Forecasting and Dynamic Real-Time Optimization of a Campus District Energy System using PI

Dr. Kody Powell and Dr. Pratt Rogers
About Me: Kody Powell, Ph.D.

• University of Utah – Dept. of Chemical Engineering
  • Previously ExxonMobil Research and Engineering
• Automation and Optimization Researcher
• Research focus on energy systems and smart grid
  • Solar energy
  • Distributed energy
  • Manufacturing/process systems
  • Building energy management
  • Energy Storage
• My goals as a professor and researcher
  • Develop technology for systems to be “smarter”
  • Develop engineers with applicable skill sets for the market
• Warning: I am a PI novice
About Me: Pratt Rogers, Ph.D.

• University of Utah – Dept. of Mining Engineering
  • Previously MISOM Technologies

• Analytics and Operations Engineering **Researcher**

• Research focus on
  • Socio-technical systems: people, processes, technology
  • Machine learning and analytics nexus
  • Management safety and production systems

• My goals as a professor and researcher
  • Operationalize cool technology
  • Develop engineers with applicable skill sets for the market
The Fundamental Problem

Solar Radiation (W/m²)

Load (GW)
The Solution(s)

• Energy Storage
  • Large scale
  • Heavy lifter
• Distributed
• Thermal Energy storage
  • “Heat things up and cool them down”

• Intelligent Systems
  • Powerful can be smart too
Smart Energy Storage

• Constraints
  • $P_1 + P_2 = P_{total}$
  • DOF=1

• Dynamic optimization
  • DOF=infinite
  • Discretize
  • Flexibility
  • Blessing and curse of dimensionality
Energy System Optimization
Results: Grid Interconnection Example

- Total Power (MWₑ)
- Exported Power (MWₑ)
- Price ($/MWhₑ)
Summary of Results

• 2.2% savings by optimizing
• Marginal benefit using storage for efficiency
• +6 MWₑ peak capacity
• Storage beneficial in market conditions
  • Additional 2.2-2.4% savings
• $1.9 M (16.5%) savings overall
How Do We Make Theoretical Results A Reality?
Building an Optimization Application Around PI

1. Timestamped Historic Data:
   - Weather
   - Demand

2. Live Data:
   - Weather Forecasts
   - Cooling Demand

3. Fit Model

4. Manufacturer Data:
   - Chiller Performance

5. Fit Model

6. Forecast Demand

7. Real Time Optimization

\[ P_i = \alpha_i + \beta_i Q_i + \gamma_i Q_i^2 \]
Building an Optimization Application around PI

- Train Artificial Neural Network
- Historic Data
- Live Sensor Data from University Server & Live Weather Forecasts
- Optimal Values
- Dynamic Optimization
- Fit Chiller Model
- Forecast

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
The PI System and current data

- Element Hierarchy – Tree Structure
- All names kept consistent with Haystack Terminology
- Multiple Attributes for each Element
- Templates
- Tags

Tag for each data source

Templates
Advanced calculations in PI AF

Using PI Unit Conversions to Measure Energy Use Intensity (EUI)

External Data Sources

- 3 minute current weather conditions
- Hourly forecasts
- Heating Degree Days

- Forecasted Electricity demand for the region
- Current electric demand for the region
- Current air pollution (PM2.5, O₃, NO₂, & CO)
Building an Optimization Application around PI

- Live Sensor Data from University Server & Live Weather Forecasts
- Optimal Values
- Dynamic Optimization
- Fit Chiller Model
- Train Artificial Neural Network
- Historic Data
- Live Data
- Forecast

$Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2$
Data Analytics – Visualizing EUI

FASB Energy Usage

Energy Used this year
9,008.5 kWh

5-Day Avg EUI (Annual Rate) 178.67 kBtu/ft²

Today’s Total
8,771.2 kWh

Yesterday at this time
8,514.2 kWh

5-Day Avg Total
13,055 kWh

Chilled Water Temp

Return Temperature 55.252 °F
Supply Temperature 85.737 °F

Temperature Today vs. Yesterday

KUTSALT/120/Temp 33.3 °F
KUTSALT/120/Temp 40.104 °F
Forecast Hourly/Forecast 38 °F
Data Analytics – Visualizing EUI

North Campus Chilled Water Plant

Energy Used This Year
84,316 kWh

Thermal Energy Storage

TES Charged
107.32 %
Analyses

• PI System Analyses – simple
  EUI (Annual Rate)
  Heating Degree Days
  Energy Load

• Python Integration – complex
  Dynamic Load Forecasting
Building an Optimization Application around PI

- **Advisory Dashboard**
- **Dynamic Optimization**
- **Optimal Values**
- **Optimal Values**
- **Historic Data**
- **Train Artificial Neural Network**
- **Live Data**
- **Live Data**
- **Forecast**
- **Live Sensor Data from University Server & Live Weather Forecasts**

**Formula:**

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
System Loads

August

February
Using AI: Load Forecasting with Recurrent Neural Networks

Adjusted $R^2$ values

<table>
<thead>
<tr>
<th>Model</th>
<th>Cooling</th>
<th>Heating</th>
<th>Electrical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static Neural Network (weather only)</td>
<td>0.906</td>
<td>0.820</td>
<td>0.808</td>
</tr>
<tr>
<td>Static Neural Network (weather and time)</td>
<td>0.945</td>
<td>0.942</td>
<td>0.910</td>
</tr>
<tr>
<td>Linear ARX (weather only)</td>
<td>0.911</td>
<td>0.932</td>
<td>0.749</td>
</tr>
<tr>
<td>Linear ARX (weather and time)</td>
<td>0.936</td>
<td>0.948</td>
<td>0.850</td>
</tr>
<tr>
<td>NARX (weather only)</td>
<td>0.948</td>
<td>0.977</td>
<td>0.864</td>
</tr>
<tr>
<td>NARX (weather and time)</td>
<td>0.964</td>
<td>0.986</td>
<td>0.933</td>
</tr>
</tbody>
</table>
Forecast Results: August

- Temperature (°C)
- Relative Humidity (%)
- Electric Load (MW)
- Heating Load (MW)
- Cooling Load (MW)
Forecast Results: February
Building an Optimization Application around PI

- Live Sensor Data from University Server & Live Weather Forecasts
- Historic Data
- Optimal Values
- Dynamic Optimization
- Fit Chiller Model
- Forecast
- Train Artificial Neural Network

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
Modeling with Manufacturing Data

- Need to determine unknown parameters of chiller model generally
- Use data from manufacturer to fit chiller performance
- Put model in quadratic form to speed up optimization
Building an Optimization Application around PI

- Train Artificial Neural Network
- Live Sensor Data from University Server & Live Weather Forecasts
- Historic Data
- Optimal Values
- Live Data
- Dynamic Optimization
- Forecast
- Fit Chiller Model

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
Comparing the Model to PI Data

![Graph comparing measured power to linear algebra fit with MFG specifications from May 2018 to June 2018.](image-url)
Dynamic fitting with Moving Horizon Estimation
Building an Optimization Application around PI

- Live Sensor Data from University Server & Live Weather Forecasts
- Historic Data
- Optimal Values
- Dynamic Optimization
- Fit Chiller Model
- Train Artificial Neural Network
- Forecast

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
Dynamic Decoupling Approach

- Combinatorial complexity
- Dynamic problem “guesses” how much energy to store / extract
- Static problems report back
- Back and forth iteration until convergence
- Static problems – MINLPs with convex relaxations
- Static problem solved 1,000-5,000 times
Dynamically Optimized Operation

Chillers, Storage, Demand vs Time

- **Chiller 1**: Red
- **Chiller 2**: Blue
- **Min/Max**: Black

- **Storage**: Green
- **Min/Max**: Black

- **Demand**: Yellow
- **Capacity, No Storage**: Cyan

- **Power**: Red
  - **Begin Peak**: Dotted
  - **End Peak**: Dashed

Time (hours):
- 0 to 70

Load (tons):
- 0 to 12000

Storage (ton-hrs):
- 0 to 20000

Demand (tons):
- 0 to 2500

Electricity (kW):
- 0 to 2500

Graph shows the interaction between chiller load, storage capacity, and demand over time, highlighting peak power usage and storage efficiency.
Summary of Results

• Dynamic optimization algorithm predicts 16.5% cost savings

• Still need to close the loop
  • Make savings a reality

<table>
<thead>
<tr>
<th></th>
<th>QPHAC</th>
<th>Manual</th>
<th>BnB</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-h</td>
<td>$190.30 (0.150 s)</td>
<td>$246.68 (∼ 0 s)</td>
<td>$165.53 (38 s)</td>
</tr>
<tr>
<td>8-h</td>
<td>$580.89 (0.150 s)</td>
<td>$632.11 (∼ 0 s)</td>
<td>$557.20 (13 min)</td>
</tr>
<tr>
<td>12-h</td>
<td>$1248.68 (0.167 s)</td>
<td>$800.55* (∼ 0 s)</td>
<td>$961.61 (24 min)</td>
</tr>
<tr>
<td>24-h</td>
<td>$871.63 (0.150 s)</td>
<td>$1314.80 (∼ 0 s)</td>
<td>Did not converge†</td>
</tr>
<tr>
<td>72-h</td>
<td>$4257.48 (0.184 s)</td>
<td>$5097.72 (∼ 0 s)</td>
<td>Did not converge†</td>
</tr>
</tbody>
</table>

*The 12-h time window manual control was unable to achieve the starting energy storage

†The 24-h and 72-h BnB failed to converge after over 24 h of computation
Building an Optimization Application around PI

Live Sensor Data from University Server & Live Weather Forecasts

Optimal Values

Dynamic Optimization

Advisory Dashboard

Historic Data

Optimal Values

Train Artificial Neural Network

Live Data

Live Data

Forecast

Fit Chiller Model

\[ Y_i = \alpha_i + \beta_i x_i + \gamma_i x_i^2 \]
Now

Temp
75.947 °F
8/9/2018 9:15:00 AM

Humidity
28.607 %
8/9/2018 9:15:00 AM

Future

Ambient Temperature

Demand Forecast

Optimized Chiller Loads

TES Optimized

Combined Load
2,862.3 kW

TES Charged
67.00% %

Simple Chiller Max

Max w/o Storage

Current Chiller Loads

Chiller 1 South Chiller Load
2,645.1 kW

Chiller 1 North Chiller Load
1,506.9 kW

Chiller 2 South Chiller Load
1,623.3 kW

Chiller 2 North Chiller Load
0 kW

#PIWorld ©2019 OSIsoft, LLC
Future Work

• More verification and validation
• Human-in-the-loop operation
  • Advisory mode using PI Vision
• Close the loop
• Stochastic + dynamic optimization
  • Account for model uncertainty using probabilistic methods
Next Steps:

- Nexus of ML and BI Analytics
  - Operationalize ML
- Educating next gen
  - Data infrastructure, analytics, computational intelligence, …
Acknowledgements

• OSISoft and John Matranga
• Utah office of Science Technology and Research (USTAR)
• Aaron Young, Landen Blackburn, Titus Quah
• University of Utah Facilities Management Group
Appendix Slides
Modeling the Chillers

First Principles Model of a Chiller by Gordon, Ng, and Chua:

\[
P = \frac{Q}{\text{COP}} = -Q + \left( \frac{T_{\text{in}}^{\text{out}}}{T_{e}^{\text{out}}} \right) Q + \left( \frac{q_{e}T_{\text{in}}^{\text{out}}}{T_{e}^{\text{out}}} - q_{c} \right) + \left( \frac{q_{e}T_{\text{in}}^{\text{out}}}{M_{c}T_{e}^{\text{out}}} \right) \left( \frac{q_{e}T_{\text{in}}^{\text{out}}}{T_{e}^{\text{out}}} - q_{c} \right) + \left( \frac{Q^{2}}{T_{e}^{\text{out}}} \right) \left( \frac{T_{\text{in}}^{\text{out}}}{T_{e}^{\text{out}}} \right) \left( \frac{1}{M_{c}} + \frac{1}{M_{e}} \right)
\]

+ \quad \frac{q_{c}}{M_{e}} + \frac{q_{e}T_{\text{in}}^{\text{out}}}{T_{e}^{\text{out}}M_{e}} + \left( \frac{T_{\text{in}}^{\text{out}}q_{e}}{T_{e}^{\text{out}} - q_{c}} \right) \left( \frac{1}{M_{c}} + \frac{1}{M_{e}} \right)

Modeling the Chillers

First Principles Model of a Chiller by Gordon, Ng, and Chua:

\[
P = \frac{Q}{\text{COP}} = Q \left( \frac{T_c^{\text{in}}}{T_e^{\text{out}}} \right) \left( \frac{q_e T_c^{\text{in}} - q_c}{T_e^{\text{out}}} \right) + \left( \frac{q_e T_c^{\text{in}}}{M_c T_e^{\text{out}}} \right) \left( \frac{q_e T_c^{\text{in}}}{T_e^{\text{out}}} - q_c \right) + \left( \frac{Q^2}{T_e^{\text{out}}} \right) \left( \frac{T_c^{\text{in}}}{T_e^{\text{out}}} \right) \left( \frac{1}{M_c} + \frac{1}{M_e} \right)
\]

\[
+ \frac{q_c}{M_e} + \frac{q_e T_c^{\text{in}}}{T_e^{\text{out}} M_c} + \left( \frac{T_c^{\text{in}} q_e}{T_e^{\text{out}}} - q_c \right) \left( \frac{1}{M_c} + \frac{1}{M_e} \right)
\]

Optimization Problem Formulation

- **Objective:** Minimize total cost

\[
\min_{u_i} F = \sum_i \left[ C_f (W_{f,\text{GT},i} + W_{f,\text{HRSG},i} + W_{f,\text{BR},i}) - C_{e,i} P_{\text{net},i} \right] (\Delta t)
\]

- **Decision variables**

\[
u_i = \begin{bmatrix} Q_{3.1}, \cdots, Q_{6.3}, \delta_{3.1}, \cdots, \delta_{6.3}, Q_{\text{IGV}}, W_{f,\text{GT}}, W_{f,\text{HRSG}}, W_{f,\text{BR}}, W_{s,\text{EXT}}, P_{\text{net}} \end{bmatrix}^T
\]

- **Load constraints**

\[
P_{\text{GT},i} + P_{\text{ST},i} - P_{\text{net},i} \geq L_{E,\text{campus},i} + \sum P_{ch,i} + \sum P_{\text{aux},i}
\]

\[
\sum_j Q_{i,j} - Q_{\text{TES},i} \geq L_{C,\text{i}} + Q_{\text{TIC},i}
\]

\[
W_{s,\text{EXT},i} \geq L_{H,\text{i}}
\]
Assumptions

• One-hour time intervals
• Steady-state models for all generation equipment
  • Max settling time ~ 15 minutes
• 24-hour time horizon
  • Storage capacity ~ 2-6 hours full load
• Discrete dynamics for storage

\[ E_{TES,i} = E_{TES,i-1} + (Q_{TES,i} - E_{loss,i}) \Delta t \]

\[ Q_{TES,i} = \sum_j Q_{i,j} - (L_{Ci} + Q_{TIC,i}) \]
Dynamic Optimization Problem Summary

• Mixed-integer Nonlinear Program (MINLP)
• 600 decision variables
• 216 binary constraints

\[ \delta_j \in [0,1] \]

\[ \delta_j Q_{j,lo} \leq Q_j \leq \delta_j Q_{j,hi} \]

• Original Approach: Full MINLP solved using BONMIN solver
  • 27-hour solve time (2.5 GHz processor)
  • Curse of dimensionality
  • Equipment chatter
Data Management Spring 2019

Objective

- Business rules
- Data characterization
- Data visualization

OSIsoft Resources:
- YouTube Videos
- Regional Seminars
- AF Public Library Templates
- Tech Support
- *OSI mentors*
  ...

Data

- Fleet events and cycles
- Crush plant
- Equipment health

Students

- Mining, chemical, graduate, undergraduate
- Expand disciplines in future courses

OSIsoft Resources:
- YouTube Videos
- Regional Seminars
- AF Public Library Templates
- Tech Support
- *OSI mentors*
## Connecting engineering and operational standards to business rules

### Excel tables & pivot

- **Business rules to engineering standards**

### SQL tables & views

- **Business rules to engineering standards**

### PI AF / Event Frames

- **Business rules to engineering & operational standards**

### Time Usage Model

- **Material Hierarchy**

### Process Flow Diagram
Contextualizing process flow diagram to AF

Microsoft PowerBI
Initial lessons learned

• Introduce concepts gradually
  • I do, we do, you do approach

• Infrastructure always a challenge

• Business rules first, visualization second
  • Visualizations important business rules foundational

• Students are enjoying it!