Enabling a responsive grid with distributed load control & optimization

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(joint appointment)

Pacific Northwest
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The UNIVERSITY of VERMONT

Power Systems Laboratory (PSL) Seminar

ETH Zürich, Switzerland

August 9th, 2023

ETH zürich

PSL Power Systems Laboratory

Short Bio

school
tems
systems
ization
l systems
rbor, Michigan)

Startup company
VC-funded energy optimization
SaaS company for industrial energy plants
(Chicago, IL)

University of Vermont (UVM)
Leading a number of DOE projects
Co-founded cleantech startup
NSF CAREER Awardee
Joint appt @ PNNL
Sabbatical @ DTU

Otto Mønsted

2008 2013 2014 2016 2017 2021 2021-22

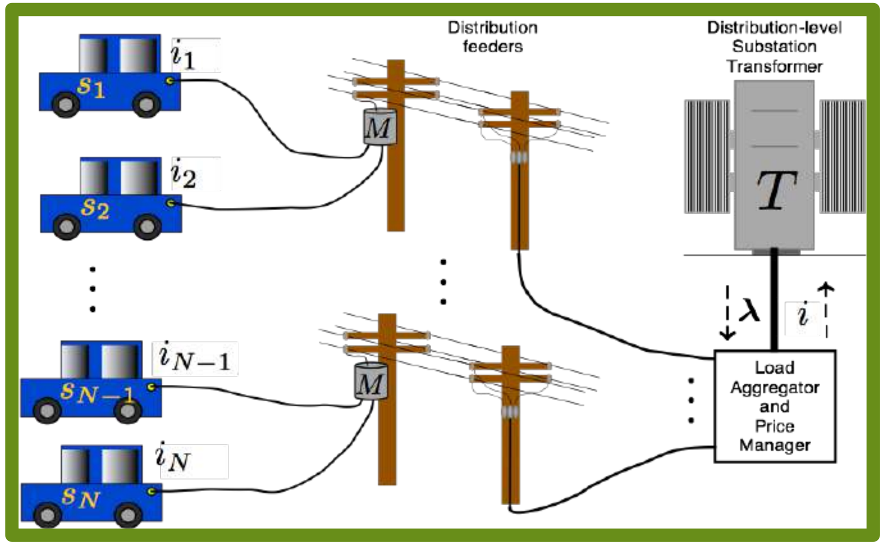
Legal Disclaimer

M. Almassalkhi was co-founder of and holds equity in *Packetized Energy*, which commercialized energy/grid technologies.

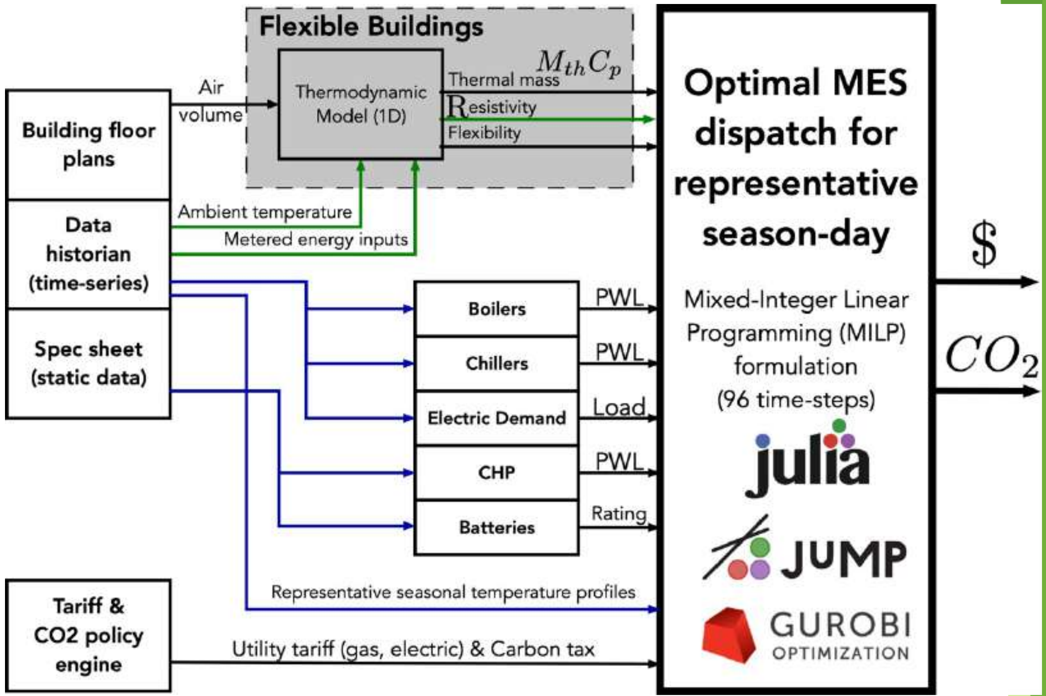
PACKETIZED ENERGY

Non-topics today

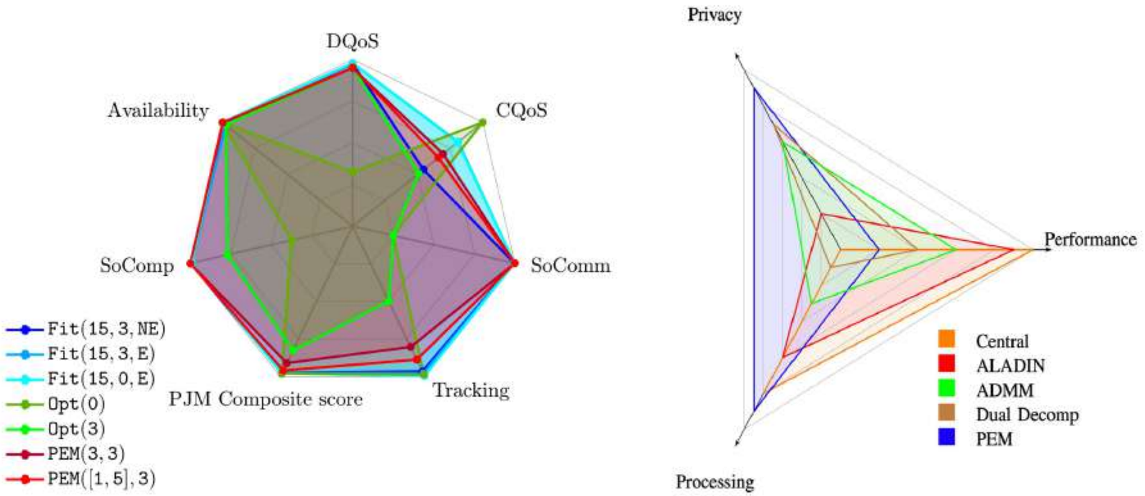
Optimal EV charging via distributed optimization



Multi-energy systems / sector coupling



Methodologies for characterizing energy transitions



Collision-free trajectory optimization of swarms

Vermont is amazing platform for power/energy R&D

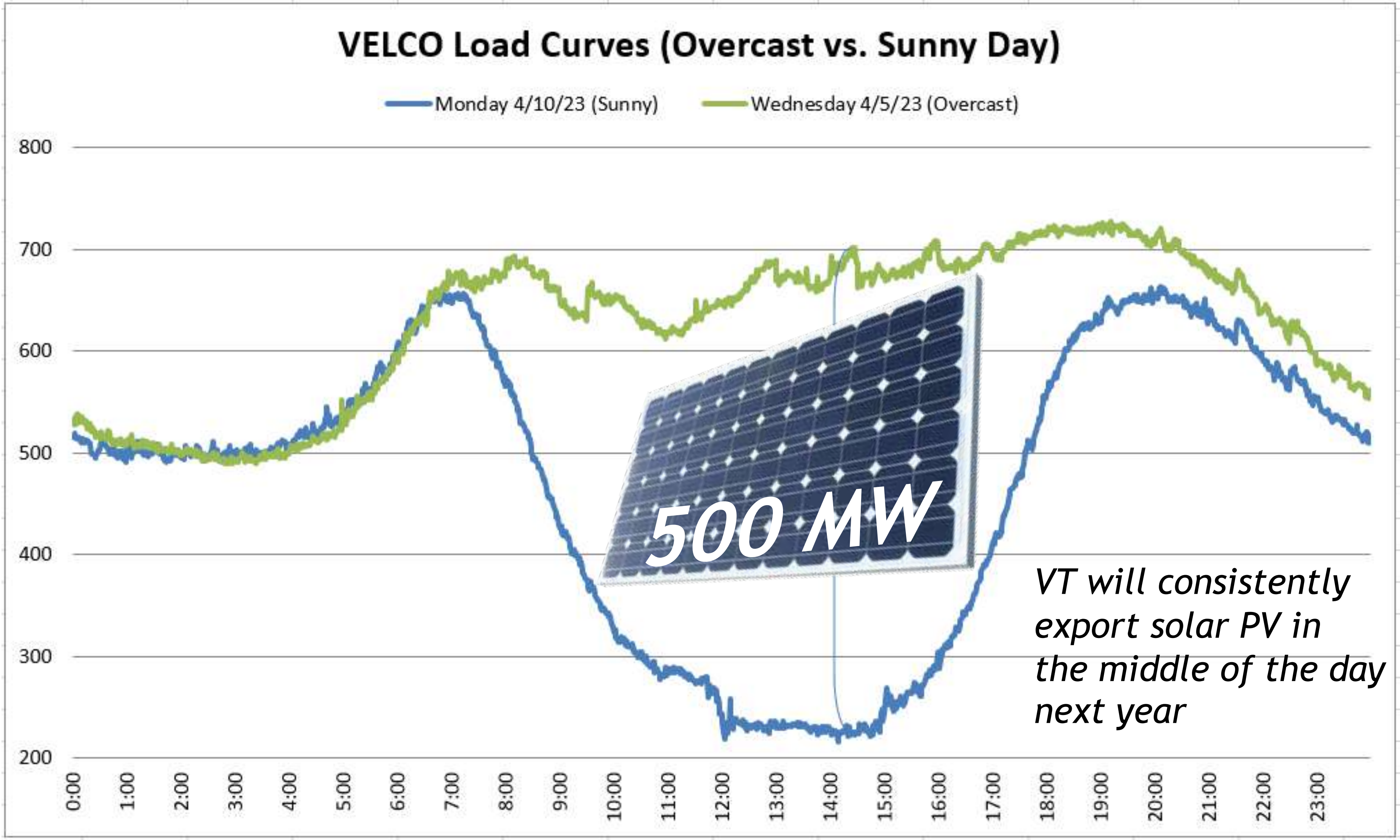
- ✓ **VT is 8% of the population of Switzerland and 60% land area.**
- ✓ **VT population: 650,000 people with a peak load of ca. 1GW**
  - ▶ *AMI deployed at >95% of customers in State*
Vermont Renewable Portfolio Standard (RPS): 75% by 2032
- ✓ **University of Vermont** (UVM = *Universitas Viridis Montis)*
  - ✓ Founded 1791, 12,000 students, 4,100 faculty, one of the smallest EE programs in USA
- ✓ Small state ➔ easy to collaborate, test ideas, create change, make an impact
- ✓ Close partnerships with nationally-recognized innovative energy industries
  - ▶ *VELCO, GMP, BED, VEIC, Dynapower, Vermont Gas, Beta Technologies, etc.*
- ✓ Joint appointment program with national lab (PNNL)
- ✓ Strong presence with competitive federal E programs
  - ▶ *Past funding from ARPA-E NODES, SETO ENERGISE, NSF CAREER, CRISP, DOE GMLC*
- ✓ Outstanding interdisciplinary collaborations with the UVM *Complex Systems Center* and *Gund Institute for Environment*
- ✓ **VT is #2 state in U.S. for Clean Energy Momentum** (UofCS, 2017)
  - 5.4% of workforce is clean energy economy (#1 in 2021)
    - ▶ *Next largest are at ~3%*
  - 99.9% of VT *generation* is renewable (#1 in US in 2019)
  - 66% of consumed electricity is renewable (2019)
  - 15% of electricity from solar PV (#4 in US in 2020; #6 per capita)
  - 5.4% of new cars sold are EVs in 2021 (VT was #9 in 2018)

Vermont is amazing platform for power/energy R&D

First U.S.
efficiency utility
(2000)

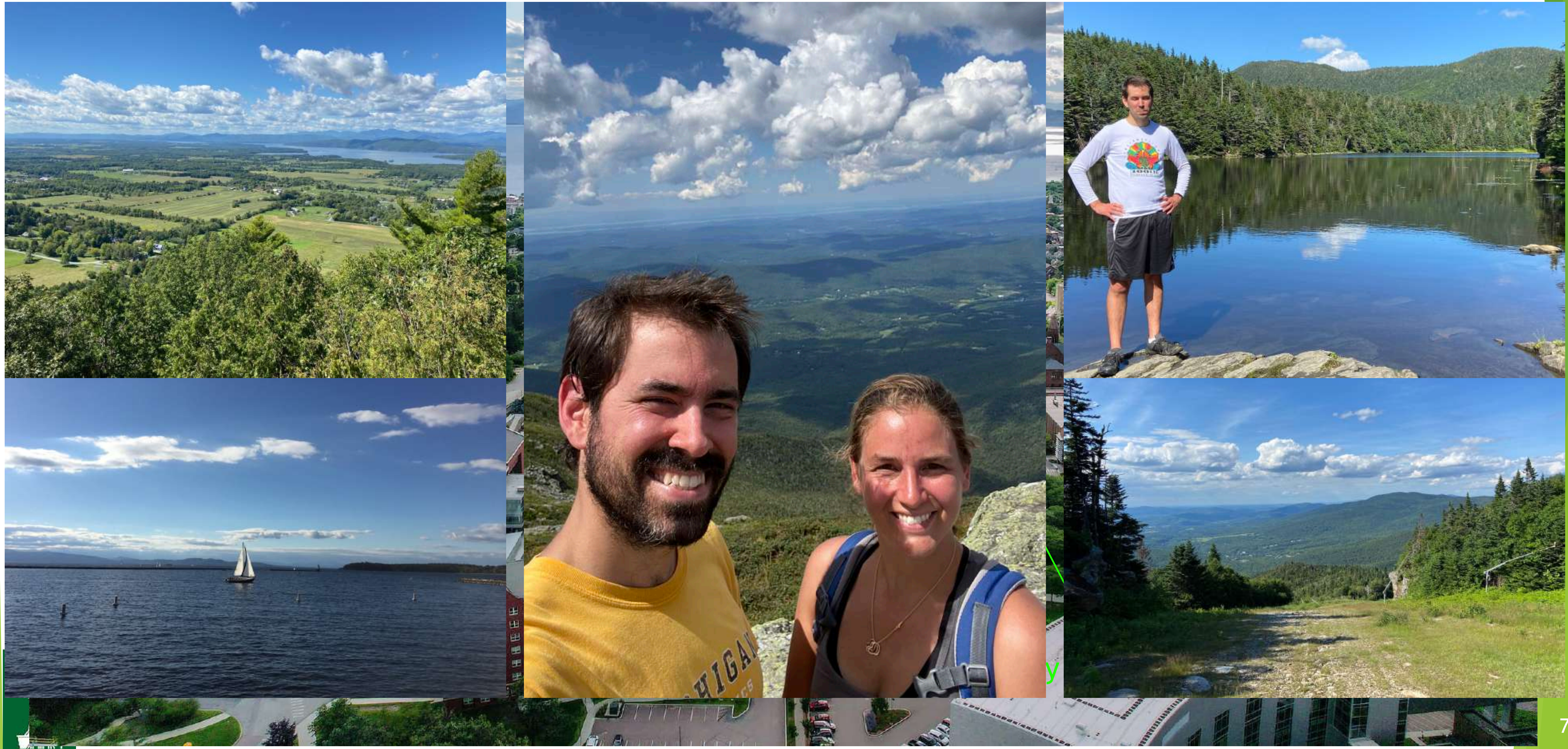
First U.S. utility to
be 100% renewable (2014)

#1 in 2018 (Energy)
#5 in 2019 (Energy)



VT will consistently export solar PV in the middle of the day next year

Vermont is amazing platform for power/energy R&D



Interdisciplinary group: energy & autonomous systems

Objective: sustain and strengthen UVM’s research impact in the area of understanding, controlling, and optimizing sustainable, resilient, and autonomous systems and networks by leveraging a group of diverse, interdisciplinary, and research-active faculty.


Mads R. Almassalkhi
(Founding Director)


Jeff Frolik


Amrit Pandey


Bindu Panikkar


Hamid Ossareh


James Bagrow


Luis D. Espinosa


Jeff Marshall


Sam Chevalier

Broad expertise
- Power/energy
- Grid modeling
- Optimization
- Control theory
- Network science
- IoT/Comms
- Data science
- Machine learning
- Energy equity/justice

Impactful R&D with industry & research partners

Recent and ongoing industry-supported projects with

Burlington Electric Department

Sandia National Laboratories

VT Transco VELCO VETCO

conEdison

Orange & Rockland

pjm

Green Mountain Power

Ford

Global Foundries

Pacific Northwest National Laboratory

Recent and ongoing funding partners

Department of Defense United States of America

arpa·e

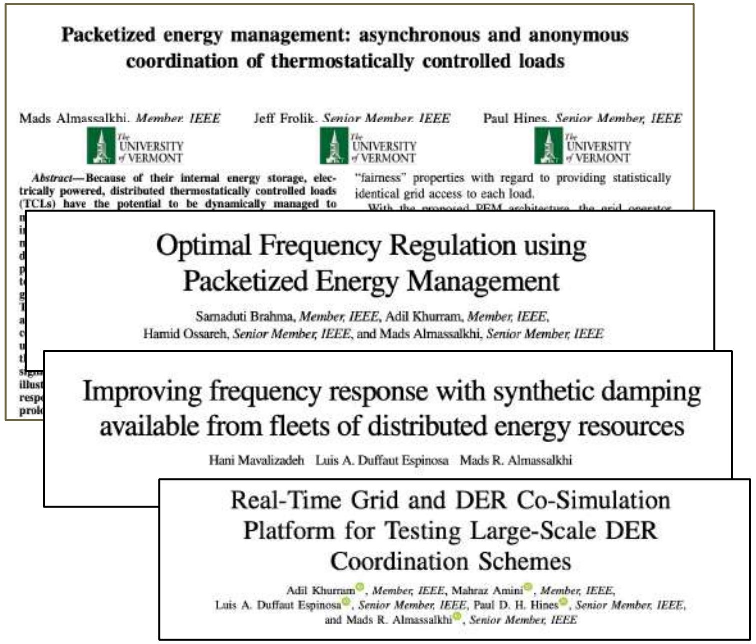
NIST National Institute of Standards and Technology

Department of Energy United States of America

NSF

NASA

Recent success with translational research



Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads

Mads Almassalkhi, *Member, IEEE* Jeff Frolik, *Senior Member, IEEE* Paul Hines, *Senior Member, IEEE*

***Abstract*—Because of their internal energy storage, electrically powered, distributed thermostatically controlled loads (TCLs) have the potential to be dynamically managed to**

"fairness" properties with regard to providing statistically identical grid access to each load.

Optimal Frequency Regulation using Packetized Energy Management

Samaduti Brahma, *Member, IEEE*, Adil Khurram, *Member, IEEE*, Hamid Ossareh, *Senior Member, IEEE*, and Mads Almassalkhi, *Senior Member, IEEE*

Improving frequency response with synthetic damping available from fleets of distributed energy resources

Hani Mavalizadeh Luis A. Duffaut Espinosa Mads R. Almassalkhi

Real-Time Grid and DER Co-Simulation Platform for Testing Large-Scale DER Coordination Schemes

Adil Khurram, *Member, IEEE*, Mahraz Amini, *Member, IEEE*, Luis A. Duffaut Espinosa, *Senior Member, IEEE*, Paul D. H. Hines, *Senior Member, IEEE*, and Mads R. Almassalkhi, *Senior Member, IEEE*

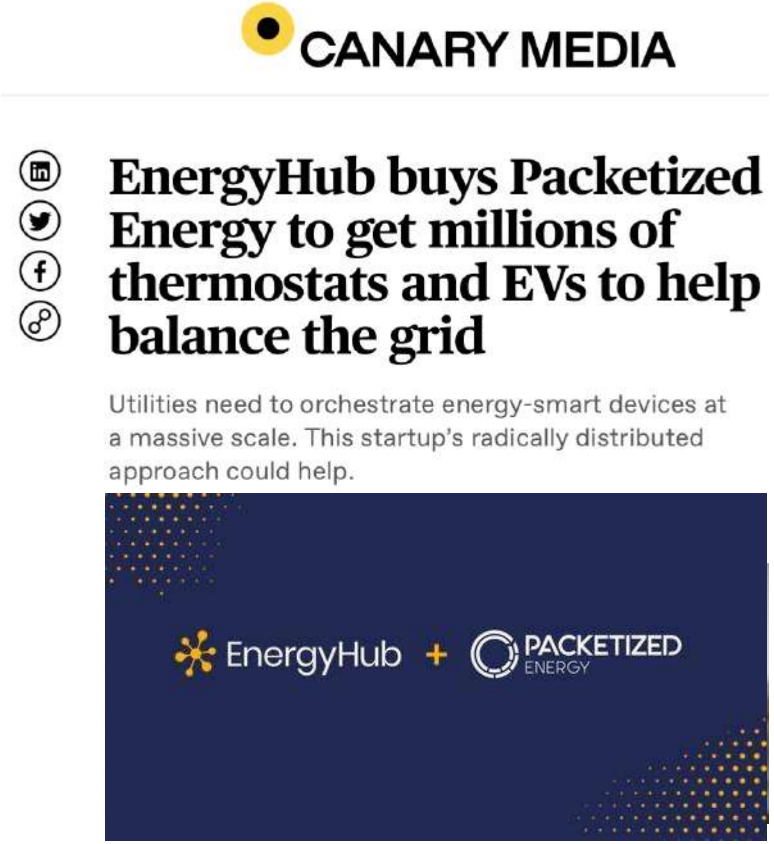
Numerous academic papers+ research projects+ IP + industry partners (2012-present)

+

PACKETIZED ENERGY

Co-founded startup company (2016)

=



CANARY MEDIA

EnergyHub buys Packetized Energy to get millions of thermostats and EVs to help balance the grid

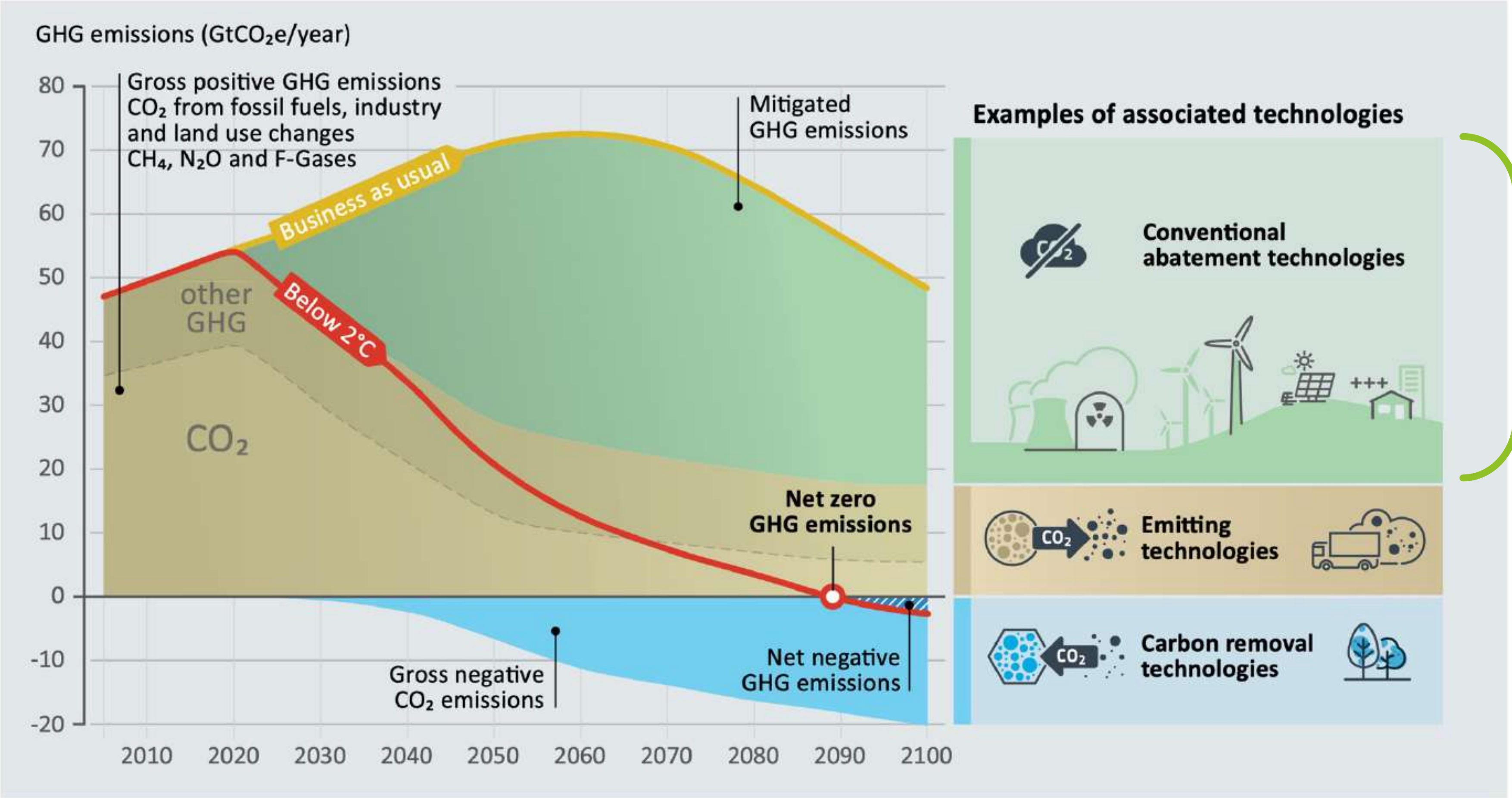
Utilities need to orchestrate energy-smart devices at a massive scale. This startup's radically distributed approach could help.

Company acquired!

Technology now has access to scale with 1,000,000 devices

(2022)

Focus on decarbonization & electrification



Requires massive TW-scale renewable integration

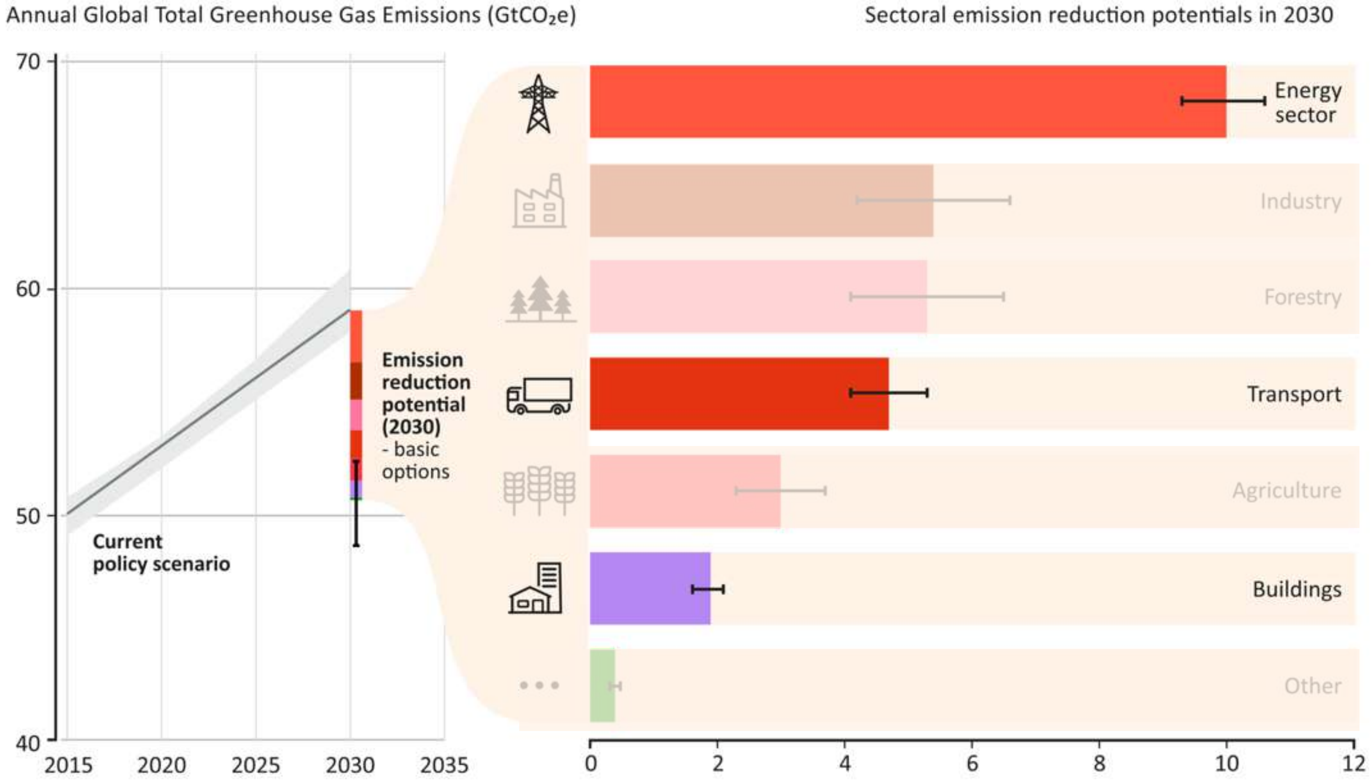
A massive power systems challenge!

Key: power systems is *climate change mitigation engineering* with a global impact!

UN Environmental Program, Emission Gap Report 2017 (Chapter 7)

Flexibility can help: *intelligent electrification*

Energy, transportation, and building sectors are key!



Combine renewable and efficiency with **electrification of end use.** [1]

Flexible demand enables significantly more renewable generation and reduces duck-curve ramping effects [2]

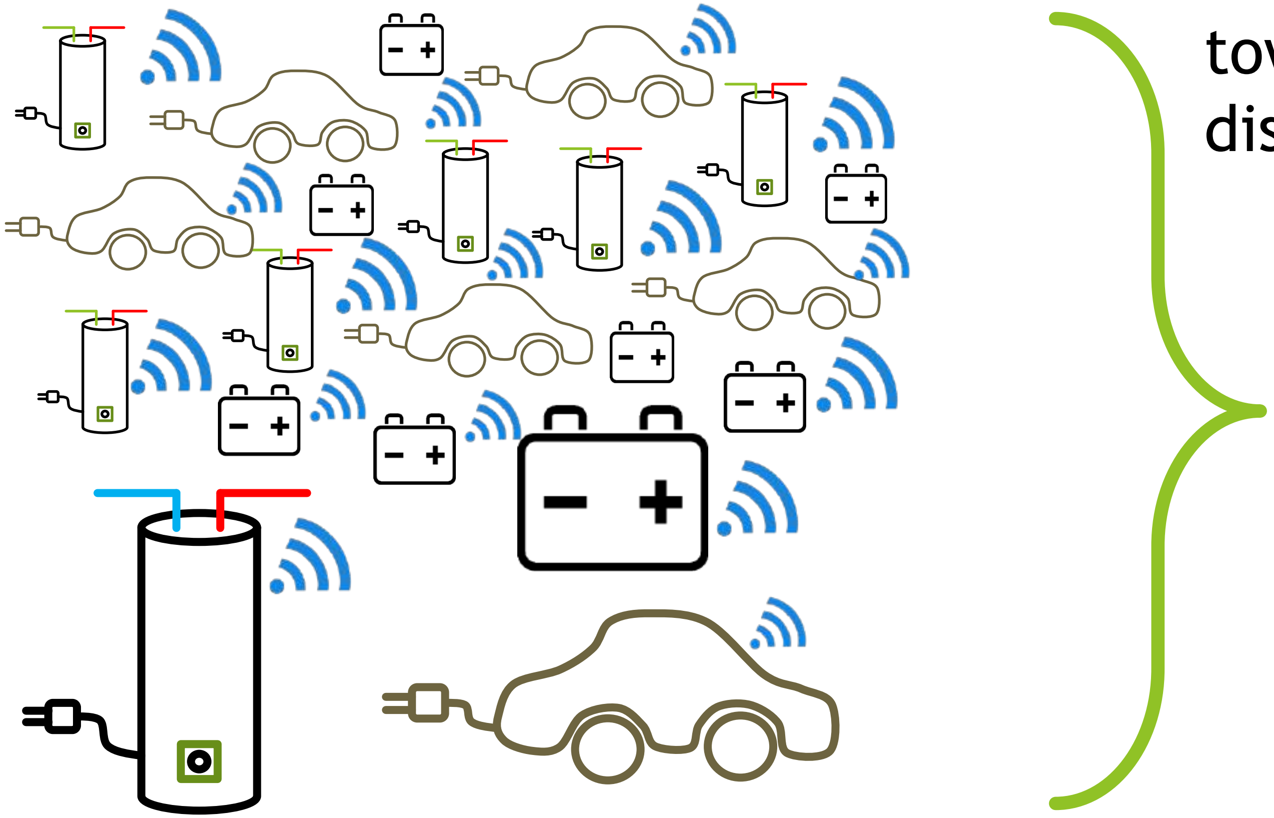
59GW of DR today will become **200GW of flexible demand by 2030** [3,4]

Need to coordinate <u>billions</u> of energy assets!

[1] UN Environmental Program, Emission Gap Report 2019 (source for figure, too)
[2] Goldenberg, et al, "Demand Flexibility: The Key To Enabling A Low-cost, Low-carbon Grid," Tech. Rep., Rocky Mountain Institute, 2018.
[3] Hledik et al, "The National Potential for Load Flexibility: Value And Market Potential Through 2030," *Tech. Rep.*, The Brattle Group, 2019
[4] Almassalkhi and Kundu, "Intelligent Electrification as an enabler of Clean Energy and Decarbonization," *Current Sustainable/Renewable Energy Reports (under review)*

Simple idea: turn connected loads into flexible demand

Demand-side DERs + communication + control



Every device, home, neighborhood, town, and state can become a dispatchable resource

Value-stacking can be significant for flexibility

Fast

GRID BALANCING,
ANCILLARY SERVICES

LMP ENERGY ARBITRAGE,
RENEWABLE SMOOTHING

AVOIDED T&D CAPEX,
NON-WIRES ALTERNATIVES,
DIST. GRID MANAGEMENT

AVOIDED GEN CAPACITY

Slow

$100 to $1000

per kW_{flex} per year*

Virtual power plant™
Virtual battery™
Prosumer™

TESLA

sunrun

GENERAC

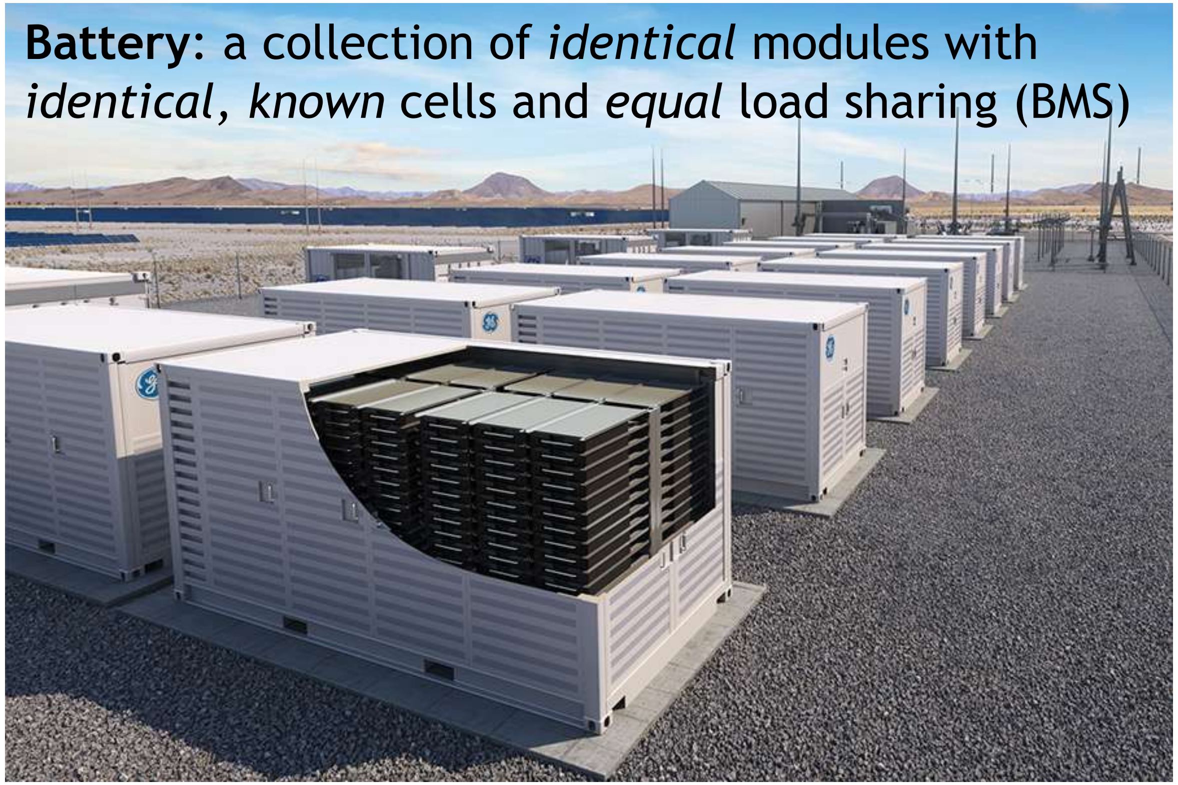
EnergyHub

*Values from representative 2019 ISO New England market prices and services and from RMI/Brattle.

How do we define *flexibility* (kW_{flex})?

Proposal: How much power, how fast, and for how long?

- *"Magnitude, response rate, and duration"*



Battery: a collection of *identical* modules with *identical*, *known* cells and *equal* load sharing (BMS)

Lumped parameters of a battery's flexibility

- State of charge (SoC)
- Net injections (power limits)
- Capacity (energy limits)

Flexibility is defined by set of admissible u(t) to

$$\dot{x}(t) = -\tau x(t) + \eta_c u_c(t) - \frac{1}{\eta_d} u_d(t)$$

$$u(t) = u_c(t) - u_d(t)$$

$$0 = u_c(t) u_d(t)$$

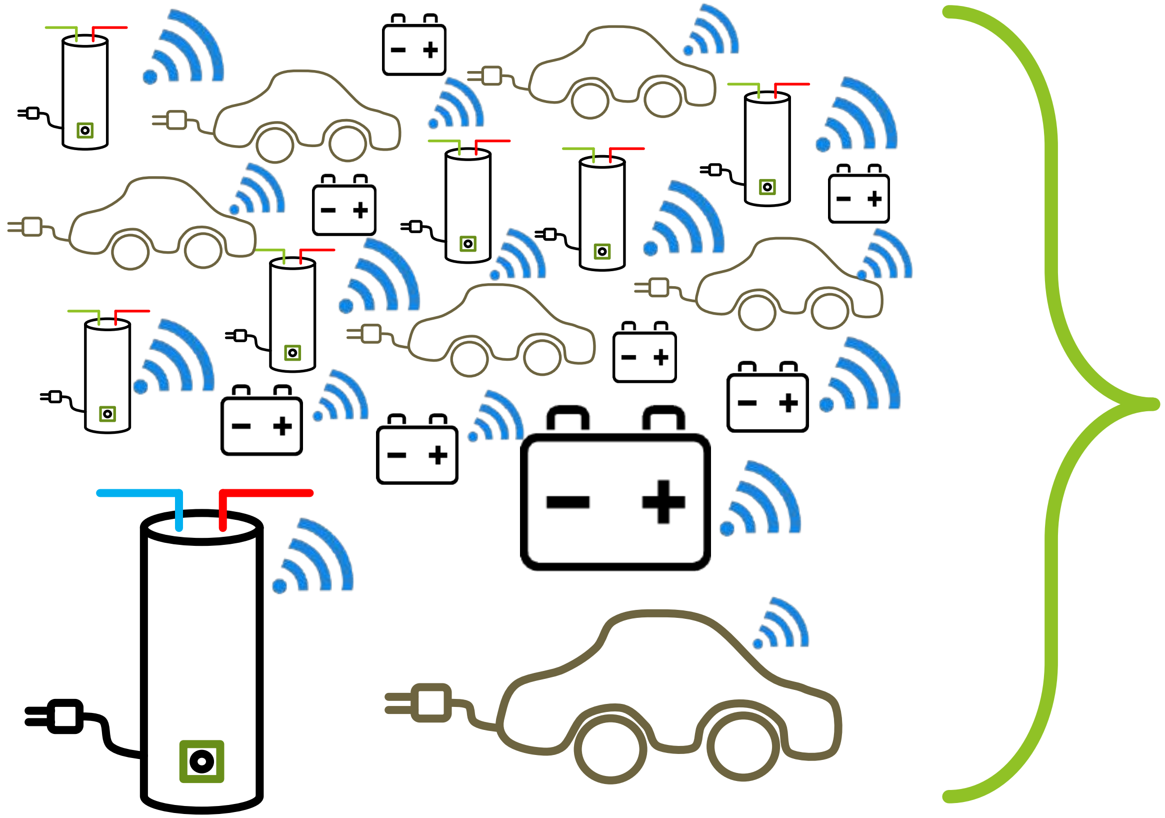
$$0 \leq u_c(t), u_d(t) \leq \bar{u}$$

$$0 \leq x(t) \leq \bar{x}$$

$$x(0) = x_0$$

How do we define *flexibility* (kW_{flex}) from virtual batteries?

A collection of *heterogeneous* DERs with *unequal* load sharing



How much power, how fast, and for how long?

What is even the model?
What are the parameters?
What is control (load sharing) policy?

Coordination must respect the human in the loop

Almost all flexible demand today = static DR programs:

- ComEd Smart HVAC program pays bill credit for $5-10/mo
- "*Two-pint problem*", "Zurich Zopf problem"

NAVIGANT

National Grid Smart Energy Solutions Pilot

Final Evaluation Report

Prepared for:

National Grid

nationalgrid

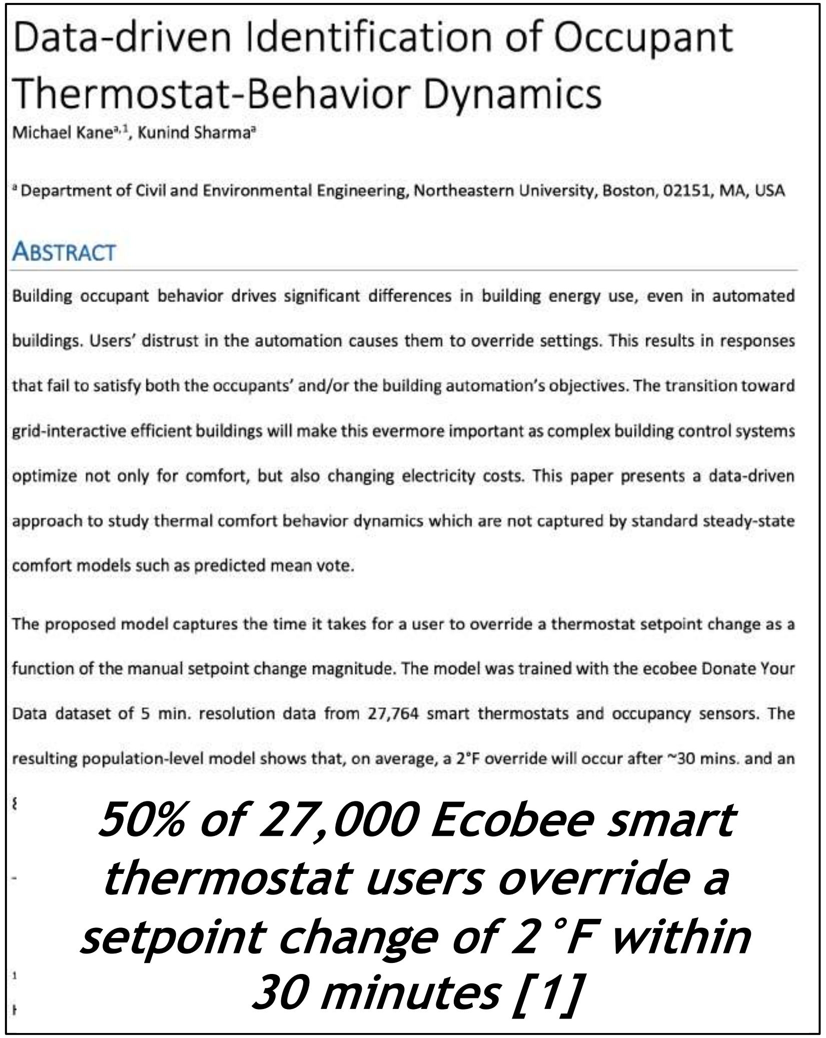
Submitted by:
Navigant
1375 Walnut Street
Suite 200
Boulder, CO 80302

303.728.2500
navigant.com

May 5, 2017

- ***10% of participants are overriding 3hr events.***
- ***25% are overriding 8hr events.***

It's really about quality of service (QoS)!



Data-driven Identification of Occupant Thermostat-Behavior Dynamics

Michael Kane[a,1], Kunind Sharma[a]

[a] Department of Civil and Environmental Engineering, Northeastern University, Boston, 02151, MA, USA

ABSTRACT

Building occupant behavior drives significant differences in building energy use, even in automated buildings. Users' distrust in the automation causes them to override settings. This results in responses that fail to satisfy both the occupants' and/or the building automation's objectives. The transition toward grid-interactive efficient buildings will make this evermore important as complex building control systems optimize not only for comfort, but also changing electricity costs. This paper presents a data-driven approach to study thermal comfort behavior dynamics which are not captured by standard steady-state comfort models such as predicted mean vote.

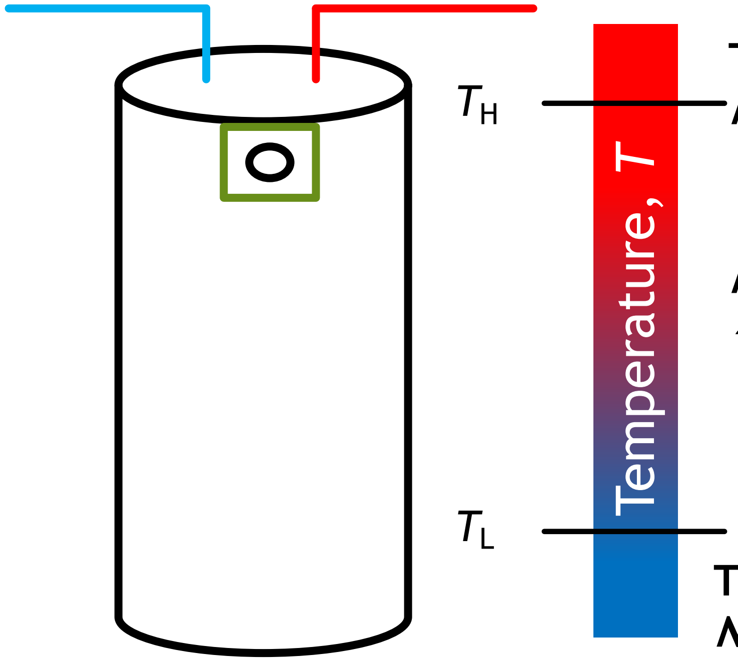
The proposed model captures the time it takes for a user to override a thermostat setpoint change as a function of the manual setpoint change magnitude. The model was trained with the ecobee Donate Your Data dataset of 5 min. resolution data from 27,764 smart thermostats and occupancy sensors. The resulting population-level model shows that, on average, a 2°F override will occur after ~30 mins. and an

50% of 27,000 Ecobee smart thermostat users override a setpoint change of 2°F within 30 minutes [1]

[1] Michael B Kane and Kunind Sharma, "Data-driven Identification of Occupant Thermostat-Behavior Dynamics," arXiv preprint:1912.06705, 2019.

Quality of service (QoS): a *need for energy (NFE)*

<u>Example</u>: An electric water heater



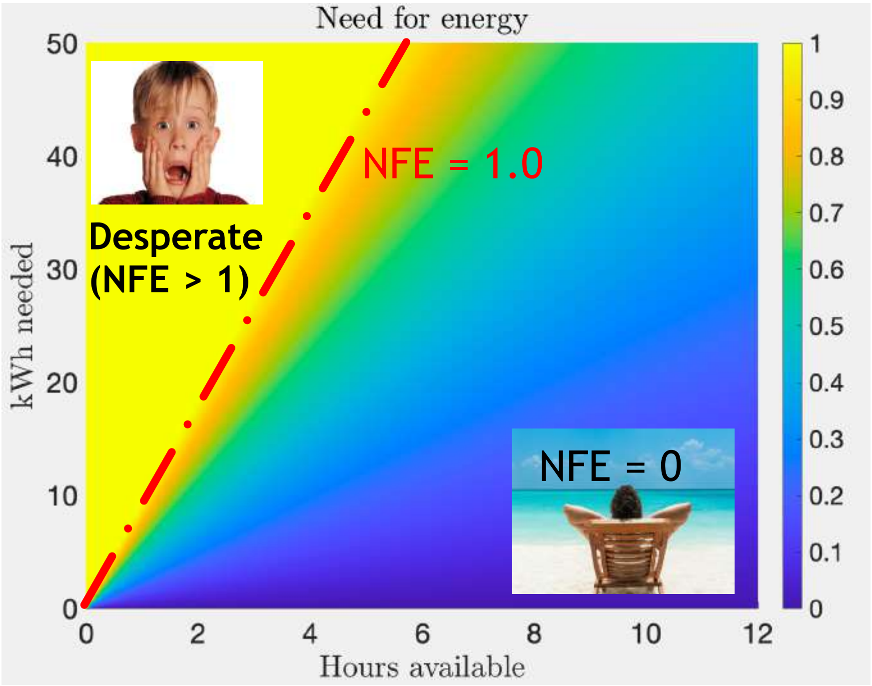
Turn OFF
Need for energy is <u>low</u>!

NFE increases with
~1/Temperature

Turn ON
Need for energy is <u>desperate</u>!

<u>Example</u>: An electric vehicle

$$\text{NFE} = \frac{\text{kWh needed now}}{\eta p^{\text{max}} \times \text{hours remaining}}$$



Key: coordination schemes can embed NFE to dynamically prioritize responses

Some challenges with aggregated resources

1

Estimate end-use parameters

Stochastic end-use

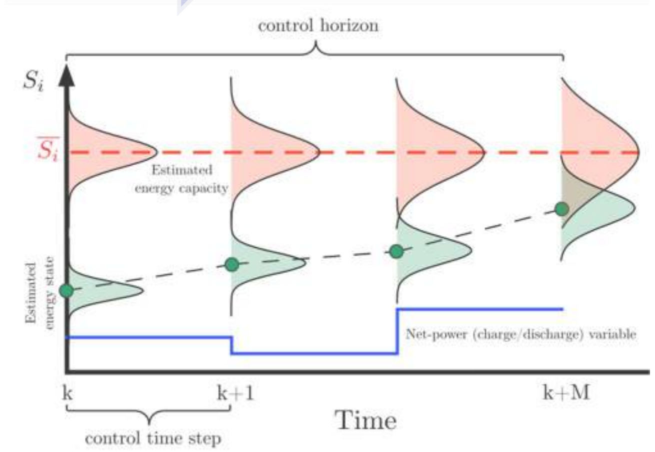
2

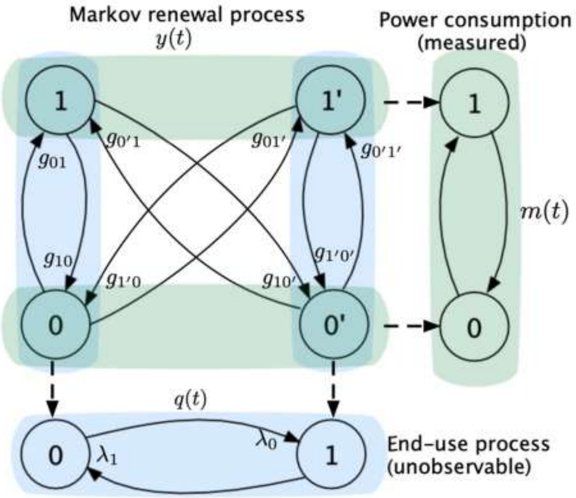
Modeling & control

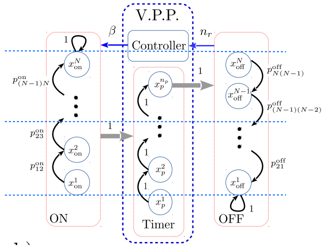
Uncertain resource

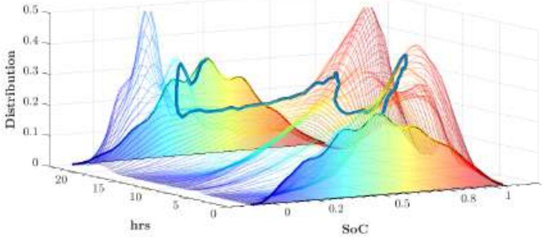
3

Optimize dispatch





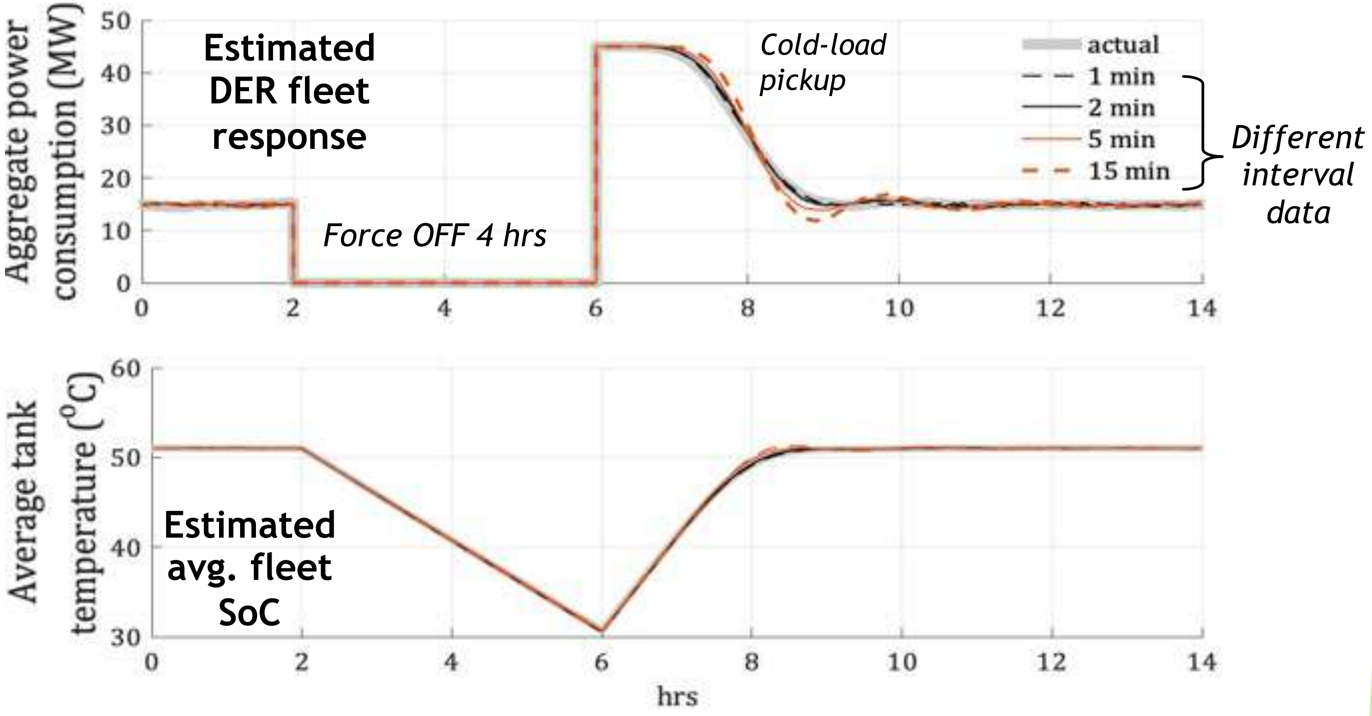




(1) **A. Khurram**, Luis Duffaut Espinosa, Roland Malhamé, Mads Almassalkhi, “Identification of Hot Water End-use Process of EWHs from Energy Measurements,” EPSR, 2020
(2a) L. Duffaut and M. Almassalkhi, “A packetized energy management macromodel with QoS guarantees for demand-side resources,” IEEE Trans. on Power Systems, 2021
(2b) L. Duffaut, **A. Khurram**, and M. Almassalkhi “Reference-Tracking Control Policies for Packetized Coordination of Diverse DER Populations,” IEEE Trans. on Control Systems Tech., 2021
(2c) L. Duffaut Espinosa, **A. Khurram**, and M. Almassalkhi, “A Virtual Battery Model for Packetized Energy Management,” in *IEEE Conference on Decision and Control (CDC)*, 2020
(3a) **M. Amini** and M. Almassalkhi, “Corrective optimal dispatch of uncertain virtual energy resources,” IEEE Transactions on Smart Grid, 2020
(3b) N. Qi, P. Pinson, M. Almassalkhi, et al, "Chance Constrained Economic Dispatch of Generic Energy Storage under Decision-Dependent Uncertainty," IEEE TSE. 2023

1 Estimate hot water end-use (nominal demand)

- **Problem:** how do people interact with DERs nominally?
- **Outcome:** from just kWh interval meter data and (homogeneous) tank parameters, we can estimate (constant) hot water heater consumption rate
- **Next:** time-varying usage intensity rate, relax homogeneity assumption, validate on real data and generalize to other devices.



Input

1. Measured kWh data
2. EWH parameters e.g. tank size, rating of heating element

Get statistics of power consumption

Estimation from moments

Output

Parameters of end-use process

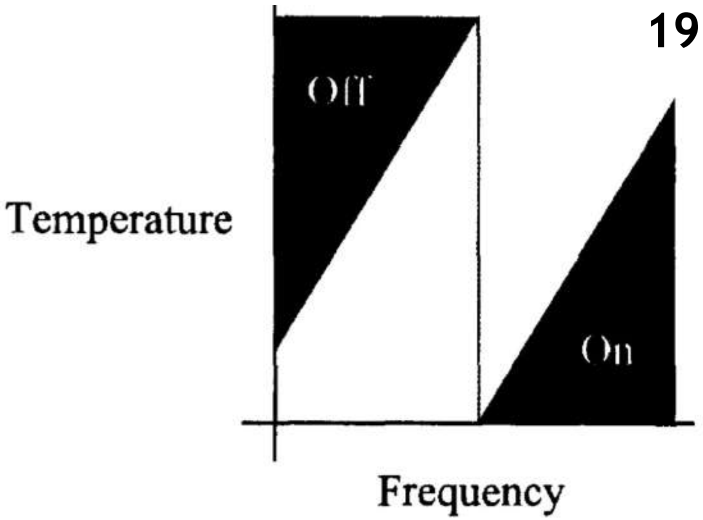
Adil Khurram, Luis Duffaut Espinosa, Mads Almassalkhi, Roland Malhamé, "*Identification of Hot Water End-use Process of Electric Water Heaters from Energy Measurements*," Power Systems Computation Conference (PSCC) and EPSR, 2020.

2 Modeling/control: foundational work in load control

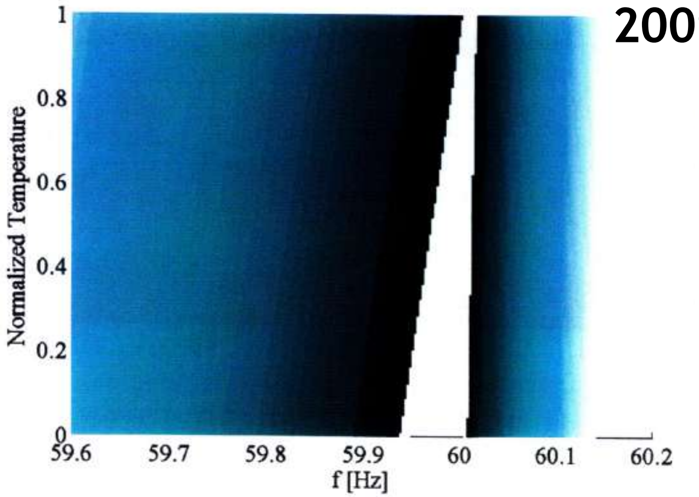
1979: Electric power load management (techno-eco-social-regulatory issues; Morgan/Talukdar)

1980: Frequency Adaptive Power and Energy Reschedulers (FAPER, Schweppe/Kirtley)

- *Used locally measured temperature to prioritize resources dynamically*
- Change temperature dead-band based on measured grid frequency ➔ devices switch ON or OFF
- Meant to provide 5-minute demand services. But challenges with synchronization & sensing ($$$)
  - (Brokish 2009) revisited FAPER and considered *Probabilistic FAPER* to reduce synchronization effects
- Topic picked up in 2009-ish with Hiskens/Callaway work on load control, then field exploded…



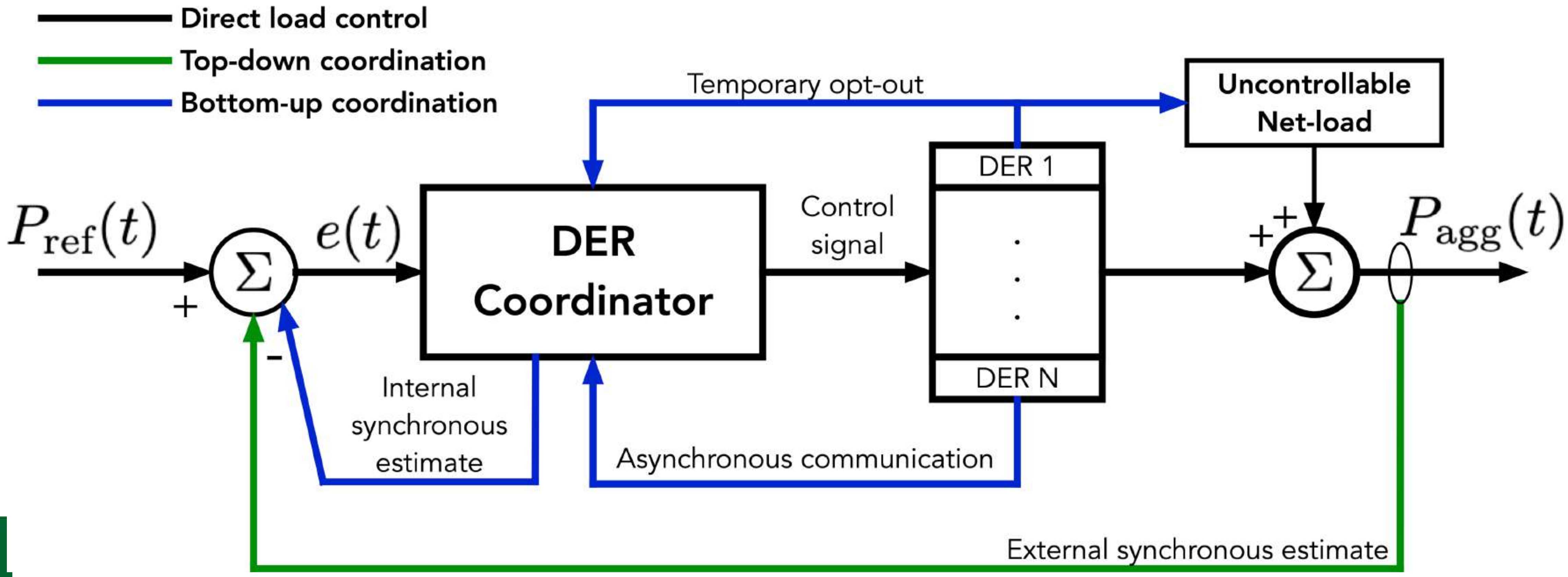
1980



2009

② Common architectures: top-down vs. bottom-up

How to coordinate DERs? What's measured/estimated?



2 A new load control policy inspired by the Internet

Packetization of data on Internet

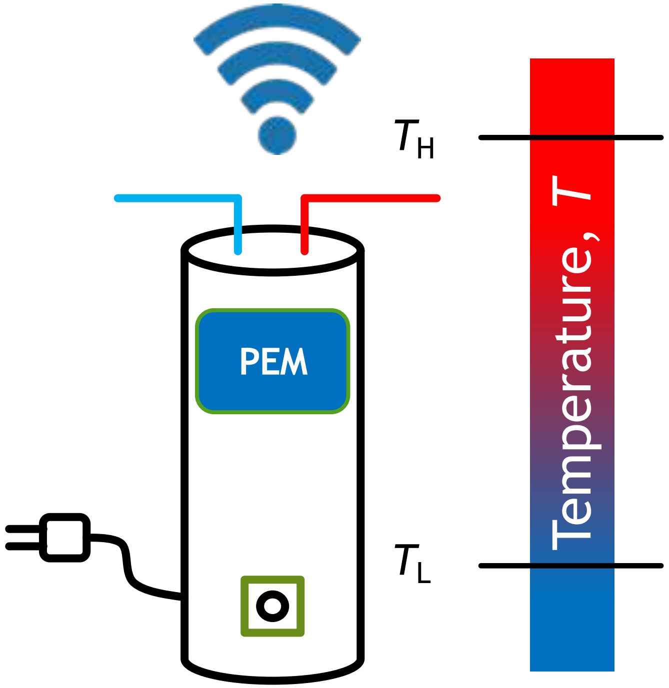
Random access protocols

Method is called packetized energy management (PEM)

M. Almassalkhi, J. Frolik, and P. Hines, "*How To Prevent Blackouts By Packetizing The Power Grid*" *IEEE Spectrum*, February, 2022.
M. Almassalkhi et al, "*Asynchronous Coordination of Distributed Energy Resources with Packetized Energy Management*," In: Energy Markets and Responsive Grids. Springer, 2018.
M. Almassalkhi, J. Frolik, and P. Hines, "*Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads*," *ACC*, 2017.

PEM example load: guaranteeing *QoS*

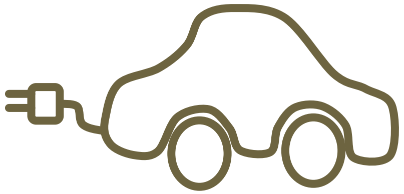
Energy packet = constant power consumed over fixed epoch = 🟦



Device's *need for energy* (NFE) drives its *mean time to request* (MTTR) → **stochastic requests**

Packetizing bulky consumption → many smaller **energy packets**

When temperature is low, heating elements turns ON and consumes energy → *bulky demand*

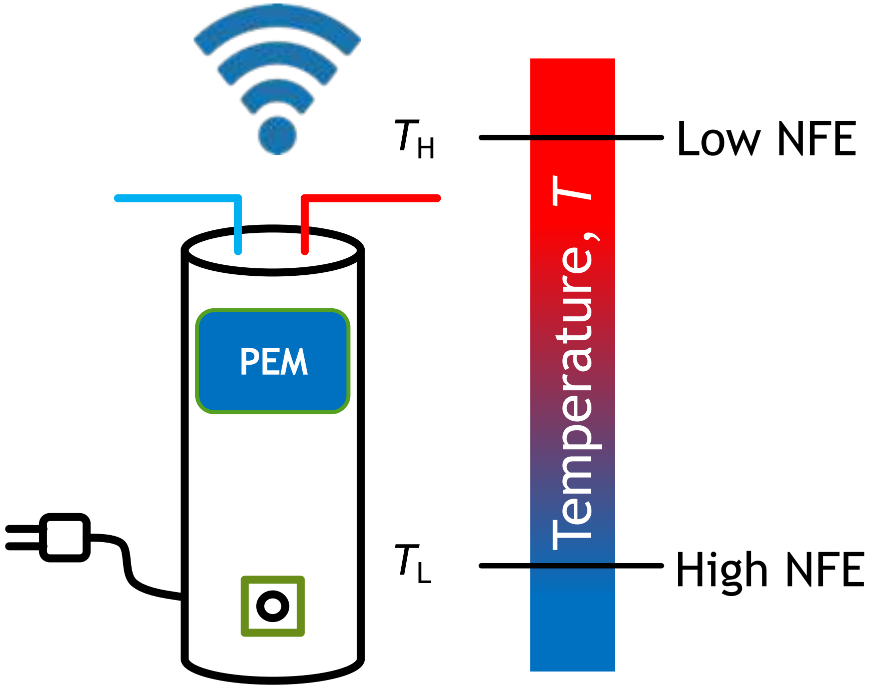


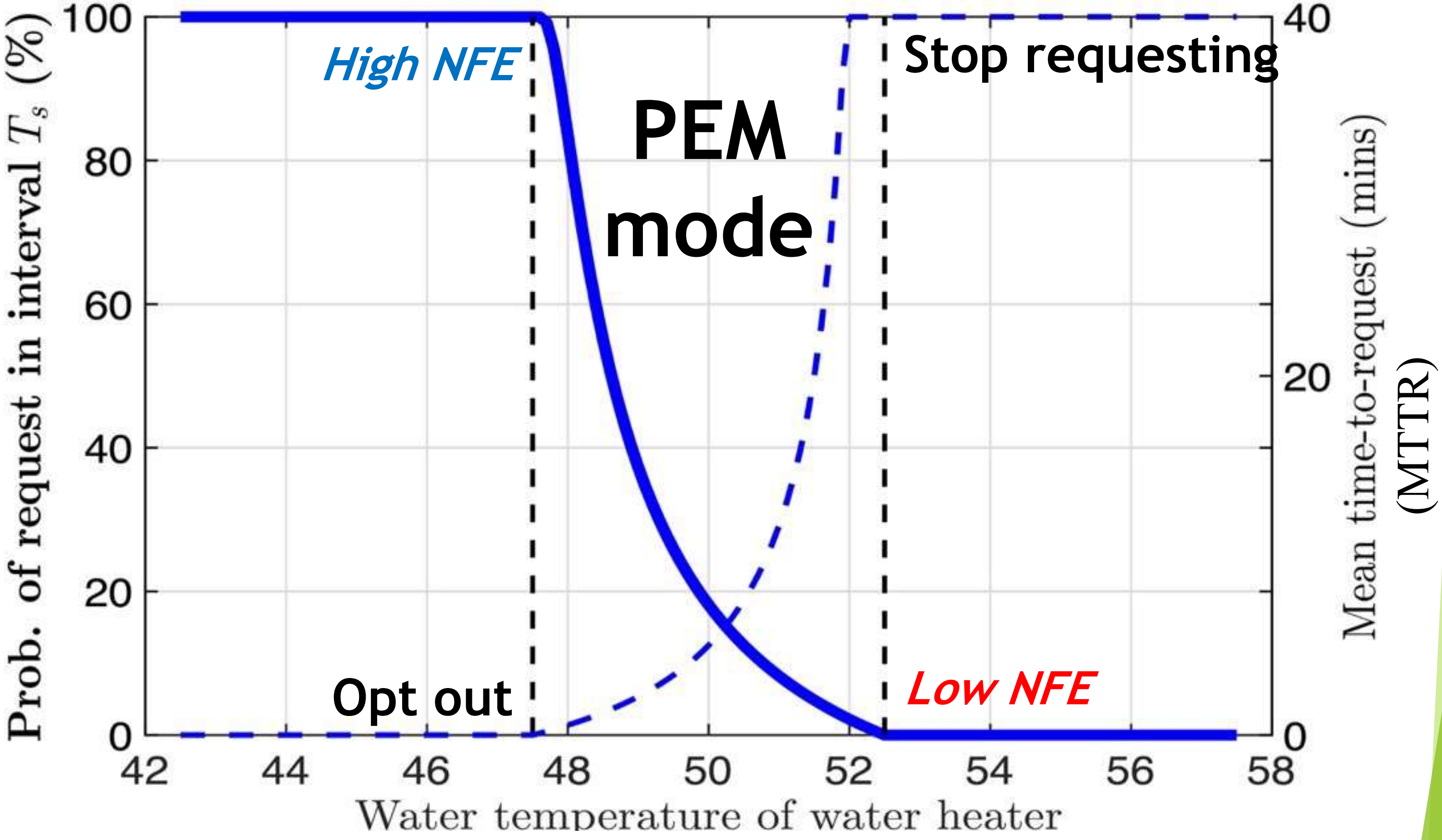
M. Almassalkhi, et al, "Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads," *ACC*, 2017
M. Almassalkhi, et al, "Asynchronous Coordination of Distributed Energy Resources with Packetized Energy Management, In: *Energy Markets and Responsive Grids.*, Springer, 2018.
O. Oyefeso, G. Ledva, I. Hiskens, M. Almassalkhi, and J. Mathieu, "Control of Aggregate Air-Conditioning Load using Packetized Energy Concepts," *IEEE CCTA*, 2022.

PEM example load: guaranteeing *QoS*

Stochastic request process based on NFE

NFE dynamically prioritizes devices by modulating MTTR





M. Almassalkhi, et al, “Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads,” *ACC*, 2017

M. Almassalkhi, et al, "Asynchronous Coordination of Distributed Energy Resources with Packetized Energy Management," 20th In: Meyn S., Samad T., Hiskens I., Stoustrup J. (eds) *Energy Markets and Responsive Grids*. The IMA Volumes in Mathematics and its Applications,, pp 333-361, vol 162. Springer, 2018.

Closing the loop with PEM's packet requests

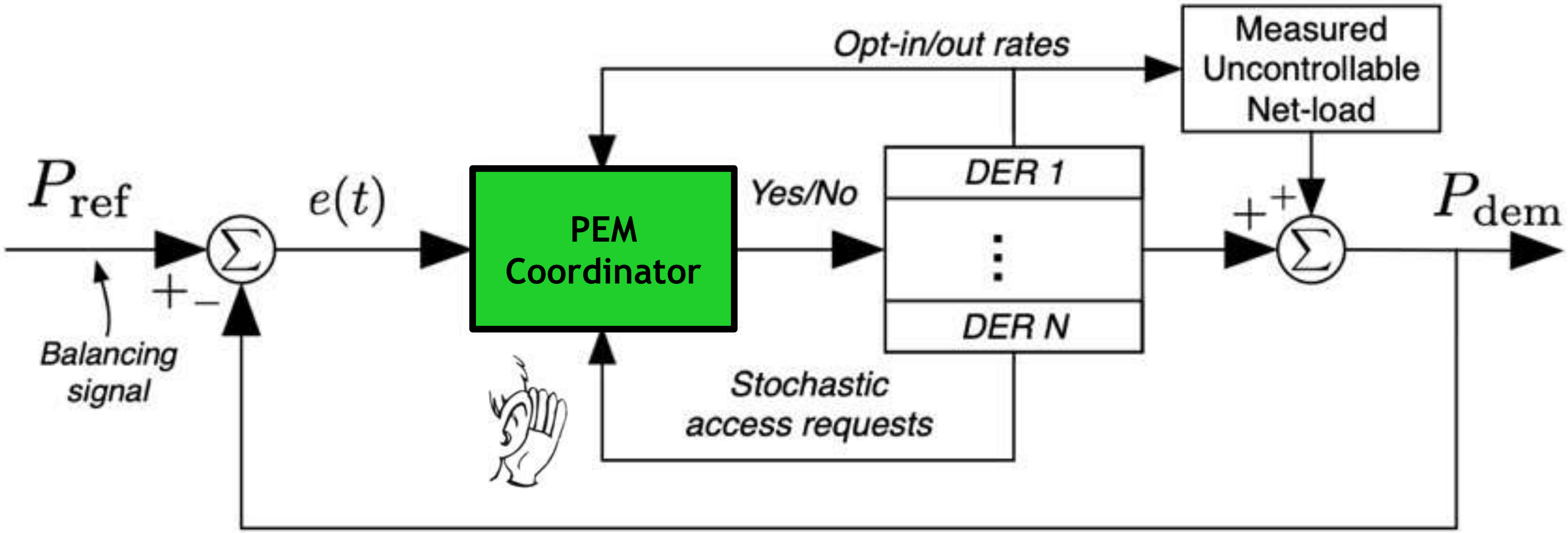
- Coordinator accepts/denies request based on tracking error

  Simple: If *error(t) < 0, then coordinator accepts incoming request; else deny request.*

  Key: Modulating acceptance rate for packet requests regulates aggregate demand

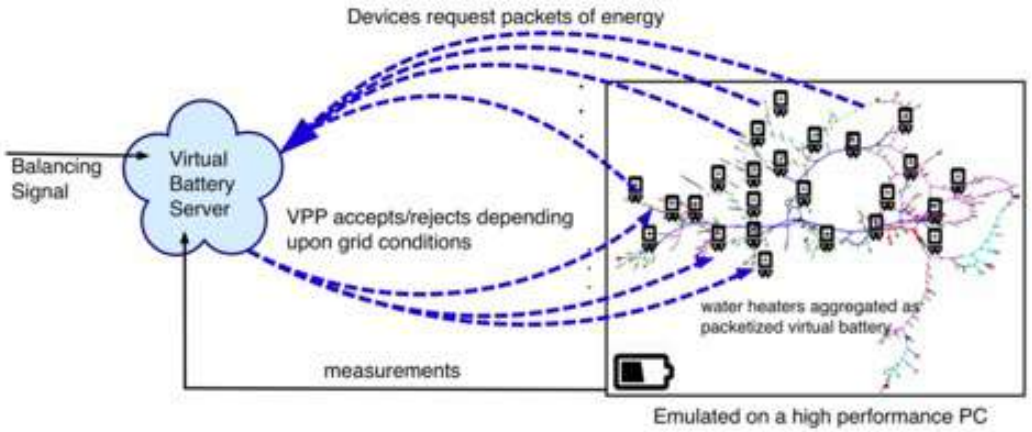
  ➔ *PEM effectively solves a hard scheduling problem in real-time*

  Next: analyze and model system when packet length is randomized

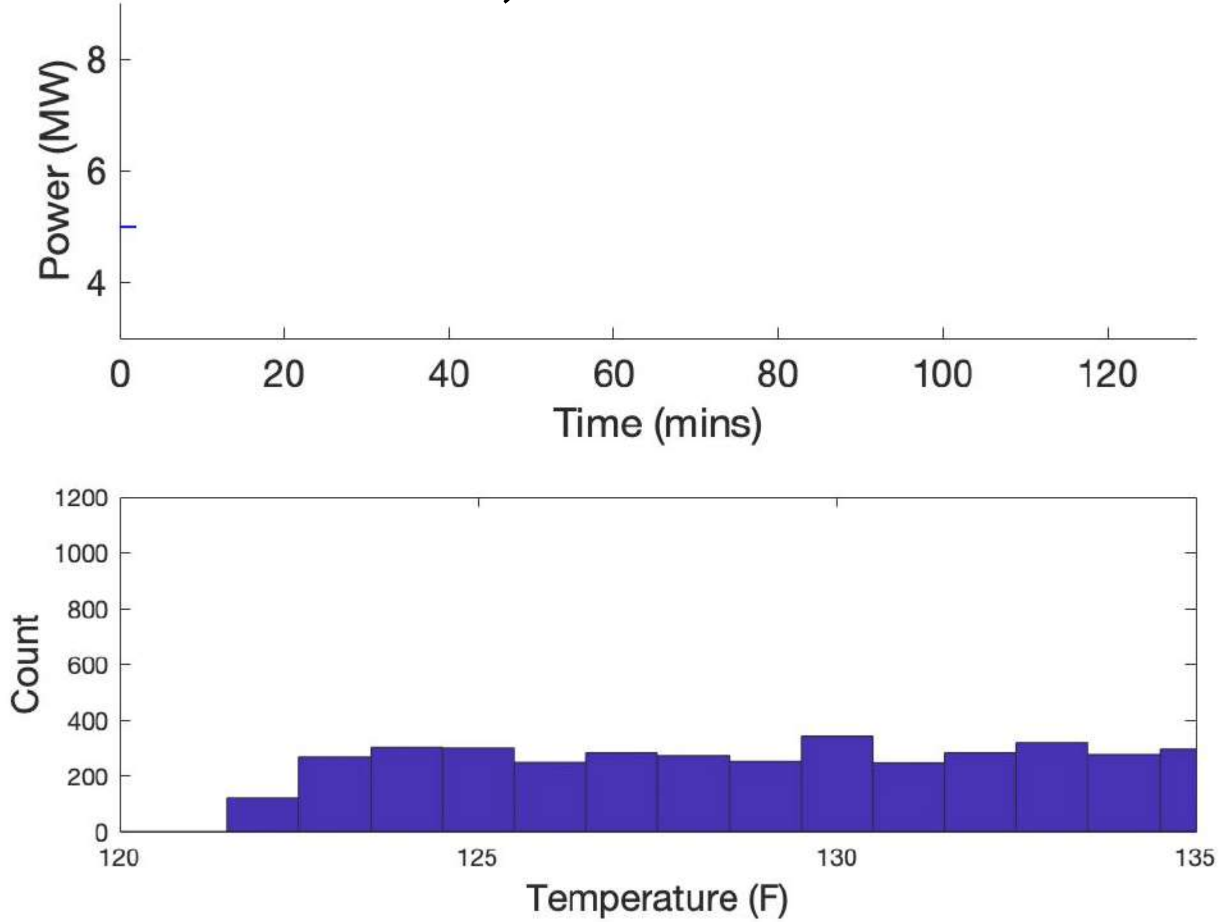


Incoming request rates are based on devices' NFE and leads to scalable event-based comm overhead!

Milestone 1: built real-time, scalable DER platform



5000 real-time, emulated PEM water heaters

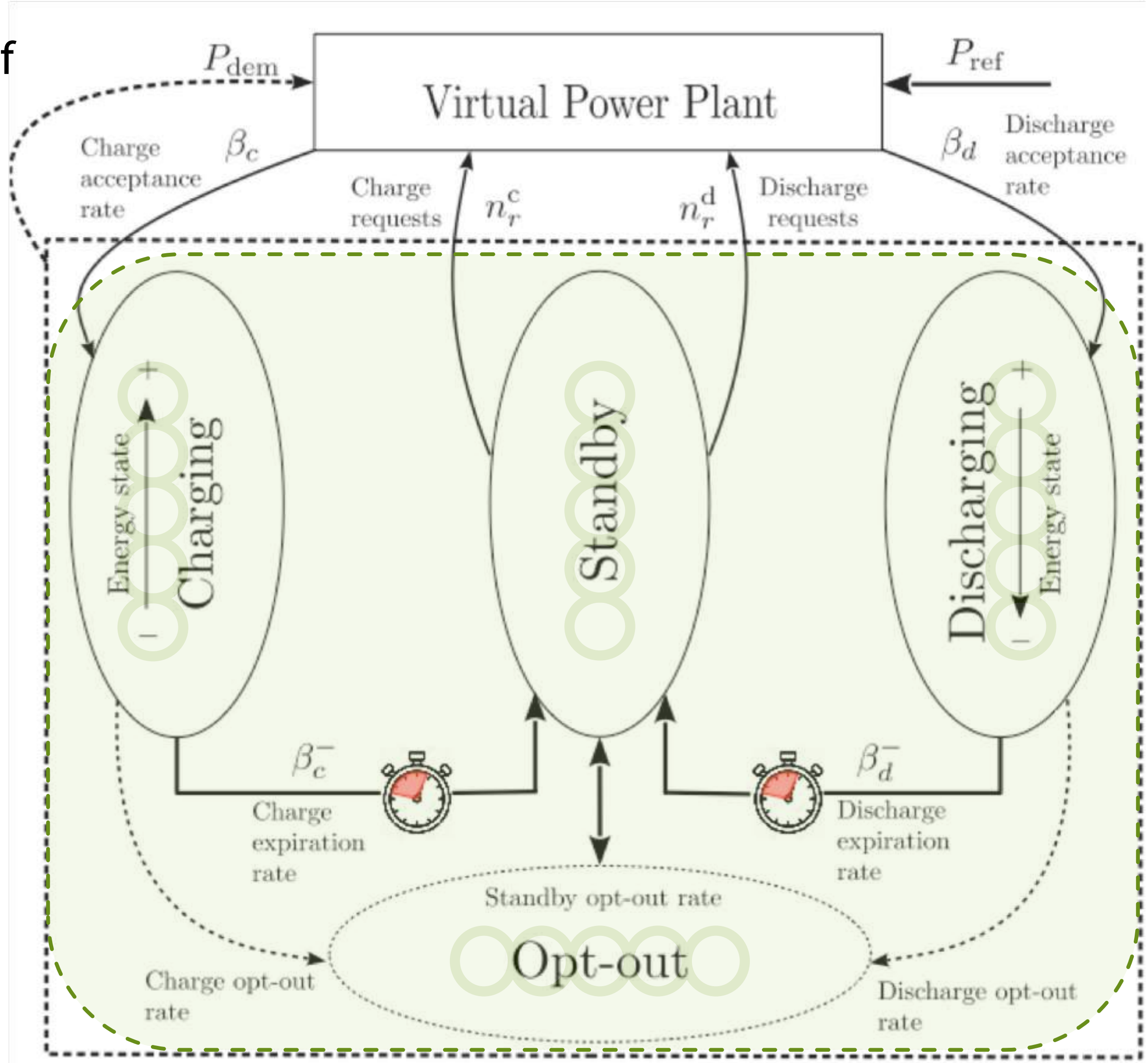


M. Amini, et al. “A Model-Predictive Control Method for Coordinating Virtual Power Plants and Packetized Resources, with Hardware-in-the-Loop Validation”. In: *IEEE PES General Meeting*. Atlanta, Georgia, 2019

A. Khurram, M. Amini, L. Duffaut Espinosa, P. H. Hines, and M. Almassalkhi, "Real-Time Grid and DER Co-Simulation Platform for Testing Large-Scale DER Coordination Schemes," *IEEE Transactions on Smart Grid*, 2022

2 Modeling system under PEM to aid analysis and control

Coordinator controls rate of accepting charging and discharging requests (β_d, β_c)



Charge & discharge requests (n_r^c, n_r^d) arrive stochastically from aggregated Standby bins

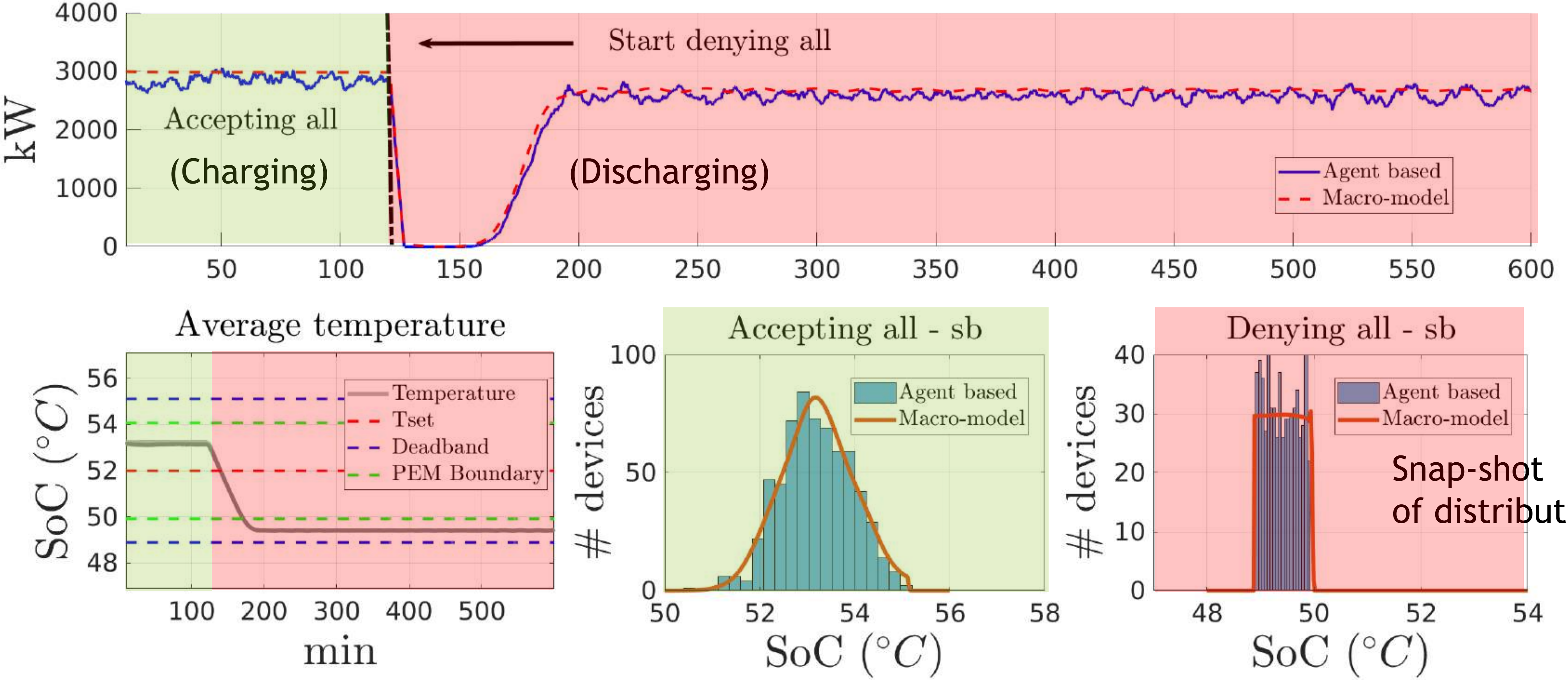
Transitions can occur from any Standby mode based on request probability

Timer states *capture how long energy packets take to complete* $(\beta^-_{c/d})$

Opt-out control guarantees comfort/QoS

② Validating PEM state bin transition model:

Incorporating opt-out dynamics and hot water usage pulse process statistics into dynamics



(Charging)

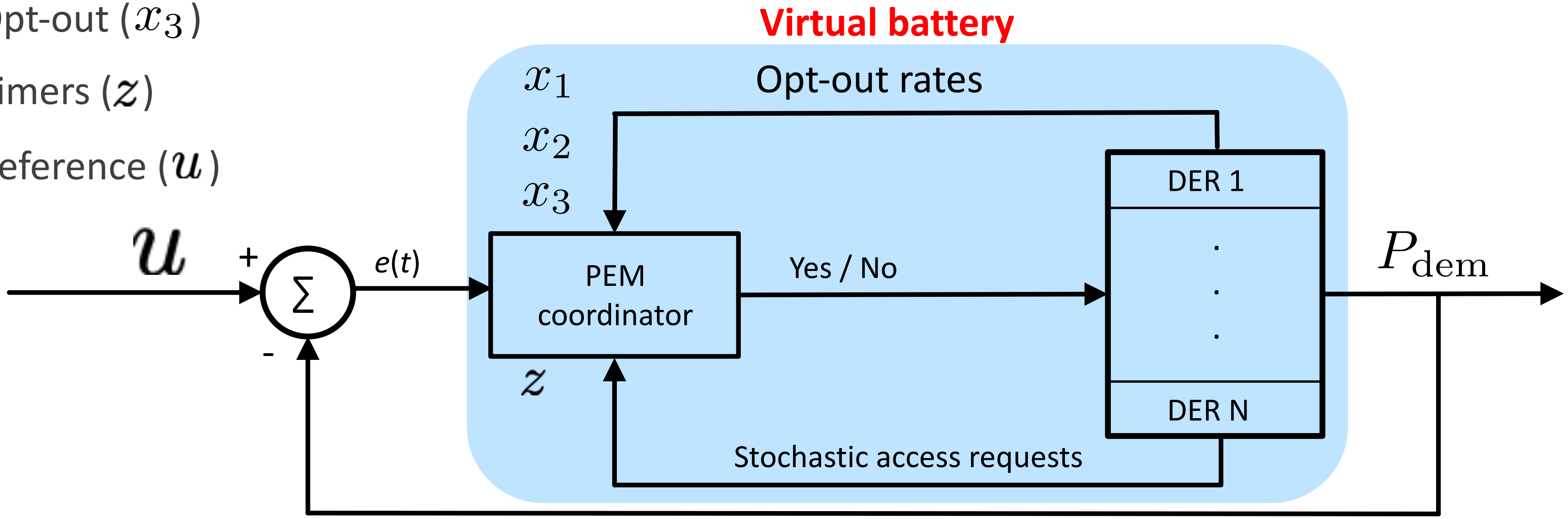
(Discharging)

Snap-shot
of distribution

L. Duffaut and M. Almassalkhi, “A packetized energy management macromodel with QoS guarantees for demand-side resources,” IEEE Trans. on Power Systems, 2020.

2 Low-order predictive VB model

- Low-order **virtual battery** model captures average energy and aggregate power dynamics.
- Consists of **four states (3+n_p) and one input**
  1. Average SoC (x_1)
  2. ON (x_2)
  3. Opt-out (x_3)
  4. Timers (z)
  5. Reference (u)



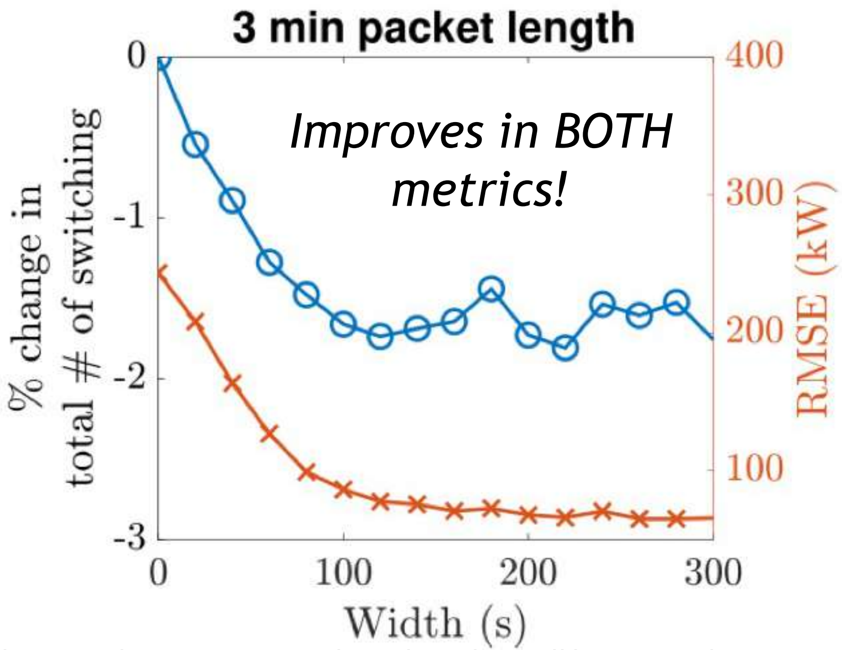
Closed loop feedback system for PEM.

L. Duffaut Espinosa, A. Khurram, and M. Almassalkhi, "A Virtual Battery Model for Packetized Energy Management," *IEEE Conference on Decision and Control*, 2020.

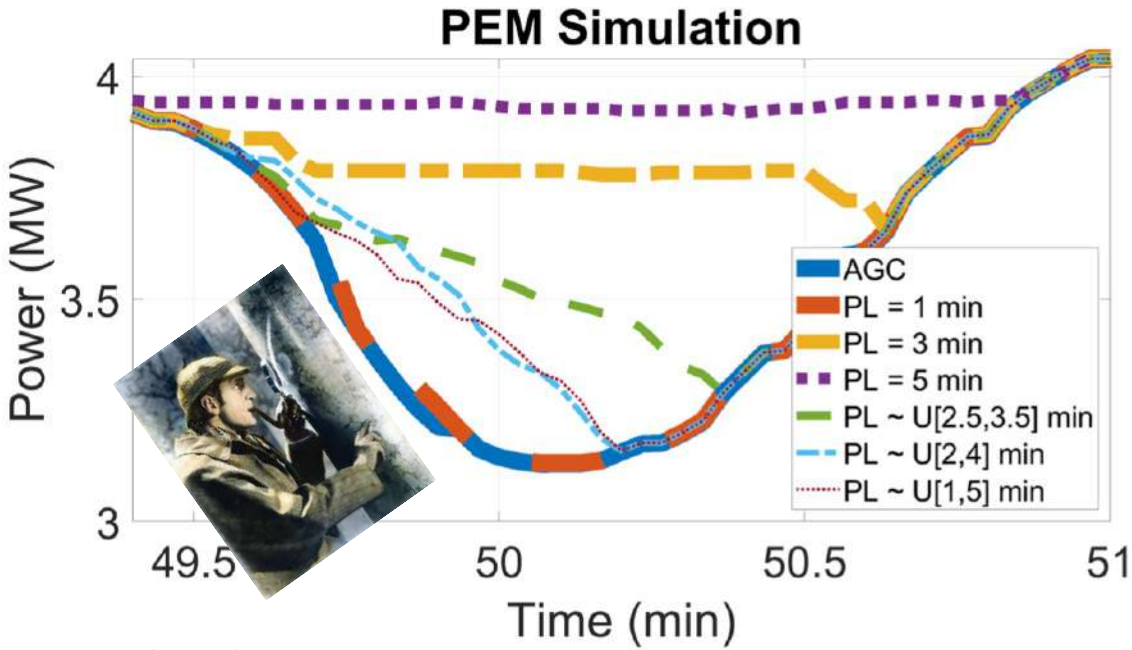
2 Low-order predictive VB model in action

Case #1: MPC-based pre-compensator for (PJM) frequency regulation [1]

- Linearizes aggregate fleet power dynamics to predict when output is down ramp-limited
- Energy-neutral frequency regulation (PJM): SoC is approximately constant ➔ linearization works well!
  - Freg regulation signal is fairly predictable 20-30 seconds out [2]
  - RHMPC pre-emptively reject packets to avoid down ramp-limited situation: allow PEM “*cuts corner*”
- **Next**: incorporate new OFF-requests into model, consider data-driven methods [3], analyze randomized PL [1]



Improves in BOTH metrics!



[1] S. Brahma, A. Khurram, H. Ossareh, and M. Almassalkhi, "Optimal Frequency Regulation using Packetized Energy Management," *IEEE Transactions on Power Systems*, 2022.
[2] S. Brahma, H. Ossareh, and M. R. Almassalkhi, "Statistical Modeling and Forecasting of Automatic Generation Control Signals,". *IREP*, 2022.
[3] Mustafa Matar and Hani Mavalizadeh,, "Learning the state-of-charge of heterogeneous fleets of distributed energy resources with temporal residual networks," *Journal of Energy Storage*, *2023*

2 Low-order predictive VB model: results

<u>Case #2</u>: **Optimize fleet's economic dispatch: enforce energy limits from s-s operating point**

- *Assumes homogeneous parameters for fleet of electric water heater*
- Explicit energy limits are used to eliminate (complex/fast) opt-out dynamics
- EKF is used online to infer SoC state (of aggregate) based on: 1) total fleet power and 2) number of requests
- Predictive model is implemented as NLP via Julia+IPOPT (solves in 7 secs)
- **Next steps**: generalize to heterogeneous fleet, model opt-out dynamics, and derive QoS limit from opt-out bounds

NLP formulation

$$\min_{P_{\text{ref}}[k],g[k],x[k]} \chi(P_{\text{ref}}[k],g[k],x[k])$$

$$\text{s.t. } x[k+1]=f(x[k],P_{\text{ref}}[k]) \text{ and } (12),$$

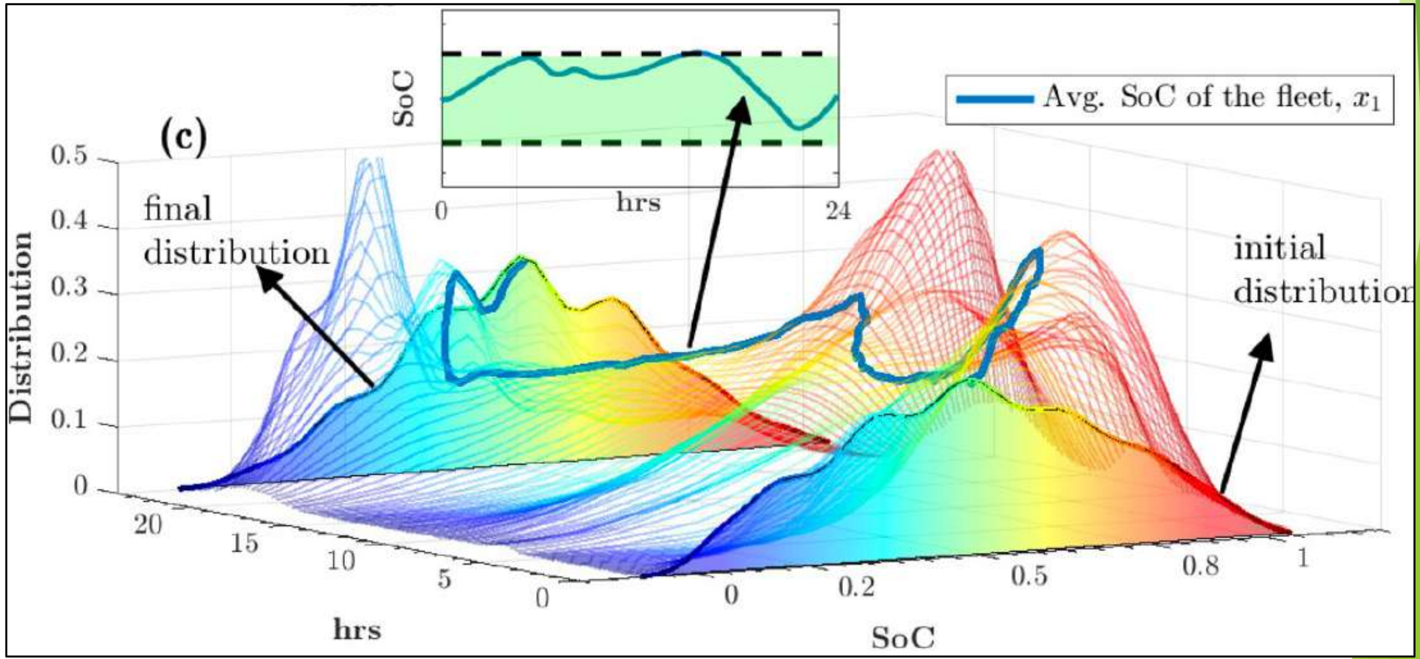
$$P_{\text{ref}}[k]\geq P_{\text{rate}}x_2[k],$$

$$P_{\text{ref}}[k]\leq P_{\text{rate}}(P_{\text{req}}(x_1[k])(N-x_2[k])+x_2[k]),$$

$$P_{\text{f}}[k]=\Delta P_{\text{dev}}[k]+g[k],$$

$$\underline{x}\leq x[k]\leq\overline{x},\forall k=1,\ldots,K+1,$$

$$x[0]=x_0,x_1[K+1]=[10]x_0,$$



L. Duffaut Espinosa, A. Khurram, and M. Almassalkhi, "A Virtual Battery Model for Packetized Energy Management," *IEEE Conference on Decision and Control*, 2020.

3 Defining flexibility from virtual batteries

Admissible inputs are defined from *stochastic* energy states/parameters

➔ begets a risk of saturation.

➔ can be managed with chance constraints

+ info on decision-independent uncertainties

$$\dot{x} = ax + bu$$

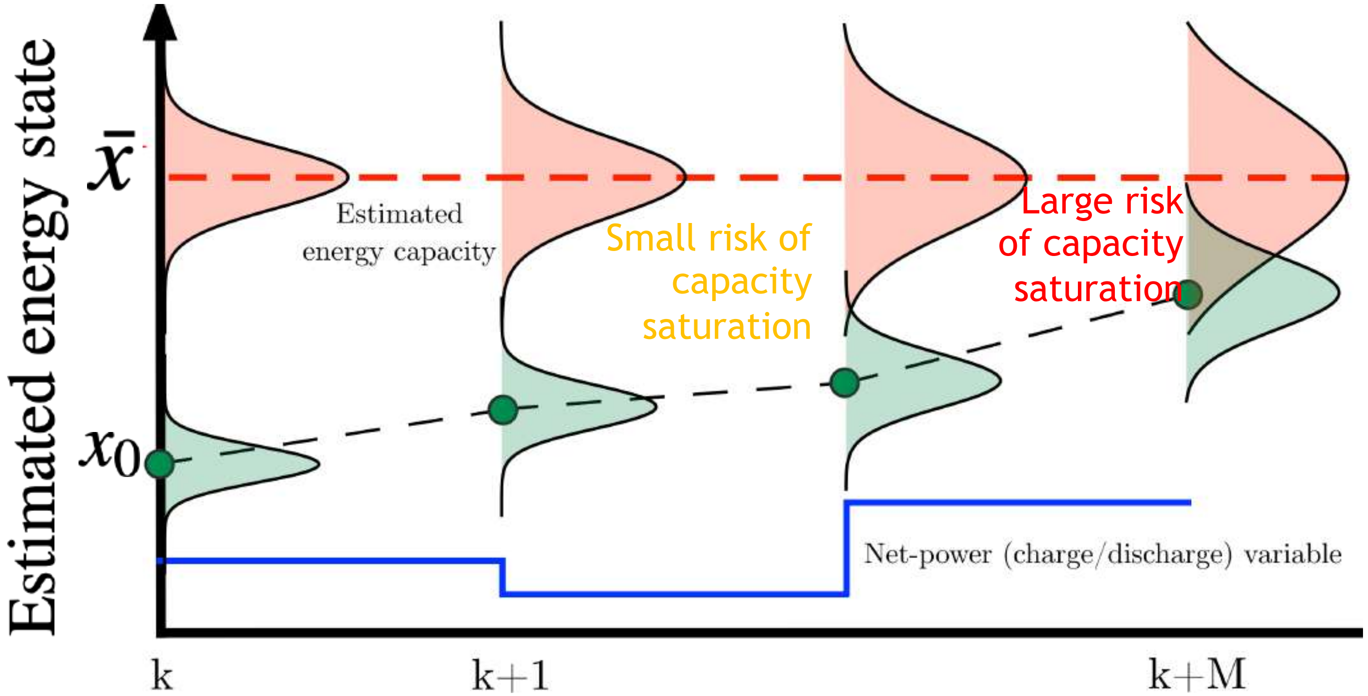
$$\dot{u} = cx + du + v$$

$$\underline{x} \leq x \leq \bar{x}$$

$$\underline{u} \leq u \leq \bar{u}$$

$$\underline{v} \leq v \leq \bar{v}$$

$$x(0) = x_0, u(0) = u_0$$



M. Amini and M. Almassalkhi, "Optimal Corrective Dispatch of Uncertain Virtual Energy Storage Systems," *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 4155 – 4166, 2020.

3 Defining flexibility from virtual batteries

What if we have control inputs that can actively shape the distribution?

➔ Decision-independent uncertainty (DIU) ➔ *decision-dependent uncertainty* (DDU)

Example: incentives expands range by temporarily overriding discomfort (contracts range)

$$\dot{x} = ax + bu$$

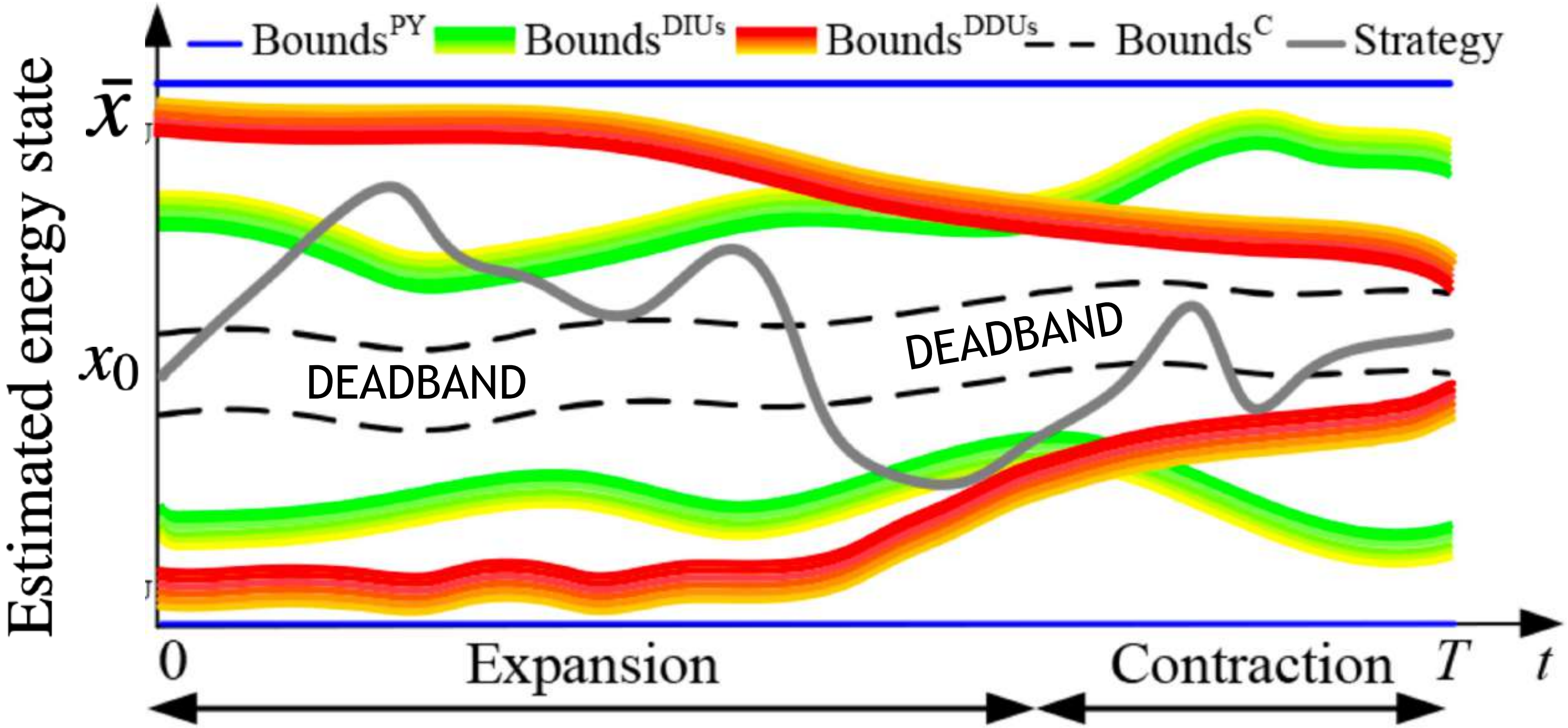
$$\dot{u} = cx + du + v$$

$$\underline{x}(u,x) \leq x \leq \bar{x}(u,x)$$

$$\underline{u} \leq u \leq \bar{u}$$

$$\underline{v} \leq v \leq \bar{v}$$

$$x(0) = x_0, u(0) = u_0$$



N. Qi, P. Pinson, M. Almassalkhi, L. Cheng, and Y. Zhuang, "*Chance Constrained Economic Dispatch of Generic Energy Storage under Decision-Dependent Uncertainty*," IEEE TSE, 2023.

arpa·e

Milestone 2: field trial with 150+ loads in 2019

The UNIVERSITY of VERMONT

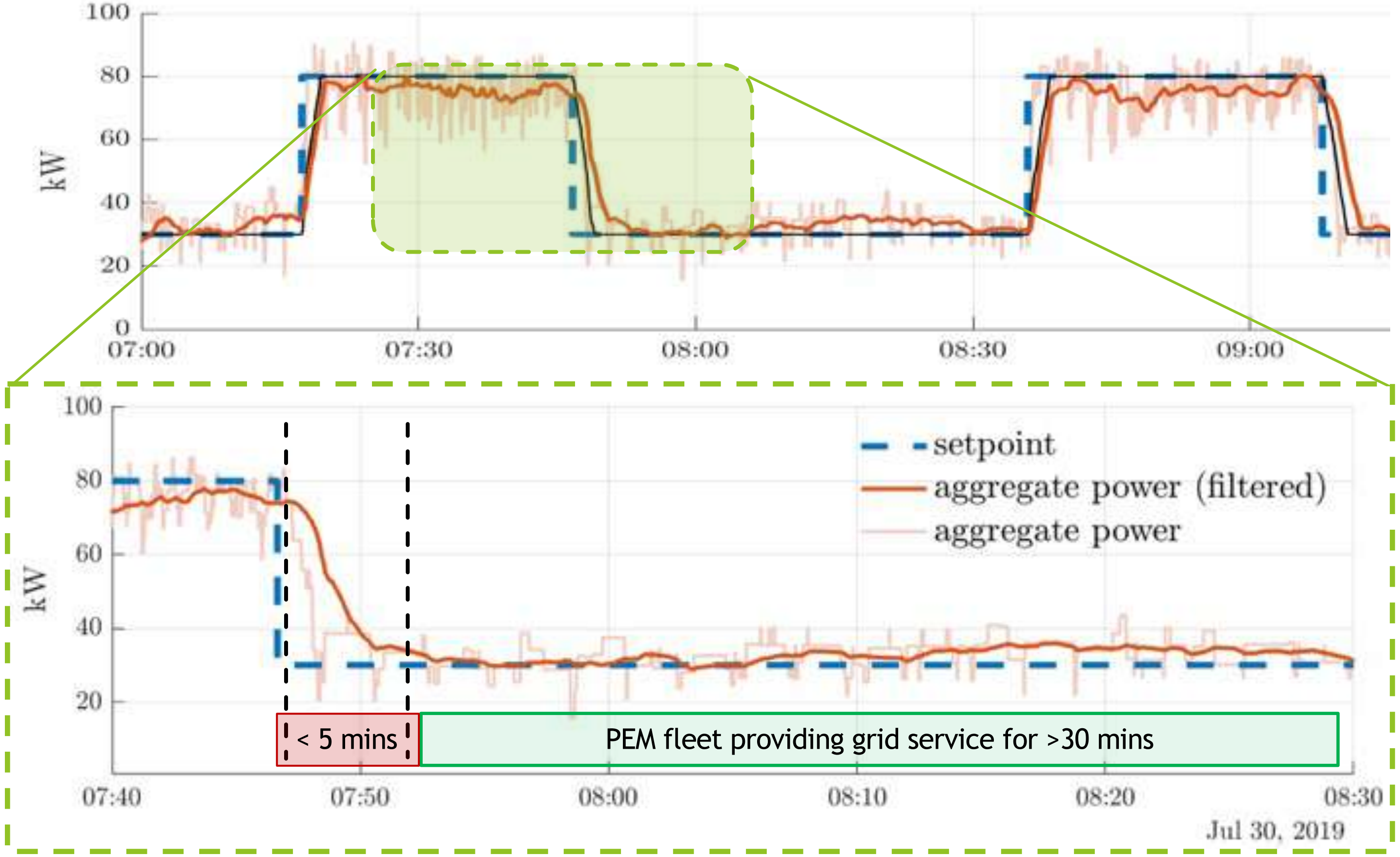
VERMONT ELECTRIC CO OP

BURLINGTON Electric DEPARTMENT

GREEN MOUNTAIN POWER

vermont electric power company VELCO

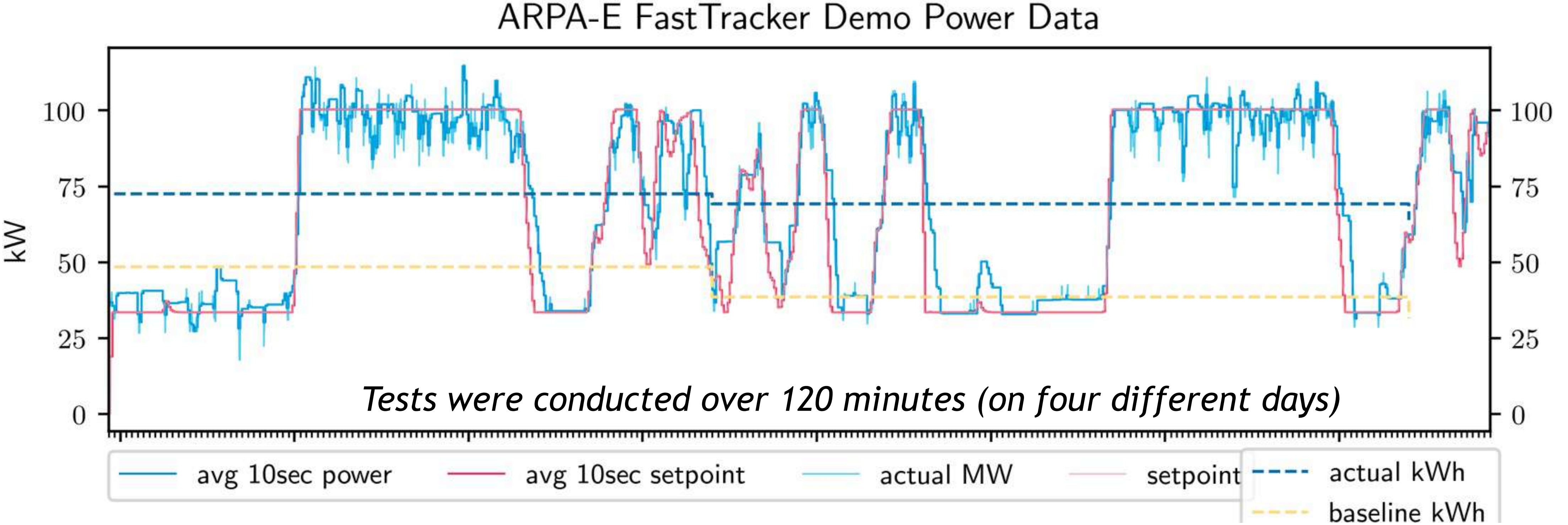
PACKETIZED ENERGY



The dynamics of the Aggregation is a function of PEM parameters

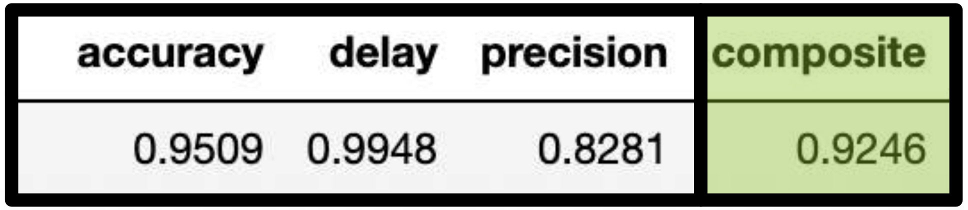
Milestone 3: field trial with 200+ loads in 2021

PEM demonstrates frequency regulation!



Tests were conducted over 120 minutes (on four different days)

Pay-for-performance:
PJM Performance score



accuracy	delay	precision	composite
0.9509	0.9948	0.8281	0.9246

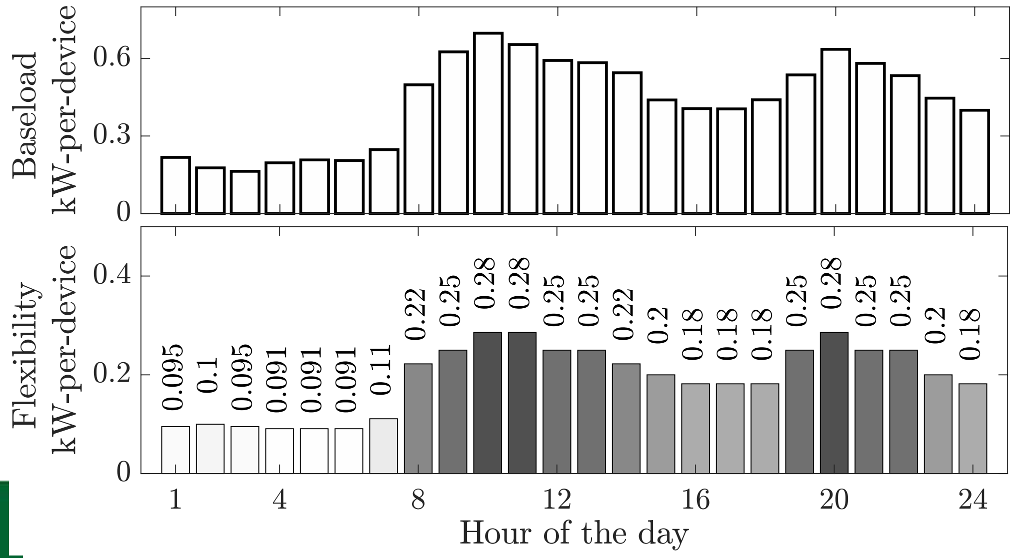
Better than PJM's avg system performance (80-90%) and outperforms all assets but MW-scale energy storage

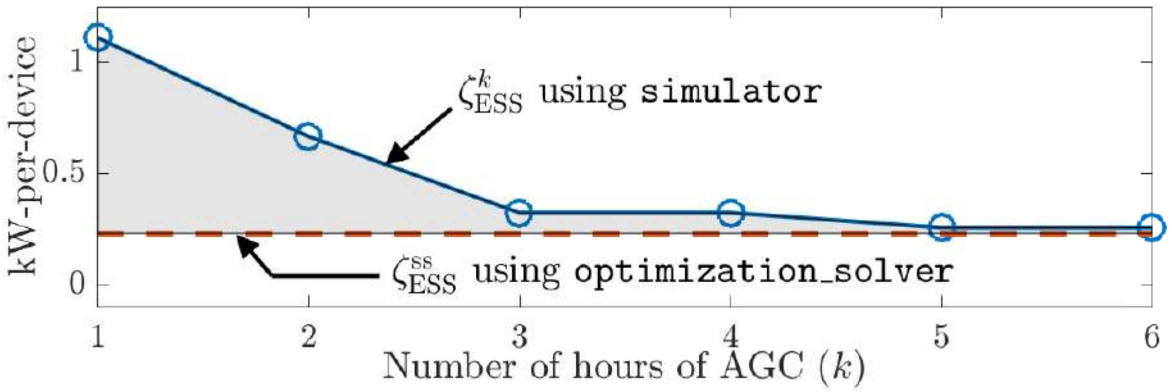
S. Brahma, A. Khurram, H. Ossareh, and M. Almassalkhi, "*Optimal Frequency Regulation using Packetized Energy Management*," IEEE Transactions on Smart Grid, 2023
M. Almassalkhi, J. Frolik, and P. Hines, "*How To Prevent Blackouts By Packetizing The Power Grid*" *IEEE Spectrum*, February, 2022.

Estimating power capacity/flexibility of VB

- Data-driven methodology to answer questions:
  - How many devices for 1MW flexibility?
  - What is flexibility (±kW) per device?
- Define flex-kW by fleet's ability to track AGC signal

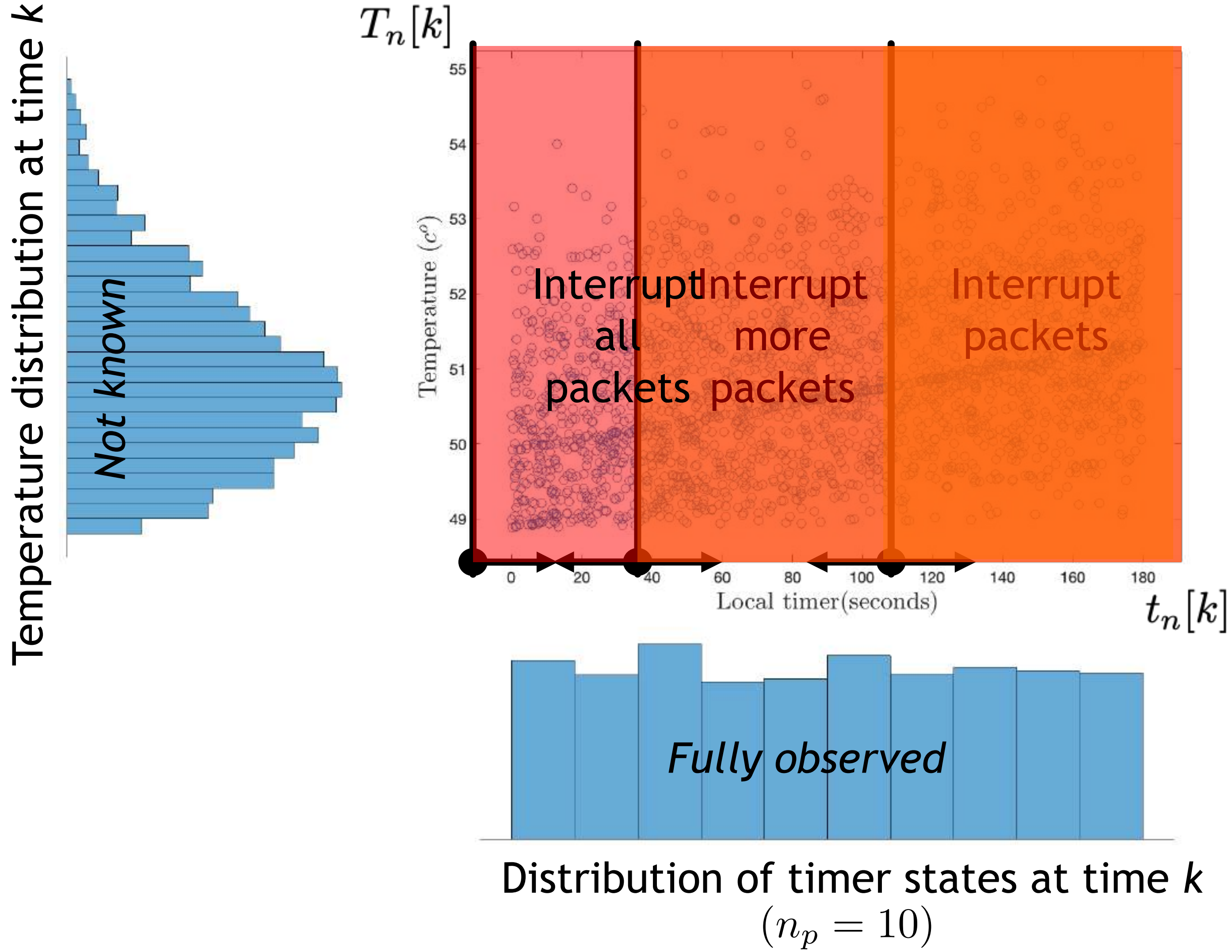
Electric water heaters





Adil Khurram, Luis Duffaut Espinosa, Mads Almassalkhi, *"A Methodology for quantifying flexibility in a fleet of diverse DERs,"* IEEE PES PowerTech, 2021.

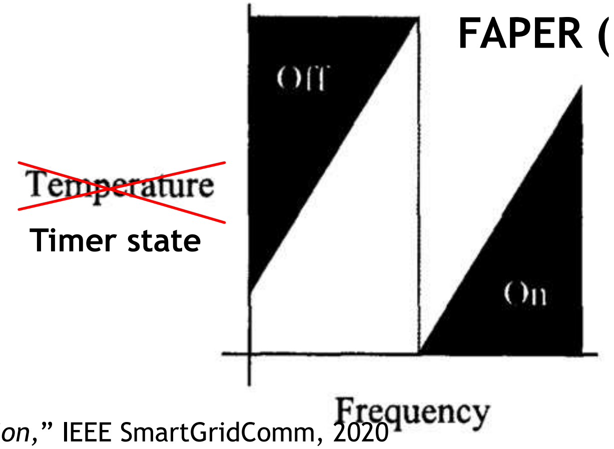
”Can you go faster yet with grid services?”



In PEM, TCLs consuming a packet are defined by their temperature states (not directly observable) and timer state (known)

Adapt PEM to leverage local frequency measurements with a local control policy to inform a TCL when to ***interrupt*** its packet

FAPER (1980)

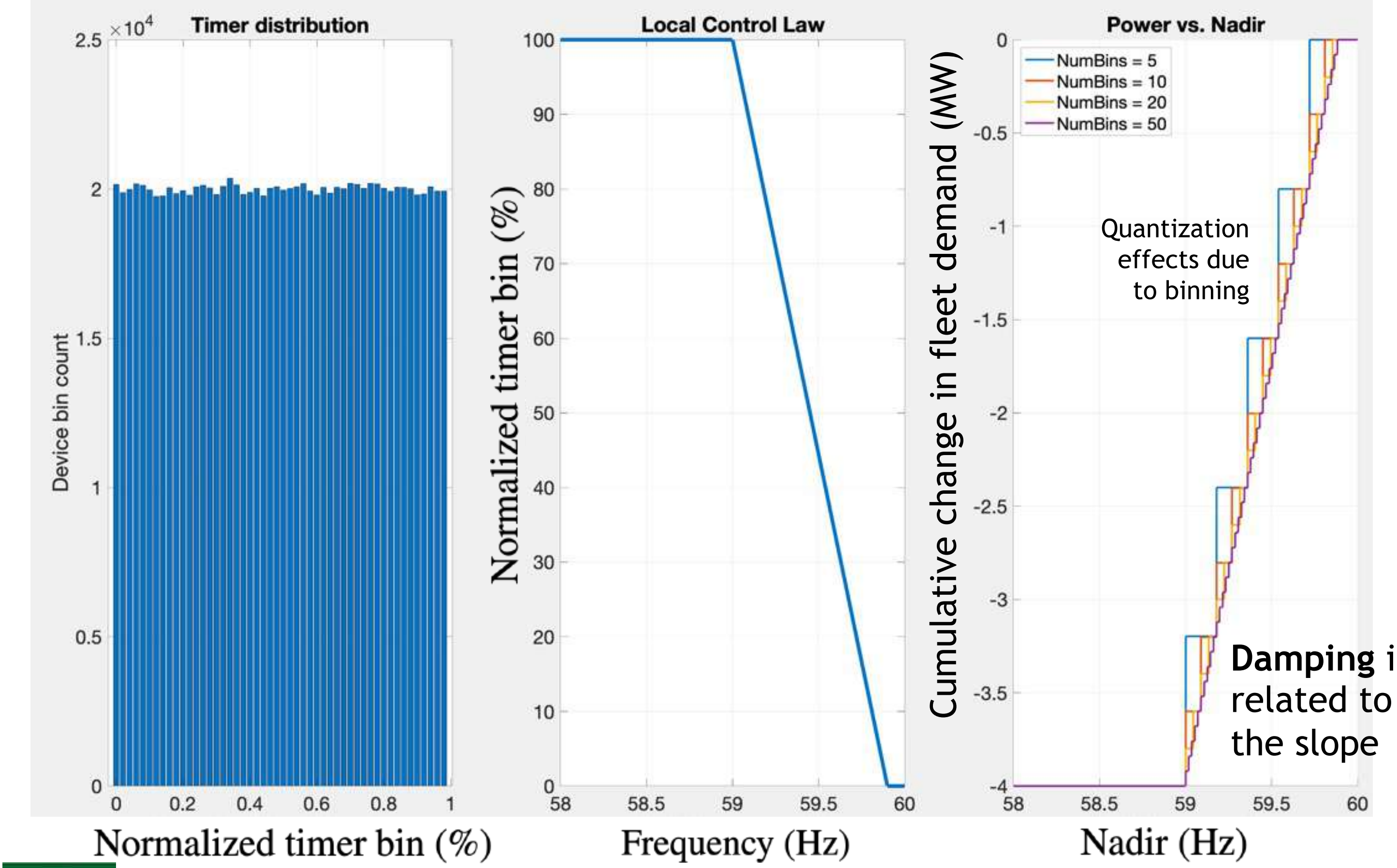


H. Mavalizadeh, L. Duffaut Espinosa, and M. Almassalkhi, “*Decentralized Frequency Control using Packet-based Energy Coordination*,” IEEE SmartGridComm, 2020

-, “*Improving frequency response with synthetic damping available from fleets of distributed energy resources*,” IEEE TPWRS (accepted)

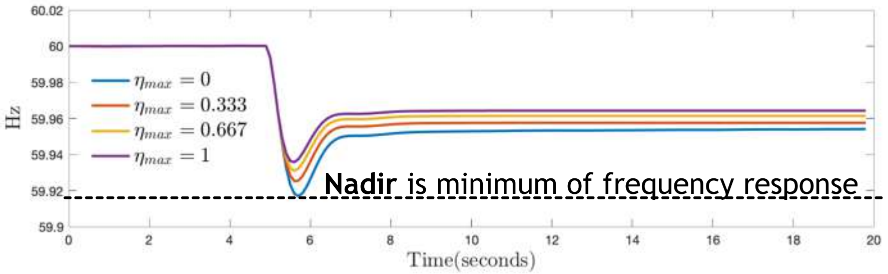
Example: TCL packet interruption control policy

Since no packets are resumed from interruptions, the **nadir** defines the total interruptions ➔ **Damping**

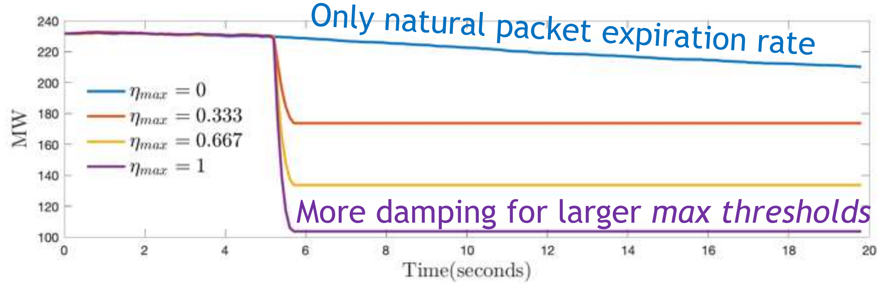


Quantization effects due to binning

Damping is related to the slope

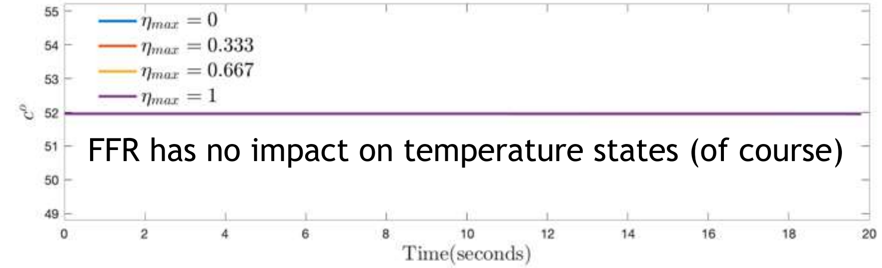


Nadir is minimum of frequency response



Only natural packet expiration rate

More damping for larger *max thresholds*



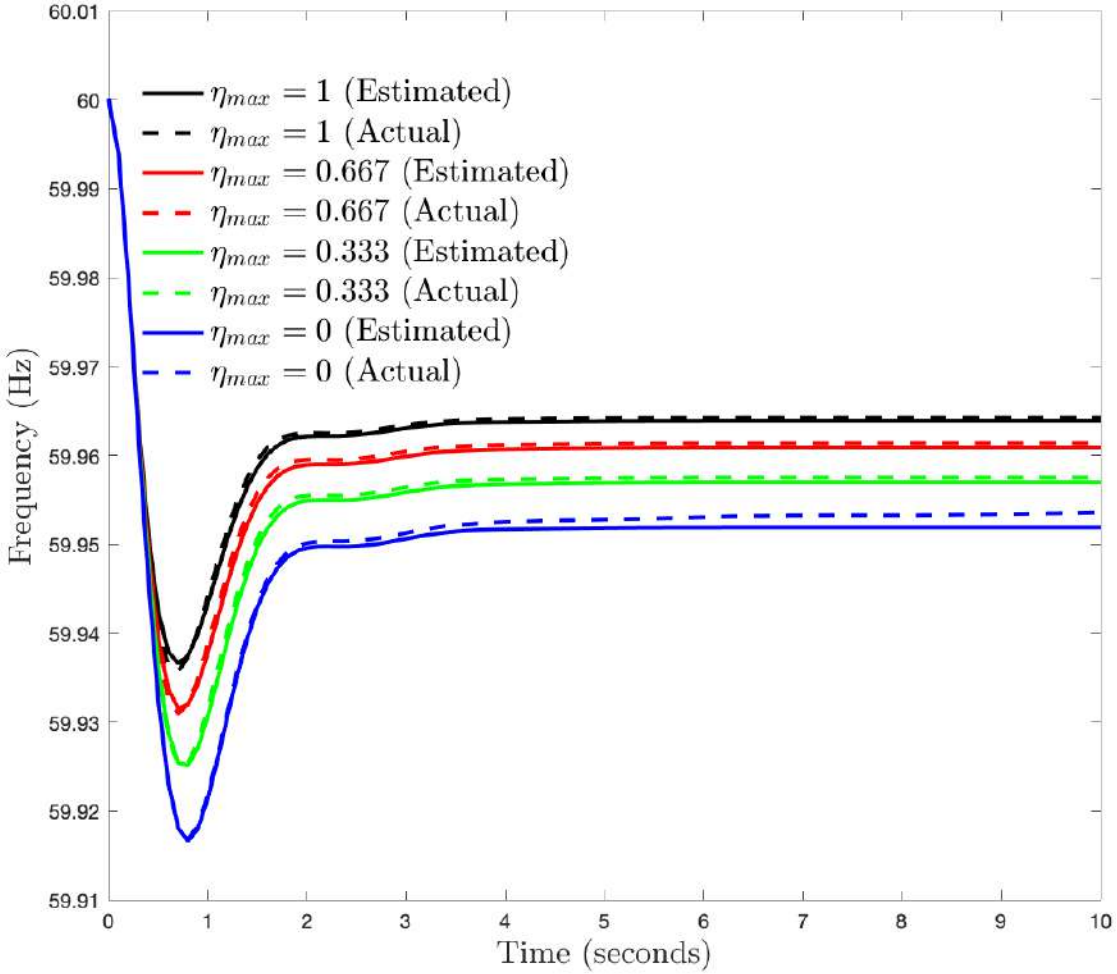
FFR has no impact on temperature states (of course)

Decentralized FFR policy works well!

H. Mavalizadeh, L. Duffaut Espinosa, and M. Almassalkhi, “*Decentralized Frequency Control using Packet-based Energy Coordination*,” IEEE SmartGridComm, 2020

Frequency-responsive PEM (fully decentralized)

- We adapt PEM scheme for fast frequency response.
- Design local control law around packet interruption threshold mechanism that begets responsiveness to frequency.
- Importantly, we show how **DER coordinator can estimate the equivalent damping *online*** from timer distribution [2]
- Analyze tradeoff between available synthetic damping vs. frequency regulation capacity [2]

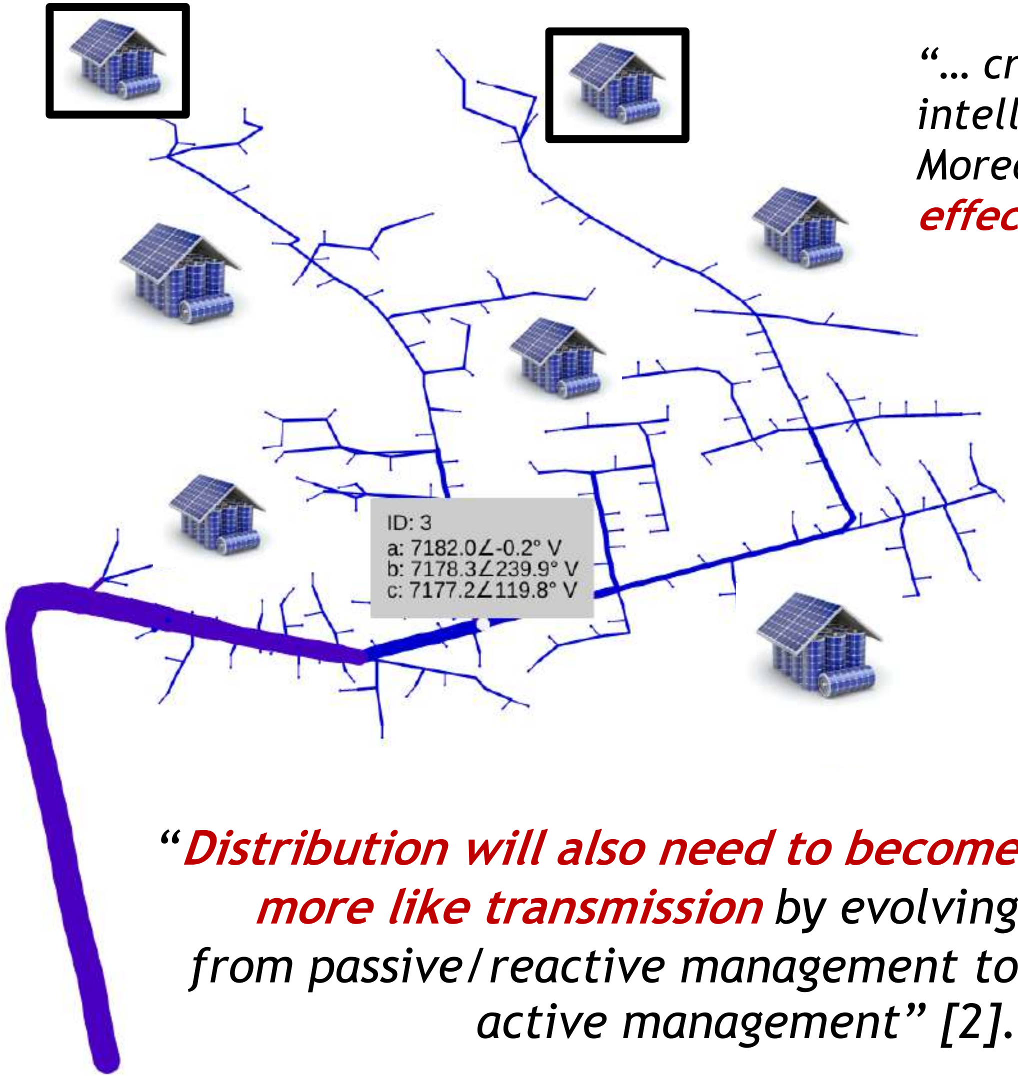


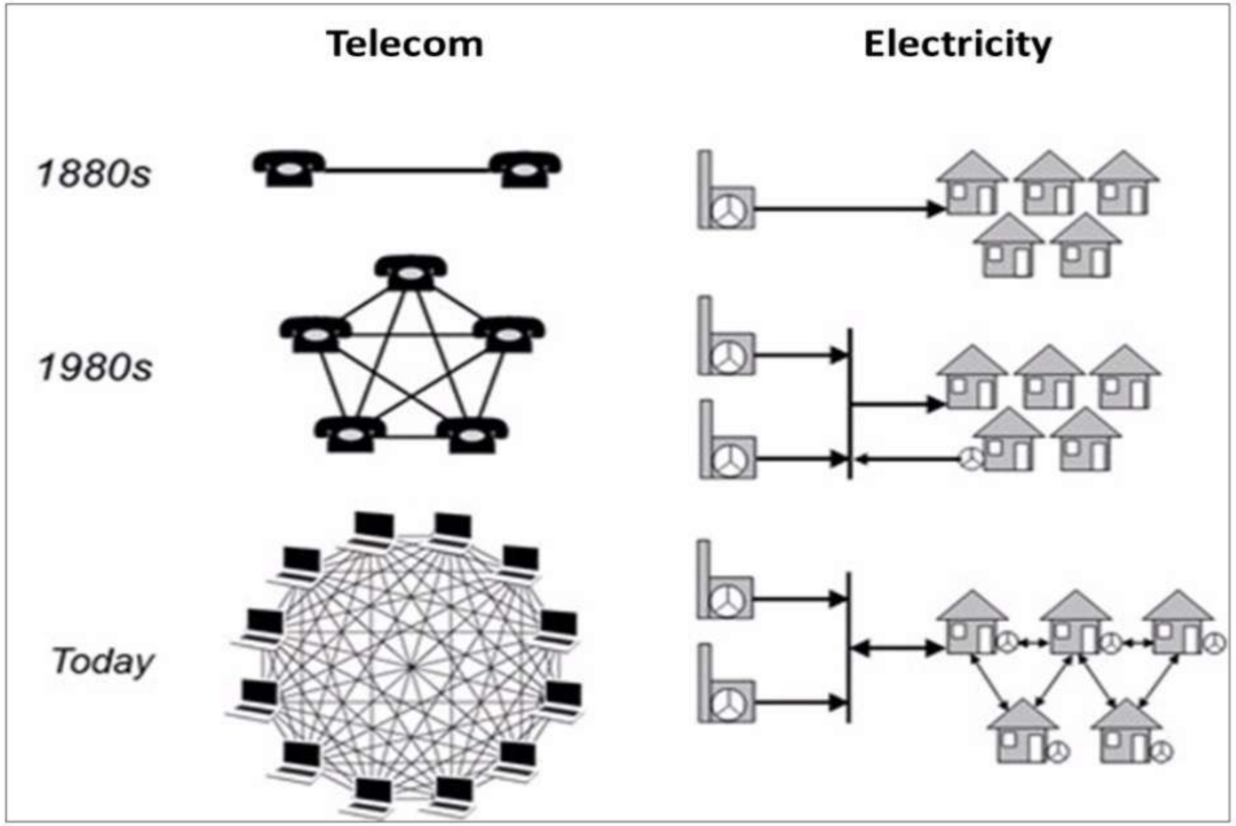
[1} **H. Mavalizadeh**, L. Duffaut Espinosa, and M. Almassalkhi, "*Decentralized Frequency Control using Packet-based Energy Coordination*," IEEE SmartGridComm, 2020

[2] **H. Mavalizadeh**, L. Duffaut Espinosa, and M. Almassalkhi, "*Improving frequency response with synthetic damping available from fleets of distributed energy resources*," IEEE TPWRS, 2023

What active role should the grid operator play?

*"… create open networks that increase value through the interaction of intelligent devices on the grid and prosumerization of customers Moreover, even **greater value can be realized through the synergistic effects of convergence of multiple networks**" [1].*





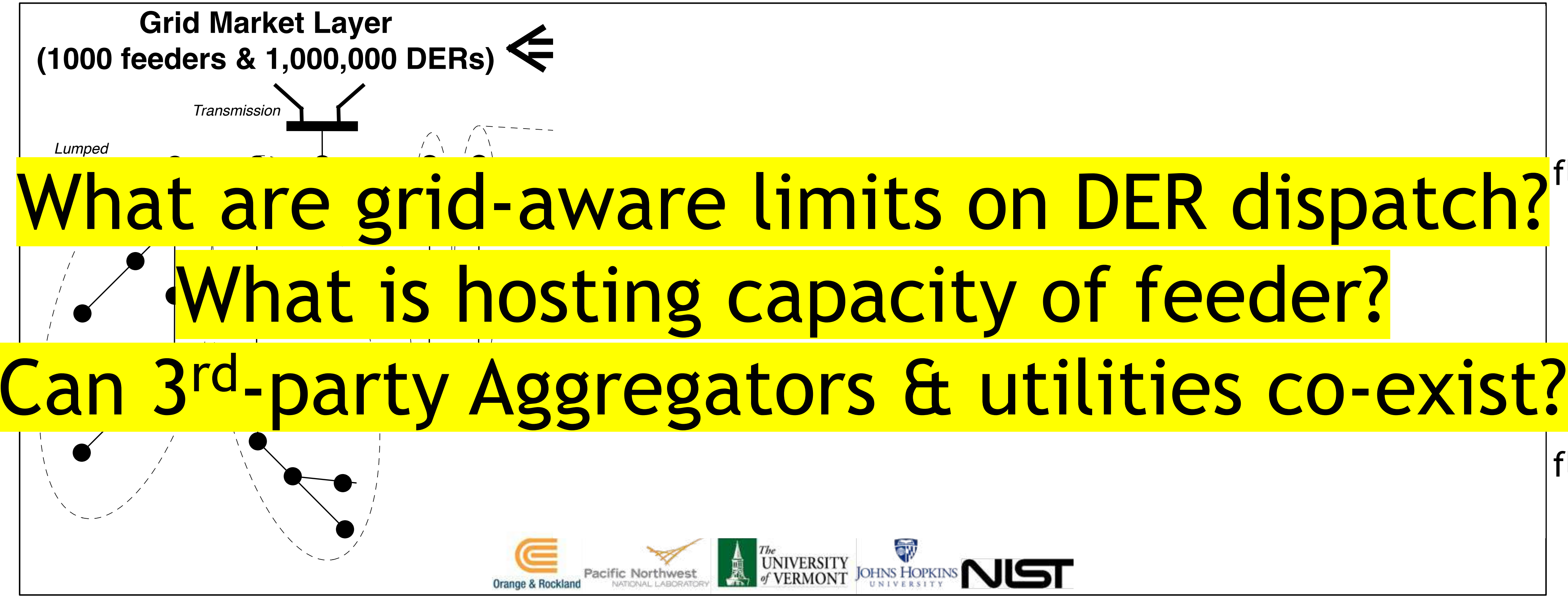
*"**Distribution will also need to become more like transmission** by evolving from passive/reactive management to active management" [2].*

Source [1]: Taft/DOE, Grid Architecture 2, 2016

Source [2]: De Martini/EEI, Future of Distribution, 2012

Past experiences with ”utility-centric” approaches

Utility-centric = utility does it all: network ops, DER coordination/dispatch, markets



What are grid-aware limits on DER dispatch?

What is hosting capacity of feeder?

Can 3rd-party Aggregators & utilities co-exist?

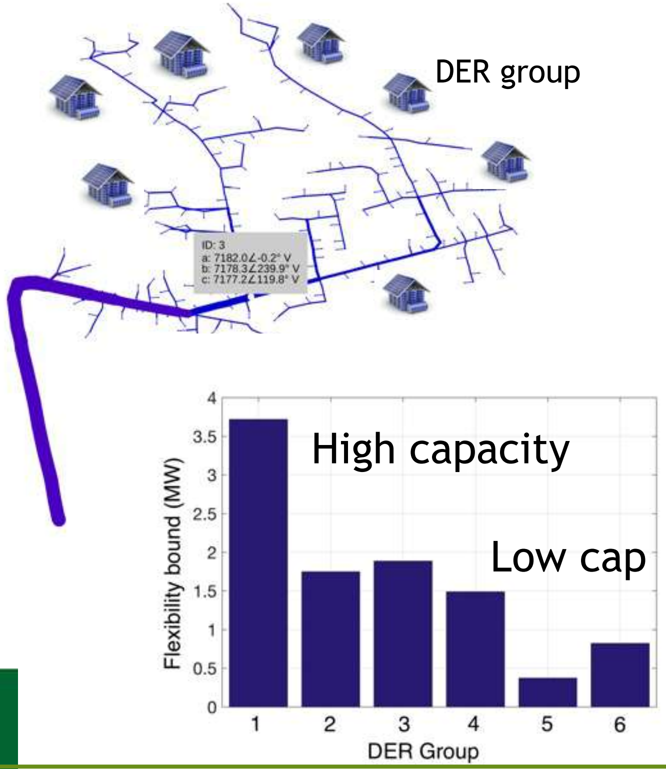
Local flexibility

Local flexibility

[W] Almassalkhi, et al, “Hierarchical, Grid-Aware, and Economically Optimal Coordination of Distributed Energy Resources in Realistic Distribution Systems,” Energies, 2020.
[X] Nawaf Nazir, Pavan Racherla, and Mads Almassalkhi, “Optimal multi-period dispatch of distributed energy resources in unbalanced distribution feeders”, IEEE Trans. on Power Systems, 2020
[Y] Nawaf Nazir and M. Almassalkhi, “Voltage positioning using co-optimization of controllable grid assets,” IEEE Trans. on Power Systems, 2020.
[Z] S. Brahma, Nawaf Nazir, et al, “Optimal and resilient coordination of virtual batteries in distribution feeders,” IEEE Trans. on Power Systems, 2020

Fundamental asymmetries in information & control

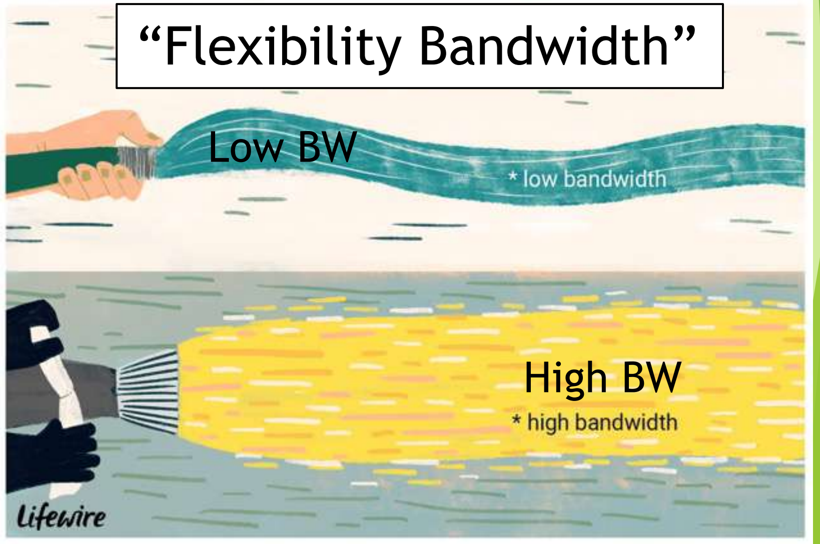
Utility (grid information+data)
- Need to ensure grid reliability
- Need to protect grid data
- Lack access to devices
- Knows grid capacity



Prices to devices?

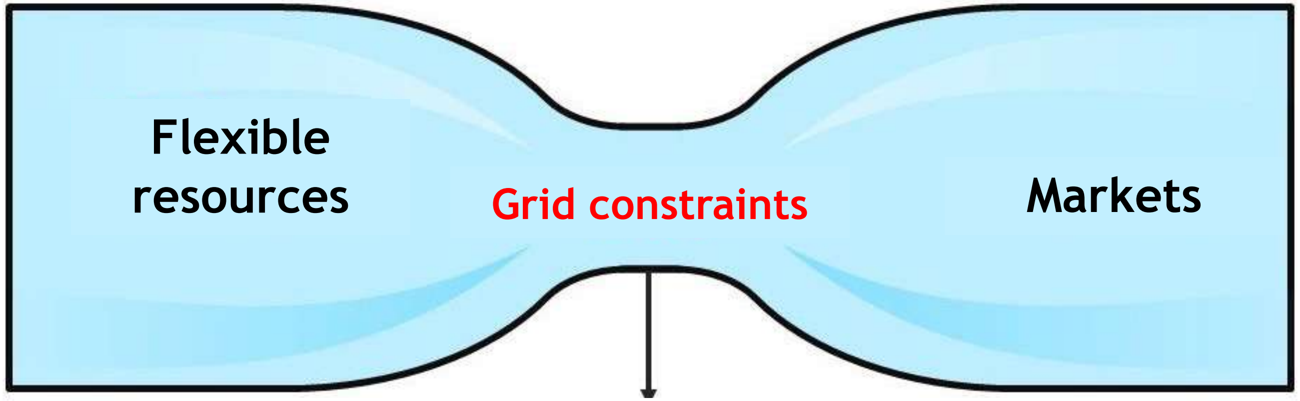
Let's try something different!

Aggregators (device access, markets)
- Need to ensure device QoS
- Need to provide market services
- Lacks access to grid data
- Knows device flexibility

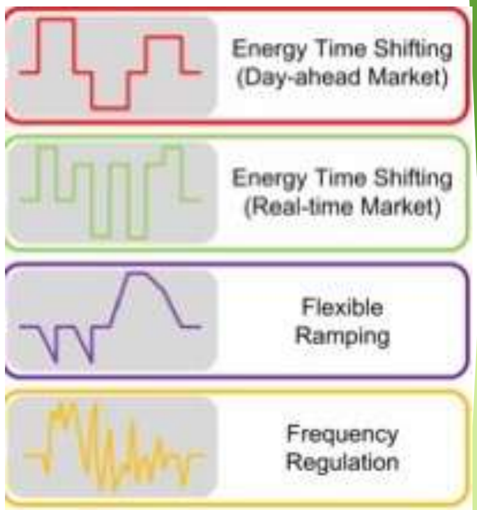


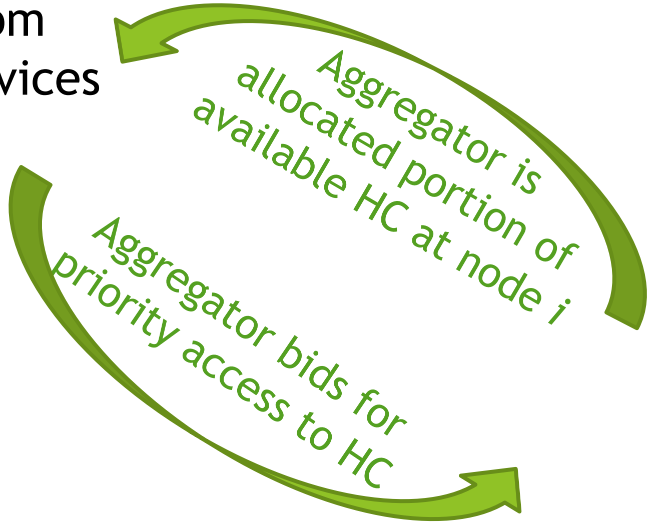
Idea: *think like an internet service provider (ISP)*

Aggregators:
flexibility from
coordinated devices



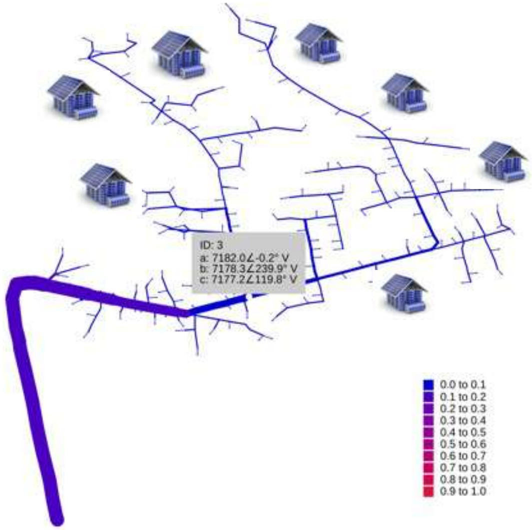
Utility: Decompose feeder HC at each node

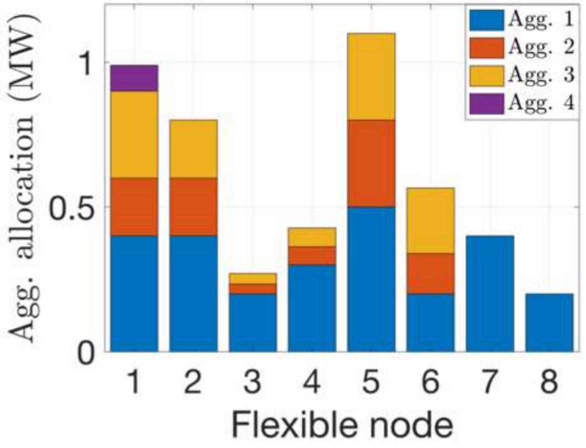




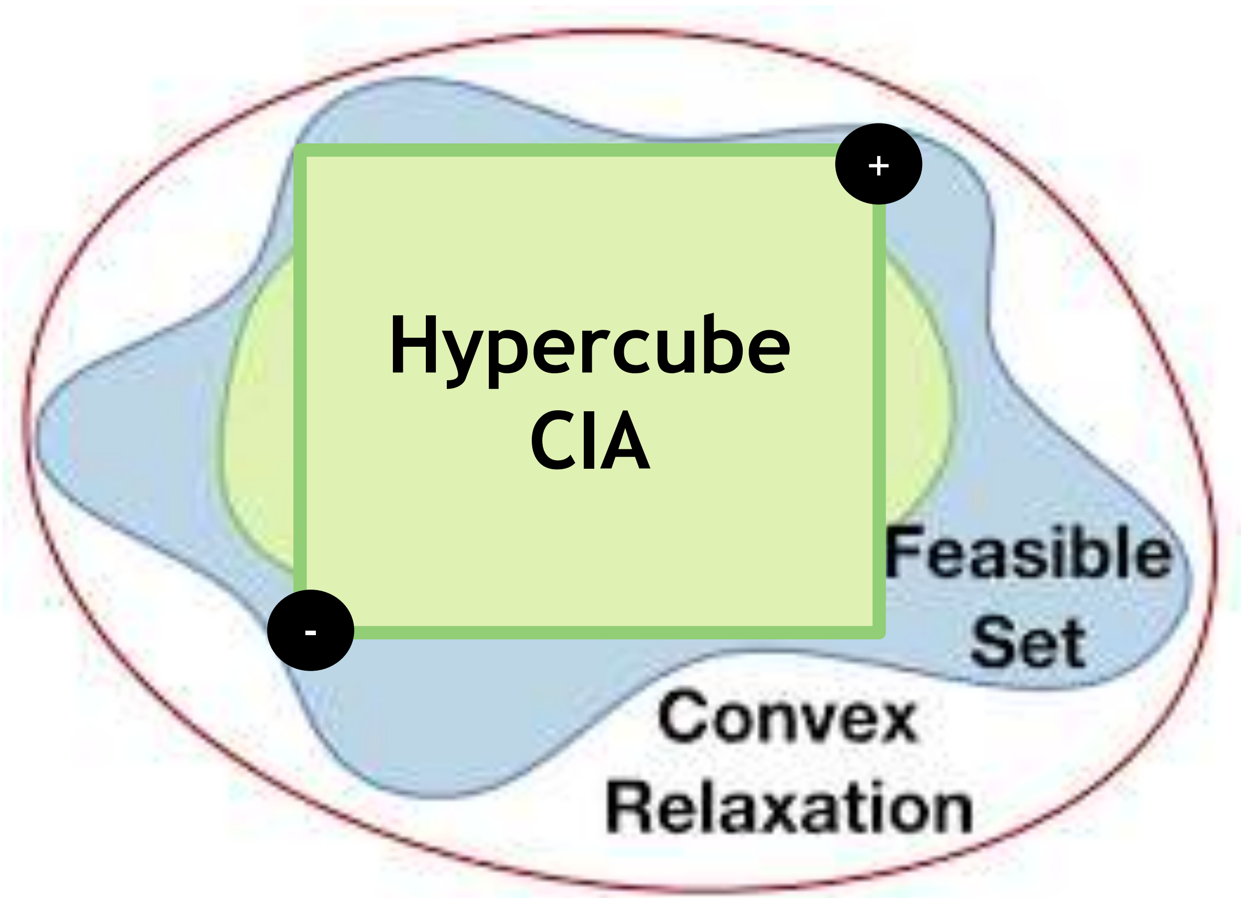
Aggregator is allocated portion of available HC at node *i*

Aggregator bids for priority access to HC





Convex inner approximation unlocks hosting capacity



Original Image source: D. Lee, H. D. Nguyen, K. Dvijotham and K. Turitsyn, "Convex Restriction of Power Flow Feasibility Sets," in *IEEE Transactions on Control of Network Systems*, vol. 6, no. 3, pp. 1235-1245, Sept. 2019.

Feasible set contains all dispatch solutions that are admissible (i.e., satisfy all constraints)

Convex relaxation contains feasible set + some solutions that are not admissible (infeasible).

Convex inner approximation (CIA) contains a convex subset of admissible solutions (suboptimal).

Goal: find largest hypercube to determine HC

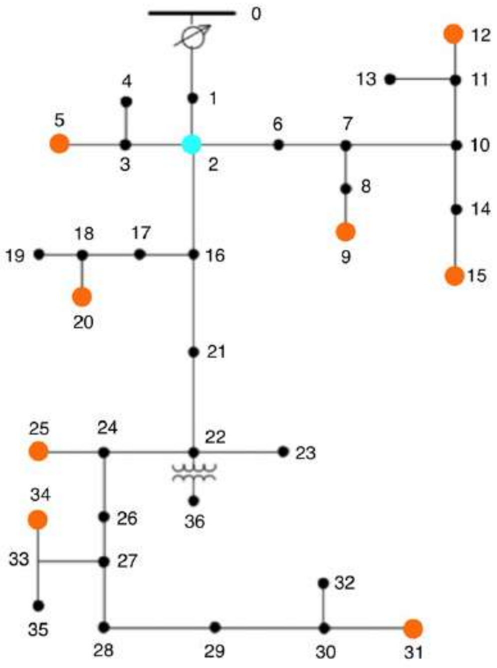
Approach: eliminate **non-convexity** via convex bounds

$$\underbrace{l_{\text{lb},ij}}_{\text{Shown to be affine}} \leq \boxed{l_{ij}(P_{ij},Q_{ij},v_j)=\frac{P_{ij}^2+Q_{ij}^2}{v_j},} \leq \underbrace{l_{\text{ub},ij}}_{\text{Shown to be convex}}$$

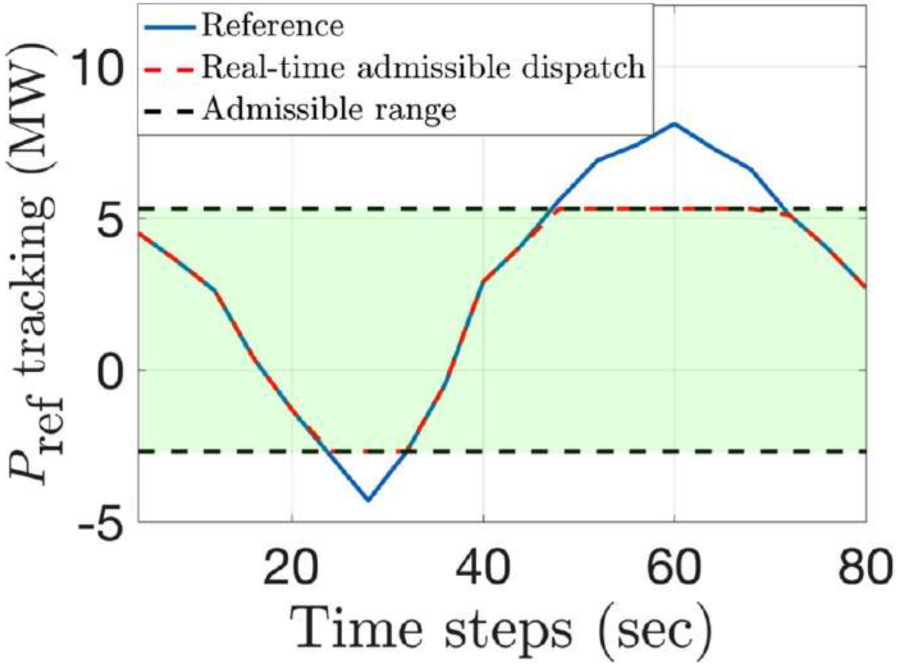
Nawaf Nazir and Mads Almassalkhi. "*Grid-aware aggregation and realtime disaggregation of distributed energy resources in radial networks,” IEEE TPWRS, 2021.*

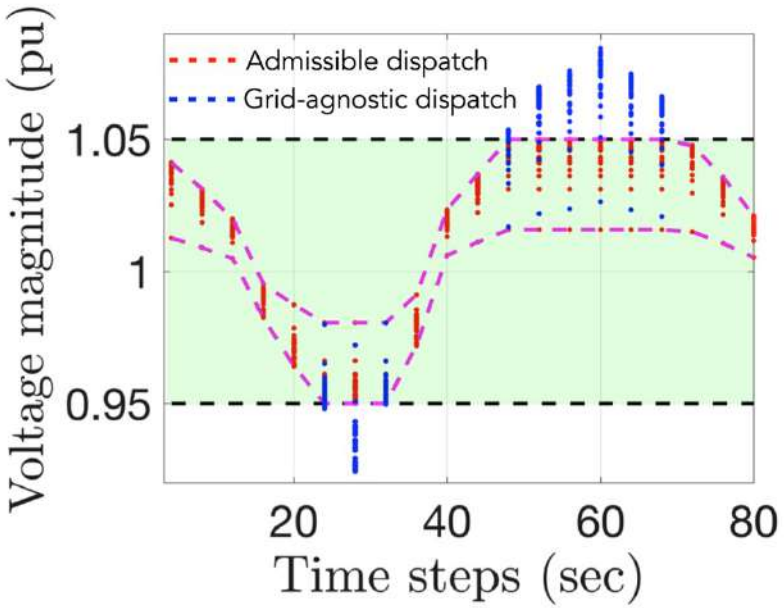
Inner approximations enable grid-aware disaggregation

Nodal capacities $[p_i^-, p_i^+]$ enable an open-loop, distributed, and **grid-aware DER control policy**



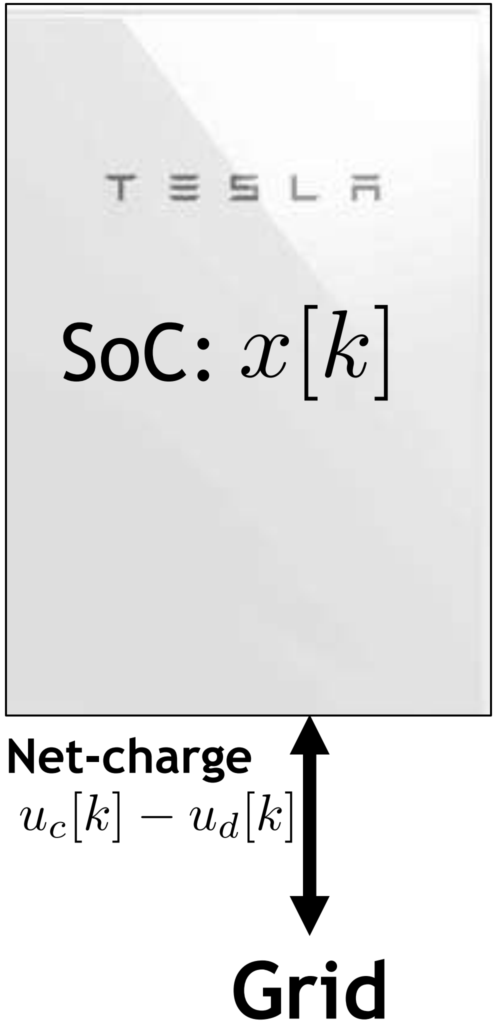
IEEE 37-node network
(from Baker/Dall'Anese)





N. Nazir and M. Almassalkhi, "Market mechanism to enable grid-aware dispatch of Aggregators in radial distribution networks,". IREP 2022.
N. Nazir and M. Almassalkhi, "Voltage positioning using co-optimization of controllable grid assets," *IEEE Transactions on Power Systems* vol. 36, no. 4, pp. 2761-2770, July 2021.
N. Nazir and M. Almassalkhi, "Grid-aware aggregation and realtime disaggregation of distributed energy resources in radial networks", IEEE Transactions on Power Systems, 2021

Another inner approximation: fast battery dispatch



SoC: $x[k]$

Net-charge

$u_c[k] - u_d[k]$

Grid

Nonlinear Battery Dispatch Model

$$x[k+1] = \alpha x[k] + \Delta t \eta_c u_c[k] - \frac{\Delta t}{\eta_d} u_d[k], \quad \forall k \in \mathcal{T}$$

$$\xcancel{u_c[k] u_d[k] = 0 \quad \forall k \in \mathcal{T}}$$

Non-convex

(Simultaneous dis/charging)

$$x[0] = x_0$$

$$0 \leq u_c[k] \leq P, \quad \forall k \in \mathcal{T}$$

$$0 \leq u_d[k] \leq P \quad \forall k \in \mathcal{T}$$

$$0 \leq x[k+1] \leq E, \quad \forall k \in \mathcal{T}$$

Linear (Robust) Battery Dispatch Model

$$\bar{x}[k+1] = \alpha \bar{x}[k] + \Delta t \eta \left(u_c[k] - u_d[k]\right), \quad \forall k \in \mathcal{T}$$

$$\underline{x}[k+1] = \alpha \underline{x}[k] + \Delta t \left(\eta_c u_c[k] - \frac{u_d[k]}{\eta_d}\right), \quad \forall k \in \mathcal{T}$$

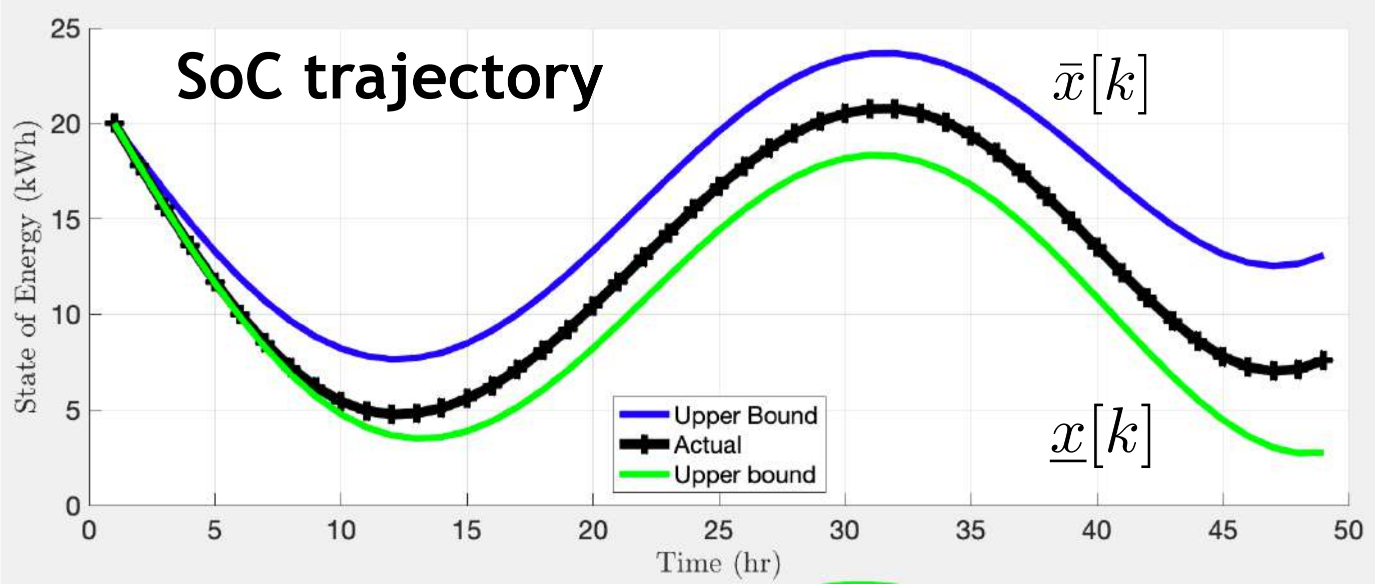
$$0 \leq u_c[k] \leq P, \quad \forall k \in \mathcal{T}$$

$$0 \leq u_d[k] \leq P \quad \forall k \in \mathcal{T}$$

$$0 \leq \underline{x}[k+1], \quad \forall k \in \mathcal{T}$$

$$\bar{x}[k+1] \leq E, \quad \forall k \in \mathcal{T}$$

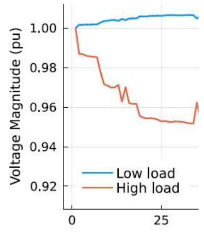
$$x[0] = x_0$$

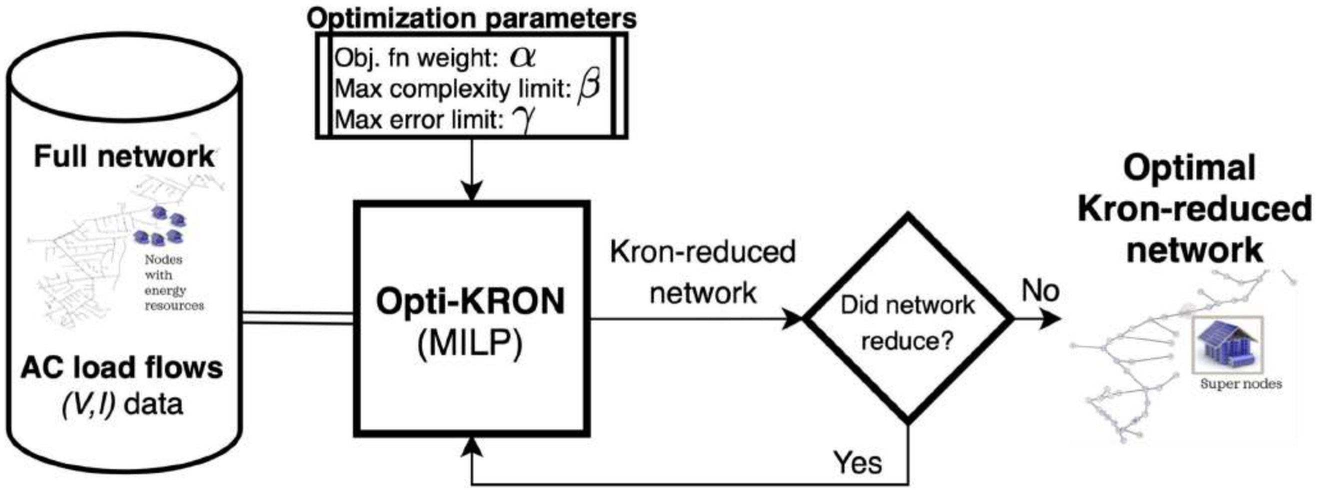


If robust model has dispatch, then nonlinear model does too.

Mazen Elsaadany and Mads R. Almassalkhi, "Battery Optimization for Power Systems: Feasibility and Optimality," *IEEE Conference on Decision and Control*, 2023.
N. Nazir and M. Almassalkhi "Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints," *IEEE TSG, 2021*

Scaling grid optimization with Opti-KRON




Optimization parameters
Obj. fn weight: α
Max complexity limit: β
Max error limit: γ

Full network

AC load flows
(V,I) data

Opti-KRON
(MILP)

Kron-reduced network

Did network reduce?

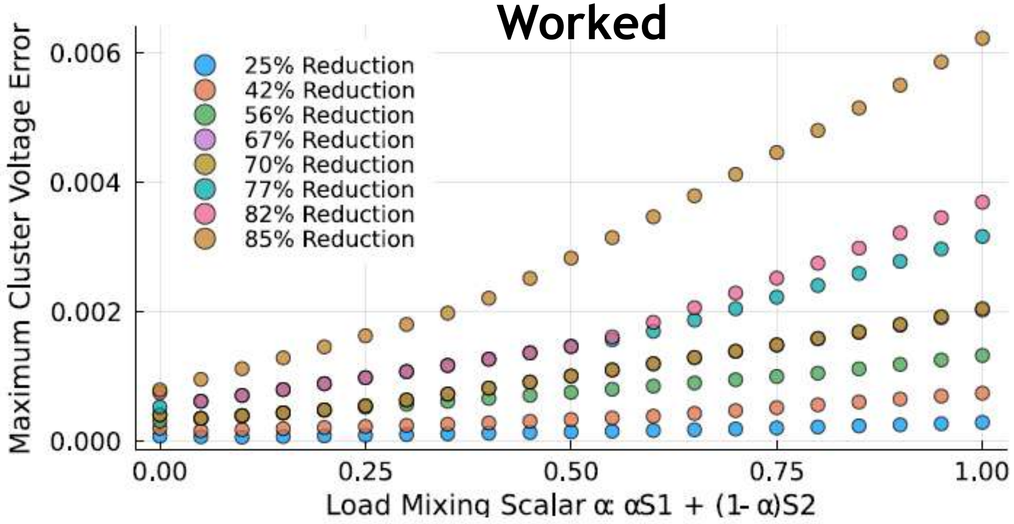
No

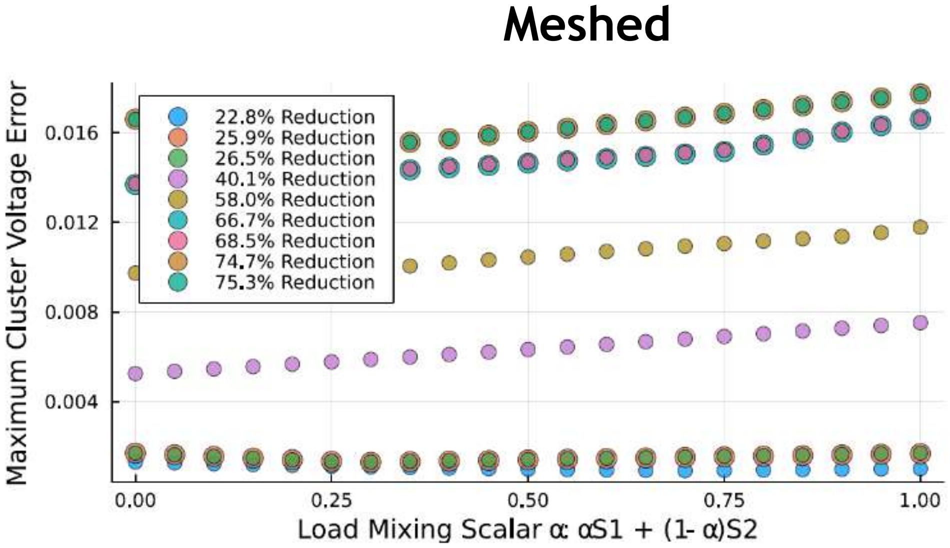
Yes

Optimal Kron-reduced network

Take-aways:

- Radial networks solved (0% gap) within 5 seconds
- Reduction up to 85%
- Meshed network much slower (10’s/100s seconds)
- Algorithm is sensitive to weighting parameters. Sometimes, it would make very interesting reduction decisions!


Worked


Meshed

S. Chevalier and M. Almassalkhi, "Towards Optimal Kron-based Reduction Of Networks (Opti-KRON) for the Electric Power Grid," *IEEE Conference on Decision and Control*, 2022.

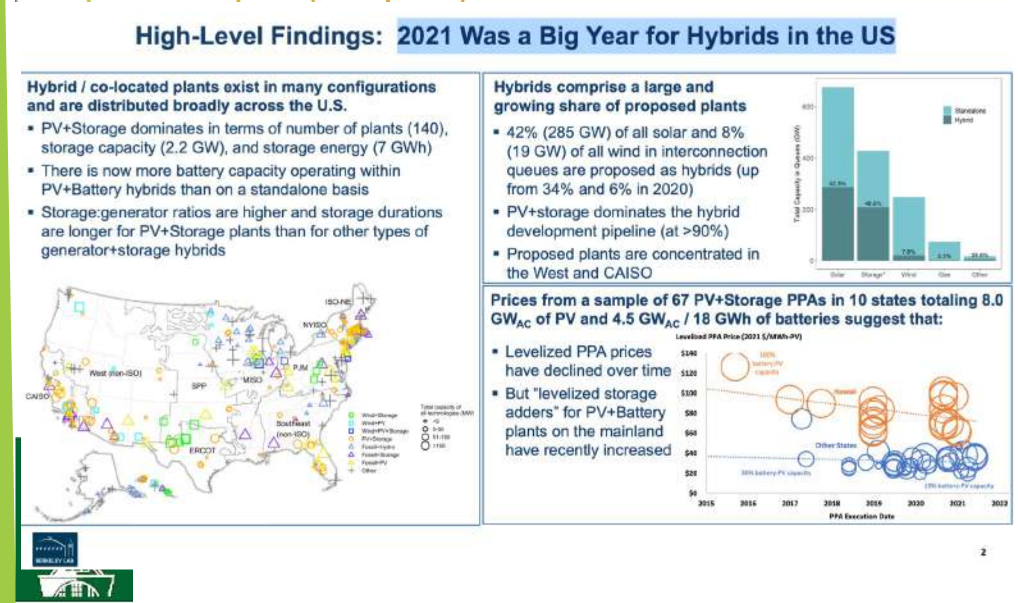
Hybrid Energy Systems

From virtual batteries to physical batteries

DOE is looking for answers. We can help!

Hybrid Energy Systems:

Opportunities for Coordinated Research



High-Level Findings: 2021 Was a Big Year for Hybrids in the US

Hybrid / co-located plants exist in many configurations and are distributed broadly across the U.S.

- PV+Storage dominates in terms of number of plants (140), storage capacity (2.2 GW), and storage energy (7 GWh)
- There is now more battery capacity operating within PV+Battery hybrids than on a standalone basis
- Storage:generator ratios are higher and storage durations are longer for PV+Storage plants than for other types of generator+storage hybrids

Hybrids comprise a large and growing share of proposed plants

- 42% (285 GW) of all solar and 8% (19 GW) of all wind in interconnection queues are proposed as hybrids (up from 34% and 6% in 2020)
- PV+storage dominates the hybrid development pipeline (at >90%)
- Proposed plants are concentrated in the West and CAISO

Prices from a sample of 67 PV+Storage PPAs in 10 states totaling 8.0 GW_{AC} of PV and 4.5 GW_{AC} / 18 GWh of batteries suggest that:

- Levelized PPA prices have declined over time
- But "levelized storage adders" for PV+Battery plants on the mainland have recently increased

2

Markets, Policy, and Regulation Opportunities

The objectives of the markets, policy, and regulation research area are to evaluate regulations, policies, ownership structures, and market products that are emerging or needed to ensure efficient operation of HES. To relate the greater sense of urgency for the markets, policy, and regulation opportunities, they are presented prior to those for valuation and technology development; in oth
conventional approaches in markets, policy, and regulation. Th
better understanding of the evolving development status, rule
responding to the potential impacts of higher penetrations of I
operations; improving the analysis of HES within interconnect
providing analytical and technical support to state regulatory

Markets Database

Synthesize and disseminate current

HES Integrati Studies

Analyze the impacts o

Technology Development Opportunities

Controls Development and Testing

Expand efforts to develop robust and efficient control solutions for additional technology combinations and service types, and improve coordination for related research activities across DOE offices.

Plant-Level Design Optimization

Improve coordination across efforts to develop methods and tools for evaluating the optimal sizing, linkages, and operations of HES for a wide array of technology combinations.

Advanced Computational Methods for Design: *Coordinate research activities related to the use of advanced computational methods for optimizing the design of the HES system and subsystems, including informing sizing, financial performance, technical performance, and lifetime estimations to maximize the value proposition of the HES.*

Dynamic Models: *Develop reduction techniques to accurately model and simulate HES in dynamic models.*

Components Development and Testing

Coordinate efforts to develop and test power electronics, devices, communications, heat exchangers, and intermediate loops for application at various time steps, leveraging recent and ongoing capabilities development for independent technologies.

Hardware Development: *Coordinate activities to improve the cost and performance of electrical, thermal, and/or chemical components that enable the efficient integration of multiple technologies to form HES.*

Component Testing: *Support testing and simulation of HES components across new and existing facilities and software platforms, including through emulation focused on power electronics, high-fidelity real-time simulations, hardware-in-the-loop testing, controller and power hardware, and balance of plant systems.*

Valuation Opportunities

The valuation research area focuses on tools, methods, and metrics for quantifying the value that different HES can provide, given hybrid system configuration, energy system, and market characteristics. HES come in a variety of types, are used in a variety of applications, and produce a variety of products. Comprehensive and harmonized valuation methodologies that encapsulate these variations are essential for determining which HES, if any, can best meet the needs of the electric and broader energy system. Opportunities are presented and organized in terms of identifying sources of value, developing consistent metrics and methodologies, and applying tools to estimate HES value over different scales and time horizons.

Sources of Value

Enhance information sharing across recent and ongoing HES research in different DOE offices to achieve harmonized value definitions and categories.

Products and Services Taxonomy: *Establish a harmonized definition for the services and products that HES*

Methodologies and Metrics to Measure Value

Establish common methods and metrics for evaluating candidate HES to enable an apples-to-apples comparison of candidate HES.

Resource and Product Complementarity: *Expand ongoing complementarity analyses to new*

Estimating Value

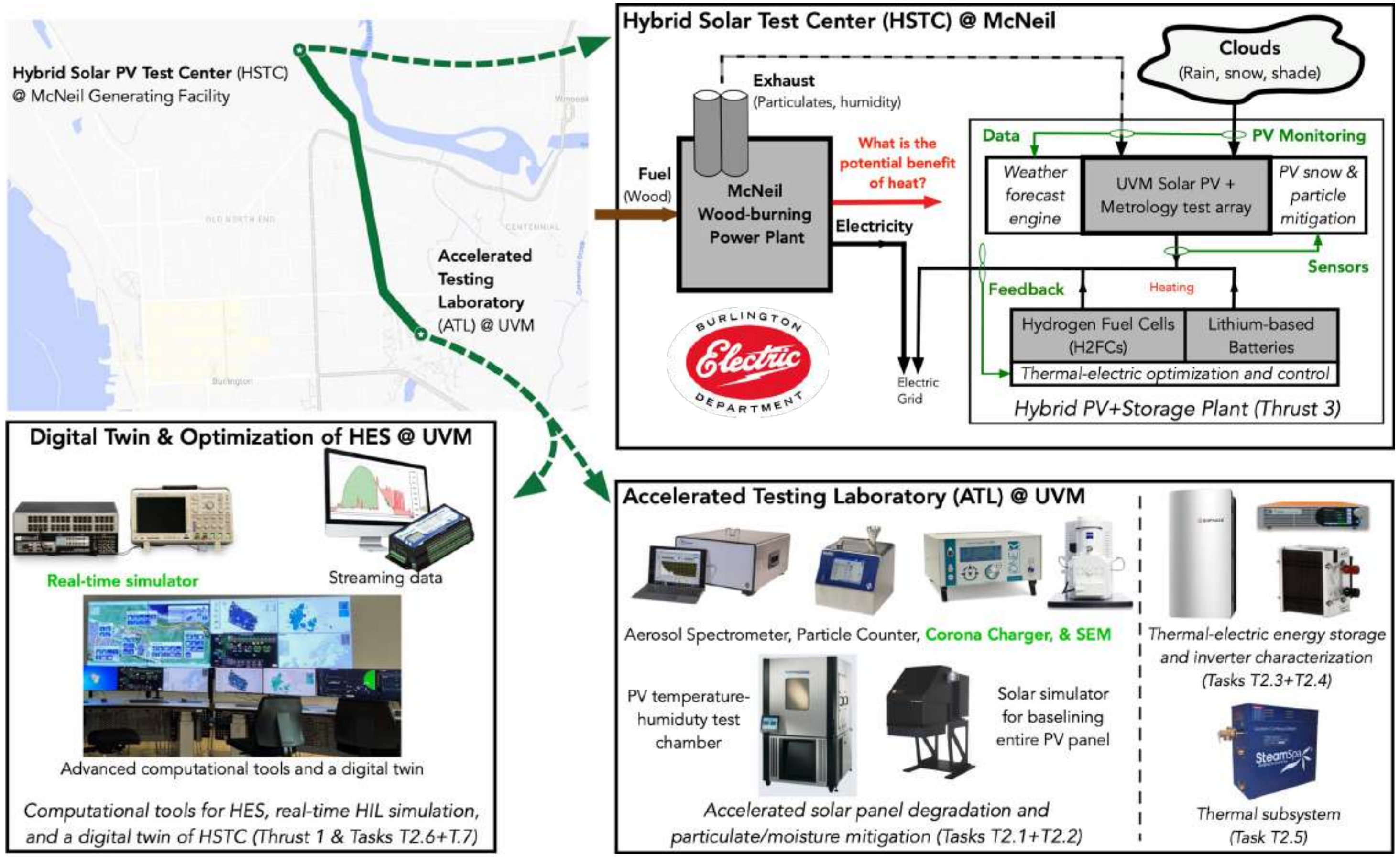
Estimate the value that HES can provide through analyses that expand and leverage past and ongoing research for select technology combinations.

Plant-Level vs. System-Level Optimization: *Evaluate how the optimal design and value of HES vary*

DOE reports from 2022

New hybrid energy systems coming to UVM!

Hybrid energy systems = *Coupling Heat* + *PV* + *Storage* + *Hydrogen* + *Power* = Lots of Data = Learning



Field deployment and validation of R&D

- integrating heat and electricity subsystems
- thermal-electric modeling, control, optimization, operations, planning
- grid services
- reliability
- lifetime analysis

Next-generation Energy Systems Simulation Testbed (NES^{2}T)

"Digital Twin of Vermont's Grid"

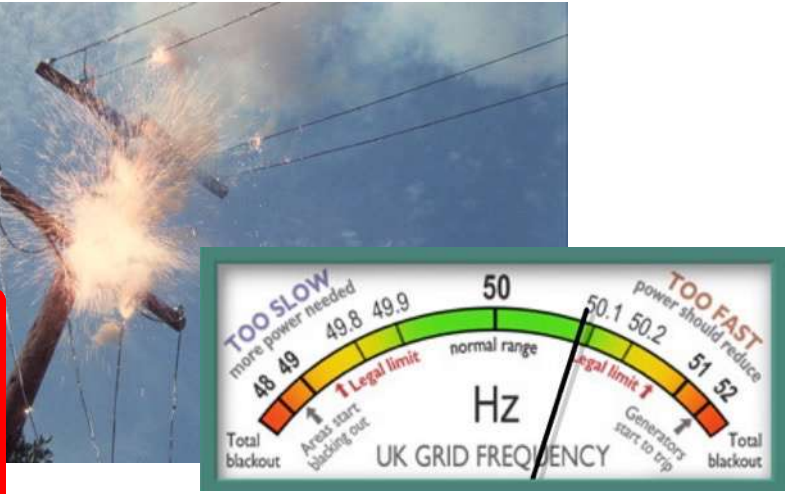
Accelerated Testing Lab (ATL) for *hardware-enabled Energy Testing*

HSTC = Hybrid Solar Test Center (1 mile from campus)

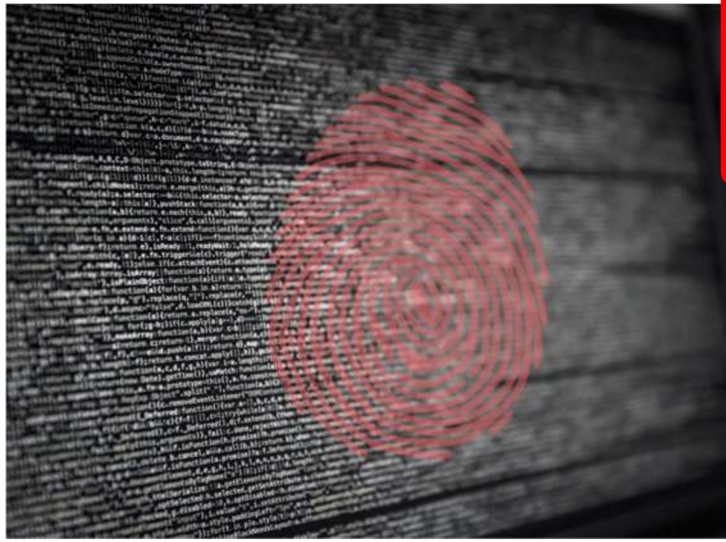
Summary: bottlenecks for *intelligent electrification*

Comfort & convenience (human constraints)

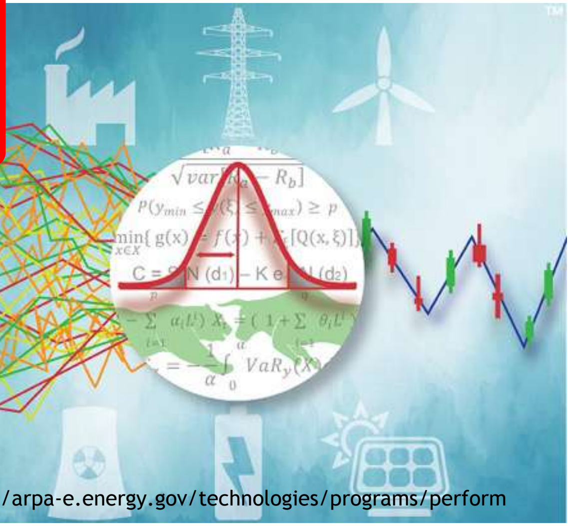
Grid conditions & reliability (network constraints)



Cyber-security & data privacy



Business models & risk management



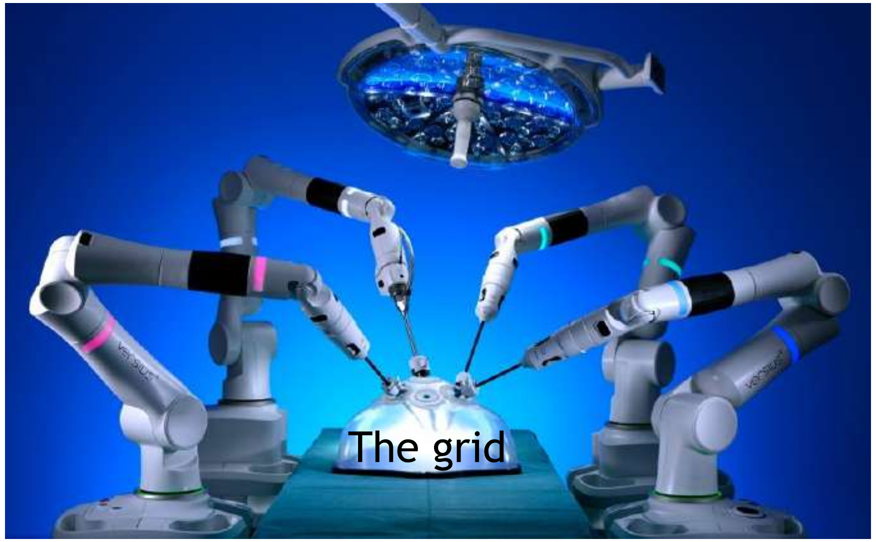
https://arpa-e.energy.gov/technologies/programs/perform

Thank you! Questions? Comments?

✉ *malmassa@uvm.edu* @theEnergyMads https://madsalma.github.io

Traditional demand response

Today's flexibility: ***not your parent's DR***



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