Enabling a responsive grid with distributed load control & optimization

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The UNIVERSITY of VERMONT

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PACKETIZED ENERGY

Michigan Control Seminar

University of Michigan, Ann Arbor, MI

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Legal Disclaimer

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

PACKETIZED ENERGY

Acknowledgements

Active/recent collaborators

- Prof. Pierre Pinson (Imperial)
- Prof. Henrik Madsen (DTU)
- Dr. Sam Chevalier (DTU/UVM)
- Dr. Sarnaduti Brahma (UVM/Siemens)
- Prof. Hamid Ossareh (UVM)
- Prof. Luis Duffaut Espinosa (UVM)
- Dr. Paul Hines (EnergyHub)
- Prof. Jeff Frolik (UVM)
- Prof. James Bagrow (UVM)
- Prof. Sumit Paudyal (FIU)
- Prof. Dennice Gayme (JHU)
- Prof. Enrique Mallada (JHU)
- Dr. Dhananjay Anand (JHU)
- Dr. Soumya Kundu (PNNL/UVM)
- Prof. Roland Malhamé (Poly Montreal)
- Prof. Timm Faulwasser (TU-Dortmund)
- Dr. Alexander Engelmann (TU-Dortmund)
- Dr. Ning Qi (Tsinghua)
- Prof. Ian Hiskens (UMICH)
- Prof. Johanna Mathieu (UMICH)

Current group members

- Dr. Tanmay Mishra (Post-doc)
- Mr. Hani Mavalizadeh (PhD student)
- Mr. Waheed Owonikoko (PhD Student)
- Mr. Mazen El-Saadany (PhD Student)
- Ms. Rebecca Holt (undergraduate researcher)
- Ms. Emily Ninestein (undergraduate researcher)
- Ms. Kendall Meinhofer (undergraduate researcher)

Group Alumni

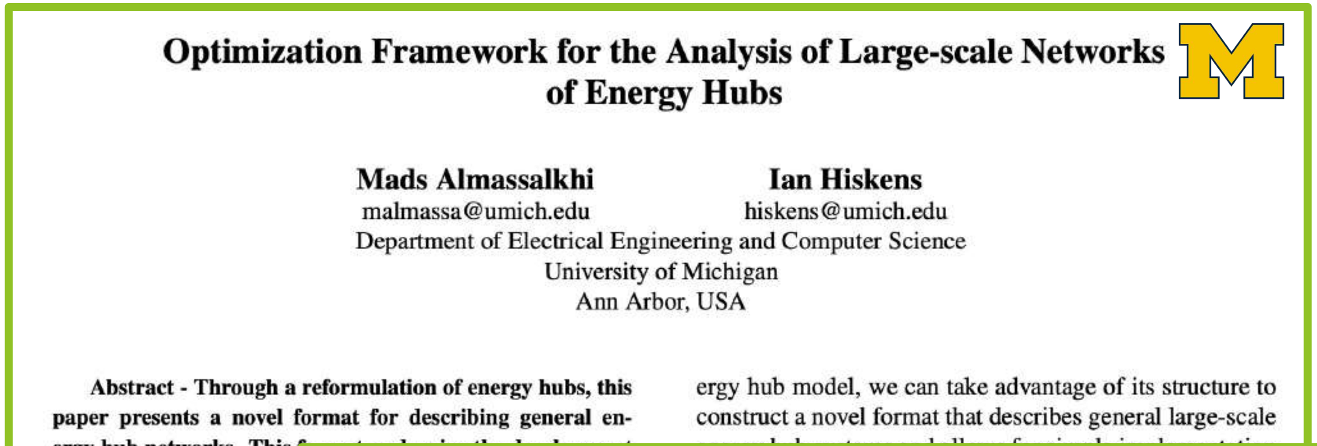
- Dr. Adil Khurram (PhD EE'21) → Scientist @ UCSD (San Diego, CA)
- Dr. Nawaf Nazir (PhD EE'20) → Research @ PNNL (Richland, WA)
- Dr. Mahraz Amini (PhD EE'19) → Strategy @ NatGrid (Dallas, TX)
- Mr. Micah Botkin Levy (MSEE'19) → Modeling @ Form Energy (SF, CA)
- Mr. Zach Hurwitz (MSME'19) → Energy @ Siemens (ME)
- Mr. Lincoln Sprague (MSEE'17) → Compliance @ Dynapower (VT)
- Ms. Anna Towle (BSEE'16) → Trader @ Fortum (Sweden)

Personal reflections: old photos and first papers

Mads in Denmark (1993-ish)

Dissertation defense (May 2013)

First papers in grad school were on Energy Hubs



Optimization Framework for the Analysis of Large-scale Networks of Energy Hubs

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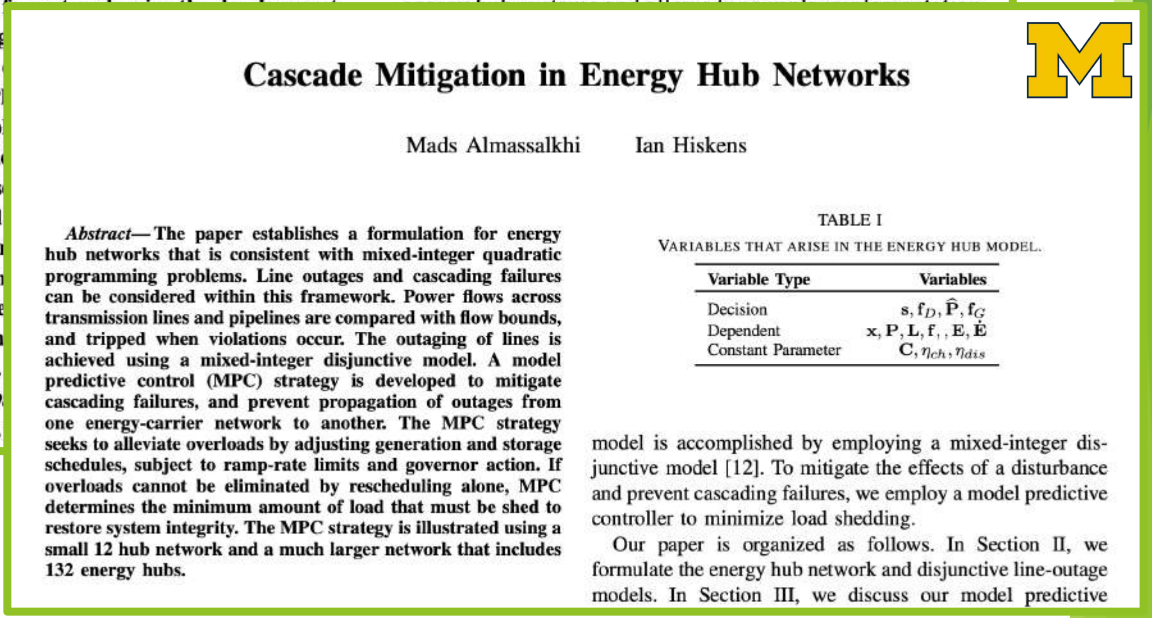
University of Michigan
Ann Arbor, USA

Abstract - Through a reformulation of energy hubs, this paper presents a novel format for describing general energy hub networks. This
of tools for analyzing larg
networks. The tools are
lessly interface with CP
low users to quickly imp
ing problems. Our applic
scription file as input, us
for the entire system, and
CPLEX. The work presen
natural gas networks, win
loads, and the main eleme
energy storage). Addition
ments is straightforward.
Keywords - Energy hub
power system modeling,

ergy hub model, we can take advantage of its structure to construct a novel format that describes general large-scale



Cascade Mitigation in Energy Hub Networks

Mads Almassalkhi Ian Hiskens

***Abstract*—The paper establishes a formulation for energy hub networks that is consistent with mixed-integer quadratic programming problems. Line outages and cascading failures can be considered within this framework. Power flows across transmission lines and pipelines are compared with flow bounds, and tripped when violations occur. The outaging of lines is achieved using a mixed-integer disjunctive model. A model predictive control (MPC) strategy is developed to mitigate cascading failures, and prevent propagation of outages from one energy-carrier network to another. The MPC strategy seeks to alleviate overloads by adjusting generation and storage schedules, subject to ramp-rate limits and governor action. If overloads cannot be eliminated by rescheduling alone, MPC determines the minimum amount of load that must be shed to restore system integrity. The MPC strategy is illustrated using a small 12 hub network and a much larger network that includes 132 energy hubs.**

TABLE I
VARIABLES THAT ARISE IN THE ENERGY HUB MODEL.

Variable Type	Variables
Decision	$\mathbf{s}, \mathbf{f}_D, \hat{\mathbf{P}}, \mathbf{f}_G$
Dependent	$\mathbf{x}, \mathbf{P}, \mathbf{L}, \mathbf{f}, , \mathbf{E}, \dot{\mathbf{E}}$
Constant Parameter	$\mathbf{C}, \eta_{ch}, \eta_{dis}$

model is accomplished by employing a mixed-integer disjunctive model [12]. To mitigate the effects of a disturbance and prevent cascading failures, we employ a model predictive controller to minimize load shedding.

Our paper is organized as follows. In Section II, we formulate the energy hub network and disjunctive line-outage models. In Section III, we discuss our model predictive

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
(Starts Aug 2023)

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

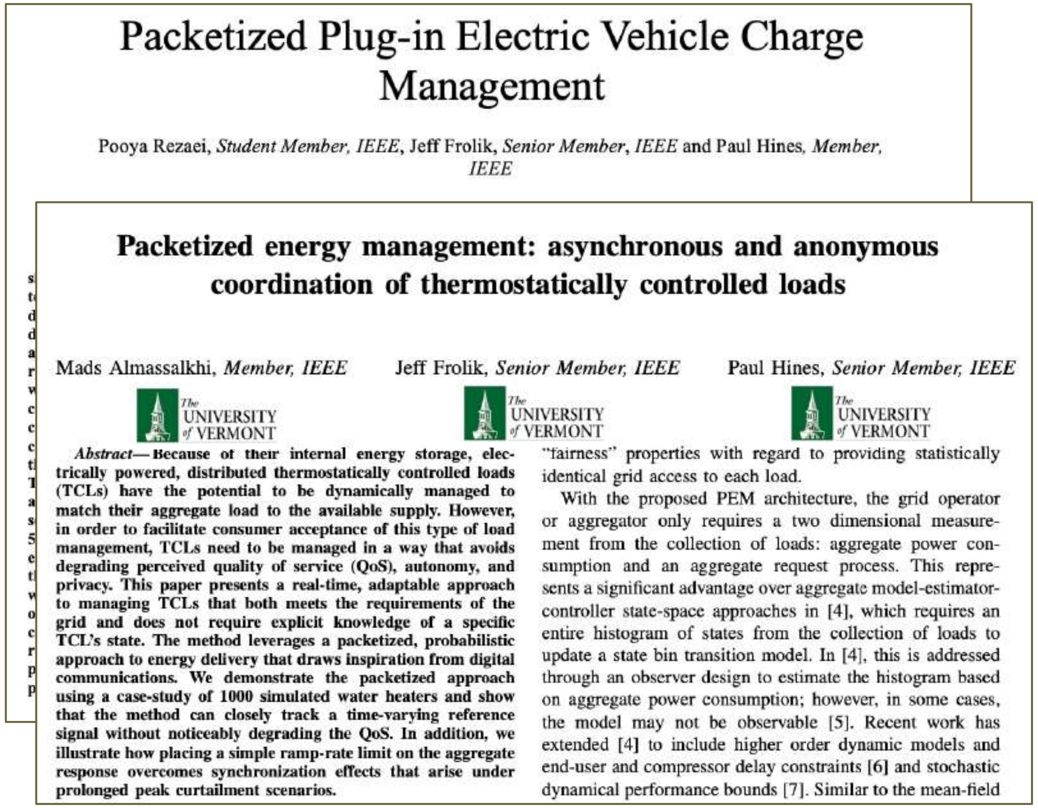
NIST National Institute of Standards and Technology

DEPARTMENT OF ENERGY UNITED STATES OF AMERICA

NSF

NASA

Recent success with translational research



Packetized Plug-in Electric Vehicle Charge Management

Pooya Rezaei, *Student Member, IEEE*, Jeff Frolik, *Senior Member, IEEE* and Paul Hines, *Member, IEEE*

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*

The UNIVERSITY of VERMONT The UNIVERSITY of VERMONT The UNIVERSITY of VERMONT

***Abstract*— Because of their internal energy storage, electrically powered, distributed thermostatically controlled loads (TCLs) have the potential to be dynamically managed to match their aggregate load to the available supply. However, in order to facilitate consumer acceptance of this type of load management, TCLs need to be managed in a way that avoids degrading perceived quality of service (QoS), autonomy, and privacy. This paper presents a real-time, adaptable approach to managing TCLs that both meets the requirements of the grid and does not require explicit knowledge of a specific TCL's state. The method leverages a packetized, probabilistic approach to energy delivery that draws inspiration from digital communications. We demonstrate the packetized approach using a case-study of 1000 simulated water heaters and show that the method can closely track a time-varying reference signal without noticeably degrading the QoS. In addition, we illustrate how placing a simple ramp-rate limit on the aggregate response overcomes synchronization effects that arise under prolonged peak curtailment scenarios.**

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

With the proposed PEM architecture, the grid operator or aggregator only requires a two dimensional measurement from the collection of loads: aggregate power consumption and an aggregate request process. This represents a significant advantage over aggregate model-estimator-controller state-space approaches in [4], which requires an entire histogram of states from the collection of loads to update a state bin transition model. In [4], this is addressed through an observer design to estimate the histogram based on aggregate power consumption; however, in some cases, the model may not be observable [5]. Recent work has extended [4] to include higher order dynamic models and end-user and compressor delay constraints [6] and stochastic dynamical performance bounds [7]. Similar to the mean-field

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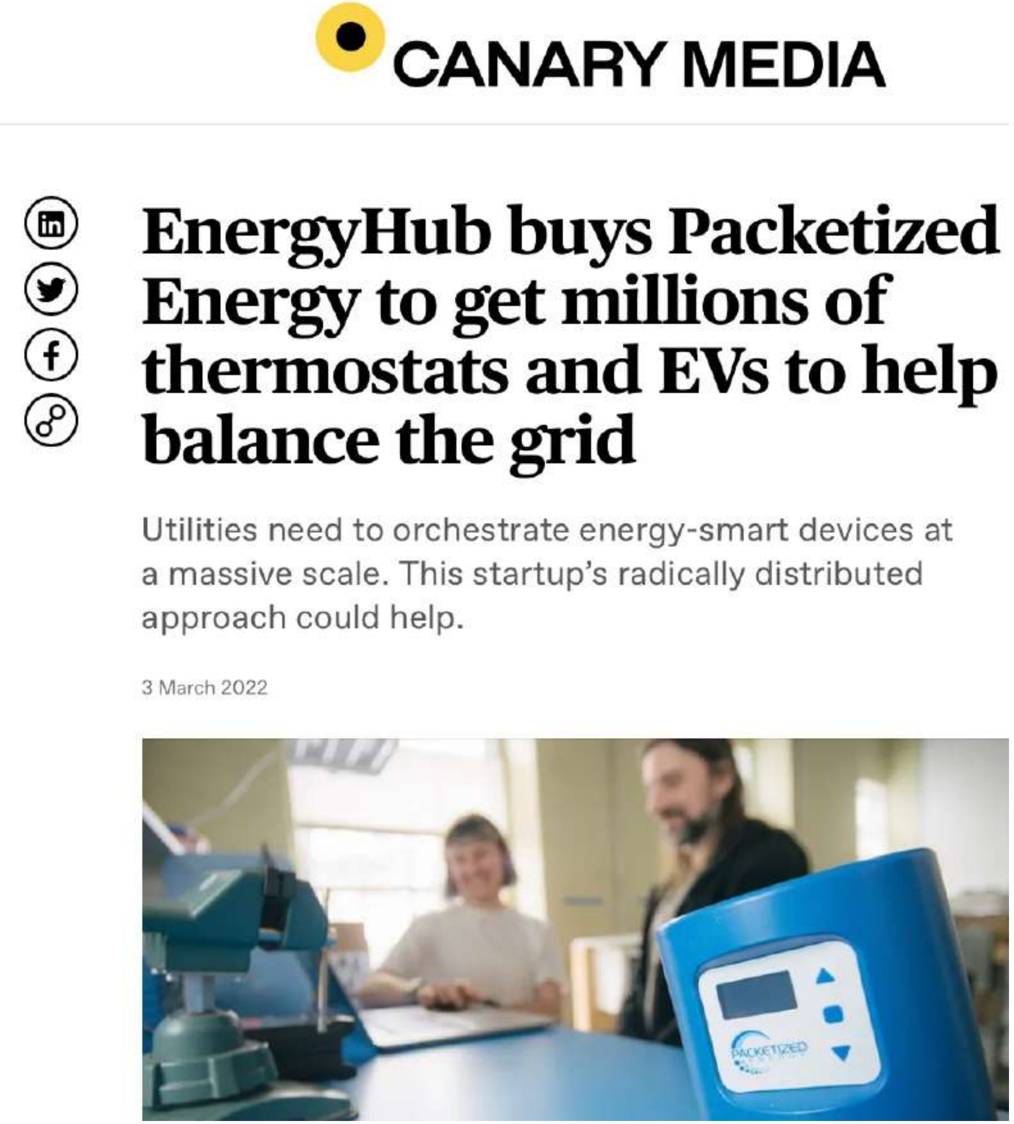
Numerous academic papers+ research projects+ IP + industry partners (2012-present)

\+ PACKETIZED ENERGY

Co-founded startup company (2016)

Accessing scale with tech: 700 devices → 900,000



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.

3 March 2022

EnergyHub + PACKETIZED ENERGY

1000X

Why does it matter? Green economies are rising….

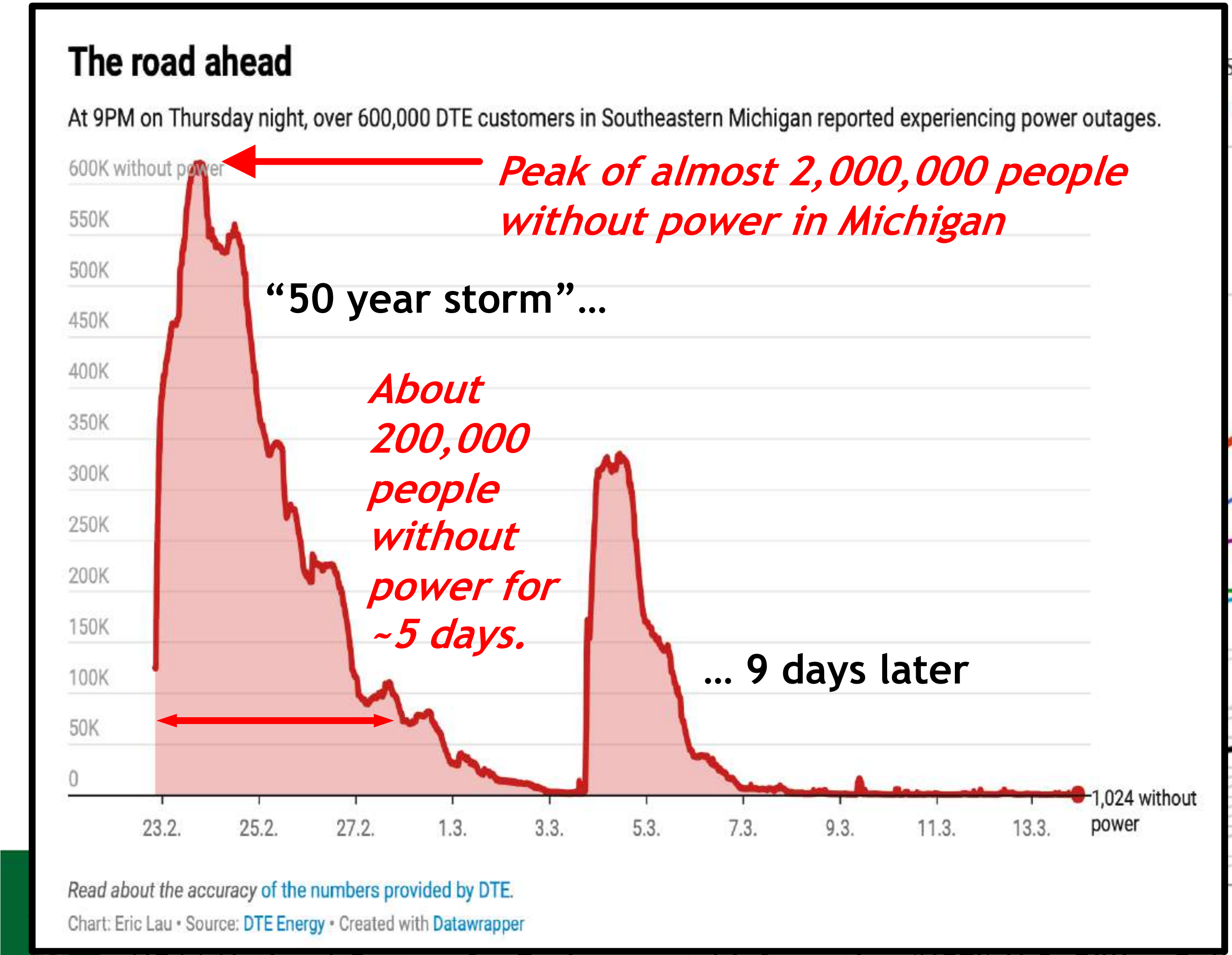
$1.3T Annual sales revenue

10M Jobs supported

Green economy := environmental, low carbon and renewable energy activities

Georgeson, L., Maslin, M. “Estimating the scale of the US green economy within the global context.” *Palgrave Communications* 5, 121 (2019)

…but so are climate challenges



The road ahead

At 9PM on Thursday night, over 600,000 DTE customers in Southeastern Michigan reported experiencing power outages.

Peak of almost 2,000,000 people without power in Michigan

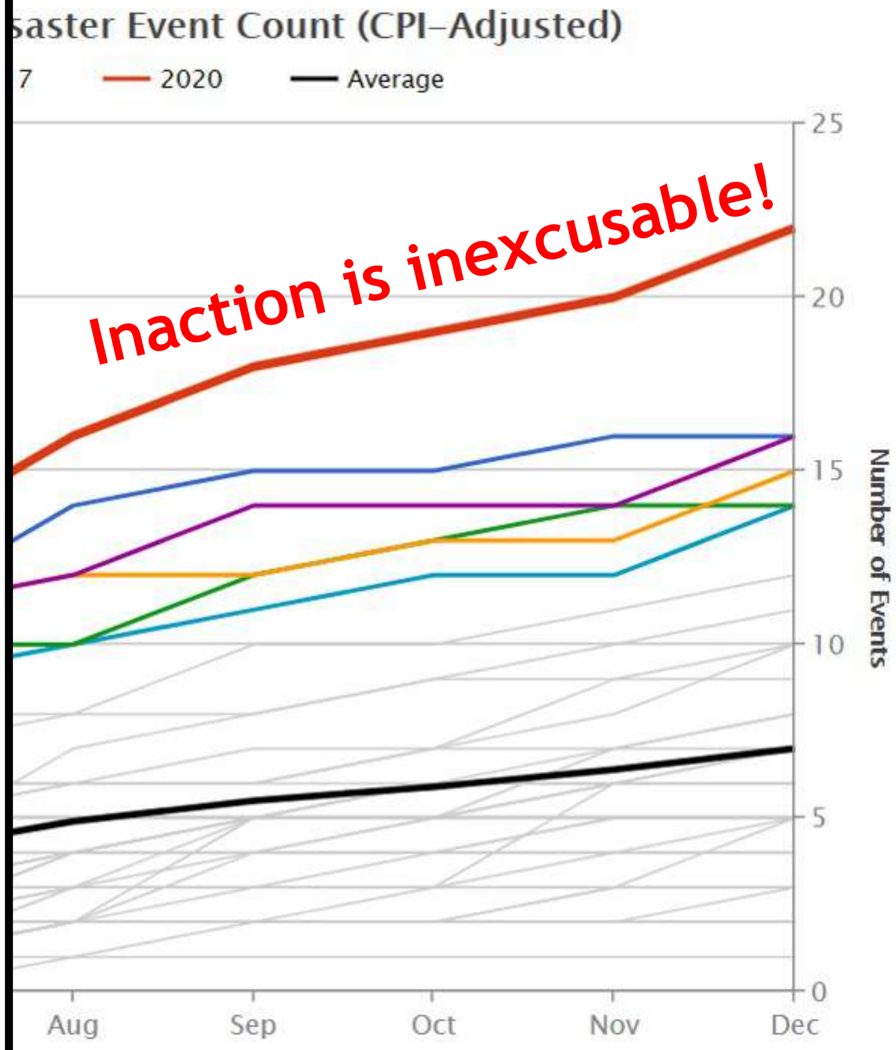
"50 year storm"…

About 200,000 people without power for ~5 days.

… 9 days later

Read about the accuracy of the numbers provided by DTE.

Chart: Eric Lau • Source: DTE Energy • Created with Datawrapper

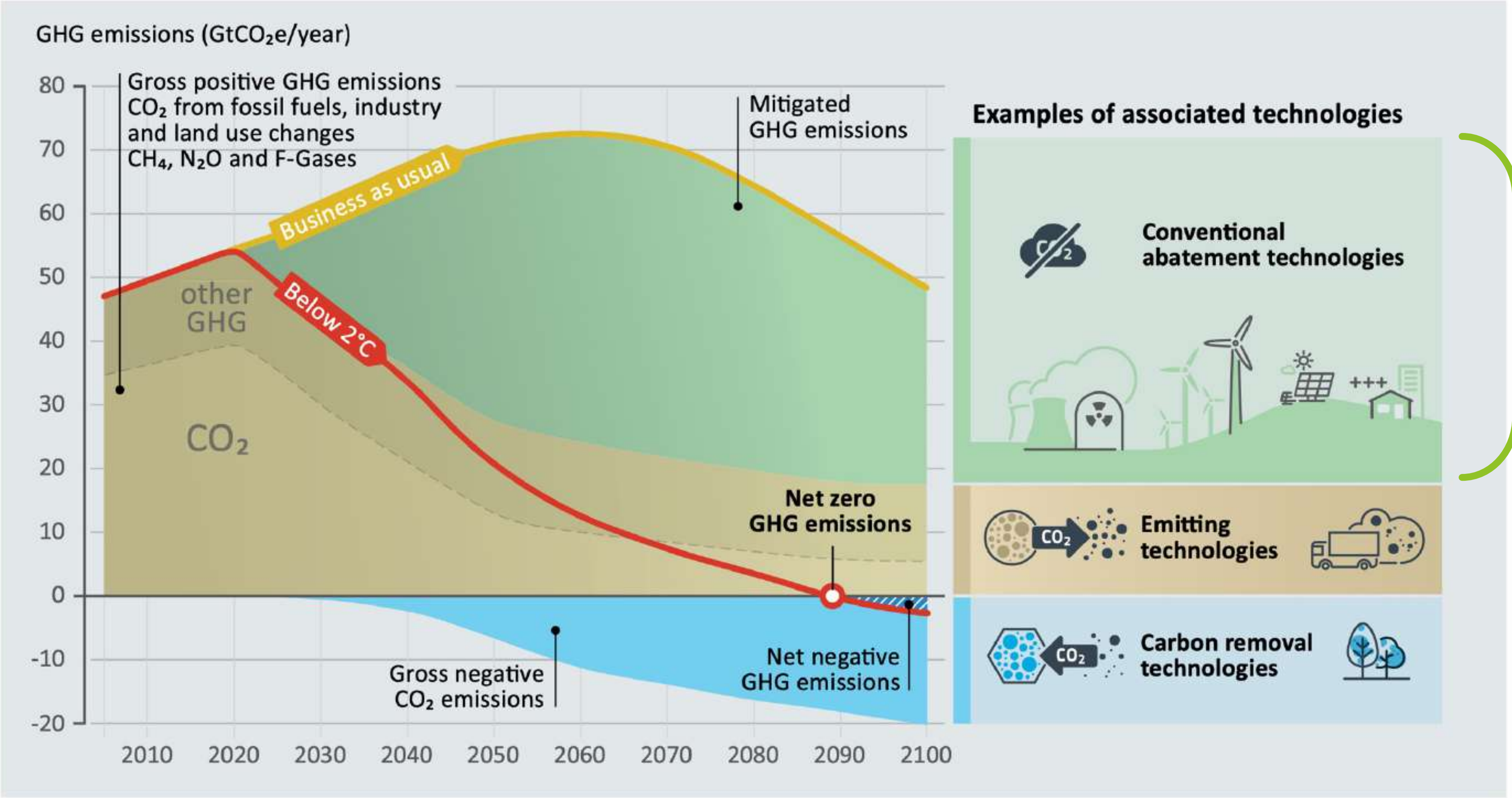


saster Event Count (CPI–Adjusted)

Inaction is inexcusable!

NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2020)

Solutions? If they work, they will matter!



Requires massive TW-scale renewable integration

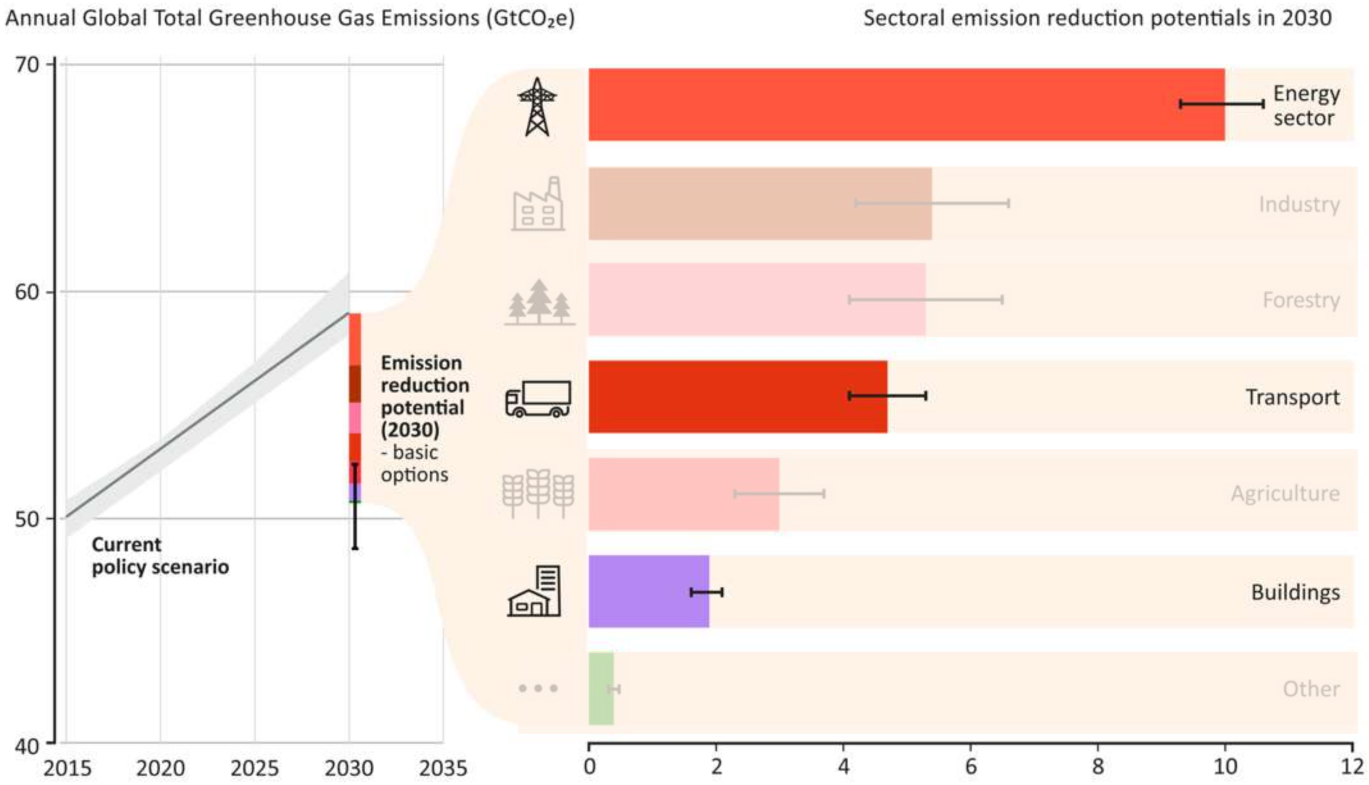
A massive power systems challenge!

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]

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

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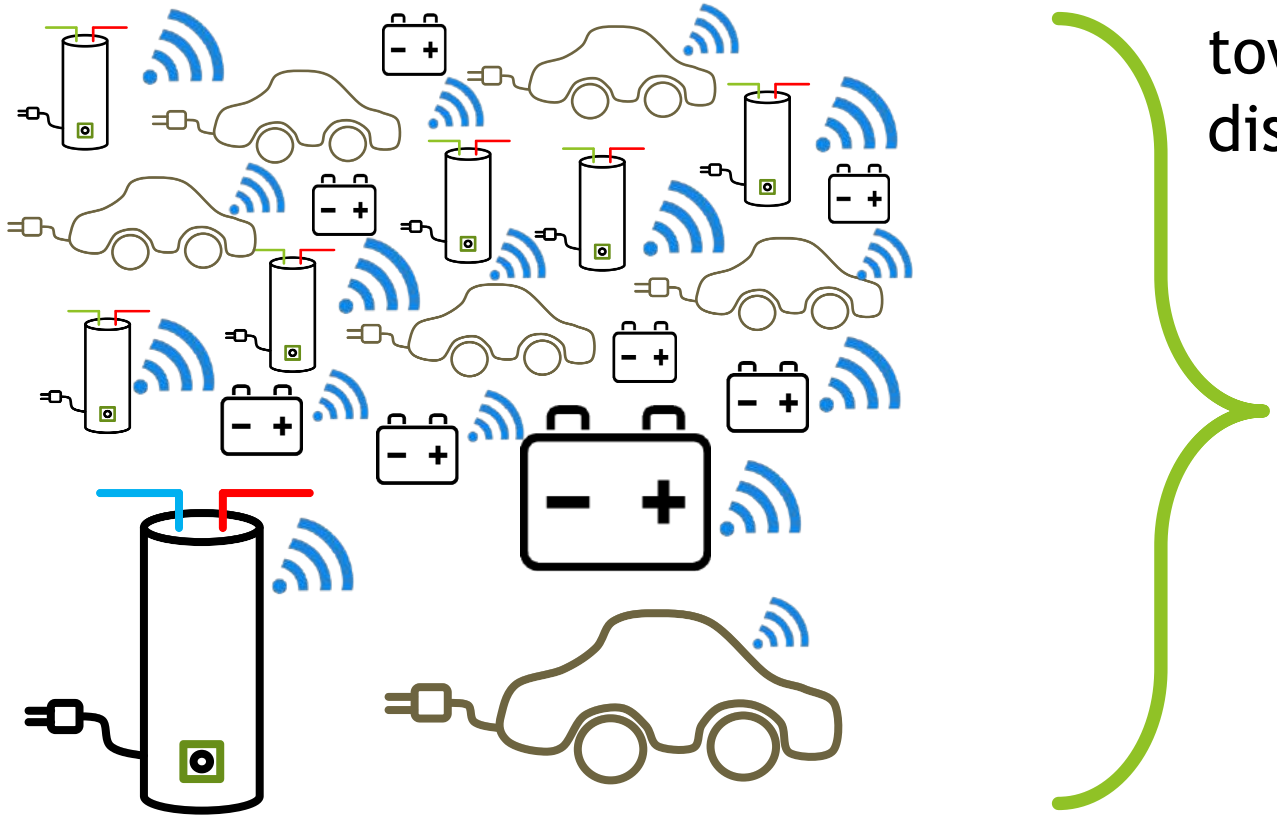
[1] UN Environmental Program, Emission Gap Report 2019 (source for figure, too)
[2] Goldenberg, et al, "Demand Flexibility: The Key To Enabling A Low-cost, Low-carbon Grid," Tech. Rep., Rocky Mountain Institute, 2018.
[3] Hledik et al, "The National Potential for Load Flexibility: Value And Market Potential Through 2030," *Tech. Rep.*, The Brattle Group, 2019.

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

GRID BALANCING,
ANCILLARY SERVICES

LMP ENERGY ARBITRAGE,
RENEWABLE SMOOTHING

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

AVOIDED GEN CAPACITY

$100 to $1000
per kW_{flex} per year*

Virtual power plant™
Virtual battery™
Prosumer™

TESLA

sunrun

GENERAC

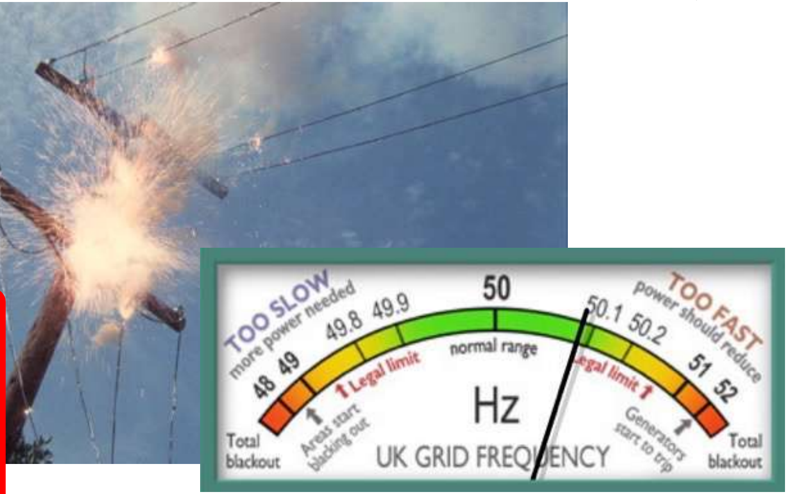
EnergyHub

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

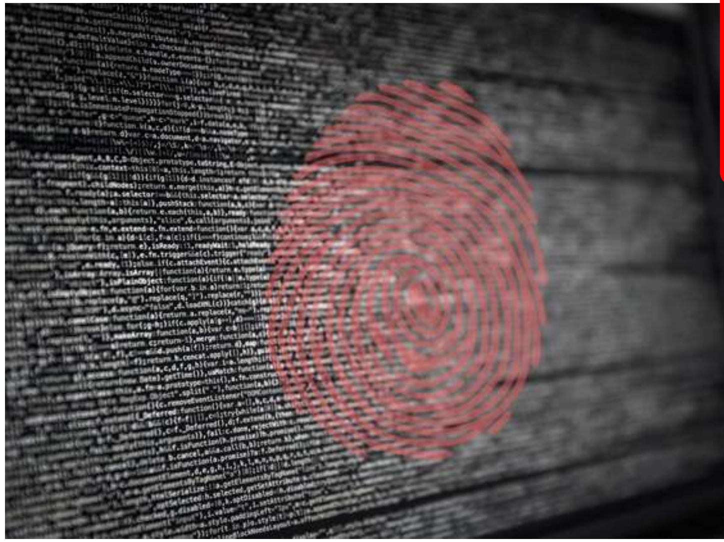
Technical challenges for intelligent electrification

Comfort & convenience (human constraints)

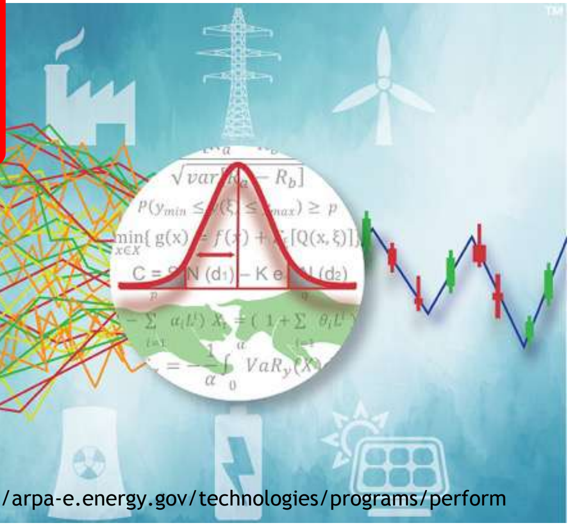
Grid conditions & reliability (network constraints)



Cyber-security & data privacy



Business models & risk management



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

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
- "*Fenway frank problem*" and "*Two-pint problem*"

NAVIGANT

National Grid Smart Energy Solutions Pilot

Final Evaluation Report

Prepared for:

National Grid

nationalgrid

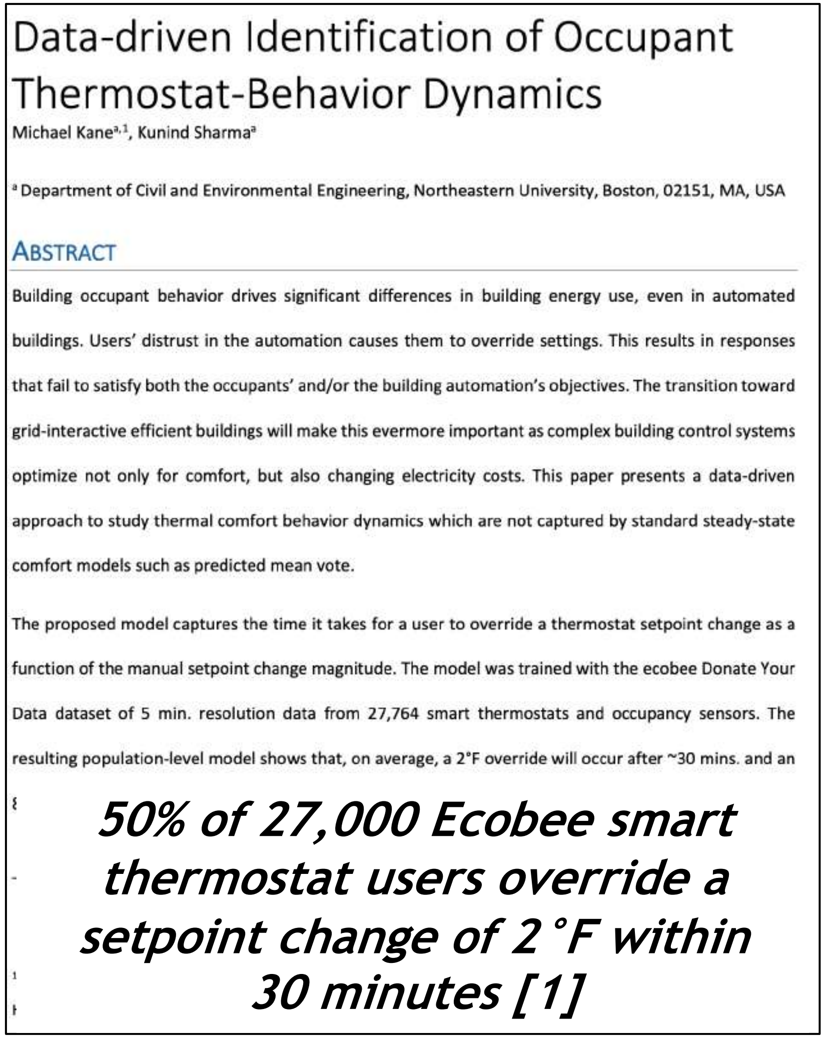
Submitted by:
Navigant
1375 Walnut Street
Suite 200
Boulder, CO 80302

303.728.2500
navigant.com

May 5, 2017

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

It's also 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.

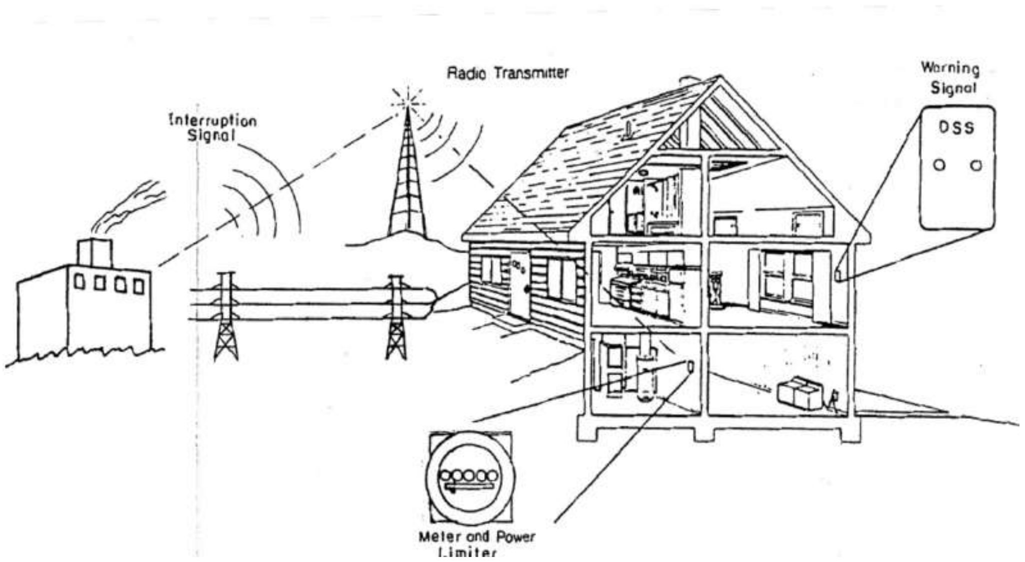
The proposed model captures the time it takes for a user to override a thermostat setpoint change as a function of the manual setpoint change magnitude. The model was trained with the ecobee Donate Your Data dataset of 5 min. resolution data from 27,764 smart thermostats and occupancy sensors. The resulting 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]

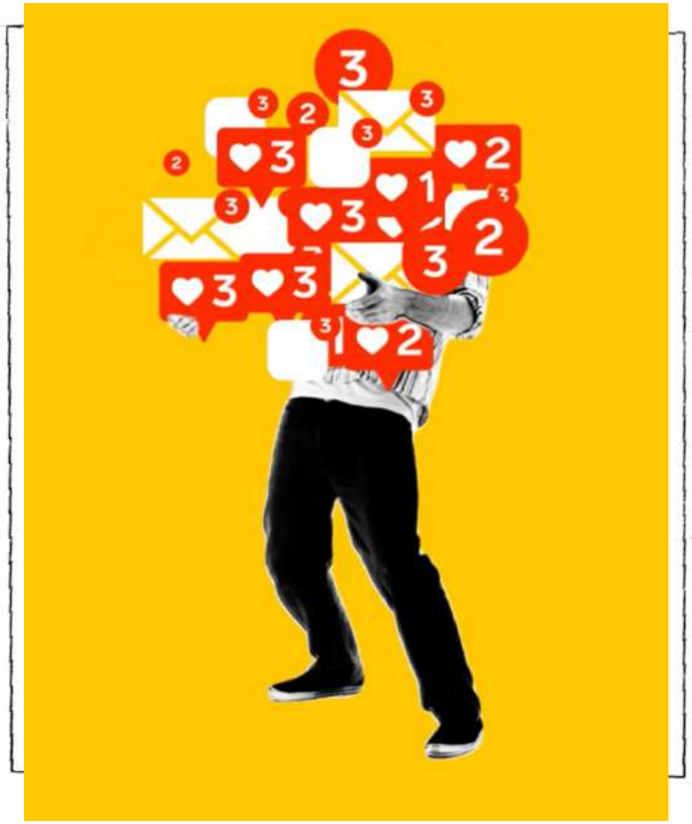
[1] Michael B Kane and Kunind Sharma, "Data-driven Identification of Occupant Thermostat-Behavior Dynamics," arXiv preprint:1912.06705, 2019.

Respecting humans too much: California in 1982

Demand subscription service (DSS): radio-controlled fuse limits demand to subscribed level



Thanks to Shmuel Oren for sharing this story from SCE in 1982



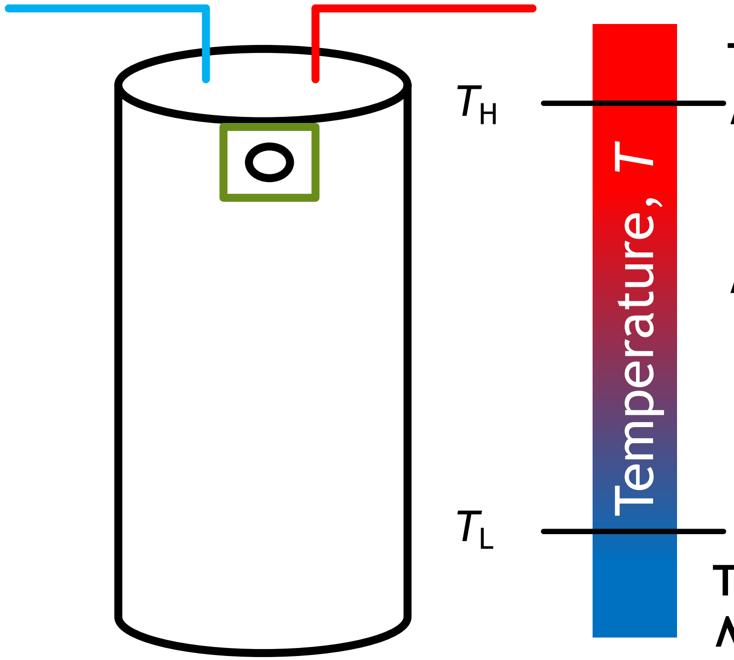
Today, some utilities use SMS

Human becomes the actuator in-the-loop

Source: VectorStock.com/7537816

Quality of service (QoS): a device's *need for energy*

Example: An electric water heater



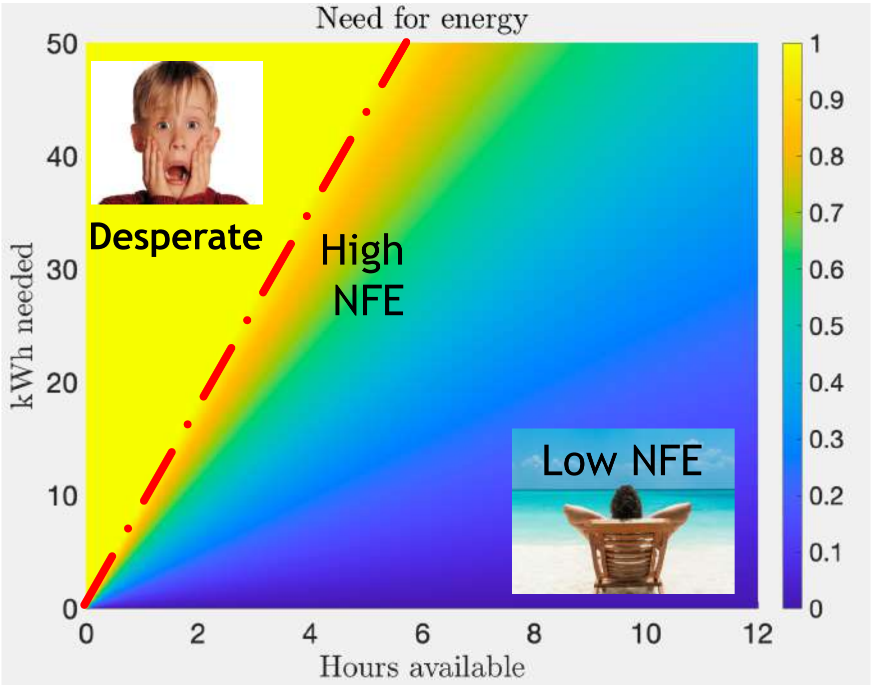
Turn OFF
Need for energy is low!

NFE increases with ~1/Temperature

Turn ON
Need for energy is desperate!

Example: An electric vehicle

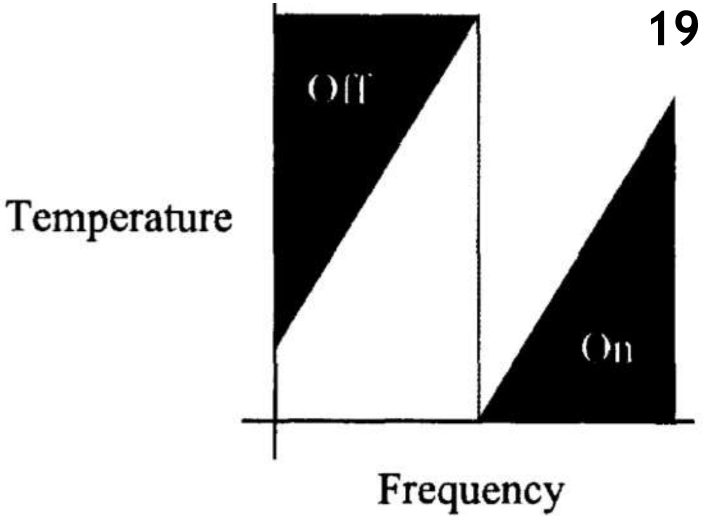
$$\text{NFE} = \frac{\text{kWh needed now}}{\eta p^{\max} \times \text{hours remaining}}$$



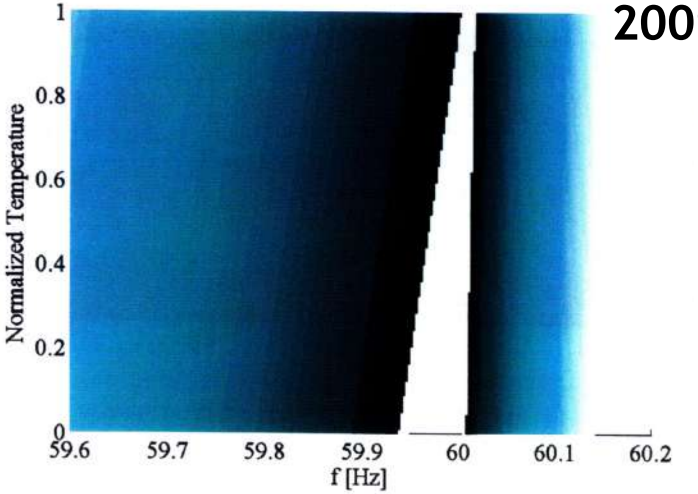
Key: coordination schemes can embed NFE to dynamically prioritize responses

Foundational work in demand-side flexibility

- **1979: Electric power load management** (techno-eco-social-regulatory issues; Morgan/Talukdar)
- **1980: Frequency Adaptive Power and Energy Reschedulers** (FAPER, Schweppe/Kirtley)
  - Change temperature dead-band based on measured grid frequency ➔ devices switch ON or OFF
  - Meant to provide 5-minute demand services. But had challenges with synchronization and satisfying QoS
    - They were well ahead of their time: sensors were not quite economical
    - (Brokish 2009) revisited and added probabilistic FAPER to reduce synchronization effects
  - Topic picked up in 2009-ish with Hiskens/Callaway work on load control, then field exploded…



1980



2009

Some recent work since 2009

Top-down control / broadcast

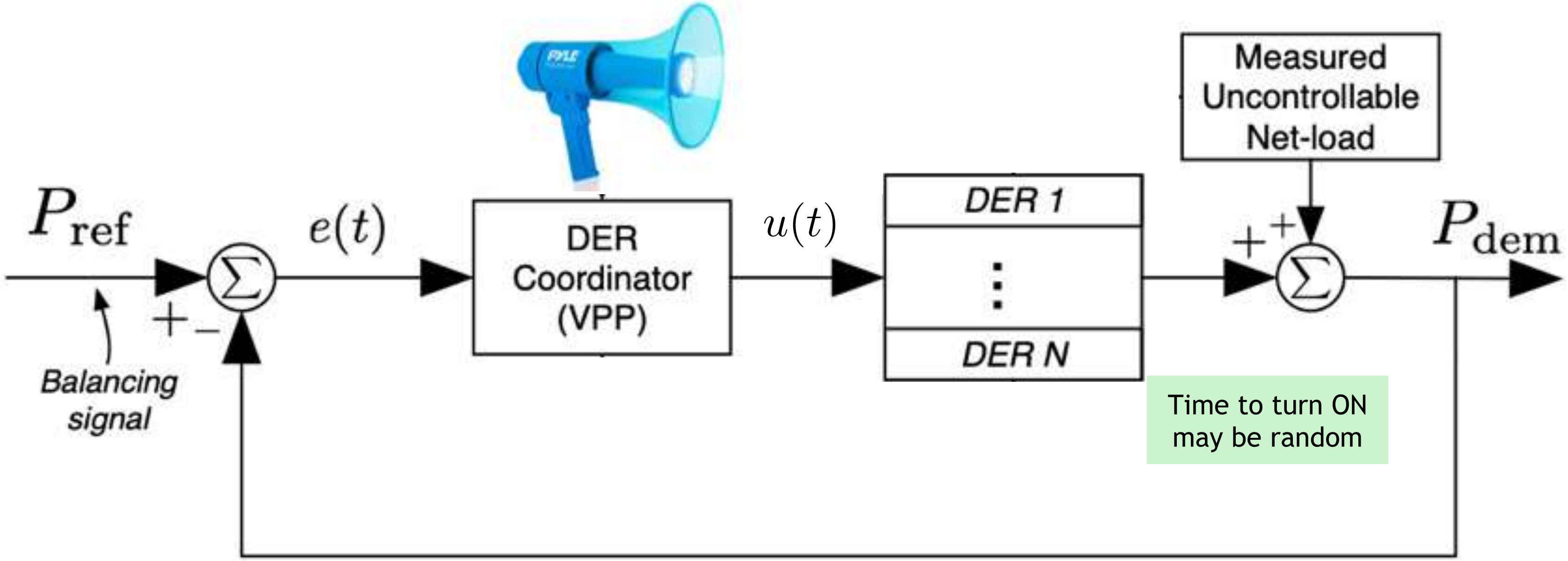
- **Lu/Chassin** (TCLs; bin-based)
- **Hiskens/Callaway** (TCLs; deadband control)
- **Mathieu** (TCLs; randomization)
  - State bin transition models for control
  - Assumes aggregate demand can be estimated
- **Wei Zhang** (higher order/lock-out)
  - State bin transition models; control
- **Majidian/Dahleh** (energy/power bounds)
  - Characterize deferrable demand limits
  - Assumes perfect information/full control
- **Busic/Meyn** (randomization)
  - Mean field; QoS guarantee; opt-out
  - Assumes aggregate demand is known
- **Bravlavsky/Perfumo** (system ID for TCLs)
  - ODEs; heterogeneity in some parameters

Bottom-up / device-driven

- **Brokish (TCLs): probabilistic FAPER**
- **Zhang/Bailieul** (TCLs)
  - Binary information packet requests
  - Analyze avg. performance under static limit
  - Stores packet request in queue
- **Turitsyn/Chertkov** (Diverse loads)
  - Modeling with MDPs, price-based mechanism
- **Stüdli/Middleton** (EVs)
  - AIMD regulates EV charging; no QoS guarantee
- **Almassalkhi et al**
  - **Packetized energy management (PEM)**
    - **Randomization, control, QoS guarantee**
    - **State bin transition models for analysis**

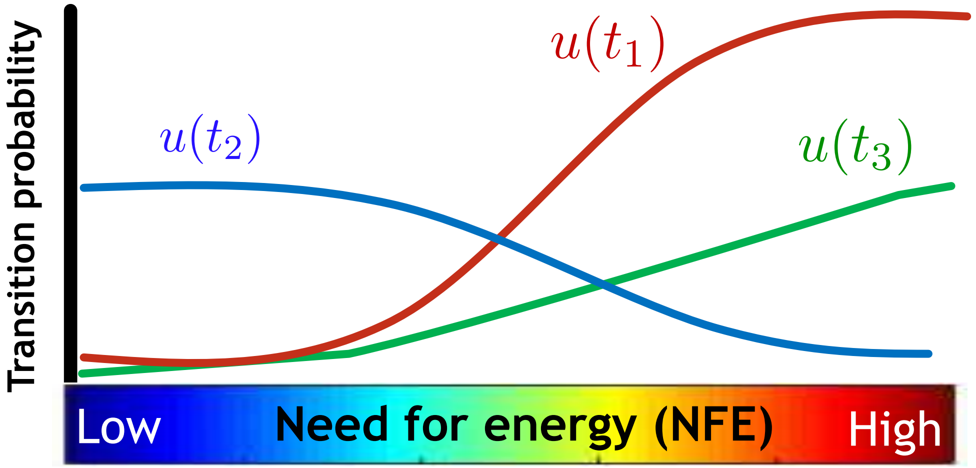
Industry example of direct load control (or TOU)

Architecture #1: Broadcast-based/top-down coordination



Time to turn ON may be random

Local device logic can guarantee QoS

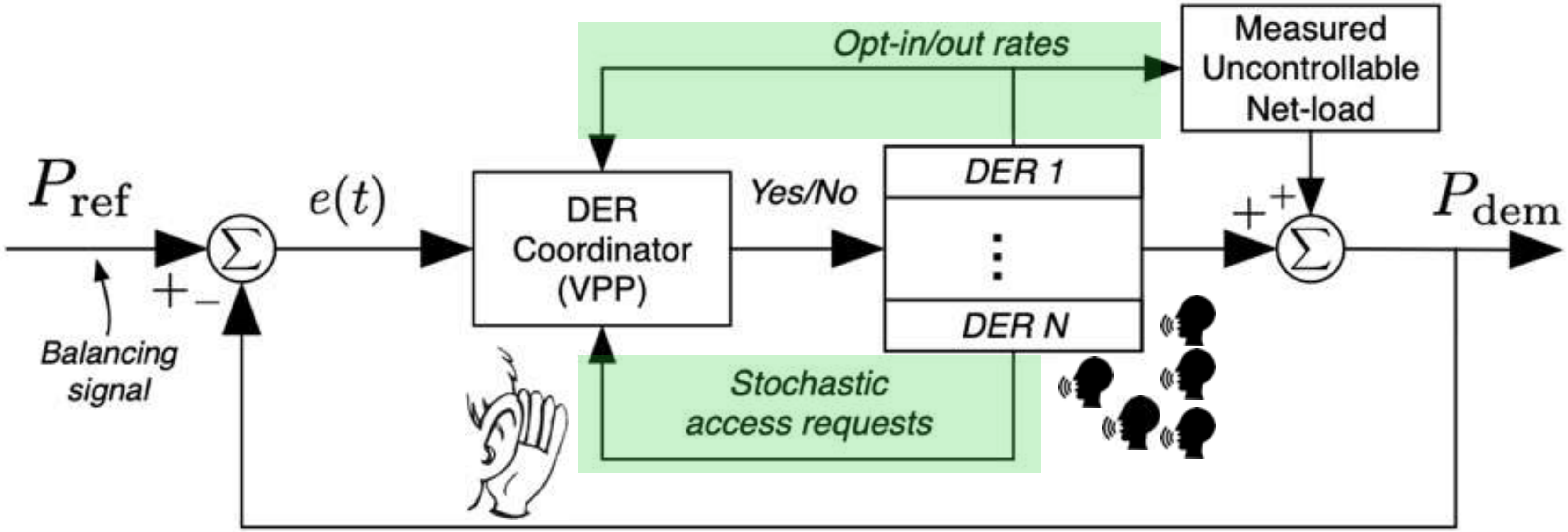


Broadcast control signal to all devices **synchronously.** Control signal is **explicit incentive (transactive) or pdf.**

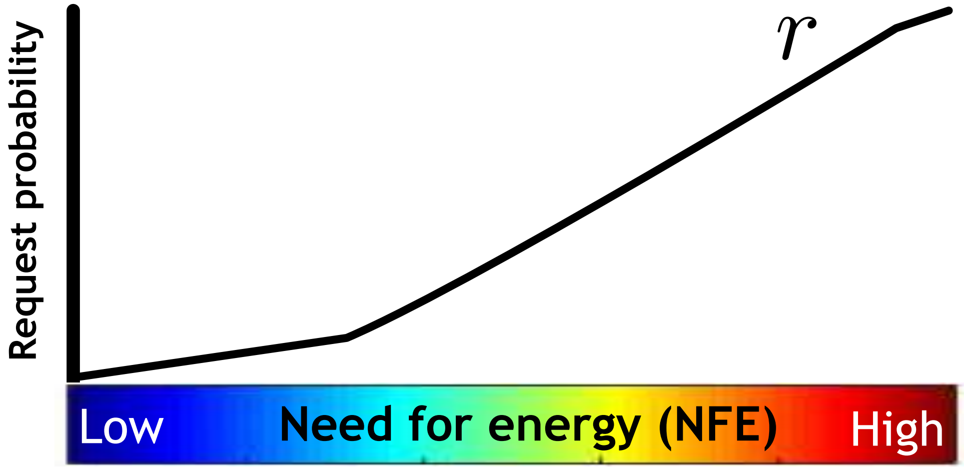
Requires feedback from actual/estimated demand and/or having devices stream back data/status. Else is **open-loop**

But challenging to get feedback, hard to distinguish individual device constraints or grid locations (i.e., DER cycling and local grid conditions).

Architecture #2: Device-driven/bottom-up coordination



Local device logic can guarantee QoS



Leverage **asynchronous** device-to-cloud comms to have devices **request** temporary access to grid

Controller accepts or denies all packet request, so **can estimate total demand of fleet (feedback)**

Request logic can include device constraints to manage **device health** and Requests can embed network location to enable **network-aware coordination**

Device-driven coordination inspired by The Internet

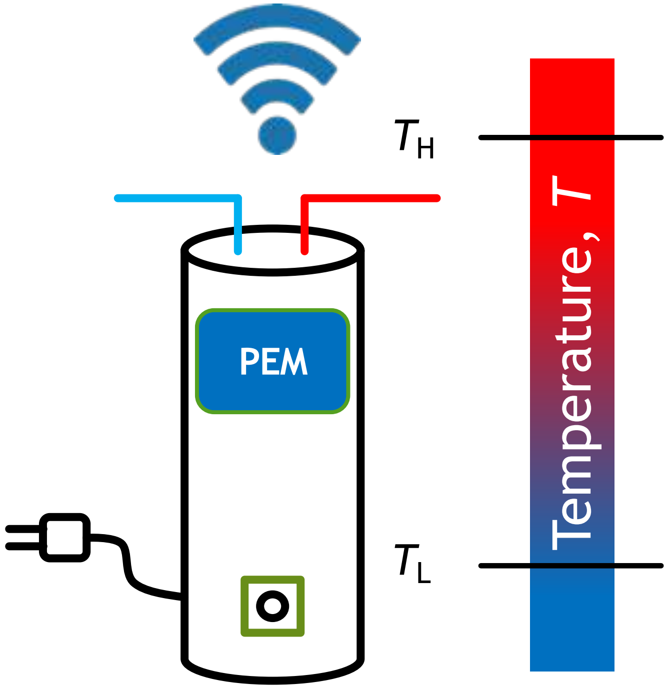
Packetization of data on Internet

Random access protocols

Method is called <u>packetized energy management </u>(PEM)

PEM example load: guaranteeing *QoS*

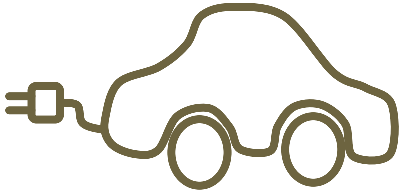
Energy packet = constant power consumed over fixed epoch = 🟦



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

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

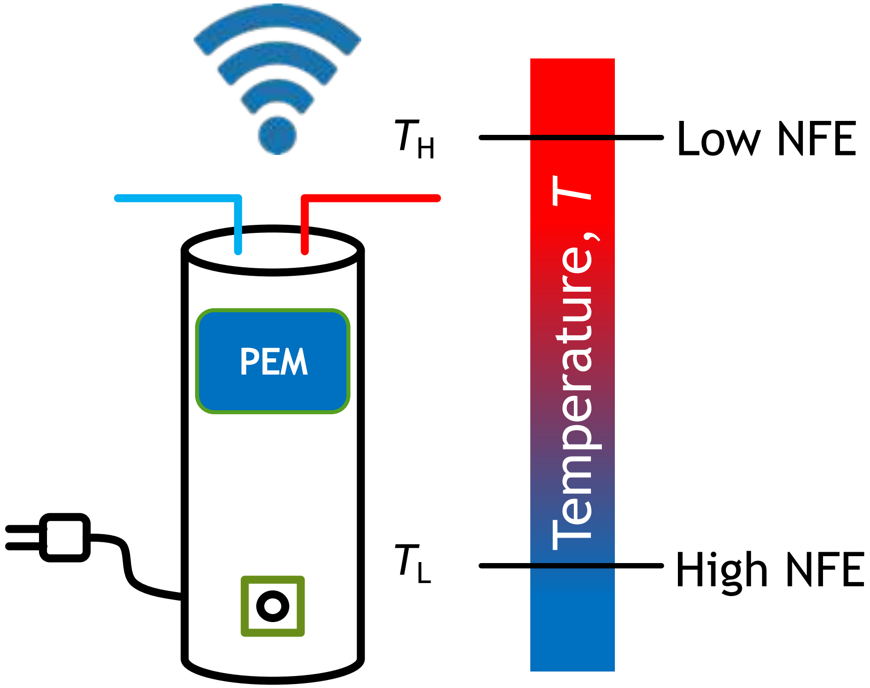
When temperature is low, heating elements turns ON and consumes energy → *bulky demand*

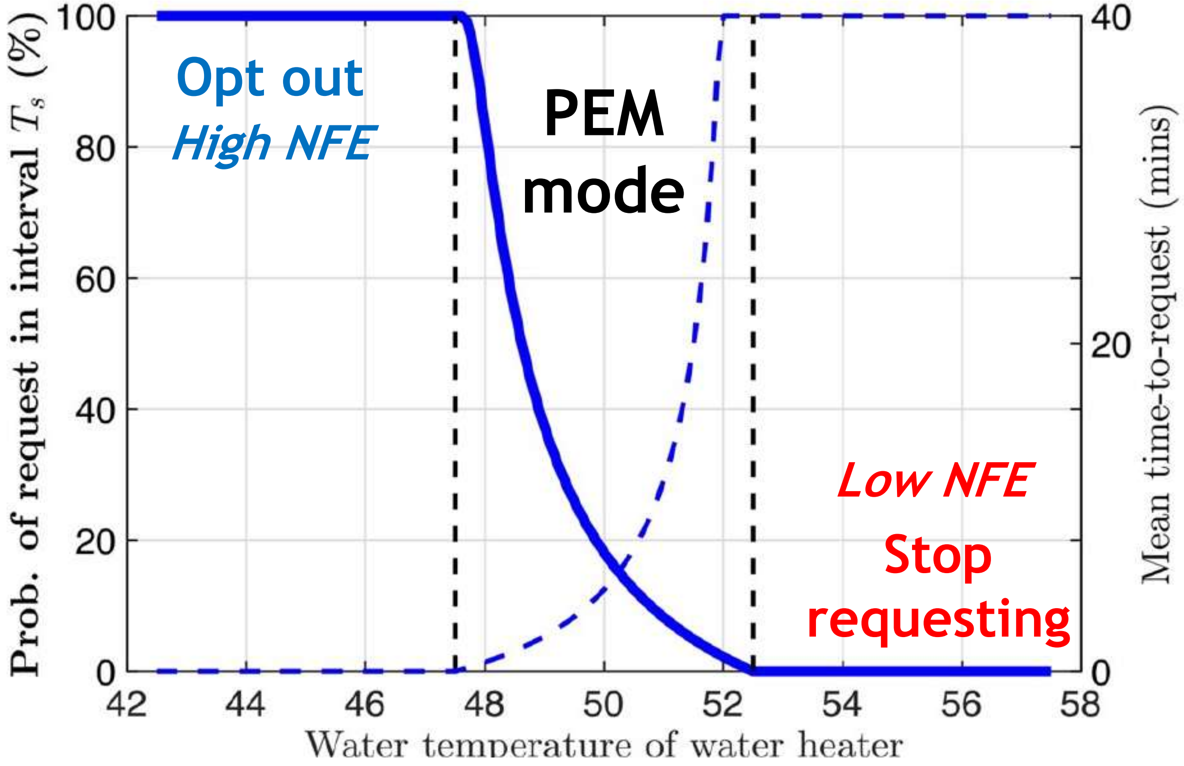


M. Almassalkhi, et al, "Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads," *ACC*, 2017
M. Almassalkhi, et al, "Asynchronous Coordination of Distributed Energy Resources with Packetized Energy Management," 20th In: Meyn S., Samad T., Hiskens I., Stoustrup J. (eds) *Energy Markets and Responsive Grids*. The IMA Volumes in Mathematics and its Applications,, pp 333-361, vol 162. Springer, 2018.

PEM example load: guaranteeing *QoS*

Stochastic request process is based on NFE and defines MTTR
NFE dynamically prioritizes devices while MTTR reduces synchronization





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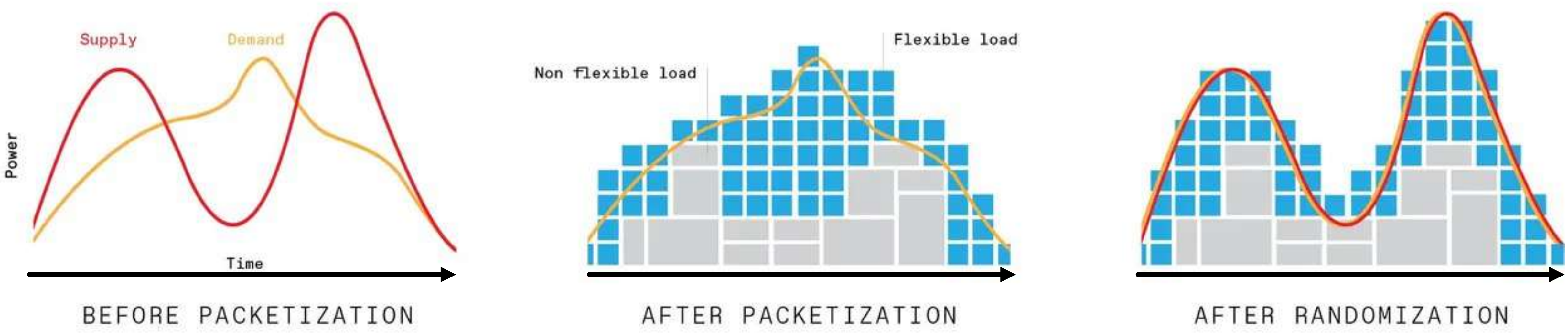
PEM for a fleet: coordination & flexibility

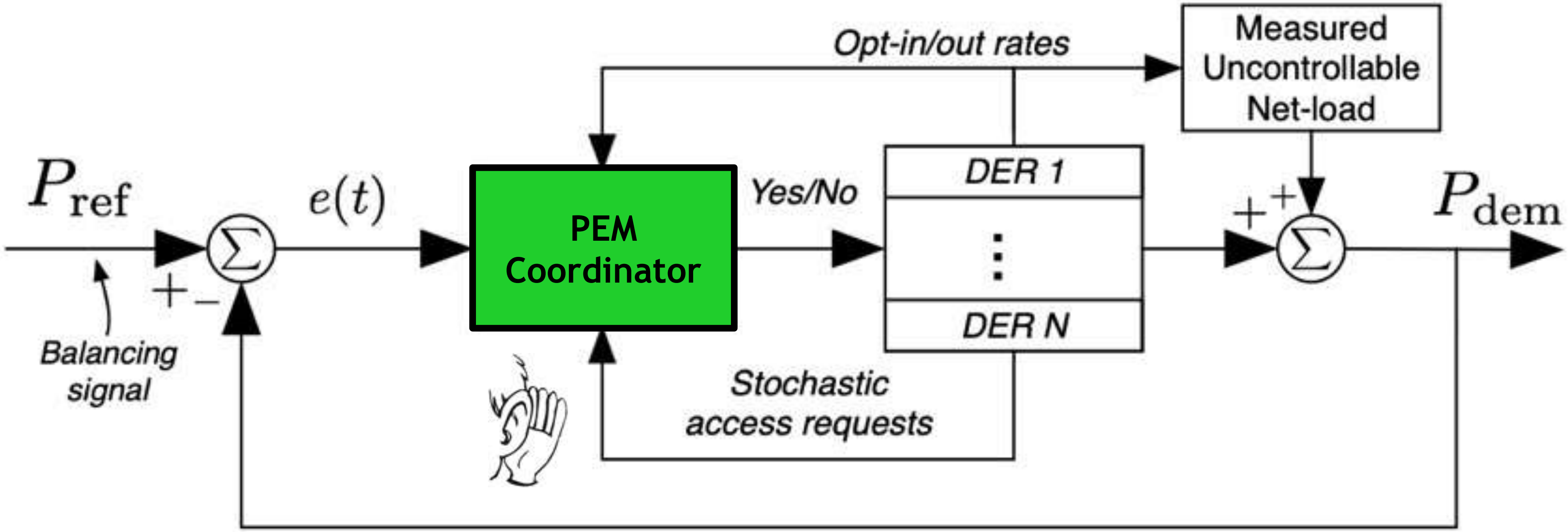
- **Inspired by how the Internet works:** PEM is a scalable concept
  - **Bottom-up** approach: local intelligence enables devices to learn their **need for energy** (comfort)
  - **Randomization** of requests: device stochastically request a packet based on **need for energy**
  - **Packetization** of device demand: all devices interact with coordinator the same way (requests)



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

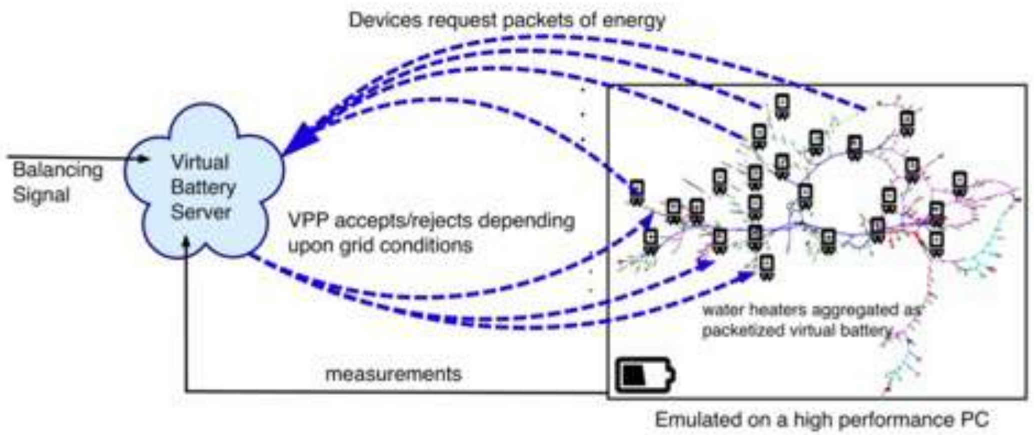
Closing the loop with PEM's packet requests

- 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



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

Milestone 1: built real-time, scalable DER platform



Devices request packets of energy

Balancing Signal

Virtual Battery Server

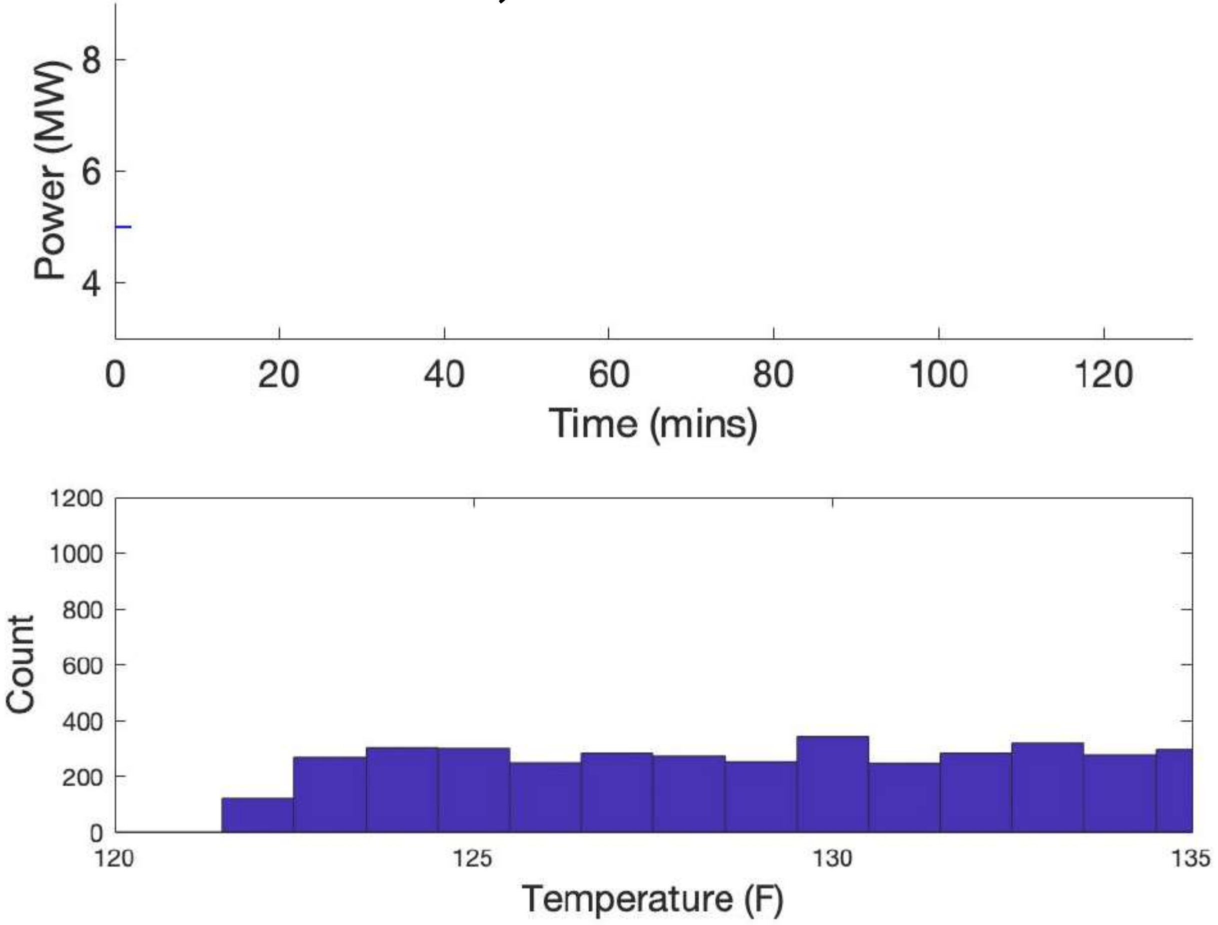
VPP accepts/rejects depending upon grid conditions

water heaters aggregated as packetized virtual battery

measurements

Emulated on a high performance PC

OPAL-RT TECHNOLOGIES



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

Milestone 2: field trial with 150+ loads in 2019

arpa·e

The UNIVERSITY of VERMONT

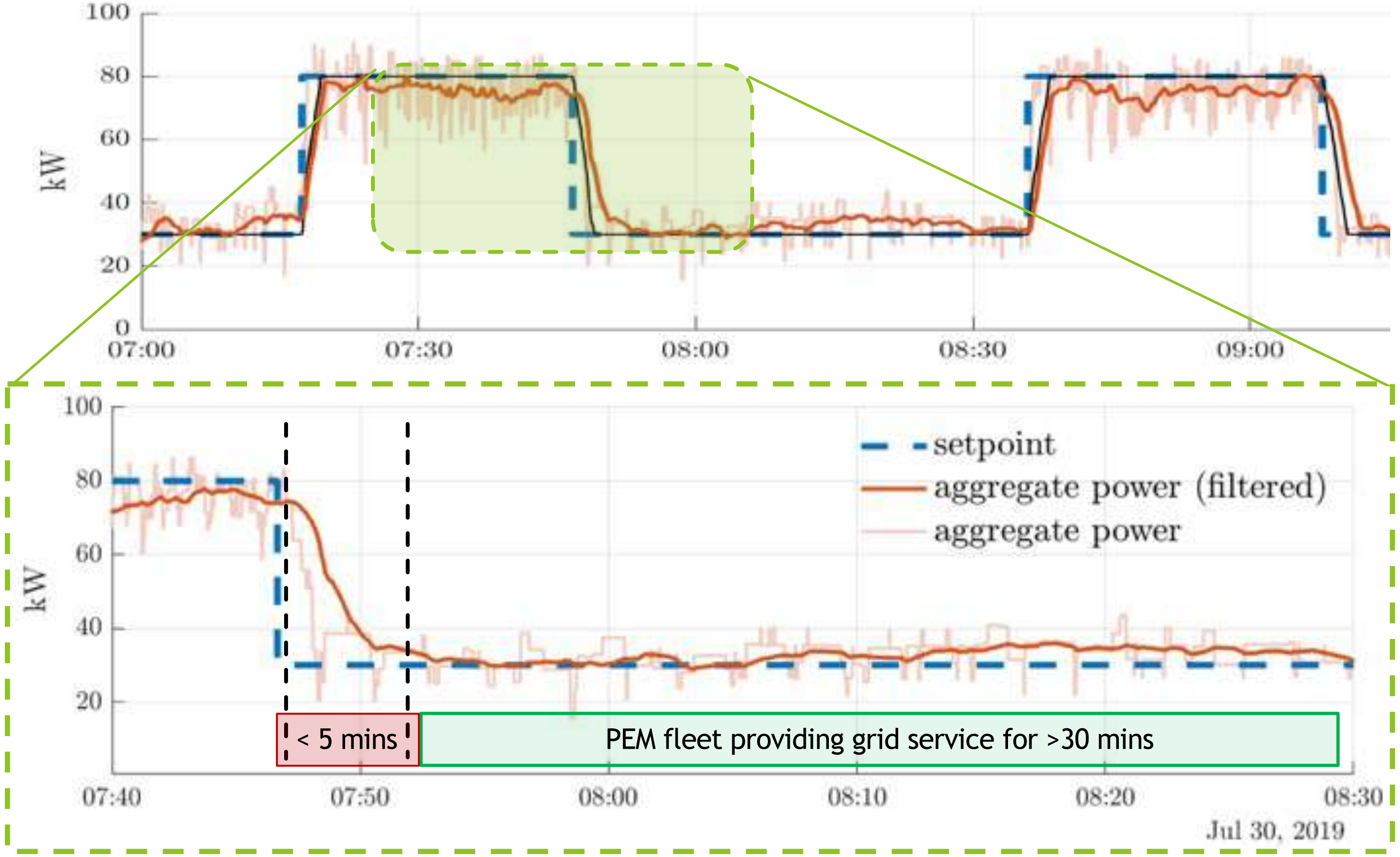
VERMONT ELECTRIC CO OP

BURLINGTON Electric DEPARTMENT

GREEN MOUNTAIN POWER

vermont electric power company VELCO

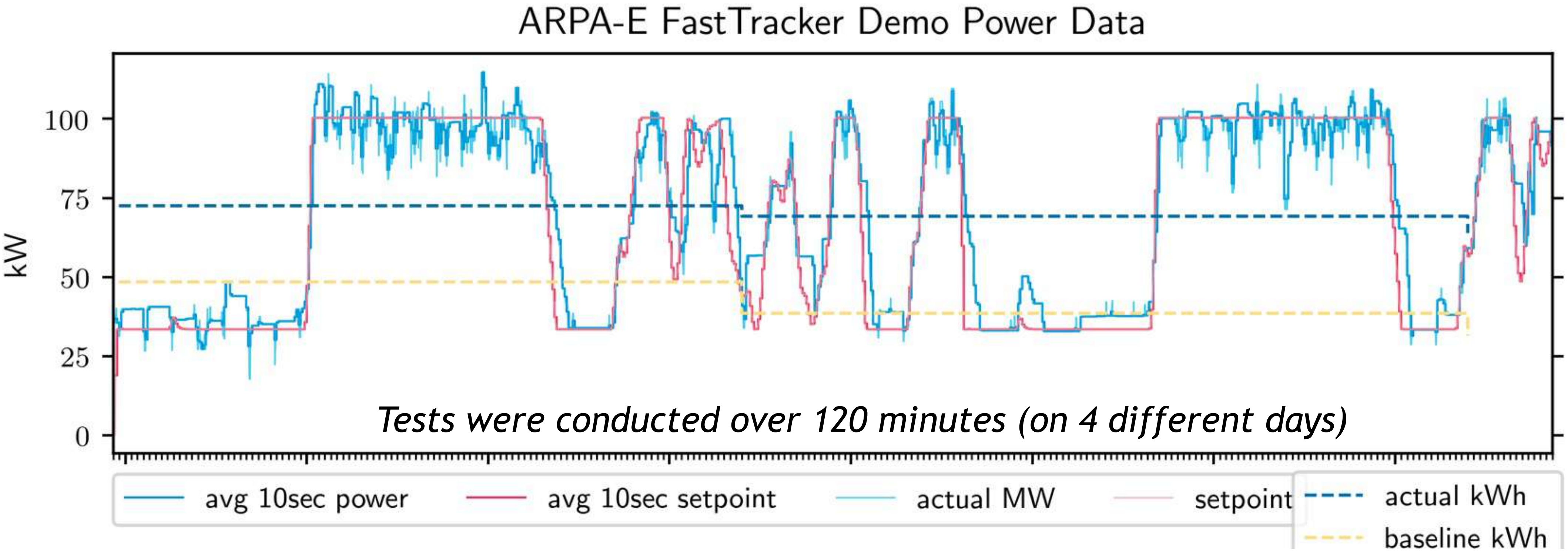
PACKETIZED ENERGY



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 4 different days)

Pay-for-performance:
PJM Performance score

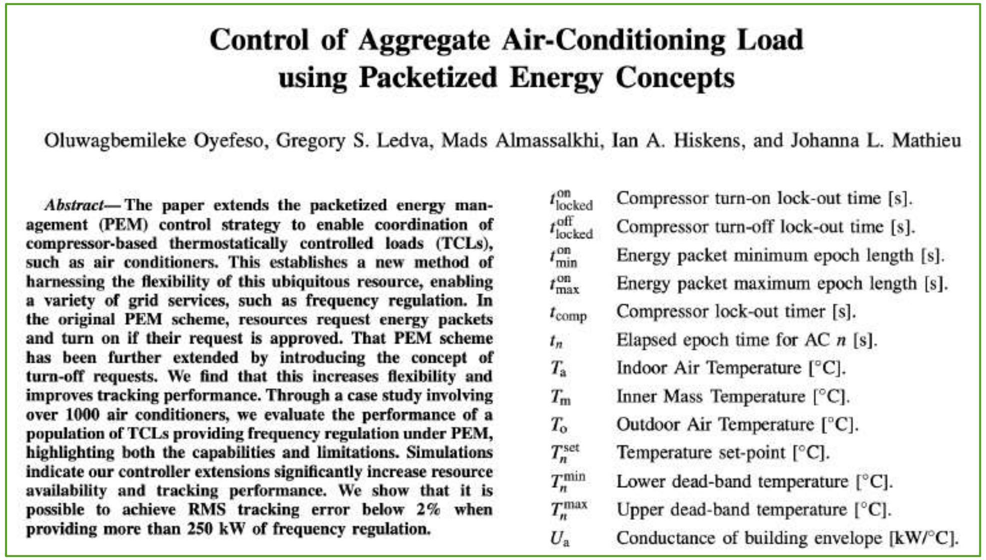
accuracy	delay	precision	composite
0.9509	0.9948	0.8281	0.9246

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.

Follow up collaboration with colleagues at UMICH

- Thanks to Leke, Johanna, Ian, et al
- Adapted PEM to AC loads.
- Augmented PEM with new request type to turn OFF when ON (similar to batteries)
    - Accepting request to turn OFF active drives down demand (”discharges”)
    - Increases ability to track down ramps
    - Improves ability to track frequency regulation signal



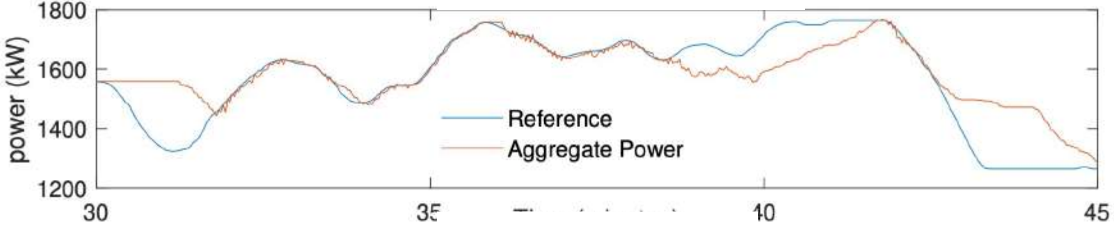
Control of Aggregate Air-Conditioning Load using Packetized Energy Concepts

Oluwagbemileke Oyefeso, Gregory S. Ledva, Mads Almassalkhi, Ian A. Hiskens, and Johanna L. Mathieu

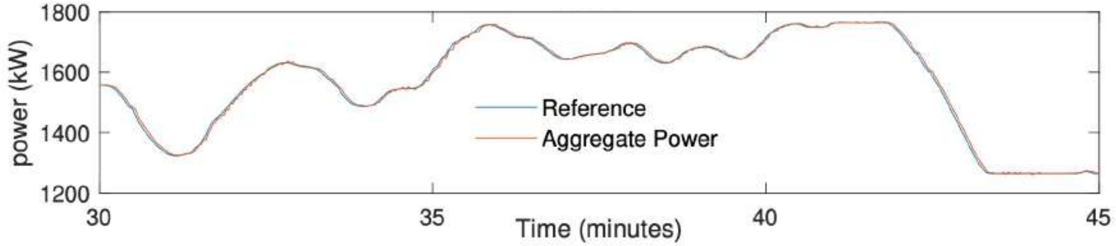
***Abstract*— The paper extends the packetized energy management (PEM) control strategy to enable coordination of compressor-based thermostatically controlled loads (TCLs), such as air conditioners. This establishes a new method of harnessing the flexibility of this ubiquitous resource, enabling a variety of grid services, such as frequency regulation. In the original PEM scheme, resources request energy packets and turn on if their request is approved. That PEM scheme has been further extended by introducing the concept of turn-off requests. We find that this increases flexibility and improves tracking performance. Through a case study involving over 1000 air conditioners, we evaluate the performance of a population of TCLs providing frequency regulation under PEM, highlighting both the capabilities and limitations. Simulations indicate our controller extensions significantly increase resource availability and tracking performance. We show that it is possible to achieve RMS tracking error below 2% when providing more than 250 kW of frequency regulation.**

$t_{\text{locked}}^{\text{on}}$	Compressor turn-on lock-out time [s].
$t_{\text{locked}}^{\text{off}}$	Compressor turn-off lock-out time [s].
$t_{\text{min}}^{\text{on}}$	Energy packet minimum epoch length [s].
$t_{\text{max}}^{\text{on}}$	Energy packet maximum epoch length [s].
t_{comp}	Compressor lock-out timer [s].
t_n	Elapsed epoch time for AC n [s].
T_{a}	Indoor Air Temperature [°C].
T_{m}	Inner Mass Temperature [°C].
T_{o}	Outdoor Air Temperature [°C].
T_n^{set}	Temperature set-point [°C].
T_n^{min}	Lower dead-band temperature [°C].
T_n^{max}	Upper dead-band temperature [°C].
U_{a}	Conductance of building envelope [kW/°C].

Without new requests



With new requests



Research directions with PEM

1

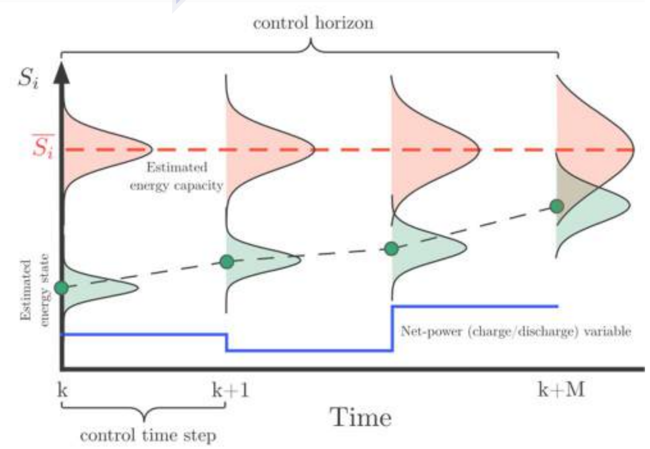
Estimate background end-use

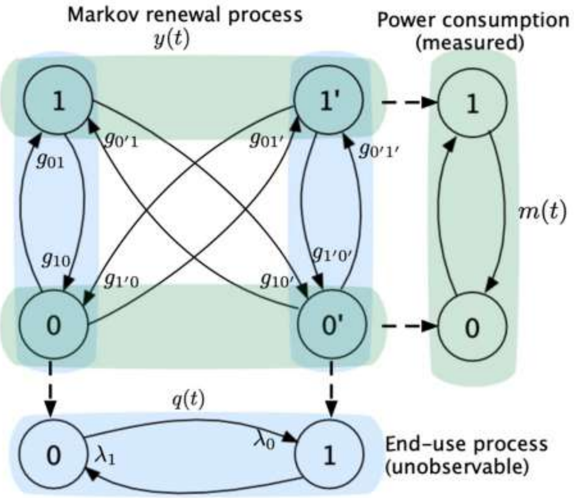
Stochastic end-use

Uncertain resource

3

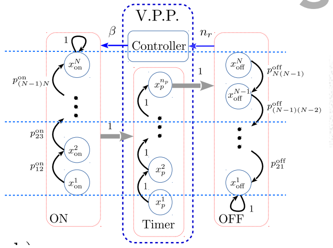
Optimal dispatch

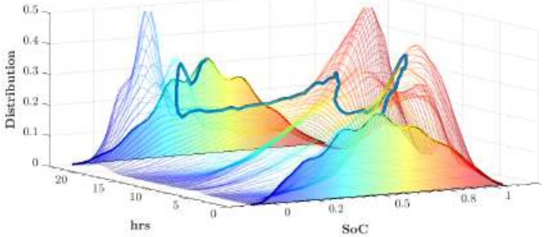




2

Modeling and control

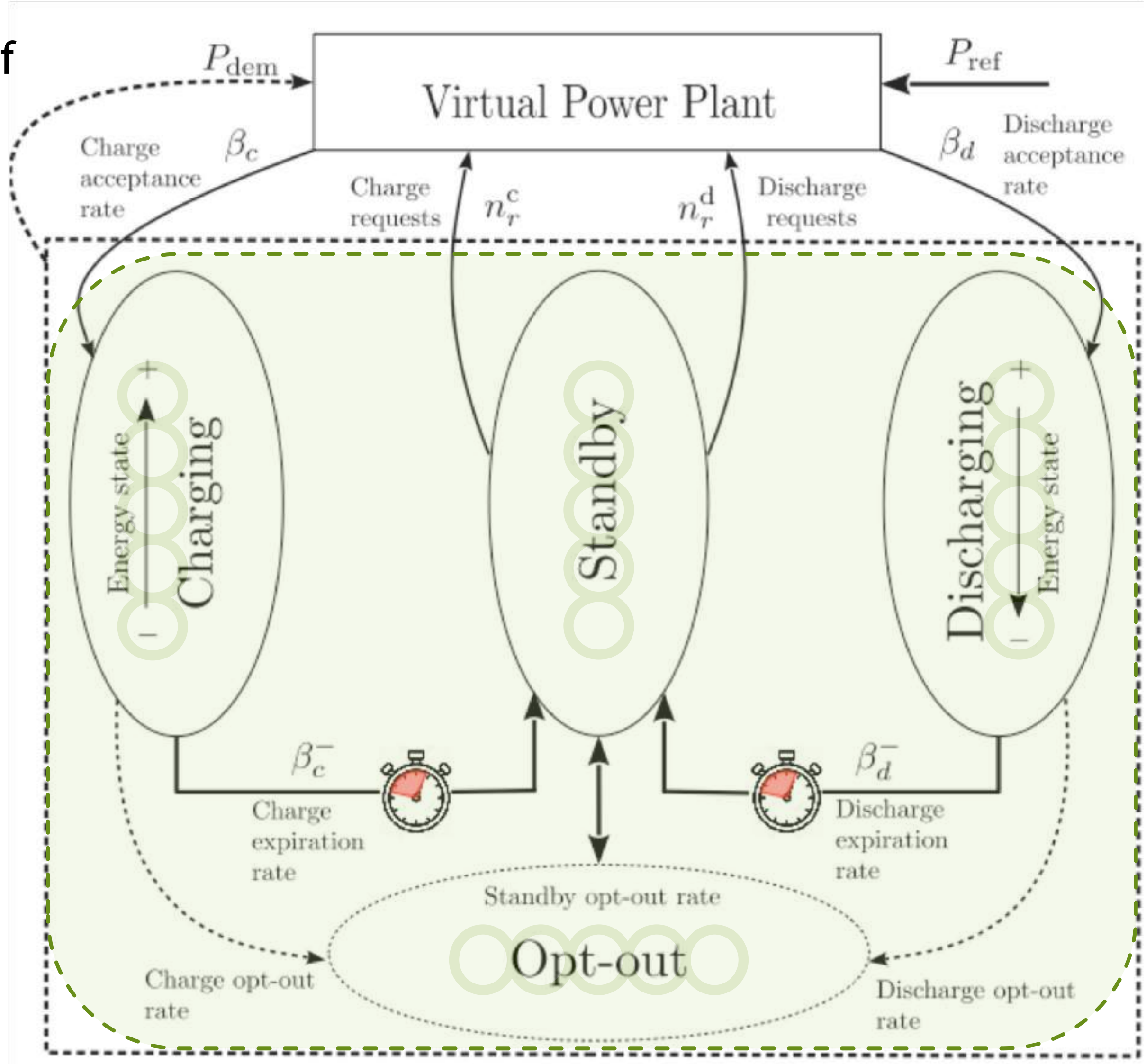




(1) **A. Khurram**, Luis Duffaut Espinosa, Roland Malhamé, Mads Almassalkhi, “Identification of Hot Water End-use Process of EWHs from Energy Measurements,” EPSR, 2020
(2a) L. Duffaut and M. Almassalkhi, “A packetized energy management macromodel with QoS guarantees for demand-side resources,” IEEE Trans. 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 (under review)

2 Modeling PEM system 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

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

Opt-out control guarantees comfort/QoS

A nonlinear macro-model for PEM for c/sb/d DERs:

Consider a state bin transition model with hybrid c/sb/d dynamics and N bins per mode

Input: $(\beta_c, \beta_d) \in [0,1]^2$

Dynamics: $q[k+1] = M M_\beta q[k]$

States: $q[k+1] := \begin{pmatrix} q_{\mathrm{c}}[k+1] \\ q_{\mathrm{sb}}[k+1] \\ q_{\mathrm{d}}[k+1] \end{pmatrix}$

Transitions from c→sb

Some packets completing

Transitions from sb→c

Packets commencing each bin

$$q[k+1] = M \begin{pmatrix} (1-\beta_c^-[k])I & \beta_c[k]T^c_{\mathrm{req}} & 0 \\ \beta_c^-[k]I & I - \beta_c[k]T^c_{\mathrm{req}} - \beta_d[k]T^d_{\mathrm{req}} & \beta_d^-[k]I \\ 0 & \beta_d[k]T^d_{\mathrm{req}} & (1-\beta_d^-[k])I \end{pmatrix} q[k]$$

Transitions from sb→d

Transitions from d→sb

Agg. power (c minus d)

Output: $$y[k] = \begin{pmatrix} \bar{P}_c \mathbf{1}_N^\top & \mathbf{0}_N^\top & -\bar{P}_d \mathbf{1}_N^\top \\ 0 & \mathbf{1}_N^\top T^c_{\mathrm{req}} & 0 \\ 0 & \mathbf{1}_N^\top T^d_{\mathrm{req}} & 0 \end{pmatrix} q[k] = \begin{pmatrix} P_{\mathrm{dem}}[k] \\ n_r^c[k] \\ n_r^d[k] \end{pmatrix}$$

Agg. requests ~ c/d

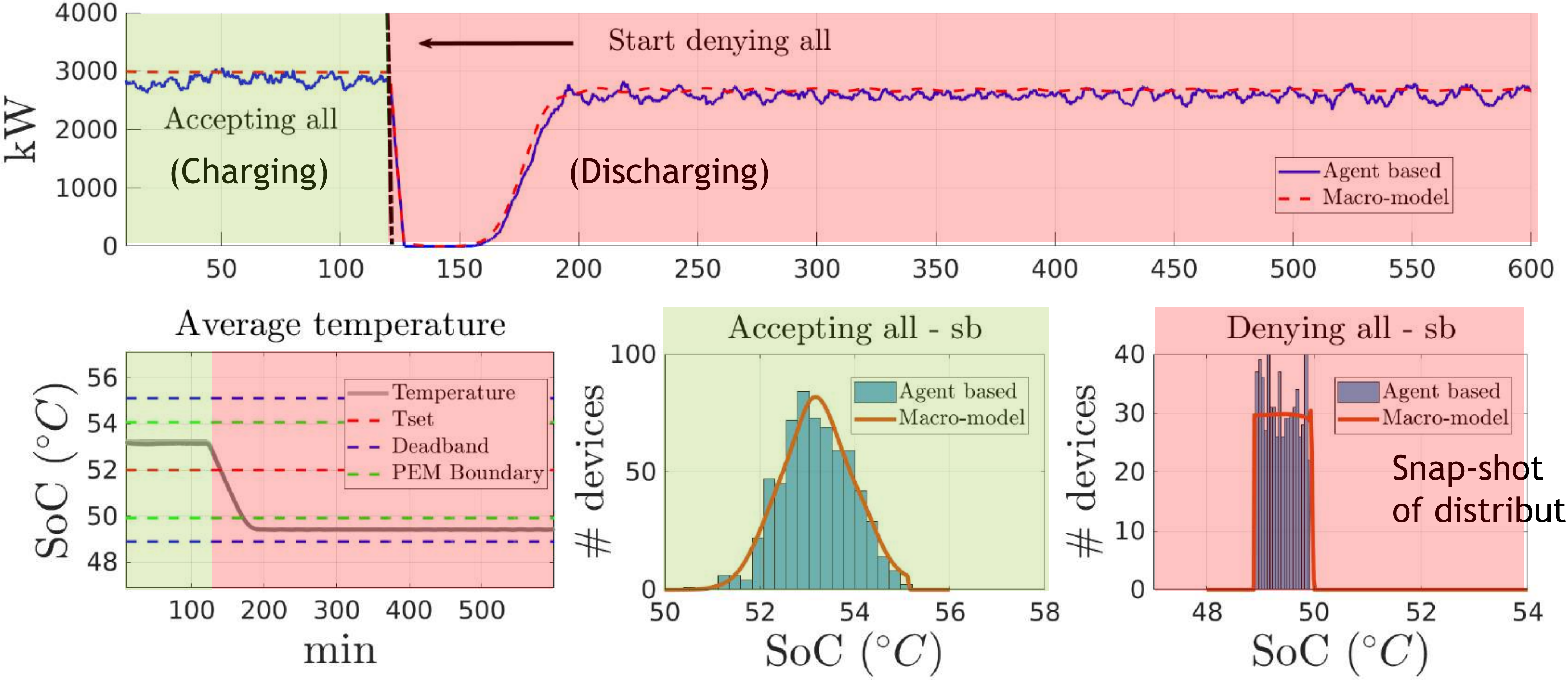
What happens in model, if all requests are rejected (i.e., beta$_c$ = 0 = beta$_d$)?

➔ Devices *accumulate in lowest sb-bin for EWHs/EVs* ➔ *QoS suffers* ➔ *Fix: augment opt-out mechanism*

L. Duffaut and M. Almassalkhi, “A packetized energy management macromodel with QoS guarantees for demand-side resources,” IEEE Trans. on Power Systems, 2021

Validating the macro-model (for EWHs)

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



(Charging)

(Discharging)

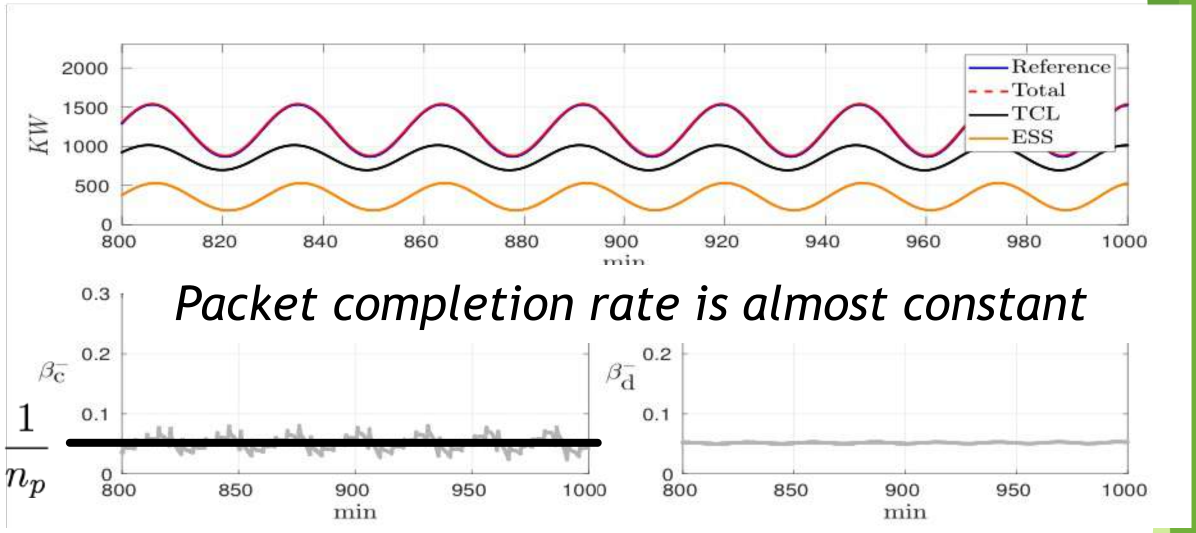
Snap-shot
of distribution

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

System properties of PEM macromodel

Result on packet completion rates, β^-

- At steady state, we have an upper bound on β^-
- Upper bound is tight without packet interruptions.
- Tracking around nominal keeps β^- **close to** constant



Packet completion rate is almost constant

Analytical estimate $\approx \dfrac{1}{n_p}$

Nominal response: *minimum constant power that allows the fleet to satisfy pre-defined QoS target*

Find nominal response: set β^- to $1/n_p$

Compute steady-state
β that solves :

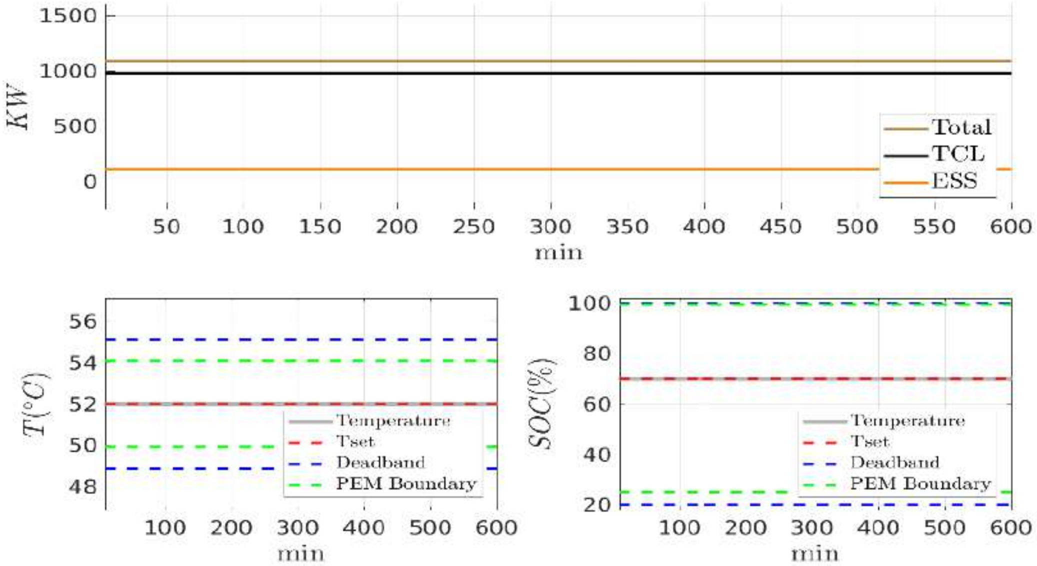
$$\beta_c^*, \beta_d^* = \arg\min_{\beta_c,\beta_d} \sum_{i=1}^{n} C_i q_i^*$$

$$\text{s.t.} \quad q_i^* = M(\beta, \beta^-) q_i^*$$

$$(x_{\mathrm{v}}^i)^\top q_i^* \geq z_{\mathrm{set}}^i$$

$$\beta_c, \beta_d \in [0, 1]$$

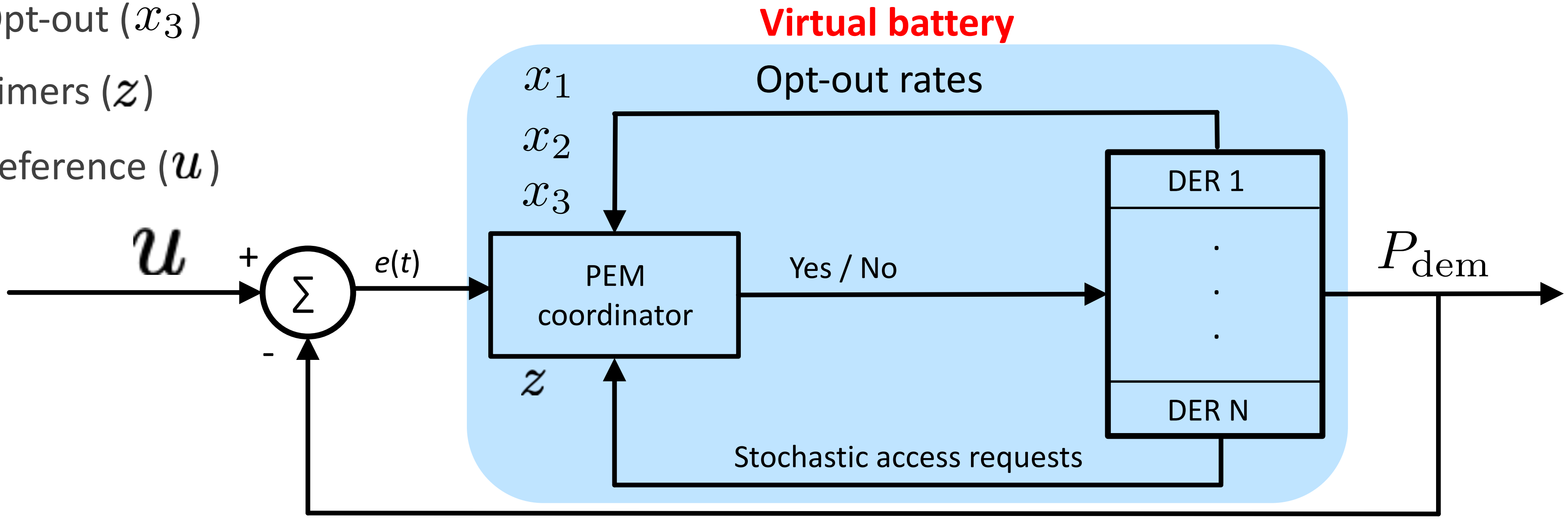
i = DER class *i*
x^i_{v} = *parameter with bin values*



L. Duffaut and M. Almassalkhi, “A packetized energy management macromodel with QoS guarantees for demand-side resources,” IEEE Trans. on Power Systems, 2021

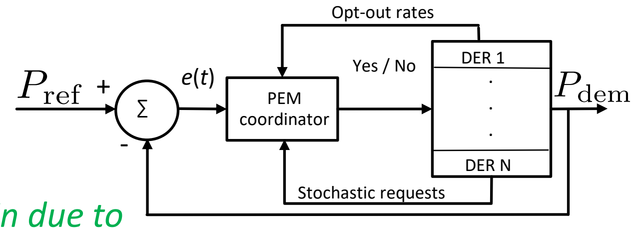
Low-order predictive VB model

- Low-order **virtual battery** model is developed that captures 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.

Low-order predictive VB model



- **Average SoC:**

Standing losses *avg end-use consumption* *energy gain due to ON and Opt-out*

$$x_1[k+1] = x_1[k] + \alpha(x_{\text{amb}} - x_1[k]) - \gamma\bar{Q} + \gamma\frac{P_{\text{rate}}}{N}(x_2[k] + x_3[k])$$

- **Number of ON devices**

ON devices *Opt-outs* *Packet completion rate*

$$x_{\text{on}}[k] = x_2[k] + x_3[k] - z_{n_p}[k]$$

- **Number of requests and accepted packets:**

$$x_r[k] = P_{\text{req}}(x_1[k])(N - x_{\text{on}}[k]) \qquad x_{\text{acc}}[k] = \beta[k]x_r[k]$$

Accepted requests from OFF populations

- **Total number of consuming (charging) loads:**

$$x_2[k+1] = x_2[k] - z_{n_p}[k] + \beta[k]x_r[k] \qquad \beta[k] = \frac{P_{\text{ref}}[k] - P_{\text{rate}}x_{on}[k]}{P_{\text{rate}}x_r[k]}$$

Internal PEM control policy

- **Timer states:**

$$z_1[k+1] = \frac{u[k]}{P_{\text{rate}}} - x_{\text{on}}[k] \quad \wedge \quad z_i[k+1] = z_{i-1}[k] \quad \forall i = 2, \ldots, n_p$$

- **Total number of opt-outs:**

Total number of denied requests

$$x_3[k+1] = (1 - a_2)x_3[k] + a_1\left[P_{\text{req}}(x_1[k])(N - x_{\text{on}}[k]) - z_1[k]\right]$$

NONLINEAR

- **Constraints still bound the input**

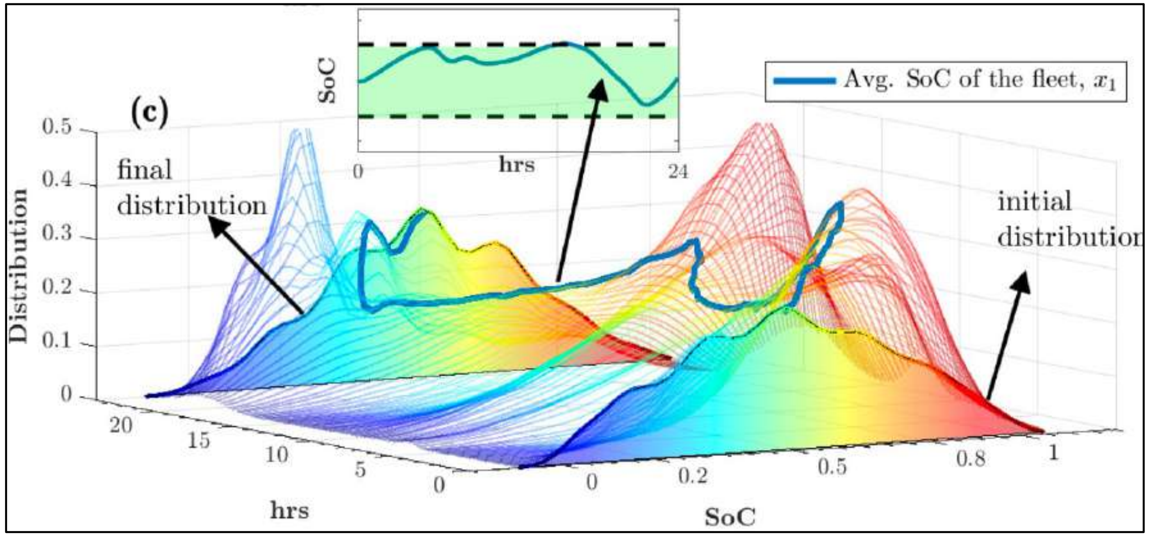
Down ramp-limited input: $P_{\text{rate}}x_{\text{on}}[k] \leq \boldsymbol{u[k]} \leq P_{\text{rate}}\left(x_{on}[k] + x_r[k]\right)$

S. Brahma, A. Khurram, H. Ossareh, and M. Almassalkhi, "*Optimal Frequency Regulation using Packetized Energy Management*," IEEE Transactions on Smart Grid, 2023
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

Low-order predictive VB model: results

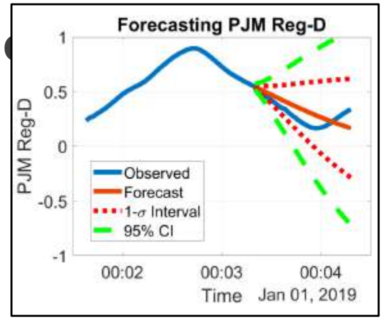
- **Case #1**: Optimize fleet's economic dispatch
  - Enforce energy limits from s-s operation pt
    - Energy limits eliminate opt-out state
    - *NLP, so Julia + IPOPT + 7secs solves:*

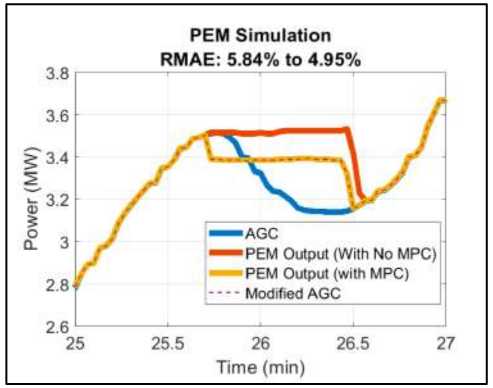
$$\begin{aligned} &\min_{P_{\text{ref}}[k],g[k],x[k]} \chi(P_{\text{ref}}[k],g[k],x[k]) \\ &\text{s.t. } x[k+1]=f(x[k],P_{\text{ref}}[k]) \text{ and } (12), \\ &\quad P_{\text{ref}}[k]\geq P_{\text{rate}}x_2[k], \\ &\quad P_{\text{ref}}[k]\leq P_{\text{rate}}(P_{\text{req}}(x_1[k])(N-x_2[k])+x_2[k]), \\ &\quad P_{\text{f}}[k]=\Delta P_{\text{dev}}[k]+g[k], \\ &\quad \underline{x}\leq x[k]\leq \overline{x}, \forall k=1,\ldots,K+1, \\ &\quad x[0]=x_0, x_1[K+1]=[10]x_0, \end{aligned}$$

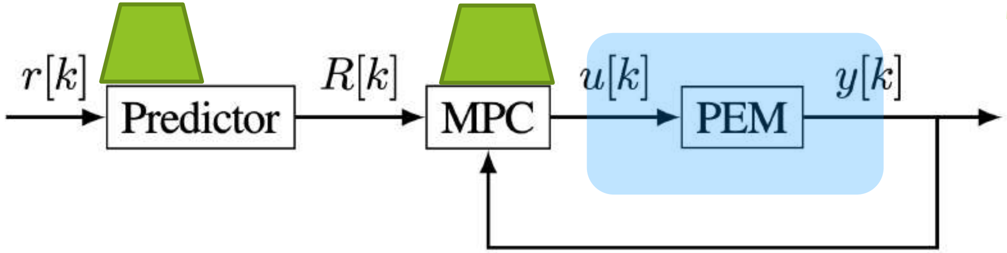


- **Case #2**: MPC-based pre-compensator for freq regulati
  - Energy-neutral regulation
    - SoC is approximately constant ➔ linearization works!
    - Freg regulation signal is <u>fairly predictable</u> 20-30 seconds out

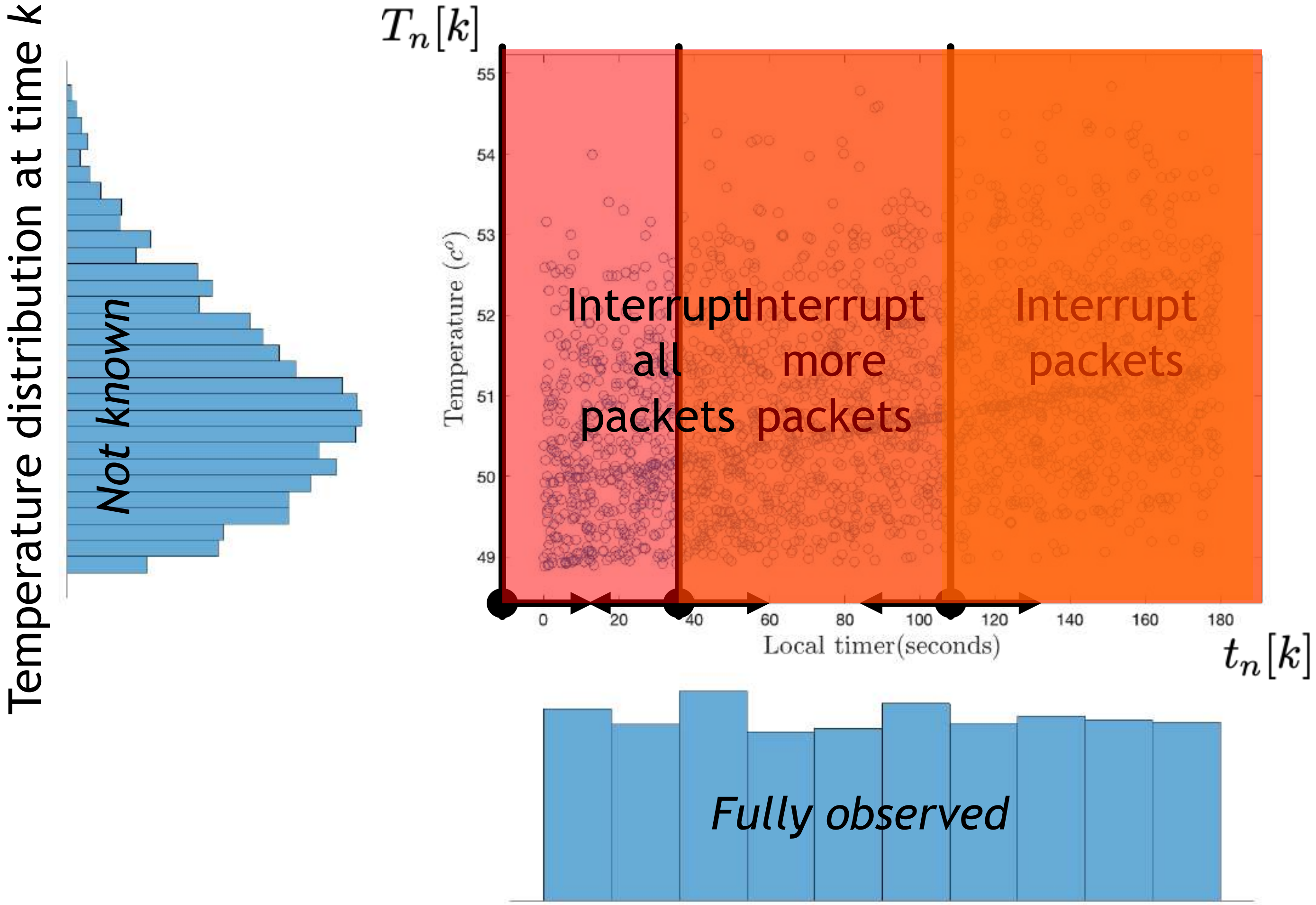
$$\begin{aligned} &\text{minimize} && \|Y_0+dY-R\|_p^p \\ &\text{over } dx, du && \\ &\text{subject to:} && dY-M_y dU=G_y \\ & && M_u dU \preceq G_{u1}-G_{u2} \end{aligned}$$







Leveraging timer states to estimate synthetic damping

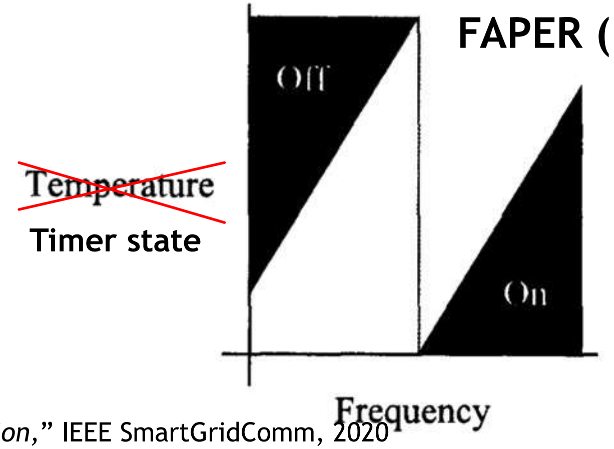


Distribution of timer states at time *k*
$(n_p = 10)$

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

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

FAPER (1980)

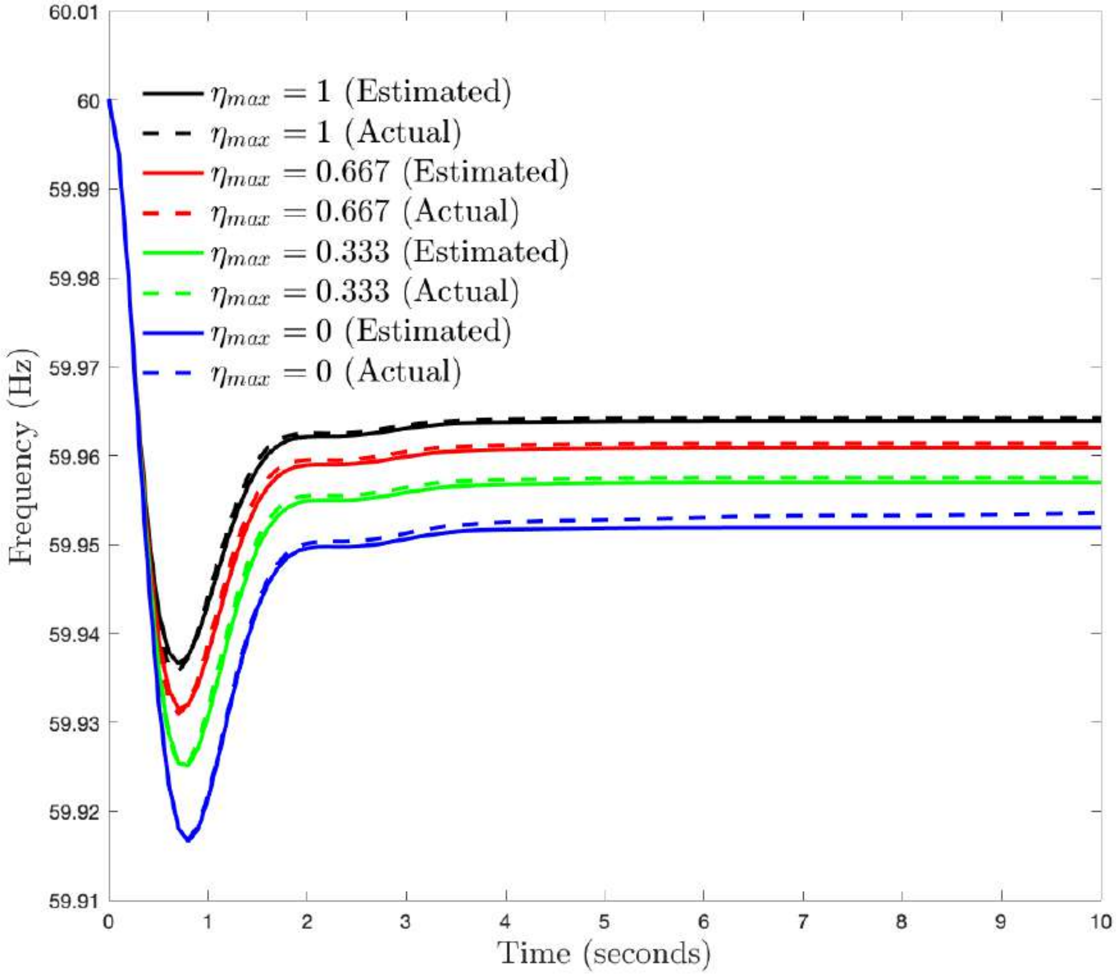


H. Mavalizadeh, L. Duffaut Espinosa, and M. Almassalkhi, "*Decentralized Frequency Control using Packet-based Energy Coordination*," IEEE SmartGridComm, 2020

-, "*Improving frequency response with synthetic damping available from fleets of distributed energy resources*," IEEE TPWRS (under review)

Frequency-responsive PEM (fully decentralized)

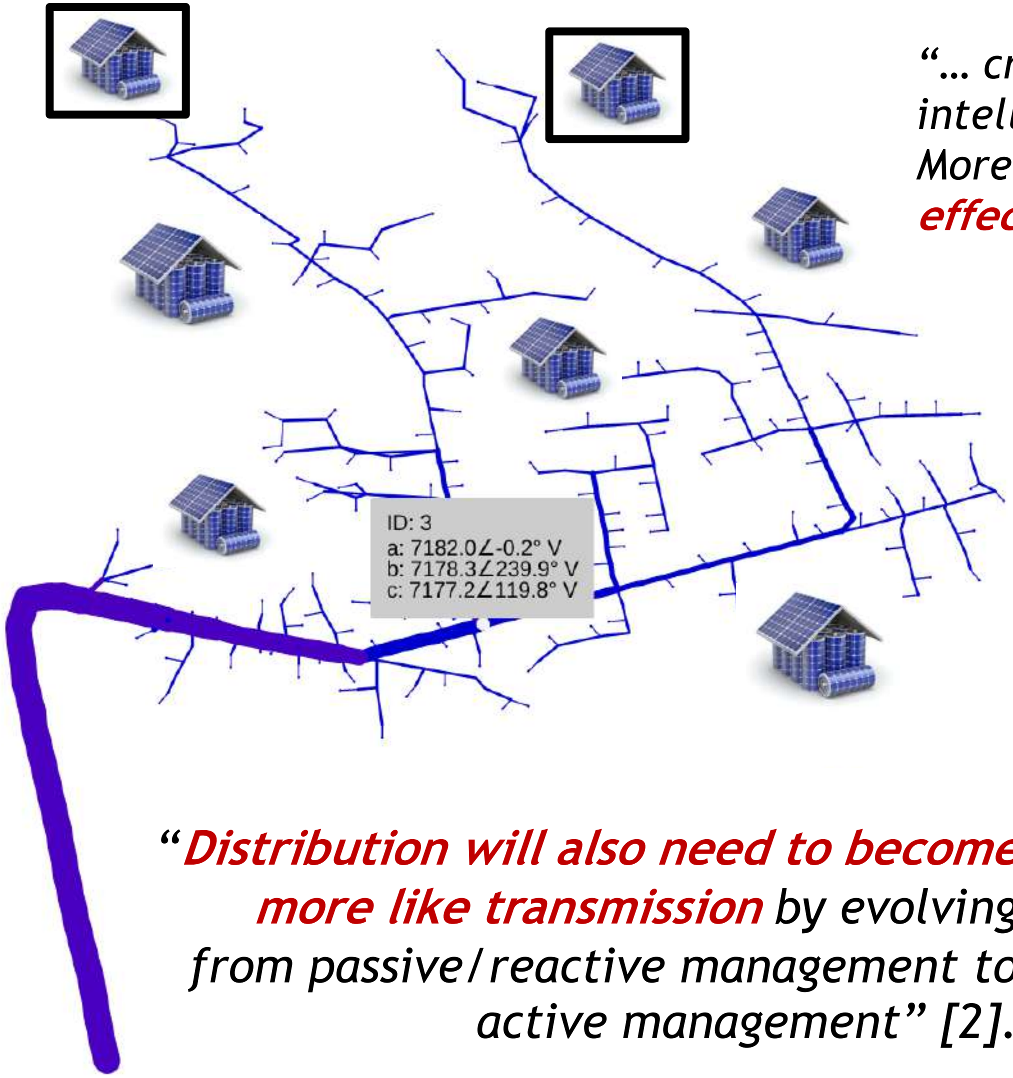
- We adapt PEM scheme for fast frequency response.
- Design local control law around packet interruption threshold mechanism that begets responsiveness to frequency.
- Importantly, we show how **DER coordinator can estimate the equivalent damping *online*** from previously accepted packets
- Characterize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



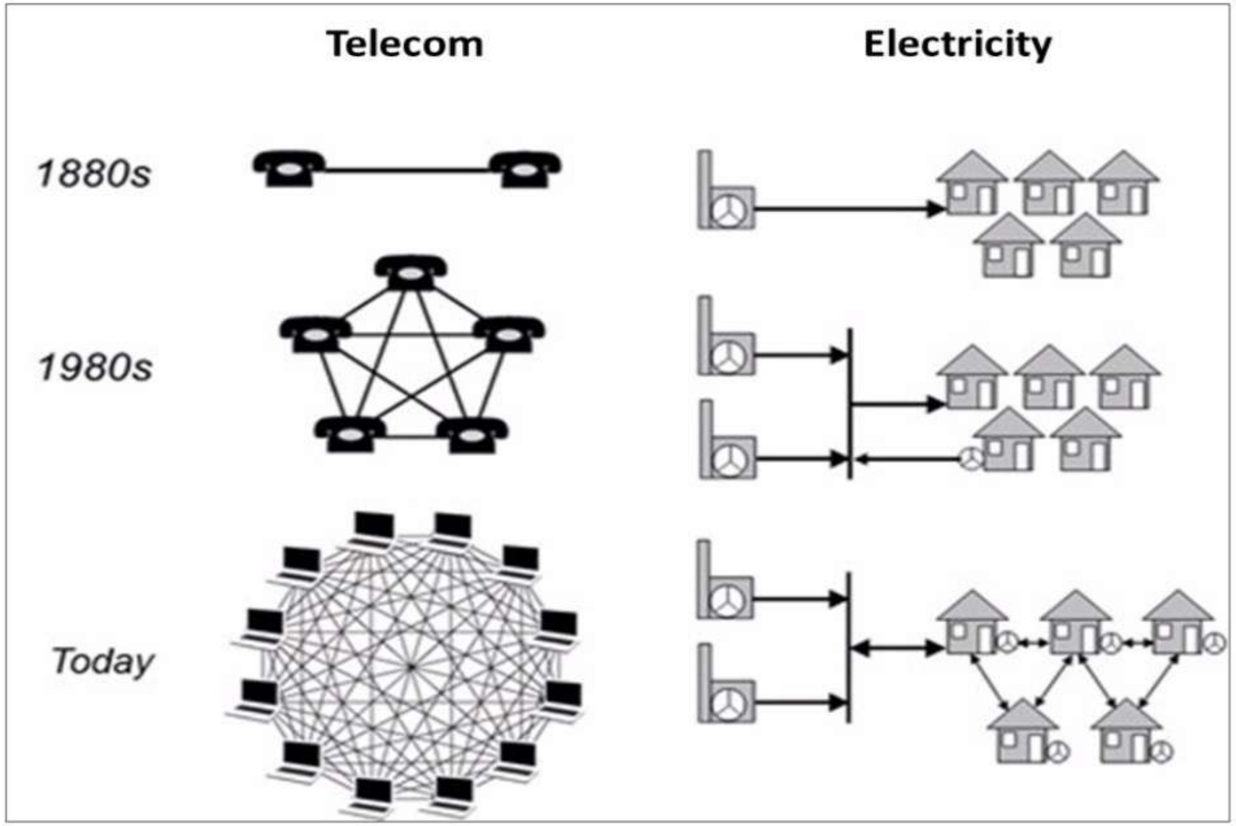
H. Mavalizadeh, L. Duffaut Espinosa, and M. Almassalkhi, “*Decentralized Frequency Control using Packet-based Energy Coordination,*” IEEE SmartGridComm, 2020

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

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].



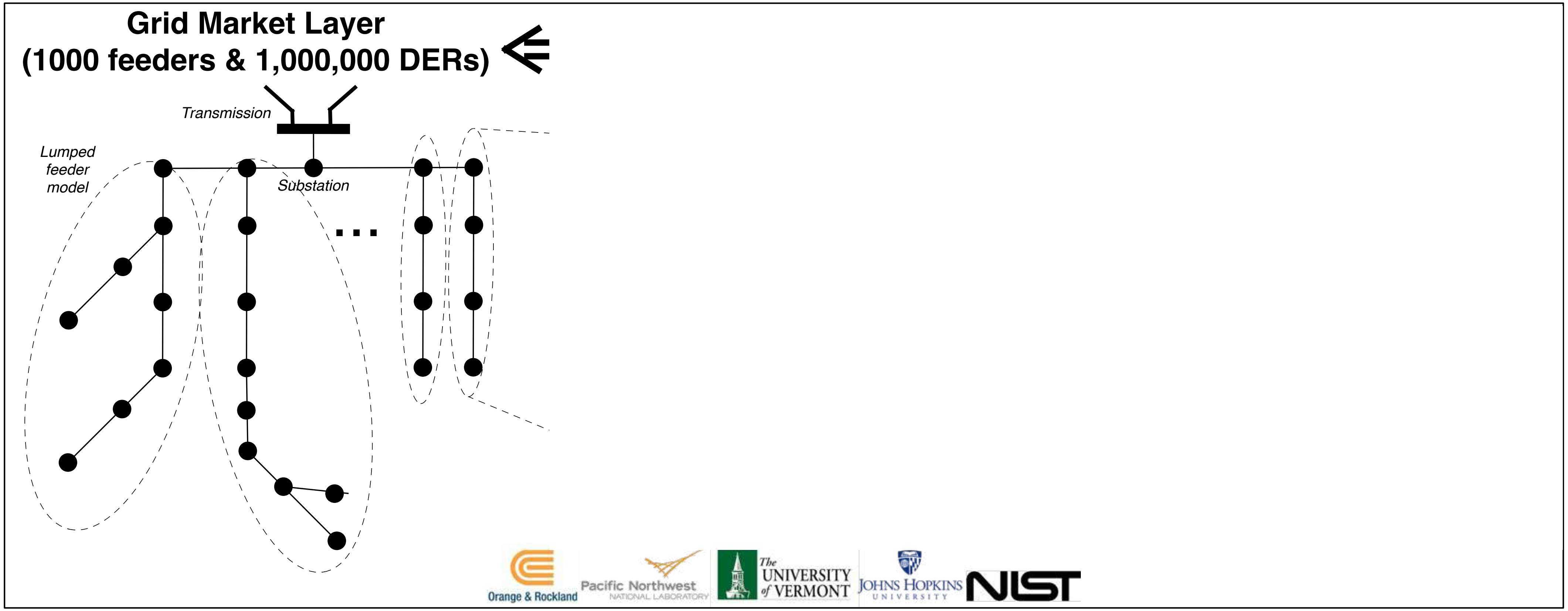
*"****Distribution will also need to become more like transmission*** *by evolving from passive/reactive management to active management"* [2].

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

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

Past experience with ”*utility-centric*” approaches

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



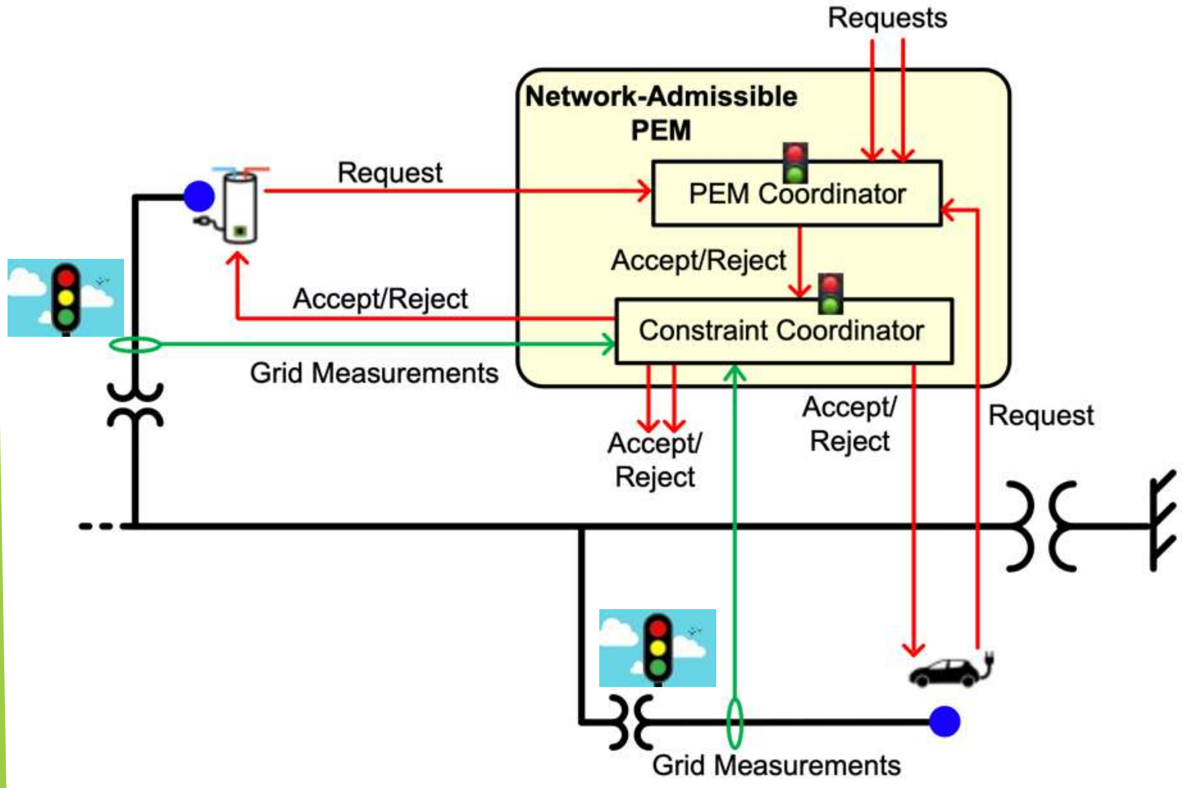
Local flexibility

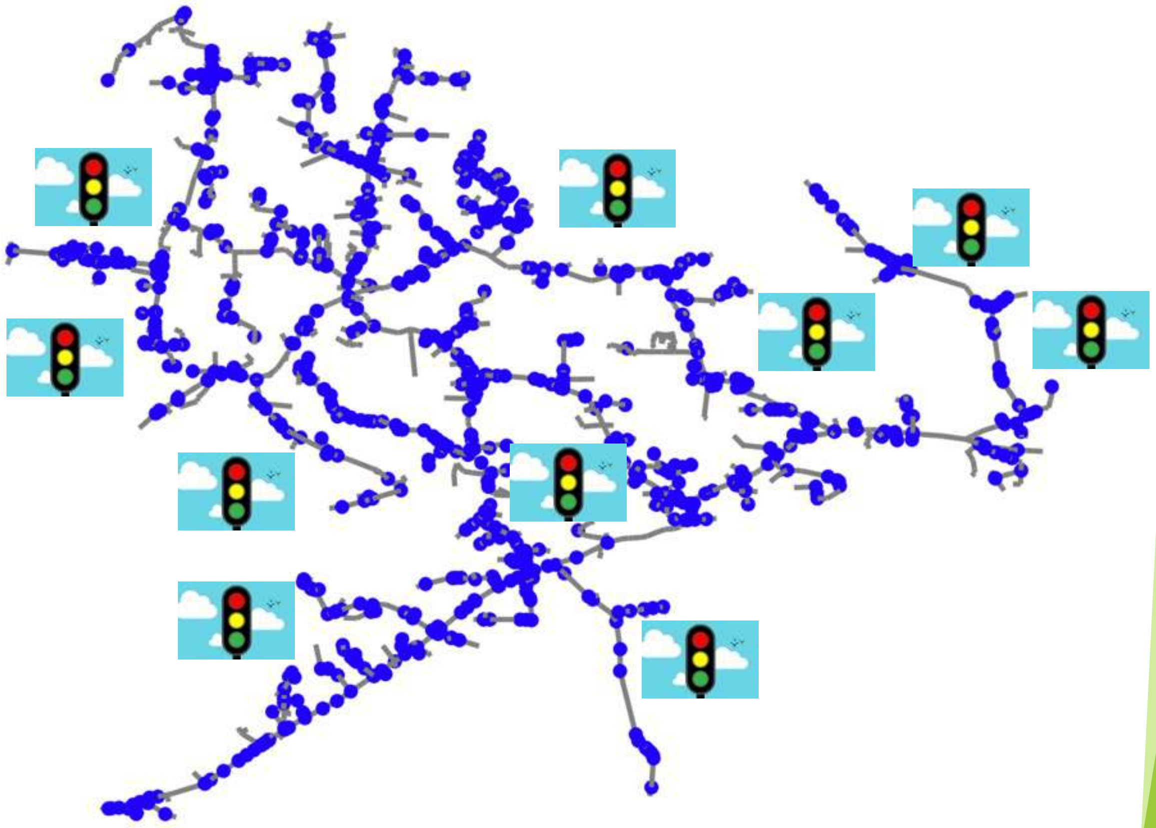
Local flexibility

[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

Past experience with network-aware PEM

Grid-aware PEM augments packet request mechanism with live grid conditions + traffic-light device logic



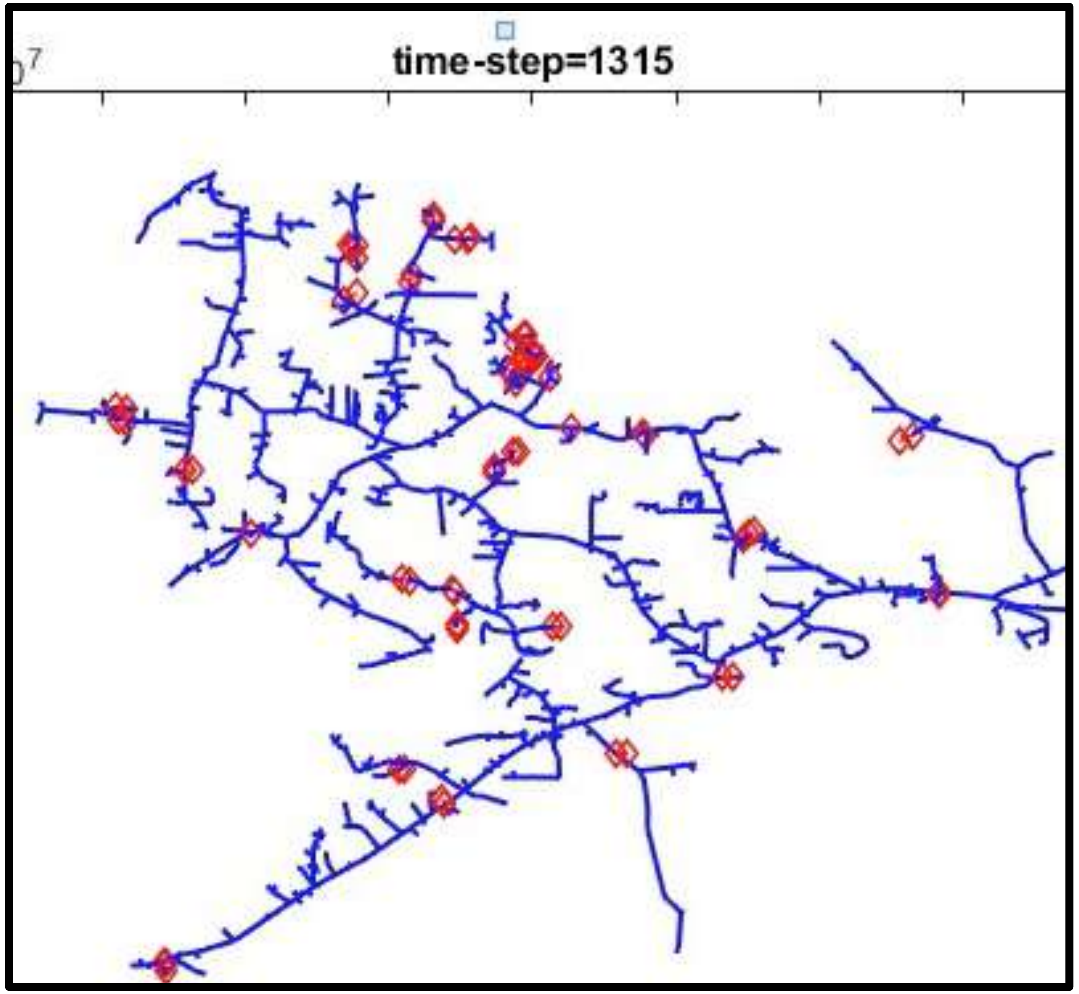


Open questions: measurement types, locations, update rates, data integrity, etc…

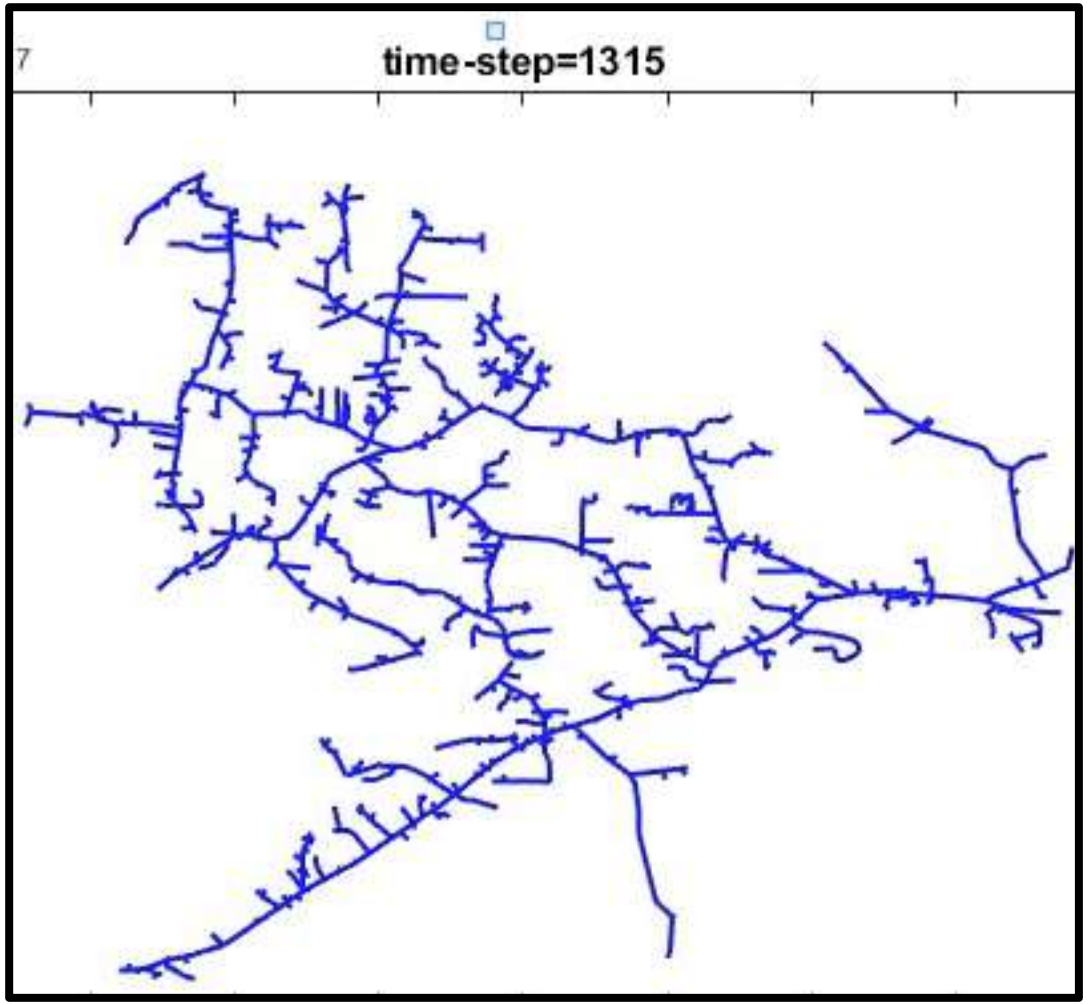
A. Khan, S. Paudyal, and M. Almassalkhi, "Performance Evaluation of Network-Admissible Demand Dispatch in Multi-Phase Distribution Grids,". *IREP* 2022

Performance of network-aware PEM (NA-PEM)

Vanilla PEM



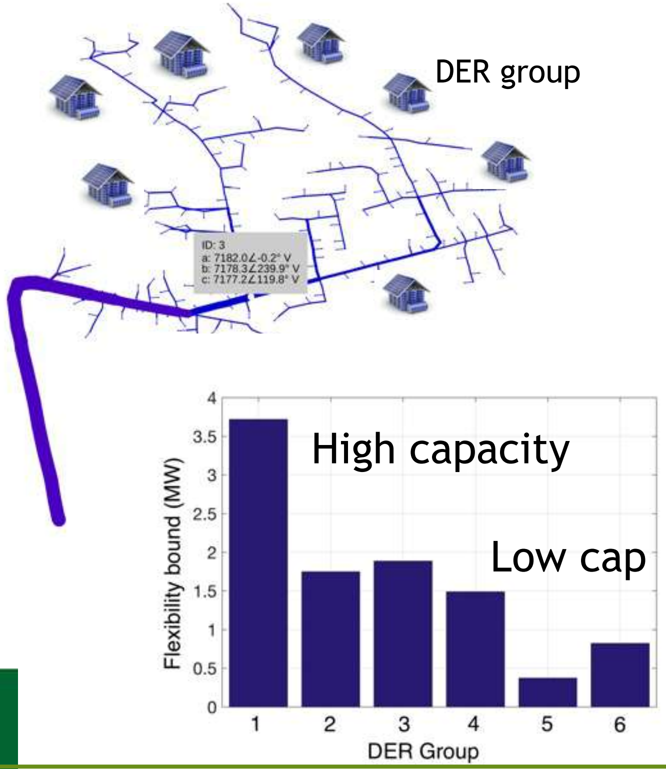
Network-Aware PEM



NA-PEM significantly reduces the number of grid violations w/o performance loss

Fundamental asymmetries in information & control

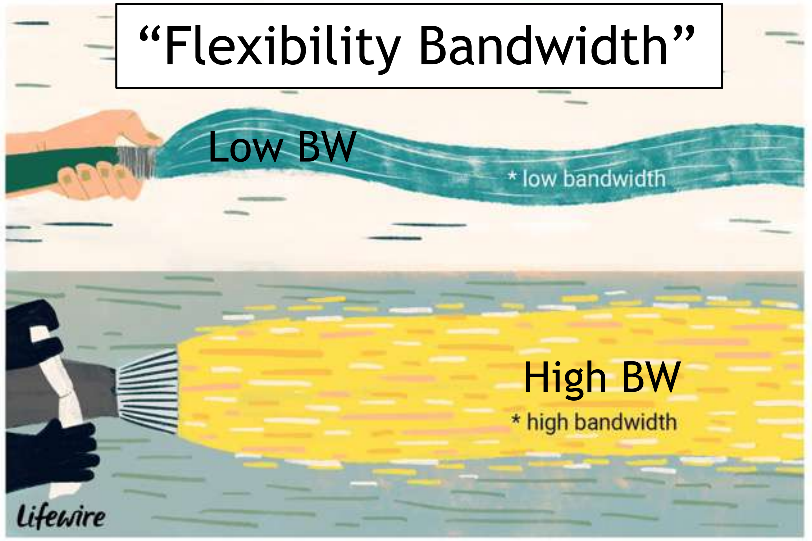
Utility (grid information+data)
- Need to ensure grid reliability
- Need to protect grid data
- Lack access to devices
- Knows grid capacity



Prices to devices?

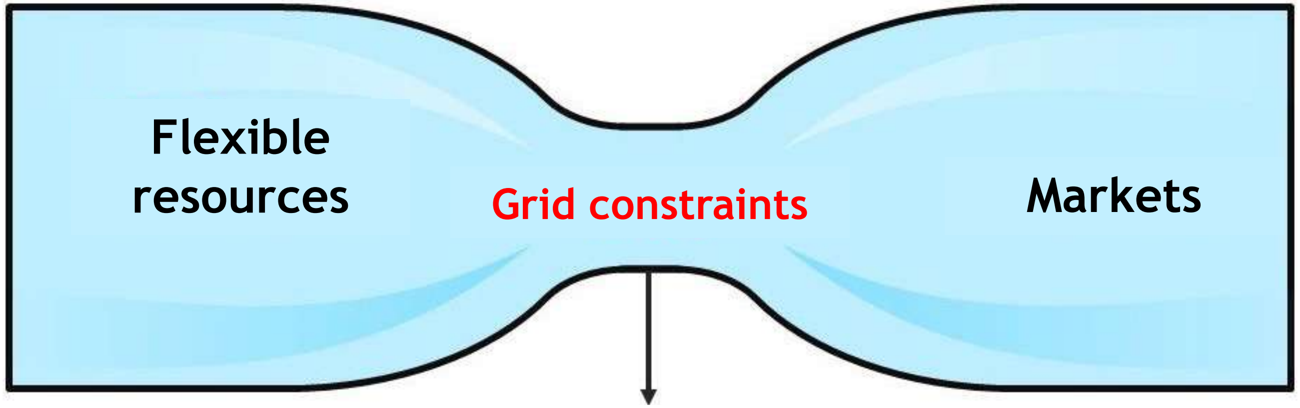
Let's try something different!

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 ISP*

Aggregators:
flexibility from
coordinated devices

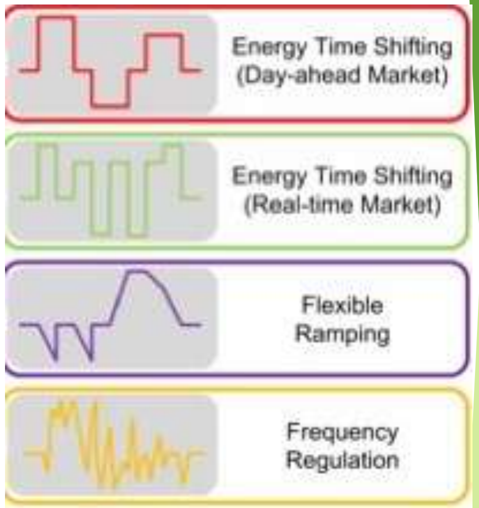


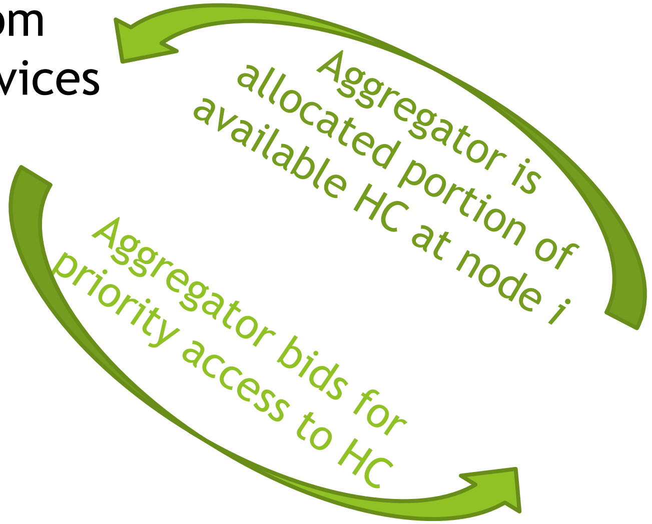
Flexible resources

Grid constraints

Markets

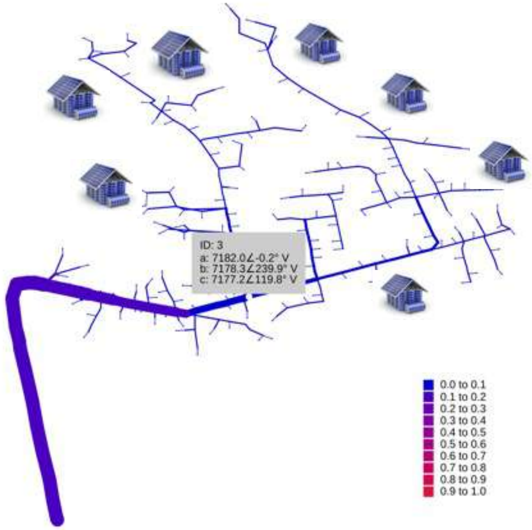
Utility: Find hosting capacity (HC) for each node

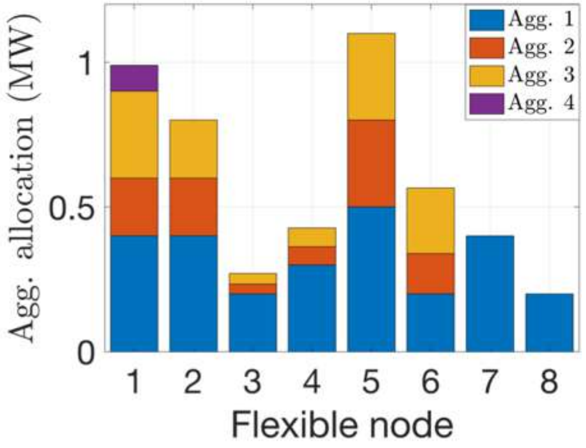




Aggregator is allocated portion of available HC at node i

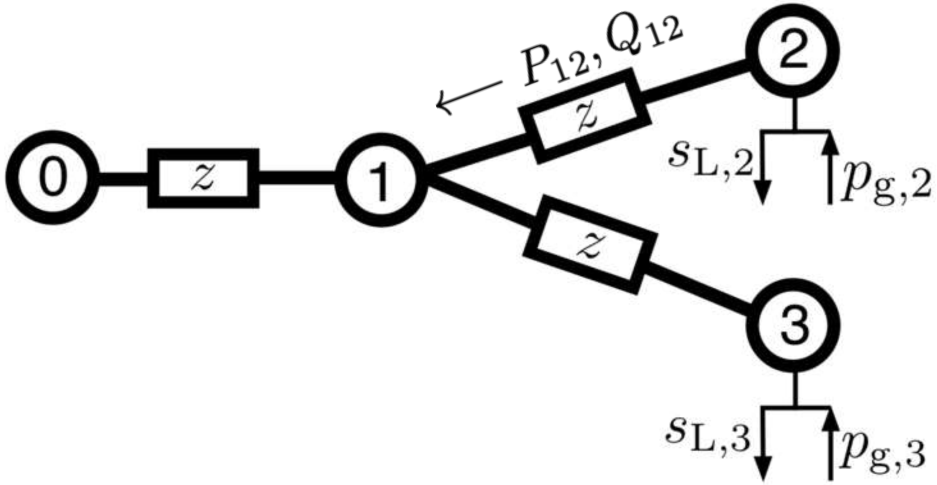
Aggregator bids for priority access to HC





Finding set of admissible (active) injections

- Simple 3-node balanced distribution feeder with 2 controllable nodes modeled with *DistFlow*:



$v_i := |V_i|^2$ and $l_{ij} := |I_{ij}|^2$

$$v_j = v_i + 2r_{ij}P_{ij} + 2x_{ij}Q_{ij} - |z_{ij}|^2 l_{ij}$$

$$P_{ij} = p_j + \sum_{h:h\to j} (P_{jh} - r_{jh}l_{jh})$$

$$Q_{ij} = q_j + \sum_{h:h\to j} (Q_{jh} - x_{jh}l_{jh})$$

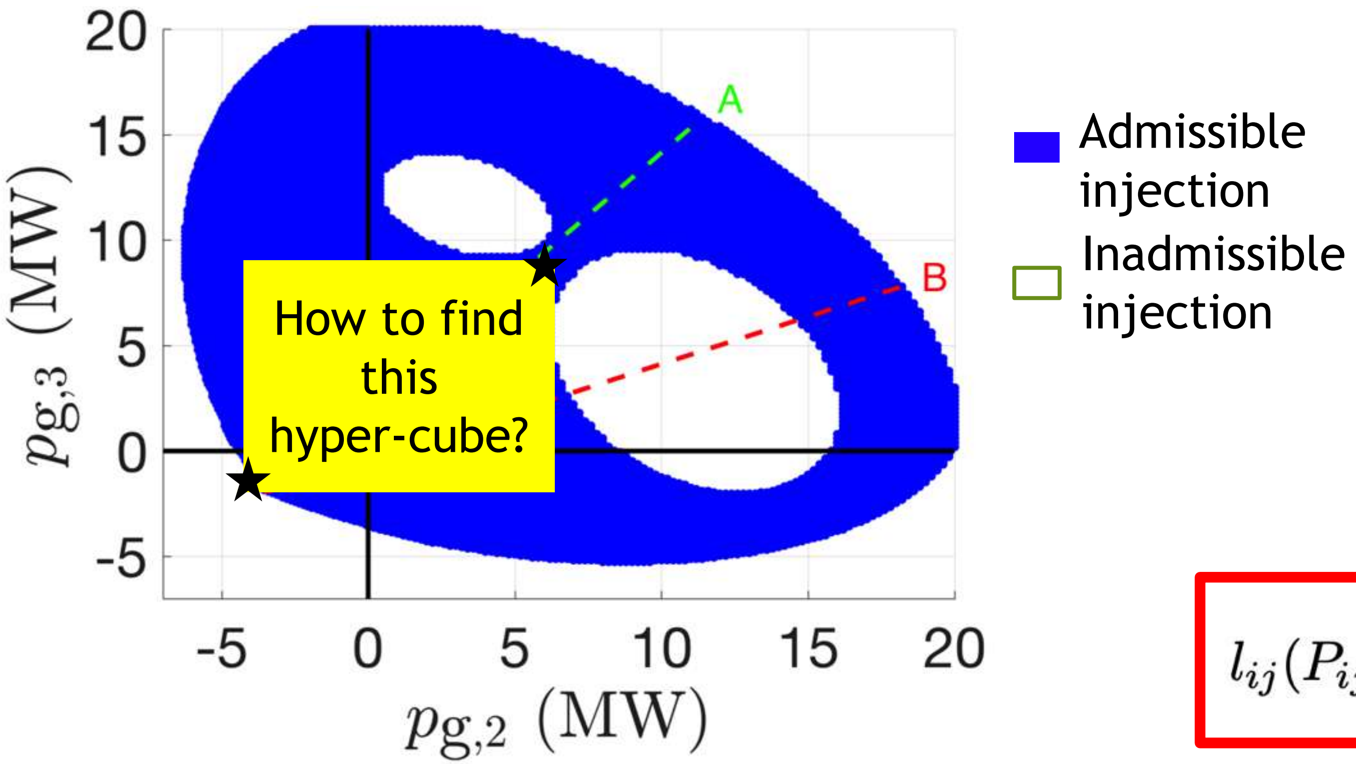
$$l_{ij}(P_{ij}, Q_{ij}, v_j) = \frac{P_{ij}^2 + Q_{ij}^2}{v_j},$$

The only nonlinear relation

Network limits: $v_i \in [\underline{v}_i, \bar{v}_i], l_{ij} \in [\underline{l}_{ij}, l_{ij}]$

Finding set of admissible (active) injections

- **Goal**: find largest hyperrectangle to determine p_g limts (decoupled)



How to find this hyper-cube?

$$v_j = v_i + 2r_{ij}P_{ij} + 2x_{ij}Q_{ij} - |z_{ij}|^2 l_{ij}$$

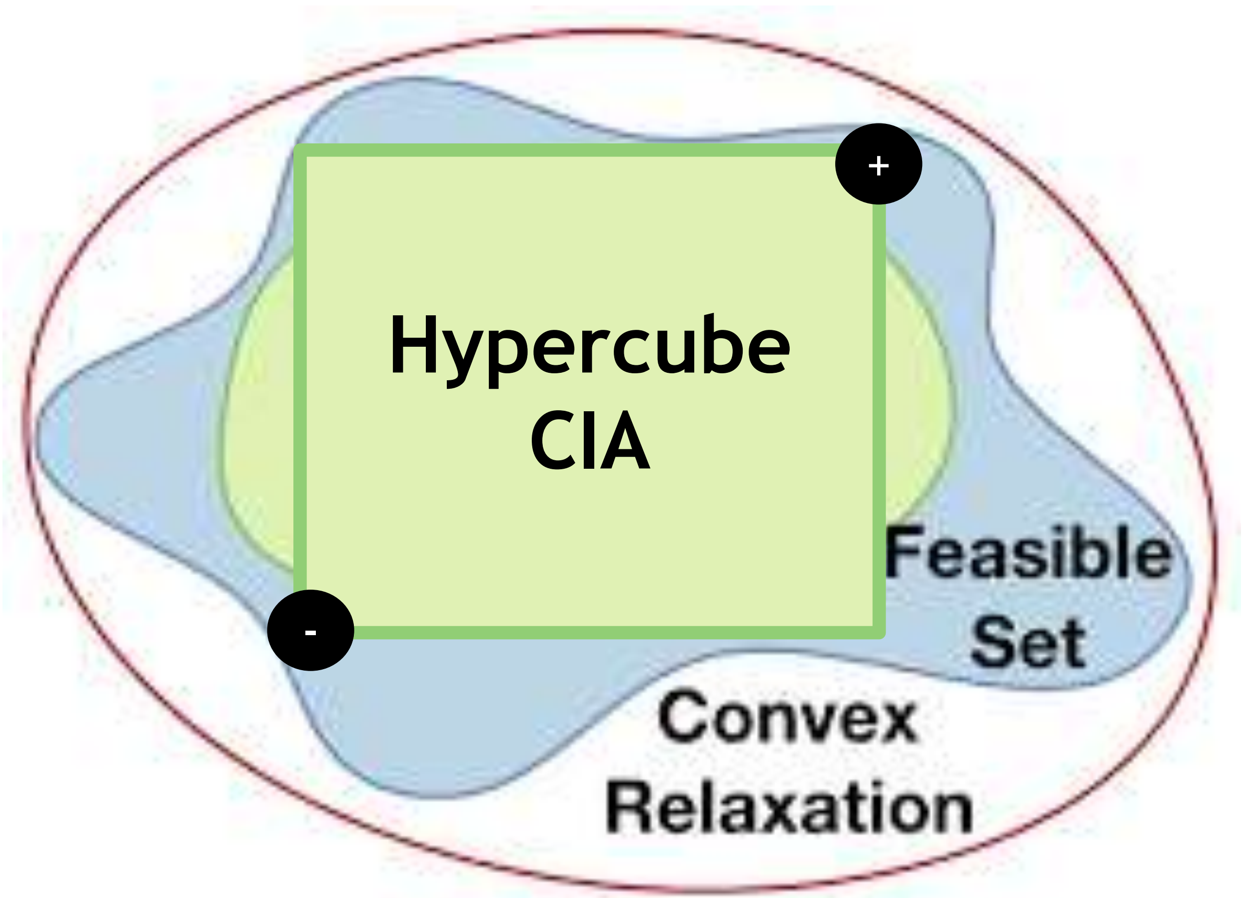
$$P_{ij} = p_j + \sum_{h:h\to j} (P_{jh} - r_{jh}l_{jh})$$

$$Q_{ij} = q_j + \sum_{h:h\to j} (Q_{jh} - x_{jh}l_{jh})$$

$$\boxed{l_{ij}(P_{ij}, Q_{ij}, v_j) = \frac{P_{ij}^2 + Q_{ij}^2}{v_j},}$$

Idea: replace non-convex constraint with a convex inner approximation

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

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

For mathematical details, please see:

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

Convex inner approximation via proxy variables

If we can find envelope $l_{\text{lb},ij} \leq \boxed{l_{ij}(P_{ij},Q_{ij},v_j) = \frac{P_{ij}^2 + Q_{ij}^2}{v_j},} \leq l_{\text{ub},ij}$

Then, we can create proxy variables that upper (+) and lower (-) bound the actual (P, Q, V)

$$
\left.\begin{aligned}
P^+ &:= Cp - D_{\text{R}} l_{\text{lb}} \\
P^- &:= Cp - D_{\text{R}} l_{\text{ub}} \\
Q^+ &:= Cq - D_{\text{X}_+} l_{\text{lb}} - D_{\text{X}_-} l_{\text{ub}} \\
Q^- &:= Cq - D_{\text{X}_+} l_{\text{ub}} - D_{\text{X}_-} l_{\text{lb}} \\
V^+ &:= v_0 \mathbf{1}_n + M_{\text{p}} p + M_{\text{q}} q - H_+ l_{\text{lb}} - H_- l_{\text{ub}} \\
V^- &:= v_0 \mathbf{1}_n + M_{\text{p}} p + M_{\text{q}} q - H_+ l_{\text{ub}} - H_- l_{\text{lb}}
\end{aligned}\right\}
$$

Given a nominal operating point, $x_{ij}^0 := (P_{ij}^0, Q_{ij}^0, v_j^0)$

$$\boxed{l_{ij} \approx l_{ij}^0 + \mathbf{J}_{ij}^\top \delta_{ij} + \frac{1}{2} \delta_{ij}^\top \mathbf{H}_{\text{e},ij} \delta_{ij}}$$

$$\delta_{ij} := \begin{bmatrix} P_{ij} - P_{ij}^0 \\ Q_{ij} - Q_{ij}^0 \\ v_j - v_j^0 \end{bmatrix}, \ \mathbf{J}_{ij} := \begin{bmatrix} \frac{\partial l_{ij}}{\partial P_{ij}} \\ \frac{\partial l_{ij}}{\partial Q_{ij}} \\ \frac{\partial l_{ij}}{\partial v_j} \end{bmatrix} \Bigg|_{x_{ij}^0} = \begin{bmatrix} \frac{2P_{ij}^0}{v_j^0} \\ \frac{2Q_{ij}^0}{v_j^0} \\ -\frac{(P_{ij}^0)^2 + (Q_{ij}^0)^2}{(v_j^0)^2} \end{bmatrix}$$

$$\mathbf{H}_{\text{e},ij} := \begin{bmatrix} \frac{2}{v_j^0} & 0 & \frac{-2P_{ij}^0}{(v_j^0)^2} \\ 0 & \frac{2}{v_j^0} & \frac{-2Q_{ij}^0}{(v_j^0)^2} \\ \frac{-2P_{ij}^0}{(v_j^0)^2} & \frac{-2Q_{ij}^0}{(v_j^0)^2} & 2\frac{(P_{ij}^0)^2 + (Q_{ij}^0)^2}{(v_j^0)^3} \end{bmatrix} \succeq 0^*$$

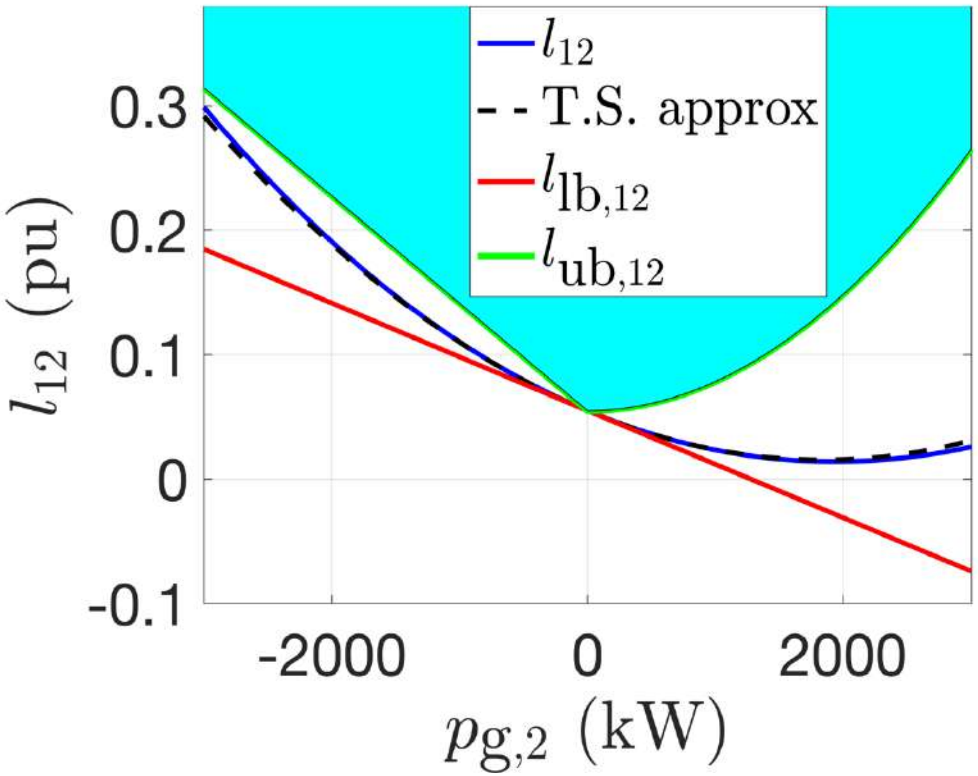
and from this model, we can explicitly define upper and lower bounds on l_{ij} that yield a convex inner approximation.

N. Nazir and M. Almassalkhi, "Voltage Positioning Using Co-Optimization of Controllable Grid Assets in Radial Networks," in *IEEE Transactions on Power Systems*, vol. 36, no. 4, pp. 2761-2770, July 2021, doi: 10.1109/TPWRS.2020.3044206.

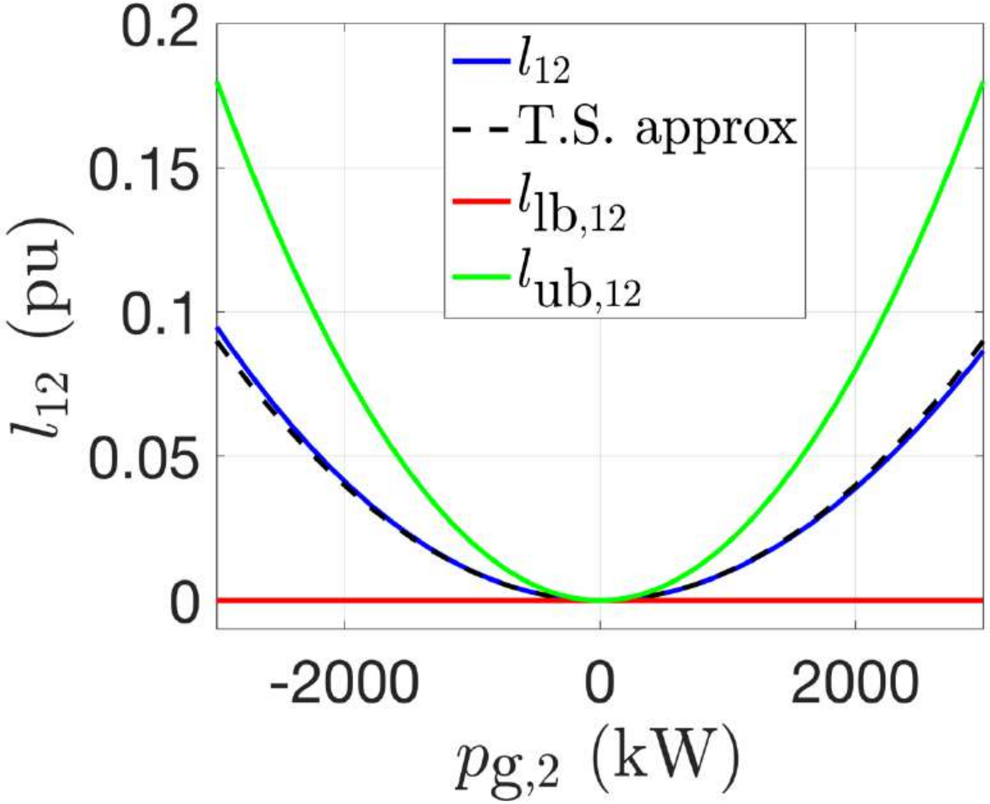
Convex inner approximation via proxy variables

$$l_{\mathrm{lb},ij} \leq \boxed{l_{ij}(P_{ij},Q_{ij},v_j)=\frac{P_{ij}^2+Q_{ij}^2}{v_j},} \leq l_{\mathrm{ub},ij}$$

Full-load conditions



No-load conditions



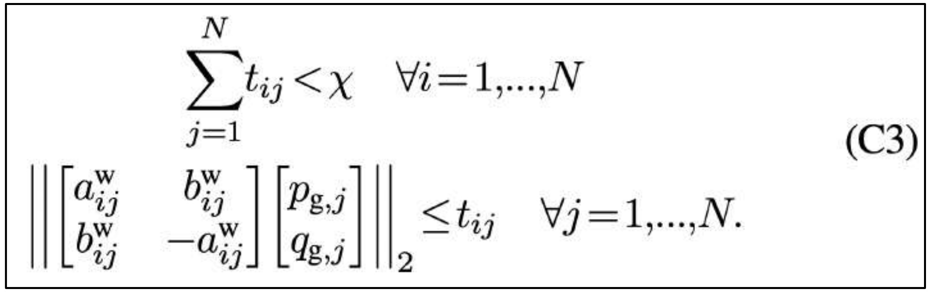
For mathematical details, please see:

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

What about existence of solution?

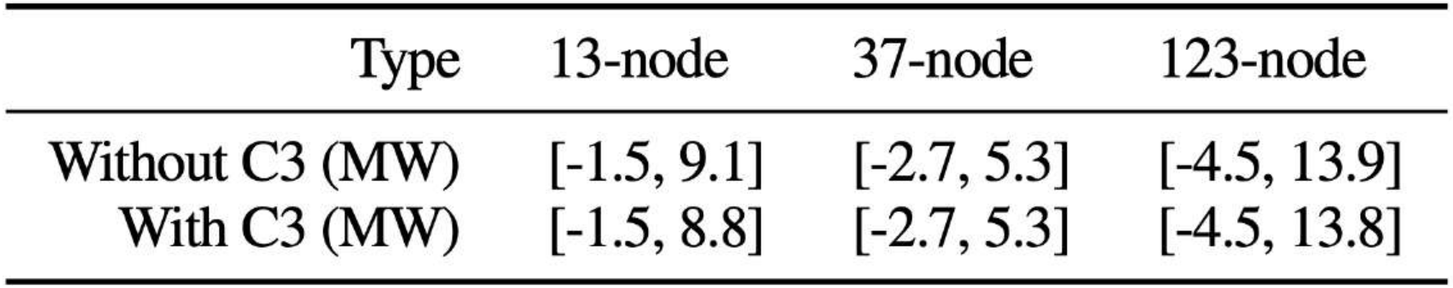
Leverage sufficient conditions from [*] in two ways:

- At each iteration, verify existence of (new) operating point x_0 with explicit test condition
- Augment CIA formulation with *N* linear inequalities and *N* SOC constraints (still convex)



$$\begin{aligned} &\sum_{j=1}^{N} t_{ij} < \chi \quad \forall i=1,\dots,N \\ &\left\| \begin{bmatrix} a_{ij}^{\mathrm{w}} & b_{ij}^{\mathrm{w}} \\ b_{ij}^{\mathrm{w}} & -a_{ij}^{\mathrm{w}} \end{bmatrix} \begin{bmatrix} p_{\mathrm{g},j} \\ q_{\mathrm{g},j} \end{bmatrix} \right\|_2 \leq t_{ij} \quad \forall j=1,\dots,N. \end{aligned} \qquad \text{(C3)}$$

Added conservativeness from existence guarantees: *small impact*

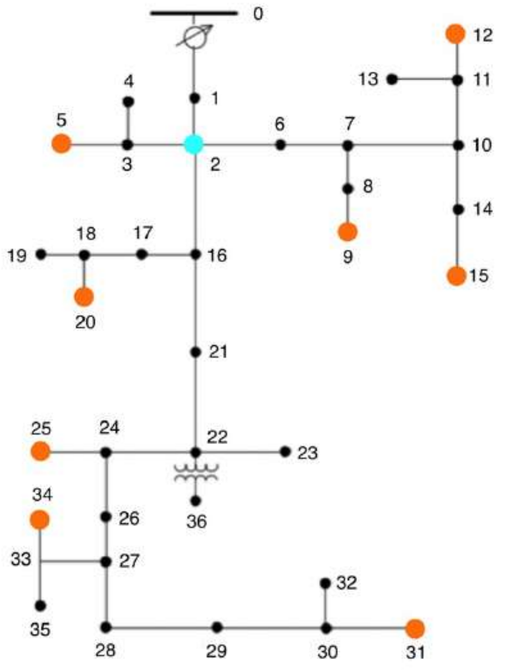


Type	13-node	37-node	123-node
Without C3 (MW)	[-1.5, 9.1]	[-2.7, 5.3]	[-4.5, 13.9]
With C3 (MW)	[-1.5, 8.8]	[-2.7, 5.3]	[-4.5, 13.8]

[*] C.Wang, A.Bernstein, J.LeBoudec, and M.Paolone,“*Explicit conditions on existence and uniqueness of load-flow solutions in distribution networks,” IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 953–962, 2018.

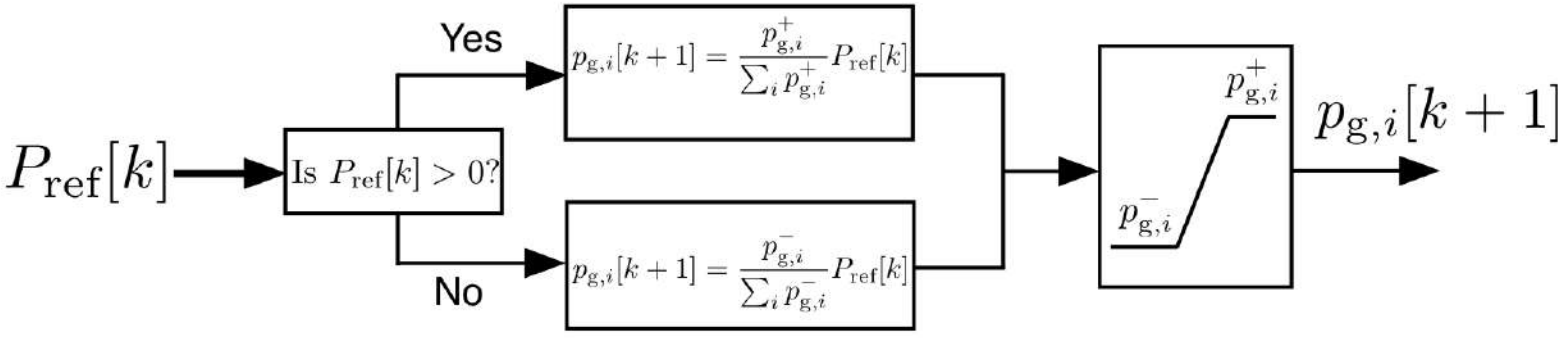
CIA enables real-time, grid-aware disaggregation

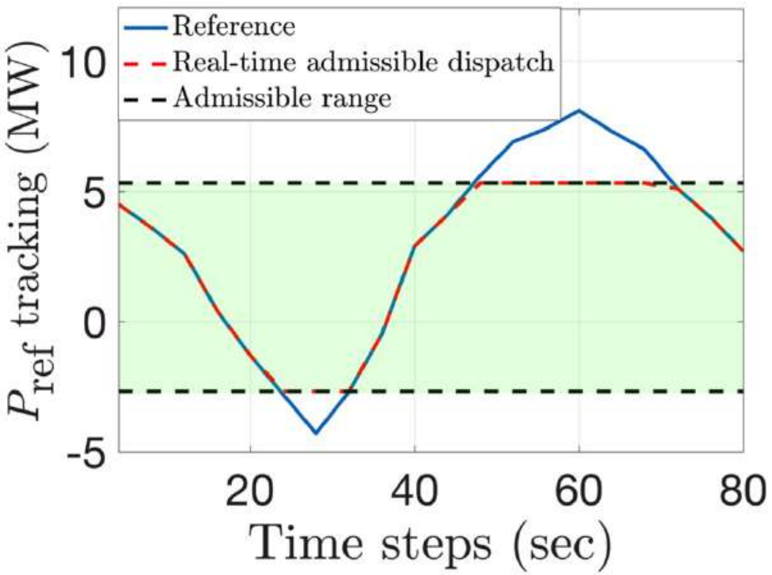
Nodal hosting capacities $[p_i^-, p_i^+]$ enable an open-loop, distributed, and **grid-aware DER control policy**

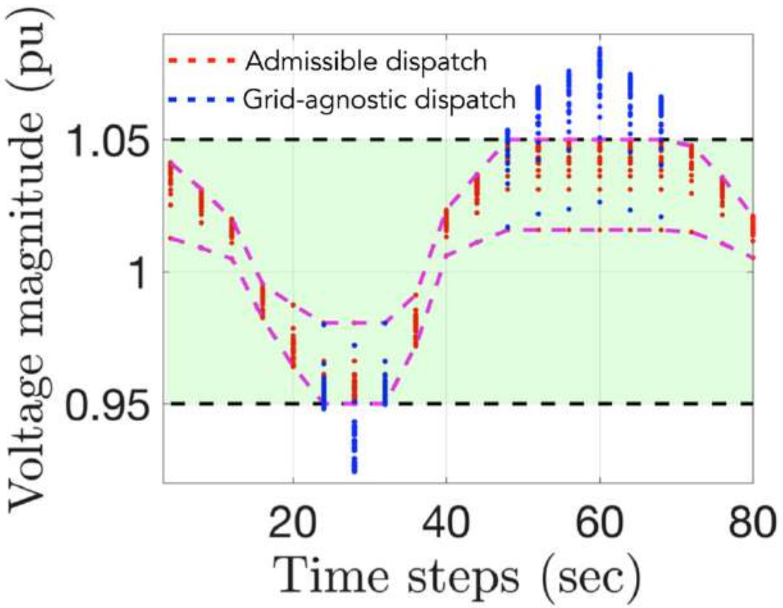


IEEE 37-node network

(from Baker/Dall'Anese)

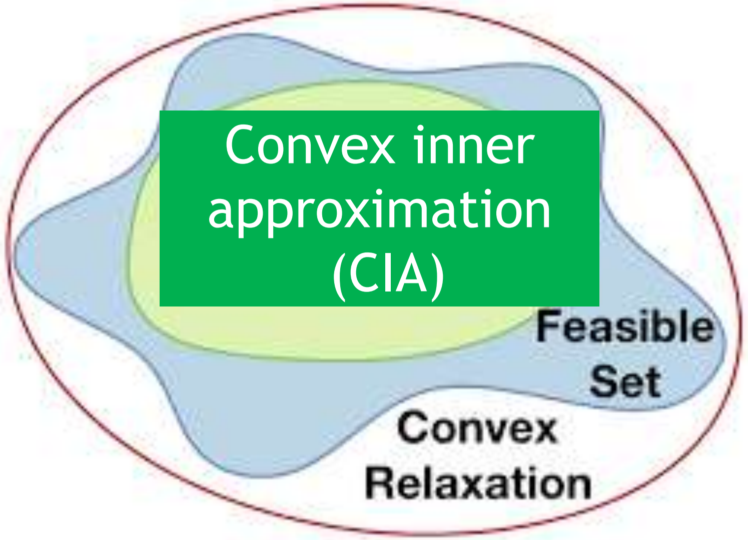






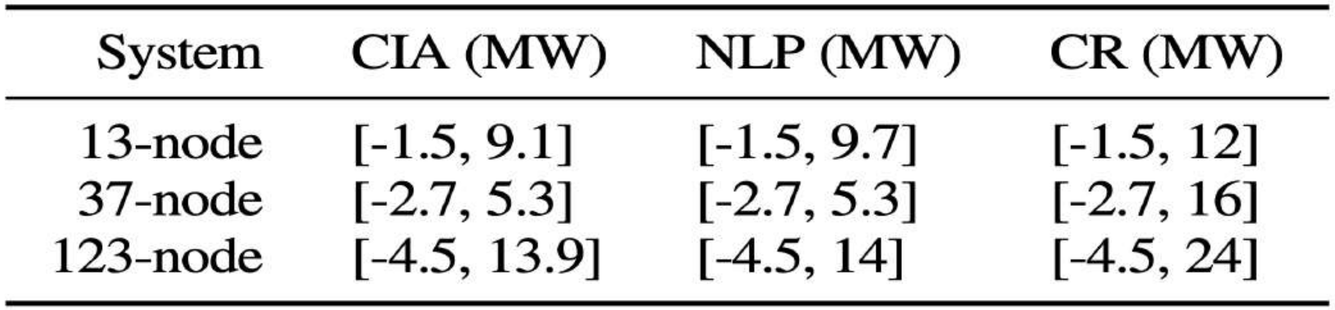
N. Nazir and M. Almassalkhi, "Grid-aware aggregation and realtime disaggregation of distributed energy resources in radial networks", IEEE Transactions on Power Systems, 2021

What about conservativeness of CIA?



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.

Comparing hosting capacity results*



System	CIA (MW)	NLP (MW)	CR (MW)
13-node	[-1.5, 9.1]	[-1.5, 9.7]	[-1.5, 12]
37-node	[-2.7, 5.3]	[-2.7, 5.3]	[-2.7, 16]
123-node	[-4.5, 13.9]	[-4.5, 14]	[-4.5, 24]

Convex relaxation (CR) over-estimates maximum reactive power capability

Nonlinear (NLP) has no optimality guarantees AND does not guarantee that entire range is admissible (i.e., no holes)

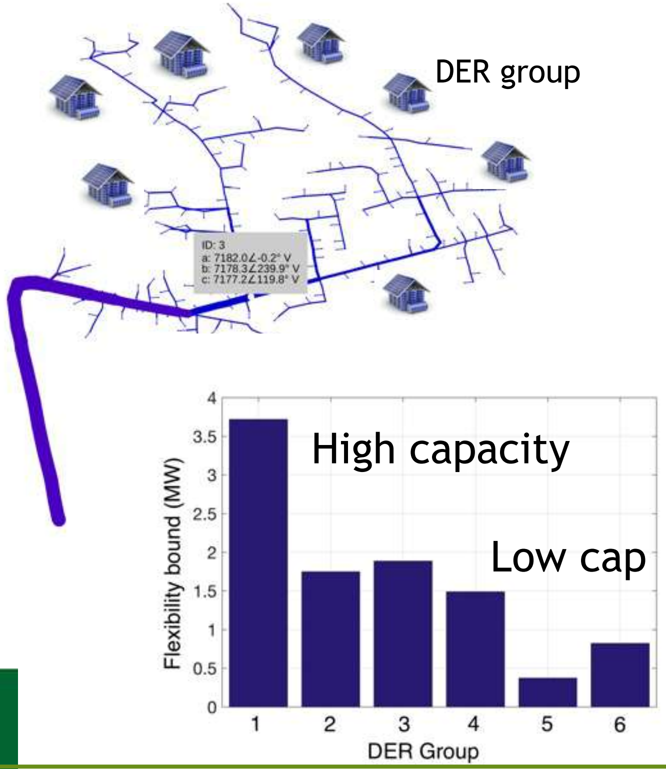
Conclusion: proposed (CIA) method is **<u>not overly conservative</u>** and entire range is admissible

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

DHC overcomes data/control asymmetry

Utility (grid information+data)

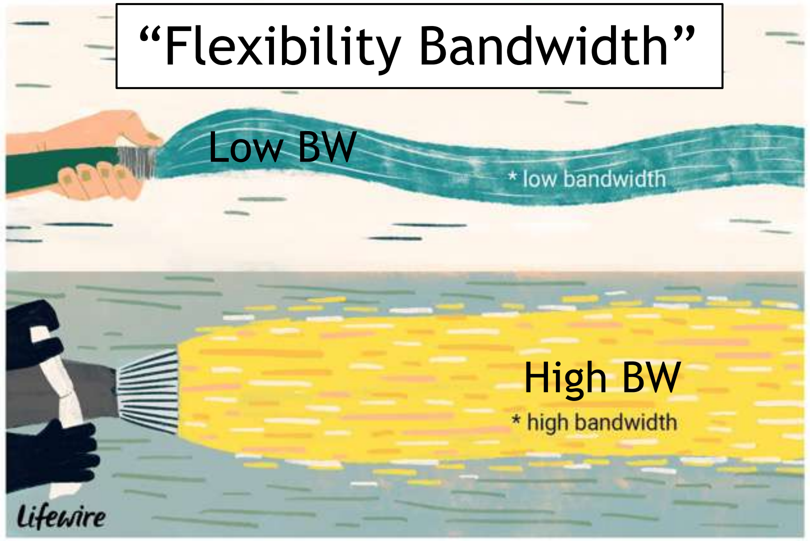
- Dynamic hosting capacities capture grid conditions and limits



Available hosting capacity

Aggregators (device access, markets)

- Flexibility captures device availability and comfort limits



Future work: find optimal control/price signals

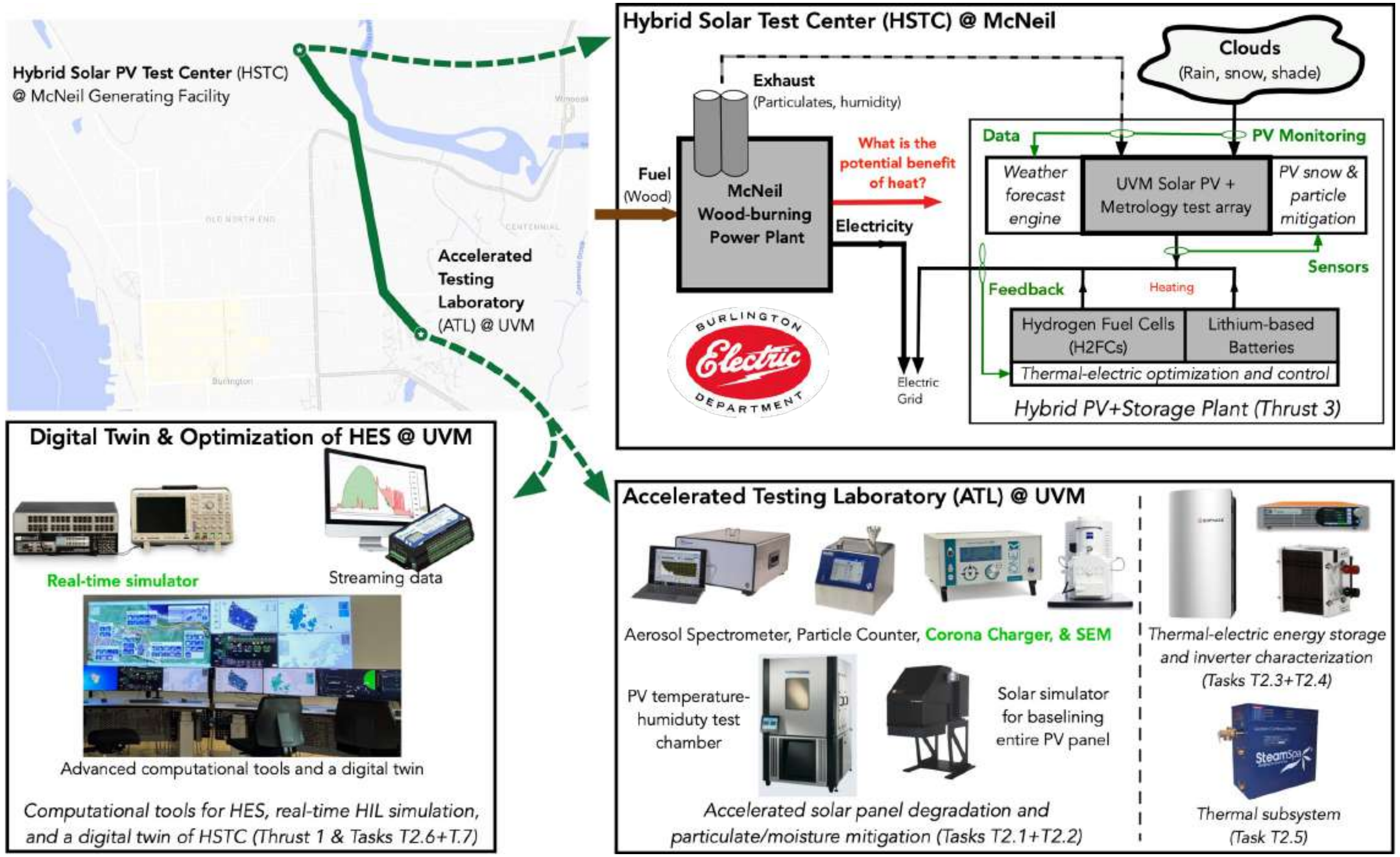
Available flexibility

Hybrid Energy Systems

From virtual batteries to physical batteries

What is a hybrid energy system?

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

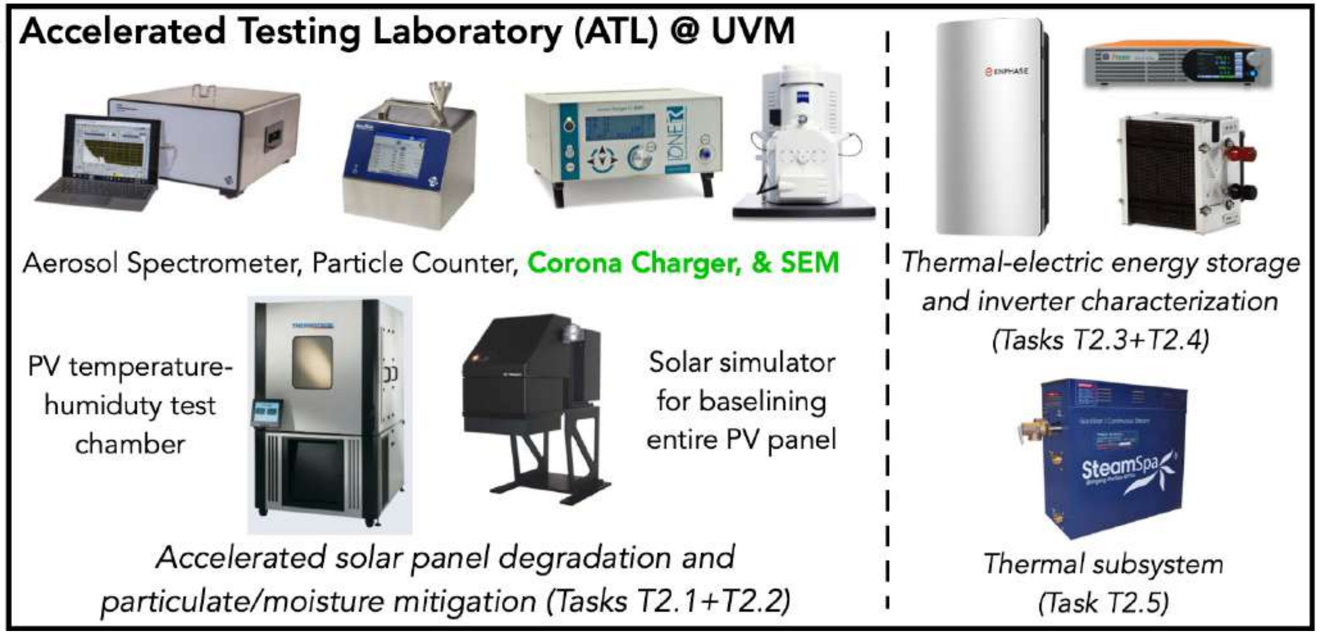
Energy Systems Simulation Lab
"Digital Twin of Vermont's Grid"

Accelerated Testing Lab (ATL)
Hardware-enabled Energy Test Bed

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

Accelerated Test Laboratory (ATL) @ UVM

R&D&D
State of the art facility
Hardware-enabled analysis



Accelerated Testing Laboratory (ATL) @ UVM

Aerosol Spectrometer, Particle Counter, **Corona Charger, & SEM**

PV temperature-humidity test chamber

Solar simulator for baselining entire PV panel

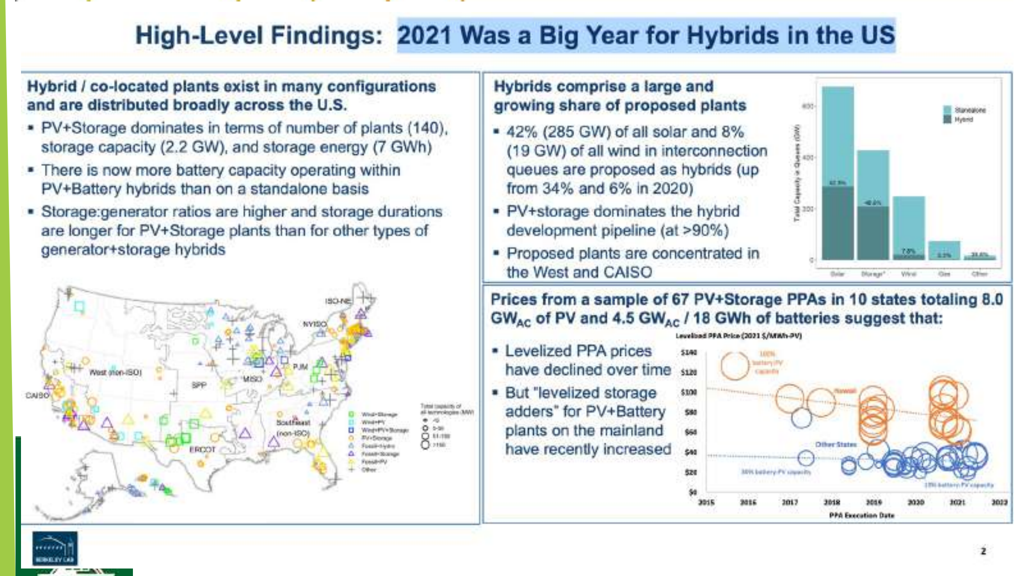
Accelerated solar panel degradation and particulate/moisture mitigation (Tasks T2.1+T2.2)

Thermal-electric energy storage and inverter characterization (Tasks T2.3+T2.4)

Thermal subsystem (Task T2.5)

DOE is looking for answers, too. 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 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.

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.

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

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

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.

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.

Estimating Value

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

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

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

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

DOE reports from 2022

Main objectives of project

Long-term planning

1

Hybrid energy system **degradation and lifetime economics and performance.**

Short-term operations

2

Optimize and control the hybrid energy system's performance and **demonstrate advanced grid services** that support reliability and resilience

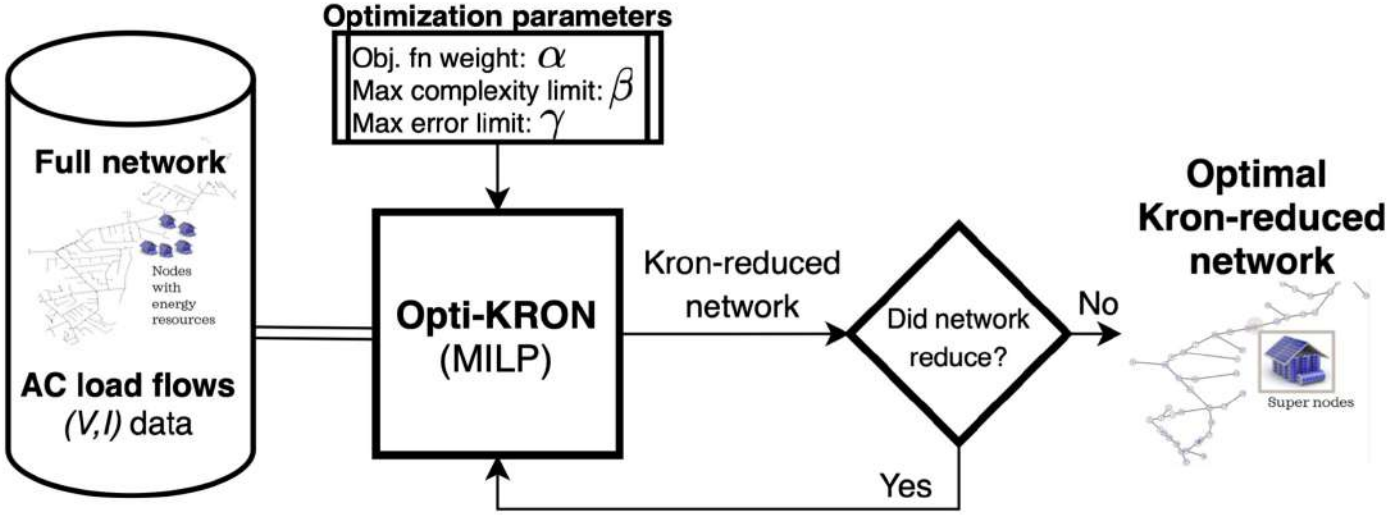
National impact

3

Develop nationally competitive **energy research infrastructure in Vermont that supports national priorities** around combating climate change & clean energy workforce development.

Topics I didn’t talk about today

Optimal (physics-informed) network reduction



Optimization parameters

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

Full network

Nodes with energy resources

AC load flows
(V,I) data

Opti-KRON
(MILP)

Kron-reduced network

Did network reduce?

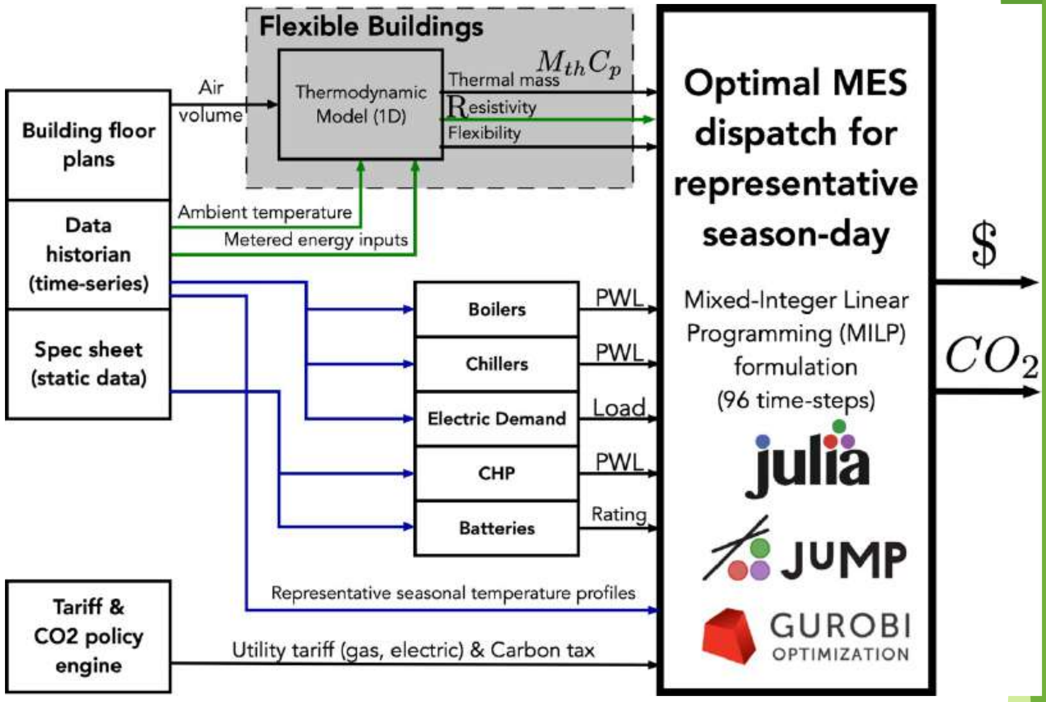
No

Yes

Optimal Kron-reduced network

Super nodes

Multi-energy systems / sector coupling



Flexible Buildings

Building floor plans

Air volume

Thermodynamic Model (1D)

$M_{th}C_p$
Thermal mass
Resistivity
Flexibility

Data historian (time-series)

Ambient temperature

Metered energy inputs

Spec sheet (static data)

Boilers

Chillers

Electric Demand

CHP

Batteries

PWL
PWL
Load
PWL
Rating

Representative seasonal temperature profiles

Tariff & CO2 policy engine

Utility tariff (gas, electric) & Carbon tax

Optimal MES dispatch for representative season-day

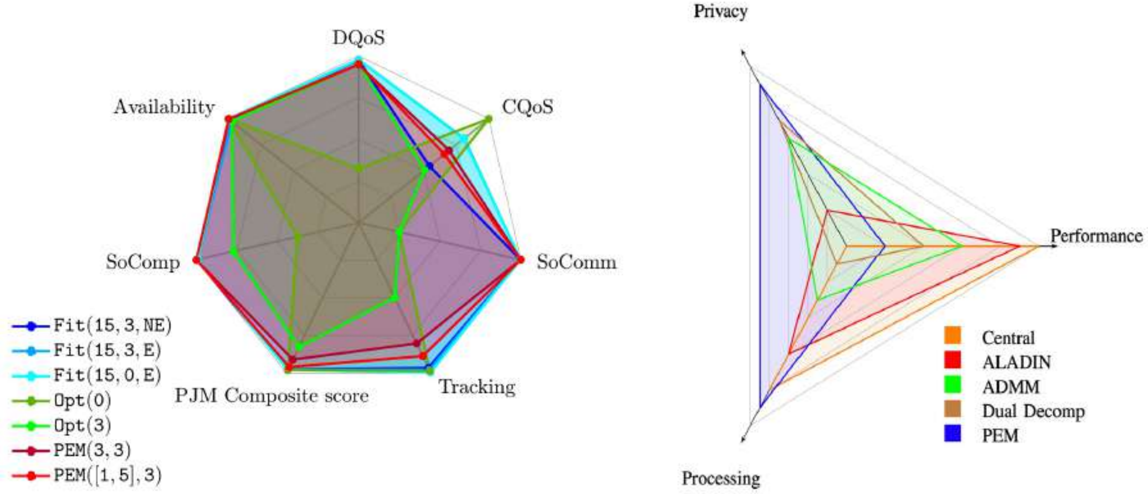
Mixed-Integer Linear Programming (MILP) formulation
(96 time-steps)

julia
JuMP
GUROBI OPTIMIZATION

$

CO_2

Methodologies for characterizing energy transitions



Collision-free trajectory optimization of swarms

Thank you! Questions? Comments?

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

Traditional demand response

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