Towards a Holistic Integration of Energy Justice and Energy System Engineering

Preliminary Exam

Samuel G. Dotson
Advanced Reactors and Fuel Cycles Group

University of Illinois at Urbana-Champaign

January 9, 2024

Outline

1. Introduction
    - Presentation Goals
    - Proposal Overview
2. Motivating Observations
3. Tale of Three Uncertainties
    - Triarchic Uncertainty
    - Parametric Uncertainty
    - Structural Uncertainty
    - Normative Uncertainty
    - Descriptive: Parametric-Structural
    - Prescriptive: Structural-Normative
    - Pre-Descriptive: Normative-Parametric
4. Conclusion

Presentation Goals

Confession: I am not a social scientist. A significant part of preparing for this prelim involved reading and developing ideas that feel original to me but may have a

I have the following goals for this presentation:

1. **Motivate** why social science and quantitative modeling *must* be more strongly integrated (based on the relations among three types of uncertainty).
2. **Demonstrate** how `Osier` currently accomplishes this goal.
3. **Propose** future work to enhance `Osier`'s capabilities and validate its usage.

and I hope to show the **layered novelty** of this work as a corrolary of the above.

Proposal Overview

I propose to:

1. **Deepen** the theoretical foundations of this work.
2. **Develop** an optimization tool (`Osier`) that
   - addresses three related uncertainties,
   - closes the gap between technical expertise and public preferences,
   - enhances justice outcomes related to energy planning.
3. **Validate** this tool by conducting a case study of energy planning processes in the Champaign-Urbana region.

moral relativism

Avoiding moral relativism. For example, in an effort to be inclusive and create a more deliberative democracy, we cannot include voices whose normative premise is antithetical (i.e., exclusionary) to an inclusive normative premise.

Outline

1 Introduction
    Presentation Goals
    Proposal Overview

2 Motivating Observations

3 Tale of Three Uncertainties
    Triarchic Uncertainty
    Parametric Uncertainty
    Structural Uncertainty
    Normative Uncertainty
    Descriptive: Parametric-Structural
    Prescriptive: Structural-Normative
    Pre-Descriptive: Normative-Parametric

4 Conclusion

Anthropogenic Climate Change

- Climate change is happening!

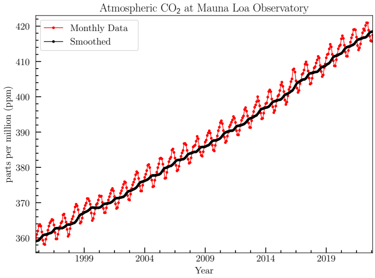


Figure 1: Observed increase in CO_2 levels at Mauna Loa Observatory [8].

Anthropogenic Climate Change Exists

- Climate change is happening!

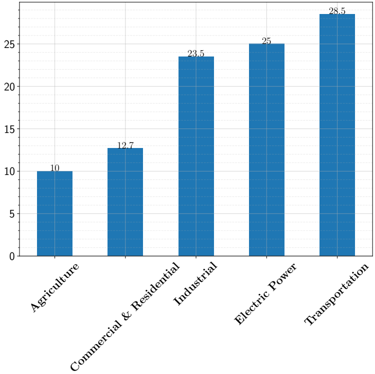


Figure 2: Carbon emissions by economic sector

Outline

1. Introduction
   - Presentation Goals
   - Proposal Overview
2. Motivating Observations
3. Tale of Three Uncertainties
   - Triarchic Uncertainty
   - Parametric Uncertainty
   - Structural Uncertainty
   - Normative Uncertainty
   - Descriptive: Parametric-Structural
   - Prescriptive: Structural-Normative
   - Pre-Descriptive: Normative-Parametric
4. Conclusion

Triarchic Theory of Model Development

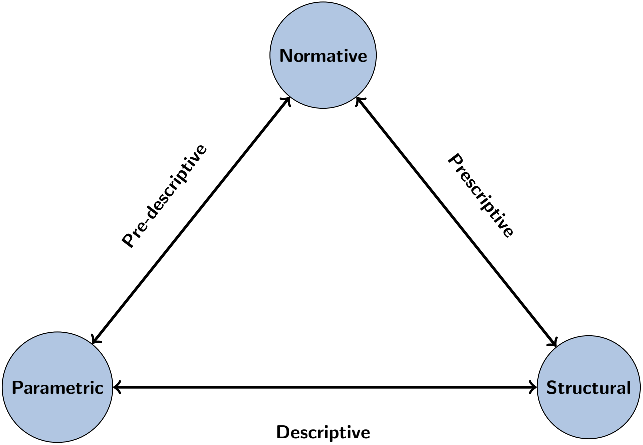
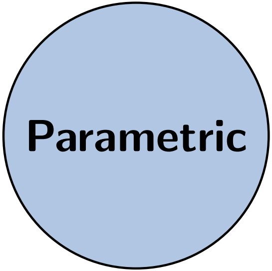


Figure 3: A summary of three uncertainties and their interactions.

Parametric Uncertainty



Definition (Parametric Uncertainty)

Related to uncertainty in model inputs (empirical values). The most commonly addressed type of uncertainty in science and engineering [17, 2, 13].

May be classified as either **aleatory** or **epistemic** [14, 10].

Examples of Parametric Uncertainty

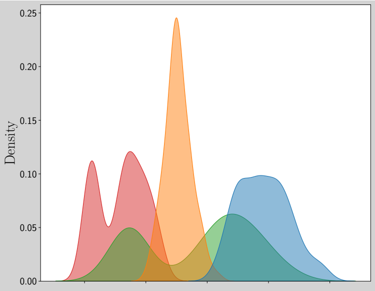


Figure 4: Possible distributions of several parameters.

- Rates (e.g., interest, learning, growth),
- costs (e.g., fuel, capital, O&M),
- aggregated energy demand,
- spent fuel burnup [5],
- nuclear cross-section data [3, 15],
- likelihood and magnitude of consequences (i.e., probabilistic risk assessment).

Addressing parametric uncertainty

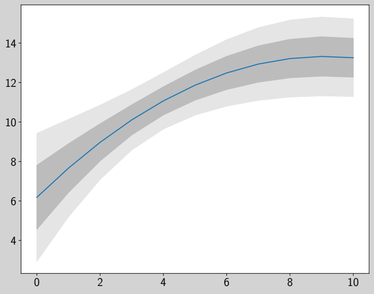


Figure 5: Addressing parametric uncertainty produces confidence intervals.

Idea: Rerun a simulation until you reach a large enough sample size to do statistics.

Formal methods to address parametric uncertainty*:

- "Monte Carlo" (i.e., statistical sampling)

Addressing parametric uncertainty

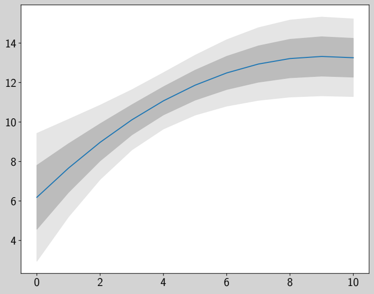


Figure 5: Addressing parametric uncertainty produces confidence intervals.

Idea: Rerun a simulation until you reach a large enough sample size to do statistics.

Formal methods to address parametric uncertainty*:

- "Monte Carlo" (i.e., statistical sampling)
- Sensitivity analysis (specific or global)

Addressing parametric uncertainty

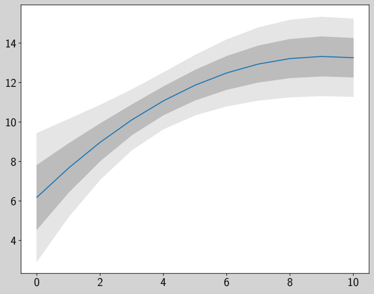


Figure 5: Addressing parametric uncertainty produces confidence intervals.

Idea: Rerun a simulation until you reach a large enough sample size to do statistics.

Formal methods to address parametric uncertainty*:

- "Monte Carlo" (i.e., statistical sampling)
- Sensitivity analysis (specific or global)
- Stochastic optimization

Addressing parametric uncertainty

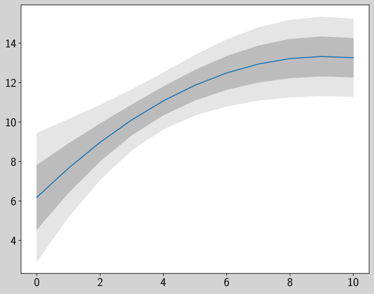


Figure 5: Addressing parametric uncertainty produces confidence intervals.

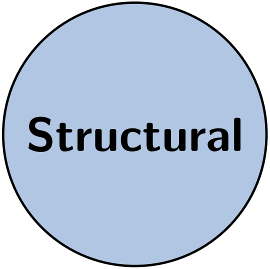
Idea: Rerun a simulation until you reach a large enough sample size to do statistics.

Formal methods to address parametric uncertainty*:

- "Monte Carlo" (i.e., statistical sampling)
- Sensitivity analysis (specific or global)
- Stochastic optimization

*These methods are appropriate for **aleatory** uncertainties.

Structural Uncertainty



Definition (Structural Uncertainty)

[R]efers to the imperfect and incomplete nature of the equations describing the system [2].

This type of uncertainty will *always* persist.

Examples of Structural Uncertainty

- Objective functions (most typical)

Examples of Structural Uncertainty

- Objective functions (most typical)
- Spatiotemporal resolution

Examples of Structural Uncertainty

- Objective functions (most typical)
- Spatiotemporal resolution
- Physics fidelity

Examples of Structural Uncertainty

- Objective functions (most typical)
- Spatiotemporal resolution
- Physics fidelity
- Solution method

Addressing Structural Uncertainty

Idea: Look for alternatives in the "near-optimal" space.

How? Modeling-to-generate-alternatives (MGA)

1. **Relax** the objective function.
2. **Search** for maximally different solutions in the design space.
3. **Iterate** until enough solutions have been generated.

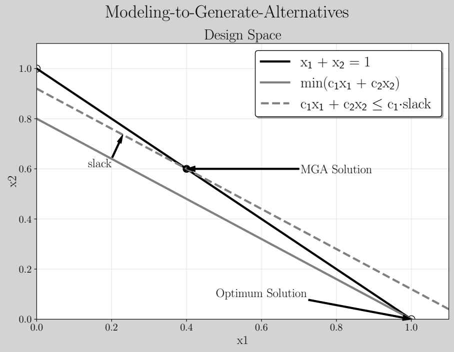
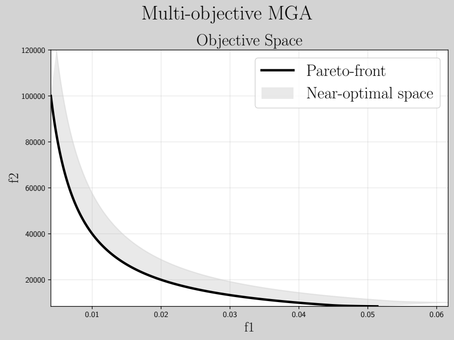
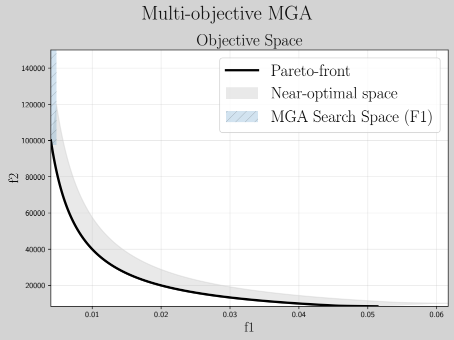


Figure 6: Illustration of the MGA algorithm.

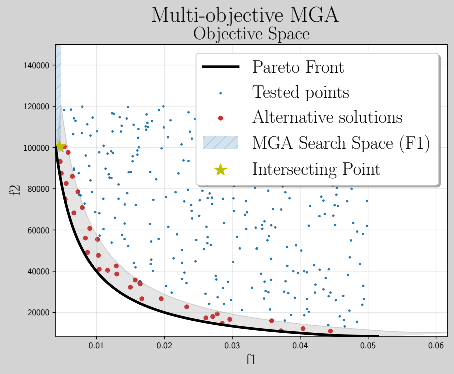
How Osier handles structural uncertainty



How `Osier` handles structural uncertainty

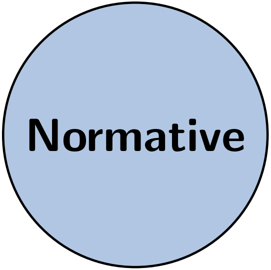


How `Osier` handles structural uncertainty



Normative Uncertainty

Stating your assumptions is a necessary but insufficient condition for addressing normative uncertainty.



Answers the question "what is acceptable and why?"

- Climate change is happening!

Descriptive: Parametric-Structural

- What is being modeled?
- How are time series represented? (e.g., weather / demand data)?
- Which technologies are included in the simulation?
- (maybe this axis runs between short run and long run uncertainties?)

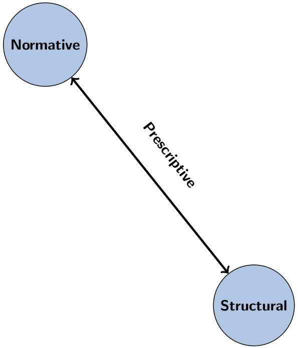
Prescriptive: Structural-Normative

Generating prescriptive conclusions is the primary reason to model energy systems.

If the solution to structural uncertainty was identifying alternative, “sub-optimal” solutions, then the prescriptive stage means deciding among these diverse alternatives.

What are the consequences of Arrow’s Theorem?

1. There is no one-size-fits-all method for public engagement or decision-making.
2. The methods of engagement must “open up” debate rather than “close it down” [16]. Expanding on this idea, multiobjective optimization “help



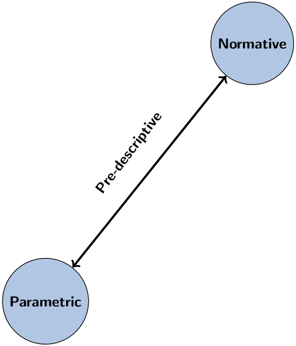
Purpose of Multiobjective Methods

The second purpose of multiobjective methods is to help participants in the planning process define and articulate their values, apply them rationally and consistently, and document the results. The object is to inspire confidence in the soundness of the decision without being unnecessarily difficult. Multiobjective methods used in this manner can also help negotiation, by quantifying and communicating the priorities held by different interests [7].

Although the usefulness of these methods were recognized long ago, the application of these methods was stunted by computational tools and data visualization capabilities.

Prior articulation methods vs interactive methods.

How normativity influences parametric uncertainty



Definition (Knightian/Deep/Epistemic Uncertainty)

Unknowable unknowns — uncertainties that cannot be quantified or measured due to a lack of knowledge or understanding [11].

Definition (Ambiguity Aversion / Ellsberg Paradox)

A decision maker will choose a highly risky option with quantifiable uncertainties over an option with deep uncertainties [4].

How are representative probability distributions chosen?

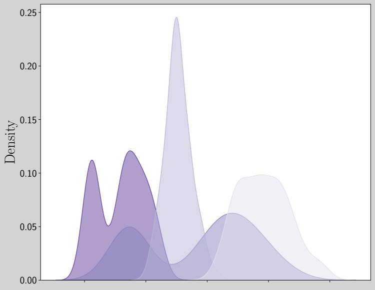


Figure 7: Possible distributions for a single parameter. Which is best?

The probability distributions are usually obtained through modelers' judgement or expert elicitations [17].

Problem: Without understanding how or why a modeler created or chose a distribution, the twin goals of reproducibility and transparency are challenged.

How do modellers choose or create distributions?

Definition (Knightian/Deep/Epistemic Uncertainty)

Unknowable unknowns — uncertainties that cannot be quantified or measured due to a lack of knowledge or understanding [11].

Definition (Ambiguity Aversion / Ellsberg Paradox)

A decision maker will choose a highly risky option with quantifiable uncertainties over an option with deep uncertainties [4].

Consequences of Ambiguity Aversion

1

Outline

1. Introduction
   - Presentation Goals
   - Proposal Overview
2. Motivating Observations
3. Tale of Three Uncertainties
   - Triarchic Uncertainty
   - Parametric Uncertainty
   - Structural Uncertainty
   - Normative Uncertainty
   - Descriptive: Parametric-Structural
   - Prescriptive: Structural-Normative
   - Pre-Descriptive: Normative-Parametric
4. Conclusion

Conclusion

We showed many things. This slide is an example of how you can animate bulleted lists, for more information about using beamer animations, checkout the overleaf article on overlay specifications in the group's guide.

- Cats are peculiar

Conclusion

We showed many things. This slide is an example of how you can animate bulleted lists, for more information about using beamer animations, checkout the overleaf article on overlay specifications in the group's guide.

- Cats are peculiar
- Blue and Orange are fierce colors

Conclusion

We showed many things. This slide is an example of how you can animate bulleted lists, for more information about using beamer animations, checkout the overleaf article on overlay specifications in the group's guide.

- Cats are peculiar
- Blue and Orange are fierce colors
- Math can be rendered nicely

Conclusion

We showed many things. This slide is an example of how you can animate bulleted lists, for more information about using beamer animations, checkout the overleaf article on overlay specifications in the group's guide.

- Cats are peculiar
- Blue and Orange are fierce colors
- Math can be rendered nicely
- Cite your sources

We also tested citations [12]

Acknowledgement

Acknowledgements should include both people who helped and funding streams. If you are funded by an NEUP grant, that number usually goes here. .

References I

[1] Kenneth J. Arrow.
A difficulty in the concept of social welfare.
58(4):328–346.
Publisher: University of Chicago Press.

[2] Joseph F. DeCarolis.
Using modeling to generate alternatives (MGA) to expand our thinking on energy futures.
33(2):145–152.
Publisher: Elsevier.

[3] Michael J. Eades, Ethan S. Chaleff, Paolo F. Venneri, and Thomas E. Blue.
The influence of xe-135m on steady-state xenon worth in thermal molten salt reactors.
93:397–405.

[4] Daniel Ellsberg.
Risk, ambiguity, and the savage axioms.
75(4):643–669.

[5] B. Feng, S. Richards, J. Bae, E. Davidson, A. Worrall, and R. Hays.
Sensitivity and uncertainty quantification of transition scenario simulations.

References II

[6] Maarten Franssen.
Arrow's theorem, multi-criteria decision problems and multi-attribute preferences in engineering design.
16(1):42–56.

[7] Benjamin F. Hobbs.
Optimization methods for electric utility resource planning.
83(1):1–20.

[8] R. P. Kane and E. R. de Paula.
Atmospheric CO2 changes at mauna loa, hawaii.
58(15):1673–1681.

[9] Joseph R. Kasprzyk, Shanthi Nataraj, Patrick M. Reed, and Robert J. Lempert.
Many objective robust decision making for complex environmental systems undergoing change.
42:55–71.

[10] Armen Der Kiureghian and Ove Ditlevsen.
Aleatory or epistemic? does it matter?
31(2):105–112.

References III

[11] Frank Hyneman Knight.
Risk, Uncertainty and Profit.
Houghton Mifflin.

[12] Doug McAdam and Hilary Schafer Boudet.
Putting Social Movements in Their Place: Explaining Opposition to Energy Projects in the United States from 2000-2005.
Cambridge University Press.

[13] Millett Granger Morgan, Max Henrion, and Mitchell Small.
Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.
Cambridge University Press.
Google-Books-ID: ajd1V305PgQC.

[14] Stefan Pfenninger, Adam Hawkes, and James Keirstead.
Energy systems modeling for twenty-first century energy challenges.
33:74–86.

References IV

[15] Majdi I. Radaideh and Tomasz Kozlowski.
Combining simulations and data with deep learning and uncertainty quantification for advanced energy modeling.
43(14):7866–7890.

[16] James Wilsdon and Rebecca Willis.
See-through science: why public engagement needs to move upstream.
Demos.
OCLC: 60615114.

[17] Xiufeng Yue, Steve Pye, Joseph DeCarolis, Francis G.N. Li, Fionn Rogan, and Brian Gallachóir.
A review of approaches to uncertainty assessment in energy system optimization models.
21:204–217.