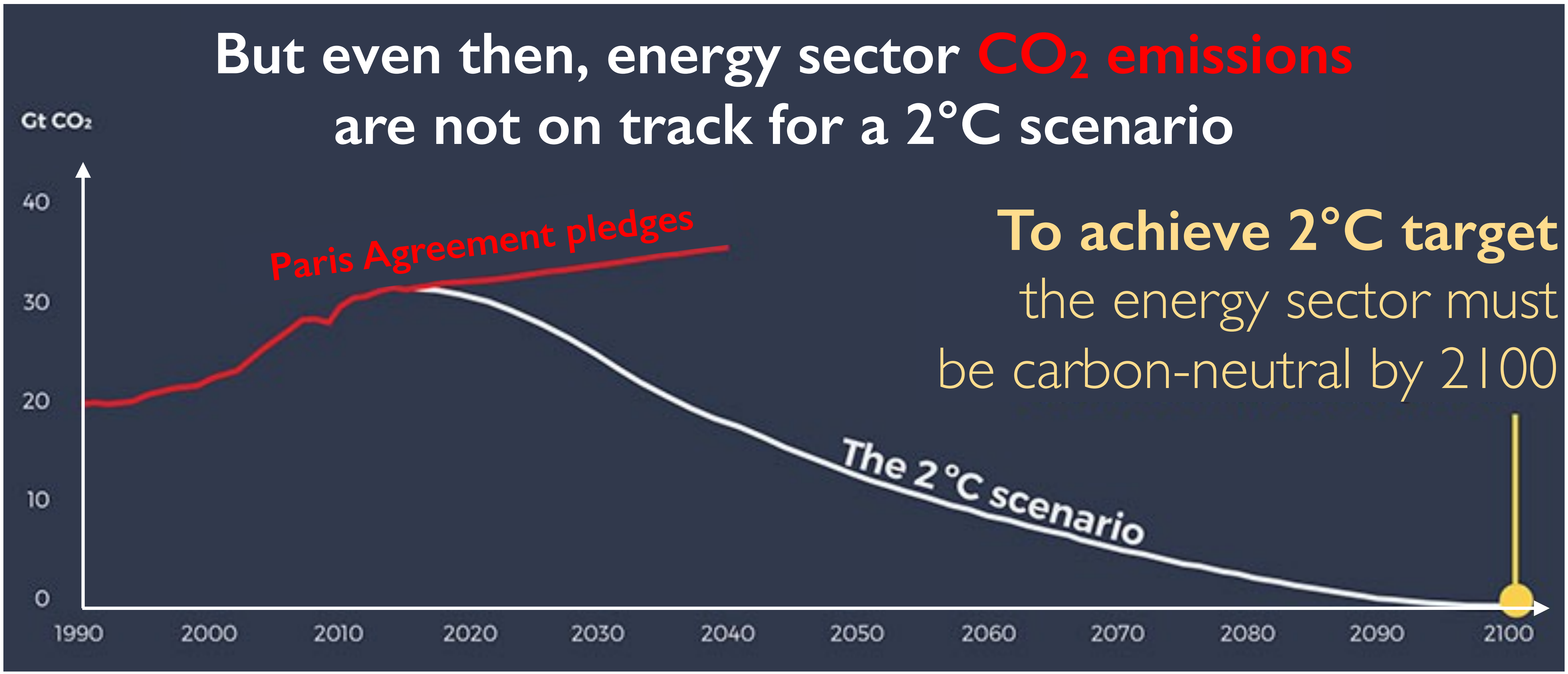


Source: IEA World Energy Outlook 2016

Urgent Action Needed to Reduce Carbon Emissions

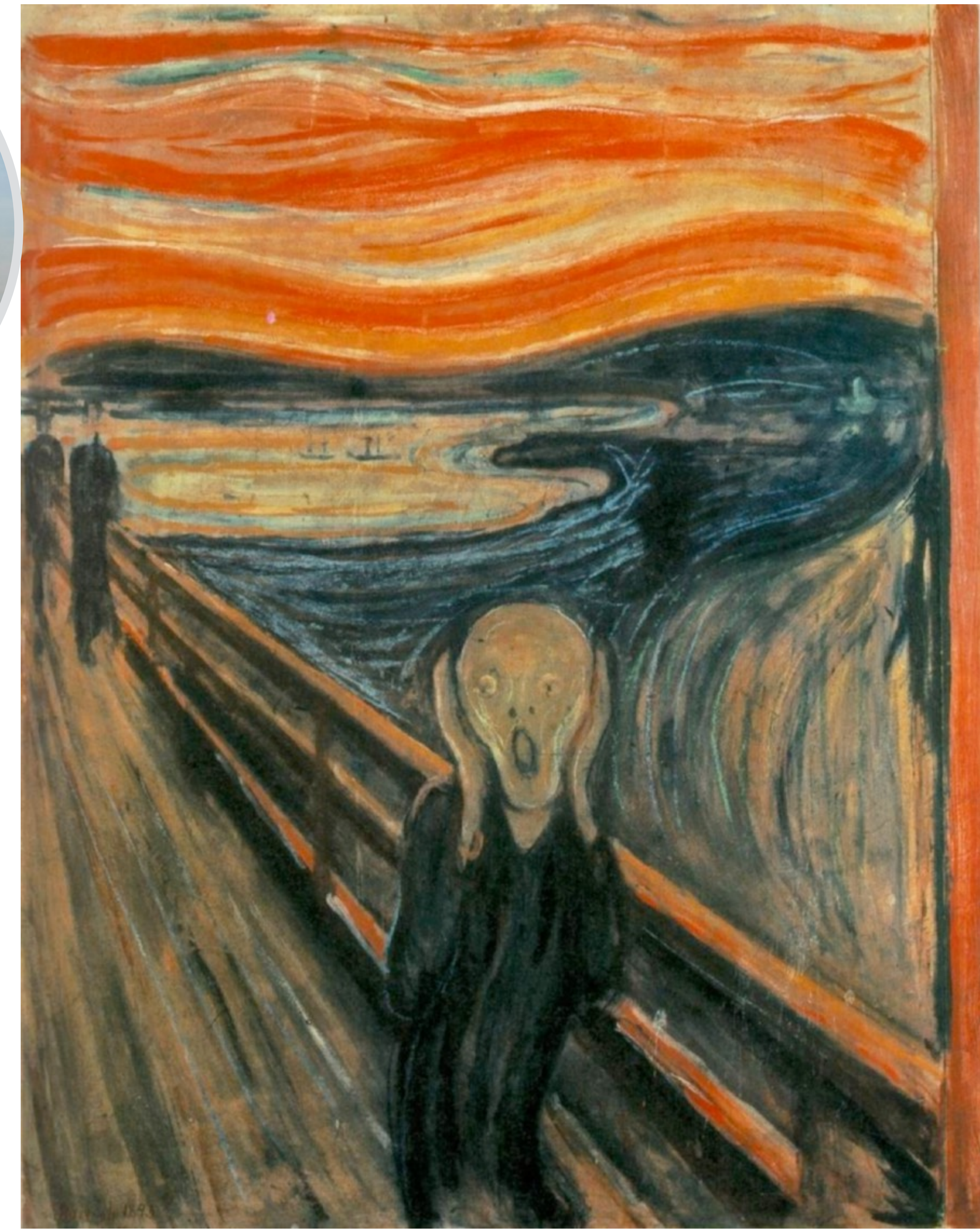
Urgent Action Needed to Reduce Carbon Emissions

14%

18%

39%

IEA World Energy Outlook 2016



Urgent Action Needed to Reduce Carbon Emissions

How to integrate low-carbon and renewable energy resources into the energy portfolio?

How to increase efficiency, utilization, and economic viability of energy systems?

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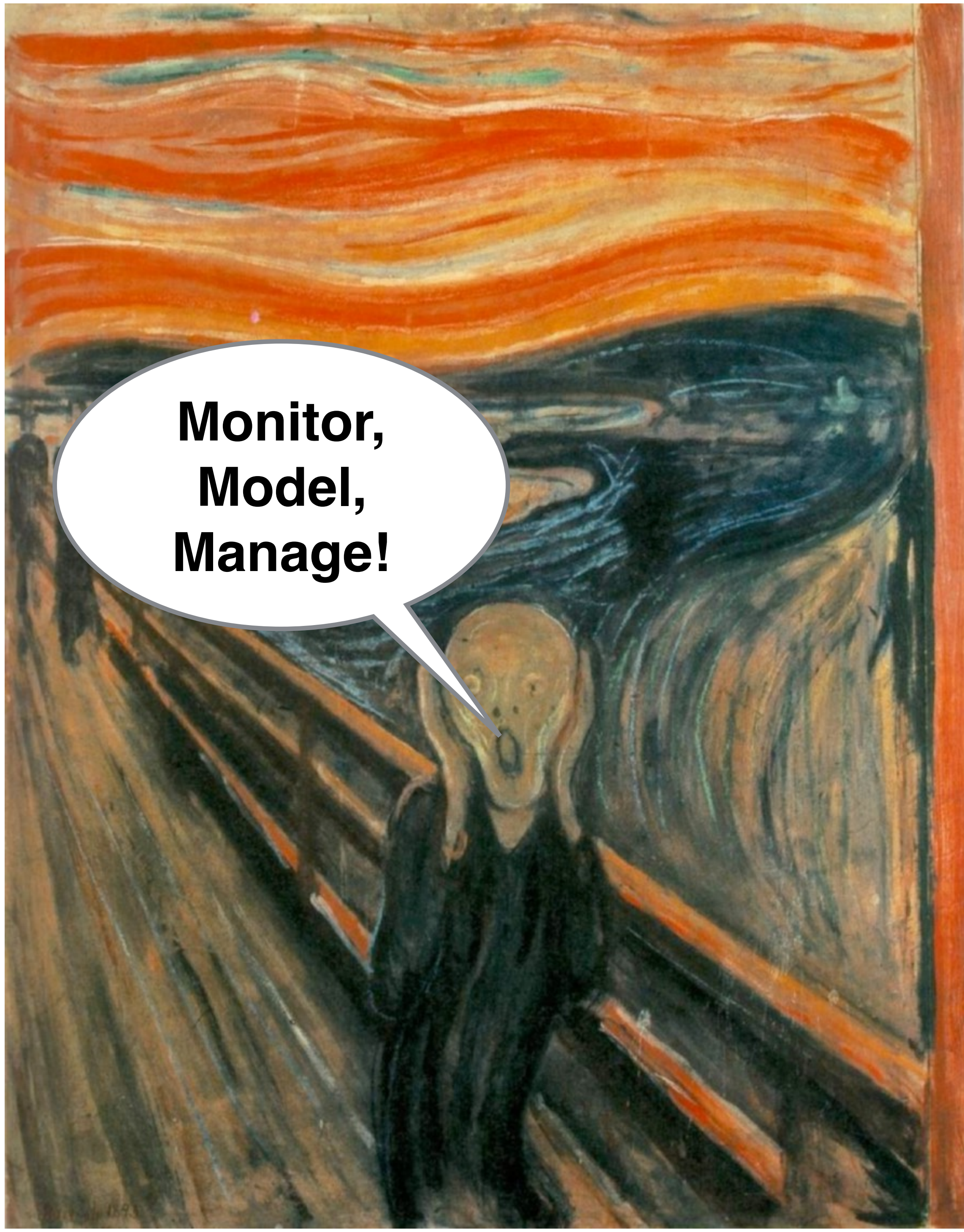
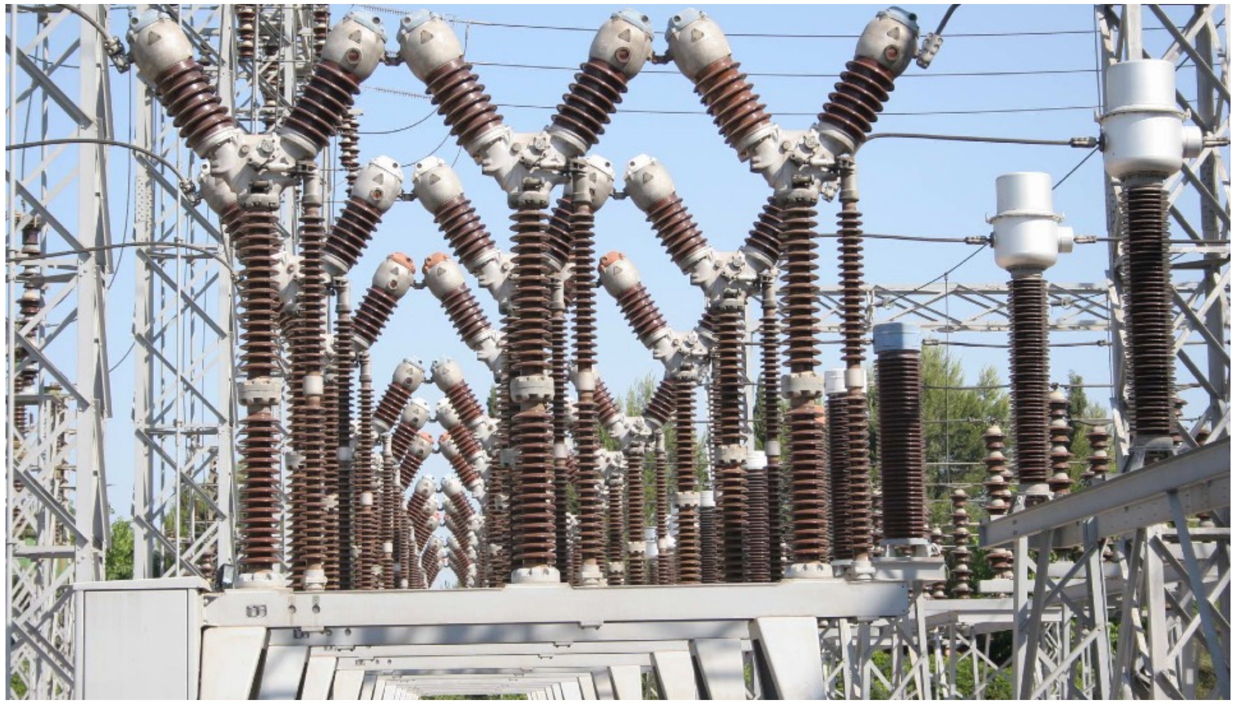


Unprecedented Opportunities

Unprecedented Opportunities

- Aging infrastructure



Unprecedented Opportunities

- Aging infrastructure
- New economic and social needs

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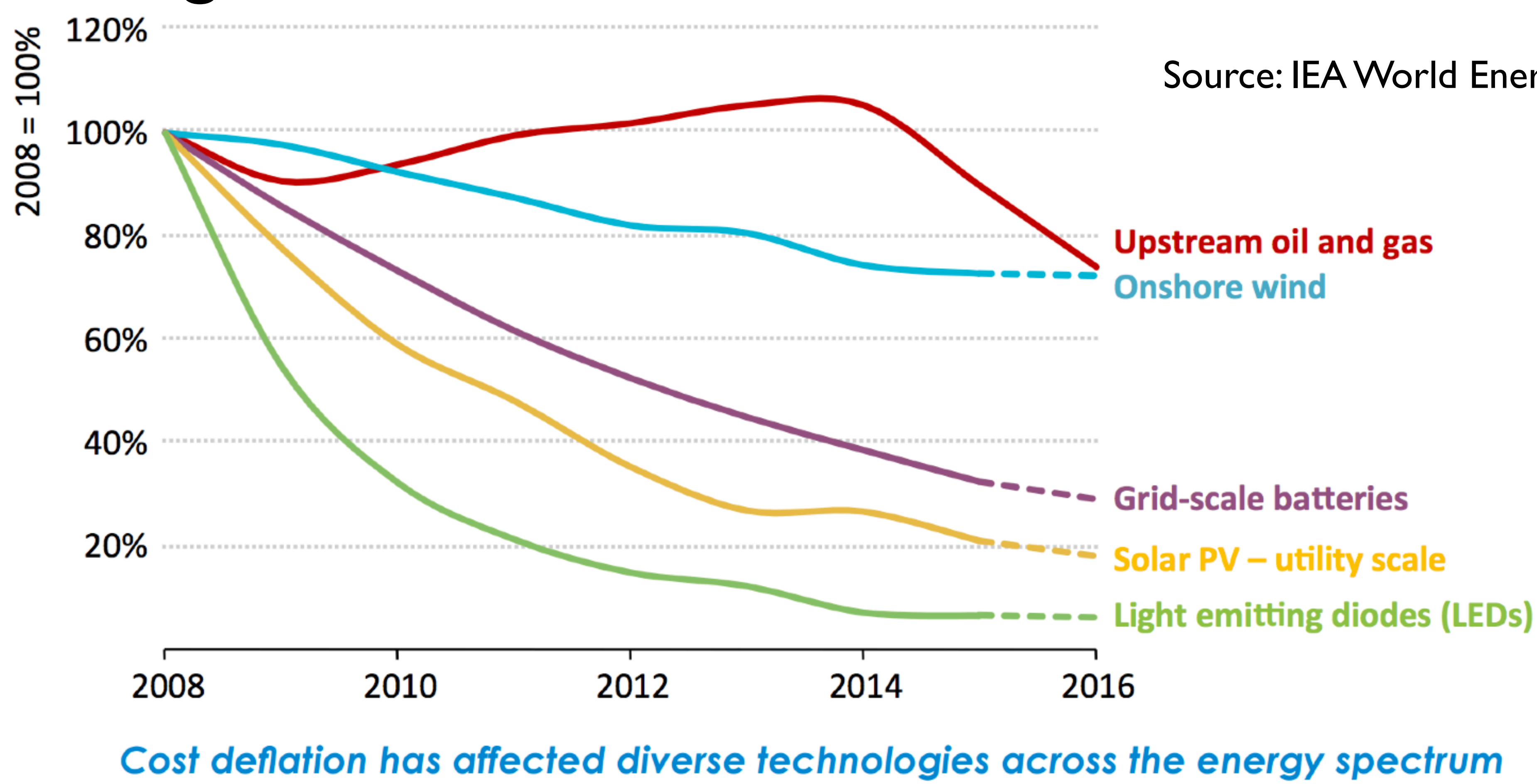
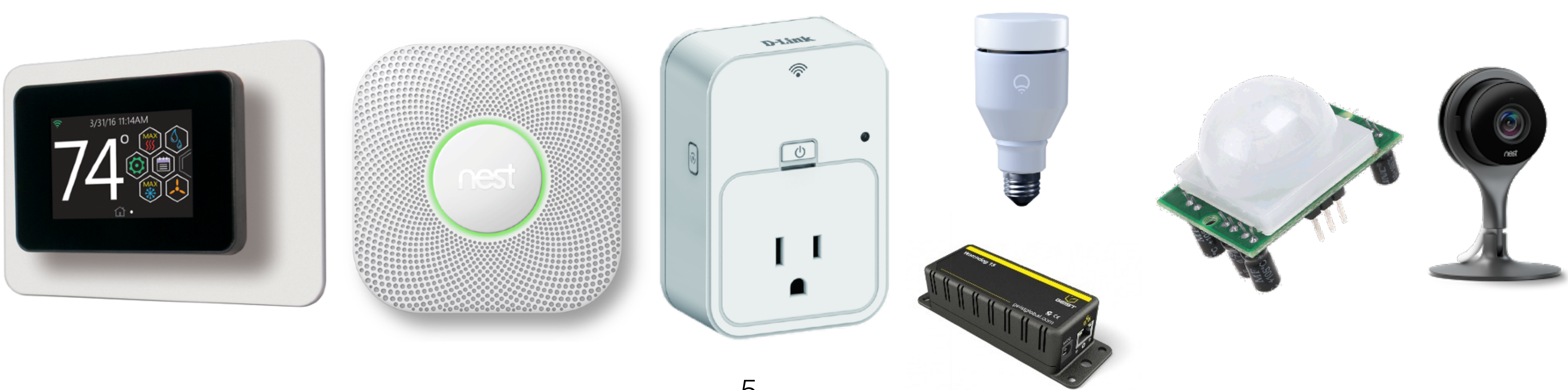
- Aging infrastructure
- New economic and social needs
- Declining costs of low-carbon and renewable technologies

Source: IEA World Energy Investment 2016

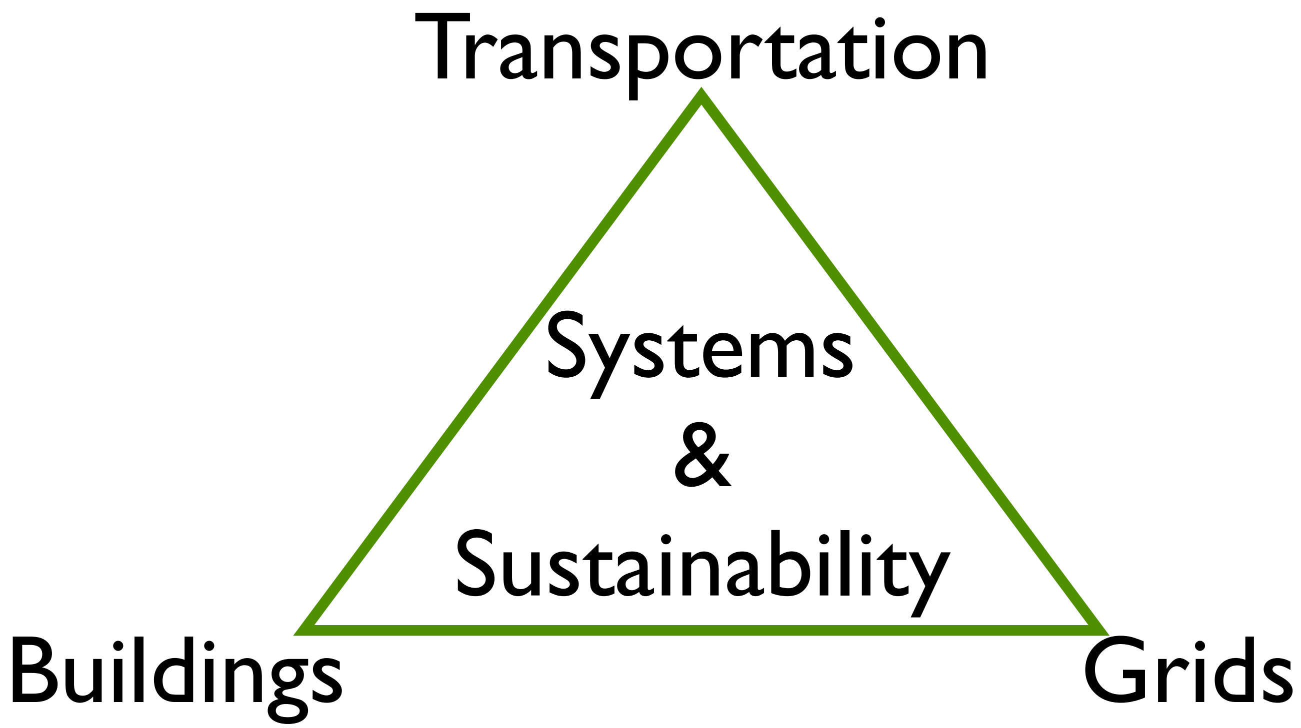


Unprecedented Opportunities

- Aging infrastructure
- New economic and social needs
- Declining costs of low-carbon and renewable technologies
- Pervasive sensing and control



Research on Sustainable Computing



Research on Sustainable Computing

	Monitor	Model	Manage
Transportation Systems			
Buildings			
Power Grids			

Research on Sustainable Computing

	Monitor	Model	Manage
Transportation Systems			**Home EV Charging** *GreenMetrics'12* *eEnergy'13* *ToSG'14* **Solar EV Charging** *SmartGridComm'14*
Buildings	**Sub-Metering** *GreenNets'11*		**HVAC** *BuildSys'16* **Residential Buildings** *EnDM'14*
Power Grids	**Phasor Measurement Units** *ongoing*	**Distribution Component Sizing** *eEnergy'12* *GreenMetrics'12*	**PV and Storage Integration** *SpringerBrief'16* **System Identification** *PES GM'17* **Event Detection & Classification** *ISGT'17*

Energy Data Collection and Analysis

Energy Data Collection and Analysis

2010

WeatherDuck

<u>every 10 sec</u>
temperature
humidity
air flow
acoustic
light

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<u>every 10 sec</u>
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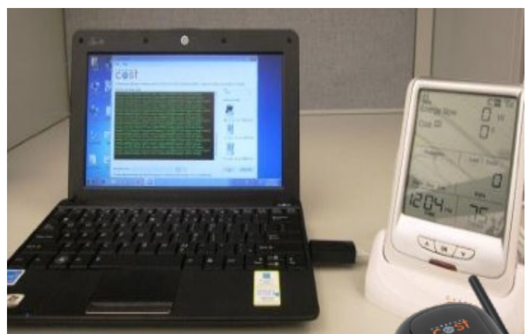

2010

WeatherDuck

<u>every 10 sec</u>
temperature
humidity
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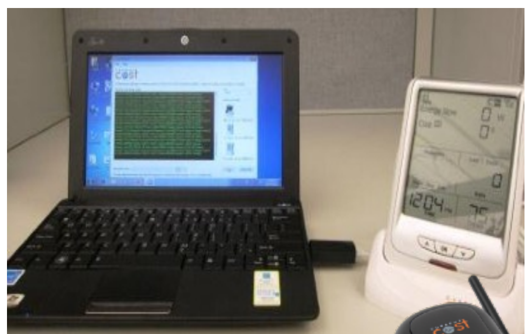
light

2011

CurrentCost Envi

<u>every 6 sec</u>
per phase current

Energy Data Collection and Analysis



2010 | 2011 | 2014

WeatherDuck

<u>every 10 sec</u>
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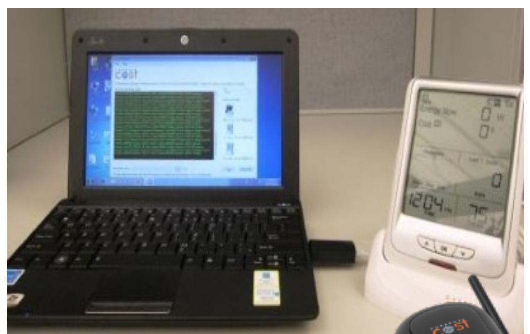
CurrentCost Envi

<u>every 6 sec</u>
per phase current

Smart Meters

<u>hourly</u>
electricity
consumption

Energy Data Collection and Analysis



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<u>every 10 sec</u>
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CurrentCost Envi

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per phase current

2014

Smart Meters

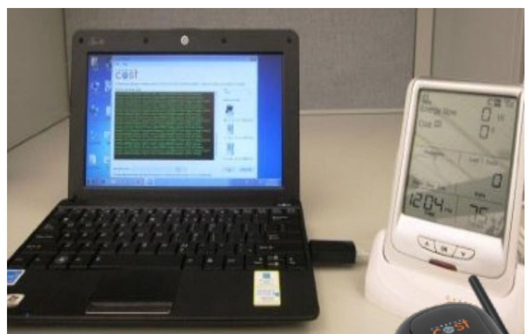
<u>hourly</u>
electricity
consumption

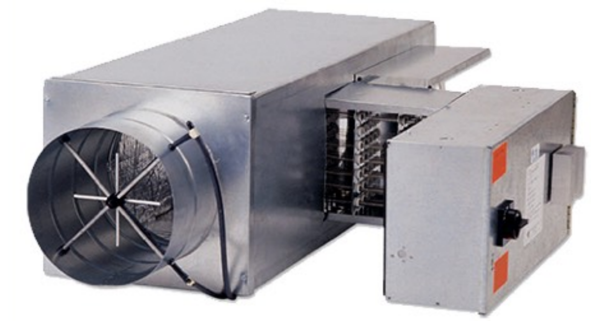
2015

PMUs

<u>120Hz</u>
voltage and current
phasors

Energy Data Collection and Analysis





2010	2011	2014	2015	2016
WeatherDuck	**CurrentCost Envi**	**Smart Meters**	**PMUs**	**HVAC Sensors**
every 10 sec temperature humidity air flow acoustic light	every 6 sec per phase current	hourly electricity consumption	120Hz voltage and current phasors	every 10-15 min supply air flow, temperature, …

OUTLINE

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Transportation Electrification			**Home EV Charging** *GreenMetrics'12* *eEnergy'13* *ToSG'14* **Solar EV Charging** *SmartGridComm'14*
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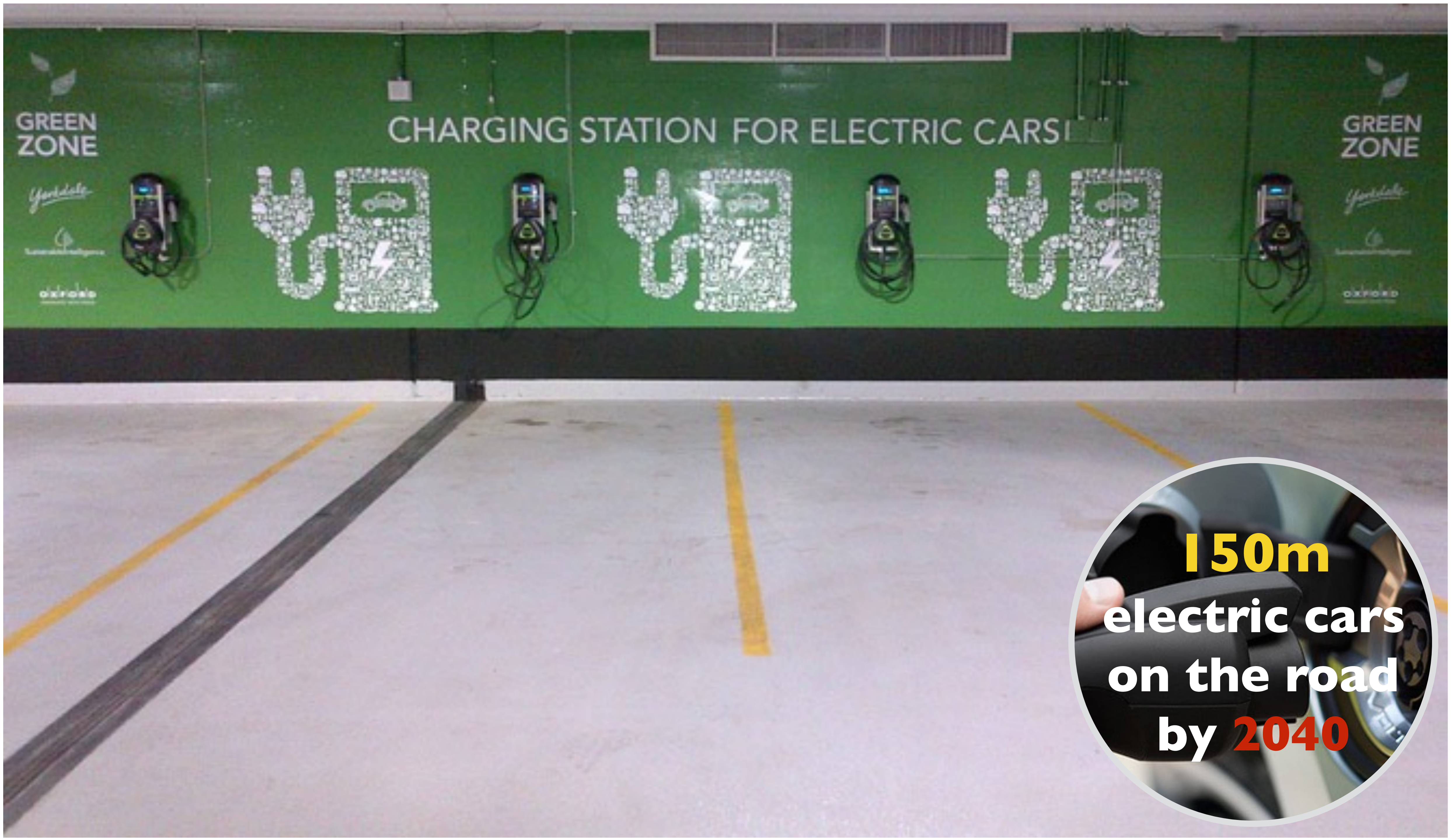
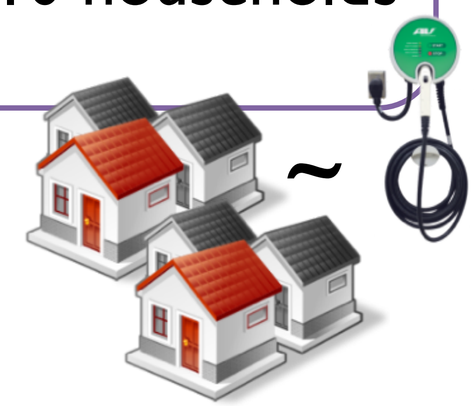
- **Omid Ardakanian**, S. Keshav, Catherine Rosenberg, "Real-Time Distributed Control for Smart Electric Vehicle Chargers: From a Static to a Dynamic Study", IEEE Transactions on Smart Grid, vol.5, no.5, pp.2295-2305, 2014.
- **Omid Ardakanian**, Catherine Rosenberg, S. Keshav, "Quantifying the Benefits of Extending Electric Vehicle Charging Deadlines with Solar Generation", In Proceedings of IEEE SmartGridComm, pp.620-625, 2014.
- **Omid Ardakanian,** Catherine Rosenberg, S. Keshav, "Distributed Control of Electric Vehicle Charging", In Proceedings of ACM International Conference on Future Energy Systems (e-Energy), pp.101-112, 2013. **Winner of Best Paper Award.**
- **Omid Ardakanian,** Catherine Rosenberg, S. Keshav, "Real-time distributed congestion control for electrical vehicle charging", invited paper, ACM SIGMETRICS Performance Evaluation Review, vol.40, no.3, pp.38-42, 2012.

Penetration of Electric Vehicles is Expected to Increase in Future



Opportunistic EV Charging Leads to Grid Congestion

1 EV charger ~ 5-10 households



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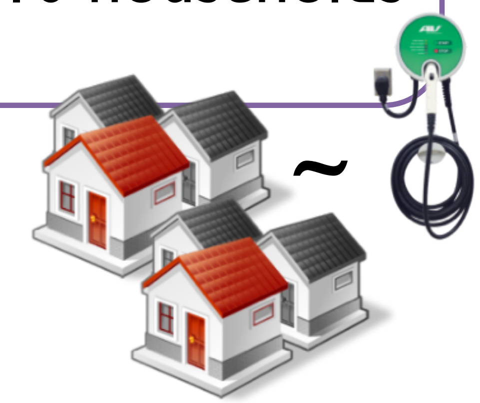

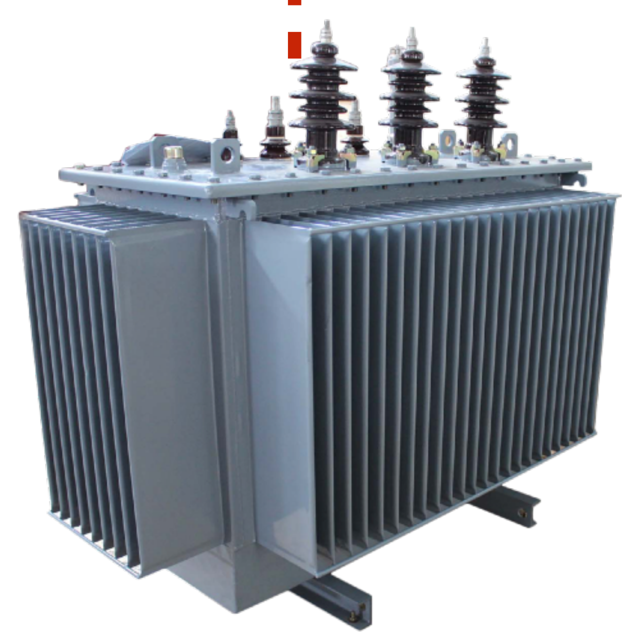

1) Overloads transformers
2) Increases peak demand

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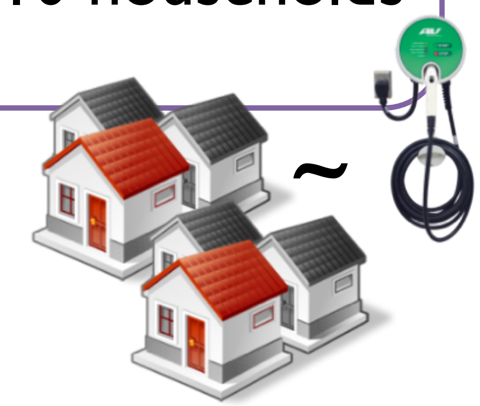
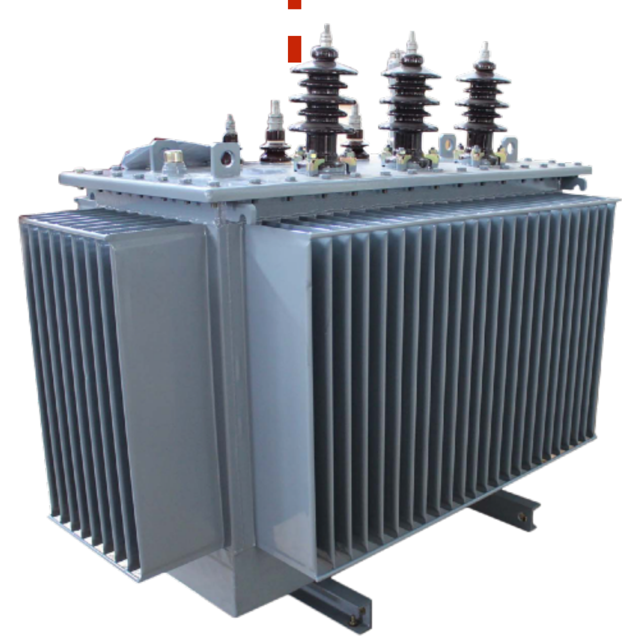




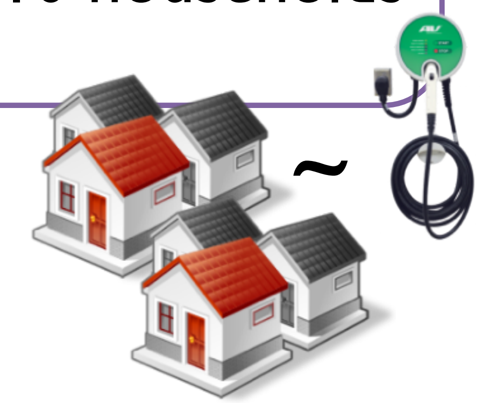
Schedule charging of EVs

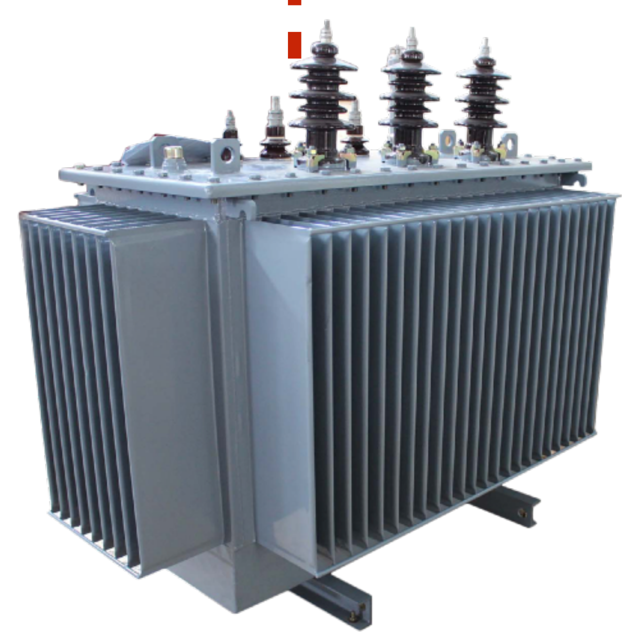
1) Overloads transformers
2) Increases peak demand

Opportunistic EV Charging Leads to Grid Congestion

Spatial/temporal uncertainties

1 EV charger ~ 5-10 households





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Possible Approaches to Coordinate EV Charging

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- **Scheduling:** solve an optimal power flow (OPF) problem to determine the charge powers
  - a non-convex optimization problem solved hours ahead
  - precise model of the distribution network (unavailable)
  - EV arrival and departure times (unknown)

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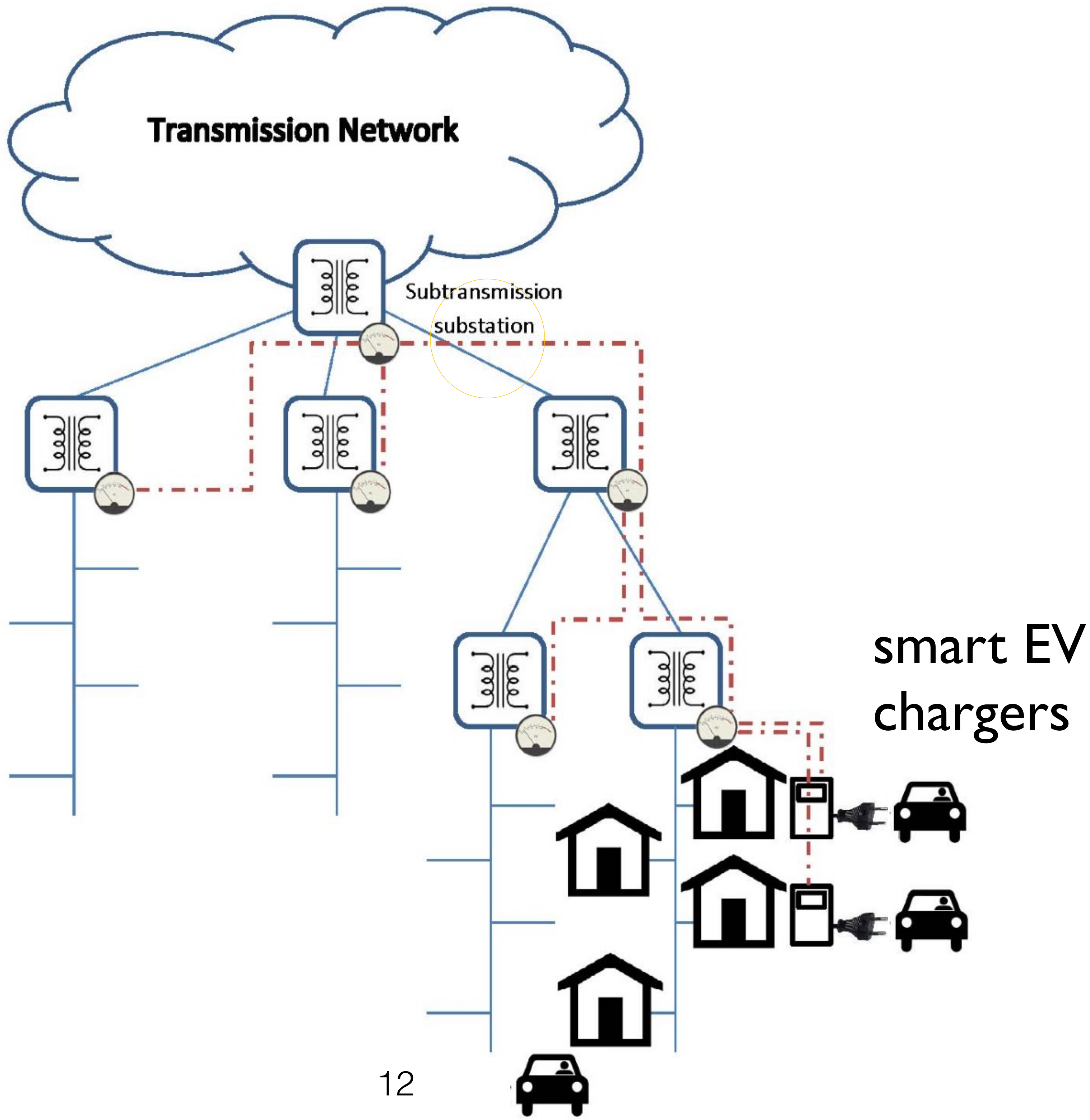
It is a TCP-like congestion control algorithm!

Pervasive Sensing and Control in Radial Distribution Systems



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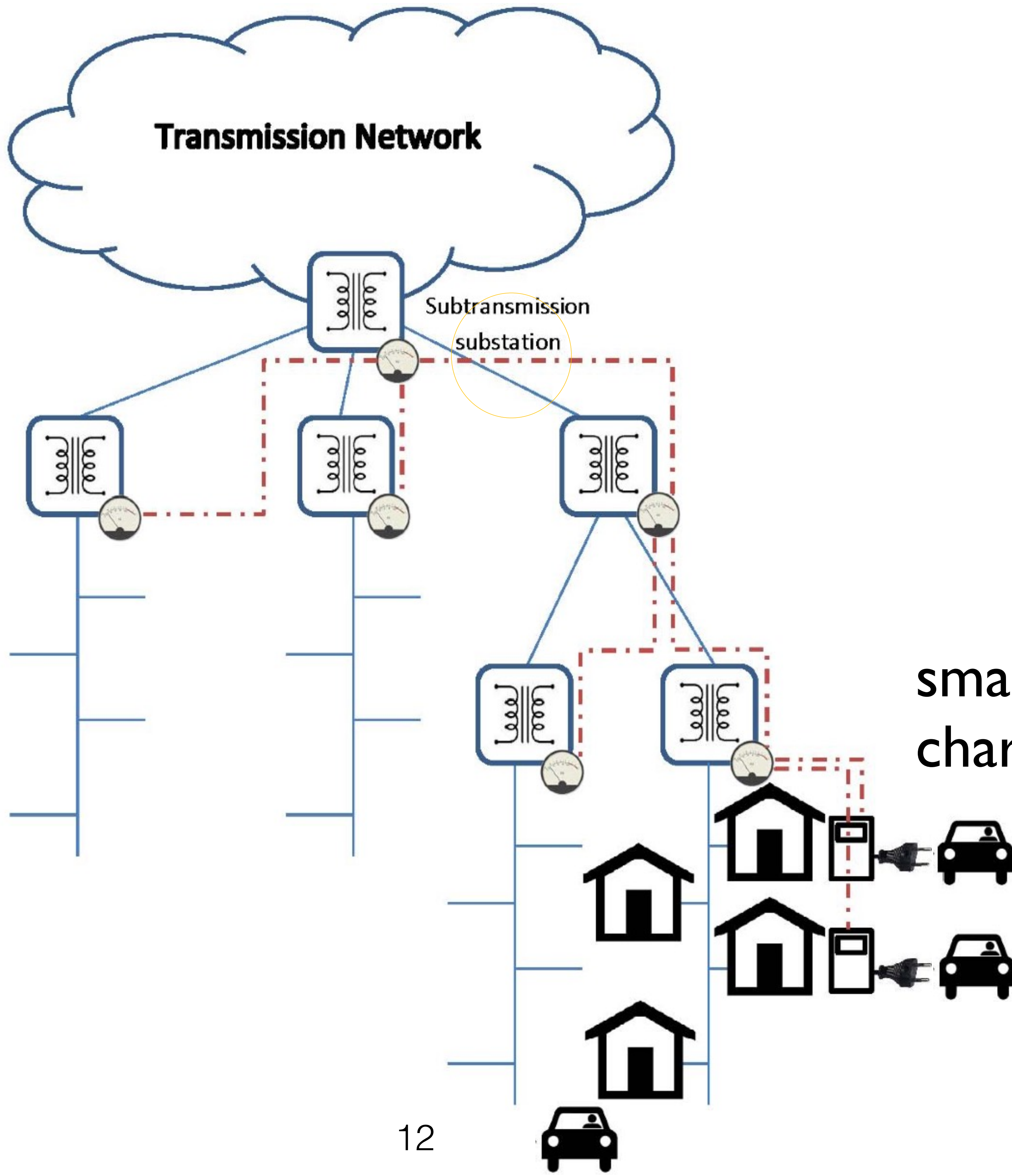
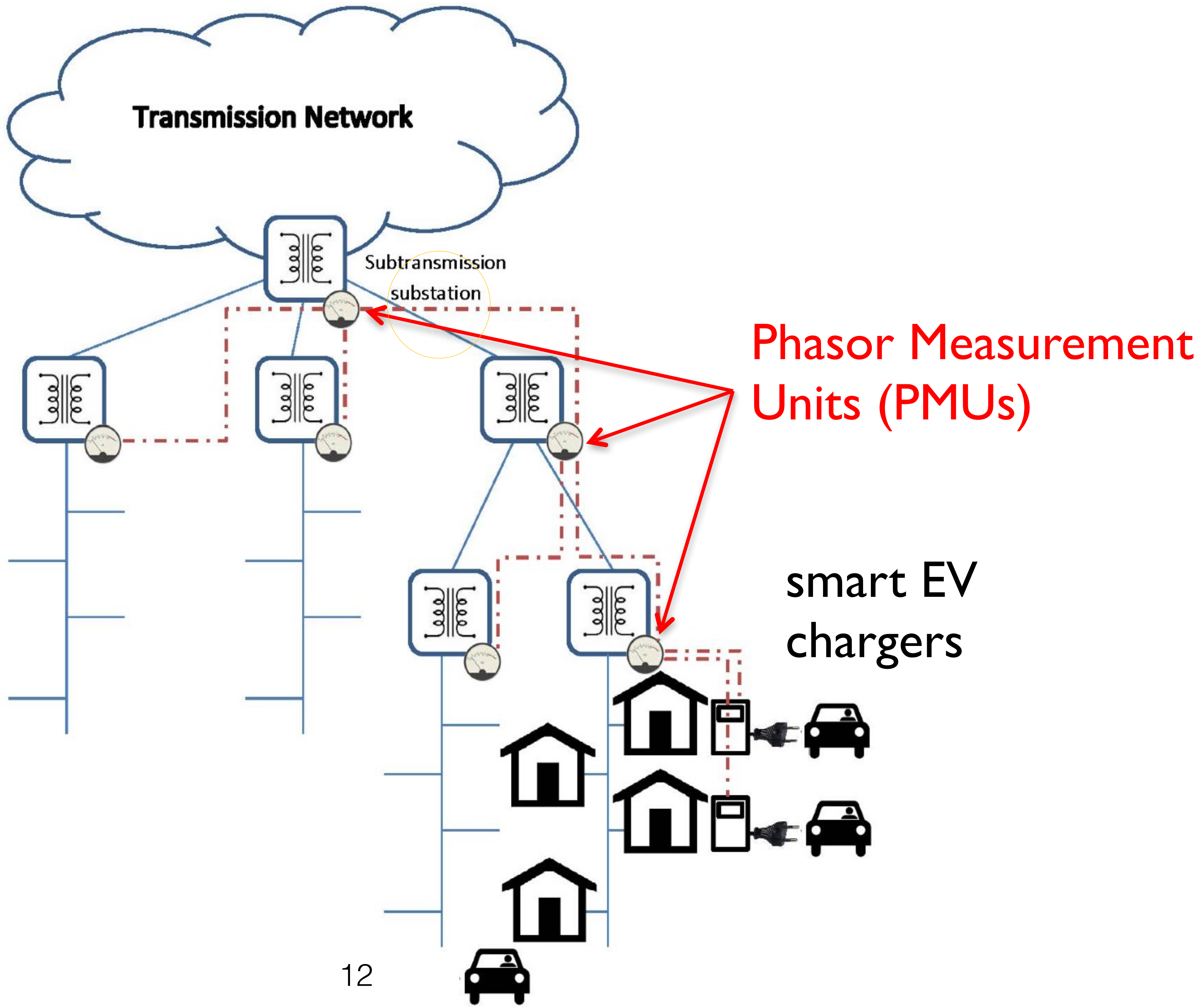


every line or transformer has a rated capacity and a setpoint

smart EV chargers

Pervasive Sensing and Control in Radial Distribution Systems



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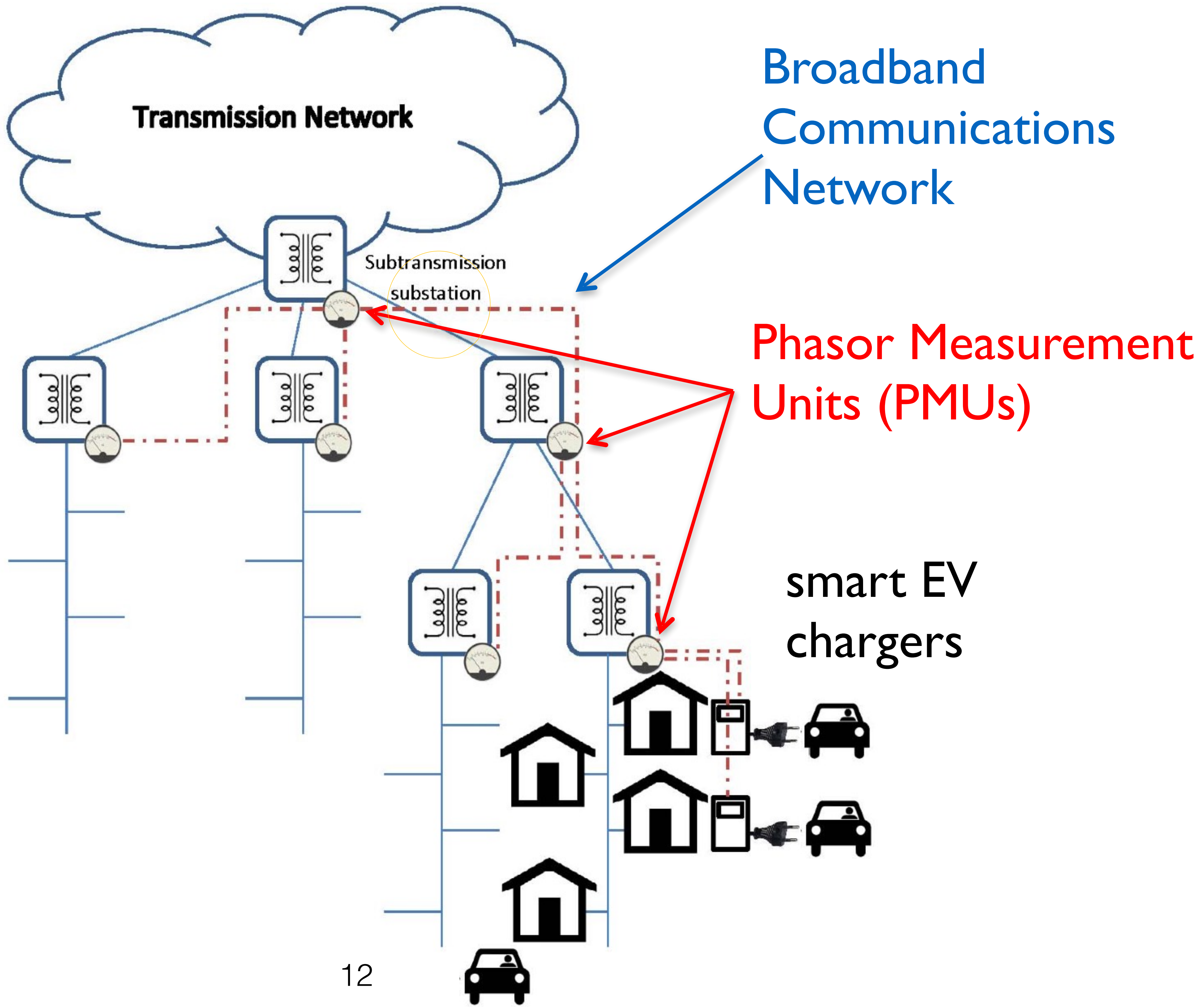

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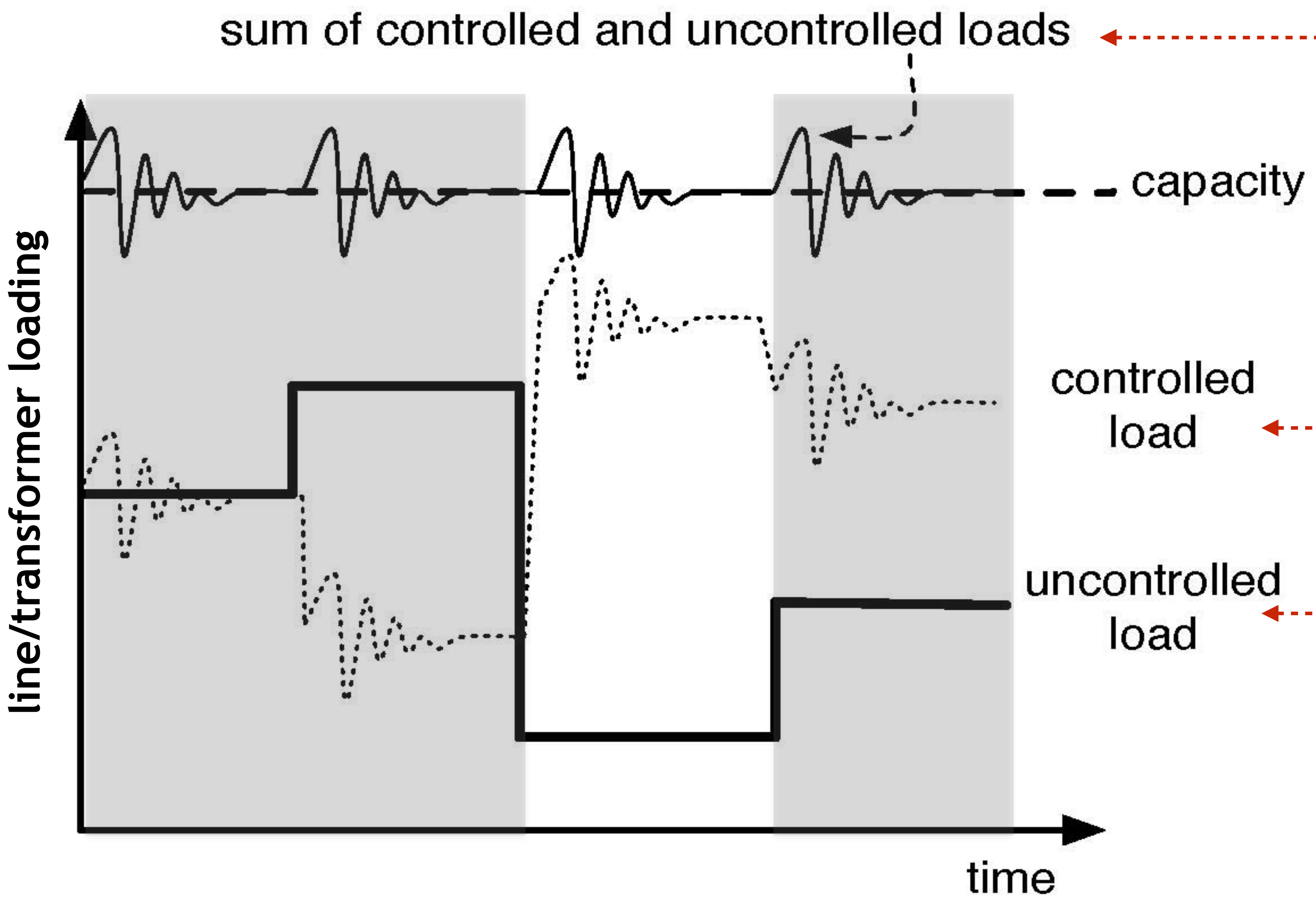
TCP-Inspired Control



measured equipment loading

=

demands of EV chargers

+

household demands

Fair Allocation of Available Capacity

Network Utility Maximization Problem:

$$\max_{rate_x} \sum_{x \in C} \log(rate_x)$$

proportional fairness

[Kelly98], [Low99], [Yaïche00]

subject to

charge power

$$0 \le rate_x \le \mathrm{maxrate}_x \qquad \forall x \in C$$

$$\sum_{x \in C(l)} rate_x + \mathrm{homeload}_l \le \mathrm{setpoint}_l \qquad \forall l \in L$$

chargers in subtree l

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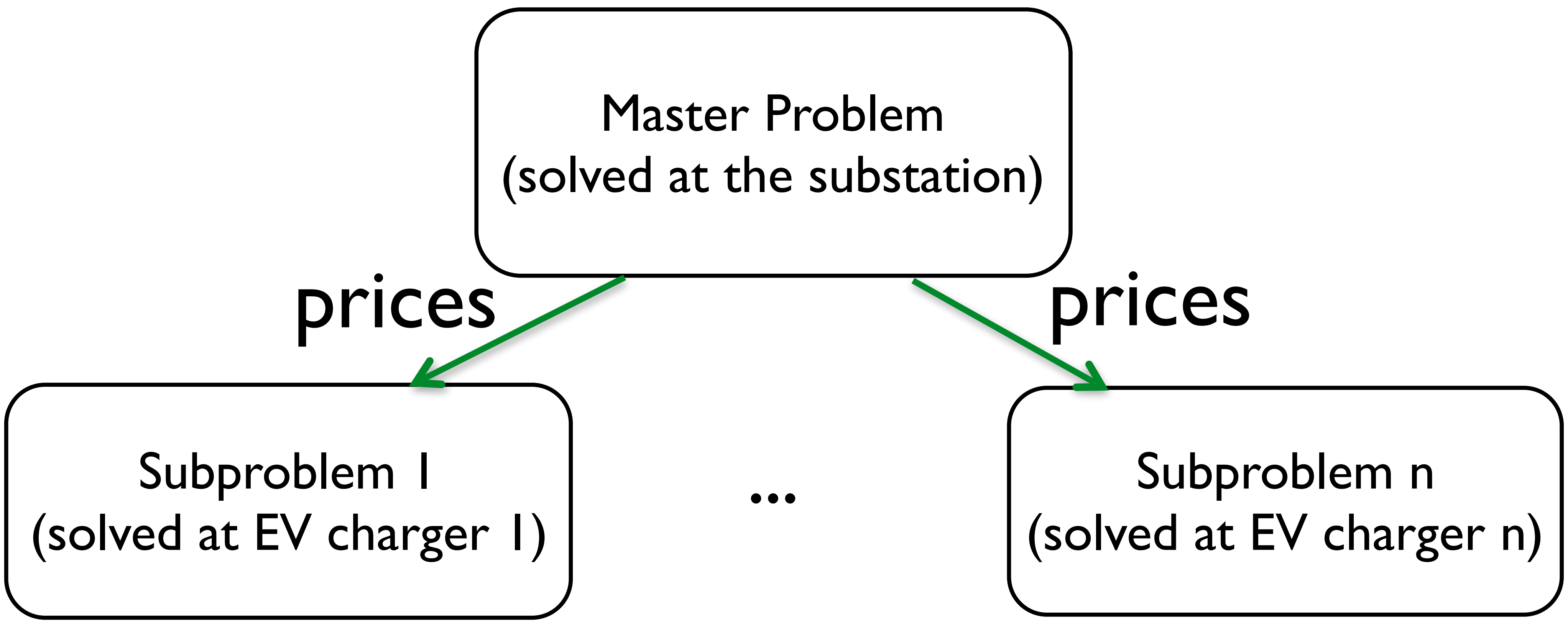
Control rules are obtained by solving this optimization problem

Dual Decomposition for Distributed Control

Iteration K, Phase 1

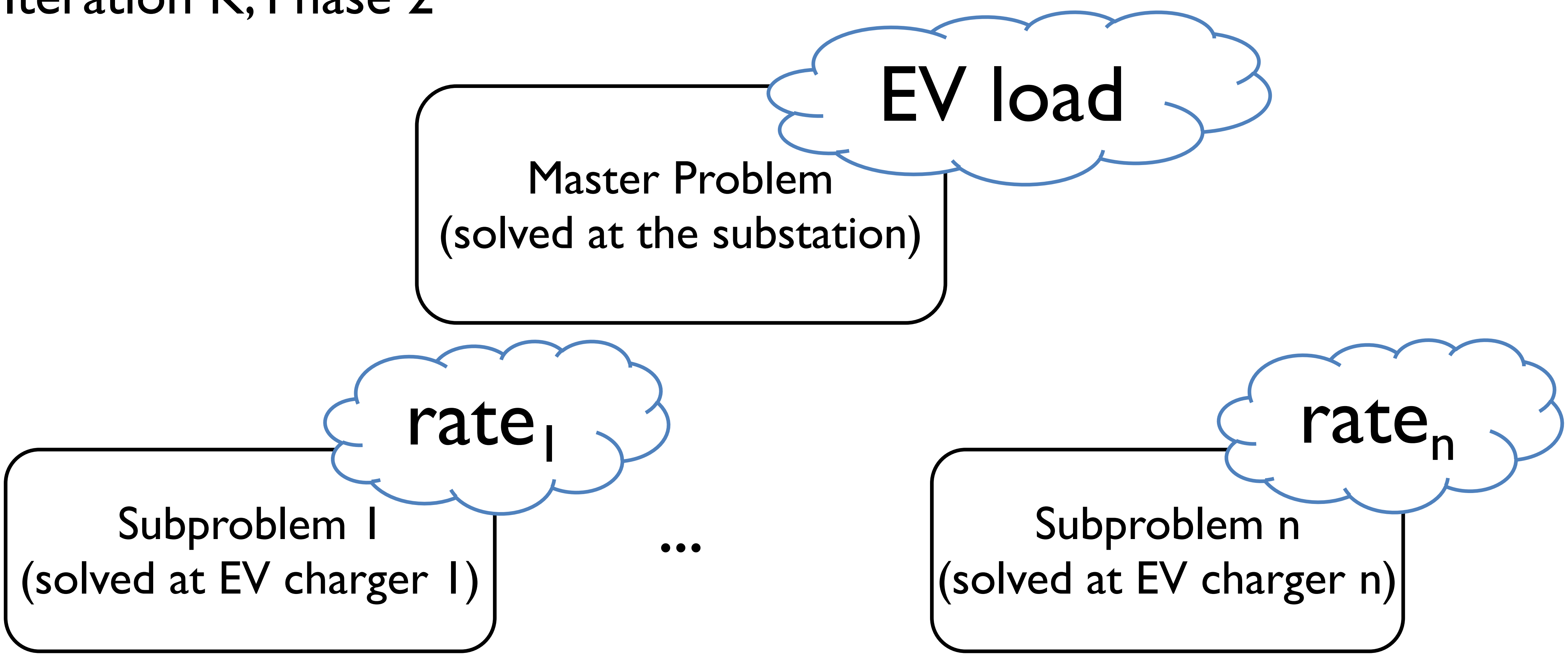


1. PMUs update congestion prices and send them to downstream EV chargers

$$price_l \leftarrow \max\{price_l - stepsize \times (setpoint_l - load_l), 0\}$$

Dual Decomposition for Distributed Control

Iteration K, Phase 2

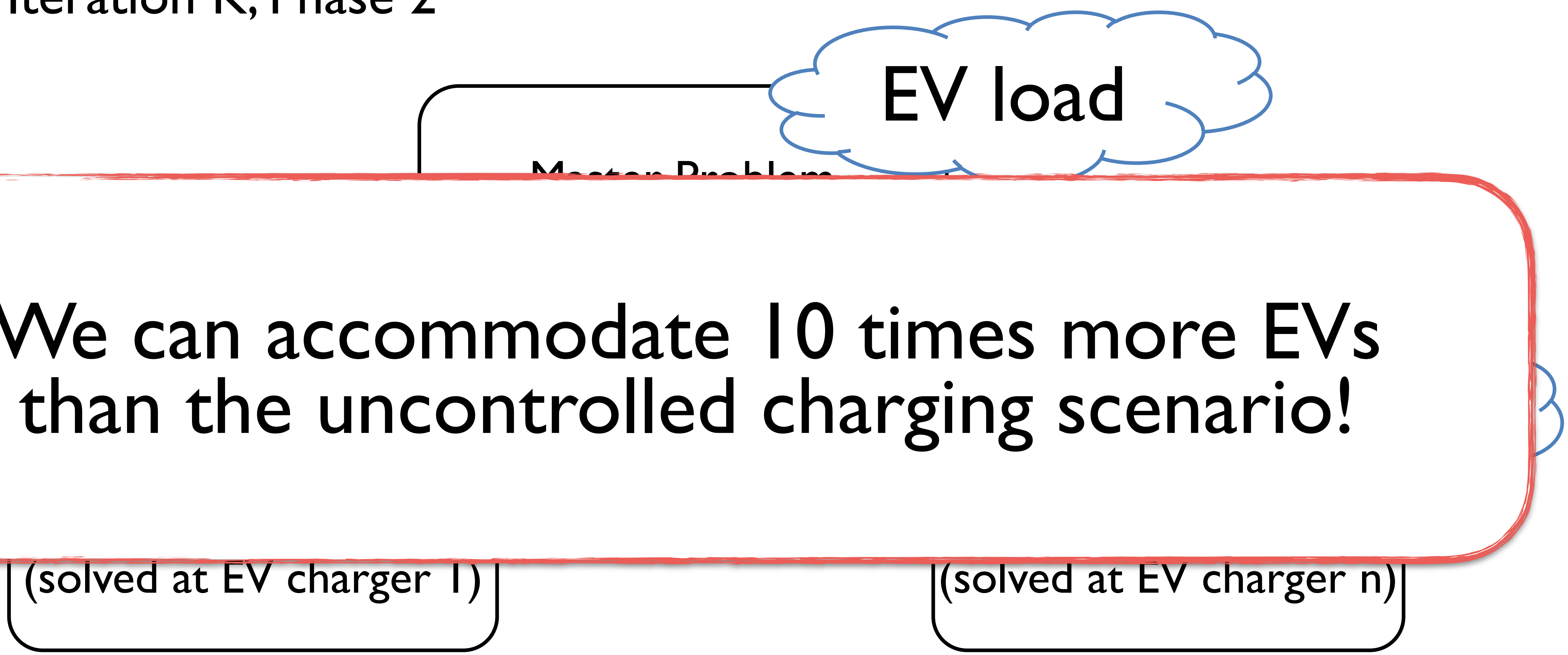


Phase 2: New rates are obtained from solving subproblems using new congestion prices

$$rate_s \leftarrow \min\left\{\frac{1}{path\ price_s}, maxrate_s\right\}$$

Dual Decomposition for Distributed Control

Iteration K, Phase 2

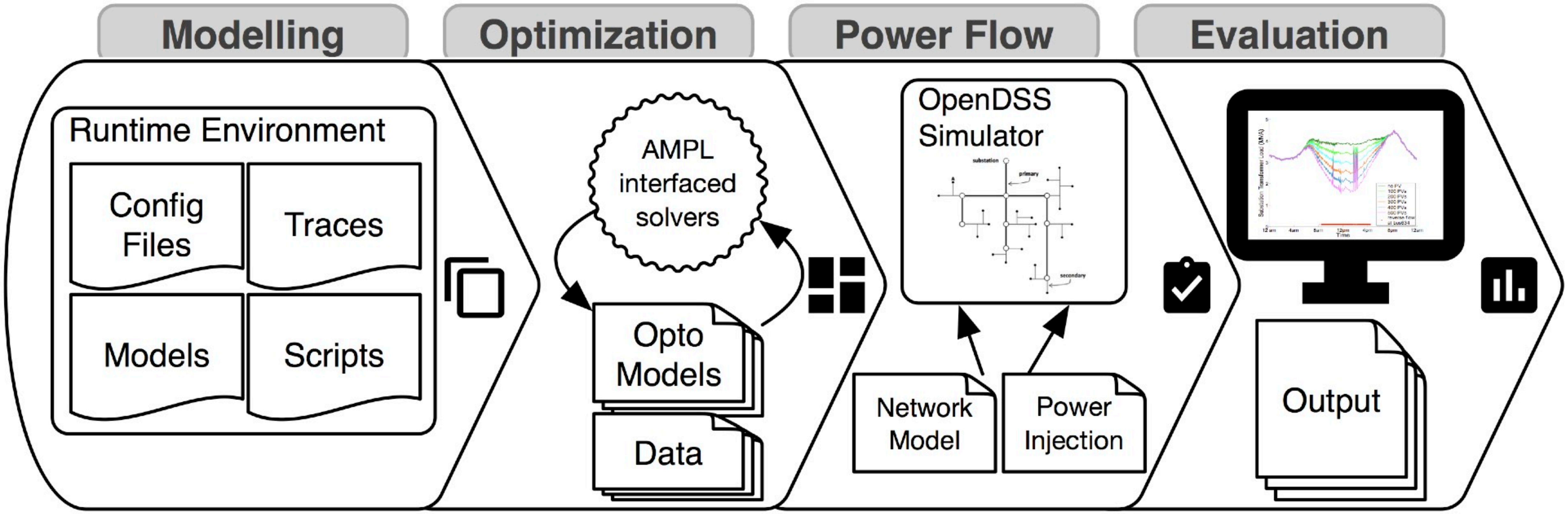


We can accommodate 10 times more EVs than the uncontrolled charging scenario!

Phase 2: New rates are obtained from solving subproblems using new congestion prices

$$rate_s \leftarrow \min\left\{\frac{1}{path\ price_s}, maxrate_s\right\}$$

Open-Source Simulation Software



- Modular design, suitable for defining large-scale simulation scenarios
- Interfaces with optimization software and power flow solvers
- Includes plotting and reporting services

Download code from GitHub

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- **Omid Ardakanian**, Negar Koochakzadeh, Rayman Preet Singh, Lukasz Golab, S. Keshav, "Computing Electricity Consumption Profiles from Household Smart Meter Data", In Proceedings of the Workshops of the EDBT/ICDT Joint Conference (EnDM), pp.140-147, 2014.

Reducing Energy Consumption of Commercial Buildings

Image: Google Maps

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HVAC accounts for 40-60% of energy use in commercial buildings

Reducing Energy Consumption of Commercial Buildings

Software Defined Buildings
Berkeley
UNIVERSITY OF CALIFORNIA

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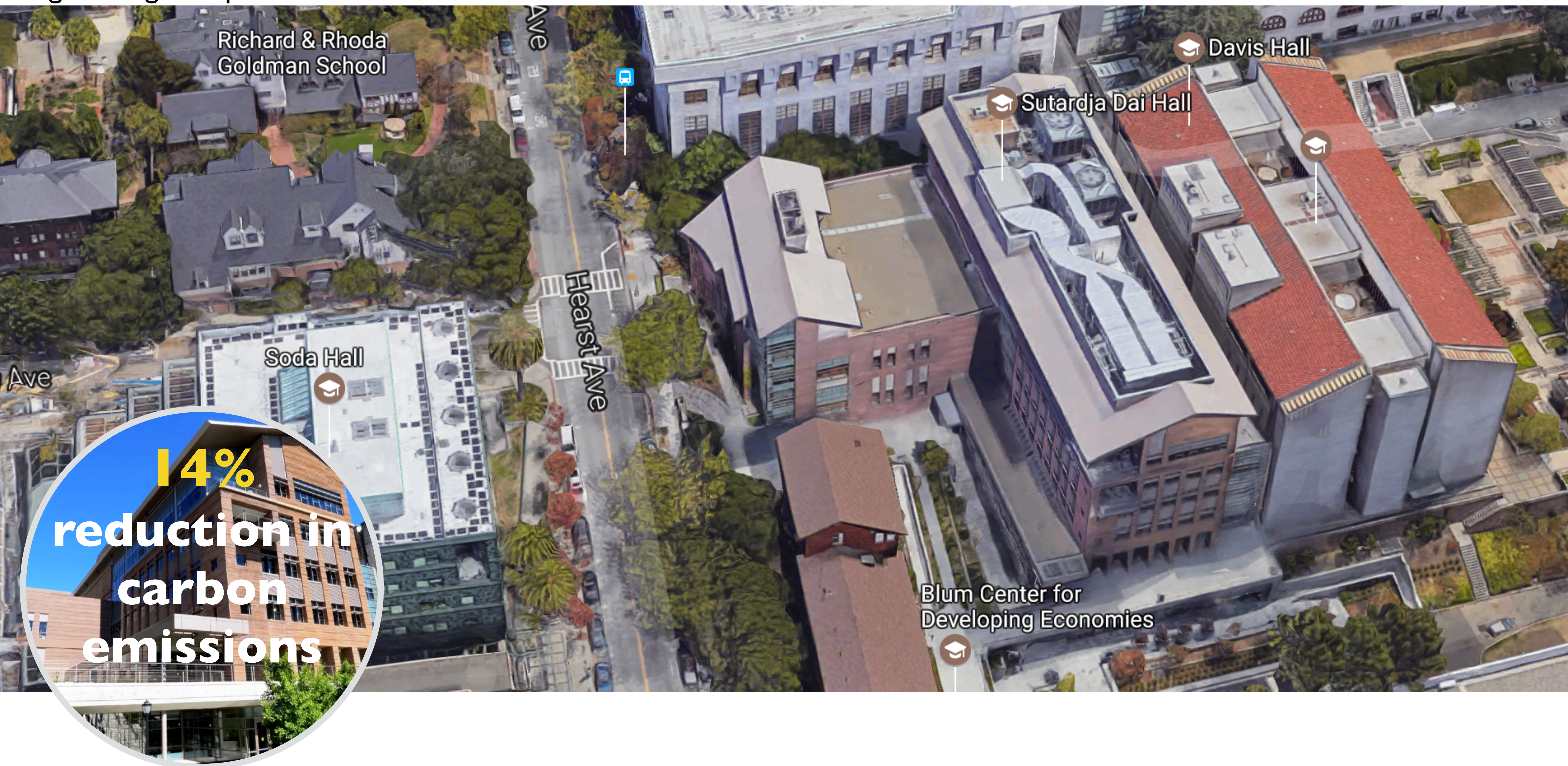

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HVAC in Moderate Climates

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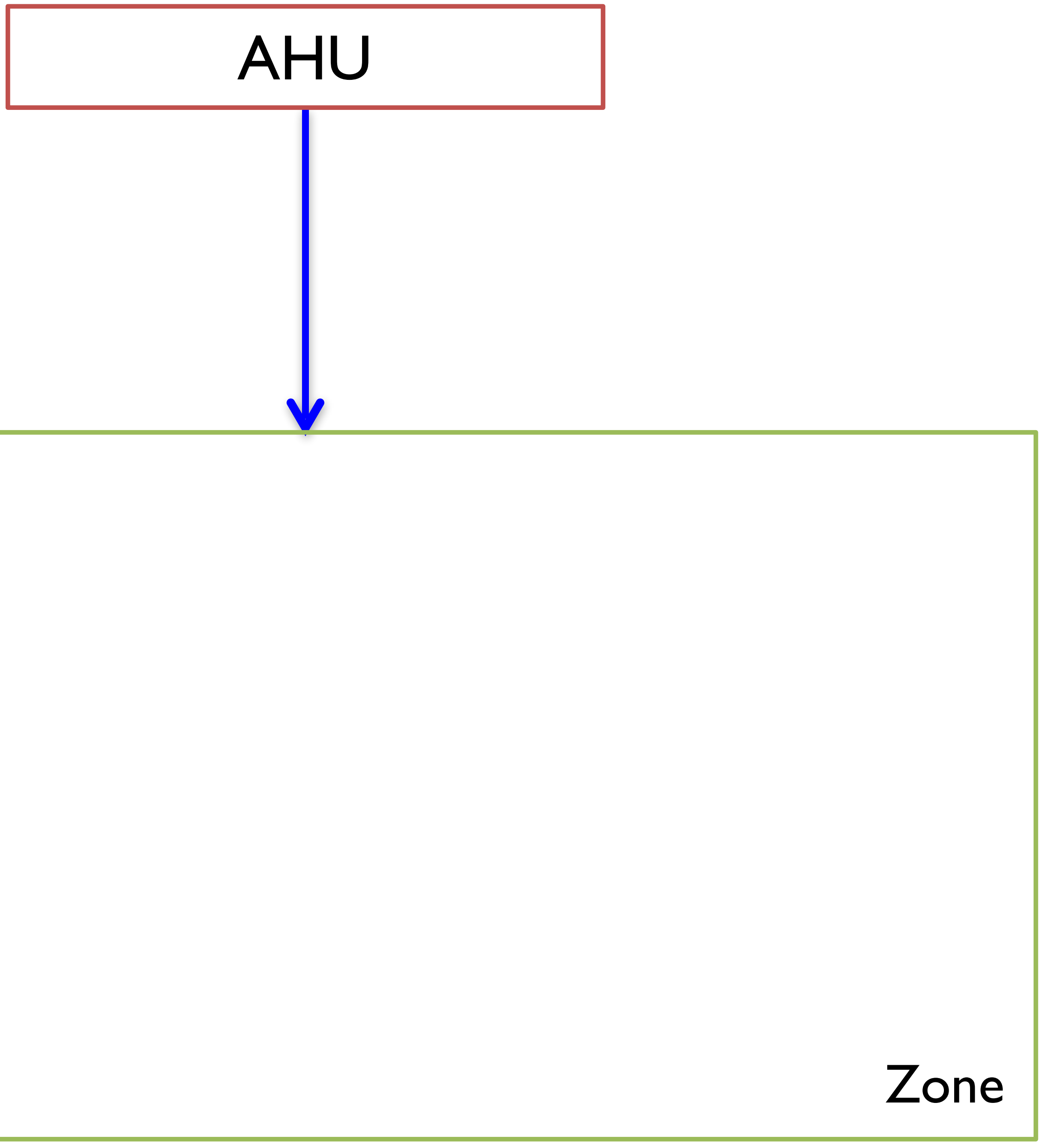
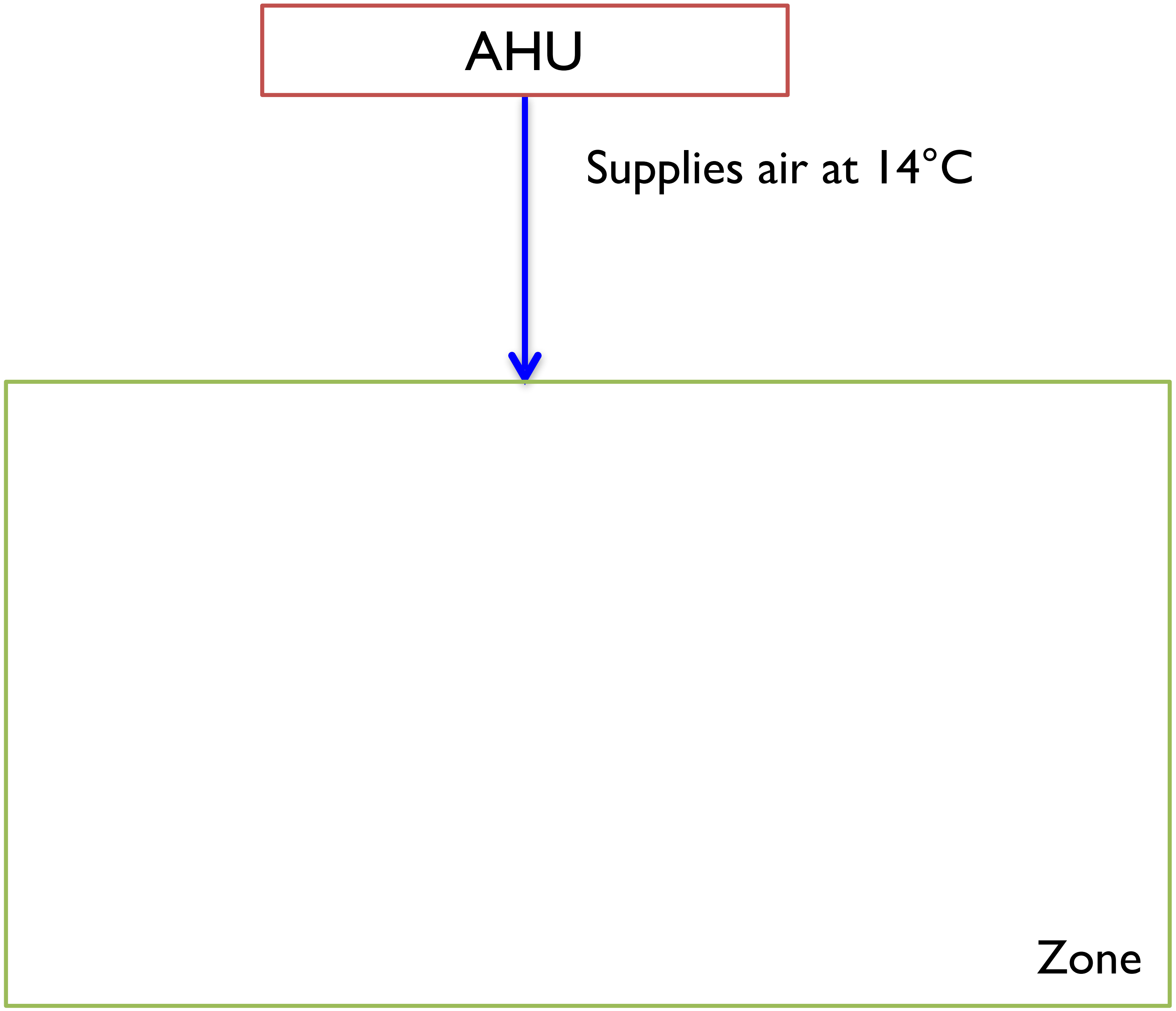


HVAC in Moderate Climates



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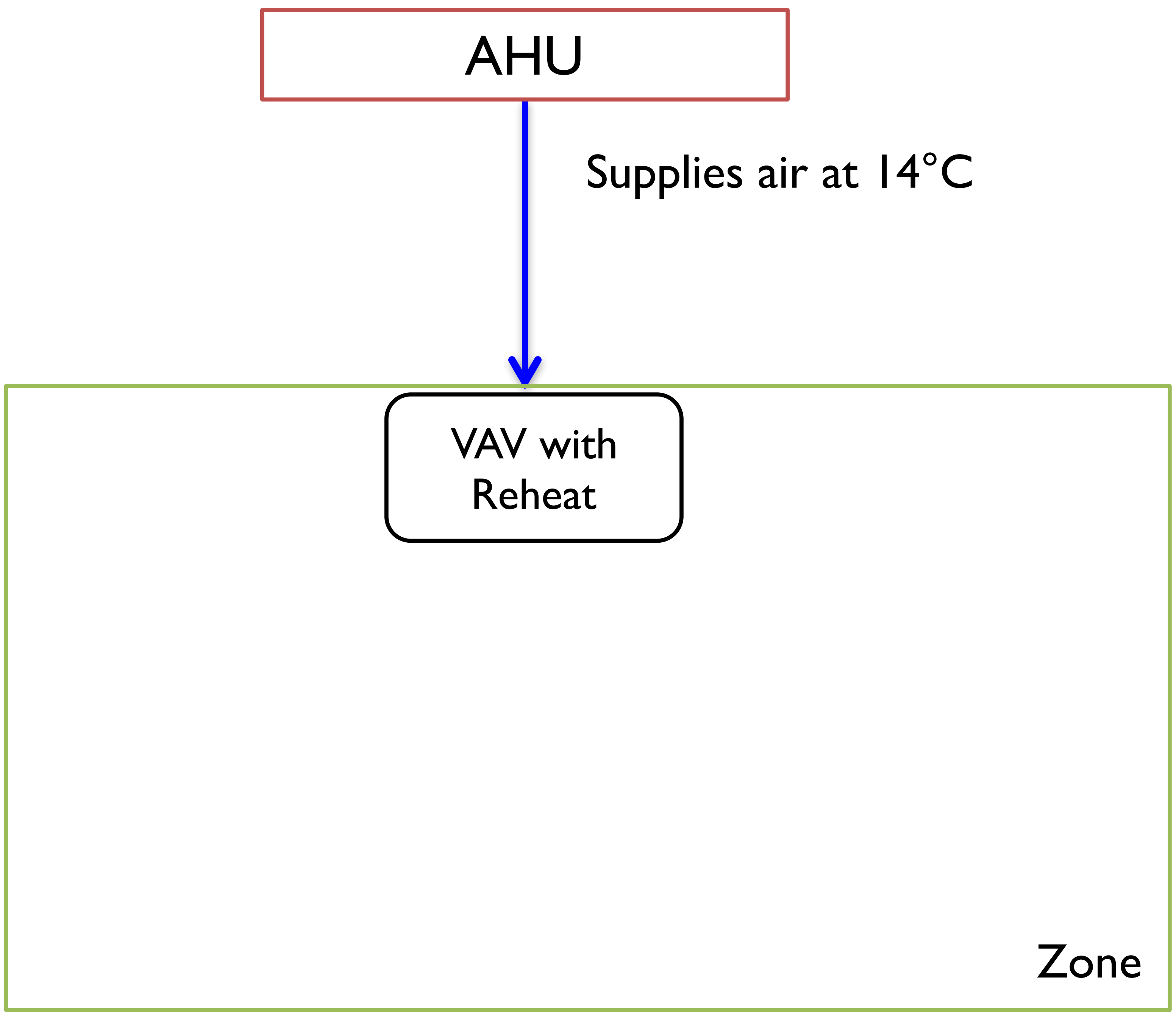

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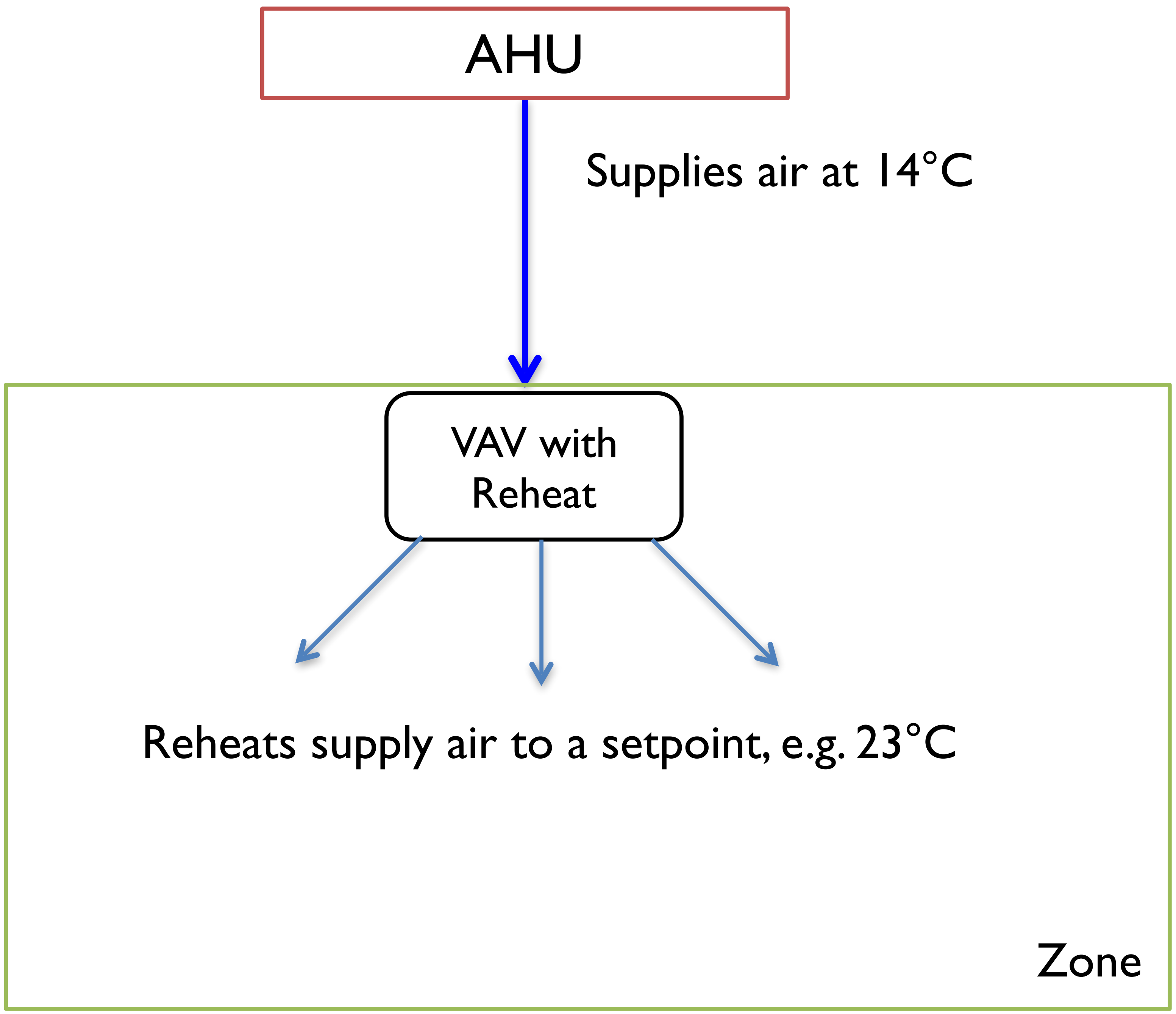

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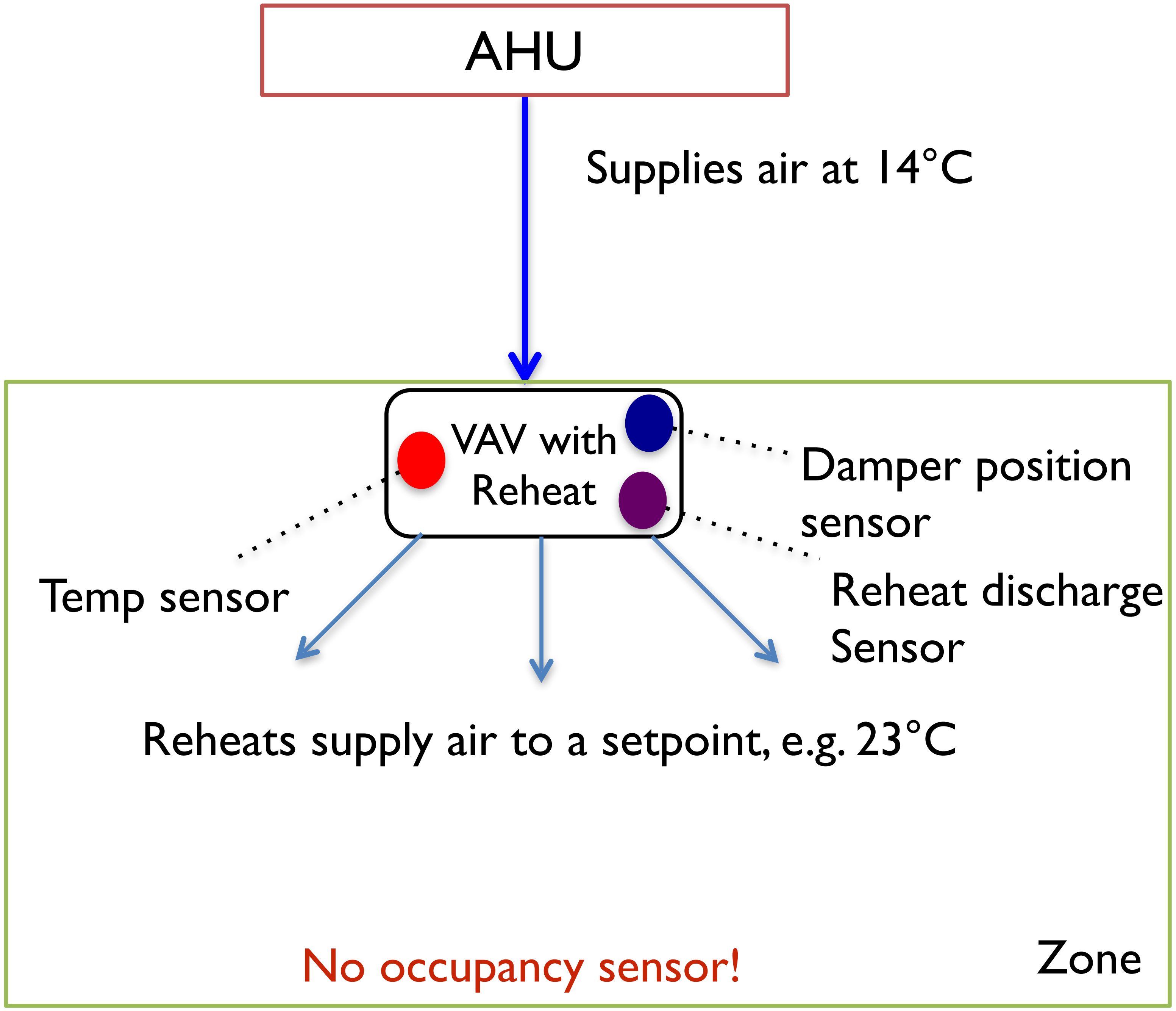
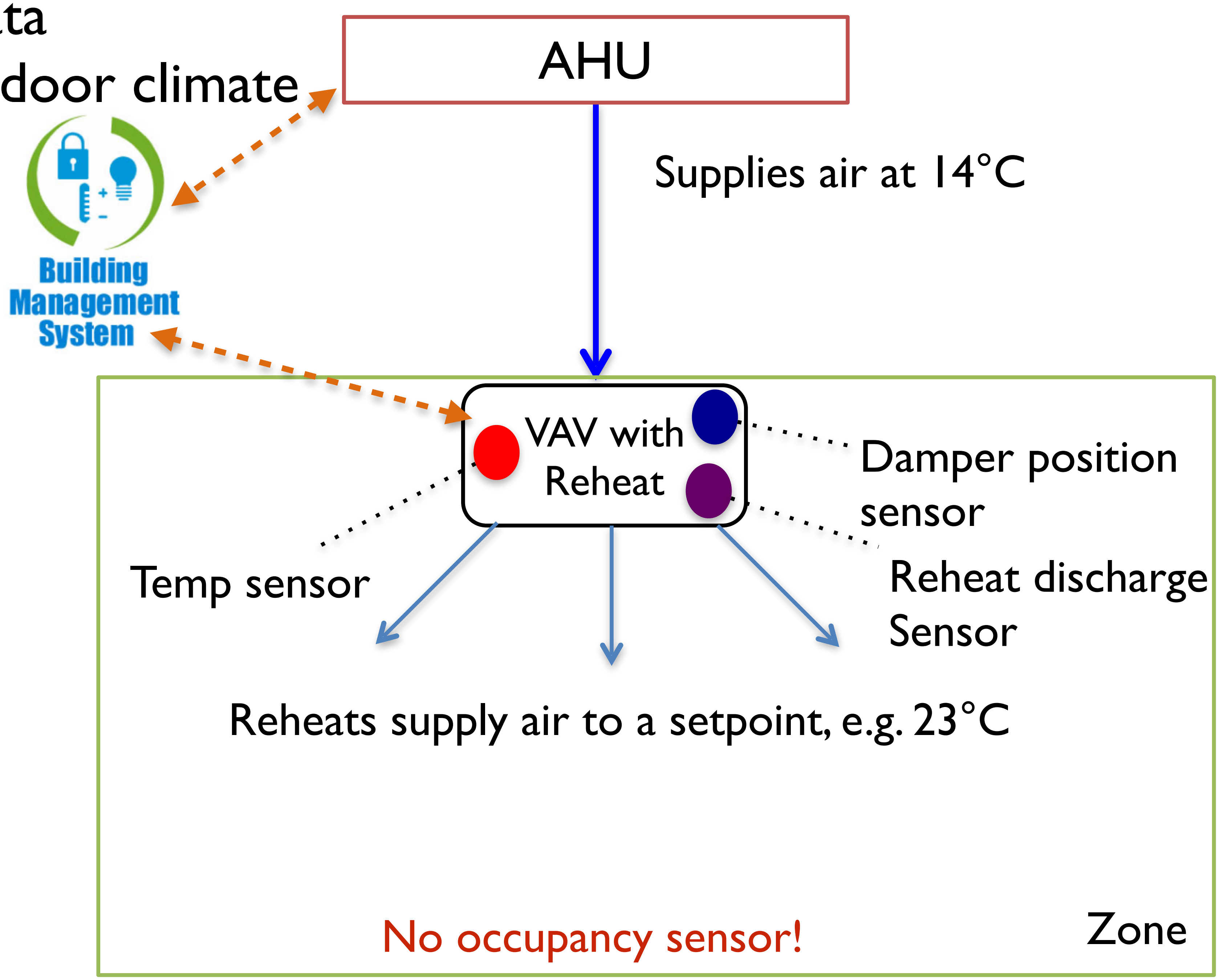


HVAC in Moderate Climates

BMS

- Archives data
- Controls indoor climate



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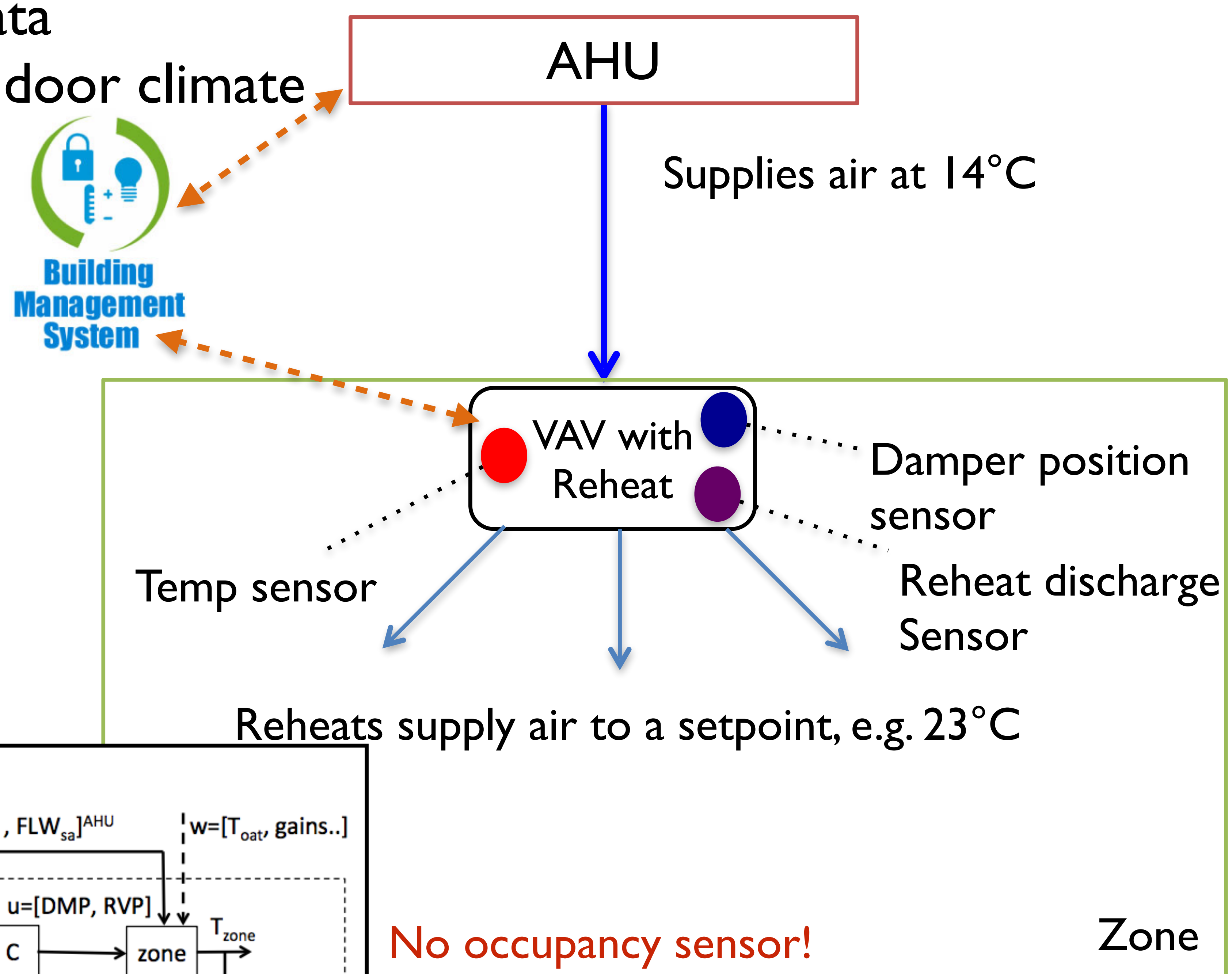

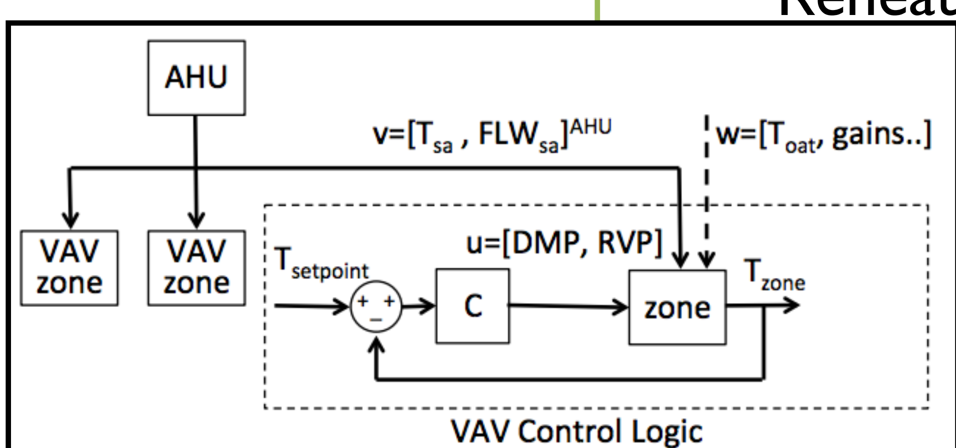

HVAC Systems are Inefficient

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- HVAC systems run on a static schedule based on building manager's intuition.
  - Does not take occupancy into account
  - Wastes energy in conditioning empty or partially-occupied spaces

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  - Does not take occupancy into account
  - Wastes energy in conditioning empty or partially-occupied spaces
- To optimize HVAC energy consumption, zones should be conditioned only when occupied

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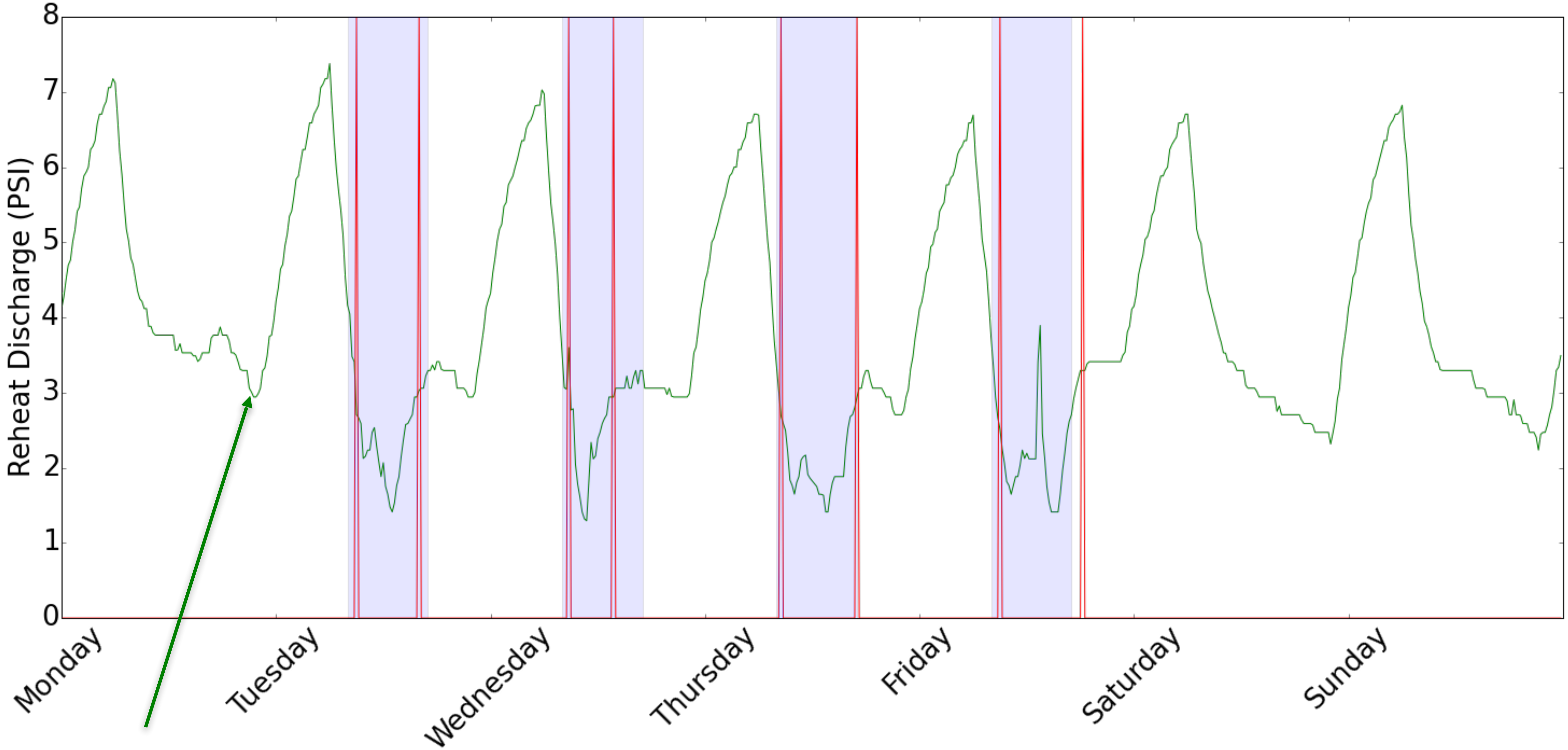
Occupancy sensors are not available!
Retrofitting is costly and intrusive.

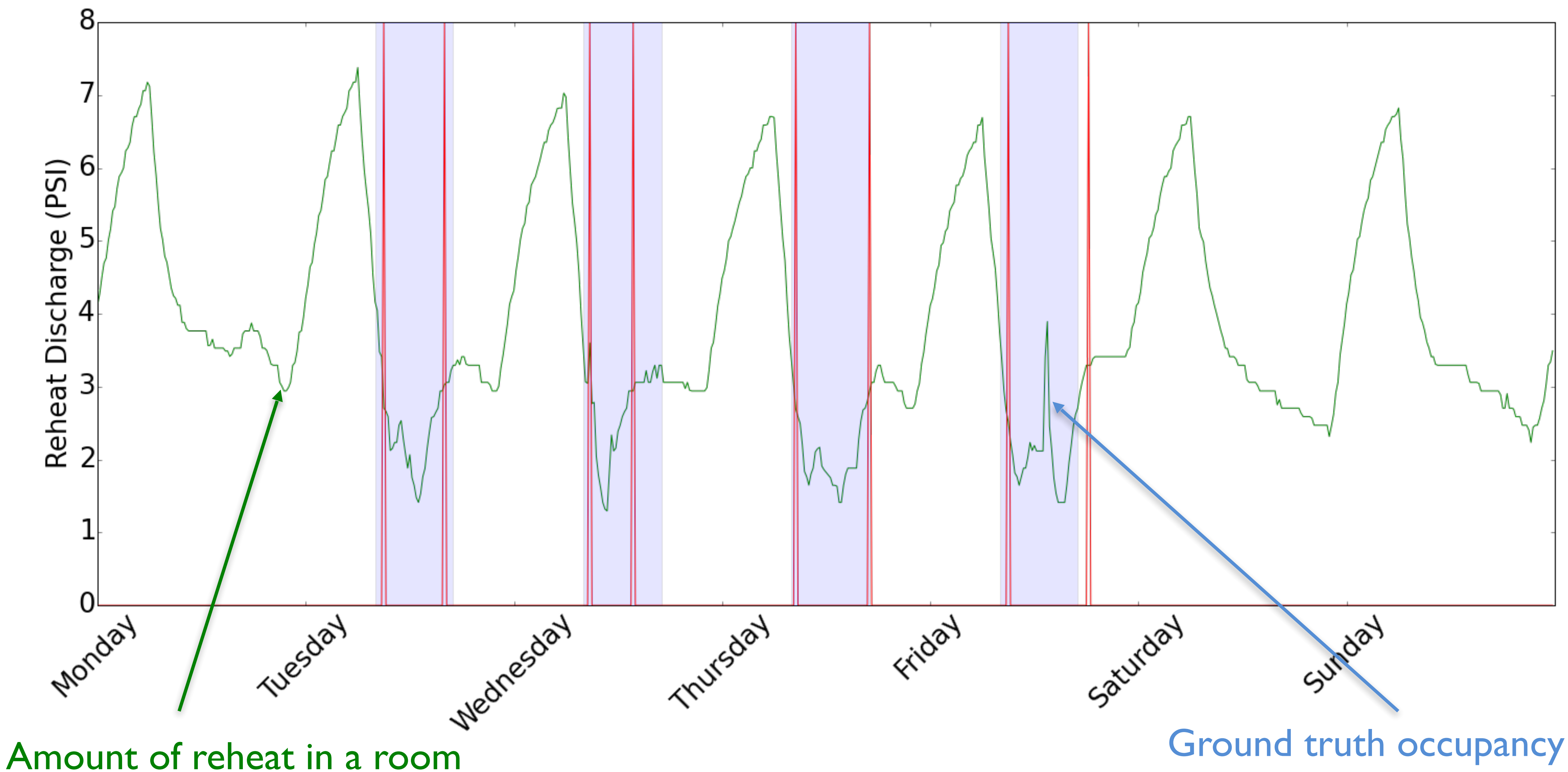
Exploiting Existing HVAC Sensors

Exploiting Existing HVAC Sensors



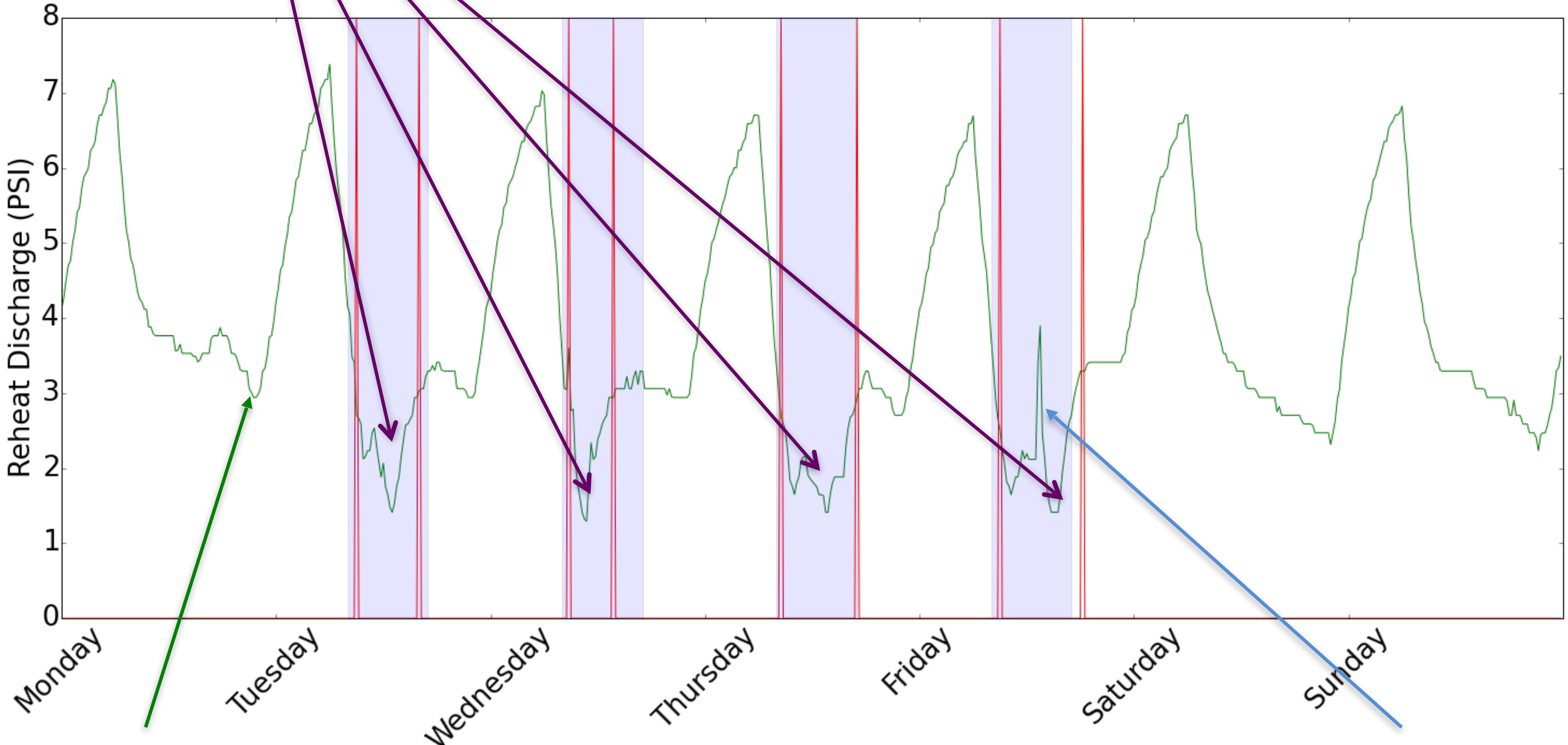
Amount of reheat in a room

Exploiting Existing HVAC Sensors



Exploiting Existing HVAC Sensors

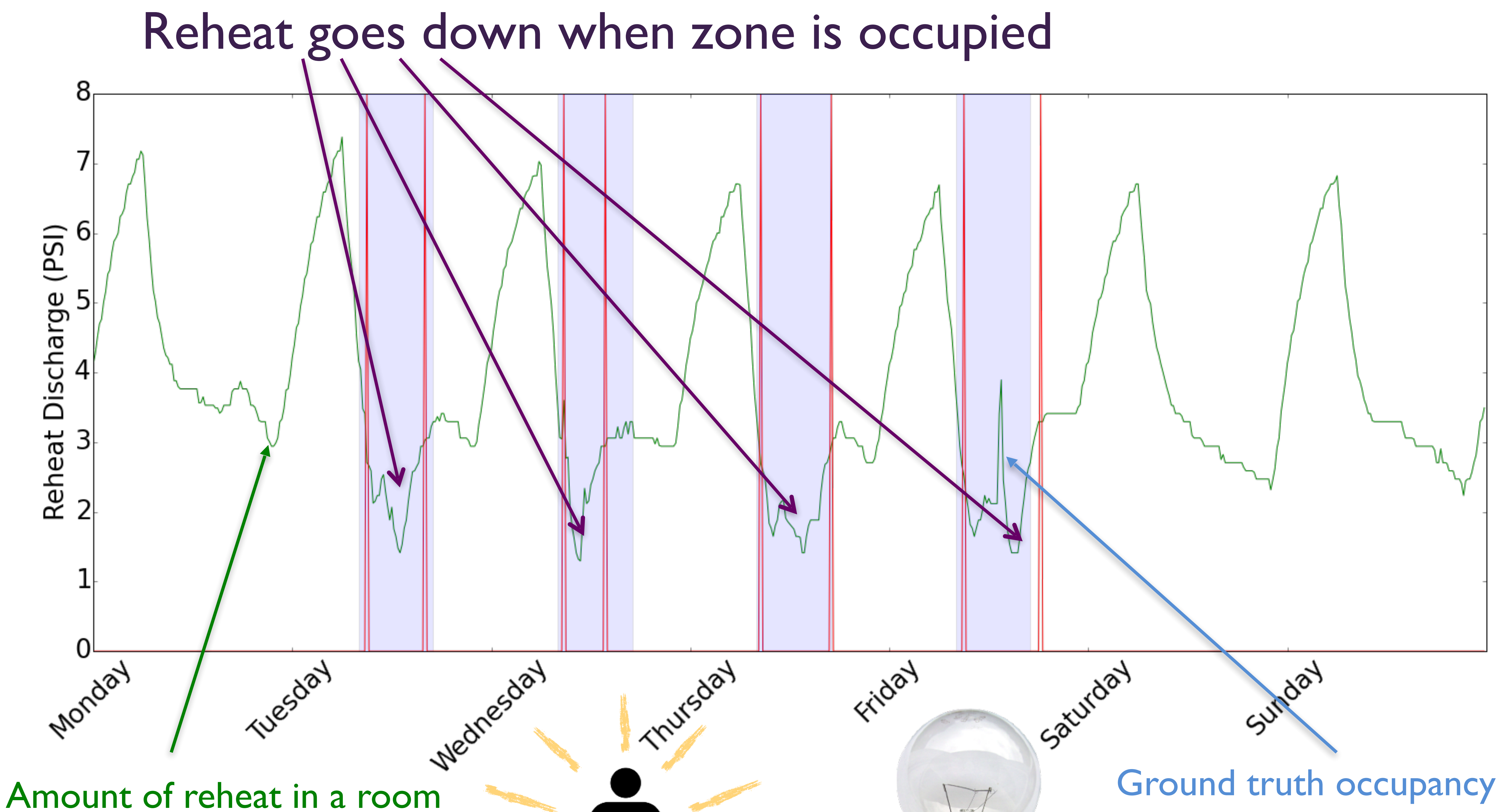
Reheat goes down when zone is occupied

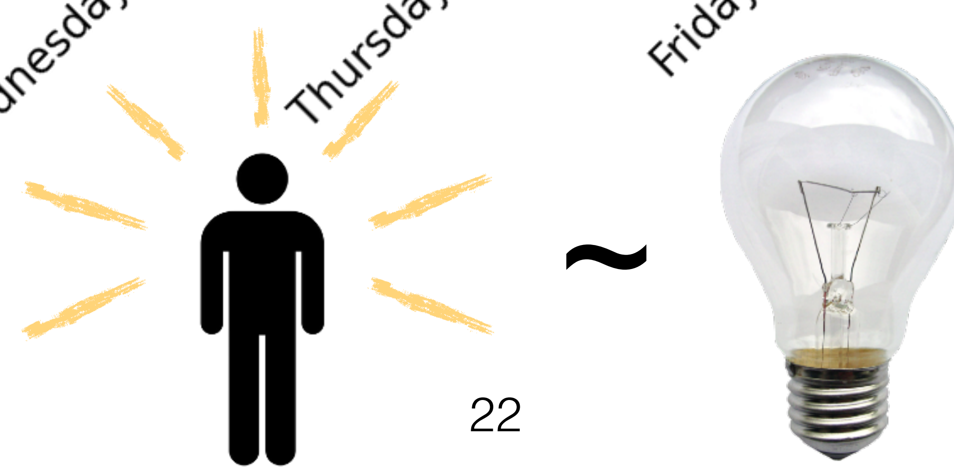


Amount of reheat in a room

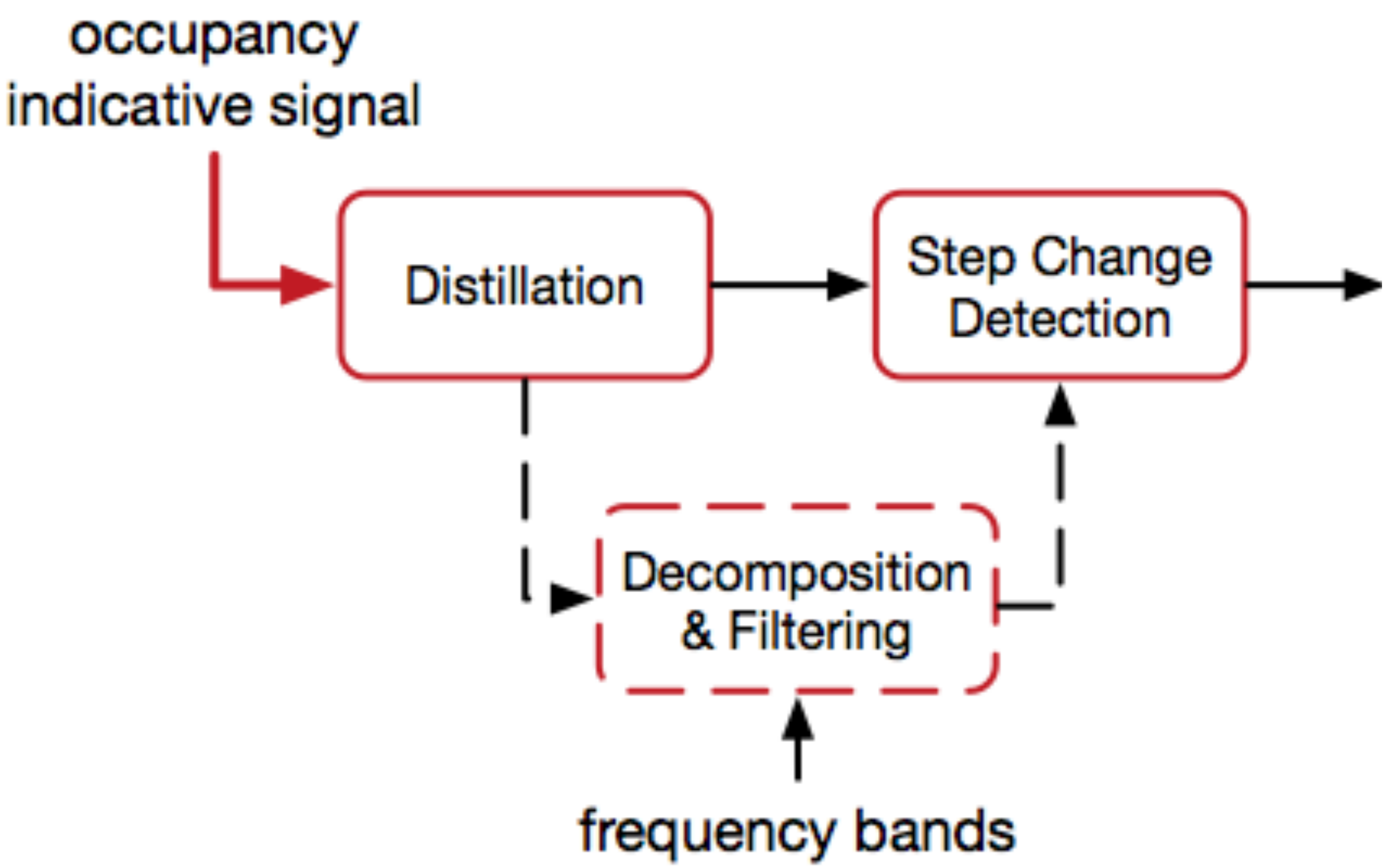
Ground truth occupancy

Exploiting Existing HVAC Sensors





Overall Analysis Pipeline



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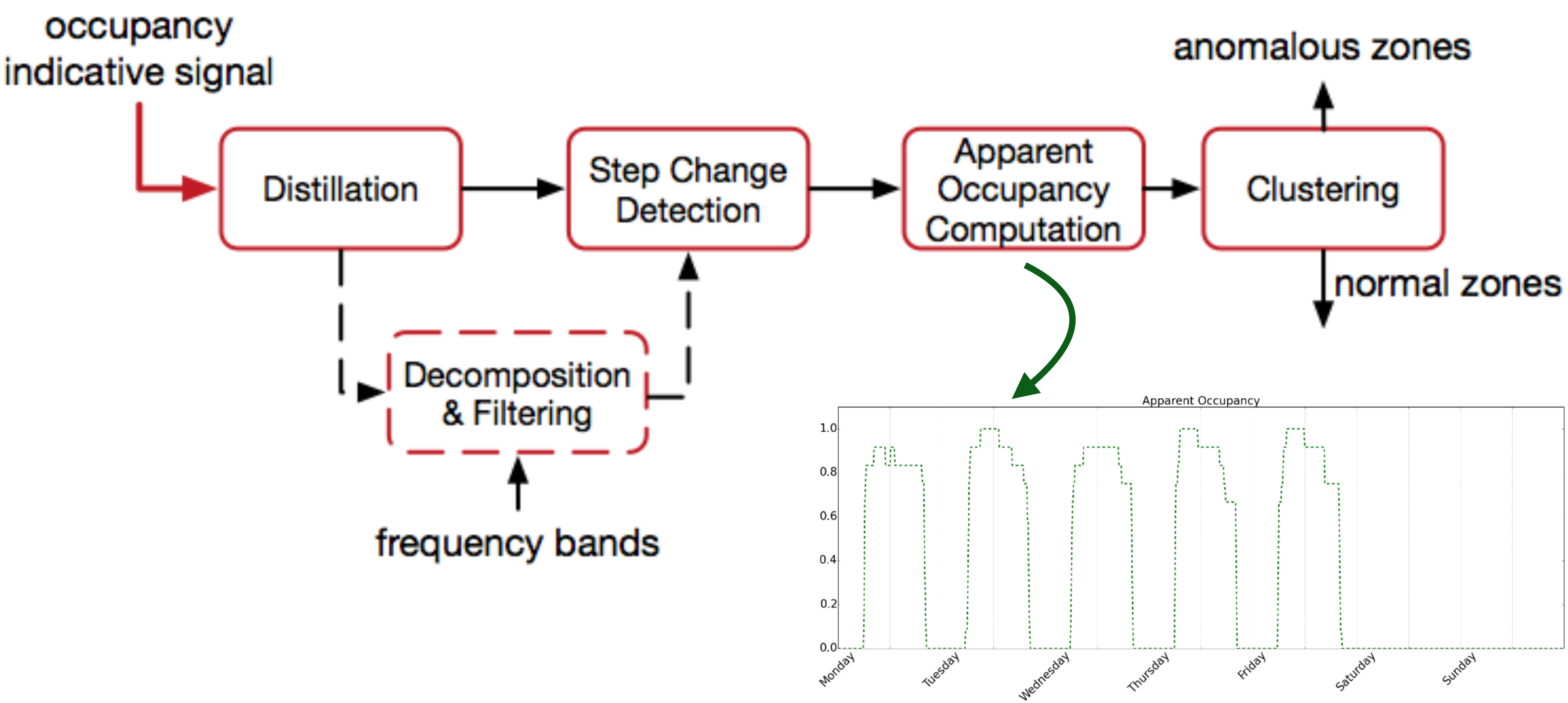

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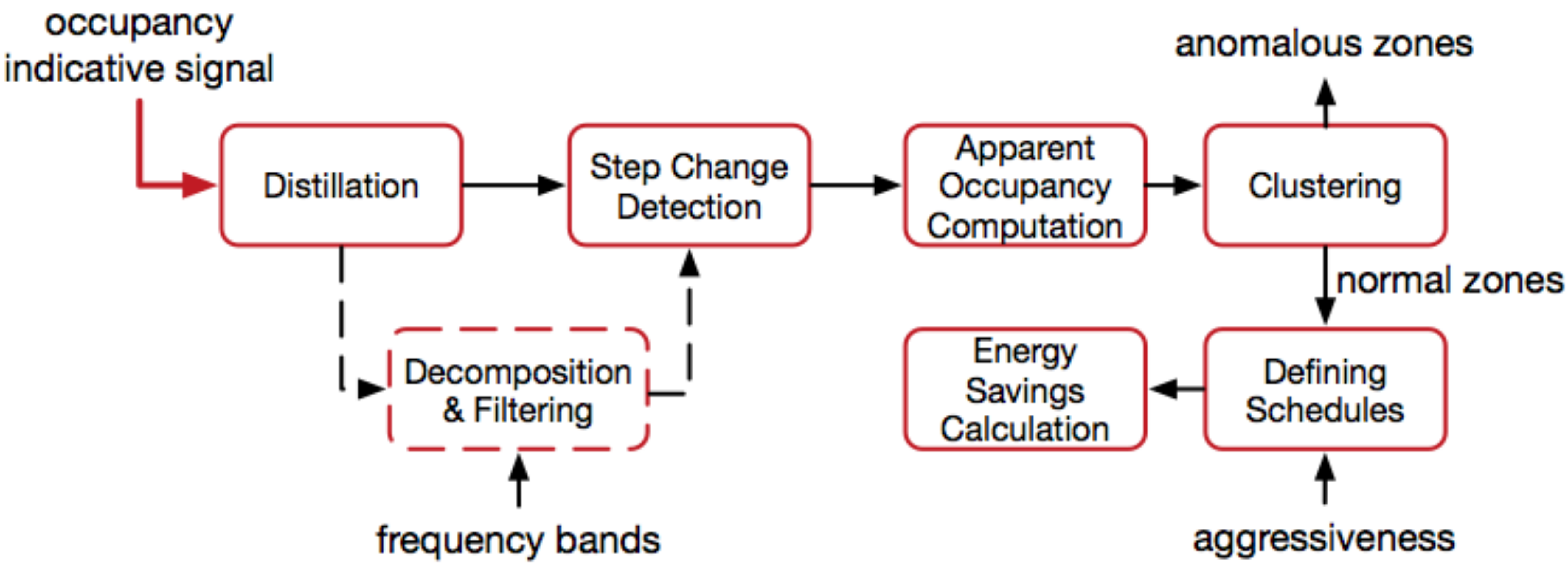

Testbed

Testbed

Three large UC Berkeley campus buildings
- 117, 109 and 270 zones respectively
- Buildings had different BMS systems
- 3-6 months of data analyzed

Validation

Collected limited ground truth data:

- Manually logged occupancy hours of 7 shared and private offices in our testbed
- Extracted occupancy hours from video recordings (a security camera installed in a lab)

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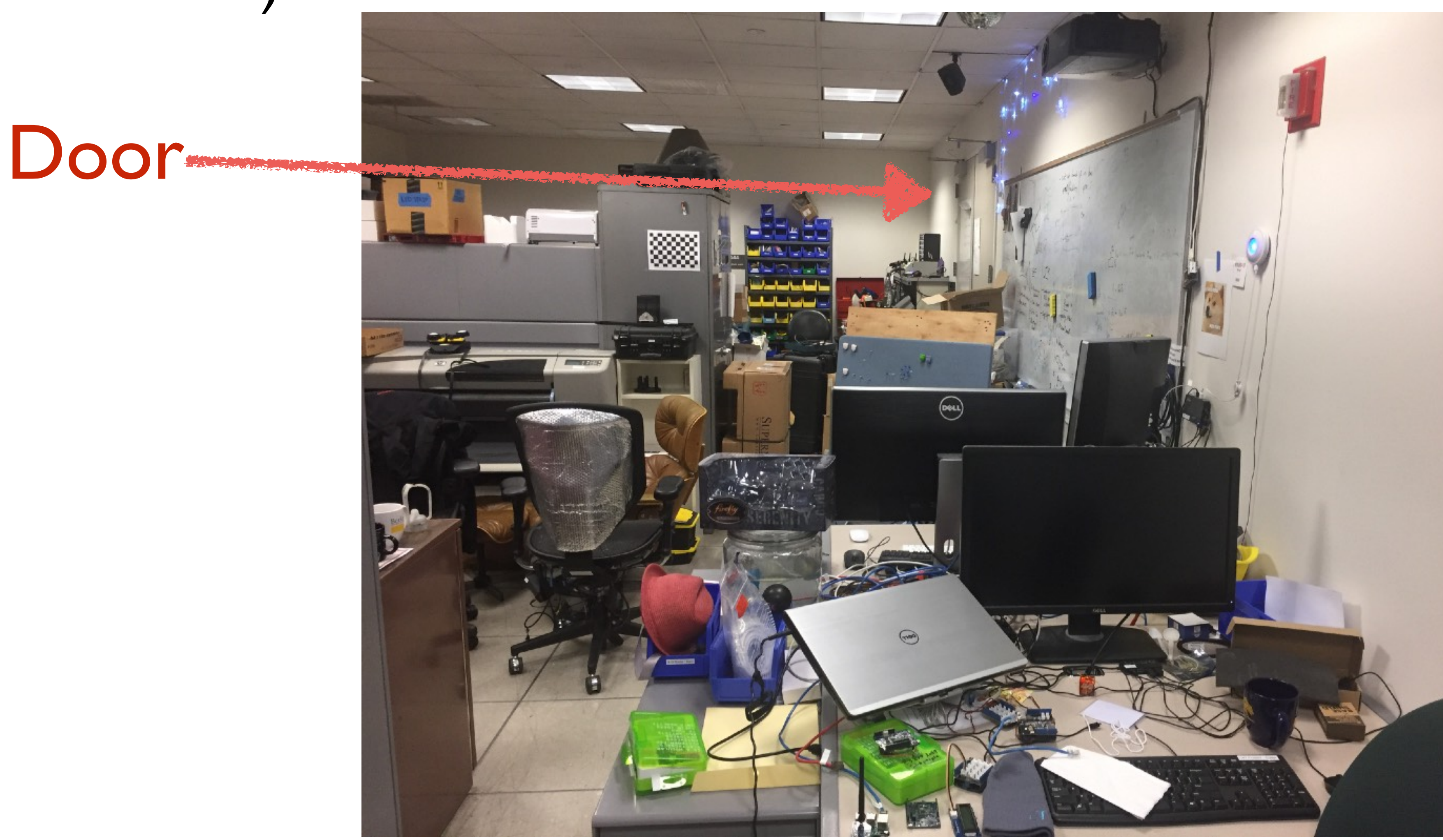
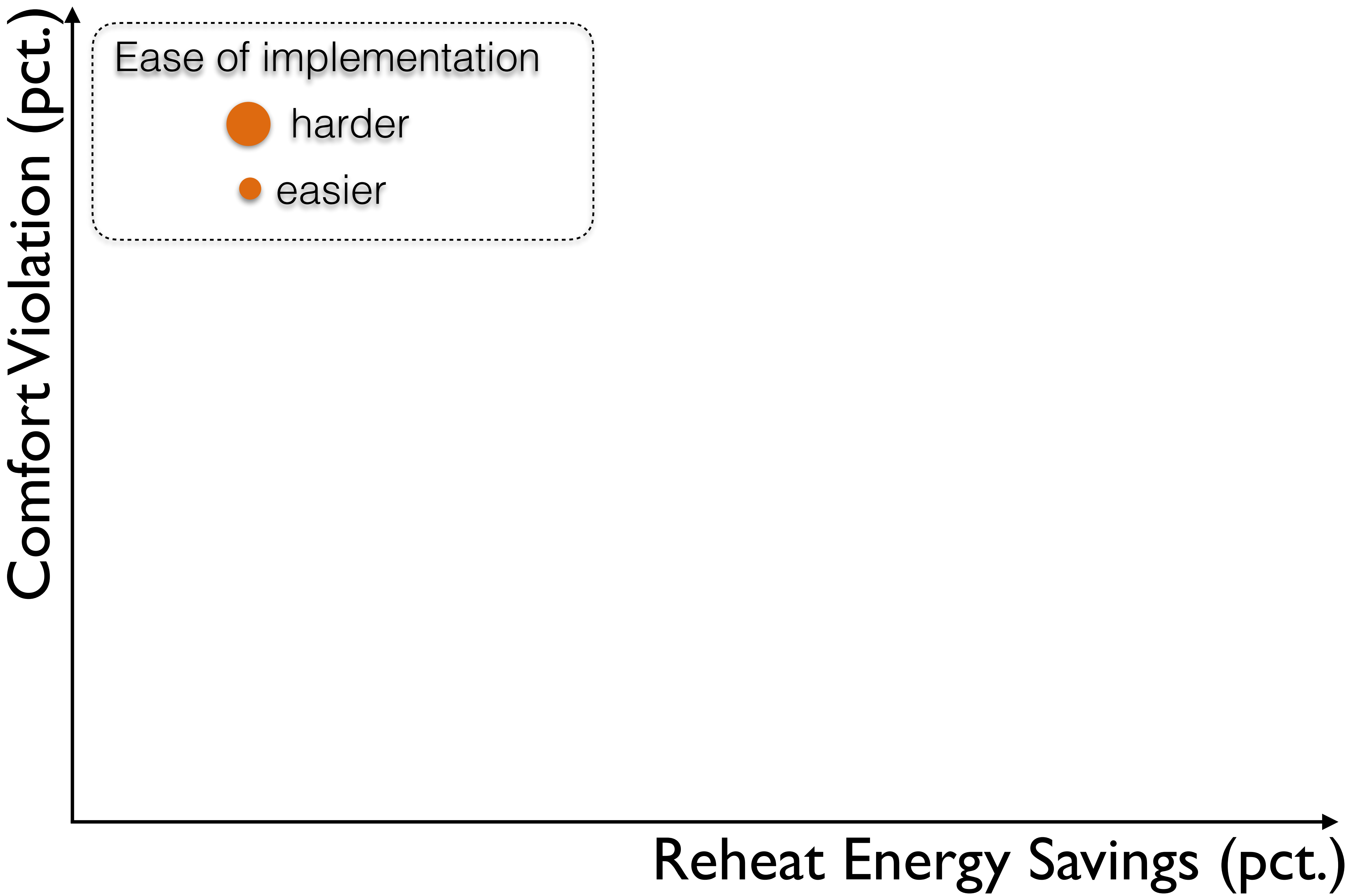


Schedules and Tradeoffs



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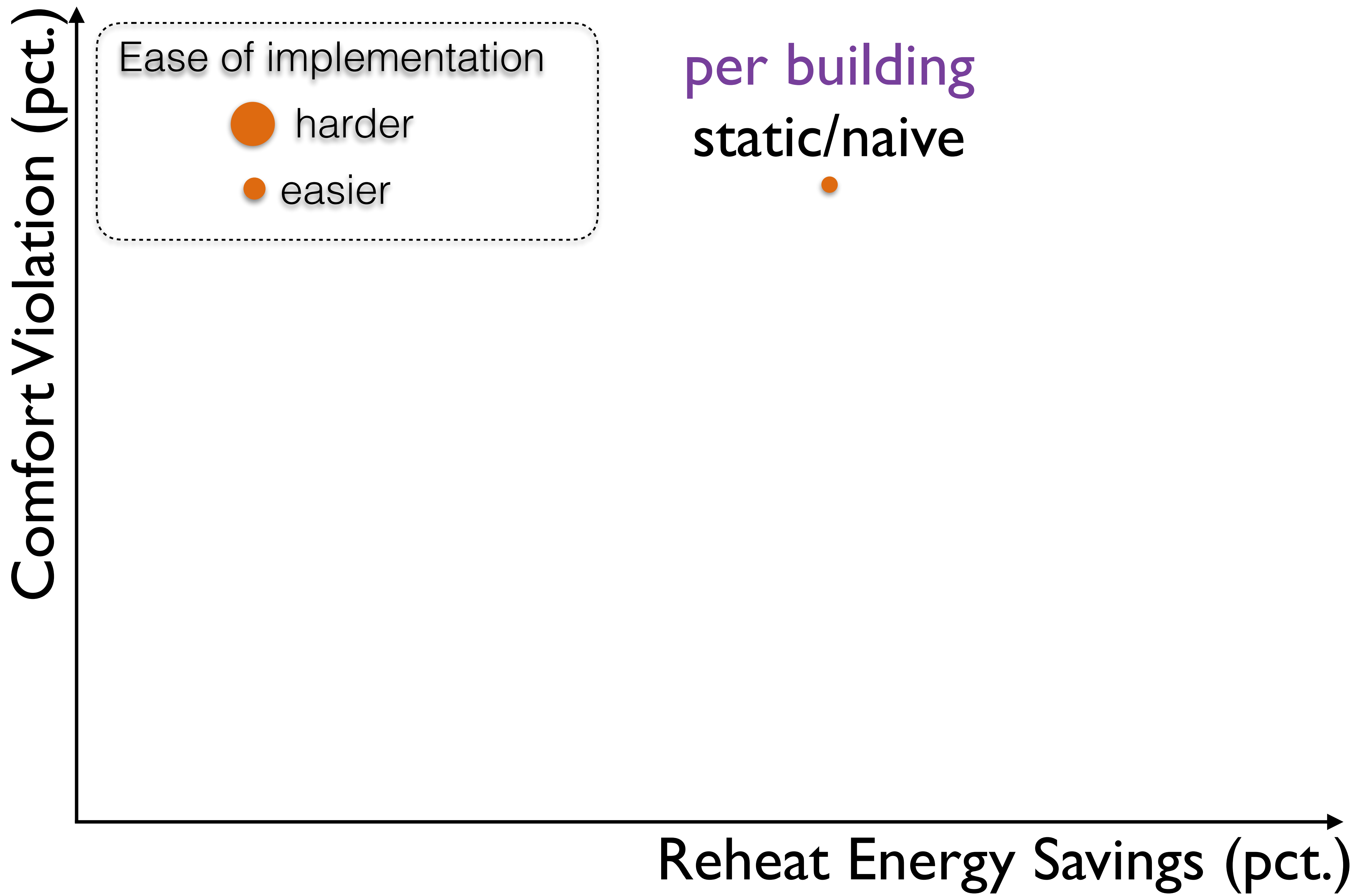

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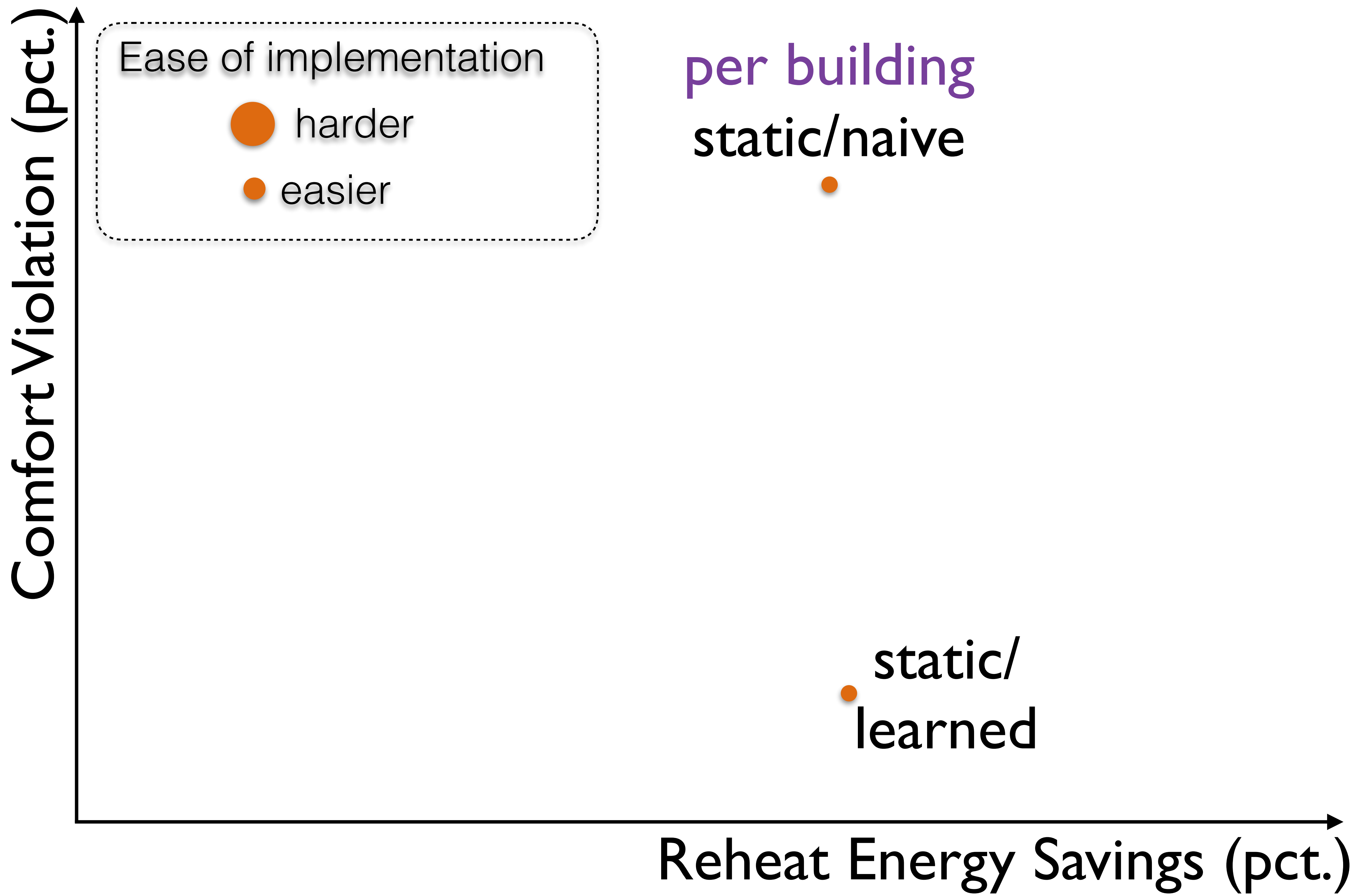

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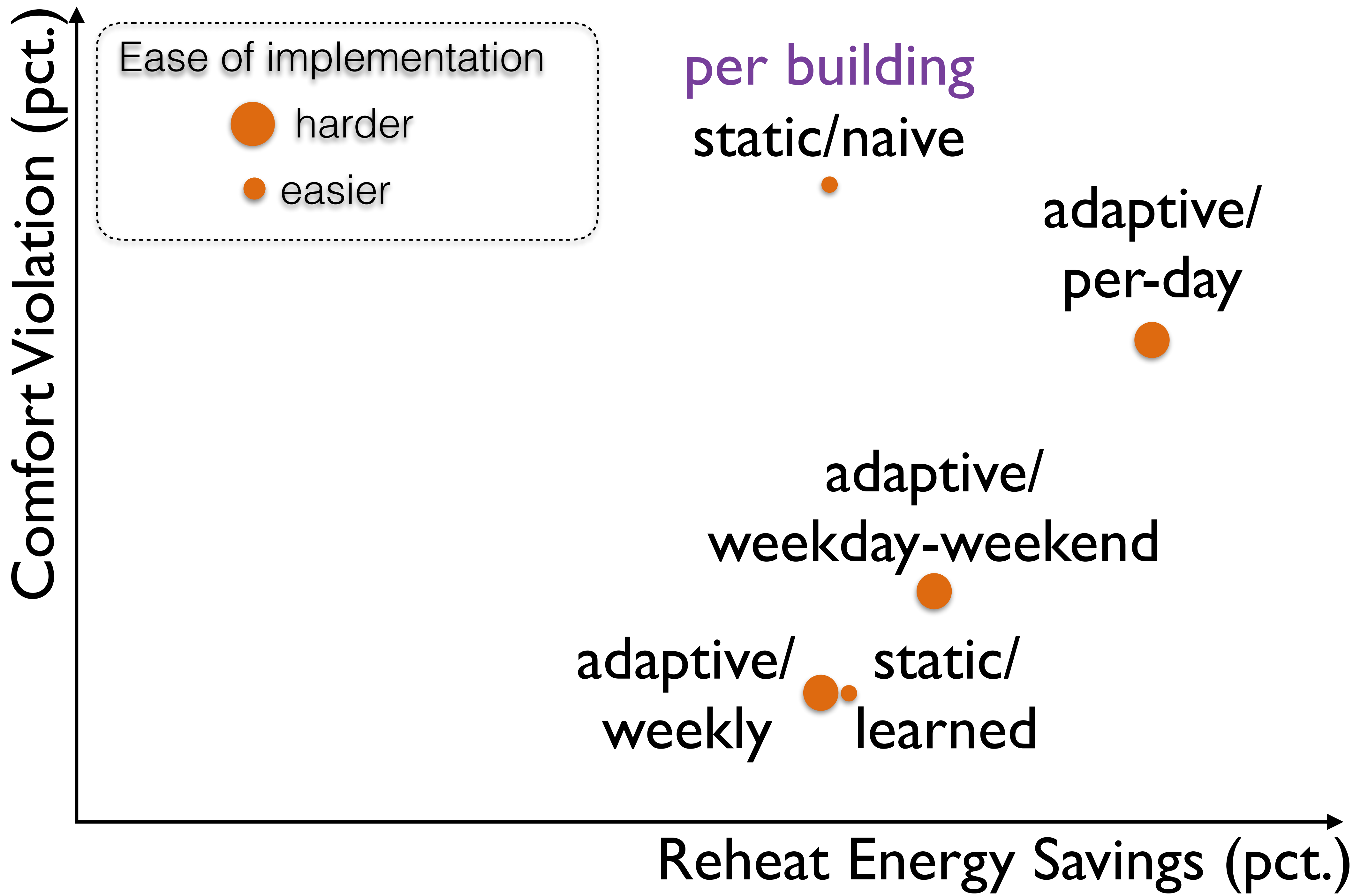

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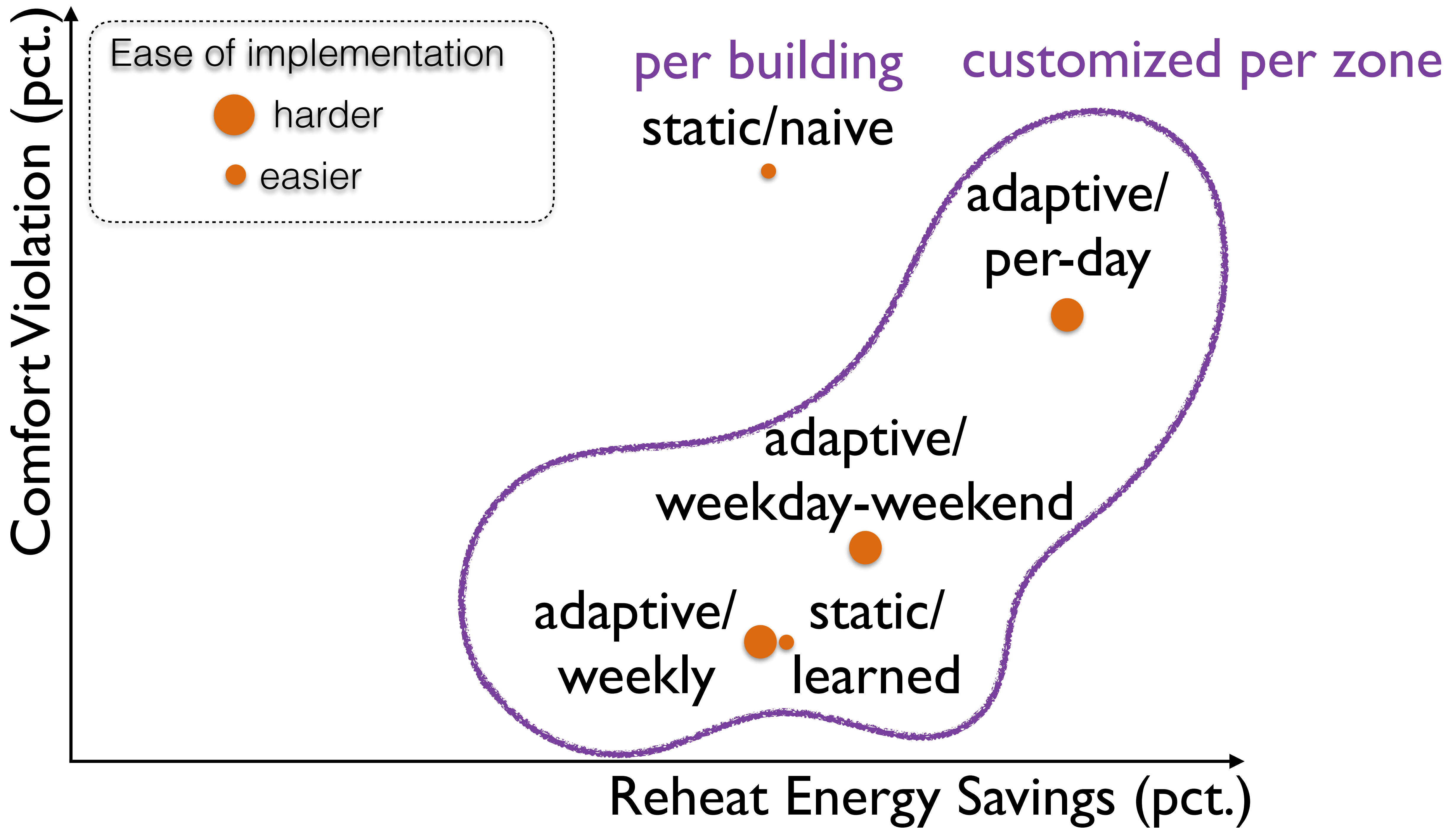

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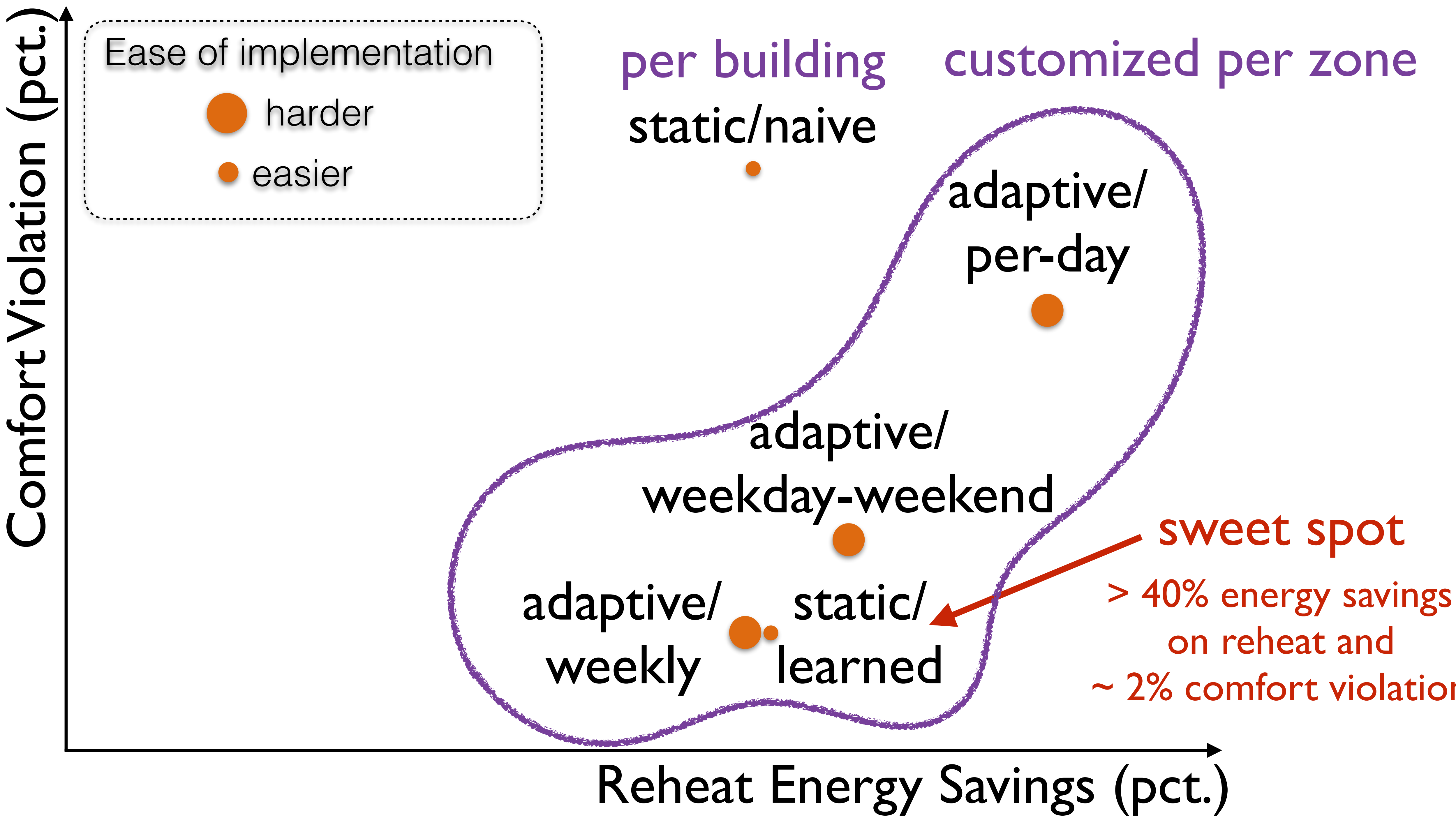
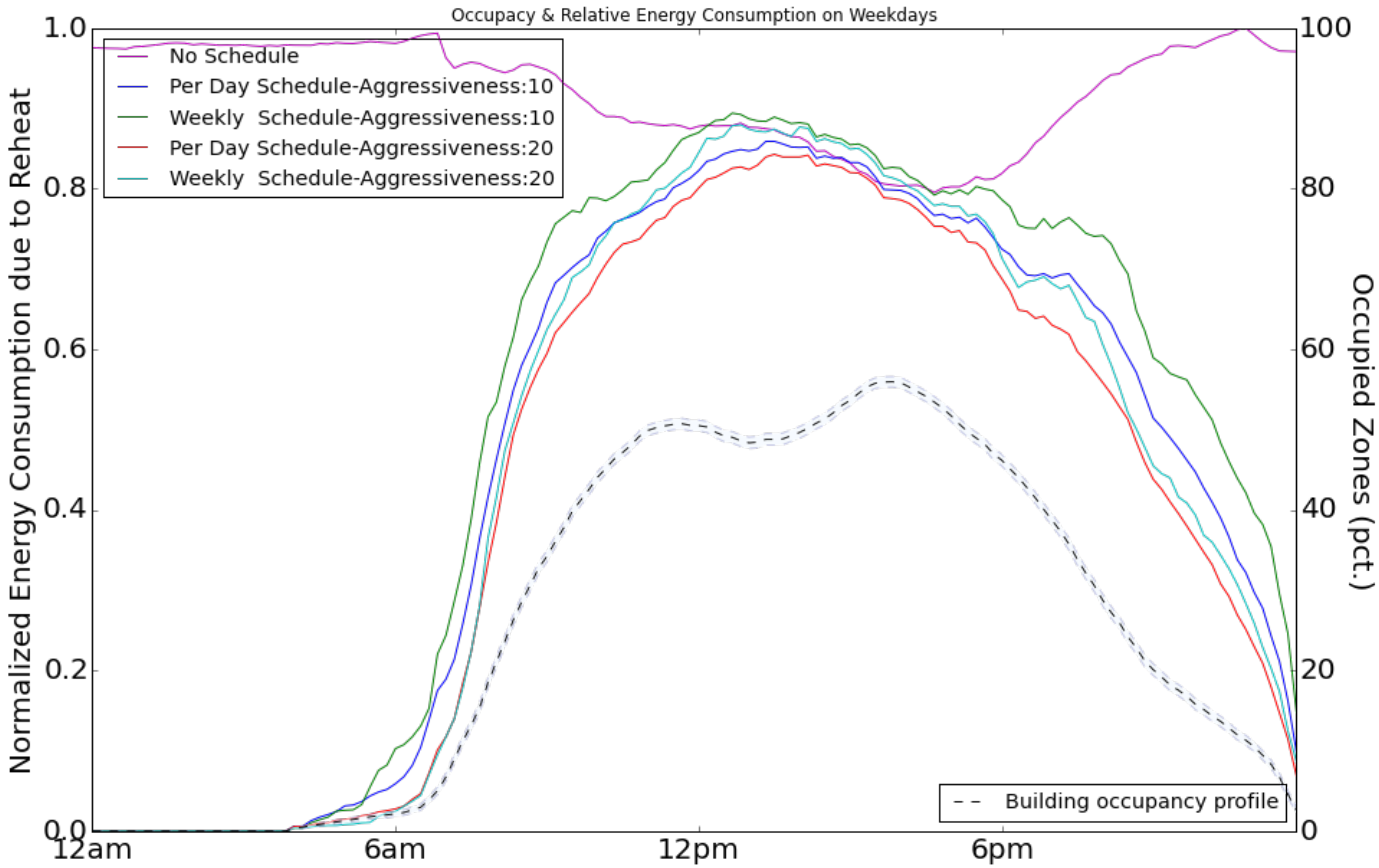


Saving on Reheat Energy



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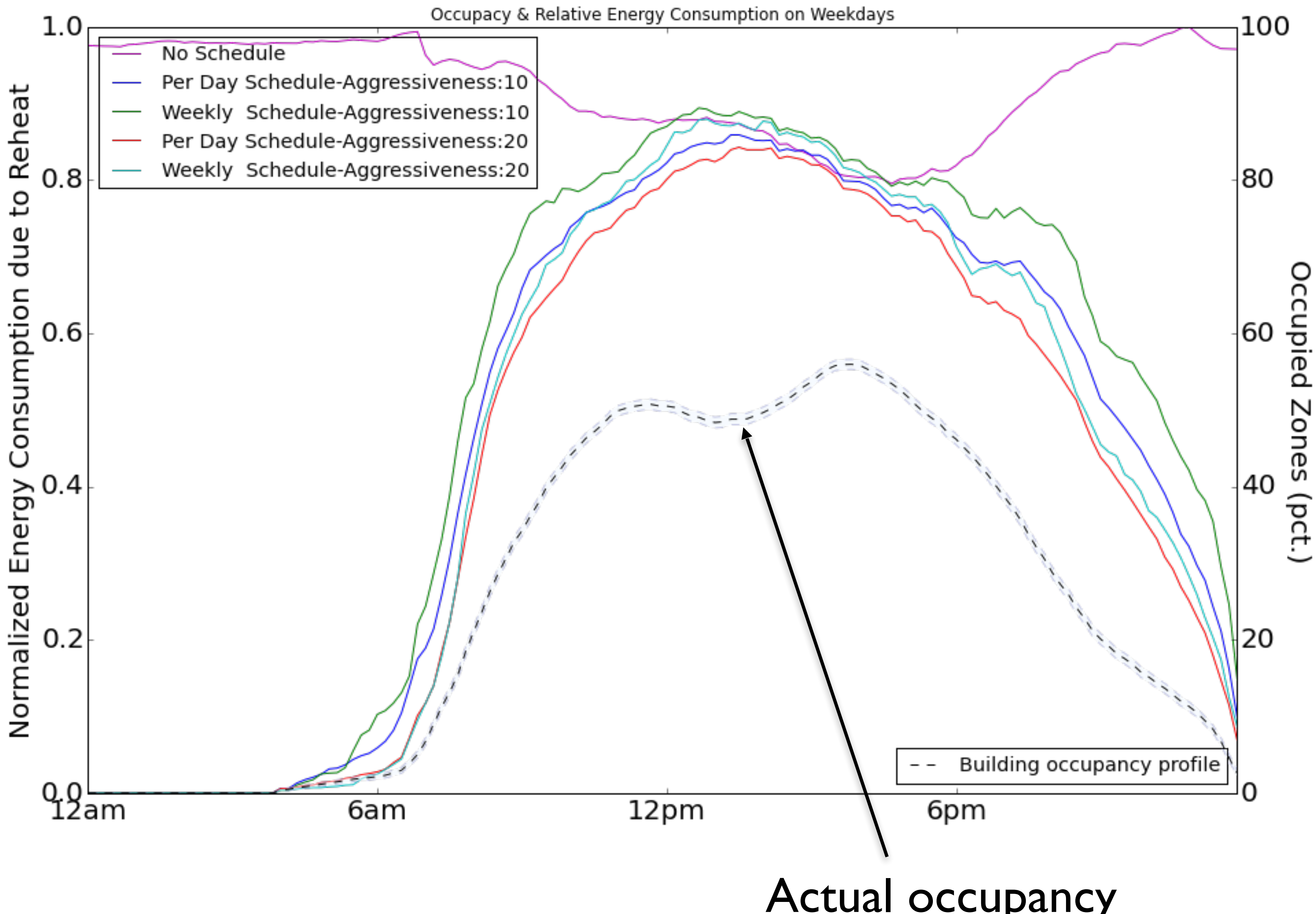

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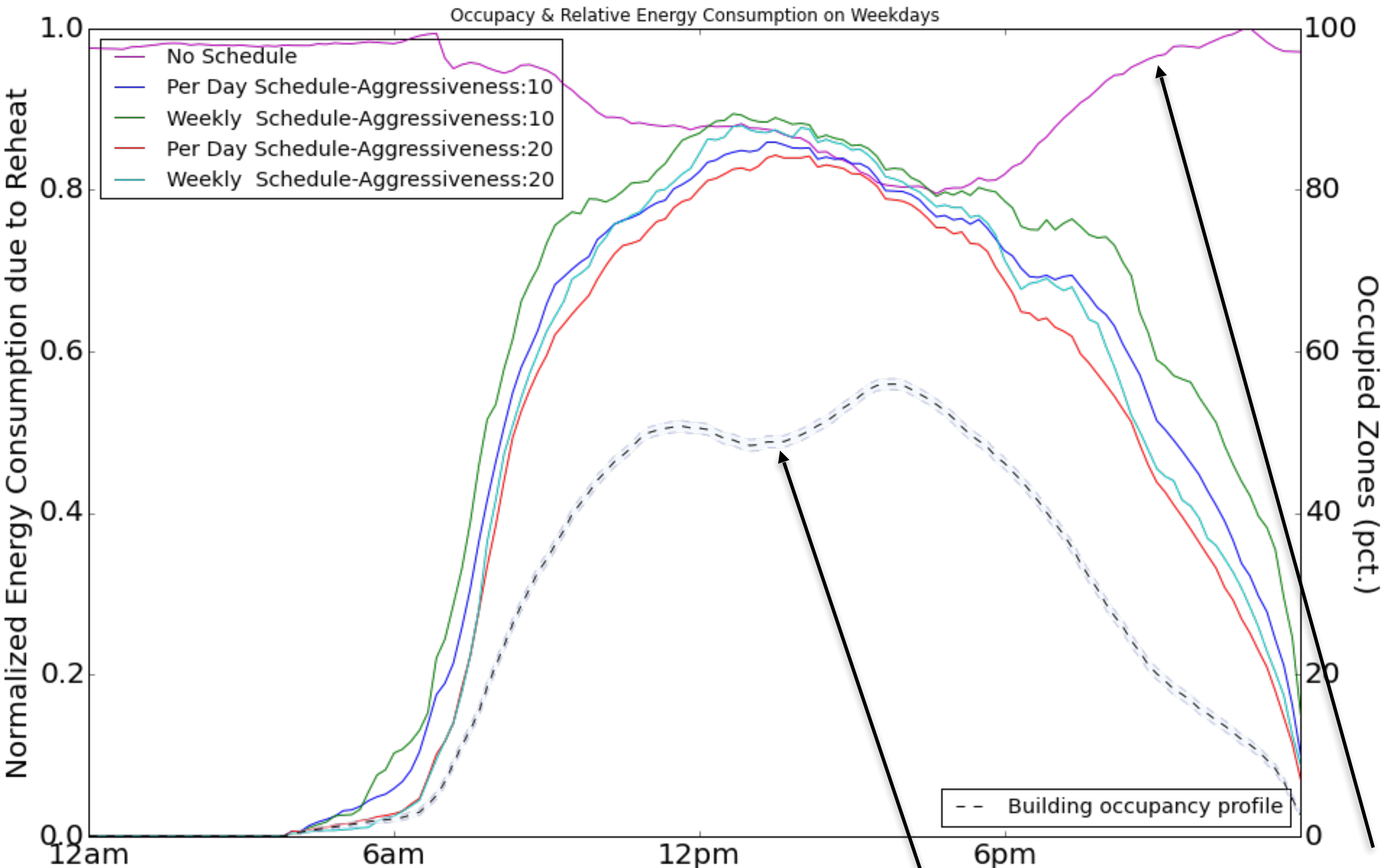
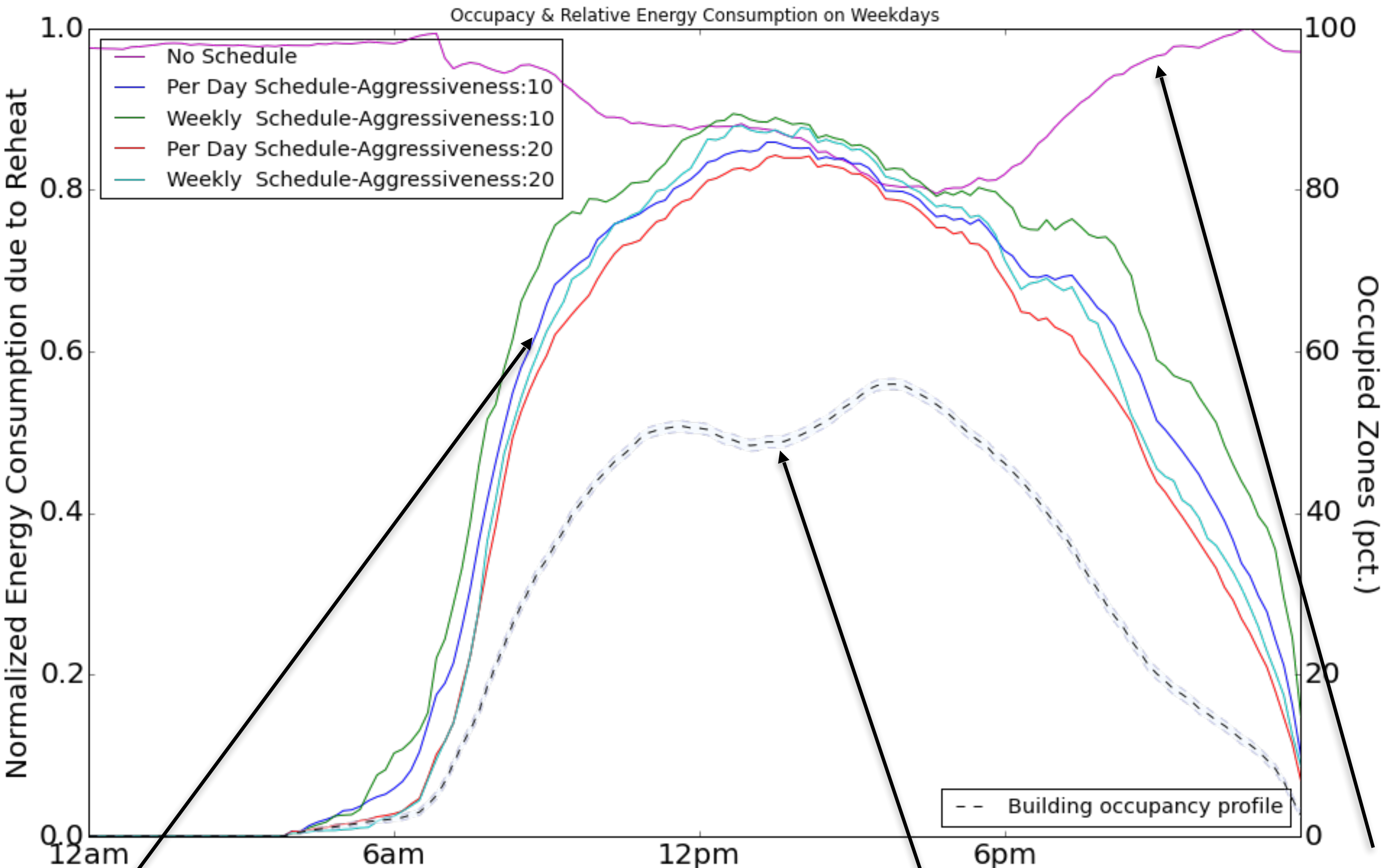


Actual occupancy

Current reheat schedule

Saving on Reheat Energy



Reheat profiles under our smarter schedules

Actual occupancy

Current reheat schedule

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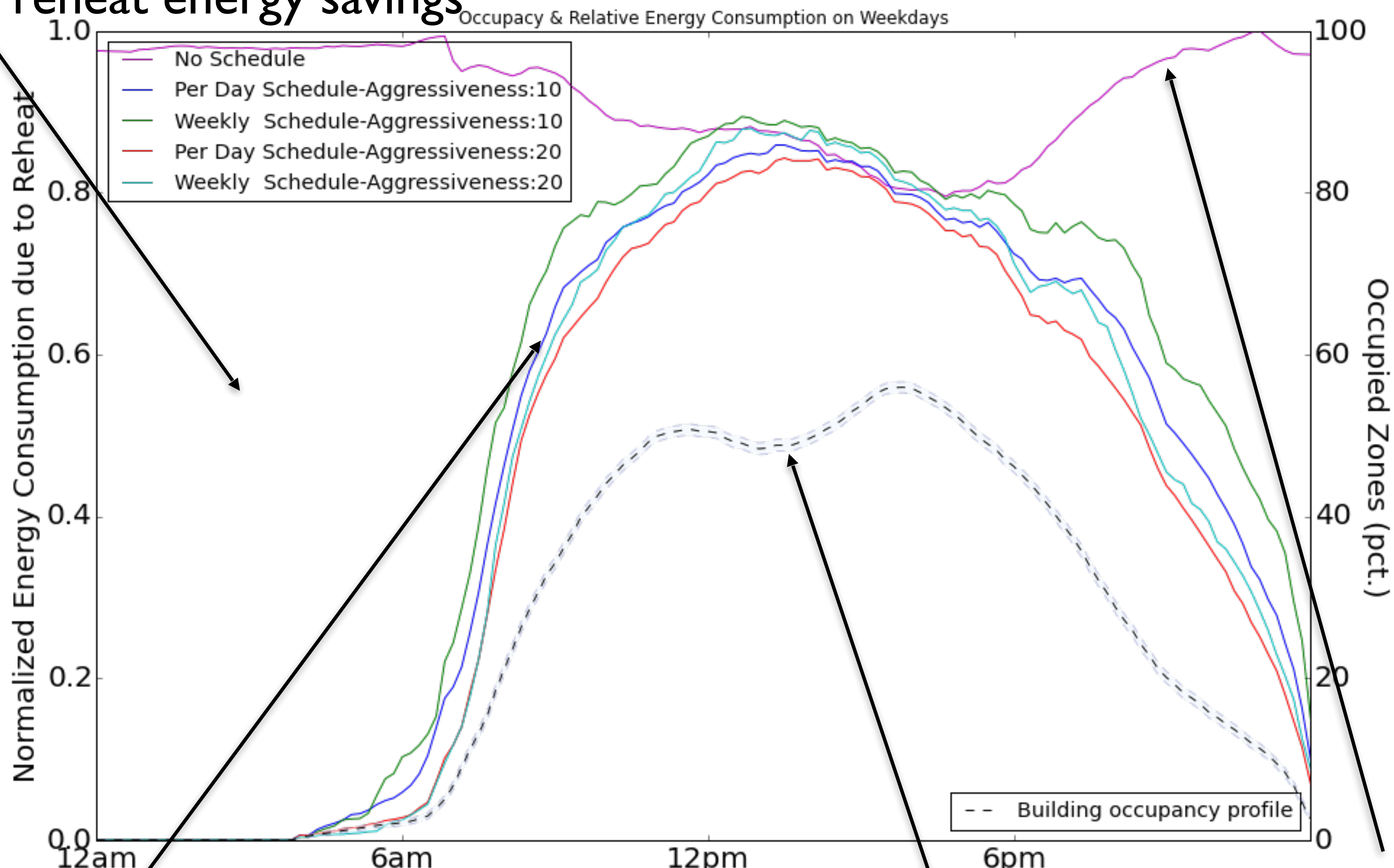

Possible reheat energy savings

Reheat profiles under our smarter schedules

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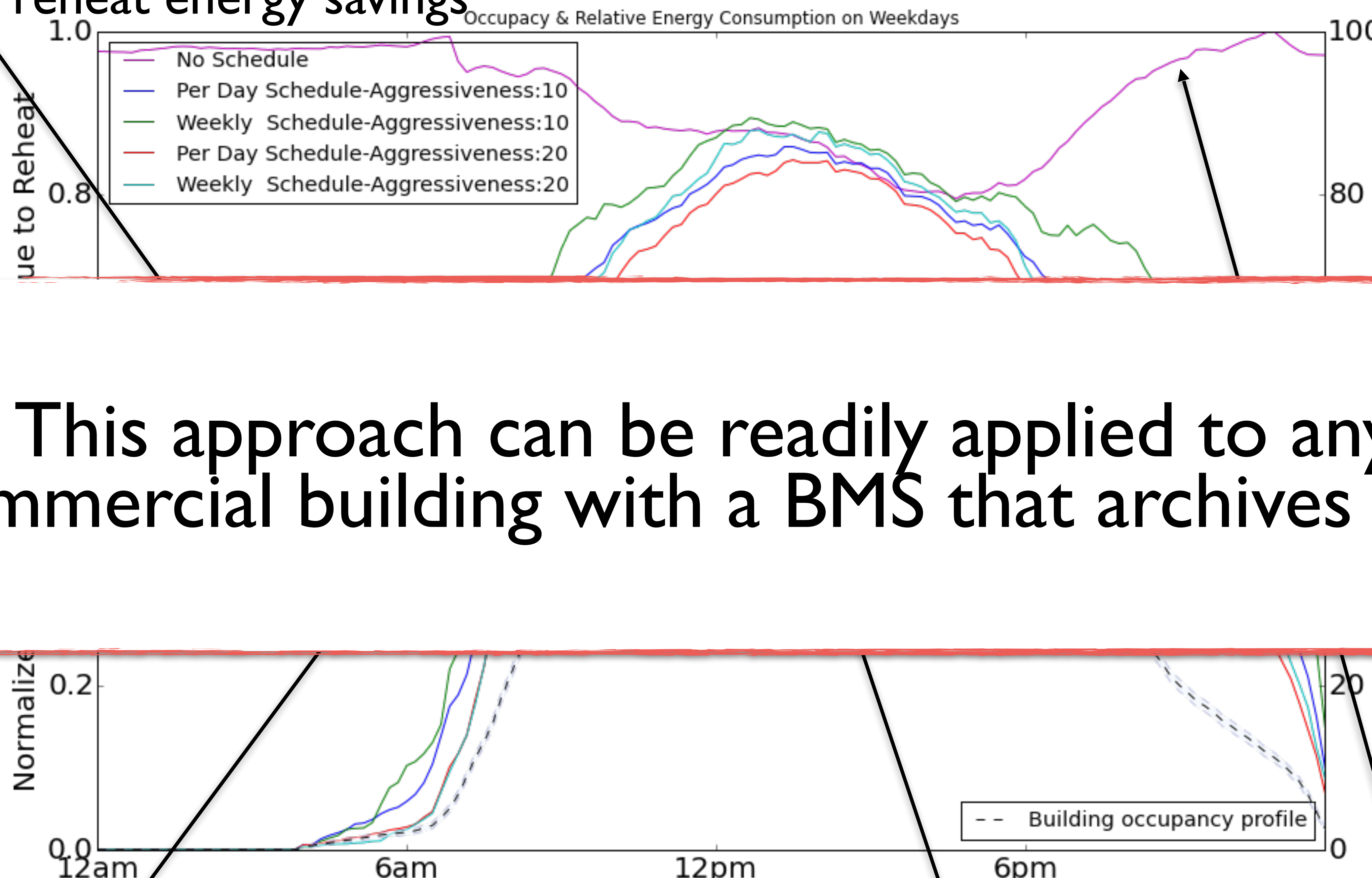
Possible reheat energy savings



This approach can be readily applied to any commercial building with a BMS that archives data

Reheat profiles under our smarter schedules

Actual occupancy

Current reheat schedule

OUTLINE

	Monitor	Model	Manage
Transportation Electrification			**Home EV Charging** *GreenMetrics'12* *eEnergy'13* *ToSG'14* **Solar EV Charging** *SmartGridComm'14*
Buildings	**Sub-Metering** *GreenNets'11*		**HVAC** *BuildSys'16* **Residential Buildings** *EnDM'14*
Power Grids	**Phasor Measurement Units** *ongoing*	**Distribution Component Sizing** *eEnergy'12* *GreenMetrics'12*	**System Identification** *PES GM'17* **Event Classification** *ISGT'17* **PV and Storage Integration** *SpringerBrief'16*

- **Omid Ardakanian**, S. Keshav, Catherine Rosenberg, "Integration of Renewable Generation and Elastic Loads into Distribution Grids", Springer Briefs in Electrical and Computer Engineering, 2016.
- **Omid Ardakanian**, Ye Yuan, Roel Dobbe, Alexandra von Meier, Steven Low, Claire Tomlin, "Event Detection and Localization in Distribution Grids with Phasor Measurement Units", To appear in IEEE PES General Meeting, 2017.
- Daniel Arnold, Ciaran Roberts, **Omid Ardakanian**, Emma Stewart, "Synchrophasor Data Analytics in Distribution Grids", To appear in IEEE Innovative Smart Grid Technologies (ISGT), 2017.

Power Grid Modernization

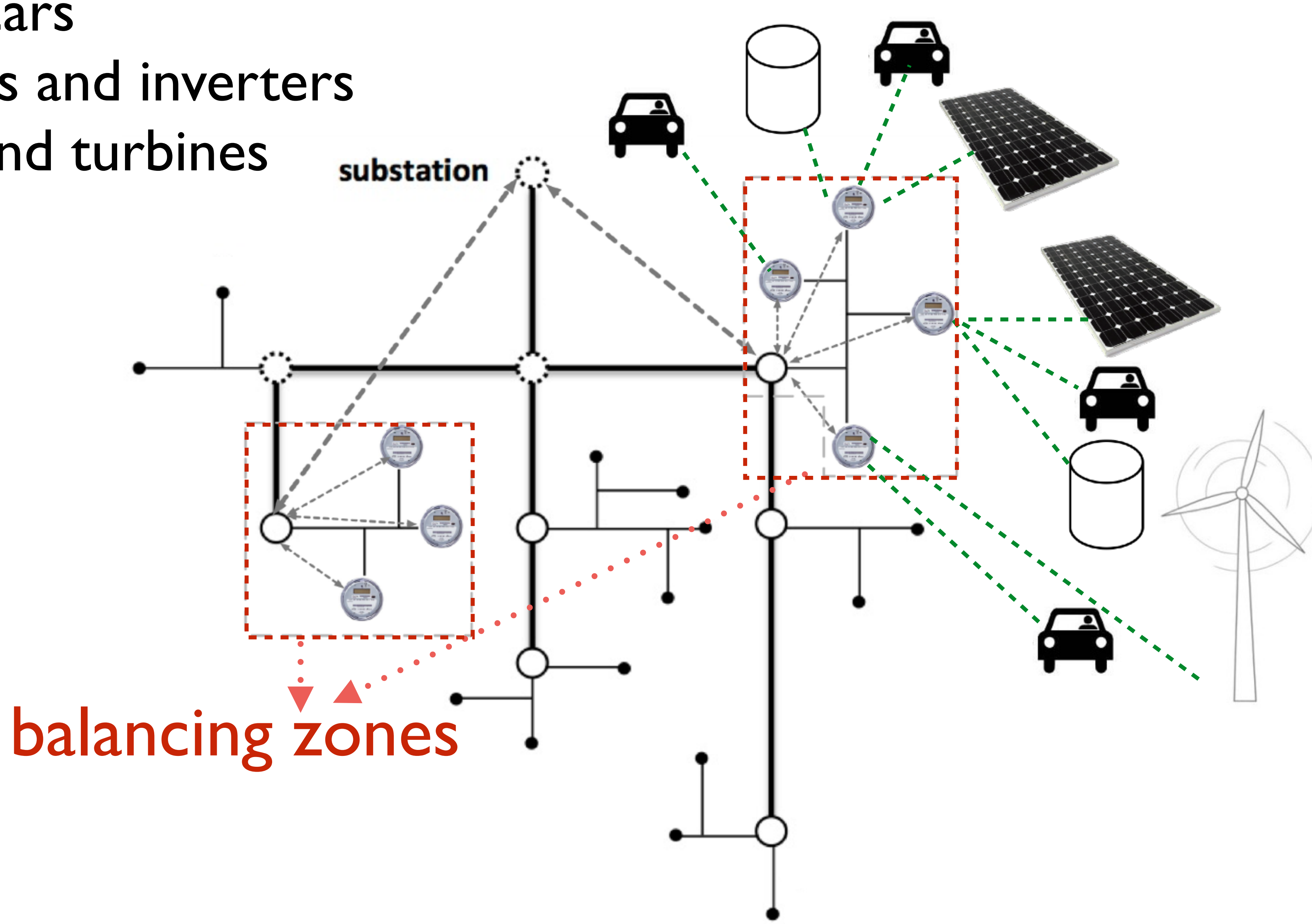
BECI
BERKELEY ENERGY & CLIMATE INSTITUTE
LBNL & UC BERKELEY
ciee California Institute for Energy and Environment

Power Grid Modernization

Power Grid Modernization

Enabling Large-Scale Integration of Active End-Nodes

- electric cars
- solar cells and inverters
- micro wind turbines
- batteries



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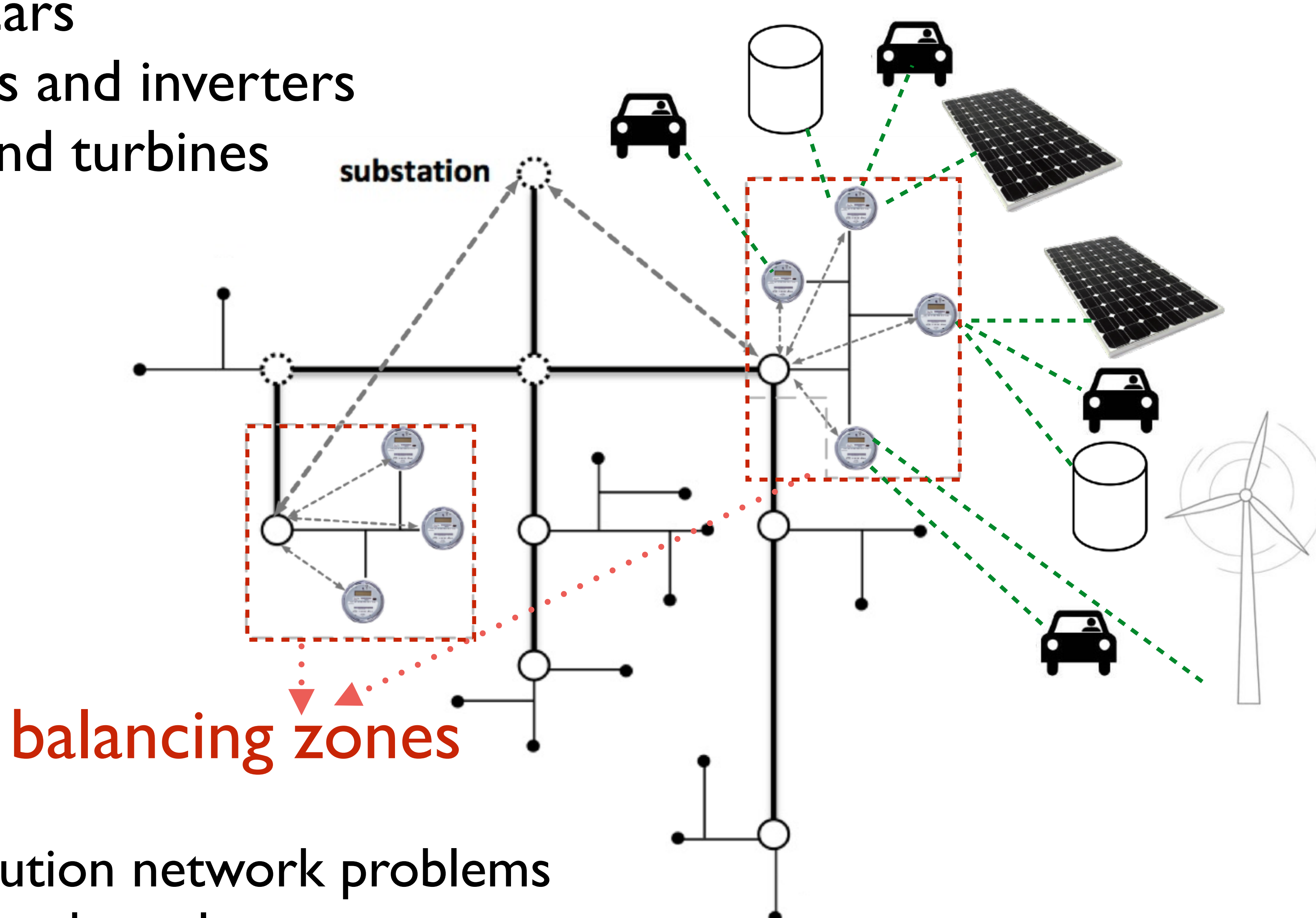

Avoid distribution network problems

- over- and under-voltage
- overloads
- reverse power flows

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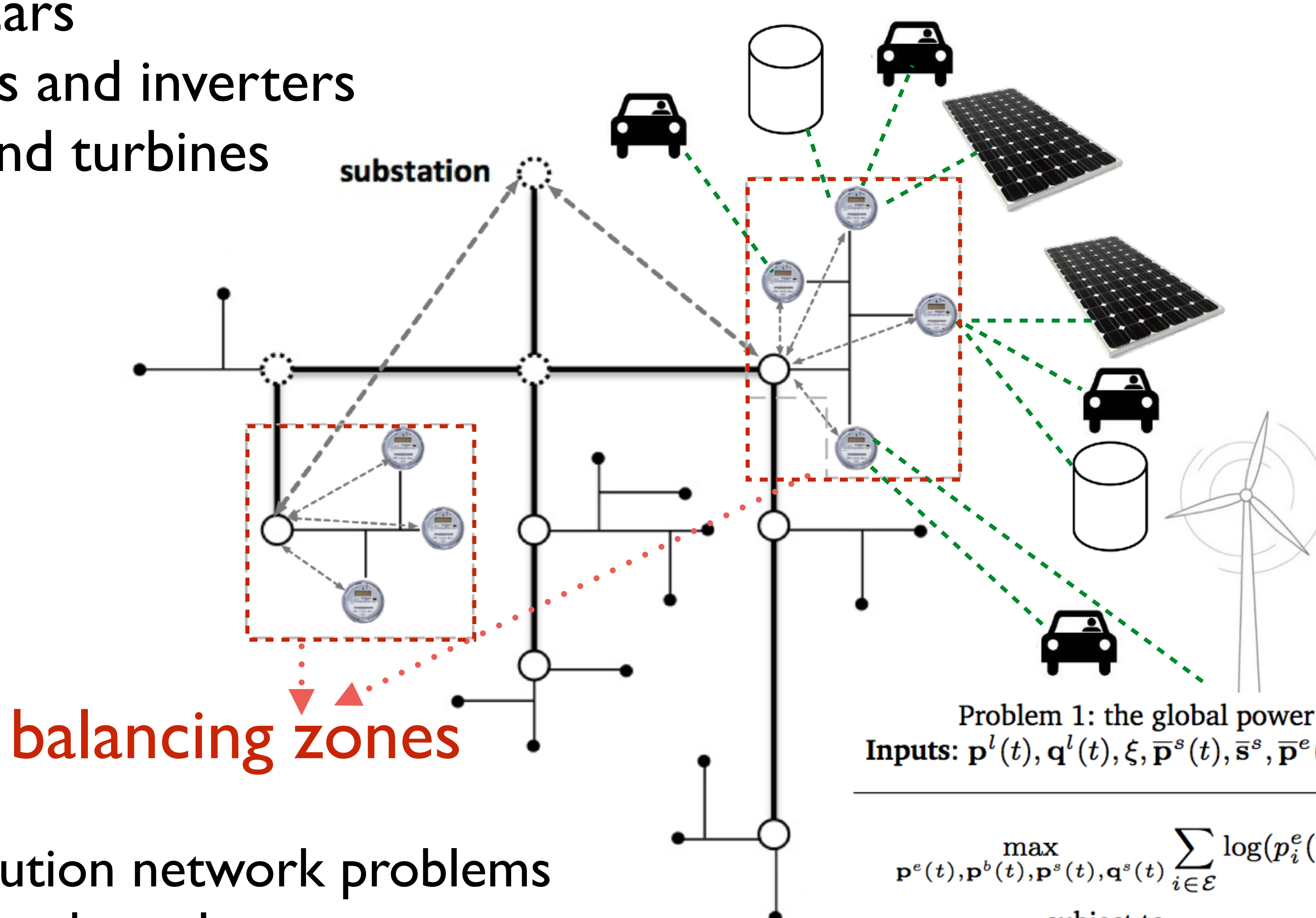

Avoid distribution network problems

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Problem 1: the global power allocation problem

Inputs: $\mathbf{p}^l(t), \mathbf{q}^l(t), \xi, \overline{\mathbf{p}}^s(t), \overline{\mathbf{s}}^s, \overline{\mathbf{p}}^e(t), \overline{\mathbf{p}}^b(t), \underline{\mathbf{p}}^b(t), \mathcal{I}, \mathcal{E}, \mathcal{J}, \mathcal{S}$

$$\max_{\mathbf{p}^e(t), \mathbf{p}^b(t), \mathbf{p}^s(t), \mathbf{q}^s(t)} \sum_{i \in \mathcal{E}} \log(p_i^e(t)) + \sum_{i \in \mathcal{J}} p_i^s(t)$$

subject to

End-node Constraints

System Constraints

Bus Injection Equations

Power Flow Equations

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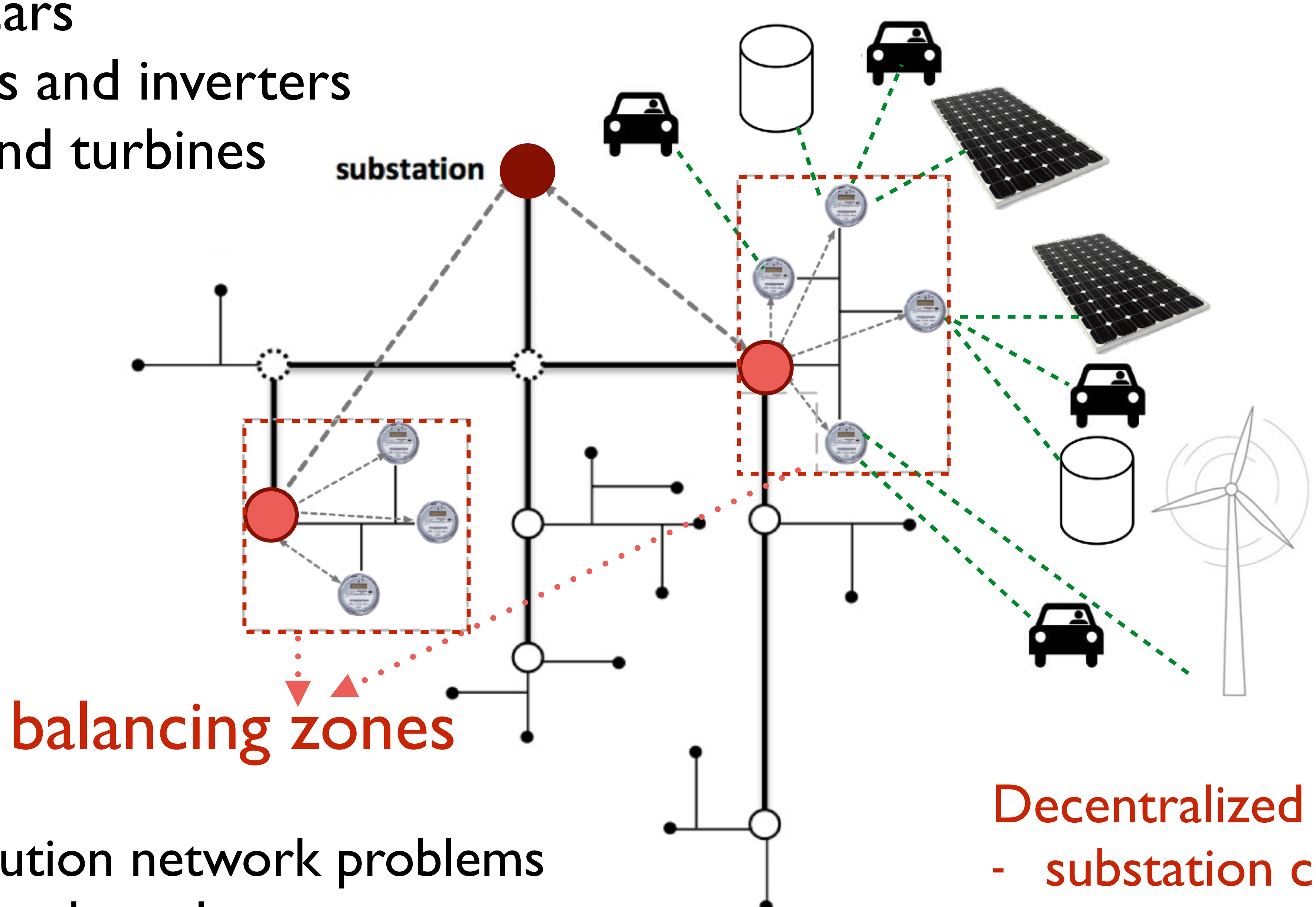

Avoid distribution network problems
- over- and under-voltage
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Decentralized control
- substation controller
- balancing zone controllers
- end-nodes

Detecting Rare Events in Massive Amounts of Data in Real-Time

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image: power standards lab

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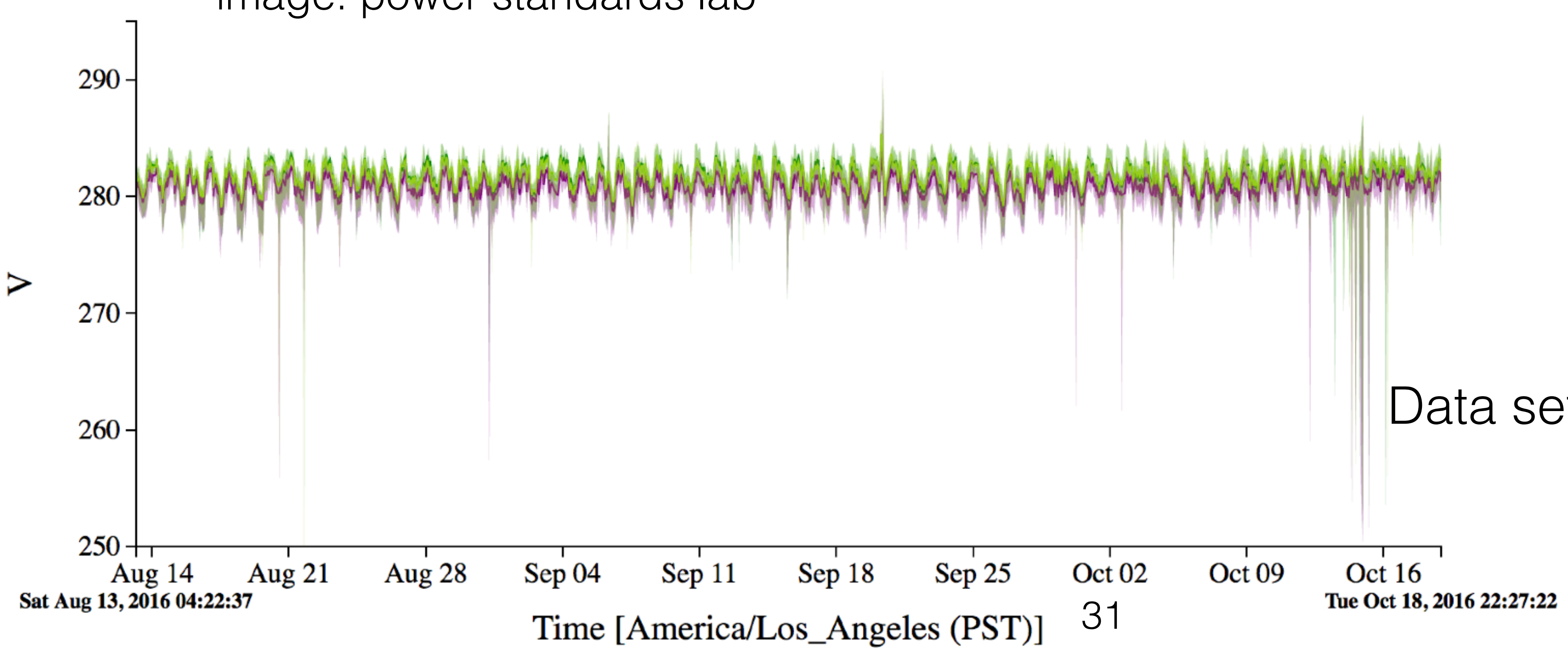

Data set available at plot.upmu.org

Detecting Rare Events in Massive Amounts of Data in Real-Time

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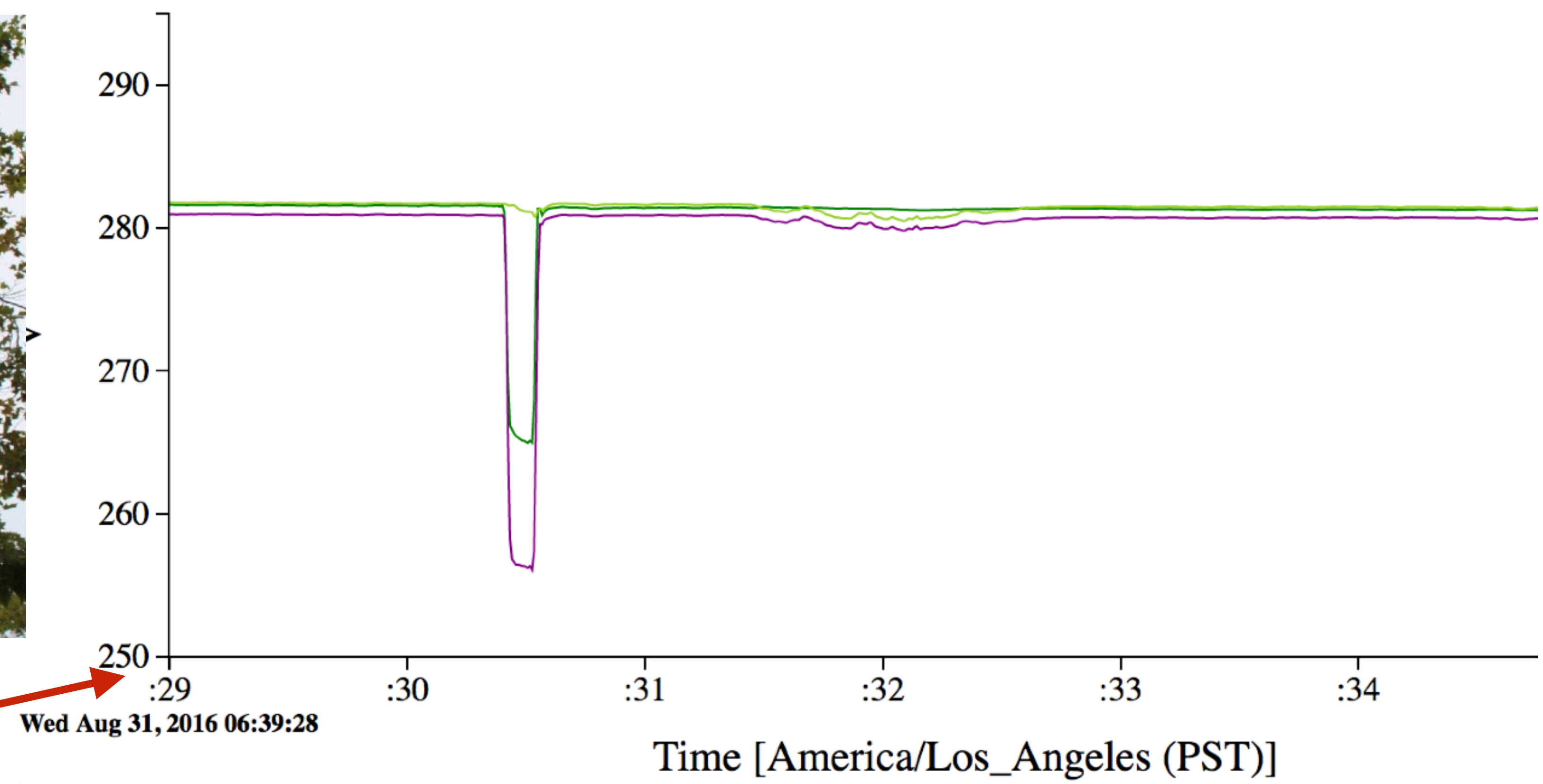

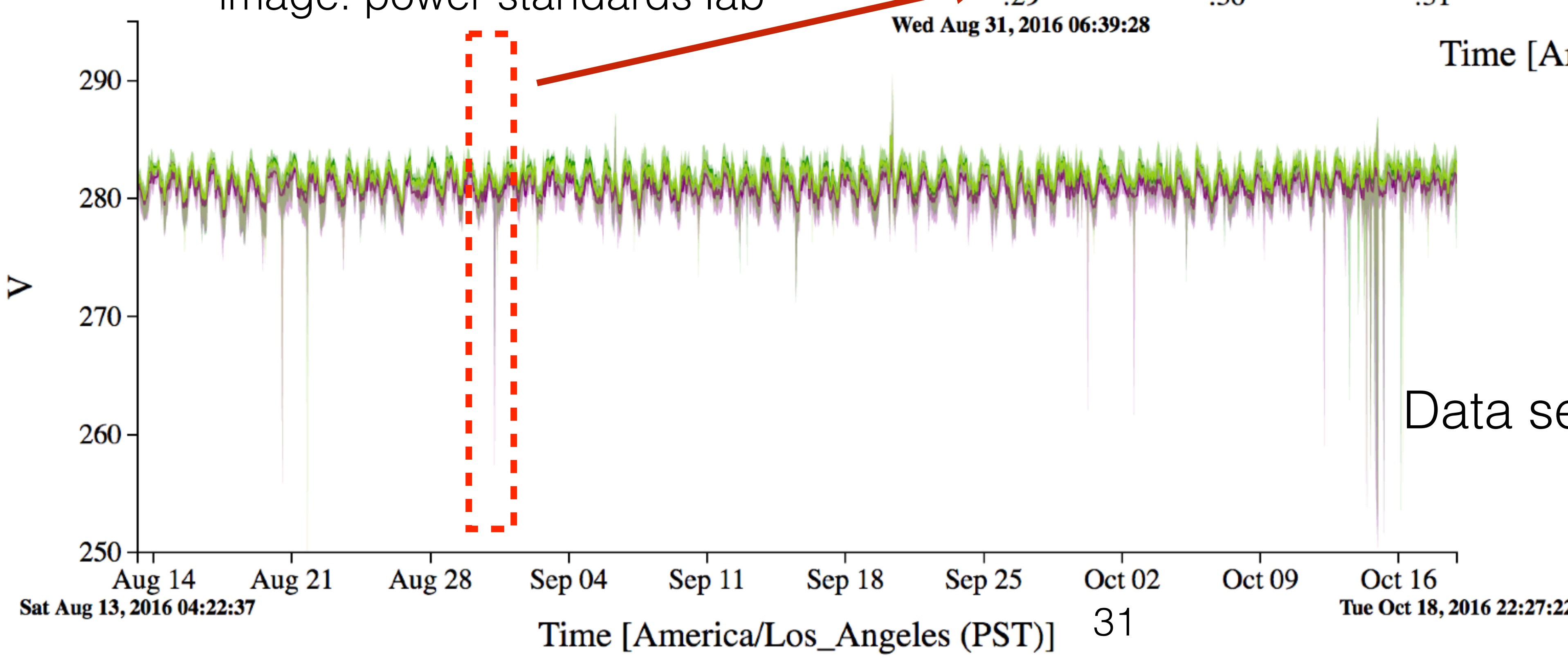

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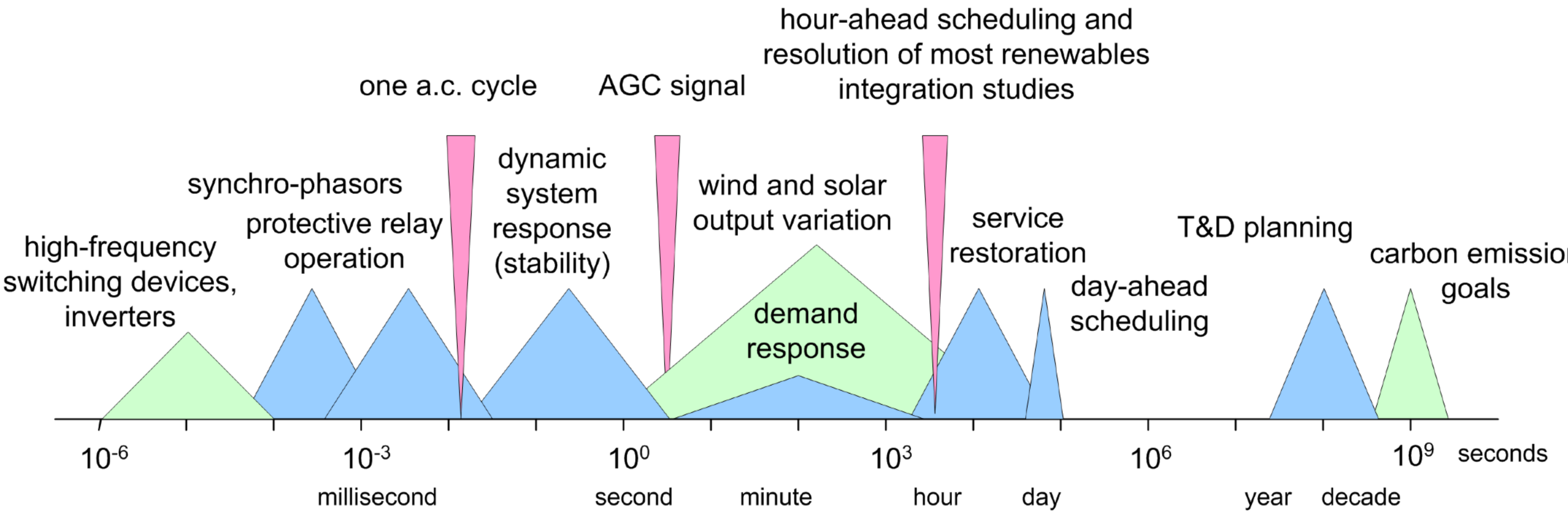
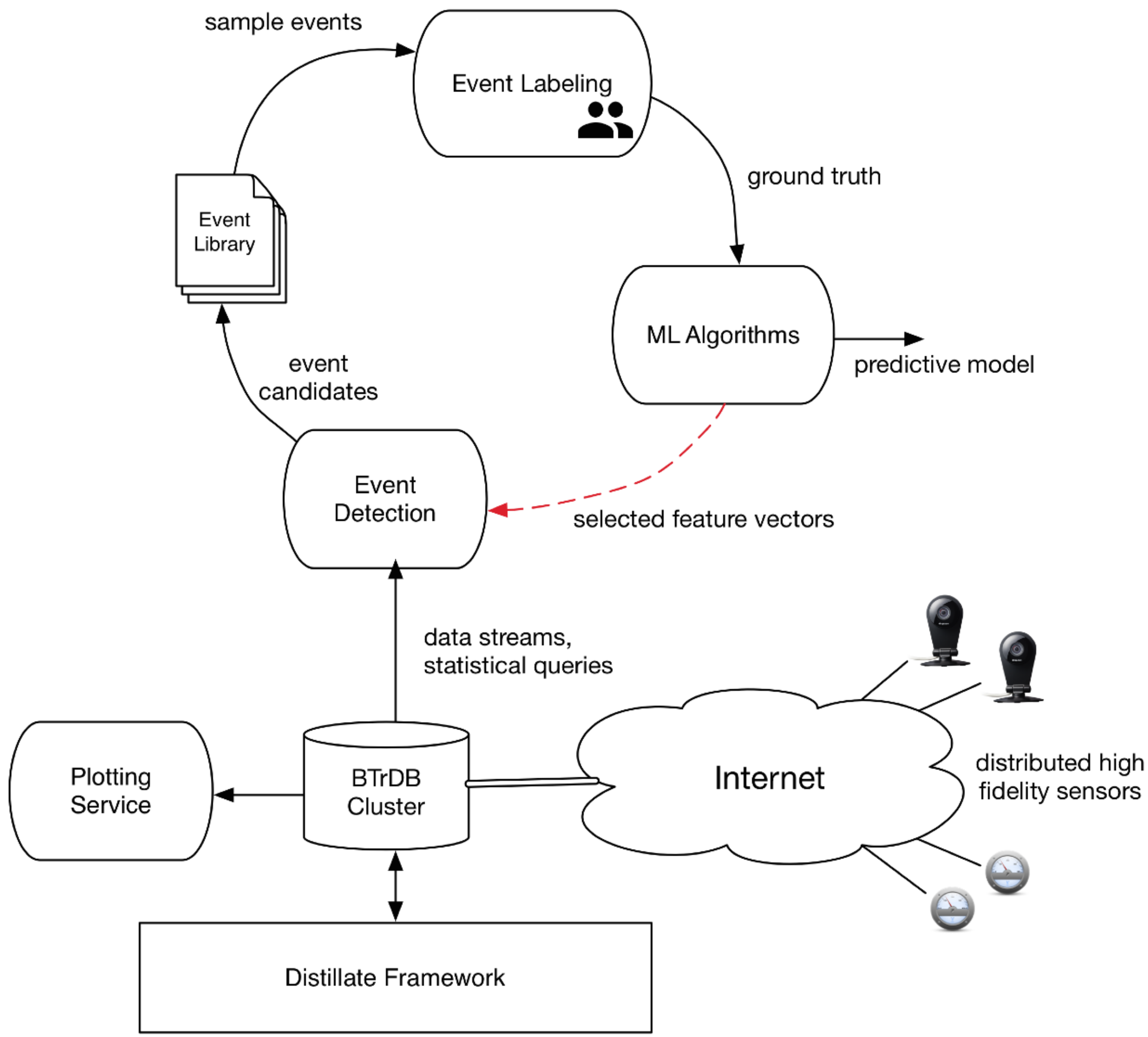
The Range of Relevant Time Increments in Power System Planning and Operation Spans 15 Orders of Magnitude!

[vonMeier14]



Data Storage and Analysis Infrastructure



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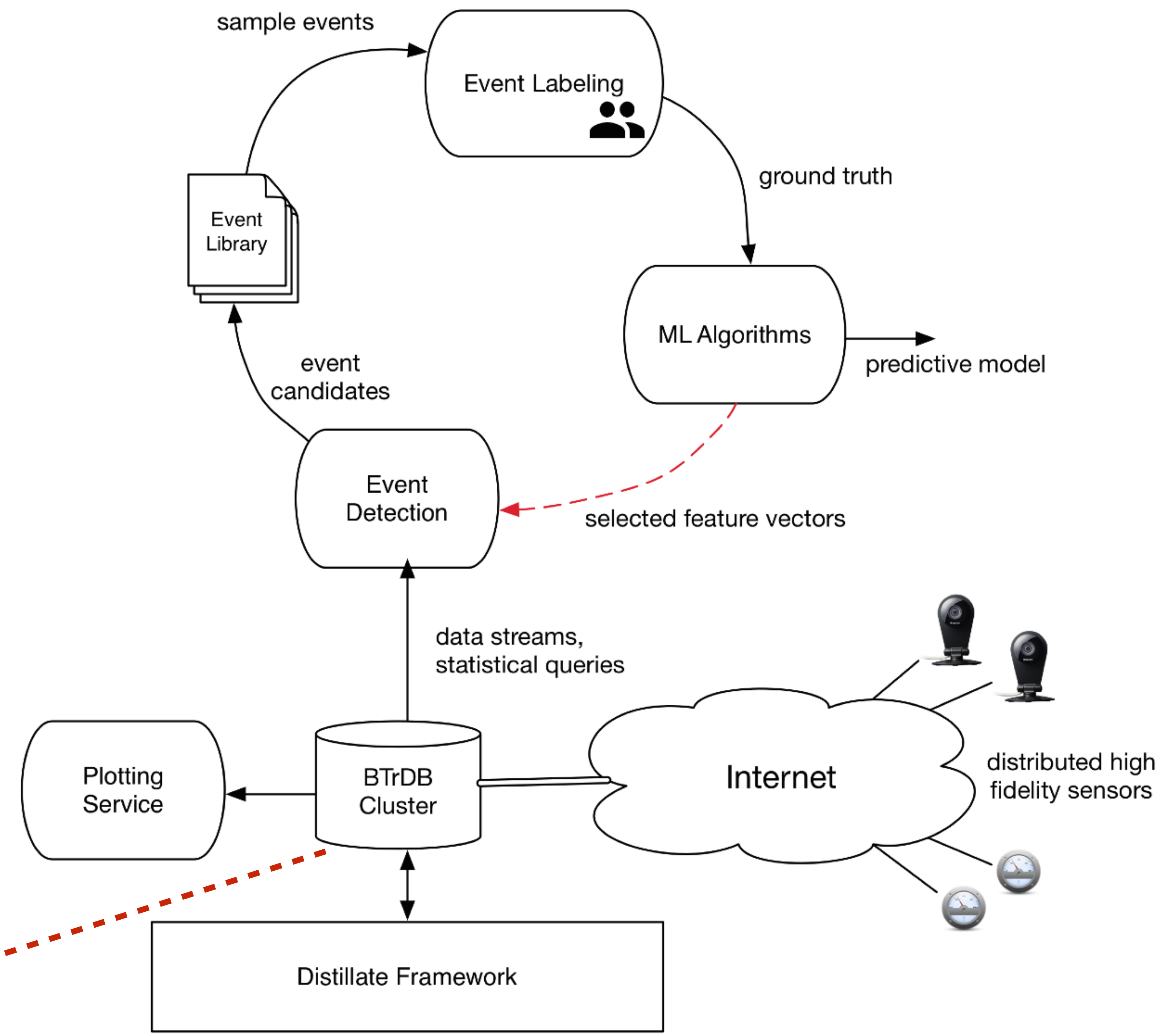

statistical summaries of data can be efficiently retrieved at different temporal resolutions

Data Storage and Analysis Infrastructure

detectors rely on a multi-resolution search algorithm

logarithmic in the size of data and linear in the number of events

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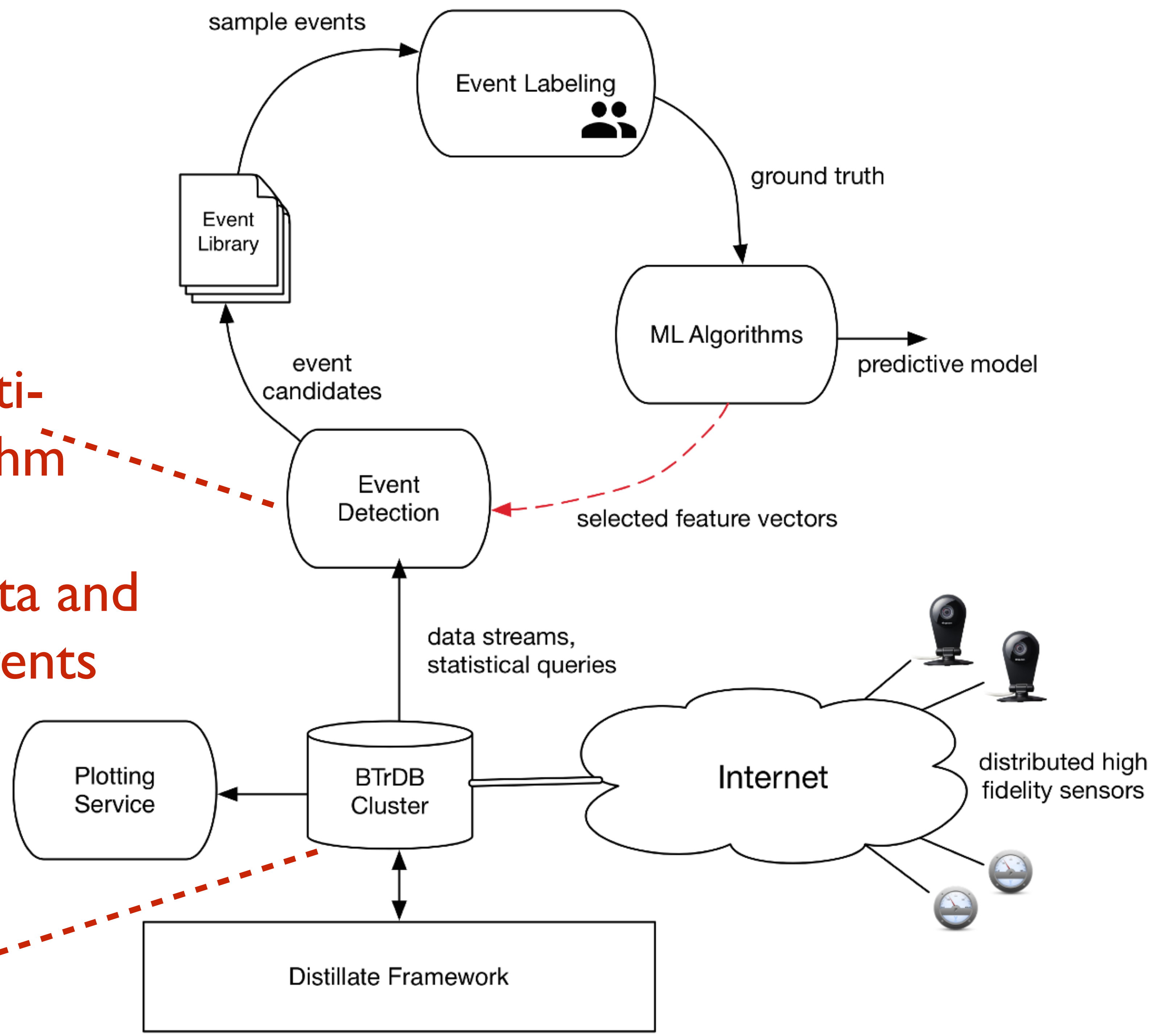

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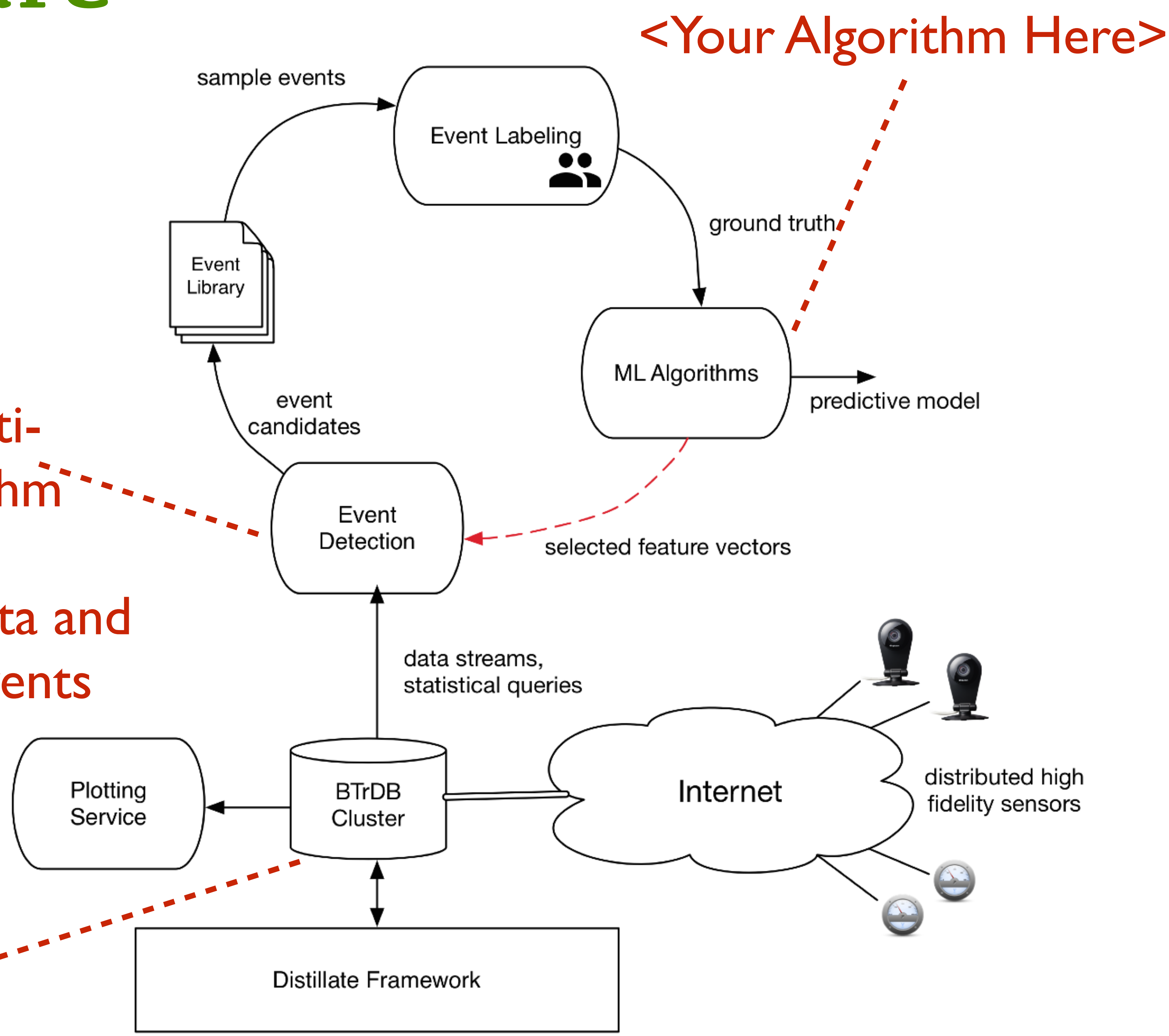

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Beyond Predictive Analytics

Model Validation

- Inferring the admittance matrix from time-synchronized measurements: $\mathbf{I} = \mathbf{Y}\mathbf{V}$
- Sparse recovery techniques

Event Detection and Classification

- Data-driven approach
- Candidate events labelled by domain experts
- A library of various events

high-precision, high-sample-rate data from many locations

Equipment Health Monitoring

- Predictive maintenance
- Informed recommendations

Beyond Predictive Analytics

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This analytics framework is currently used by several power system operators in California

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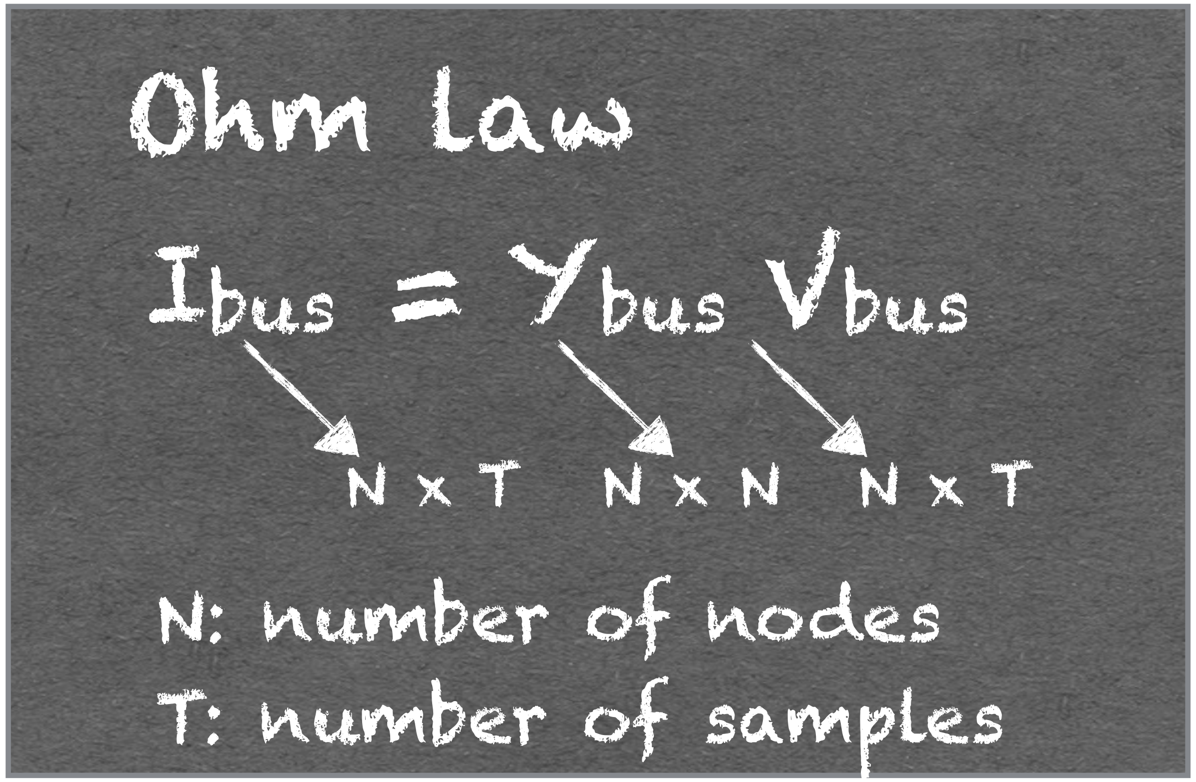
System Identification

System Identification

- Inferring network topology from voltage and current phasor measurements



System Identification

- Inferring network topology from voltage and current phasor measurements
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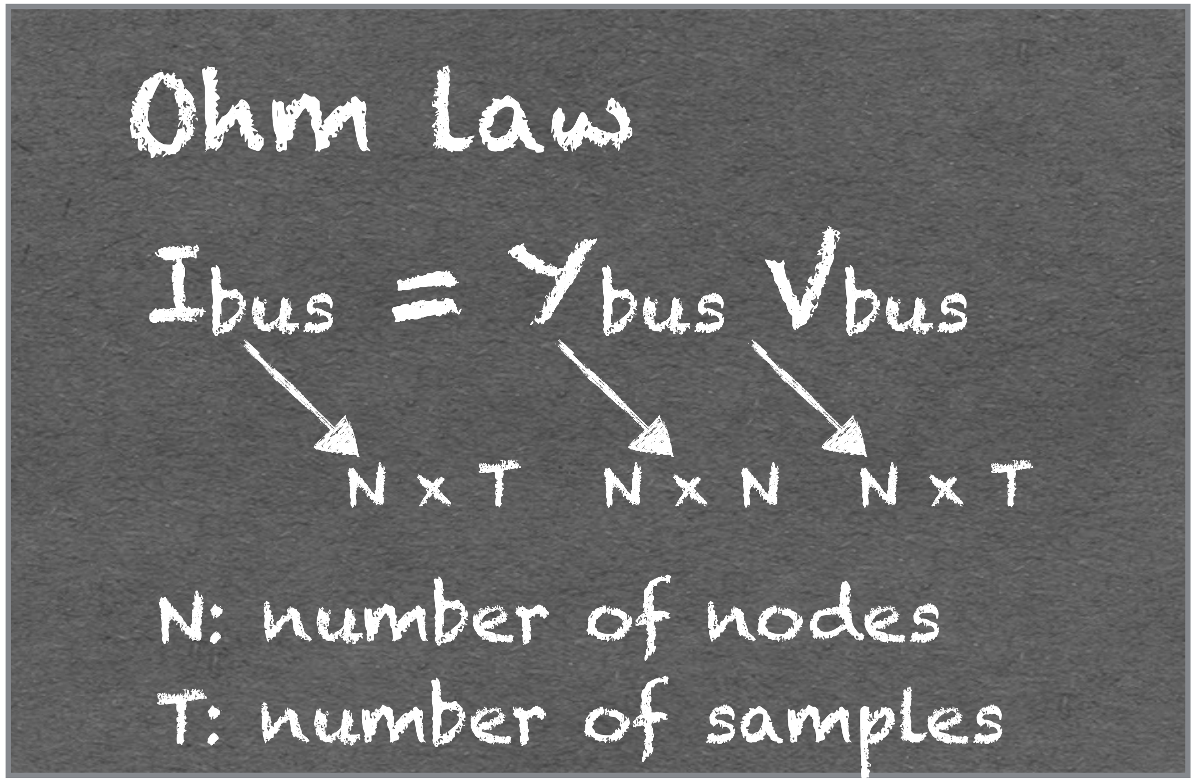

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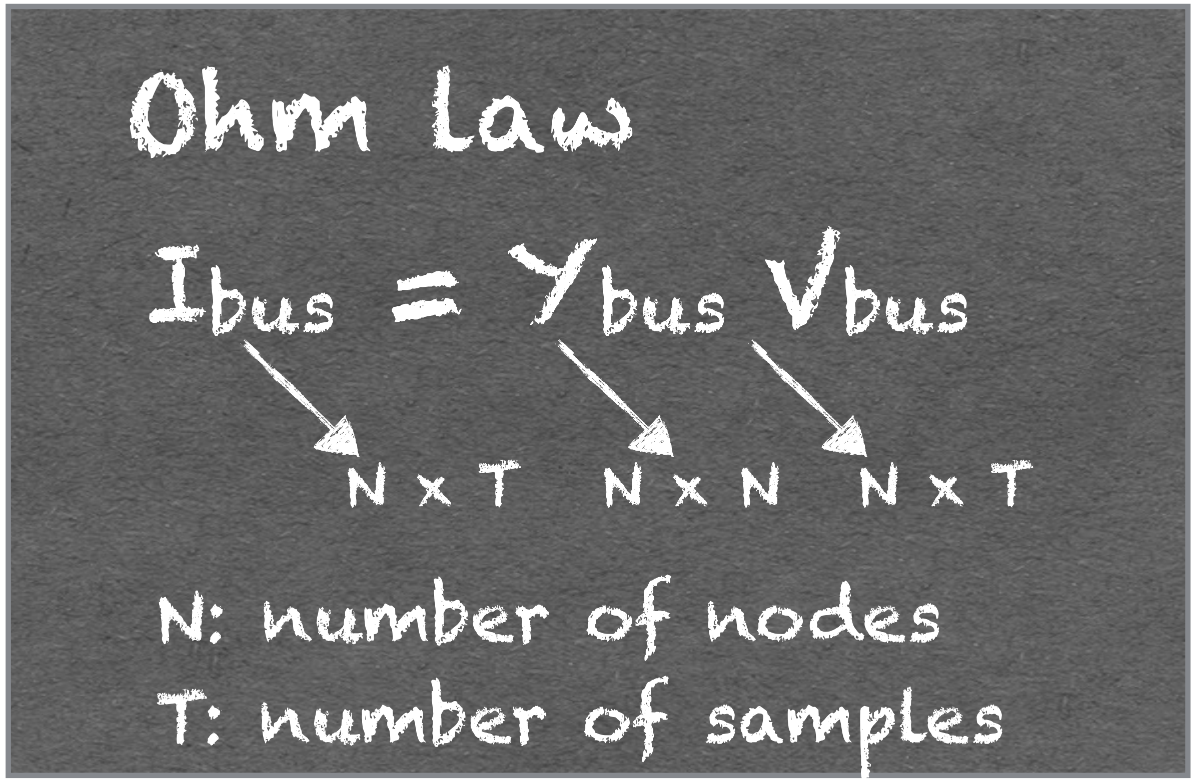

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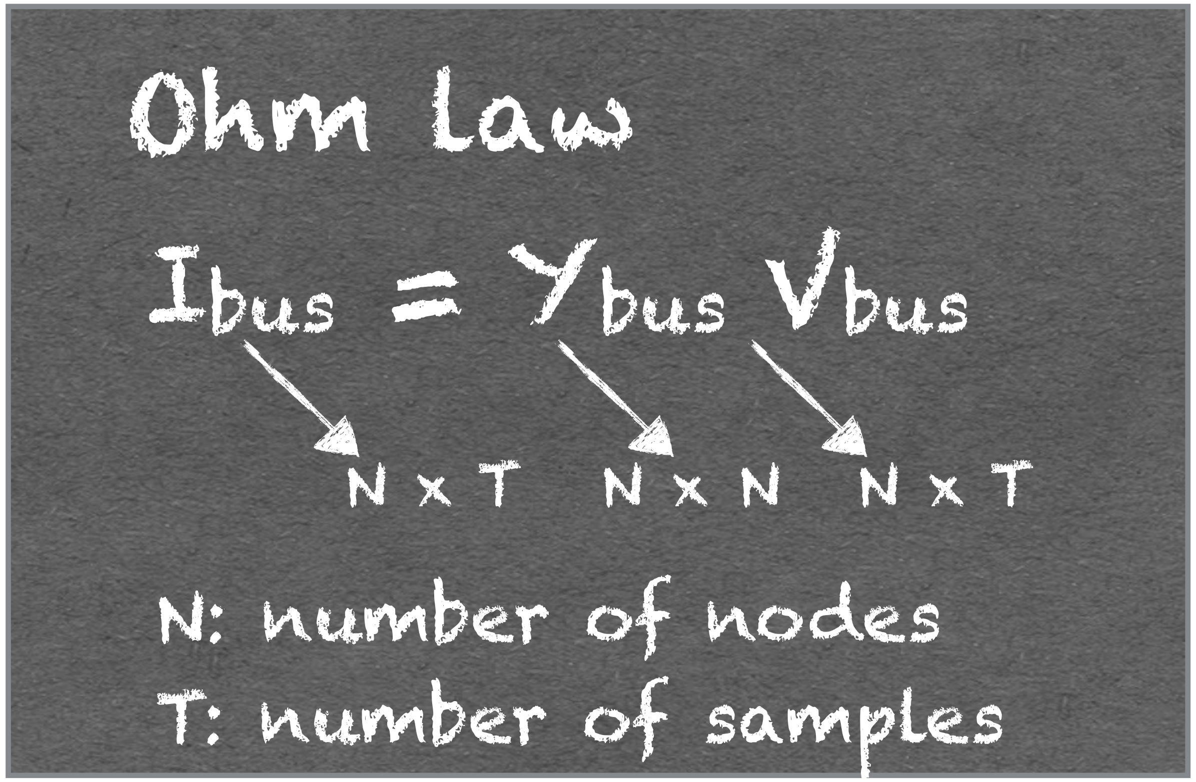

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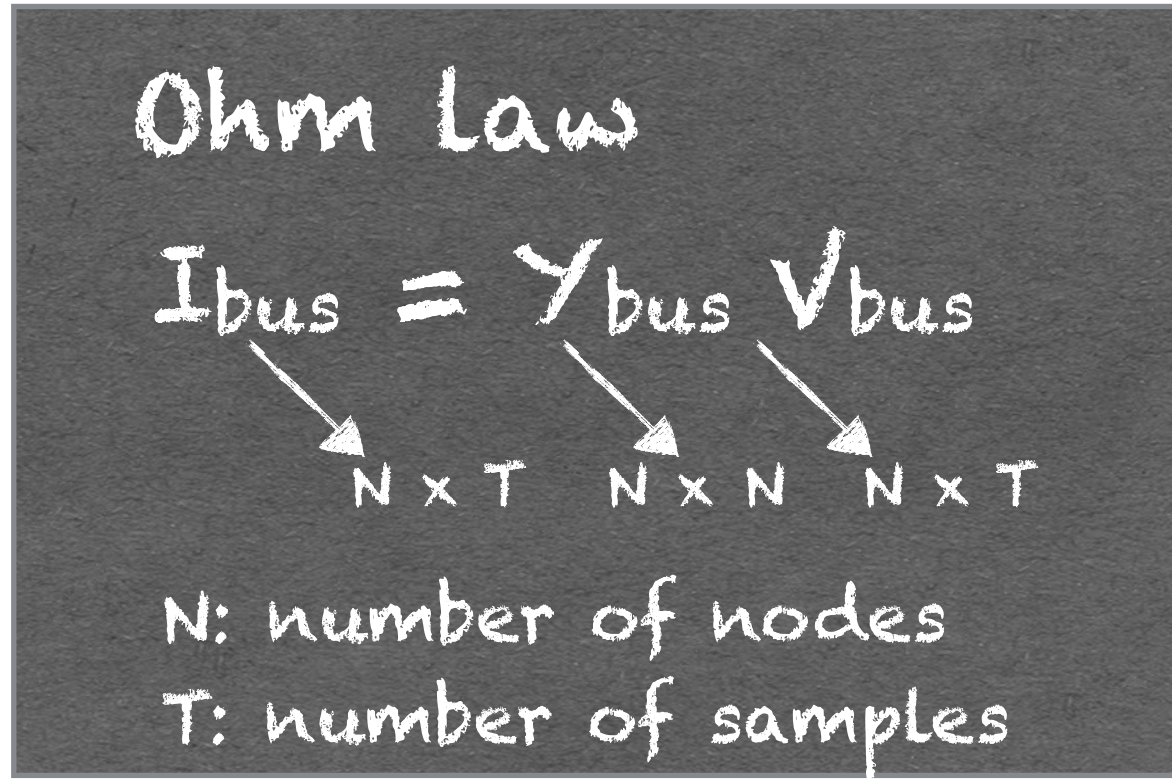

$$\widehat{Y_{\text{bus}}} = \arg \min_{Y \in \mathbb{C}^{N \times N}} \left\| (V_{\text{bus}}^K \otimes \mathbb{1}^N)\text{vec}(Y) - \text{vec}(I_{\text{bus}}^K) \right\|_2$$

$$\text{s.t.:}\ \ Y \in \mathbb{S}^N, \quad \|\text{vec}(Y)\|_0 \leq \delta$$

System Identification

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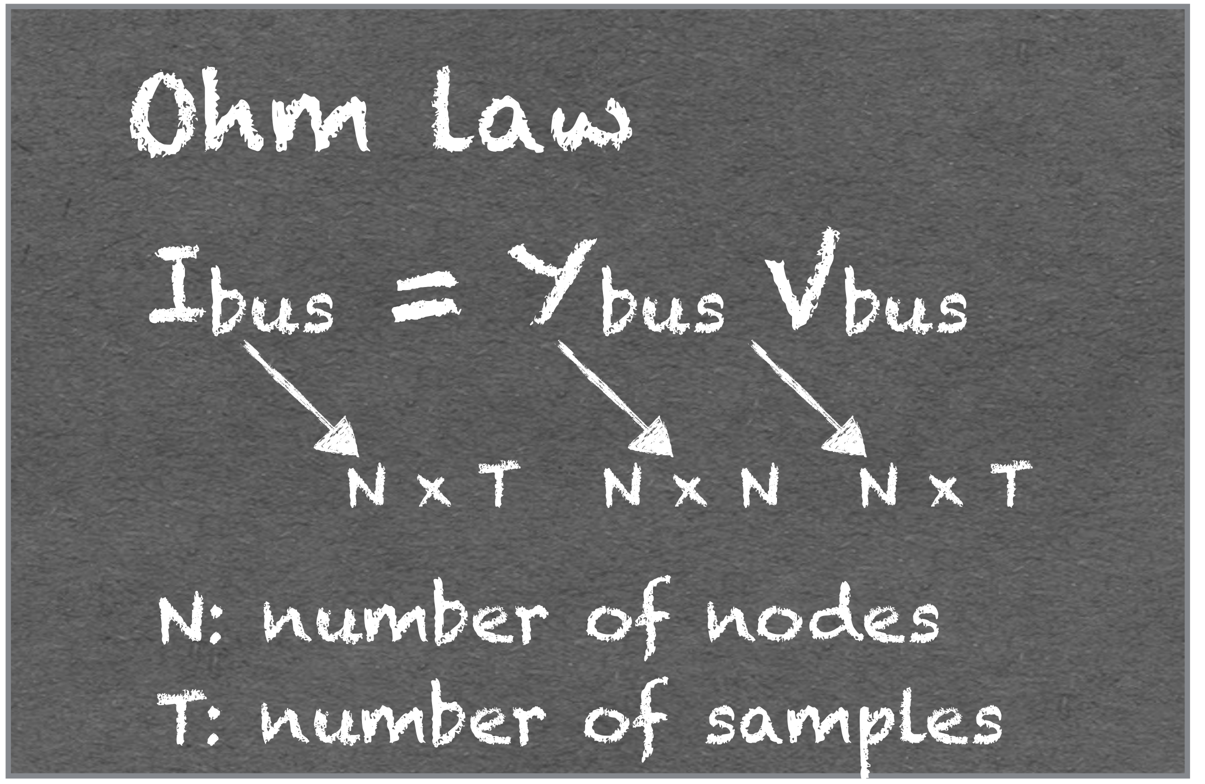
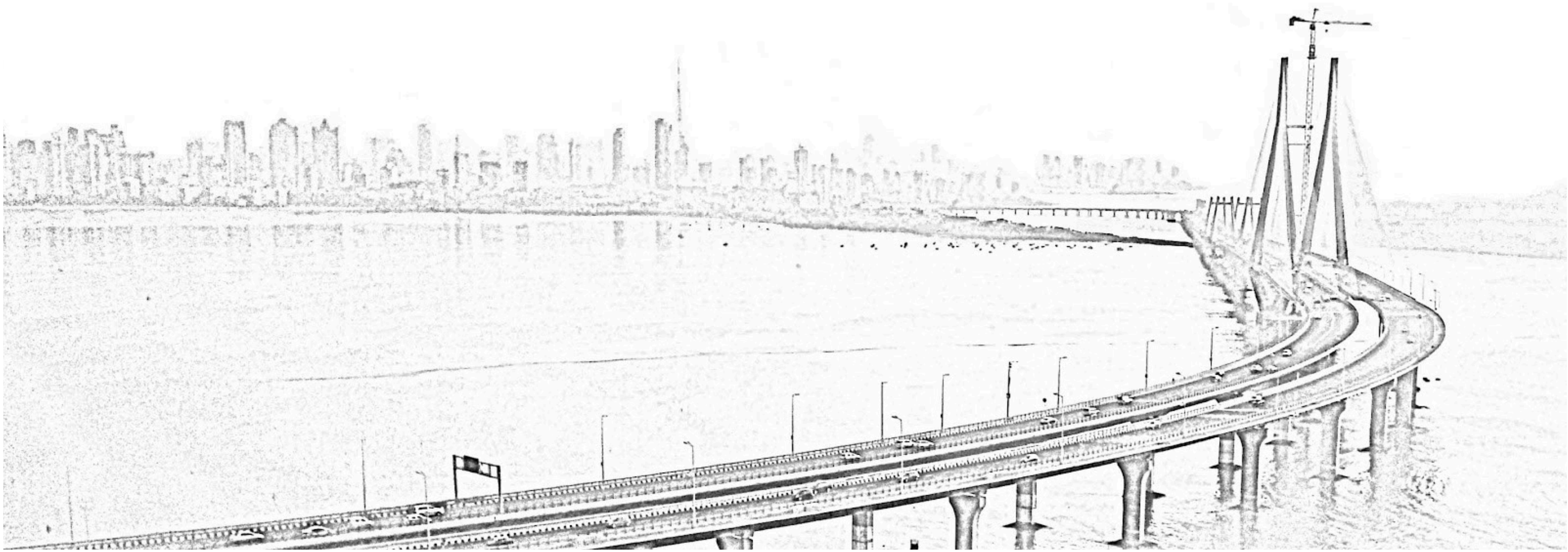
- Online detection and localization of events



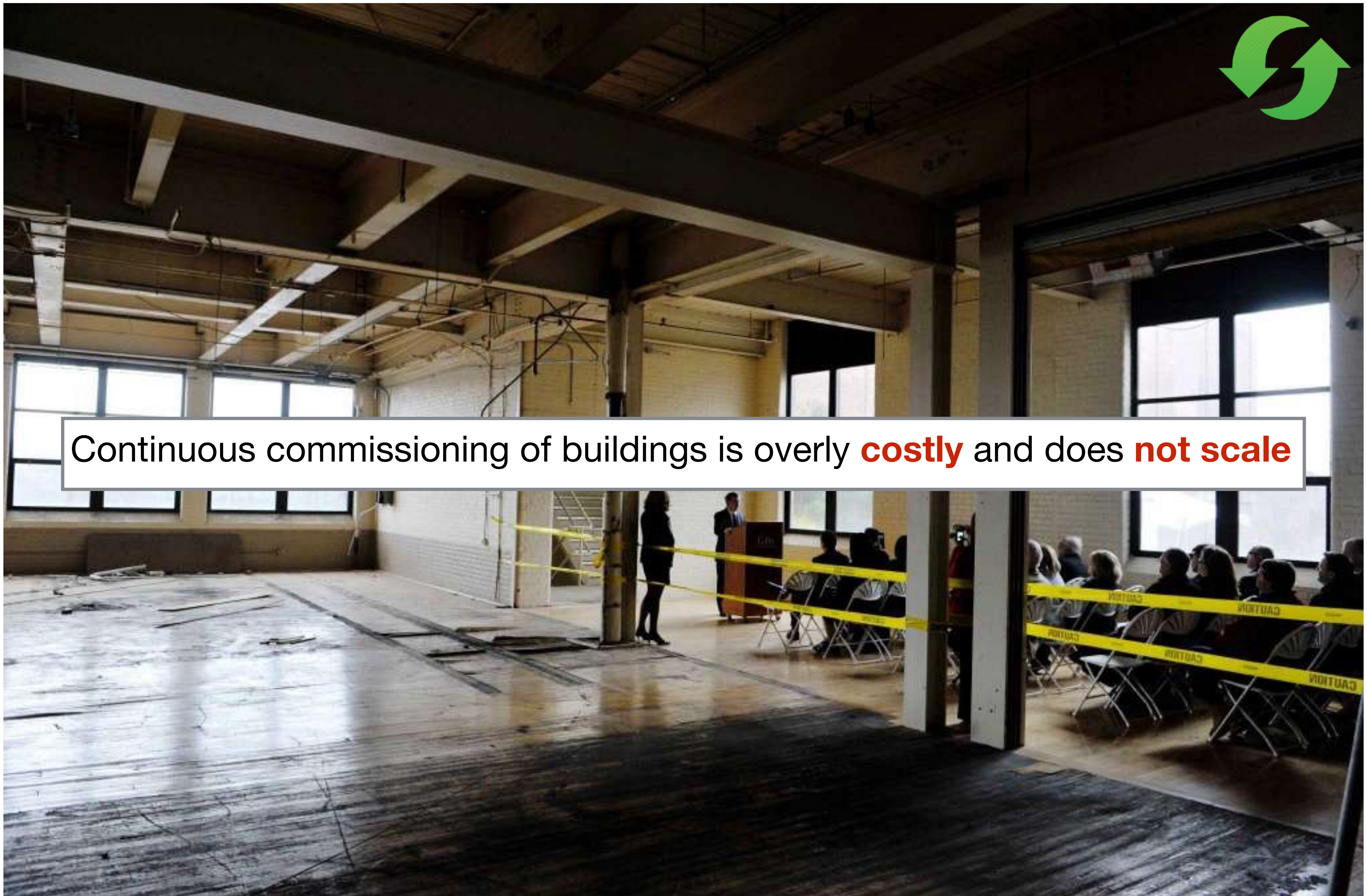
Future Work



smarter, greener, more adaptive and resilient against climate change and natural disasters

Smart Buildings

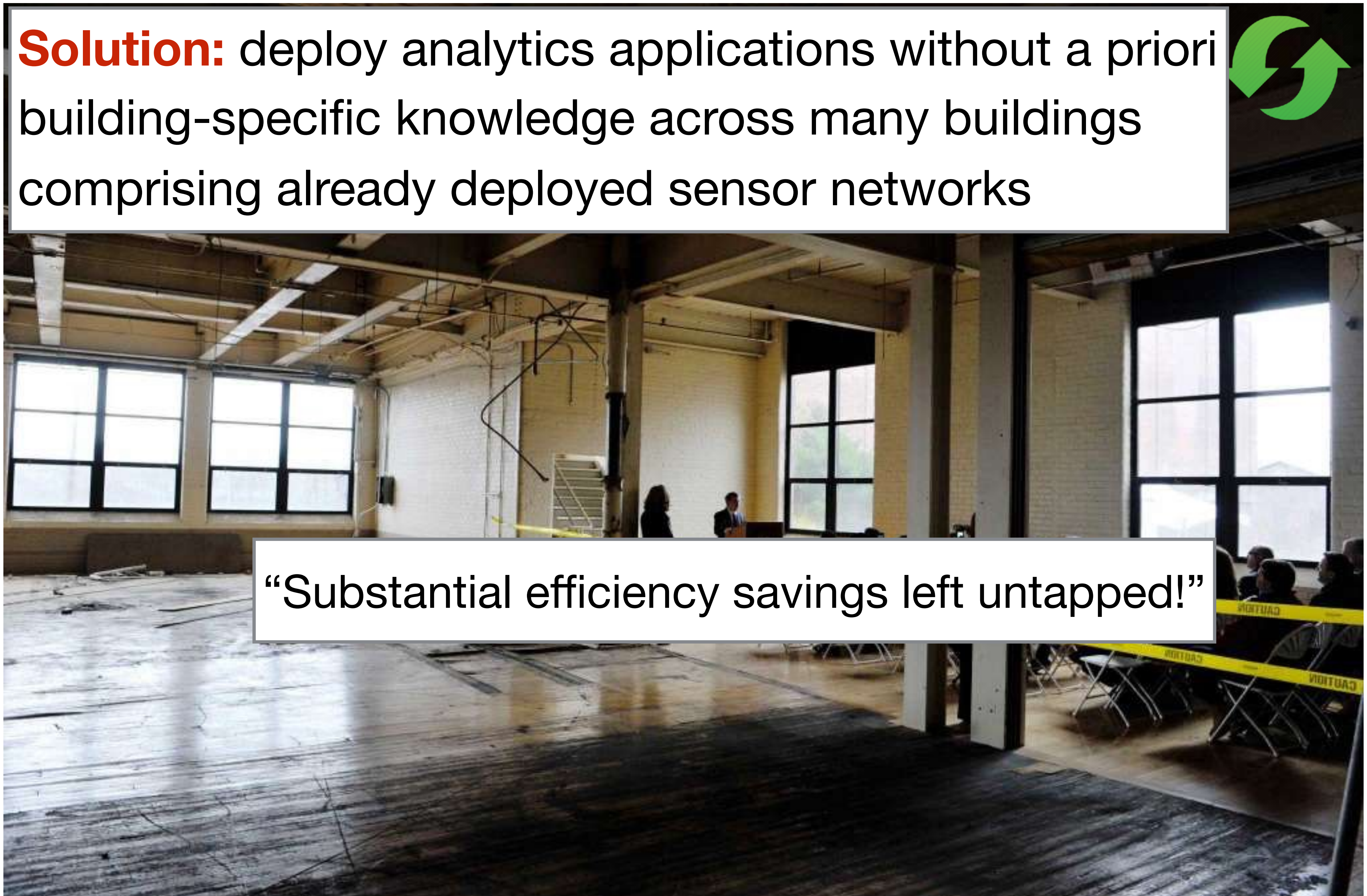
Smart Buildings



Smart Buildings

Smart Buildings

Solution: deploy analytics applications without a priori building-specific knowledge across many buildings comprising already deployed sensor networks



“Substantial efficiency savings left untapped!”

Adaptive Fault-Tolerant Buildings

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- Automated point mapping

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  - requires a concrete ontology for sensors, control points, subsystems and relationships among them

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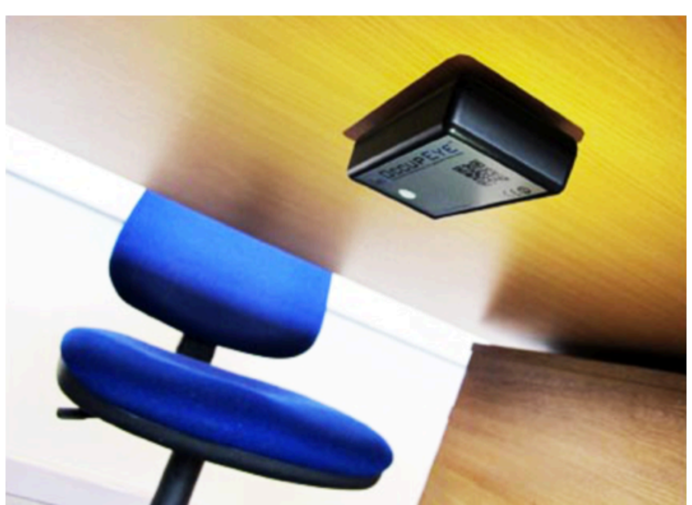
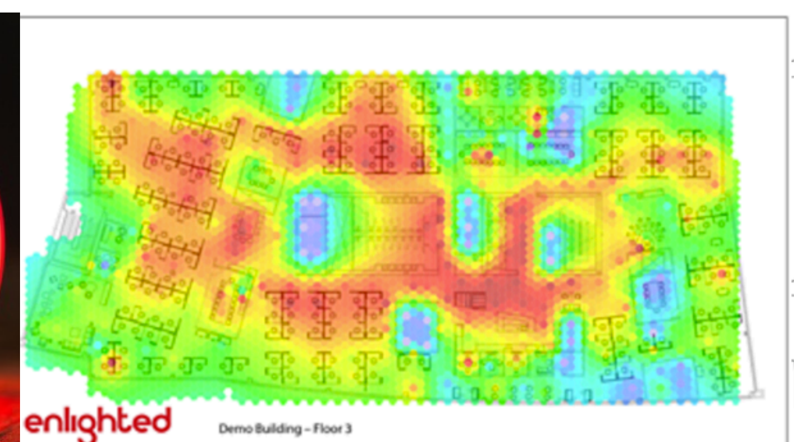


Image: OccupEye sensor



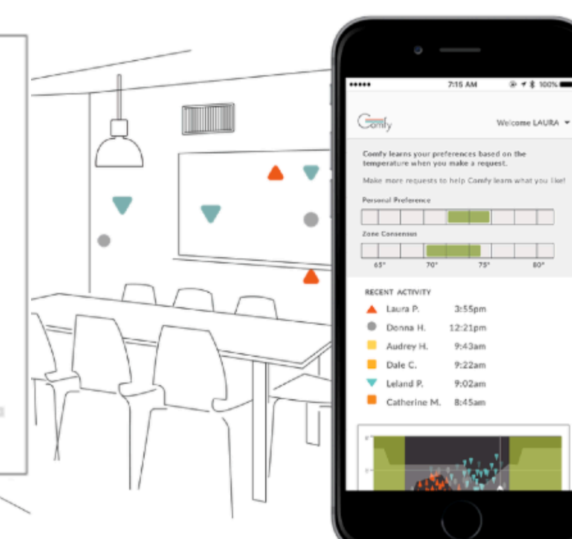


Image: Comfy, Building Robotics

Adaptive Fault-Tolerant Buildings

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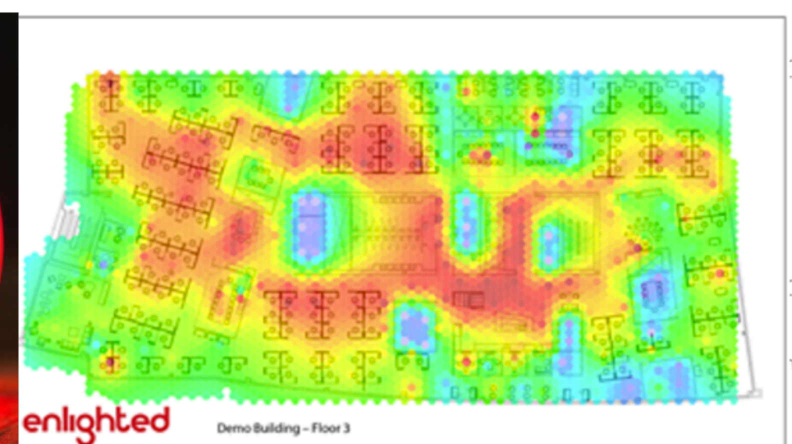
  - e.g., rouge zones, sensors drifted out of calibration, mechanical issues, improper controls
- Sensor fusion for workspace utilization, personalized comfort, and smart lighting
  - addressing privacy concerns (differential privacy, downsampling, …)



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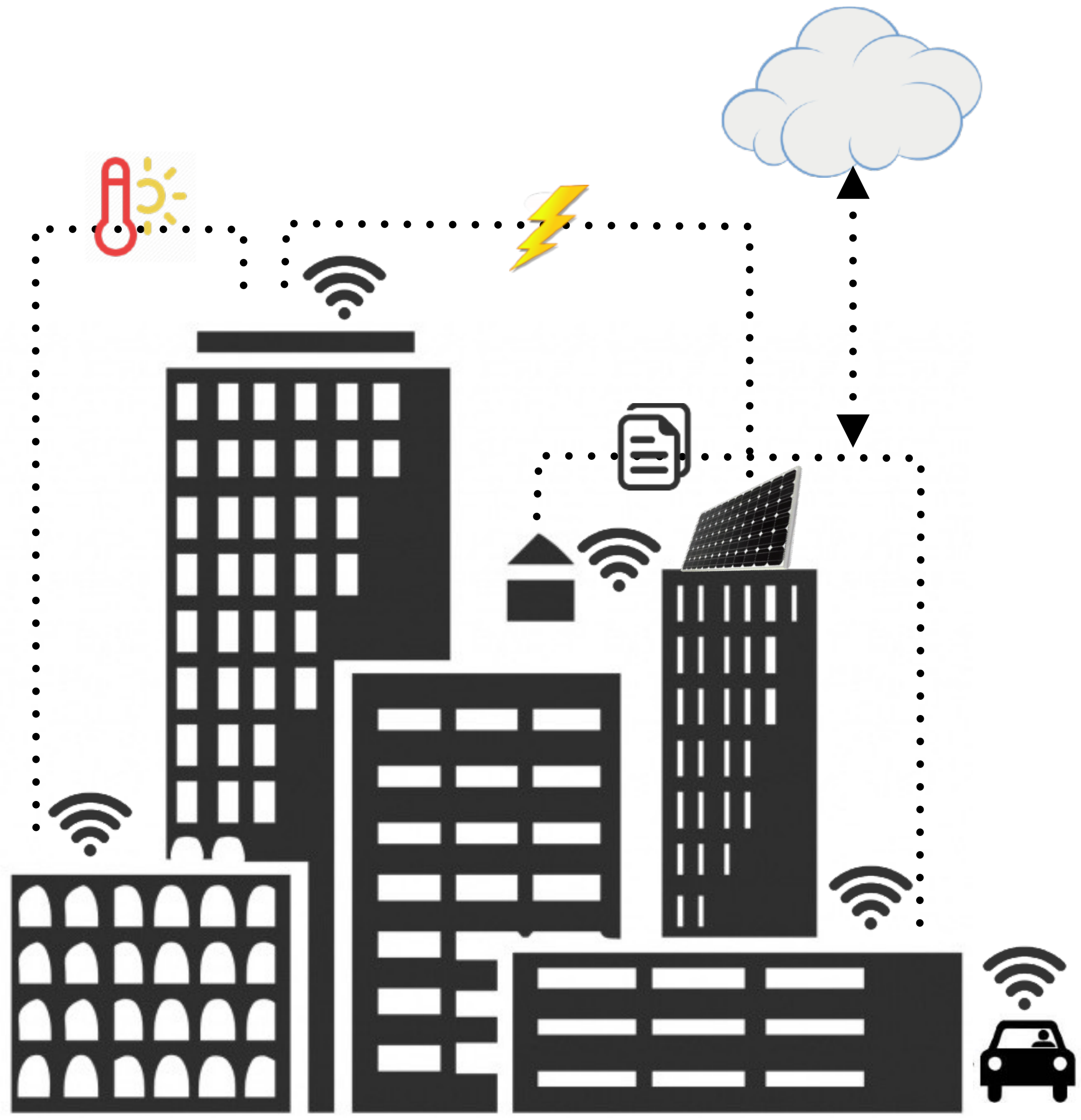
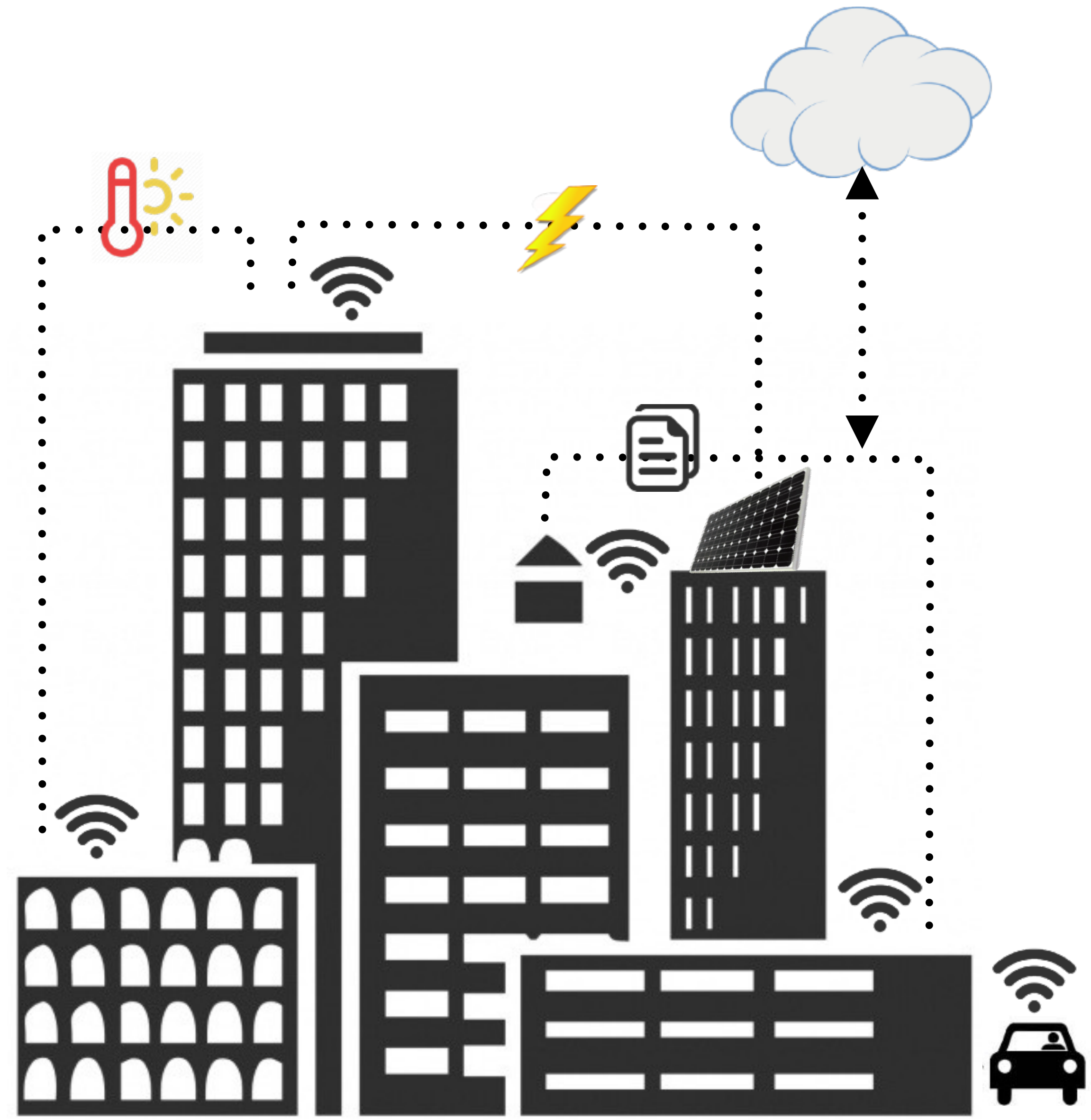
Smart Cities



Smart Cities

A city is a complex system comprised of a large number of distributed physical resources delivering a wide range of services to citizens



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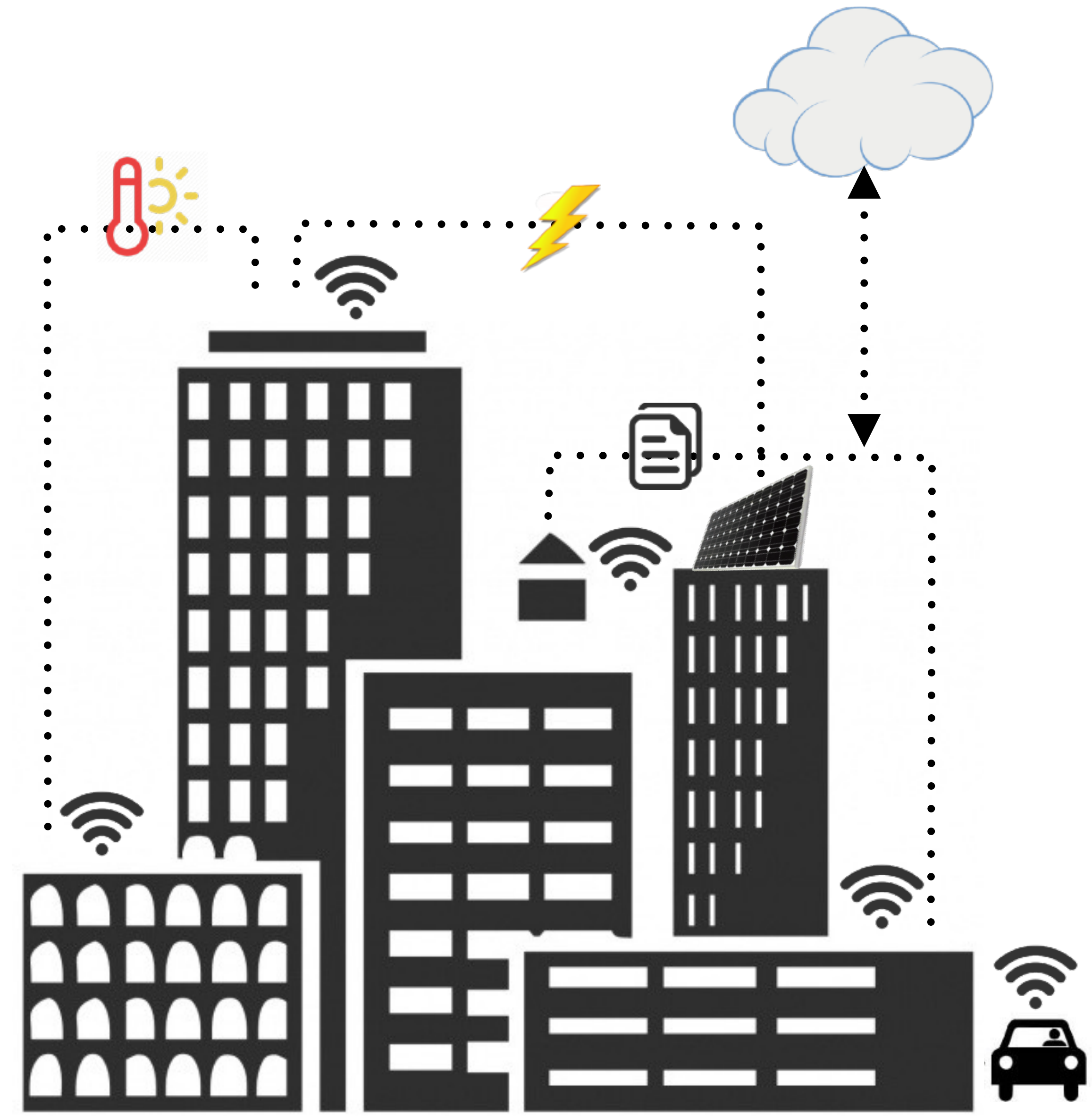

Sensors and real-time analytics are employed in a smart city to solve problems in various urban sectors

- Water
- Energy
- Transport
- Buildings
- Urban Farming
- Urban Manufacturing

Smart Cities

Smart Cities

- Optimal control of coupled infrastructures (gas, water, electricity, …) and active end-nodes

Smart Cities

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    - convex relaxations (SDP or SOCP)

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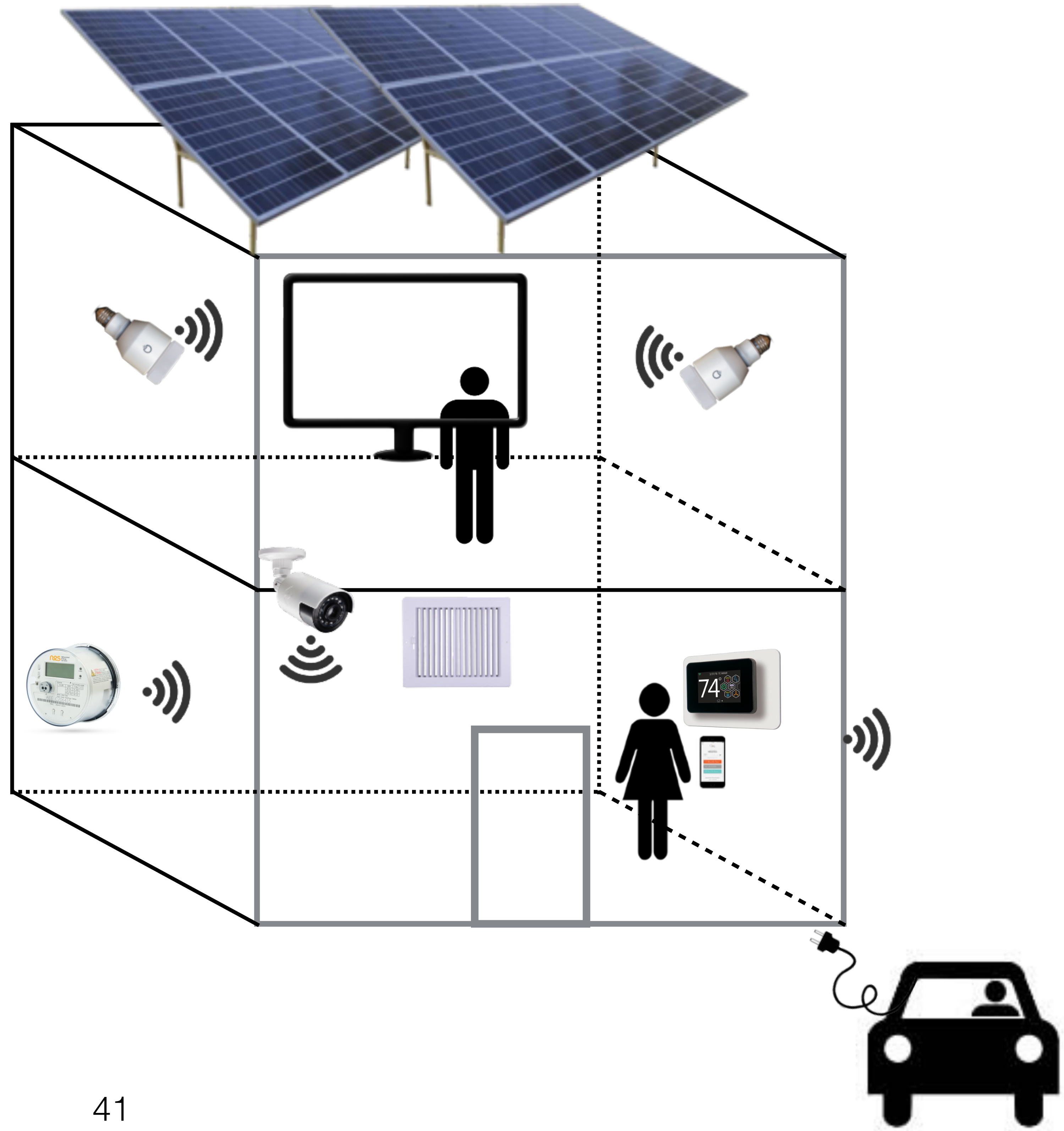
  - partial observability and hidden states
- Turning historical data into actionable information for urban planners

Building Prototype Energy Systems

Campus as a living laboratory!



Building Prototype Energy Systems

Deploy

- Controlled plug loads
- Sub-metering devices
- PV cells and inverters
- Batteries
- Electric cars/bikes

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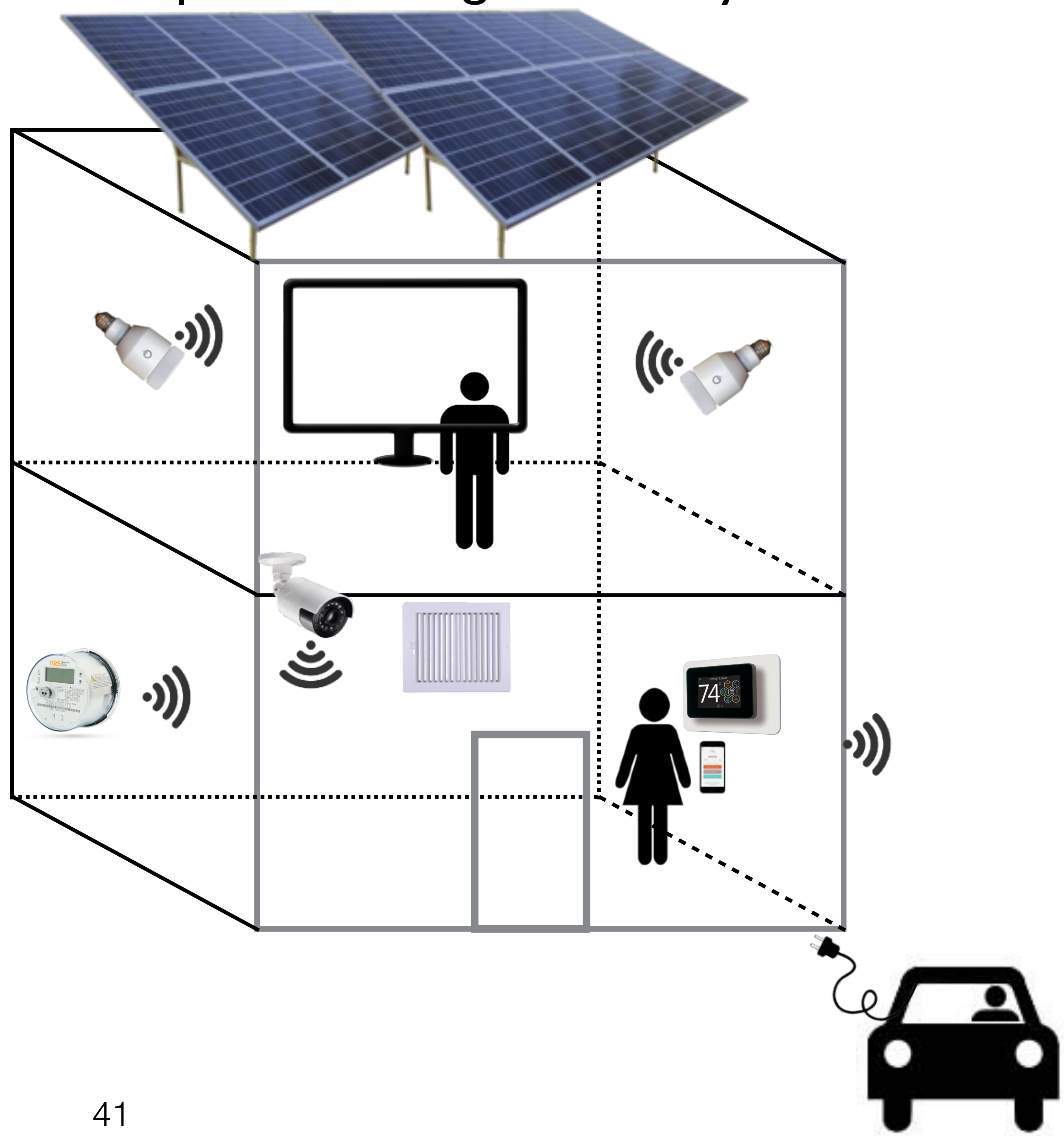

Building Prototype Energy Systems

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Implement and evaluate

- Demand response
- Building-to-grid applications
  Turning buildings into already deployed, low-cost storage options for the grid
- Indoor climate control
- Smart lighting
- Fault detection and diagnosis
- System identification

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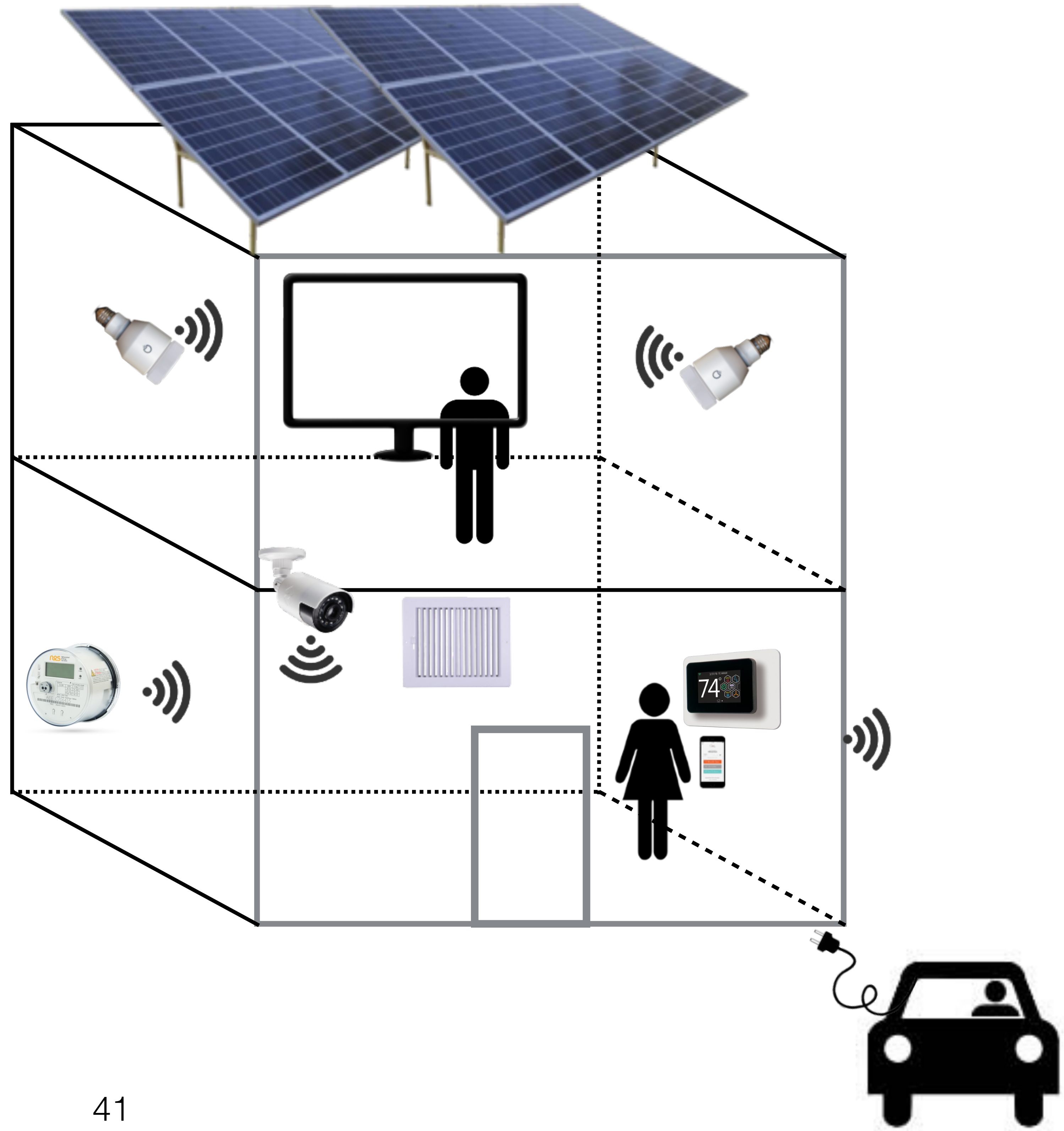

 

  

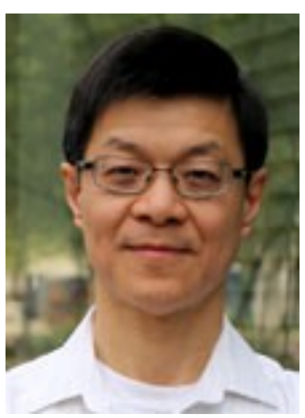    

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