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

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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

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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

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AES Capabilities

Distributed optimization and control of millions of DERs
Distributed optimization with measurement feedback

- Obtain measurement of the system 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

\[ x^{(k+1)} = \text{proj}_{x^{(k)}} \left\{ x^{(k)} - \alpha (J^{(k)})^T \nabla_y f^{(k)}(y^{(k)}) \right\} \]
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

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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)
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)

\[
\max_{\{\overline{p}_i, \overline{g}_i, \overline{q}_i, \overline{g}_i\}} \sum_{i=1}^{N} \alpha_i (\overline{p}_i - p_i) + \sum_{i=1}^{N} \beta_i (\overline{q}_i - q_i) \\
\text{s.t.: } u_i = (p_i, q_i), \ i = 1, \ldots, N \\
p_i \leq \overline{p}_i, \ i = 1, \ldots, N \\
q_i \leq \overline{q}_i, \ i = 1, \ldots, N \\
\Pr \{x_i = u_i + w_i \in \mathcal{X}_i, \ i = 1, \ldots, N\} \geq 1 - \delta \\
\Pr \{v = \mathbf{M}x + \mathbf{m} \in \mathcal{V}\} \geq 1 - \lambda.
\]
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

\[ h(x) \]

- 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

\[ x^{(k+1)} = \text{proj}_{\mathcal{X}(k)} \left\{ x^{(k)} - \alpha \nabla F^{(k)} \right\} \]
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 (ODDeePC)

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

\[
\begin{align*}
\text{minimize} & \quad \sum_{k=0}^{N-1} \left( \| y_k - r_{t+k} \|^2_Q + \| u_k \|^2_R \right) \\
\text{subject to} & \quad \begin{pmatrix} U_P \\ Y_P \\ U_f \\ Y_f \end{pmatrix} g = \begin{pmatrix} u_{\text{ini}} \\ y_{\text{ini}} \\ u \\ y \end{pmatrix}, \\
& \quad u_k \in U, \ \forall k \in \{0, \ldots, N-1\}, \\
& \quad y_k \in \mathcal{Y}, \ \forall k \in \{0, \ldots, N-1\}.
\end{align*}
\]
AES Capabilities

Adaptive control for improving system real-time resilience
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

Loads experience a dangerous undervoltage. They respond using their flexibility.

Generator 1 asks for assistance from Generator 5, which start raising its voltage output until all loads have an acceptable voltage.

Generator 1 kicks in to raise the last load voltage, but even its effort is not enough.
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

*Loads not shown

- Distributed Energy Resources
- Voltage/frequency master DER
- Sectionalizing Switches
- Cells
- Microgrids

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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

\[ M_t \text{ measurements at time } t \]
\[ y(t) \]
\[ x(t - 1) \]
\[ x(t) \]
\[ N \text{ states at time } t \]
\[ M_t \leq N \]

Dynamic State Estimation (Least-Squares + Feedback)

delay

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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

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

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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