Towards a Holistic Integration of Energy Justice and Energy System Engineering

Preliminary Exam

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Outline I

1. Introduction
    - Presentation Goals
    - Proposal Overview
2. Motivation and Background
    - Observations
    - Background: Energy system models
3. Component 1: Preliminary Results with `Osier`
    - Methodology
    - Preliminary Results
4. Motivation and Background II
    - Cognitive Myopia
    - Proposal
5. Components II+III: Details
    - Component II: How engineering relates to energy justice
    - Component III: Regional Case Study

Presentation Goals

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.

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The Challenge at Hand

Purpose of Energy System Modeling

Modeling allows us to make predictions, test hypotheses, and understand counterintuitive behavior.

Models inform energy policy with prescriptive analyses [5].

Problem

Policies affect people — energy systems models cannot adequately capture the "human dimension" [20].

What is the "human dimension?"

1. People have preferences about their sources of energy that are ignored.
2. Models cannot describe policy outcomes related to fairness or justice.

Three tenets of justice

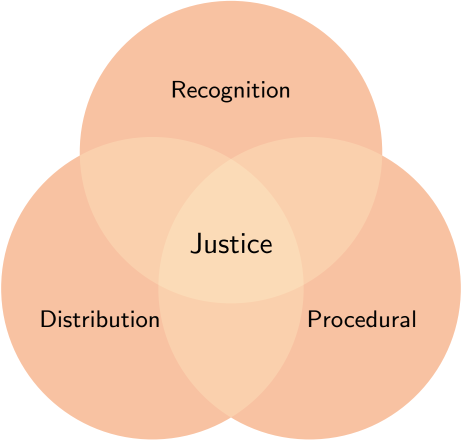
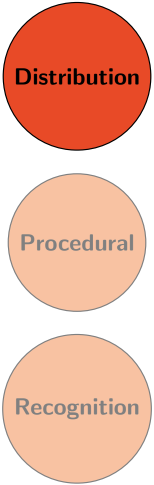


Figure 1: Three aspects of justice [25].

Distributional



Distributional Justice

Related to the distribution of burdens and benefits.

Normative Question

What is the fairest way to distribute benefits and burdens?

Examples of injustice

- Dispossession of land and benefits [35, 26].
- Poorer air quality around fossil fuel plants — primarily located in poorer communities [16].
- Solar panel subsidies and installations benefitting wealthier communities [23].

Procedural

Distribution

Procedural

Recognition

Procedural Justice

Related to decision-making processes — method and inclusion.

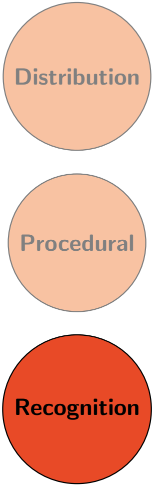
Normative Question

What is the fairest way to make decisions affecting specific groups of people?

Examples of injustice

- Dismissal of testimony for its lack of technical expertise [12].
- Lack of transparency in decision making.

Recognitional



Recognitional Justice

Related to social value of people or groups derived from relationships, laws, and cultural standing.

Normative Question

How much and in what ways should a person or group of people be valued?

Examples of injustice

- Energy policies that interfere with loving relationships (e.g., stress from energy insecurity) [31].
- Lack of labor protections for workers [31].
- Exclusion from a policy process[31].

Climate change highlights energy system injustices

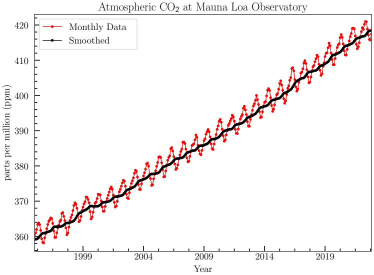


Figure 2: Observed increase in CO_2 levels at Mauna Loa Observatory [13].

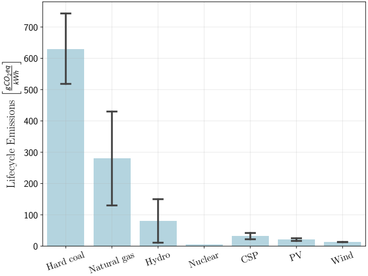


Figure 3: Lifecycle carbon emissions by energy source [29].

Addressing climate change?

Energy Transition

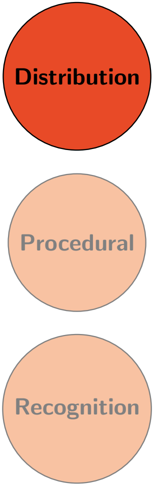
1. Requires new, low carbon, energy projects.
2. Adhering to values of democracy necessitates local support for these projects.

Public Opposition — it's not NIMBY

Perceptions of fairness and inclusion, rather than NIMBY attitudes, condition local support [15, 1, 27, 9].

Public testimony can be dismissed for being non-technical [12]. Existing energy planning processes and new energy projects (even "clean energy" projects) reproduce existing sociopolitical structures that violate principles of justice.

Energy Modeling and Distributional Justice

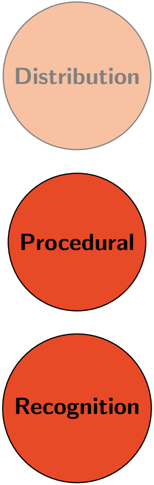


ESOMs and Distributional Justice

ESOM literature has begun considering distributional justice [18, 24, 19].

- Quantifiable
- “Objective” — research questions can be purely descriptive.

Energy Modeling and Procedural/Recognition Justice



Procedural Justice

ESOM literature now emphasizes code and data transparency [4] and highlights the importance of producing *insight* rather than *answers* [5].

However, the literature does not consider the ways its methods inform policies. Do energy system models make this more transparent or less?

Recognition Justice

As a corrolary of its lack of self-awareness, the ESOM literature does not address recognition justice at all — modeling is independent from public influence.

Why ESOMs struggle with the “human dimension”

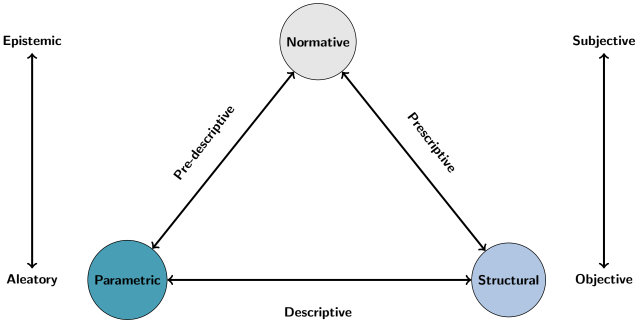


Figure 4: A summary of three uncertainties and their interactions. Note: Shading does not indicate a rigorous comparison.

Energy System Optimization Models (ESOMs)

Formulation

ESOMs consist of:

- A set of decision variables
- "An economic objective" [11]
- A set of constraints

Solution method

Linear programming (LP) / mixed-integer linear programming (MILP)

Simple Example Linear Program

Decision variables

Determine the mix of energy sources...

$$\mathbf{X} = x_1, x_2 \mid x \in \mathbf{R}+ \quad (1)$$

Objective

...that minimizes total cost...

$$\min\left(c_1 x_1 + c_2 x_2\right) \quad (2)$$

Constraint

...such that energy demand is always met.

$$x_1 + x_2 = 1 \quad (3)$$

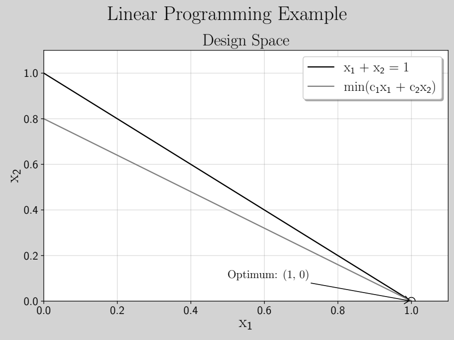
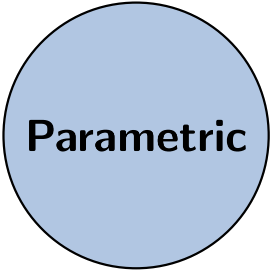


Figure 5: Solving a simple linear program by inspection.

Parametric Uncertainty



Parametric Uncertainty

Related to uncertainty in model inputs (empirical values). The most commonly addressed type of uncertainty in science and engineering [36, 5, 17].

Examples of Parametric Uncertainty

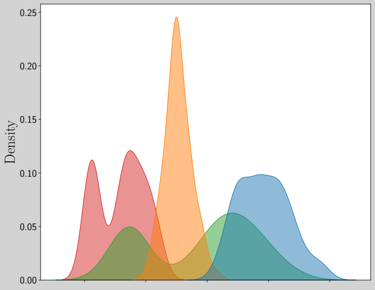


Figure 6: Possible distributions of several parameters.

- Rates (e.g., interest, learning, growth),
- costs (e.g., fuel, capital, O&M),
- aggregated energy demand,
- spent fuel burnup [8],
- nuclear cross-section data [7, 22],
- likelihood and magnitude of consequences (i.e., probabilistic risk assessment).

Considering Parametric Uncertainty in a Linear Program

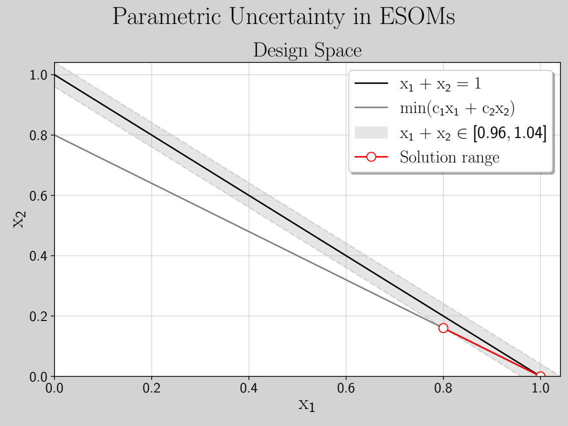
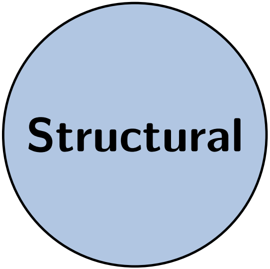


Figure 7: Solving a simple linear program by inspection.

Structural Uncertainty



Structural Uncertainty

[R]efers to the imperfect and incomplete nature of the equations describing the system [5].

This type of uncertainty will *always* persist.

Example Sources of Structural Uncertainty

Unmodeled or unmodelable aspects of the model related to:

1. Objective functions
2. Physics fidelity, for example
   - optimal power flow,
   - turbulence (air flow, water flow, etc.),
   - thermodynamics (e.g., weather impacting a power plant's ultimate heat sink)

Addressing Structural Uncertainty

Generate *insight* rather than *answers*.

Idea

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

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.

Structural Uncertainty in an ESOM

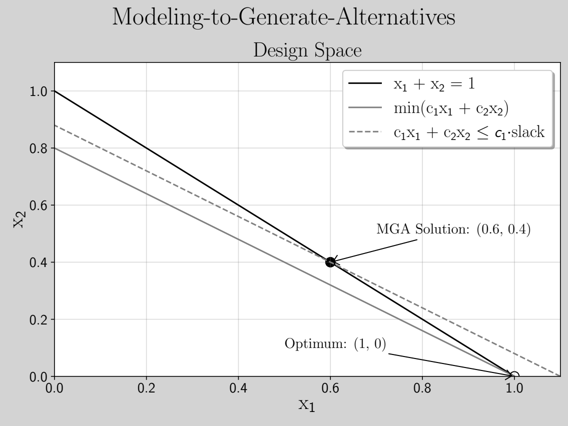


Figure 8: Illustration of the MGA algorithm.

Gap 1: Challenges with current ESOM practices

Technical Gaps

1. Exclusive optimization over system cost misrecognizes the plurality of preferences and priorities. Tradeoff analysis is impossible.
2. Even with open source code and transparent data sources, energy system models remain opaque — decision making black boxes.

Proposed Work Component I: Multi-objective optimization

- Partially address procedural/recognition justice by facilitating tradeoff analysis through multi-objective optimization with evolutionary algorithms.
- Develop an MGA algorithm for high dimensional space.

Stretch Goal — Addressing Technical Gap 2

Further enhance the transparency component of procedural justice by developing this tool in a way that provides the *capability* for anyone interested to verify model results. I.e., make accessibility a design priority.

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Open source multi-objective energy system framework (Osier)

- Hybrid methods: linear programming & evolutionary algorithms
- Novel algorithm for high dimensional MGA

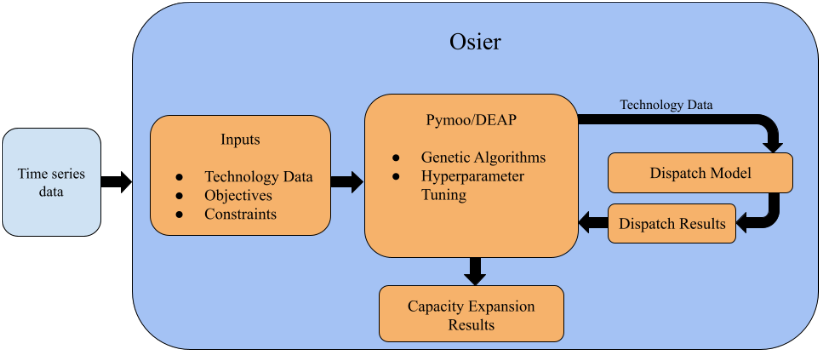


Figure 9: Flow of data through Osier.

Multi-objective Solutions

Another way to generate alternatives...

Pareto Front

Creates a **set of solutions** rather than a single optimum.

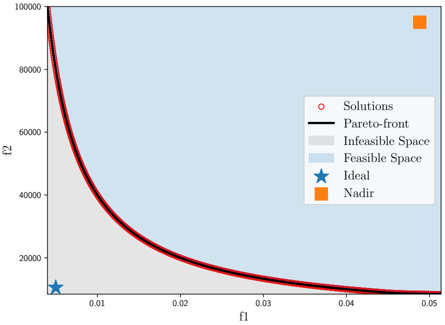


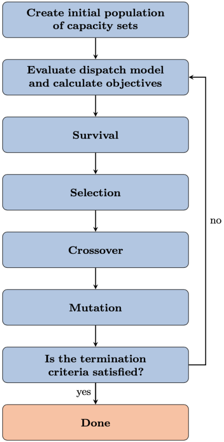
Figure 10: Pareto front example.

Evolutionary Algorithms

Evolutionary Algorithms for Energy System Optimization

- Inspired by natural selection
- Parallelizable
- Superior to pure linear programming methods for
    - independence from problem convexity
    - good sampling/spacing of points along solution set.

Right: Evolutionary algorithm flow [3].



How Osier handles structural uncertainty

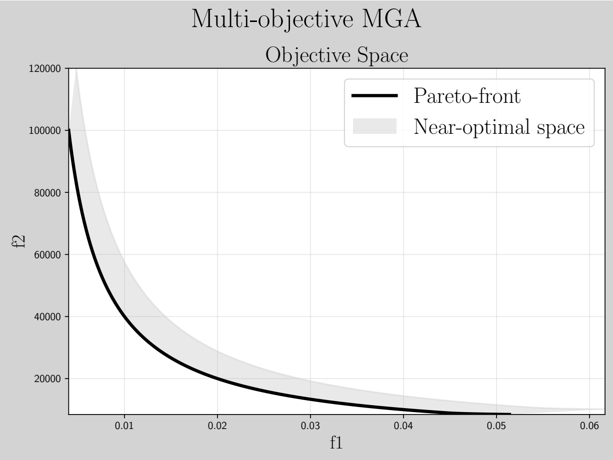


Figure 11: Near optimal space for a multi-objective problem.

Validating Osier

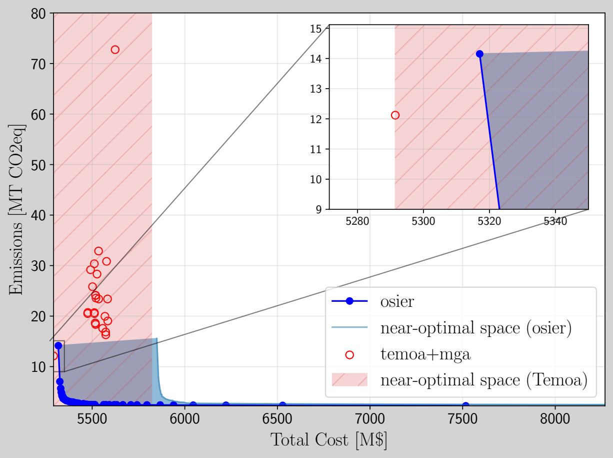


Figure 14: Comparing the results from Osier with another ESOM, Temoa.

Optimizing four objectives

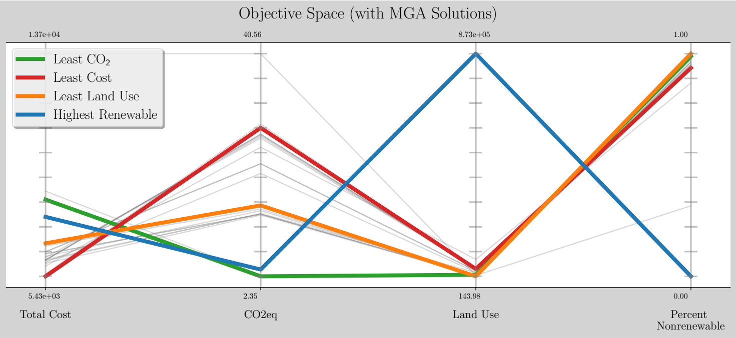


Figure 15: Pareto front and near-optimal solutions for the same problem with 4 objectives.

Optimizing four objectives

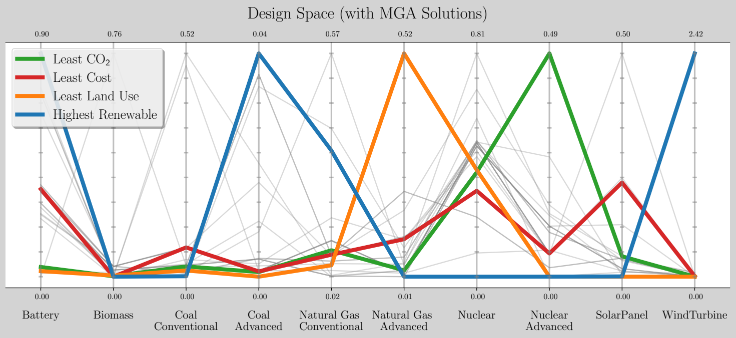


Figure 16: Design space for the 4-objective problem with near-optimal solutions.

How `Osier` improves on ESOMs — and its limits

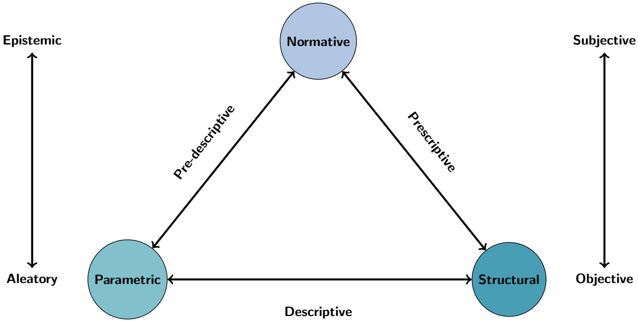


Figure 17: A summary of three uncertainties and their interactions.

Future Work for Osier

Improvement 1

Improve the MGA procedure to identify *maximally different* solutions in the design space. I.e., more efficient search.

Avenue 2

This improvement could be unlocked with a greedy, farthest-first-traversal algorithm.

Improvement 2

Take advantage of evolutionary algorithms' parralelizability.

Avenue 2

Consider a method besides linear programming for energy dispatch (e.g., hierarchical dispatch) [21].

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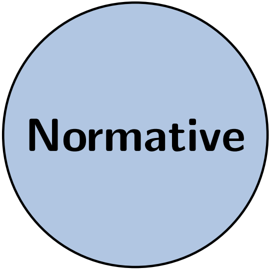
What's still missing?

Despite awareness of structural and parametric uncertainties modelers still don't address

- How parameter distributions are chosen?
- Why are certain objectives chosen (why should an economic objective be *assumed*)?
- If structural uncertainty is addressed by presenting mutliple solutions, how should society choose among those alternatives?
- What motivated the specified set of decision variables (why are technologies included/excluded)?
- How can members of the public adequately deliberate on issues perceived by experts as highly technical?

This alludes to another kind of uncertainty...

Normative Uncertainty



Normative Uncertainty

Arises from the plurality of morally defensible, but incompatible, choices; and a plurality of moral theories justifying those choices [28, 30].

Addressing Normative Uncertainty

There are no formal methods to address normative uncertainty... *in engineering.*

Gap 2: Normative Uncertainty & Deliberative Processes

Technical Gap

1. Deciding among alternative solutions is challenging without a normative premise.
2. Without direct consultation of stakeholders, it's impossible know how they would understand tradeoffs.
3. Capturing the "human dimension" requires incorporating formal methods from social science: case studies, interviews, focus groups, surveys, etc. The ESOM literature struggles to do this [20].

Proposed Work Component II: Integrative theory of uncertainties

Further develop the unifying theory of model development through the lens of addressing triple uncertainties.

Proposed Work Component III: Case study of Champaign-Urbana

Case study of energy planning processes in the Champaign-Urbana region to validate the usefulness of `Osier` and test the salience of various uncertainties.

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How energy modeling can incorporate energy justice

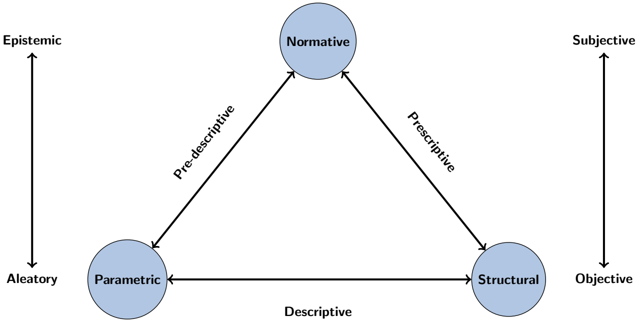


Figure 18: A summary of three uncertainties and their interactions.

Regional Case Study I

Research Question

How could deliberative processes incorporate a systems model to enhance understanding of community priorities to make derived energy policies more representative?

Methods

- **Semi-structured interviews**:
  - Understand existing procedures for creating energy visions and policies in the Champaign-Urbana region.
  - Understand how energy planners could/would understand tradeoffs presented with a systems model.
- **Potentially analyzed with:**
  - Discursive Analysis
  - Thematic Analysis
  - Process Tracing
  - or another method...

Regional Case Study II

Results

Rather than producing quantitative data to incorporate into the modeling, the results will inform a process that enhances the recognition and procedural justice aspects for developing energy visions and policies.

- Elucidate what is actually important to community members — not simply modeling assumptions.
- Update model objectives based on feedback.

Summary

1. Energy models inform policy but can't capture the "human dimension"
2. Discussed different aspects of justice and how ESOMs consider them
3. Introduced `Osier` as a solution to the problem of single-objective optimization
4. Explained three types of uncertainties and how they relate ESOMs and energy justice.
5. Proposed enhancements to `Osier` and a paradigmatic case-study for validation.

Backup Slides

Near-optimal Space for Cost and Carbon Emissions

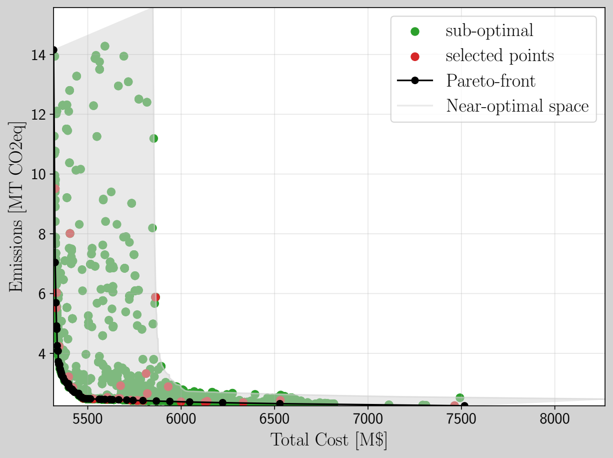


Figure 19: Sampling the near-optimal space for `Osier`'s Pareto front.

Optimizing four objectives: Alternative Visualization

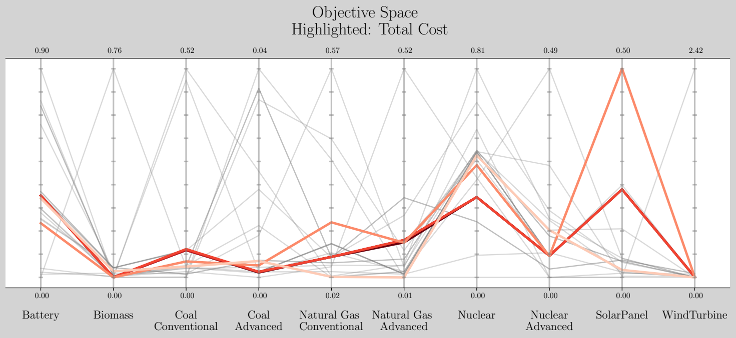


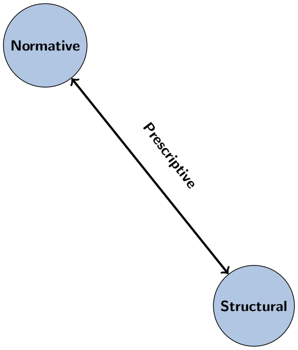
Figure 20: The five lowest cost solutions. Darker shade corresponds to lower cost.

Choosing among alternatives

Generating prescriptive conclusions is the primary reason to model energy systems [5].

Arrow's Impossibility Theorem

It is impossible to construct a utility function that maps individual preferences onto a global preference order without imposition or dictating [14, 10, 2].



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" [32, 6].
3. Ideals of justice and "just outcomes" can never be adequately captured by an aggregated "metric" — this would imply a utility function that could map individual preferences to a collective preference.

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