Multi-Objective Optimal Sensor Deployment Under Uncertainty for Advanced Power Systems

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Sensor Placement Problem

• Advanced Power Systems
  – Integrated Gasification Combined Cycle (IGCC)

• Objectives
  – Determine optimal location of network of sensors
  – Minimize number of sensors in network
  – Maximize Efficiency, Maximize Observability, Minimize Cost

• Constraints
  – Mass and Energy Balances
  – Environmental factors
  – Sensor accuracy
Main Elements of IGCC Plant

- Gasification Plant
  - Gasifier
  - Particulate Remover
  - Gas Cleaner
  - RSC
  - Compressor
  - Gaseous
  - Solids
  - Slag, Fines
  - Oxygen
  - Steam
  - Syngas, Flyash

- Syngas Cleanup Process
  - (Radiant Syngas Cooler)
  - Combustor
  - ASU
  - Compressed Air
  - Ambient Air

- Air Separation Unit
  - Compressed Air
  - Oxygen

- Power Generation Block
  - Gas Turbine
  - Heat Recovery Steam Generator
  - Steam Turbine
  - Generator
  - Electricity
Model Uncertainties

- Variations to process variables lead directly to variations in the gasification performance
- Plant with no sensors use models to control variations
  - Soft sensing
  - Introduces large errors in control resulting in large variations in output variables
  - Reduced observability
- Sensors reduce errors in control
- Cost of sensors is linked to errors in sensing
  - High cost sensors, less variation
  - Low cost sensors, high variation
Model Uncertainties

- softsensing 25% error
- low quality sensors 5% error
- medium quality sensors 2% error
- high quality sensors 1% error
Mixed Integer Nonlinear, Stochastic Optimization Problem

• Determine location of on-line sensors to maximize observability of system, maximize efficiency subject to budget constraint

\[
\begin{align*}
\max_{y_{j,\tau} \in \{0,1\}} \sum_{\tau=1}^{T} \sum_{j=1}^{S_{out}} f_{j,\tau}(\psi) y_{j,\tau}, \sum_{\tau=1}^{T} \sum_{j=1}^{S_{out}} E_{j,\tau}(\psi, y_{j,\tau}) \\
\text{s.t.} \quad \sum_{\tau=1}^{T} \sum_{j=1}^{S_{out}} C_{j,\tau} y_{j,\tau} \leq B \\
\sum_{\tau=1}^{T} y_{j,\tau} \leq 1, \quad j = 1,2,...,S_{out} \\
y_{j,\tau} \in \{0,1\}, \quad j = 1,2,...,S_{out}, \tau = 1,2,...,T
\end{align*}
\]

Mass and Energy Balances around the Plant

• \(\psi\) = network of on-line sensors;
• \(f_{j,\tau}(\psi)\) = level of observability resulting from the placement of sensor type \(\tau\) at location \(j\);
• \(E_{j,\tau}(\psi, y_j)\) = efficiency as a nonlinear function of placement of sensor type \(\tau\) at location \(j\)
Multi-objective Optimization under Uncertainty

- **Pareto Optimal Solutions**
  - Optimal Solutions
  - Defining Optimization Problems

- **Discrete Optimizer**
  - Feasible Solutions
  - Discrete decisions

- **Continuous Optimizer**
  - Probabilistic objective & constraints
  - Continuous decisions

- **Sampling**

- **Model**
Optimization under Uncertainty

Stochastic Optimization

Optimization Loop

Optimal Design

Decision Variables

Stochastic Modeler

Model

Sampling Loop

Stochastic Optimization

Stochastic Modeling

Optimizer

Output CDFs

Uncertain Variables

Model
Important Properties of Sampling Techniques

- Independence / Randomness
- Uniformity

In most applications, the actual relationship between successive points in a sample has no physical significance, hence, randomness of the sample for approximating a uniform distribution is not critical (Knuth, 1973).

Once it is apparent that the uniformity properties are critical to the design of sampling techniques, constrained or stratified sampling becomes appealing (Morgan and Henrion, 1990).
A: Monte Carlo

B: Latin Hypercube

C: Median Latin Hypercube

D: Hammersley Sequence

Wozniakowski-Hammersley
Novel Sampling Technique

- Hammersley Sequence Sampling (HSS) based on a Quasi-random number generator
- HSS sampling is at least 3 to 100 times faster than LHS or MCS.
- HSS is preferred sampling for stochastic modeling and/or stochastic optimization.
Multi-objective Optimization under Uncertainty

- Pareto Optimal Solutions
  - Optimal Solutions
  - Feasible Solutions
  - Probabilistic objective & constraints
- Discrete Optimizer
  - Discrete decisions
- Continuous Optimizer
  - Continuous decisions
- Sampling
- Model
- MOP
  - Defining Optimization Problems
Simulation Technique

• Simulate IGCC process $N_s$ times
  – Comprehensive plant model in ASPEN Plus environment
  – Hammersley sequence sampling used to generate uniform spaced samples across $d$-dimensional sample space

• Better Optimization for Nonlinear Uncertain Systems (BONUS) (Sahin and Diwekar, 2004)
Better Optimization of Nonlinear Uncertain Systems (BONUS)

- Cumulative Distribution Base Case Output $Z(X_i)$
- Probability Distribution Base Case Input $f(X_i)$
- Probability Distribution Changed Input $f(x_i)$
- Estimated Output Cumulative Distribution $Z(x_i)$

**SAMPLING LOOP**

- Stochastic Modeler
- Model
- Reweighting Scheme

Probability flowchart diagram showing the process of optimization.
Model Uncertainties

- softsensing 25% error
- low quality sensors 5% error
- medium quality sensors 2% error
- high quality sensors 1% error
Multi-objective Optimization under Uncertainty

- **Pareto Optimal Solutions**
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- **Sampling**
  - Defining Optimization Problems

- **Model**
A Simple Multi-objective Linear Example

Max \( Z_1 = 6x_1 + x_2 \)
\( Z_2 = -x_1 + 3x_2 \)

subject to:
\( 3x_1 + 2x_2 \leq 12 \)
\( 3x_1 + 6x_2 \leq 24 \)
\( x_1 \leq 3 \)
\( x_1, x_2 \geq 0 \)
Weighting Method: \( \text{Max. } Y = \omega_1 \cdot Z_1 + \omega_2 \cdot Z_2 \)
Weighting Method: $\text{Max. } Y = \omega_1 Z_1 + \omega_2 Z_2$

Objective Space

<table>
<thead>
<tr>
<th></th>
<th>$Z_1=6x_1+x_2$</th>
<th>$Z_2=-x_1+3x_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A(0,0)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B(3,0)</td>
<td>18</td>
<td>-3</td>
</tr>
<tr>
<td>C(3,1.5)</td>
<td>19.5</td>
<td>0</td>
</tr>
<tr>
<td>D(2,3)</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>E(0,4)</td>
<td>4</td>
<td>12</td>
</tr>
</tbody>
</table>
Comparison of the New MINSOOP Algorithm with the Conventional Method

![Bar graph comparing the number of optimization problems solved by the Conventional Method and the New Method, with the number of objective functions on the x-axis and the number of problems solved on the y-axis. The graph shows that the New Method outperforms the Conventional Method in terms of the number of problems solved for a given number of objective functions.]
IGCC Process Flowchart & Sensor Placement

- Generate flowchart to determine downstream variables
- Define $\gamma_{i,j} = 1$ (0) if variable $j$ is downstream of variable $i$
- Distribution

$$f_t(y_j) = f_0(y_j)^{S_{in}} \left( 1 + \gamma_{i,j} \left( \frac{f_t(x_i)}{f_0(x_i)} - 1 \right) \right)$$
Important Input, Intermediate and Output Variables

• Input process variables
  – 8 variables, including
    • Oxygen, coal slurry, air flow rates
    • Recycled HRSG steam temperature & pressure
    • Gasifier temperature & pressure

• Intermediate and output process variables
  – 24 variables, including
    • Syngas flow rate, temperature, pressure
    • CO, CO$_2$ flow rates
    • Gas turbine combustor, high & low pressure exhaust temperature
    • Oxygen, coal, air flow rates into gasifier
    • Slag & fines flow rates
Position\Accuracy ->
1 Gasifier syngas flowrate
2 Syngas CO flowrate
3 Syngas CO2 flowrate
4 Syngas temp.
5 Syngas pressure
6 LP steam turbine temp.
7 Gas turbine burn temp.
8 Gas turbine exit temp.
9 Gas turbine HP stream temp.
10 Gas turbine LP stream temp.
11 Gas turbine expand. out temp.
12 Oxygen flowrate exit expand.
13 Syngas flow solids removal
14 Coal slurry flowrate gasifier
15 Oxygen flowrate gasifier
16 Oxygen flowrate exit ASU
17 Acid gas flowrate FUEL1
18 Gas turbine compre. flowrate
19 HP steam turbine flowrate
20 Coal feed flow rate
21 Slag from syngas
22 Fines from syngas
23 Gasifier heat output
24 HRSG steam heat output
Sample Space

- \( N_s = 800 \), uniformly distributed using Hammersley sequence sampling method
- Sensors placed on input variables with six-sigma variation spanning +/-20% of the nominal value
- Resulting Fisher information about the downstream variables obtained when no sensors are placed in the network, \( l_{y_j}^{ns}(\theta_{y_j}) \) and reweighting
- Resulting efficiency is obtained by reweighting
## Solutions

### Maximize Observability: Sensor Locations

| Cost      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | Efficiency | FI  |
|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|--------|-----|
| 0         | - | - | - | - | - | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.3614 | 0   |
| 1055000   | - | - | - | - | - | - | - | - | - | -  | -  | -  | -  | H  | H  | -  | -  | -  | H  | -  | -  | -  | -  | -  | 0.3656 | 52.41 |
| 2110000   | H | H | H | - | - | - | - | - | - | -  | -  | -  | -  | H  | H  | -  | -  | -  | H  | -  | -  | -  | -  | -  | 0.3805 | 101.78|
| 3000000   | H | H | H | - | H | - | - | - | - | -  | -  | -  | -  | H  | H  | -  | -  | -  | H  | -  | -  | -  | -  | -  | 0.4017 | 119.51|
| 4220000   | H | H | H | - | H | - | - | - | - | -  | -  | -  | -  | H  | H  | -  | -  | -  | H  | -  | -  | -  | -  | -  | 0.4324 | 133.18|
| 5275000   | H | H | H | H | H | - | - | - | - | -  | -  | -  | -  | H  | H  | -  | -  | -  | H  | -  | -  | -  | -  | -  | 0.4456 | 144.04|
| 6330000   | H | H | H | H | H | - | H | - | H | -  | H  | H  | H  | H  | H  | -  | H  | -  | -  | -  | -  | -  | -  | -  | 0.4464 | 148.99|
| 7385000   | H | H | H | H | H | - | H | - | H | -  | H  | H  | H  | H  | H  | -  | H  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 152.97|
| 8300000   | H | H | H | H | H | - | H | - | H | -  | H  | H  | H  | H  | H  | -  | H  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 156.91|
| 9700000   | H | H | H | H | H | - | H | - | H | -  | H  | H  | H  | H  | H  | -  | H  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 160.84|
| 10550000  | H | H | H | H | H | - | H | - | H | -  | H  | H  | H  | H  | H  | -  | H  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 160.84|

### Maximize Efficiency: Sensor Locations

| Cost      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | Efficiency | Eff FI |
|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|--------|-------|
| 0         | - | - | - | - | - | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.3614 | 0    |
| 1055000   | - | - | - | - | - | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4133 | 18.55|
| 2110000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4133 | 18.55|
| 3000000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4444 | 56.82|
| 4220000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4466 | 61.77|
| 5275000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
| 6330000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
| 7385000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
| 8300000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
| 9700000   | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
| 10550000  | H | - | - | H | H | - | - | - | - | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | -  | 0.4478 | 96.39|
Conclusions

• Sensor placement in power plant is a stochastic mixed integer nonlinear programming problem
• Novel sampling approach and BONUS algorithm can solve this large scale stochastic programming problem
• Maximize efficiency, maximize observability and minimize cost for good performance coverts the problem into multi-objective stochastic programming problem
• Novel algorithmmic framework can provide solution to this real world problem.