Evaluation of Policy Options using Uncertainty Analysis of Complex-system Model Results

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• We construct CASoS models to understand real-world systems
• Since we are engineers, we also want to do stuff to and with the models
  - Perturb system with shocks to see how it responds and recovers
  - Find where to push the system to get it to modify emergent properties
• We often deal with big social and organizational problems
• Policy is one of society’s ways of effecting changes to real-world complex systems.
• Uncertainty can help determine best policies
Overview

• Intro to uncertainty analysis
  – Get more information out of model runs
  – Provide estimate of quality and reliability of results
  – Determine when the model sufficiently detailed

• Robust policy options overview
  – What makes a policy robust?
  – Why are robust policies superior?

• Example of robust policy design:
  – Sandia/VA pandemic influenza study
  – Lessons learned
  – Methods for uncertainty-driven policy design
• Uncertainty analysis: Determining how different types of uncertainty affect model output.

• Categories of uncertainty
  – Structural: How well do you understand the system
  – Parametric: How well have you characterized the inputs
  – Stochastic: Resulting from random processes

• Alternative view:
  – Aleatory (Stochastic): Irreducible randomness
  – Epistemic (Structural and Parametric): lack of knowledge

• Design of Experiment (DOE): Planning model runs and parameter variations to answer question adequately and efficiently
Complex System Model as a Black Box

Mathematical operations

Inputs

Outputs

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Basics of Uncertainty Analysis

- Create design of experiment to answer your question efficiently
- Run the model many times with different inputs.
- Perform Sensitivity Analysis (SA) to determine which inputs have the most effect on outputs
- Run uncertainty quantification (UQ) to identify sources of model uncertainty and how best to reduce it
- Run statistical significance tests to gauge reliability and quality of study results
- Repeat until satisfactory level of confidence reached.
Simple Sensitivity Analysis

Change One Input

Mathematical operations

Measure Changes in Outputs

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Simple Sensitivity Analysis

• Parameter sweeps
  - Run model many times
  - Vary single model input while holding all others fixed
  - Plot output vs. each input

• Pros:
  - Fast to set up
  - Easy to interpret

• Cons:
  - Takes a lot of runs
  - Ignores interactions
  - Only looks at small portion of parameter space.
Multivariate Sensitivity Analysis

Change Many Inputs

Mathematical operations

Measure Changes in Outputs
Multivariate Sensitivity Analysis Overview

• Multivariate Global Sensitivity Analysis:
  - Run model many times
  - Vary all of the input parameters for each run
  - Analyze relationship of all inputs to outputs

• Pros:
  - Looks at all possible values of all parameters.
  - Lets you analyze interaction effects

• Cons
  - Can’t interpret results visually
  - Standard methods require HUGE numbers of runs (e.g. 35,000 runs for simple 5-parameter model)
Meta-models for Sensitivity Analysis

Meta-model is a model of the model’s output.

Small sample of possible inputs to interpolate model results.
Meta-models for Sensitivity Analysis

Traditional Approach

Model → 10,000 Input/Output Sets → Sensitivity Analysis

- Run 10,000 Times

Meta-Model Approach

Model → Meta-Model → 10,000 Input/Output Sets → Sensitivity Analysis

- Run 100 Times
- Run Once
- Query 10k Times

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Why Use Meta-models?

- Far fewer model runs needed (~1%)
- More flexible and stable estimates
- Determine interaction effects
- Fast, approximate model results for input combinations that weren’t run
- Best bets: Gaussian process, radial basis functions, adaptive splines, and polynomial chaos expansion

```
Model Report

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<th>Column</th>
<th>Theta</th>
<th>Sensitivity</th>
<th>Main Effect</th>
<th>sensitivity Interaction</th>
<th>hMid Interaction</th>
<th>pFill Interaction</th>
<th>lFull Interaction</th>
<th>consumptionTime Interaction</th>
<th>productionTime Interaction</th>
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<td>0.0001599</td>
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<td>1.3507e-8</td>
<td>1.1883e-9</td>
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<tr>
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\[ \mu = 63.366829 \quad \sigma^2 = 527.00581 \]

-2^*LogLikelihood  
864.15235

Fit using the Cubic correlation function.
```
What Does Uncertainty Analysis Provide?

• Determines which parameters are most effective in changing model results
• Shows where improved data are needed
  - Better estimates of insensitive parameters not important
  - Important but poorly known parameters can use better data.
• Shows what you can safely ignore in your model
• Gives hard estimates on quality of model results under different scenarios.
• Answers questions of how trustworthy model results really are.
Robust Policy Options

- Single policies or combinations which create the desired outcome under a wide range of possible uncertainties
- Options or interventions often designed for specific scenario conditions
- Policies are implemented in a wide range of scenarios
- Some policies may not perform well under unexpected conditions.
- Modeling policy outcomes over all conceivable implementation scenarios helps to find robust options.
- Robust policy options: give good results wherever they are applied
Example of Robust Policy Design

- **Effective, Robust Design of Community Mitigation for Pandemic Influenza: A Systematic Examination of Proposed US Guidance** (Davey, Glass, Min, Beyeler, Glass, 2008)

- Evaluated seven interventions (e.g. school closing, quarantine, etc.) on severity of influenza outbreak for variety of assumptions.

- About 2 million model runs to explore combinations of parameters

- Ranked treatment and mitigation strategies
### TABLE 1: 90% compliance

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<th>CTsd</th>
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<td>138</td>
<td>145</td>
<td>122</td>
<td>117</td>
<td>104</td>
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<td>Each cell represents mean of 100 model runs.</td>
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<td>Colors indicate quality of solution.</td>
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<td>S = School Closure</td>
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</table>

Pandemic Study Generated Lots and Lots of Data

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Scatter plot of pandemic study results shows numbers of people infected and variability in model runs.
Desirable Outcomes and Low Variability Characterize Robust Policies

- Each policy tried on 100 random social networks
- 2,780 cases expected with no treatment
- Closing schools is best single option
  - Mean = 137 cases
  - Moderate variation
- Social distancing is not as effective
  - Mean = 987 cases
  - Wide variation
- Both policies in conjunction create robust solution
  - Mean = 118 cases
  - Narrow variation
- Robust solution:
  - Good outcome
  - Most stable to uncertainty
Uncertainty Analysis Best Practices for Complex Adaptive System Model Evaluation

- Define policy inputs as numerical ranges rather than categorical choices whenever possible
- Run simple parameter scans to get a feel for effects
- Run near-orthogonal Latin hypercube space-filling design on small sets of runs (n = ~200)
- Document sensitivity and interactions with meta-models
- Trace uncertainty from sources to results
- Apply uncertainty to rank policy options
- Look for interesting peaks and troughs in state space and distributions
- Use uncertainty to guide further refinement
Automate and simplify routine SA/UQ

Pandemic Influenza Study re-interpretation
- Apply all available UQ/SA methods to influenza model
- Determine which methods are most effective for CASoS
- Leland, James and Pat (with help from Infect3 team)

Machine Learning for SA/UQ
- Apply data mining techniques to model run results
- Ryan working with Pat and Brian

Agile Policy Design
- Extend CASoS Robust Policy work to dynamic setting
- Adaptively select best policies based on limited information, costs and reachability
- James, Tom, and Pat