DYNAMIC OPTIMIZATION

Energy System Planning under Uncertainty

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Overview

- PRISM Group Overview
- Dynamic Optimization for:
  - Unmanned Aerial Vehicles
  - Systems Biology
  - Solid Oxide Fuel Cells
  - Energy Storage and the Smart Grid
  - Investment Planning Under Uncertainty
- Needs and resources for dynamic optimization
PRISM Group

• Methods
  ▪ Mixed Integer Nonlinear Programming (MINLP)
  ▪ Dynamic Planning and Optimization
  ▪ Uncertain, Forecasted, Complex Systems

• Research Applications
  ▪ Unmanned Aerial Vehicle (UAV) control
  ▪ Systems biology and pharmacokinetics
  ▪ Oil and gas exploration and production
  ▪ Hybrid and sustainable energy systems
Problem Formulation

- Standard Problem Formulation

\[
\max f(x) \\
\text{subject to } g \left( \frac{\partial x}{\partial t}, x, u, p \right) = 0 \\
h(x, u, p) \leq 0
\]

- Objective Function \((f(x))\)

- Dynamic model equations that relate trajectory constraints, sensor dynamics, and discrete decisions

- Uncertain model inputs as unmodeled or stochastic elements

- Solve large-scale MINLP problems (100,000+ variables)
Smart Grid Optimization

Smart grid integration with solar, wind, coal, biomass, natural gas, and energy storage

Nuclear integration with petrochemical production, processing, and distribution
Nuclear with Petrochemical Industries

- 12% of total U.S. energy use from refining and chemicals
- $57 billion annually on energy
- Potential refinery and nuclear integration with electricity, heat, hydrogen, and other production-consumption pairings
- Transportation fuels are 28% of U.S. energy total
Underwater Oil Rigs

- Petrobras, a Brazilian oil company, plans to use unmanned, highly automated underwater oil rigs beginning in 2020

- Nuclear reactors for:
  - Electricity
  - Heated pipe in pipe to discourage hydrate formation
  - Gas, water, oil processing
C. Cooling towers purify and consume 1.05 gal/kW-hr

Several nations have access to nuclear power, but limited amounts of renewable fresh water

World’s largest desalination facility in Saudi Arabia to produce electricity and water (July 2013)

KSA desalination consumes 300,000 barrels of oil per day at $3.20/m³
District Heating and Cooling
Planning of Investment Decisions
District Energy Profiles

Heat Demand (MMBTU/hr)

Electricity Demand (MW)

Avg. Power, Avg. Heat Load

- Heat Requirement, MMBTU/hr
- Electricity Requirement, MW

Hour of the day

0 5 10 15 20 25

40 50 60 70

0 10 20

-15 0 20
Uncertainty in Natural Gas Prices

**Commercial Forecasted Natural Gas Prices**

- Reference
- High Economic Growth
- Low Economic Growth
- No GHG Concern
- $10 GHG
- $15 GHG
- $25 GHG

**Industrial Forecasted Natural Gas Prices**

- Reference
- High Economic Growth
- Low Economic Growth
- No GHG Concern
- $10 GHG
- $15 GHG
- $25 GHG
Uncertainty in Electricity Prices

Commercial Forecasted Electricity Prices

Industrial Forecasted Electricity Prices
Simplifying System

- Create Model:
- Electric and Heating Demand Model (winter and summer)
Allocation of energy supply

**Winter Heating Capacity Allocation?**

- CHP
- Import

**Summer Electricity Supply Allocation?**

- Supplemental firing
- CHP
- Import
Dynamic Model for Dynamic System

Heat Demand (MMBTU/hr)

Electricity Demand (MW)

Avg. Power, Avg. Heat Load

Hour of the day
Nonlinear DAE

\[ \min J(x, y, u) = (Cost_{\text{capital}} + Cost_{\text{operating}} + Cost_{\text{environmental}}) \]

s.t. \[ 0 = f\left(\frac{\partial x}{\partial t}, x, y, u\right) \]
\[ 0 = g(x, y, u) \]
\[ 0 < h(x, y, u) \]
\[ x, y \in \mathbb{R}^n \quad u \in \mathbb{R}^m \]

- Nonlinear Cost functions
- Turbine and boiler dynamics
- Demand and operating constraints
Both capacity increase and cost effective mode of operation over a long term horizon
Turbine Max Capacity

Maximum CHP Capacity

Time (years)

CHP capacity (MW)

- Reference
- High Economic Growth
- Low Economic Growth
- No GHG Concern
- $10 GHG
- $15 GHG
- $25 GHG
Supplemental Boiler Firing Capacity

Maximum Boiler Capacity

- Boiler capacity (MMBtu/h)
- Time (years)

- Reference
- High Economic Growth
- Low Economic Growth
- No GHG Concern
- $10 GHG
- $15 GHG
- $25 GHG
Model Predictive Control Approach
L1 Norm formulation

\[
\begin{align*}
\min & \quad (obj + se_{hi} + se_{lo} + sc_{hi} + sc_{lo}) \\
\text{s.t.} & \quad 0 = f(\dot{x}, x, d) \\
& \quad m_{gap} = \frac{m_{hi} - m}{2} \\
& \quad m_{gap} = \frac{m - m_{lo}}{2} \\
& \quad e_{hi} = x - m_{hi} + se_{hi} \\
& \quad e_{lo} = m_{lo} - x + se_{lo} \\
& \quad c_{hi} = x - \hat{x} + sc_{hi} \\
& \quad c_{lo} = \hat{x} - x + sc_{lo} \\
& \quad obj = w_{meas}(e_{hi} + e_{lo}) + w_{model}(c_{hi} + c_{lo}) + (Cost_{capital} + Cost_{operating} + Cost_{environmental}) \\
& \quad se_{hi}, se_{lo}, sc_{hi}, sc_{lo} \geq 0 \\
& \quad e_{hi}, e_{lo}, c_{hi}, c_{lo} \geq 0
\end{align*}
\]
Optimize to a Target Range

Optimal sequence of moves given uncertainty in the parameters
Optimize to a Limit

Conservative movement based on worst case CV

Upper Limit

u_{opt}
x_{opt}
Dynamic Solution
Dynamic Energy System Tools

Toolbox for Object Oriented Modeling in MATLAB, Simulink, and Python

Advanced tools are required for collaborative modeling and high performance computing

Solid Oxide Fuel Cell (SOFC)
Optimization Benchmark

Summary of 494 Benchmark Problems

Not worse than $2^\tau$ times slower than the best solver ($\tau$)

- APOPT+BPOPT
- APOPT$_{1.0}$
- BPOPT$_{1.0}$
- IPOPT$_{3.10}$
- IPOPT$_{2.3}$
- SNOPT$_{6.1}$
- MINOS$_{5.5}$
Conclusions

- Powerful insights can be gained from modeling and data reconciliation over long periods of historical data.
- When data, modeling, and optimization are combined, hidden savings are discovered through dynamic optimization.
- MPC approach can allow for other control variables to be accounted for directly in optimization.
- Simulation and optimization of energy system can give stakeholders realistic options to evaluate risks and rewards with minimum cost.
- Simulation results can then be directly applied to control applications.
Development Needs

- Collaborative modeling tools
- Library of high quality models that are open source and can be adapted to new problems
- Improvements to methods to simulate and optimize large-scale and complex systems
- Interface with operations and subject matter experts – need to know the process for effective modeling and optimizing
Acknowledgements
Objective: Improve extraction of information from clinical trial data

Dynamic data reconciliation
  - Dynamic pharmacokinetic models (large-scale)
  - Data sets over many patients (distributed)
  - Uncertain parameters (stochastic)
Energy System Model

Parameters :
- $e_p =$ existing capacity of plant type $p$ [MW]
- $cc_p =$ daily fraction of capital cost of plant $p$ [MW]
- $oc_p =$ daily operating cost of plant $p$ [USD/MWh]
- $ic_{k,s} =$ electricity import cost [USD/MWh]
- $d_{k,s,i} =$ instantaneous energy demand [MW]
- $du_{k,s,i} =$ duration of demand [h]
- $r_{k,s,i} =$ required energy [MWh]
- $fhrg =$ recovered heat factor [unitless]

where the parameter $r_k$ is defined as $r_{k,s,i} = (d_{k,s,i} - d_{k-1,s,i}) \cdot du_{k,s,i}$

Indices :
- $p$ plant type \{chp, boiler\}
- $k$ demand category \{base load, peak load\}
- $s$ season \{summer, winter\}
- $i$ energy type \{electric, thermal\}

Variables :
- $x_p =$ new design of plant type $p$ [MW]
- $y_{p,k,s} =$ allocation of capacity to demand [MW]
- $z_{k,s} =$ import of electricity [MW/h]
Minimize:
\[
\sum_{p} cc_p(e_p + x_p) + \sum_{k} \sum_{s} ic_{k,s} \cdot z_{k,s} + \sum_{k} \sum_{s} \sum_{i} du_{k,s,i} \left( \sum_{p} oc_p \cdot y_{p,k,s} \right)
\]

Subject to:
\[
e_p + x_p \geq \sum_{k} \sum_{s} y_{p,k,s} \quad \text{for all } p
\]
\[
r_{k,s,electric} = z_{k,s} + du_{k,s,electric} \left( \sum_{p} y_{chp,k,s} \right) \quad \text{for all } k, s
\]
\[
r_{k,s,thermal} \leq du_{k,s,electric} \left( \sum_{p} y_{boiler,k,s} + y_{chp,k,s} \cdot f_{hrg} \right) \quad \text{for all } k, s
\]
\[
x_p \geq 0
\]
\[
y_{p,k,s} \geq 0
\]
\[
z_{k,s} \geq 0
\]
Example of Results

LP or NLP formulation, optimizing through discrete scenarios to account for uncertainty. Lacks system dynamics.
Electricity Generation Forecasts

![Summer Power Generation Forecasts](image-url)
Optimize capacity at CHP’s most efficient operating point
Heat load is optimized simultaneously
Optimize to a Target

Summer Electricity Difference Error Profile

Winter Electricity Difference Error Profile

Demand Diff (MWh)

Time (years)
Optimize above a Limit
Table 1: Computational results from the sequential and simultaneous solution methods. Computations for each method are executed using an Intel® Core 2 Duo™ (2.54 GHz) processor with 4 GB RAM.

<table>
<thead>
<tr>
<th></th>
<th>Sequential</th>
<th>Simultaneous</th>
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<tbody>
<tr>
<td>Objective function value</td>
<td>0.0094</td>
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<td>System model evaluations</td>
<td>3,336</td>
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<td>Computation time (s)</td>
<td>331.6</td>
<td>1.1</td>
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## Survey of DAE Solvers

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<thead>
<tr>
<th>Software Package</th>
<th>Max DAE Index</th>
<th>Form</th>
<th>Adaptive Time Step</th>
<th>Sparse</th>
<th>Partial-DAEs</th>
<th>Simultaneous Estimation / Optimization</th>
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<td>Yes</td>
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<tr>
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<tr>
<td>gProms</td>
<td>1 (3+ with transforms)</td>
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<tr>
<td>Modelica</td>
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<td>Open</td>
<td>Yes</td>
<td>Yes</td>
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</tr>
</tbody>
</table>

**DAE = Differential and Algebraic Equation**