Coordinated Aggregation and Control of Distributed Energy Resources

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CERTS Program Review
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DER Coordinated Aggregation and Control  
CERTS Program Review
Risk-Limiting Dispatch for Reserve Provision

- Balance variability from renewables with reserves of various types purchased in forward markets

- Portfolio collectively behaves as reliably as dispatchable generation at lower cost
Research Thrusts

Virtual Battery Models for Load Flexibility

- Quantify capability of loads with thermal storage to provide frequency regulation

- These loads can follow dynamic regulation signals better than conventional generators
Aggregated Coordination of DERs for Ancillary Services Provision

- Develop framework for coordinating aggregate response of heterogenous DERs

- Aggregation of DERs enables participation in frequency regulation markets
Part I

Risk-Limiting Dispatch for Reserve Provision
Objective

Develop RLD with transmission constraints, assuming that

- Transmission constraints active in day-ahead dispatch will remain active when reserves to accommodate renewables are included in real-time market

- DC power flow linearized around day-ahead dispatch

Notation:

- Random vectors in uppercase boldface, \((X, Y, D)\)

- Realizations in lowercase boldface \((x, y, d)\)
Model

Given

- Network with \( n \) buses and \( m \) transmission lines
- \( T \) stage RLD: At stage \( t \), the operator buys a vector of power injections (at \( n \) buses) denoted by \( Z_t \)
- Random net load \( D \). Decision \( Z_t \) at \( t \) based on observations \( Y_t \supset Y_{t-1} \). \( D \) is \( Y_T \) measurable
- Total cost is

\[
E\left[ \sum_{t=1}^{T-1} c_t(Z_t) + q(Z_t) \right]
\]

\( c_T(\cdot), q(\cdot) \) are convex
- DC network constraint \( \sum_{t=1}^{T} Z_t - D \in \mathcal{P} \), \( \mathcal{P} \) is the convex set of feasible power injections that meet network constraints

[In unconstrained RLD, \( 1^T[\sum_{t=1}^{T} Z_t - D] = 0 \)]
Dynamic Programming

- Let \( x_t = \sum_{s=1}^{t-1} z_s \) be power acquired in first \( t - 1 \) markets
- The value function \( V_t \) at stage \( t \) in state \( x_t \) and observations \( y_t \) is given by DP recursion:

\[
V_T(x_T, d) := \min_{P} q(w + d - x_T)
\]

\[
V_t(x_t, y_t) := \min_{z_t} [c_t(z_t) + E[V_{t+1}(x_t + z_t) | Y_{t+1}] | y_t]]
\]

- \( z_t^* = \arg \min_{z_t} \) is Network Risk Limiting Dispatch

**Theorem**

\( V_t(x_t, y_t) \) is convex in \( x_t \) for each \( y_t \)

**Theorem**

If \( c_t(z_t) = c_t \cdot z_t \) is linear (constant prices), RLD obeys threshold rule. With Gaussian forecast, threshold can be pre-computed

**Current work:** algorithms to compute Network RLD
Part II

Virtual Battery Models for Load Flexibility
Load Flexibility Modeling

Definition (Load Flexibility)
Ability to vary power consumption without compromising end function

- Prior work:
  - Aggregation of thermostatically controlled loads (TCLs)
  - Captured by a battery model: simple, intuitive, accurate
  - Model parameters determined by analytical method

- Analytical method does not scale to more complex loads

- Our work:
  - General method to identify battery model parameters for complex loads
  - Based on stress-testing a detailed software model of the physical system
  - Idea illustrated using commercial HVAC system
Commercial HVAC system

Variable air volume with reheat from Kelman and Borrelli, 2011

- **Load flexibility**
  - Achieved by adjusting power consumption of supply fan and cooling coil

- Heating coils usually powered by gas
Building/HVAC System Open-Loop Dynamics

- Nonlinear state-space model:
  \[
  \frac{d}{dt} T_z(t) = g(T_z(t), \dot{m}_z(t))
  \]

- Fan and cooling coil power consumption:
  \[
  P(t) = h(T_z(t), \dot{m}_z(t))
  \]

- Equipment ratings and occupant comfort constraints:
  \[
  \underline{T}_z \leq T_z(t) \leq \overline{T}_z
  \]
  \[
  \underline{\dot{m}}_z \leq \dot{m}_z(t) \leq \overline{\dot{m}}_z
  \]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_z$</td>
<td>zone temperature vector</td>
</tr>
<tr>
<td>$\dot{m}_z$</td>
<td>zone cooled-air mass-flow rate vector</td>
</tr>
<tr>
<td>$\underline{T}_z$, $\overline{T}_z$</td>
<td>zone temperature lower and upper limit vector</td>
</tr>
<tr>
<td>$\underline{\dot{m}}_z$, $\overline{\dot{m}}_z$</td>
<td>zone cooled-air mass-flow rate lower and upper limit vector</td>
</tr>
</tbody>
</table>
Baseline and Regulation Power

Baseline Power $P^o$:
- Power consumption to maintain zone temperatures at their midpoint
- Obtained as the steady-state solution of the state-space model:

\[
0 = g(T^m_z, \dot{m}^o_z) \\
\]
\[
P^o = h(T^m_z, \dot{m}^o_z)
\]

Regulation Power $\Delta P(t)$:
- Actual fan and cooling coil power minus baseline power:

\[
\Delta P(t) = P(t) - P^o
\]
Closed-Loop Controller Design

Objective

Control $P(t)$ via $m_z(t)$ to

- track desired power consumption profile $P^*$
- while respecting equipment rating and occupant comfort constraints

Solution Approach:

- Choose $m_z(t)$ so that $T_z(t)$ is driven to $T^m_z$
- Cast as an optimization problem:

$$m^*_z(t) = \arg \min_{m_z(t)} \| T_z(t + \Delta t) - T^m_z \|_2$$

subject to

$$T_z \leq T_z(t + \Delta t) \leq \overline{T}_z$$

$$\underline{m}_z \leq m_z(t) \leq \bar{m}_z$$

$$P^*(t) - P^o - \Delta P(t) = 0$$

- $u(t)$: commanded deviation from baseline power
Virtual Battery Model

- **Hypothesis:** Closed-loop Building/HVAC System flexibility can be accurately described by a *virtual battery model*:

\[
\frac{dx(t)}{dt} = -ax(t) - u(t)
\]

\[-C \leq x(t) \leq C\]

\[-n \leq u(t) \leq \bar{n}\]

where \(x(t) \in \mathbb{R}\) is the “state of charge”

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>dissipation</td>
</tr>
<tr>
<td>(C)</td>
<td>up/down capacity</td>
</tr>
<tr>
<td>(n, \bar{n})</td>
<td>discharge/charge rate limits</td>
</tr>
</tbody>
</table>

**Objective**

*Develop a numerical method to identify virtual battery model parameters*
System Identification Setup

- Uses detailed model of building/HVAC system dynamics

- **Key idea:** software-based stress tests based on carefully constructed
  \[ u_i(t) = P_i^*(t) - P^o, \quad t \geq 0, \quad i = 1, 2, \ldots \]
  - For each \( u_i(t) \), ID algorithm records time, \( \tau_i \), it takes for optimization embedded in the controller to be unfeasible
  - The pairs \( (u_i(t), \tau_i) \) are fitted to virtual battery model
Rate Limit Identification Procedure

- Assume that initially comfort constraints are satisfied:

\[ T_z \leq T_z(0) \leq T_z \]

- For some \( u_i(t), \ t \geq 0 \), a rate limit constraint is violated if \( \tau_i = 0 \)

[Some finite time is required for an input to affect the state value]

- \( \bar{n} > 0 \ (n > 0) \), but not a priori known upper bounds

- Can perform a one-sided binary search to find \( \alpha \) and \( \beta \) such that

\[
\alpha > \bar{n} \\
\beta > n
\]

- Once obtained, \( \alpha \) and \( \beta \) are used in a binary search procedure to find \( \bar{n} \ (n) \) to arbitrary precision \( \epsilon \)
Capacity and Dissipation Identification Procedure

- For some \( u_i(t) \), \( t \geq 0 \), a capacity limit constraint is violated if \( \tau_i > 0 \)

- For \( i = 1, 2, \ldots, m \), fit \((u_i(t), \tau_i)\), \( \tau_i > 0 \), to battery model

**Example**

- For \( u_i(t) = u_i \), \( t \geq 0 \), and \( x(0) = 0 \), trajectory of virtual battery model is

\[
x(t) = \frac{u_i}{a} (e^{-at} - 1)
\]

- If \( u_i > aC \), by setting \( x(\tau_i) = -C \):

\[
\tau_i = -\frac{1}{a} \log \left( 1 + \frac{-aC}{u_i} \right)
\]

- If \( m \geq 2 \) we can solve for \( a \) and \( C \) by, e.g., using LSE

- Procedure is also suitable for \( u_i(t) \)'s that do not yield explicit expression for \( \tau_i \)
### Numerical Simulations

#### Building/HVAC System Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n$</td>
<td>5</td>
<td>zones</td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>varied</td>
<td>s</td>
</tr>
<tr>
<td>$c_p$</td>
<td>1</td>
<td>kJ/(kg K)</td>
</tr>
<tr>
<td>$mc_i$</td>
<td>1000</td>
<td>kJ/K</td>
</tr>
<tr>
<td>$R$</td>
<td>0.1</td>
<td>kW/K</td>
</tr>
<tr>
<td>$\eta_h$</td>
<td>0.9</td>
<td>dimensionless</td>
</tr>
<tr>
<td>$\kappa_f$</td>
<td>0.065</td>
<td>kW s^2/kg^2</td>
</tr>
<tr>
<td>$T_{zi}$</td>
<td>21</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{zi}$</td>
<td>24</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{oa}$</td>
<td>30</td>
<td>°C</td>
</tr>
<tr>
<td>$\dot{m}_{zi}$</td>
<td>0.025</td>
<td>kg/s</td>
</tr>
<tr>
<td>$\dot{m}_{zi}$</td>
<td>1.5</td>
<td>kg/s</td>
</tr>
<tr>
<td>$Q_{offset}$</td>
<td>0</td>
<td>kW</td>
</tr>
</tbody>
</table>
Numerical Simulations

Selected Inputs

- **Step:** $u(t) = k$, $t \geq 0$
- **Ramp:** $u(t) = kt$, $t \geq 0$
- **RC Step:** $u(t) = k(1 - e^{-5 \cdot 10^{-5} \cdot t})$
- **Monomial:** $u(t) = kt^{1/3}$
- **Regulation signal:**
  
  $$u(t) = k \cdot \text{regD}(t) \cdot (\text{regD}(t) > 0) + n_- \cdot \text{regD}(t) \cdot (\text{regD}(t) < 0)$$
Step Input

Experimental Data

Best fit bounded above by data

\( \tau (s) \)

\( k \) (kW)
Regulation Signal

Experimental Data

Best fit bounded above by data
## Consistent Results for Different Inputs

<table>
<thead>
<tr>
<th>Input</th>
<th>Parameter (a) ((s^{-1}))</th>
<th>Parameter (C) ((\text{kWh}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
<td>(1.003 \times 10^{-4})</td>
<td>2.321</td>
</tr>
<tr>
<td>Ramp</td>
<td>(1.002 \times 10^{-4})</td>
<td>2.324</td>
</tr>
<tr>
<td>RC Step</td>
<td>(1.003 \times 10^{-4})</td>
<td>2.321</td>
</tr>
<tr>
<td>Monomial</td>
<td>(1.003 \times 10^{-4})</td>
<td>2.322</td>
</tr>
<tr>
<td>RegD</td>
<td>(9.966 \times 10^{-5})</td>
<td>2.334</td>
</tr>
</tbody>
</table>
Framework Extensions to Other DER Types

- **Generator-type DERs:**
  - Examples: microturbines, fuel cells
  - Features:
    1. Capacity limited
    2. Ramp constrained
    3. ...

- **Storage-type DERs:**
  - Examples: PEVs, TCLs, flywheels
  - Features:
    1. Capacity limited
    2. Energy limited
    3. Ramp constrained
    4. ...

- More details to come shortly
Part III

Coordination of DERs for Ancillary Services Provision
Coordination of Heterogeneous DERs

- Heterogenous DERs aggregated into a single battery-like model decreases fit quality

- Better strategy is to group resources that are similar, then create multiple reduced-order models

- Aggregating entity can use these models to coordinate DER response for procuring ancillary services:
  - Reactive power for voltage control
  - Active power for up and down regulation [Focus of the rest of the talk]
Types of DERs Considered (I)

- Generator-type DERs:

\[
\frac{d}{dt} x^g(t) = u^g(t)
\]

\[
|u^g(t)| \leq r^g
\]

\[
|x^g(t)| \leq m^g
\]

- \( u^g \): aggregator command
- \( x^g \): regulation power
- \( m^g \): maximum variation around nominal power
- \( r^g \): up/down rate limit
Types of DERs Considered (II)

- **Storage-type DERs:**

\[
\begin{align*}
\frac{d}{dt} x_1^s(t) &= u^s(t) \\
\frac{d}{dt} x_2^s(t) &= -ax_2^s(t) - x_1^s(t) \\
|u^s(t)| &\leq r^s \\
|x_1^s(t)| &\leq m^s \\
|x_2^s| &\leq c
\end{align*}
\]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(u^s)</td>
<td>aggregator command</td>
</tr>
<tr>
<td>(x_1^s)</td>
<td>regulation power</td>
</tr>
<tr>
<td>(m^s)</td>
<td>maximum variation around nominal power</td>
</tr>
<tr>
<td>(r^s)</td>
<td>up/down rate limit</td>
</tr>
<tr>
<td>(x_2^s)</td>
<td>regulation energy</td>
</tr>
<tr>
<td>(a)</td>
<td>dissipation constant</td>
</tr>
<tr>
<td>(c)</td>
<td>energy capacity limit</td>
</tr>
</tbody>
</table>
DER Coordination Problem with Perfect Information

- Find functions $u^g$ and $u^s$ that minimize total cost:

\[
\int_{t_0}^{t_f} \pi^g |x^g(t)| + \pi^s |x^s_1(t)| + \pi^p |\alpha X n(t) - x^g(t) - x^s_1(t)| \ dt.
\]

- Reduces to an LP

- Requires an oracle with complete information of regulation signal  
  [Not realistic]
### Solution: Model Predictive Control with fixed prediction horizon $T$:

- **S1.** At time $t_0$, calculate next $N = \frac{T}{\Delta T}$, $\Delta T > 0$, control actions
- **S2.** Apply only first action
- **S3.** Recalculate based on new data
MPC Solution Requires a Forecast of the Regulation Signal

- Forecast methods considered:
  - Persistence
  - Linear
  - Exponential

- Solutions with different forecast methods benchmarked against oracle
  - PJM regulation signal historical data

![Graph showing regulation signal over time with different forecast methods: Past Measurements, Oracle, Persistence, Linear, Exponential.](image-url)
## Numerical Simulations

### Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^g$</td>
<td>Generator-Type DER Ramp Limit</td>
<td>0.04</td>
<td>MW/s</td>
</tr>
<tr>
<td>$m^g$</td>
<td>Generator-Type DER Regulation Limit</td>
<td>11.9</td>
<td>MW</td>
</tr>
<tr>
<td>$r^s$</td>
<td>Storage-Type DER Ramp Limit</td>
<td>0.096</td>
<td>MW/s</td>
</tr>
<tr>
<td>$m^s$</td>
<td>Storage-Type DER Regulation Limit</td>
<td>7.9</td>
<td>MW</td>
</tr>
<tr>
<td>$c$</td>
<td>Storage-Type DER Energy Limit</td>
<td>0.28</td>
<td>MWh</td>
</tr>
<tr>
<td>$a$</td>
<td>Storage-Type DER Dissipation Constant</td>
<td>0</td>
<td>s$^{-1}$</td>
</tr>
<tr>
<td>$\pi^g$</td>
<td>Generator Regulation Price</td>
<td>14.3</td>
<td>$/MWh</td>
</tr>
<tr>
<td>$\pi^s$</td>
<td>Storage Regulation Price</td>
<td>42.9</td>
<td>$/MWh</td>
</tr>
<tr>
<td>$\pi^p$</td>
<td>Imbalance Price</td>
<td>143</td>
<td>$/MWh</td>
</tr>
<tr>
<td>$\alpha X$</td>
<td>Regulation Signal Magnitude</td>
<td>18.9</td>
<td>MW</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>Time Step</td>
<td>20</td>
<td>s</td>
</tr>
<tr>
<td>$T$</td>
<td>Prediction Horizon</td>
<td>600</td>
<td>s</td>
</tr>
</tbody>
</table>
Simulations with Oracle and Linear Forecasts

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Numerical Simulations

<table>
<thead>
<tr>
<th>Base Case Forecast Method</th>
<th>Total Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oracle</td>
<td>203.89</td>
</tr>
<tr>
<td>Persistence</td>
<td>526.74</td>
</tr>
<tr>
<td>Linear</td>
<td>469.38</td>
</tr>
<tr>
<td>Exponential</td>
<td>481.45</td>
</tr>
</tbody>
</table>

- Oracle solution is clearly best performing one [Not surprising]
- Linear and exponential both improve upon persistence forecast
Both linear and exponential forecasts require a parameter $\beta$ that determines how fast forecast decays to mean value.

Local minima around $0.01 \text{s}^{-1}$ are a good starting point for an aggregator looking to forecast $n(t)$. 
Sensitivity Studies

- Imperfect forecast cost increases as imbalance penalty increases
- Generator-type DER gets used more when cheaper than storage-type
- Storage-type DER is used more when better prediction is available
- Other studies: storage size, generator size, etc
Recap

Risk-Limiting Dispatch for Reserve Provision

- Portfolio collectively behaves as reliably as dispatchable generation at lower cost

Virtual Battery Models for Load Flexibility

- These loads can follow dynamic regulation signals better than conventional generators

Aggregated Coordination of DERs for Ancillary Services Provision

- Aggregation of DERs enables participation in frequency regulation markets