Artificial Neural Network Trained with Complementary Quadratic Programming for Realtime Unit Commitment and Microgrid Optimization Dispatch with CHP

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ANN trained with cQP for Realtime Unit Commitment and Microgrid Optimization

- Introduction of problem
- Review dispatch techniques
  - cQP techniques
  - ANN techniques
- Compare Artificial Neural Network results to complementary Quadratic Programming Results
Problem: Smart Grid Management

\[ \sum Dem + Dem_{stor} = \sum Gen + Gen_{stor} \]
\[ \sum Dem_E + Dem_{storE} = \sum Gen_E + Gen_{storE} \]
\[ \sum Dem_C + Dem_{storC} = \sum Gen_C + Gen_{storC} \]
\[ \sum Dem_H + Dem_{storH} = \sum Gen_H + Gen_{storH} \]

\[ \text{min}(Cost = \sum F_{cost}(Gen)) \]
Problem: Mixed Integer Optimization Problem

- Zero intercept fit (Fit A)
  - Allows generator to shutdown/start up
- Non-Zero intercept fit (Fit B)
  - More accurate fit

Discontinuous lower bound $\rightarrow$ On/Off Decision $\rightarrow$ Unit Commitment
Problem: Economic dispatch requires solving unit commitment

- Generators:
  - Non-zero lower limit on power output
  - Non-linear efficiency curves
  - CHP use

- Energy Storage:
  - Optimal use requires dispatch planning over the entire horizon

- Generators:
  - Startup Costs require evaluation over entire horizon

Number of Dispatches to Check = \(2^{(\text{number of generators})(\text{number of timesteps})}\)

- To find minimal dispatch cost, must run an economic dispatch for all combinations of generators (off/on) at all timesteps
## Complementary QP Technique Overview

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<th>Zero-Intercept Optimization</th>
<th>Unit Commitment</th>
<th>Non-Zero-Intercept Optimization</th>
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<tr>
<td>1 optimization</td>
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<tr>
<td>Estimate Storage Dispatch</td>
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<td>Full Generator and Storage unit commitment and dispatch</td>
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<td>nS x 2^(nG) optimizations</td>
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<td>Finds optimal combination at each step for unit commitment over the horizon</td>
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Artificial Neural Network fundamentals

- Sorting
- Pattern recognition
- Image processing
- Training
  - Synapse connections “strengthen” until desired output is produced

## ANN Technique

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
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<tr>
<td>1</td>
<td><strong>cQP for historical data</strong>&lt;br&gt;Length of historical data x (nS \times 2^nG)</td>
</tr>
<tr>
<td>2</td>
<td><strong>Train Network</strong>&lt;br&gt;1 optimization</td>
</tr>
<tr>
<td>3</td>
<td><strong>Use Trained Network</strong>&lt;br&gt;1 matrix multiplication</td>
</tr>
<tr>
<td>4</td>
<td><strong>Non-Zero-Intercept Optimization</strong>&lt;br&gt;1 optimization</td>
</tr>
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Comparison of ANN and cQP

Complimentary Quadratic Programming

- Dispatch computational demand increases as \( nS \times 2^{(\text{number of generators})} \)
- Evaluates entire search space
- No training data required

Artificial Neural Network

- High computational efficiency
  - 1 time through network
- Simple ANN can be used for unit commitment
- Training data required
Test Setup: Campus Microgrid

Electric
- 1 Internal Combustion Engine
- 1 Microturbine

Heat
- Waste heat from ICE
- Waste heat from mGT
- 1 Hot Water Tank (storage)

Grid Connection
- Electric Utility with time of use pricing
- Gas Utility with flat rate pricing
Dispatch Comparison

**cQP:** 0.8813 s/dispatch

**ANN:** 0.0392 s/dispatch

**cQP** Computational demand increases as:

\[ nSx2^nG = 24x2^2 = 96 \]

**ANN** Computational demand remains the same regardless of number of generators:

1 time through ANN
Test Setup of larger grid: Campus Microgrid

**Electric**
- 2 CHP Fuel Cells
- 2 CHP microturbines
- 1 non-CHP microturbine
- 1 Diesel Generator
- 1 Battery
- 1 Solar PV Array

**Cooling/Heat**
- 3 Chillers
- 1 Absorption Chiller
- 1 Cold Water Tank (storage)
- 1 Heater
- 1 Hot Water Tank (storage)

**Grid Connection**
- Electric Utility with time of use pricing
- Gas Utility with flat rate pricing
Dispatch Comparison

cQP: 16.2207 s/dispatch

ANN: 0.03809 s/dispatch

cQP Computational demand increases as:

\[ nS \times 2^n \times nG \times 2^n \times 2^4 = 24 \times 2^6 \times 2^4 = 24576 \]

Standard deviation: 0.1785 sec

ANN Computational demand remains the same regardless of number of generators:

1 time through ANN

Standard deviation: .0501 sec
ANN Structure and Training

Zero Intercept Optimizaion (SetPt0): component setpoints over entire horizon given by the Zero Intercept fit optimization.

Generator Setpoint (GenCost): (constant) generator setpoints over entire horizon.

Generator Heat Ratios (HR): ratio of heat out to power out (constant).

Generator Costs (GenCost): O&M (constant), Fuel (time dependent).

Demand (Dem): Electric, Heat, and Cooling over time horizon.

Heater and Chiller Efficiency (HCeff): electric/fuel/heat in to heat/cooling out (constant).

Unit commitment
Conclusion

- ANN Techniques can replicate and improve upon conventional unit commitment techniques
- ANN Techniques have potential for expansion to include dispatch as well as unit commitment further reducing computational demand
- ANN Techniques have potential for expansion to include non-linear demand relationships such as active-reactive power
References


Potential Expansion of ANN

- Current ANN is very simple
- Multilayered ANN could be used for unit commitment and dispatch
- Change from 3 steps, to 1 step
- Active-Reactive Power and other non-linear relationships