

Managing volatility of renewable energy sources in the future power grid at low cost

A hurdle in greening the power grid

- Solar and wind energy are intermittent
- This requires energy storage.
- But, batteries are expensive.

Alternative to expensive batteries:

- Power demand of most loads is flexible and can be manipulated to provide *virtual energy storage* (VES).
- Low cost: no new equipment, only change in software

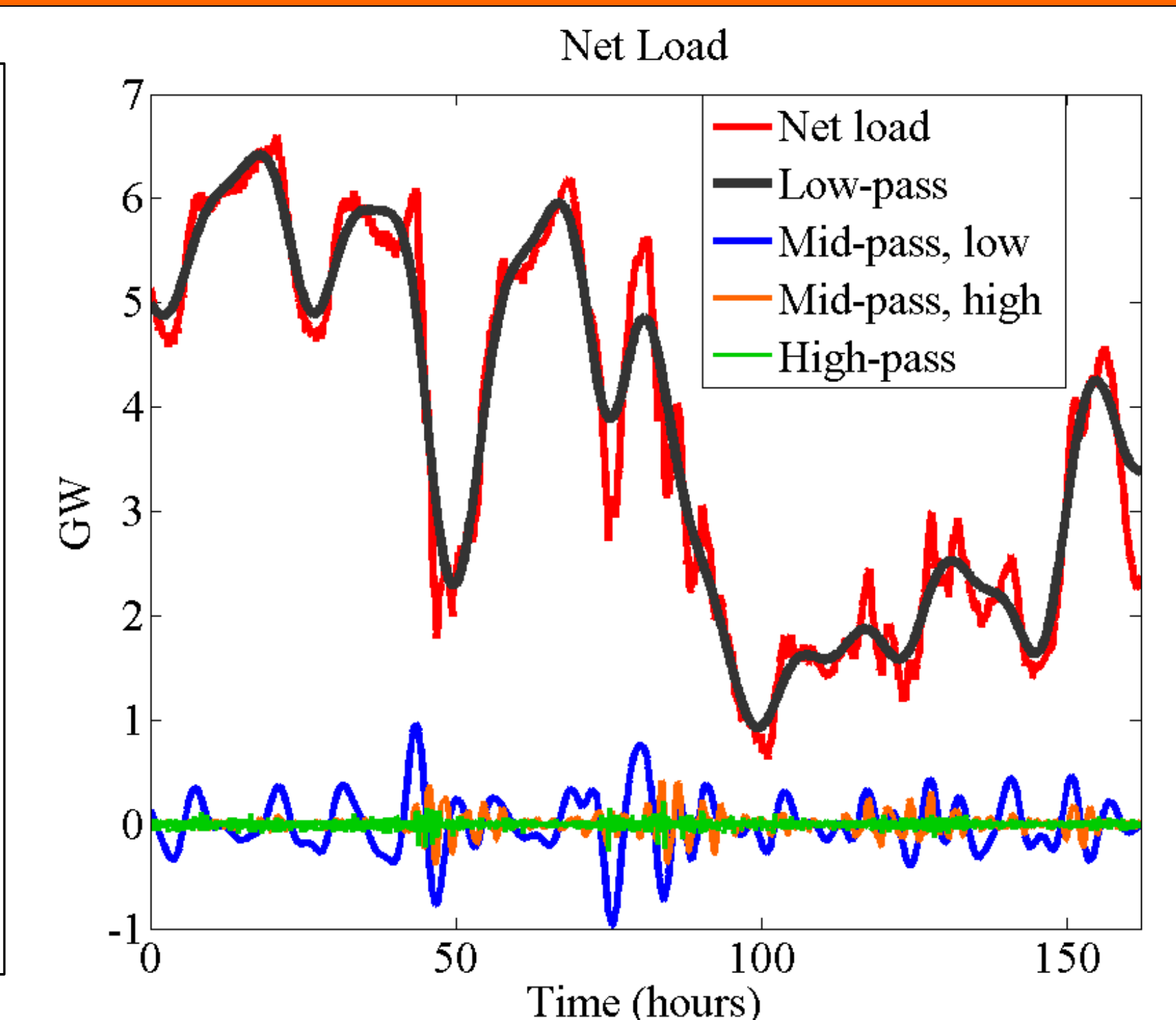
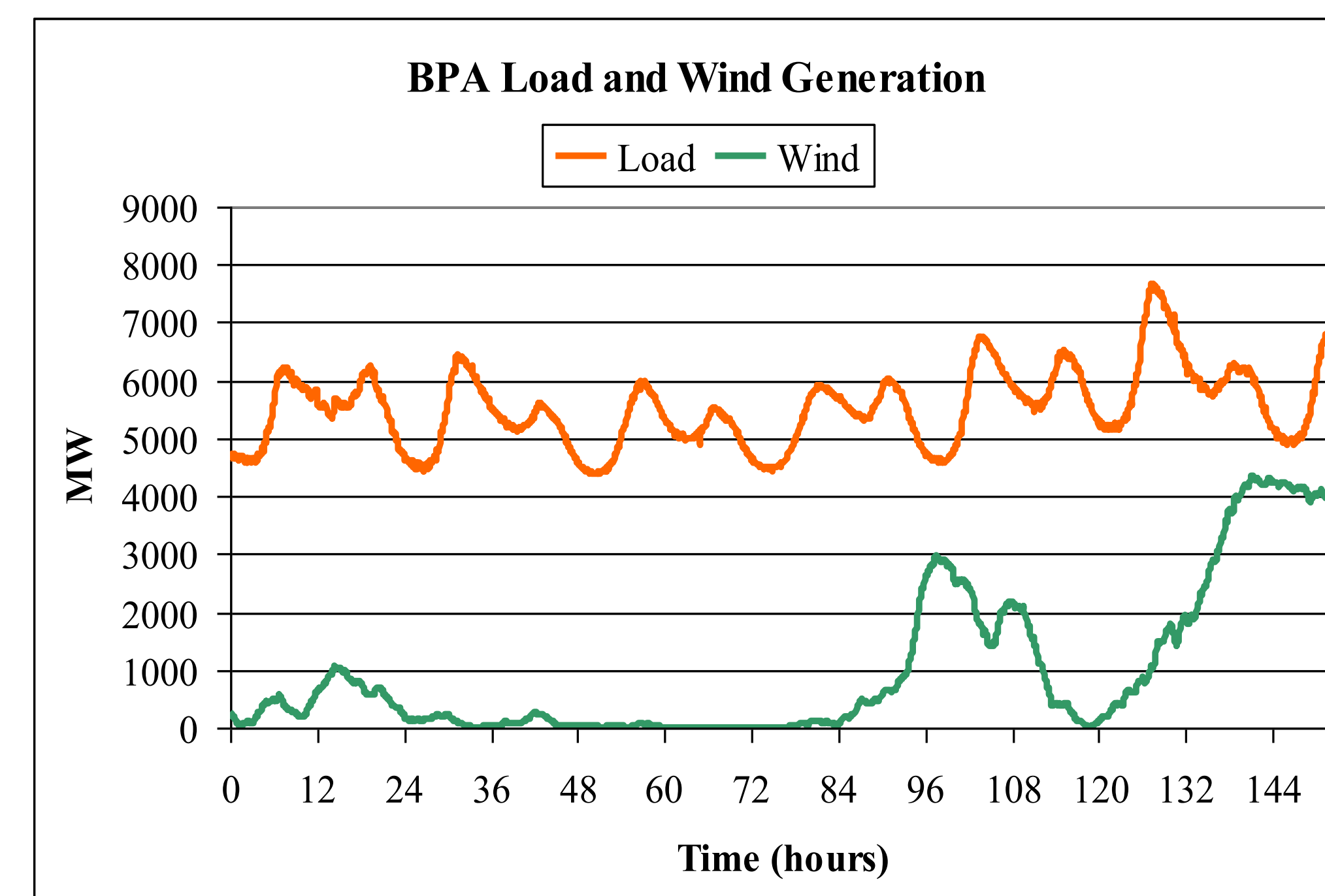
Goal: Coordinate actions of many loads to provide reliable VES

Concerns:

- Decentralized decision-making (communication, privacy)
- Consumers' quality of service (QoS)
- Robustness to uncertainty (weather, human behavior, etc.)
- Computational complexity at loads must be small

Key Innovations:

- Randomization to break the complexity barrier
- Global information from local measurements for coordination
- Optimal measurement location considering gross errors and costs



Novel reinforcement learning algorithm

Question: How to optimally control without model?

Solution: State of the art **reinforcement learning** algorithms.

Goal: Obtain a *state-feedback* policy $\phi^* : \mathcal{X} \rightarrow \mathcal{U}$

$$\phi^*(x) := \underset{u \in \mathcal{U}}{\operatorname{argmin}} Q^*(x, u) \quad Q^*(x, u) := \sum_{k=0}^{\infty} \beta^k \mathbb{E}[c(X_k, U_k) | X_0 = x, U_0 = u]$$

- \mathcal{X} : state-space. E.g., temperature and humidity of a building.
- \mathcal{U} : control-space. E.g., supply air flow rate and temperature.
- c : cost function. E.g., power reference tracking error.
- β : discount factor. How far into the future do you care about.

Solution: Use Q-learning, a reinforcement learning algorithm that estimates $Q^*(x, u)$. **Too slow.**

Goal in Q-learning: Given a parameterized family of functions $\{Q^\theta : \theta \in \mathbb{R}^d\}$, find θ^* such that

$$\bar{f}(\theta^*) = 0, \quad \bar{f}(\theta) := \mathbb{E}[(c(X_n, U_n) + \beta Q^\theta(X_{n+1}) - Q^\theta(X_n, U_n)) \partial_\theta Q^\theta(X_n, U_n)]$$

Q-learning is an approximation of the ODE:

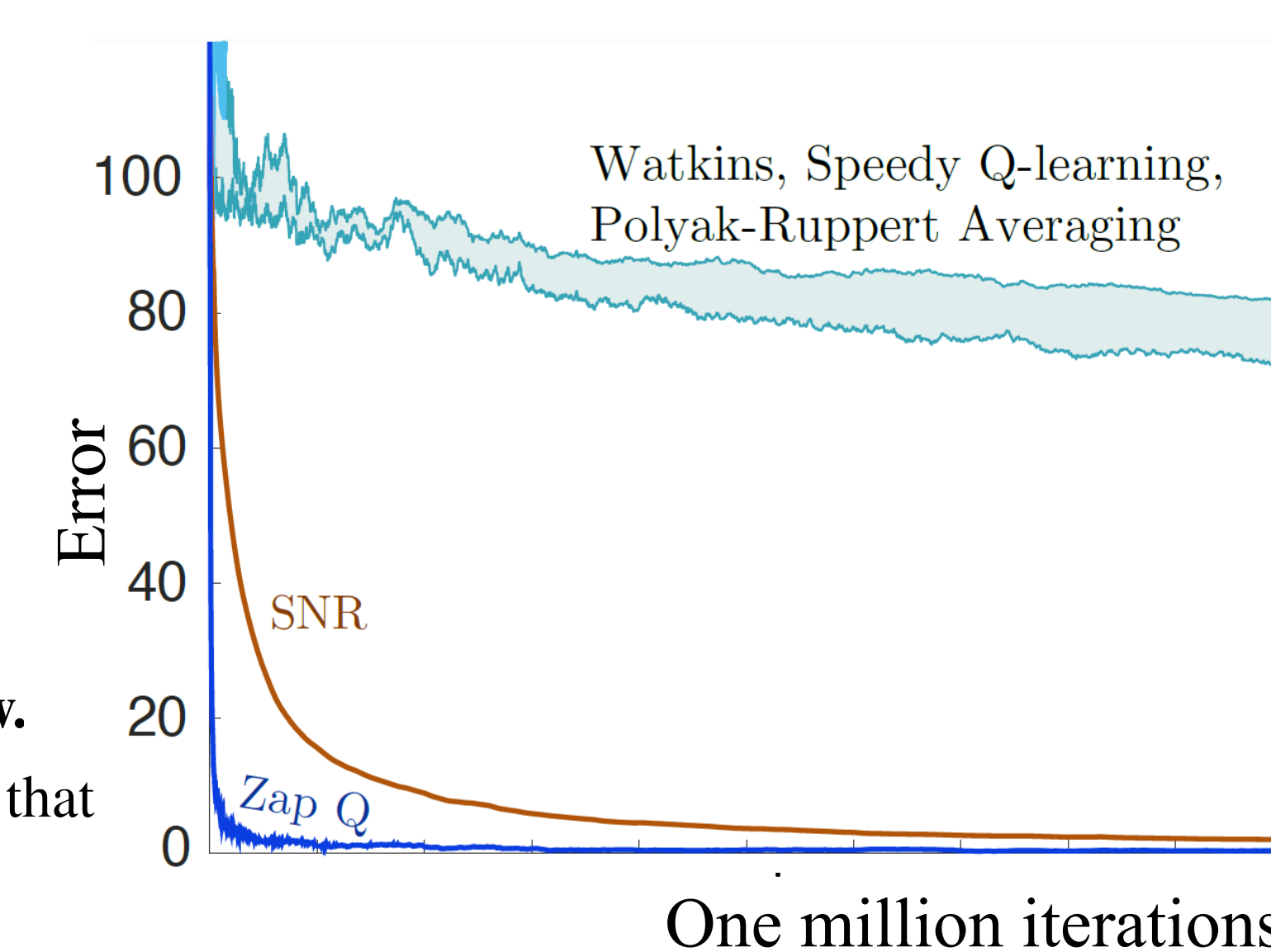
$$\frac{d}{dt} \xi_t = \bar{f}(\xi_t)$$

- Unstable in most settings of interest.

Zap Q-learning is an approximation of the ODE:

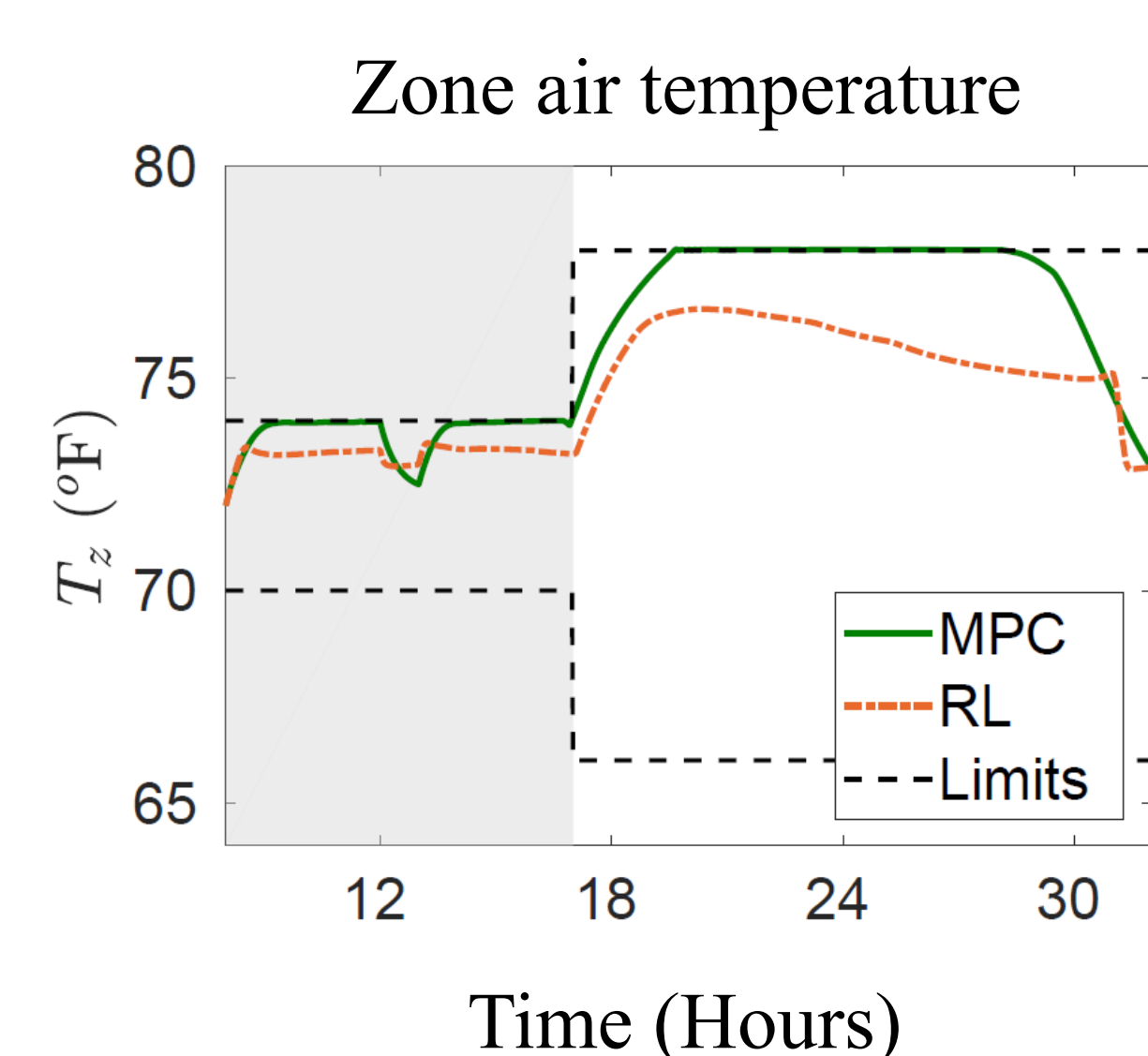
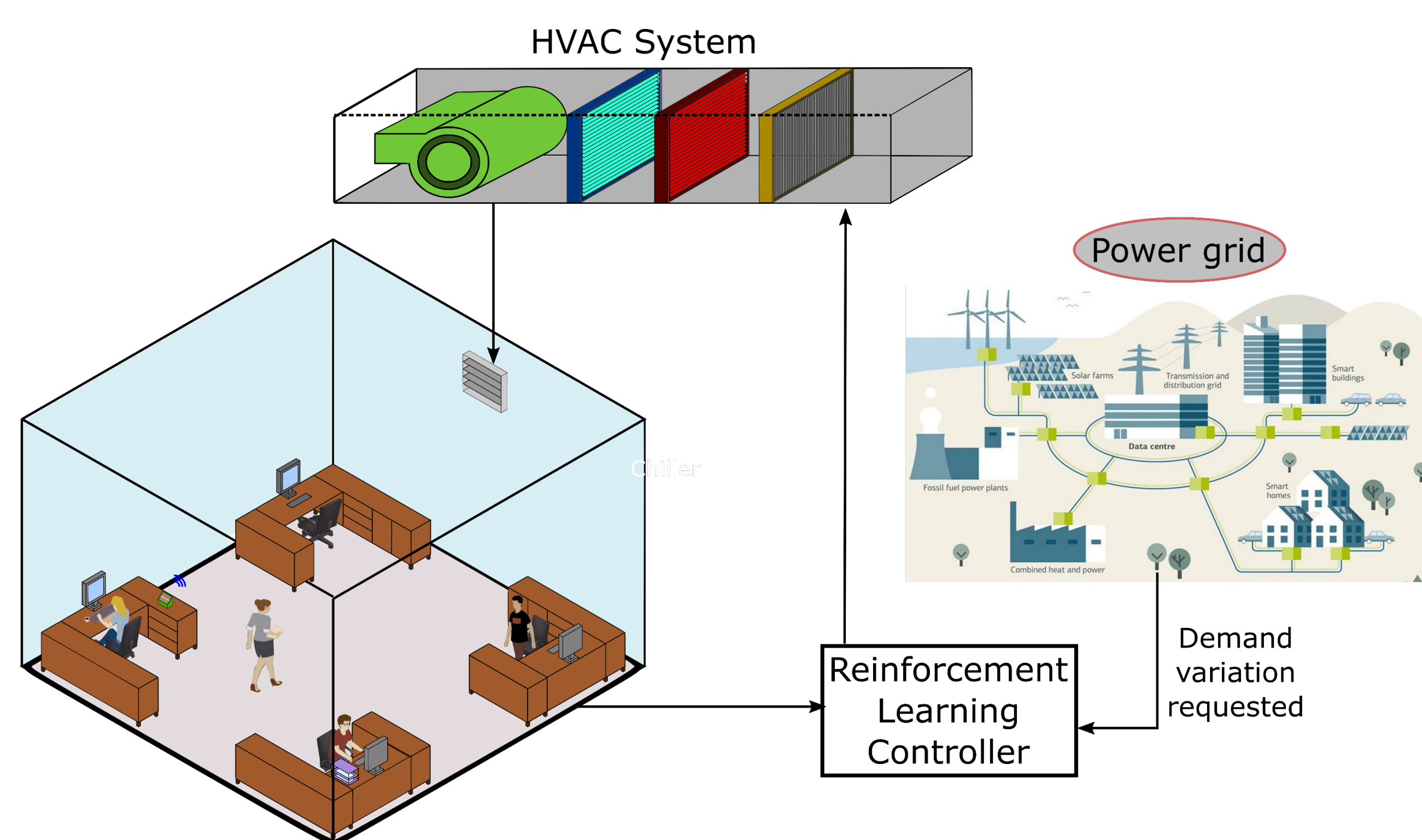
$$\frac{d}{dt} \bar{f}(\xi_t) = -[A(\xi_t)]^{-1} \bar{f}(\xi_t), \quad A(\theta) := \partial_\theta \bar{f}(\theta)$$

- Stable under very general conditions.
- Applicable to **continuous state and control spaces** that is of interest to us.



Zap Q-learning: Fastest Q-learning algorithm & stable under very general conditions.

Control of commercial building HVAC load



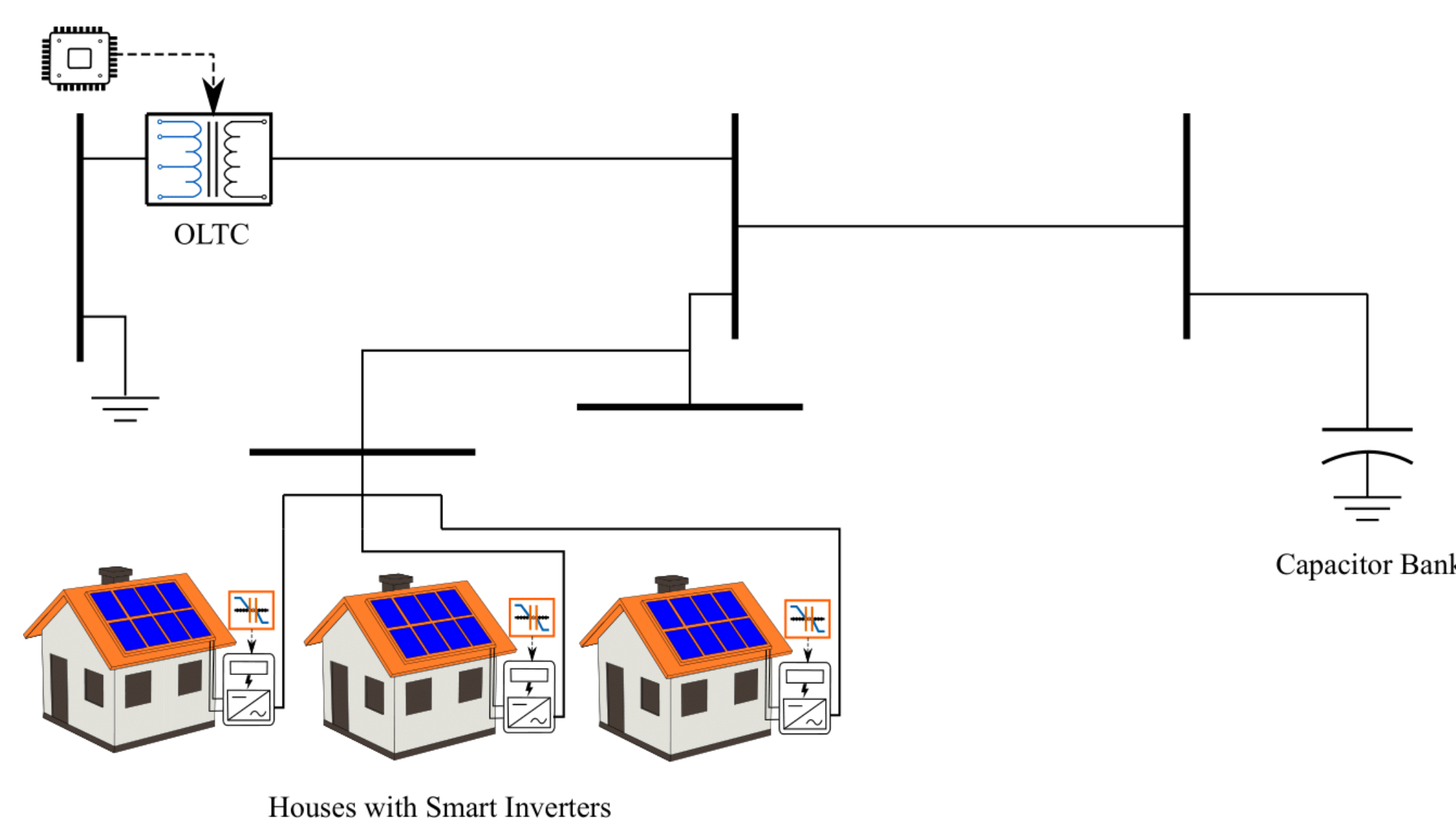
- Only Q-learning algorithm that worked.
- Maintains QoS constraints.
- Does as well as MPC.

Distribution system support

Question: How to control and improve monitoring of distribution systems with pervasive residential PV penetration?

Solution:

- Volt/VAR control to mitigate fast voltage variations using ON/OFF loads and reduce on-load tap changer actuations.
- Allocation of automatic switching devices and distributed generation to improve distribution system reliability.
- Autonomous secondary voltage network control by updating Volt/VAR curves of residential PV inverters.



Distributed coordination of loads to provide grid support

Planning phase: Compute reference for demand variation that is *feasible* for load ensemble

Novel Contribution: account for device cycling QoS of individual in planning phase.

Real time control: randomized local control for coordination

Novel Contribution: scalable and distributed control algorithm

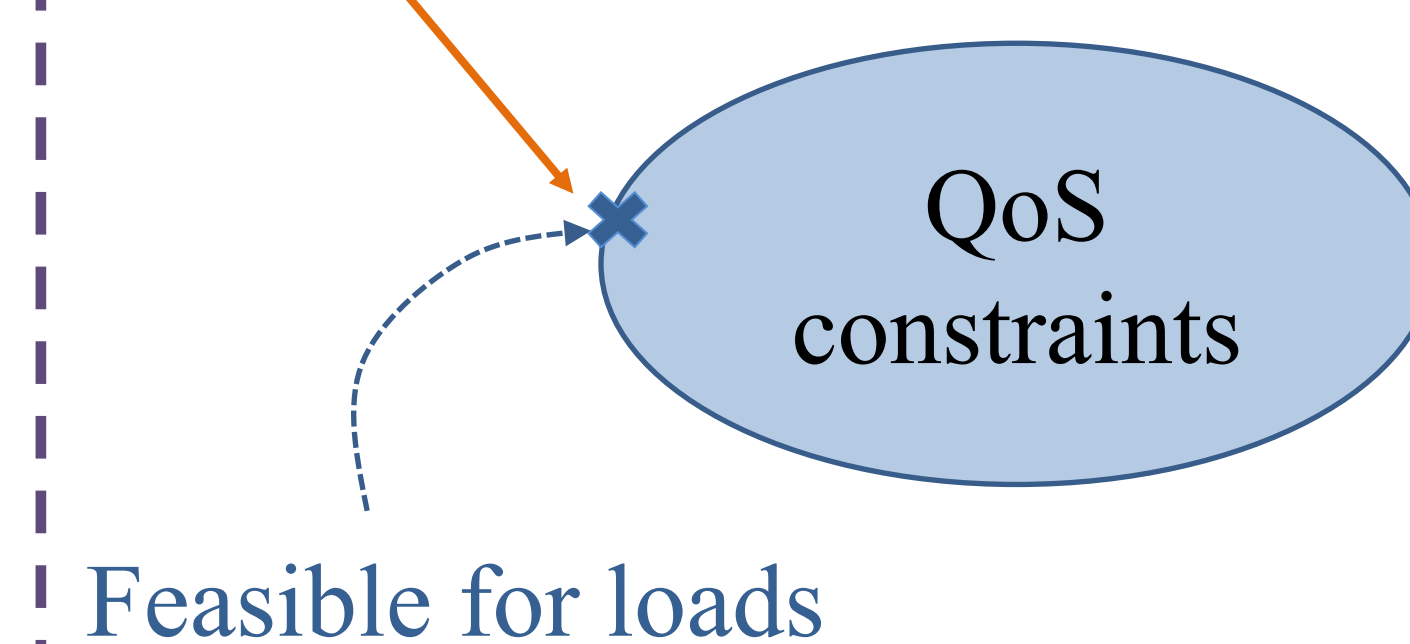
Grid's needs *must* be consistent with individual loads' QoS!

Individual load's QoS

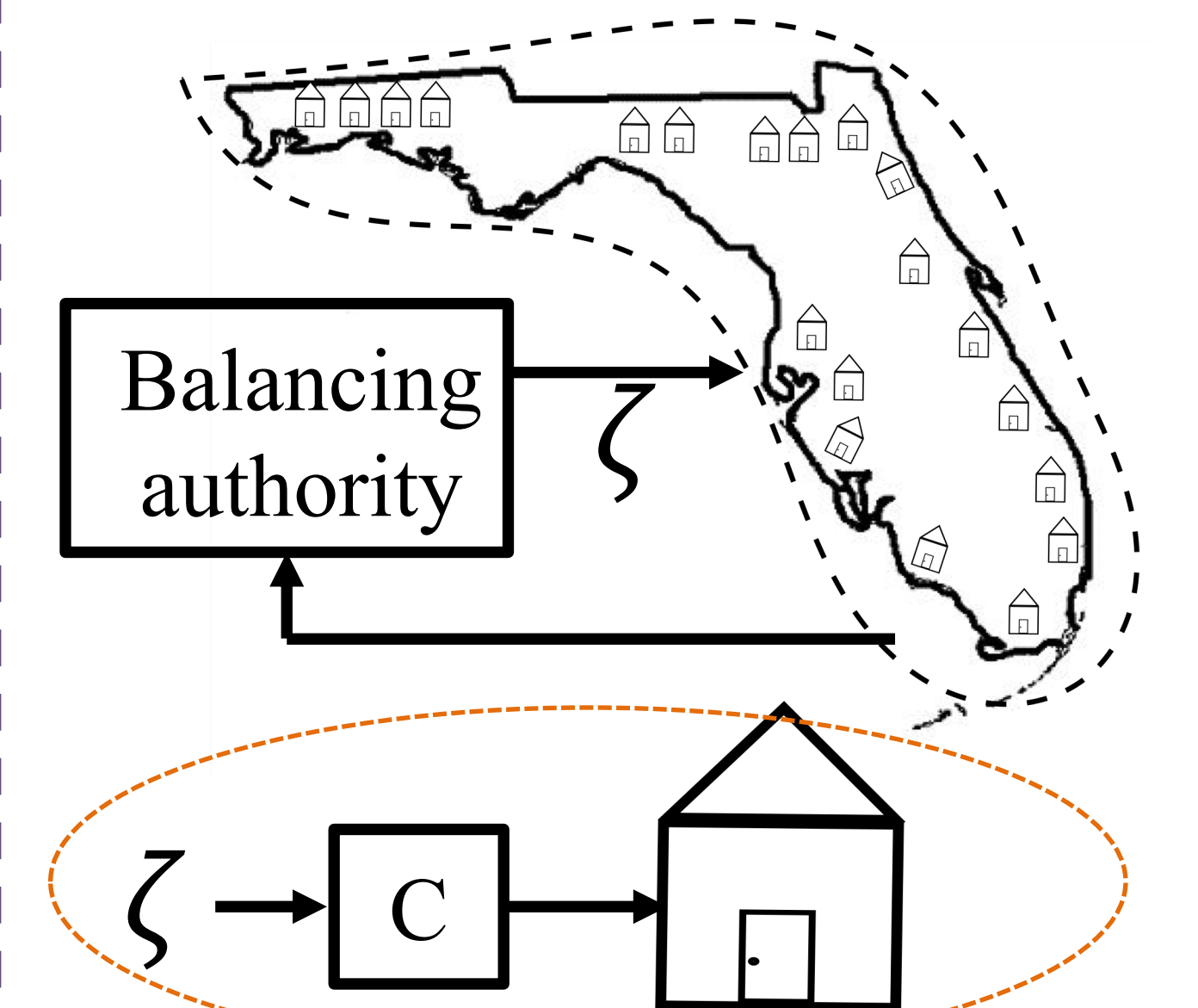
- 1) User Comfort
- 2) Energy Bill
- 3) Device Cycling

Planning

Grid's total need



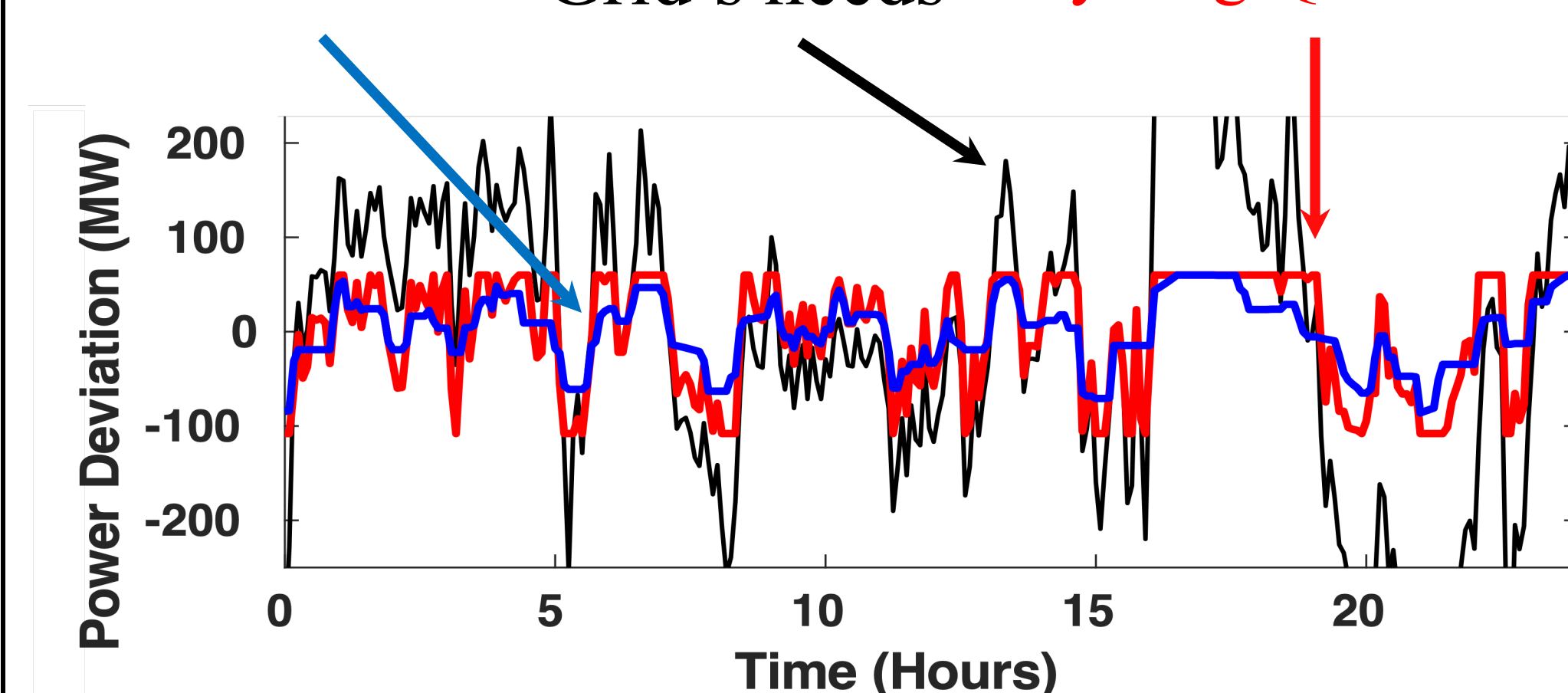
Operation



Creating a virtual battery out of 60,000 AC's

Planning a feasible reference for loads

Reference with cycling QoS (blue line), Grid's needs (black line), Reference without cycling QoS (red line)

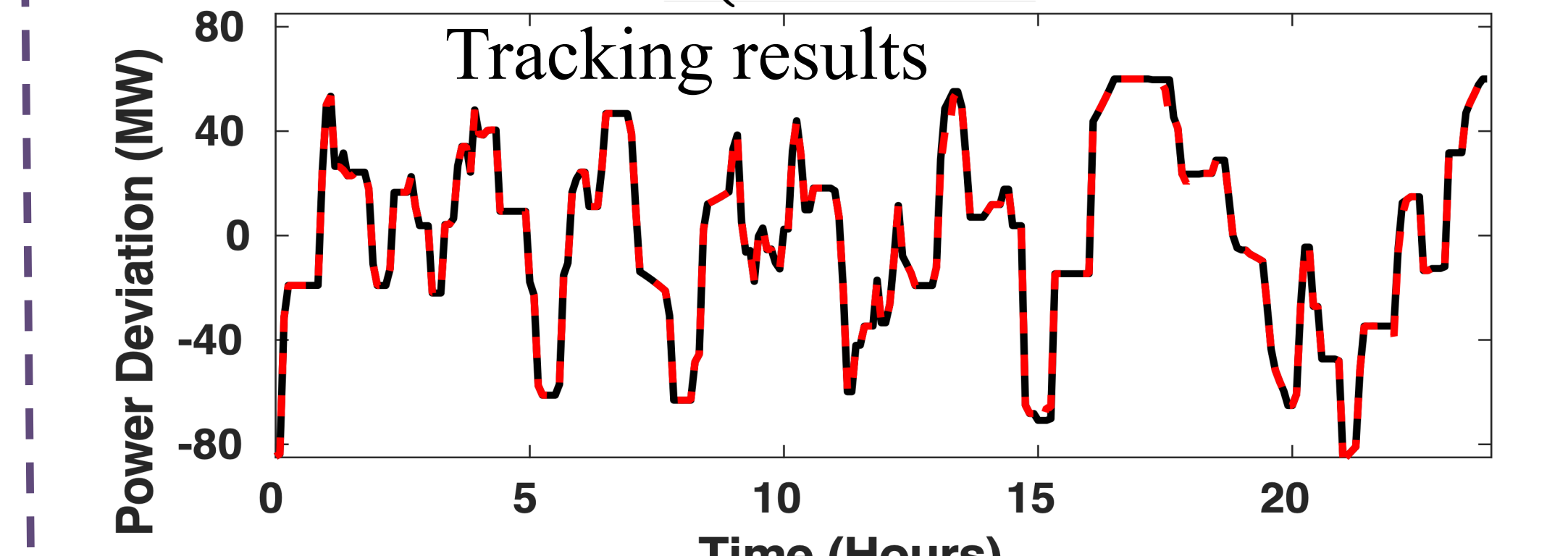


Operation: scalable distributed control

Randomized controller at load

$$R_\zeta(x, y^u) := R_0(x, y^u) \exp(\zeta \mathcal{U}(y^u) - \Lambda_\zeta(x))$$

$$\mathcal{U}(y^u) = \begin{cases} 1, & y^u = \oplus \\ 0, & y^u = \ominus \end{cases}$$



Products:

- 25 peer-reviewer journal articles and Conference proceedings published.
- Partially supported 5 (graduated) PhDs and 10 (current) Ph.D. students; two from minority and under-represented groups.
- 5 undergraduate researchers involved in the research, some through REU supplements.

Selected recent publications:

1. Raman, N. S., Devraj, A. M., Barooah, P., Meyn, S. "Reinforcement learning for control of building HVAC systems", under review, ACC 2020.
2. Coffman, Guo, and Barooah, "A spectral characterization of aggregate capacity of flexible loads for grid support", submitted, ACC 2020.
3. Barooah, P. "Virtual energy storage from flexible loads: distributed control with QoS constraints," in Smart Grid Control: An Overview and Research Opportunities, 2018.
4. Chen, Y., Hashmi, U., Mathias, J., Busic, A., and Meyn, S. "Distributed control design for balancing the grid using flexible loads," in IMA Volume on the Control of Energy Markets and Grids, 2019.
5. Devraj, A. M., Meyn, S. "Zap Q-learning", NIPS, 2017.
6. Coffman, Busic, and Barooah, "Virtual Energy Storage from TCLs using QoS preserving local randomized control", ACM BuildSys, 2018.
7. Coffman, Busic, and Barooah, "Aggregate capacity for TCLs providing virtual energy storage with cycling constraints", accepted, IEEE CDC, 2019.
8. Dhulipala, S., Monteiro, R., Teixeira, R., Ruben, C., Bretas, A., Guimaraes, G. "Distributed model predictive control strategy for distribution networks volt/VAR control: A smart buildings based approach", IEEE Transactions on Industry Applications, 2019.
9. Nader, A., Ruben, C., Dhulipala, S., Bretas, A., Da Silva, R. A. "MILP model for reliability optimization in active distribution networks", NAPS, 2018.

