NREL
Transforming ENERGY

Real-Time Optimization and Control of Autonomous Energy Systems: From Theory to Practice

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AES Industry Workshop

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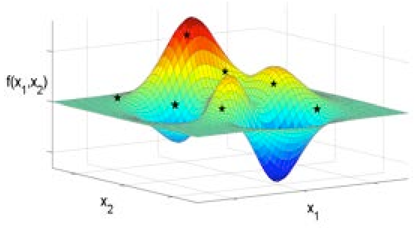
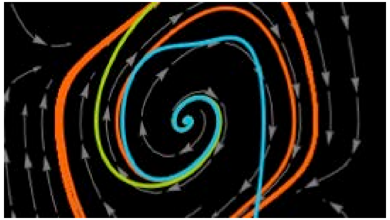
AES Control and Optimization Capabilities

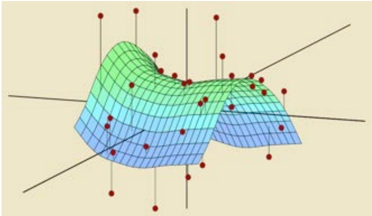
AES Capabilities Summary

Algorithms and tools development for

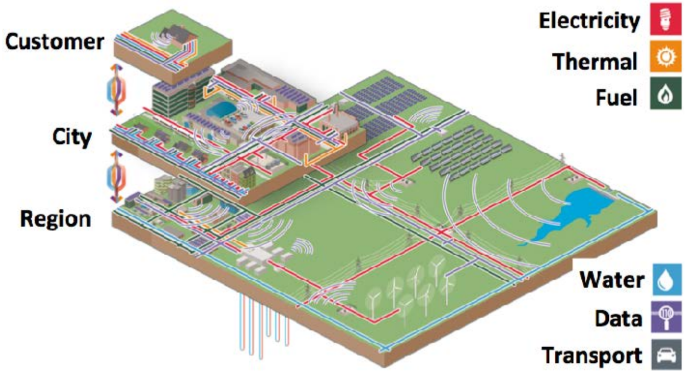
optimization **control** **estimation/prediction**







with applications to **highly distributed energy systems integration problems**



AES Capabilities

Distributed optimization and control of millions of DERs

Data-driven (ML/AI-based) optimization and optimal control

Adaptive control for improving system real-time resilience

Optimizing topology and microgrid formation

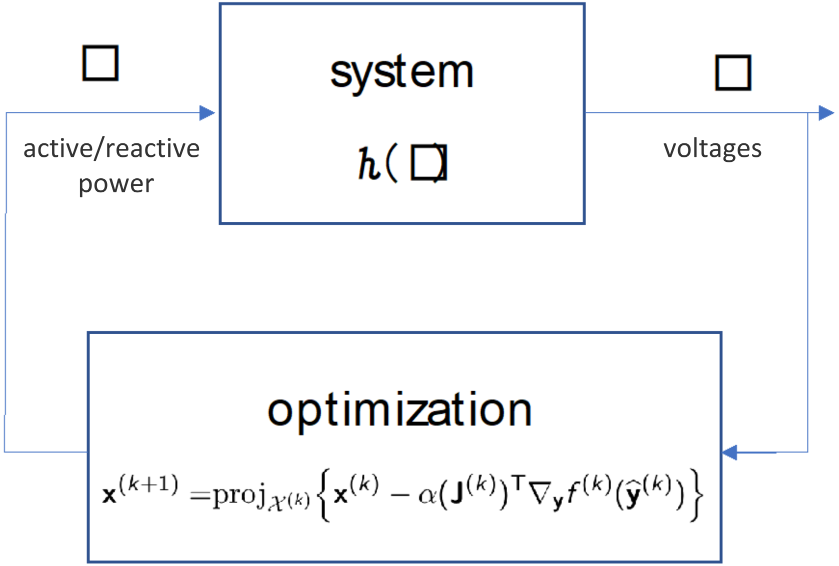
Real-time state estimation and situational awareness

AES Capabilities

Distributed optimization and control of millions of DERs

Distributed Optimization and Control

Distributed optimization with measurement feedback

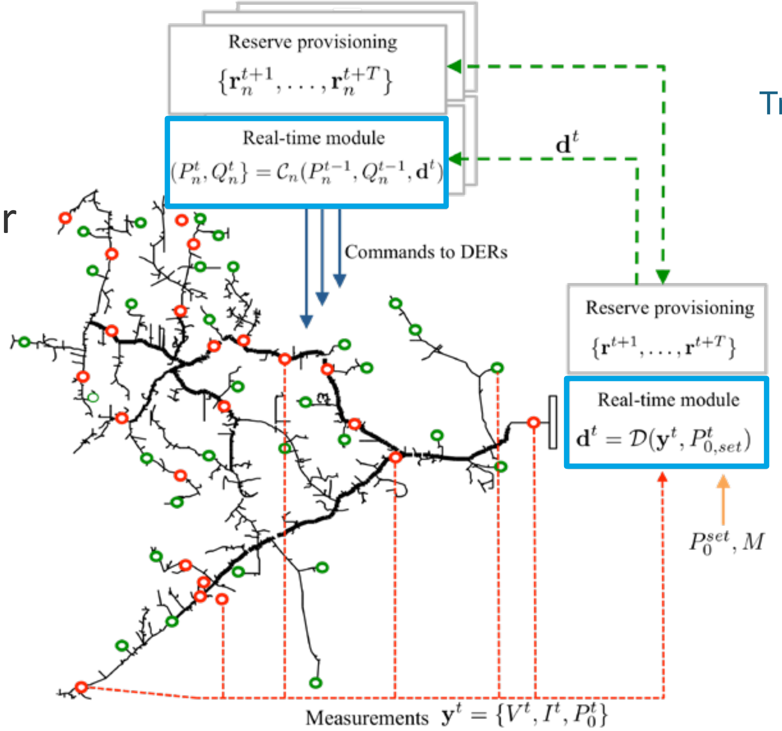


- Obtain measurement of the systems output y (e.g., voltages)
- Run a **simple/lightweight** optimization and repeat
- Application: **Real-Time Optimal Power Flow (RT-OPF)**
  - Avoids explicit modelling of power-flow equations and uncontrollable injections

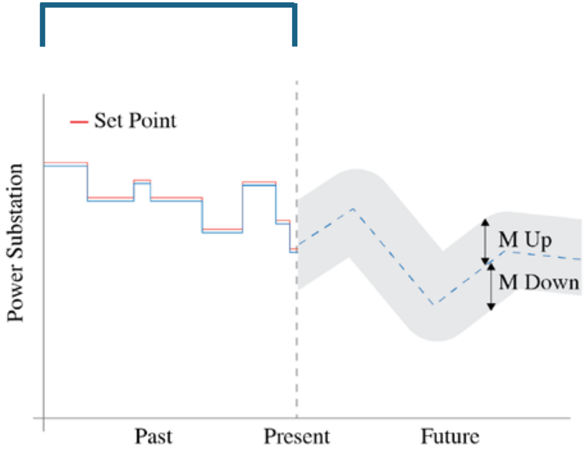
Distributed Optimization and Control

Distributed optimization with measurement feedback

- Break large-scale problem into smaller parallel ones
- Solve small-scale subproblems locally
- Coordinate to arrive at system-wide solution

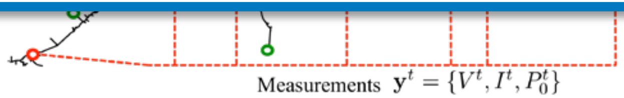


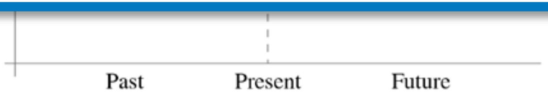
Tracking (Virtual Power Plant)
+
Cost minimization
+
Enforce limits



Distributed Optimization and Control

- Developed under ARPA-E NODES and internal LDRD funds
- Implemented in:
  - Large-scale simulation with **10s of thousands of devices** (SF Bay Area system)
  - HIL testbed at NREL with **>100 physical devices and hundreds of simulated devices**
  - **Field demo** at HCE (20 devices, 4 homes)
  - **Field demo** at Stone Edge Farm microgrid (~20 devices)

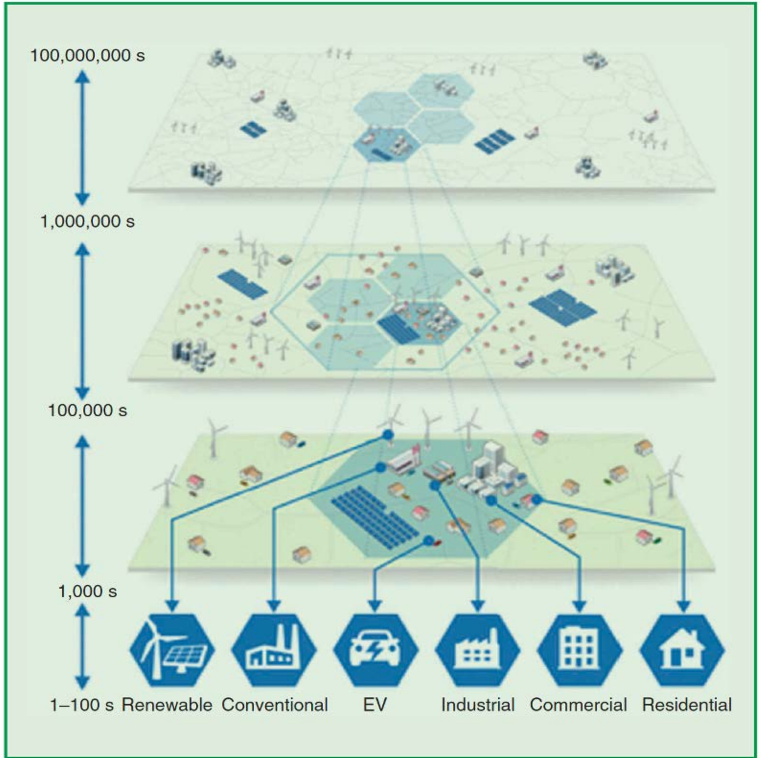




Distributed Optimization and Control

Hierarchical-distributed optimization

- **Motivation:** Fast OPF solutions for large distribution networks w/o losing optimality
- **Methodology:** Multi-level algorithms that exploit the network/OPF problem structure and improve the computational efficiency
- **Results and Impact:**
  - >10-time "free" speed improvement in a 11K distribution system
  - Enabling 1-second/iteration online OPF solving for large networks
  - **Capability of handling solutions for million-node systems**



Distributed Optimization and Control

Stochastic/robust optimization

- **Incorporate uncertainty in optimization**
- **Robust**: e.g., ensure voltage regulation no matter what the uncertainty is
- **Chance-constraints**: e.g., ensure voltage regulation with given probability (**less conservative**)

$$\max_{\{\overline{p}_i, \underline{p}_i, \overline{q}_i, \underline{q}_i\}} \sum_{i=1}^{N} \alpha_i \left(\overline{p}_i - \underline{p}_i\right) + \sum_{i=1}^{N} \beta_i \left(\overline{q}_i - \underline{q}_i\right) \qquad \text{(RBOPF)}$$

$$\text{s.to:} \quad u_i = (p_i, q_i), \; i = 1, \dots, N \qquad \text{(C1)}$$

$$\underline{p}_i \leq p_i \leq \overline{p}_i, \; i = 1, \dots, N \qquad \text{(C2)}$$

$$\underline{q}_i \leq q_i \leq \overline{q}_i, \; i = 1, \dots, N \qquad \text{(C3)}$$

$$\Pr\{x_i = u_i + w_i \in \mathcal{X}_i, \; i = 1, \dots, N\} \geq 1 - \delta \qquad \text{(C4)}$$

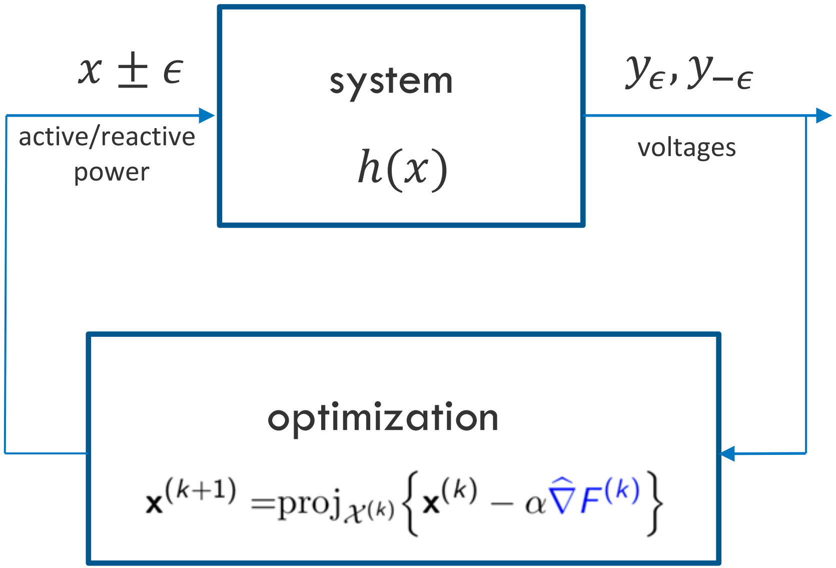
$$\Pr\{\mathbf{v} = \mathbf{M}\mathbf{x} + \mathbf{m} \in \mathcal{V}\} \geq 1 - \lambda. \qquad \text{(C5)}$$

AES Capabilities

Data-driven (ML/AI-based) optimization and optimal control
("Learning to Optimize and Control")

Data-Driven (ML/AI-based) Optimization and Optimal Control

Model-Free RT-OPF

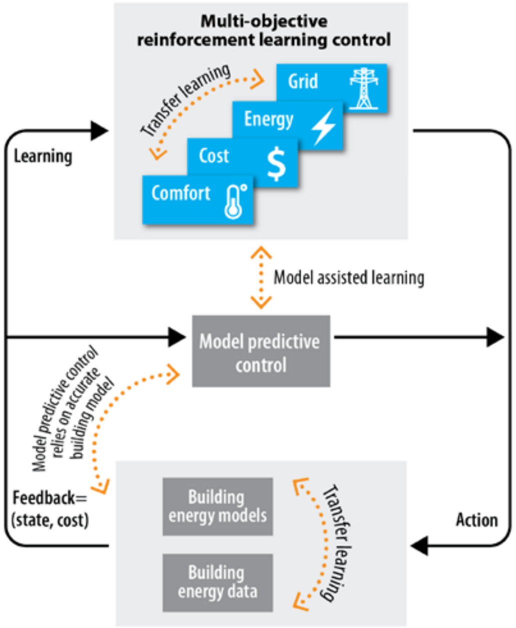


- RT-OPF: requires system information (e.g., topology, line parameters)
- Use "**probing**" and measuring the output to optimize "on the fly" **without explicit system model**
- Slower convergence than standard RT-OPF

Data-Driven (ML/AI-based) Optimization and Optimal Control

Building control using Reinforcement Learning

- Future building control requires **optimal control**
  - E.g., to implement **grid-interactive buildings**
- Classic approach: model predictive control (MPC)
  - Requires buildings model
  - Need to be tailored for each building
- **Reinforcement learning** (RL) allows to **learn the optimal controller from data and interaction with the building**
- Demonstration in real commercial building in NYC



Data-Driven (ML/AI-based) Optimization and Optimal Control

Online data-enabled predictive control (ODeePC)

- An alternative to RL
- Uses historical data directly in MPC
- Allows explicit constraints
- Online algorithms to **adapt to system changes**
- **Computationally efficient**
- Evaluated on SDG&E feeder for voltage regulation with HIL+ADMS

$$\begin{aligned}
\underset{g,u,y}{\text{minimize}} \quad & \sum_{k=0}^{N-1} \left(\|y_k - r_{t+k}\|_Q^2 + \|u_k\|_R^2 \right) \\
\text{subject to} \quad & \begin{pmatrix} U_{\mathrm{p}} \\ Y_{\mathrm{p}} \\ U_{\mathrm{f}} \\ Y_{\mathrm{f}} \end{pmatrix} g = \begin{pmatrix} u_{\mathrm{ini}} \\ y_{\mathrm{ini}} \\ u \\ y \end{pmatrix}, \\
& u_k \in \mathcal{U}, \ \forall k \in \{0, \ldots, N-1\}, \\
& y_k \in \mathcal{Y}, \ \forall k \in \{0, \ldots, N-1\}.
\end{aligned}$$

AES Capabilities

Adaptive control for improving system real-time resilience

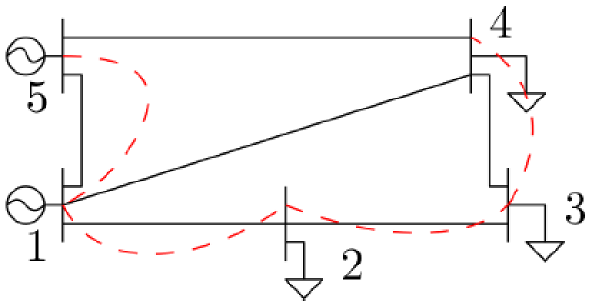
Adaptive Control for Improving System Real-Time Resilience

Emergency Voltage Control using ``Hotline” Comms

MOTIVATION

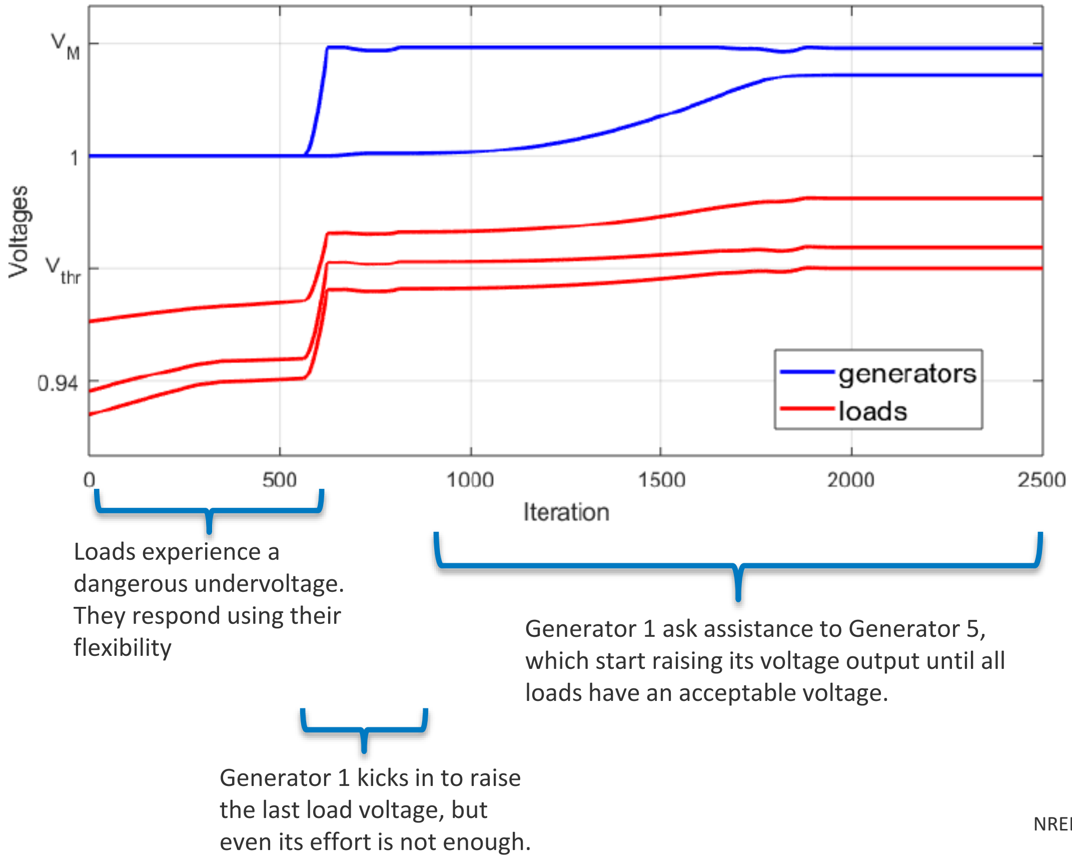
- OPF problems are solved periodically (~ 15 min)
- Abrupt change in the network (line tripping) or in the load demand might occur between 2 OPF instances
- **Real-time emergency control** for avoiding network (voltage) collapse

Adaptive Control for Improving System Real-Time Resilience



CONTROL RATIONALE AND FEATURES

- Buses **first try to fix their issue locally**
- If the control effort is not enough, **assistance is sought from neighboring buses** on a communication network **in a ripple-type manner**
- The control is a model-free feedback based scheme

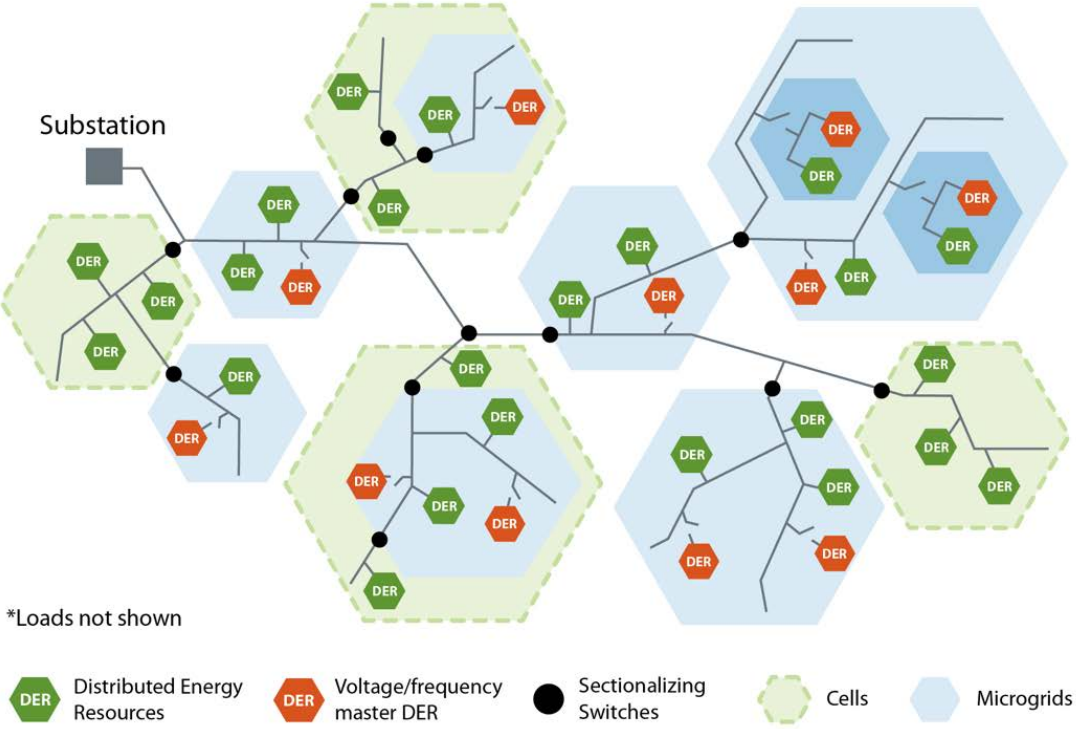


AES Capabilities

Optimizing topology and microgrid formation

Optimizing Topology and Microgrid Formation

- Co-optimizing topology (switches) and DER setpoints
- During normal operation: minimize losses and cost of generation
- During faults: island the cells/areas to become microgrids
- Restoration: reconnect microgrids to form the grid



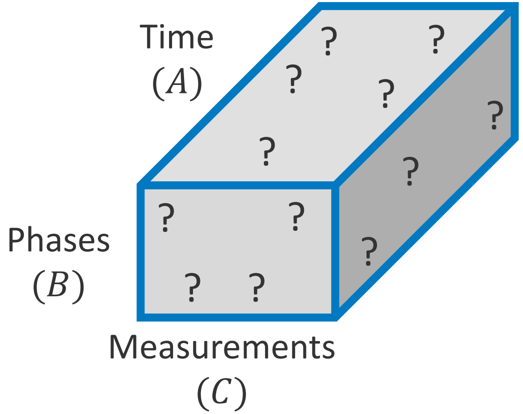
AES Capabilities

Real-time state estimation and situational awareness

Real-time state estimation and situational awareness

Low-observability state estimation

- Systems with less measurements than unknowns (states)
  - Distribution systems
  - Attacks/disruptions
- Form data in a 2D or 3D array – a matrix or tensor
- Due to correlations: matrix/tensor is low rank
- **State estimation = low-rank matrix/tensor completion**

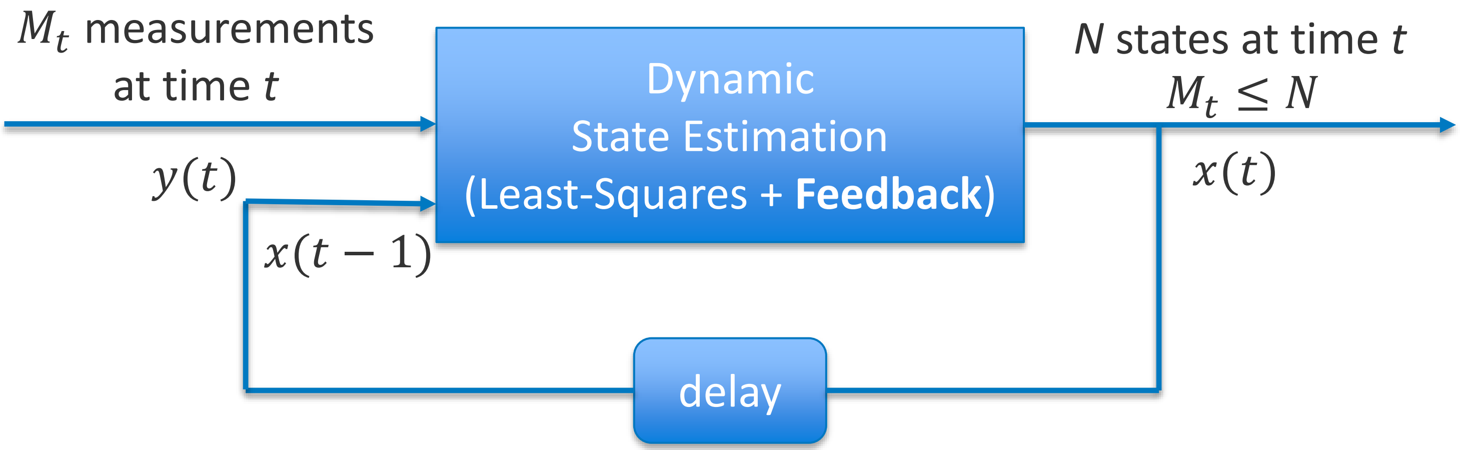


Real-time state estimation and situational awareness

Low-observability state estimation

Dynamic state estimation

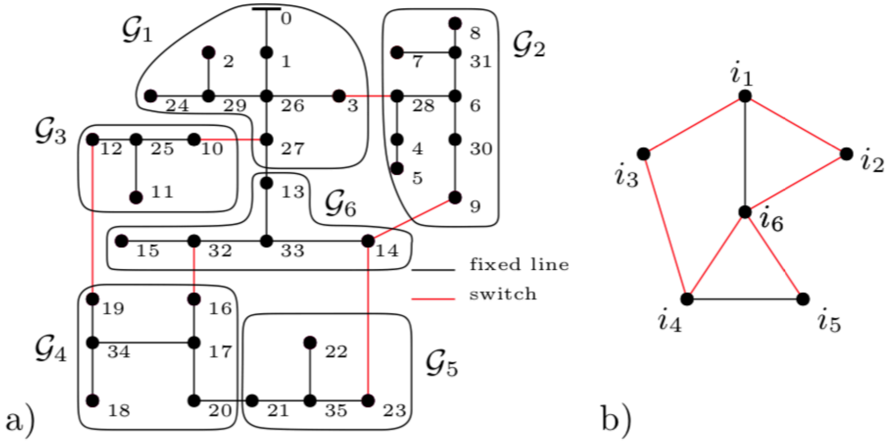
- Leverages previous estimates
- Measurements processed as they come in
- Simple update rules



Real-time state estimation and situational awareness

Topology identification

- Methods for **topology identification** using historical and real-time data
- Identification of **status of switches**
- **Bus clustering** according to substations



Examples of Demonstration and Partnerships

Demonstration and Partnerships

ARPA-E NODES: NREL, Caltech, Harvard, UM, SCE, HCE, Heila Technologies (Stone Edge Farm)

- Distributed DER control (RT-OPF)
- 100+ devices PHIL experiment, large-scale CHIL at SCE
- Field demonstration at HCE (4 homes, 20 devices)
- Field demonstration at Stone Edge Farm (~20 devices)
- Completed

Demonstration and Partnerships

SETO SolarExPert: UCF, NREL, HNEI, Duke, Siemens, OPAL-RT

- Distributed DER control
- Large-scale PHIL and CHIL experiments
- Simulation on >100k nodes system
- Completed

Demonstration and Partnerships

SETO GoSolar: NREL, HECO

- Distributed DER control + control of legacy devices
- PHIL with >100 inverters
- Simulation on >2k nodes system
- Completed

Demonstration and Partnerships

SETO AURORA: Siemens, NREL, Columbia University, HCE

- Networked microgrids and autonomous blackstart
- Demonstration on HCE system at Siemens testbed
- Ongoing

Demonstration and Partnerships

OE DynaGrid: NREL, LLNL, LANL, SNL, DTE Energy, ComEd

- Dynamic microgrid formation + distributed DER control
- Large-scale (Bay Area) simulation
- Field demo at LLNL site
- Potential field demo with DTE Energy
- Ongoing

Demonstration and Partnerships

DOE Connected Communities: PGE, NEEA, CEP, NREL, OSI

- Accelerate development and deployment of flexible load resources
- Field demo with 580 community buildings
- Ongoing

Thank you

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