Exploring Technology Pathways to Achieve Deep Decarbonization in the United States by Mid-Century

CEIC Seminar
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Talk Outline

Discuss modeling challenges associated with net-zero carbon systems

Introduce modeling framework and modeling-to-generate alternatives (MGA)

Present recent work to explore net-zero technology pathways in the United States

Outline our effort to create an Open Energy Outlook for the United States

Modeling Challenges

Need to reach net-zero carbon sometime around mid-century to limit climate change to 1.5 – 2℃

Challenges we face as system modelers:

- High renewables penetration means that capacity expansion plans depend on operational details
- Some sectors, heavy duty transport, parts of industry are hard to decarbonize
- Rapidly changing technology costs; cost and performance of key technologies at scale uncertain, e.g., DAC and BECCS
- Consumer behavior matters to outcomes, e.g., uptake of electric vehicles
- ”Easy” policies to model, e.g., a carbon cap or tax face significant political headwinds

Energy Modeling is “Post Normal” Science

According to Funtowicz and Ravetz (1993), “post normal” science involve situations where

> "... facts are uncertain, values in dispute, stakes high and decisions urgent.”
>
> "... uncertainty is not banished but is managed, and values are not presupposed but are made explicit."

In the context of energy modeling, we need:

- Open source and transparent models
- Rigorous uncertainty assessment
- Diverse teams participating in analysis

Tools for Energy Model Optimization and Analysis (Temoa)

TĒMOĀ *vt* to seek something / buscar algo, o inquirir de algún negocio. This contrasts with TEMŌHUA, the nonactive form of TEMŌ 'to descend.'

Enable repeatable analysis

- Data and code stored in a public web repository (github)
- Open source software stack

Perform rigorous uncertainty analysis

- Designed to utilize high performance computing resources
- Several methods implemented to address an array of questions

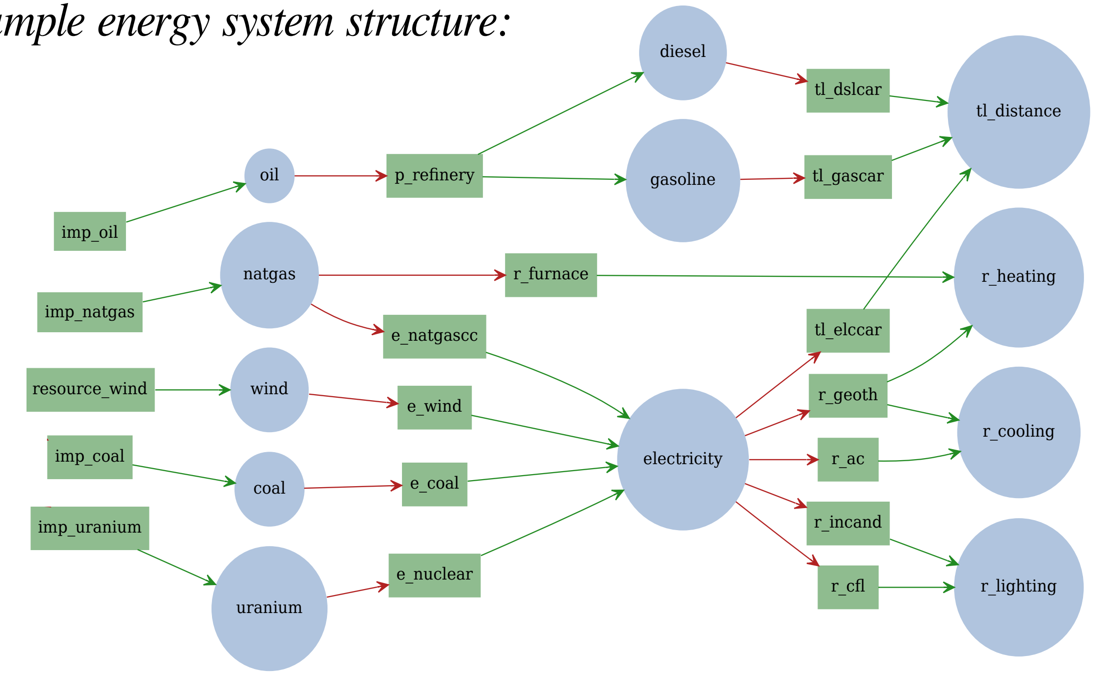
Temoa Overview

Temoa is an open source energy system optimization model

- **Objective:** Minimize the present cost of energy supply over the model time horizon
- Ensure energy balance globally and at the process level
- Perform capacity expansion across a set of user-defined time periods

- Model assumes all years within a time period are identical
- Representative year per time period further disaggregated into user-defined time slices over which supply and demand balanced

Example energy system structure:



Inputs:
Capital cost
Fixed O&M
Variable O&M
Capacity factor
Efficiency
Emissions coefficient
Existing capacity
End-Use demands

Outputs:
System-wide costs
Energy prices
Emissions
Installed technology capacity
Energy commodity flows

Basic TEMOA Model Formulation

The flow of a given energy commodity out of a process is the lowest-level decision variable in the model:

```
V_FlowOut(p, s, d, i, t, v, o)
```

output commodity

vintage

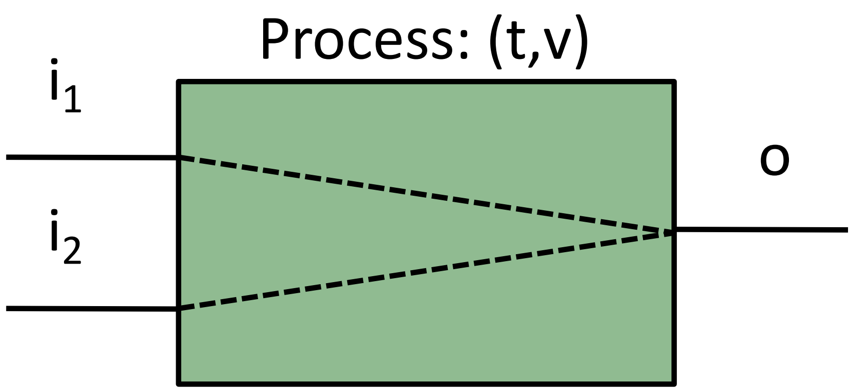
technology

input commodity

time of day

season

period



Uncertainty Analysis

Useful model-based insight should account for uncertainty. The approach depends on the question at hand.

- Method of Morris (SALib)

  Perform a random walk in input parameter space; characterize impact of each parameter on output(s) of interest

- Monte Carlo simulation

  Select ranges or distributions for uncertain input parameters, make random draws, iterate the model, examine patterns in output

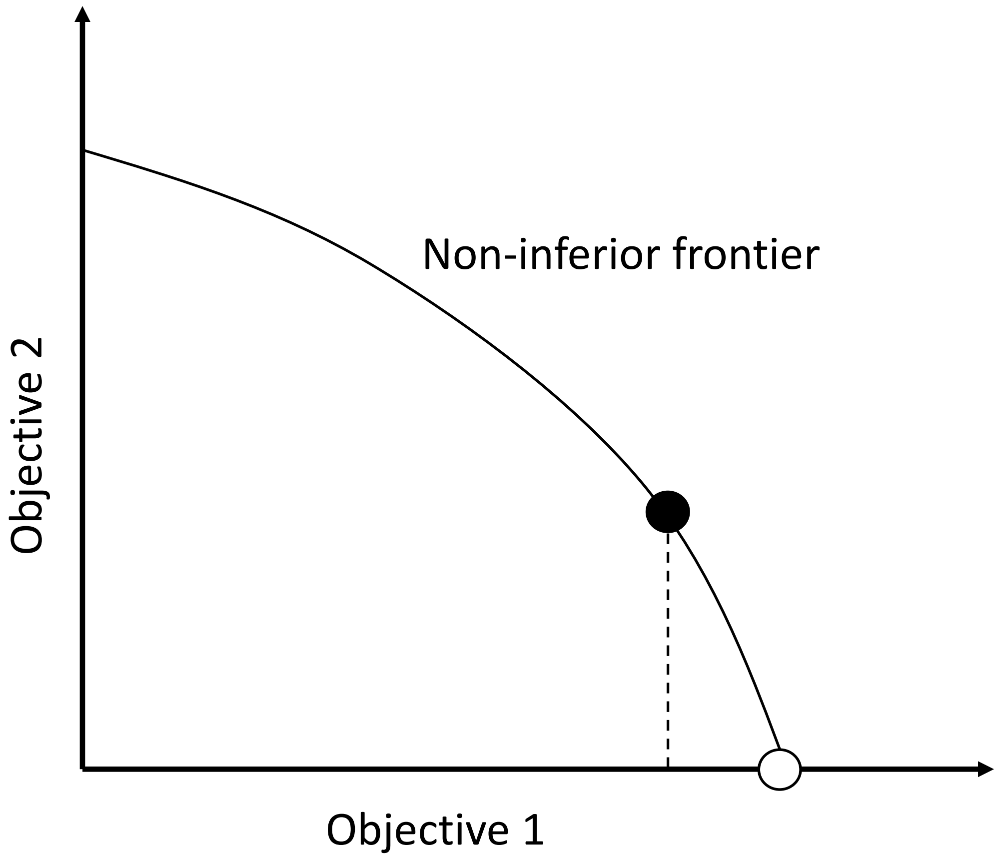
- Stochastic Optimization (Pyomo)

  Devise a scenario tree that accounts for potential future outcomes, assign probabilities, and optimize over the whole tree; produces a near-term hedging strategy

- Modeling-to-Generate Alternatives

  Modify the model structure to find feasible, near optimal solutions that are maximally different in decision space

Thinking About Structural Uncertainty



Consider an optimization model that only includes **Objective 1** and leaves **Objective 2** unmodeled. The true optimum is within the feasible, suboptimal region of the model's solution space.

Viable alterative solutions exist within the model's feasible region.

Example adopted from Brill et al. (1990).

Modeling to Generate Alternatives

A method to explore an optimization model's feasible region → "Modeling to Generate Alternatives"†

MGA generates alternative solutions that are **maximally different in decision space** but perform well with respect to modeled objectives

The resultant MGA solutions provide modelers and decision-makers with a set of alternatives for further evaluation

†Brill (1979), Brill et al. (1982), Brill et al. (1990)

MGA Formulation

What weighting scheme should we apply to basis decision variables in past iterations?

$$\min \quad p = \sum_{k \in K} x_k$$

$$\text{s.t.} \quad f_j(\vec{x}) \leq T_j \quad \forall j$$

$$\vec{x} \in X$$

How much slack should we consider when setting the budget?

where:

K represents the set of indices of decision variables with nonzero values in the previous solutions

$f_j(\vec{x})$ is the j^{th} objective function

$\boldsymbol{T_j}$ is the target specified for the j^{th} modeled objective

X is the set of feasible solution vectors

Distance-To-Selected MGA

Steps:

1. Obtain an initial optimal solution by any method
2. Add a user-specified amount of slack to the value of the objective function
3. Encode the adjusted objection function value as an additional upper bound constraint
4. Formulate a new objective function with random coefficients assigned to all decision variables
5. Iterate the model a large number of times
6. Post-process to the MGA results using the Distance-To-Selected method to identify maximally different solutions

Distance to Selected Method, Part 1

The first maximally different scenario has the largest squared Euclidean distance from the initial scenario:

$$S^2 = max\left\{S^y \in \mathbb{S}_{all} \,\middle|\, \sum_{i=1}^{n}\left[x_i^{act(S^y)} - x_i^{act(S^1)}\right]^2\right\}$$

S^1: initial scenario

S^2: first maximally different scenario

S^y: scenario *y* in the set of all MGA scenarios ($\mathbb{S}_{all}$)

$x_i^{act(S^y)}$: Activity associated with technology *i* in scenario S^y

Formulation based on Berntsen and Trutnevyte (2017).
https://archive-ouverte.unige.ch/unige:101922

Distance to Selected Method, Part 2

Additional maximally different scenarios are selected to have the largest harmonic mean of squared Euclidian distances from the set of scenarios already selected:

$$S^3 = max\left\{S^y \in \mathbb{S}_{all} \middle| \left(\sum_{S^z \in \mathbb{S}_{selected}} \frac{1}{\sum_{i=1}^{n}\left[x_i^{act(S^y)} - x_i^{act(S^z)}\right]^2}\right)^{-1}\right\}$$

Harmonic mean works well when calculating distance-to-selected, as it indicates a large distance to all of the selected scenarios.

Formulation based on Berntsen and Trutnevyte (2017). https://archive-ouverte.unige.ch/unige:101922

Using MGA to Examine Deep Decarbonization Options in the United States

with Hadi Eshraghi

Analysis Overview

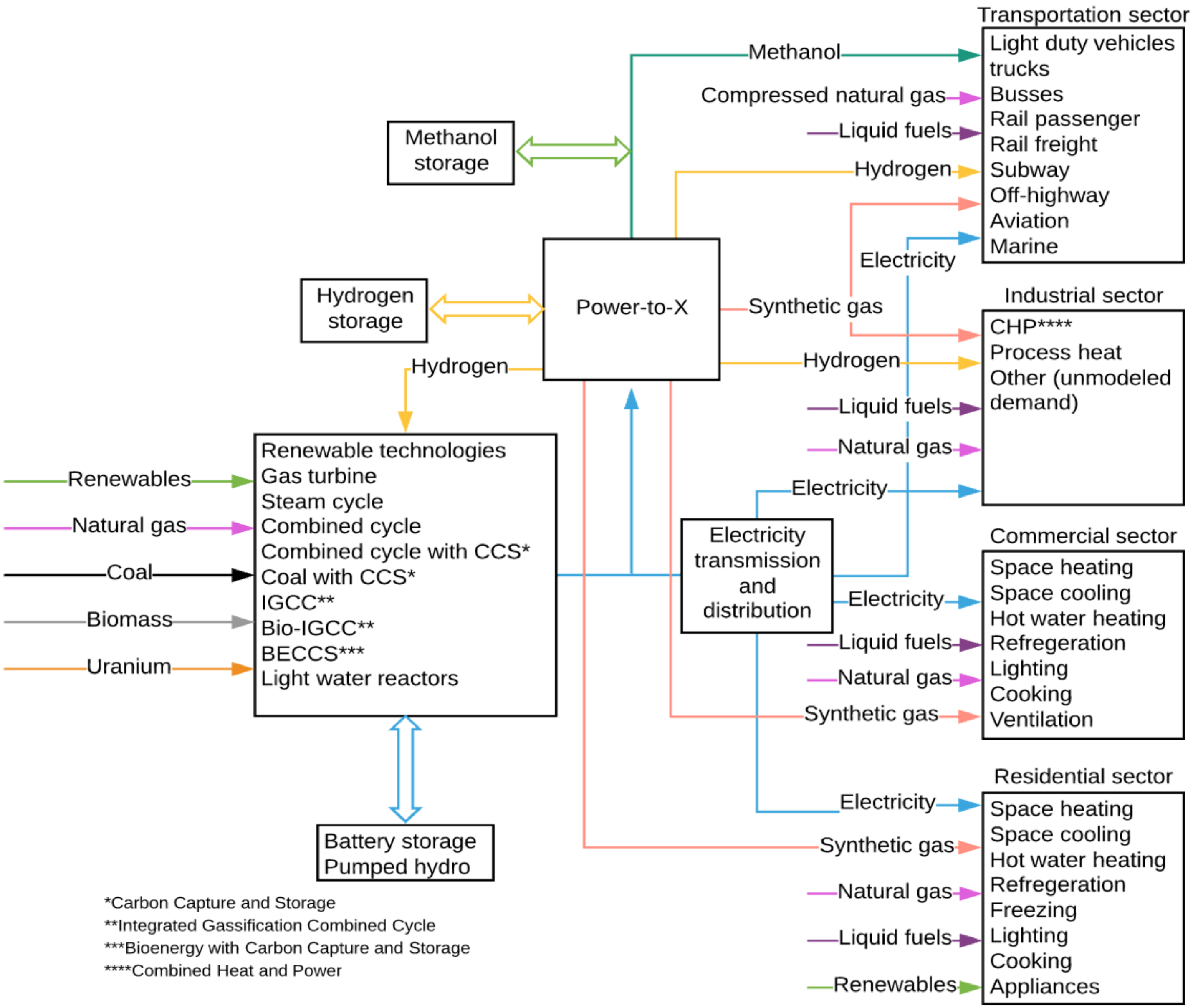
- Focus on scenarios with a linear GHG emissions decline and achieve net-zero in 2050

- Apply MGA under different slack values
- Examine raw results
- Apply distance-to-selected method
- Perform sensitivity analysis to H_2 storage costs

Overview of Input Data

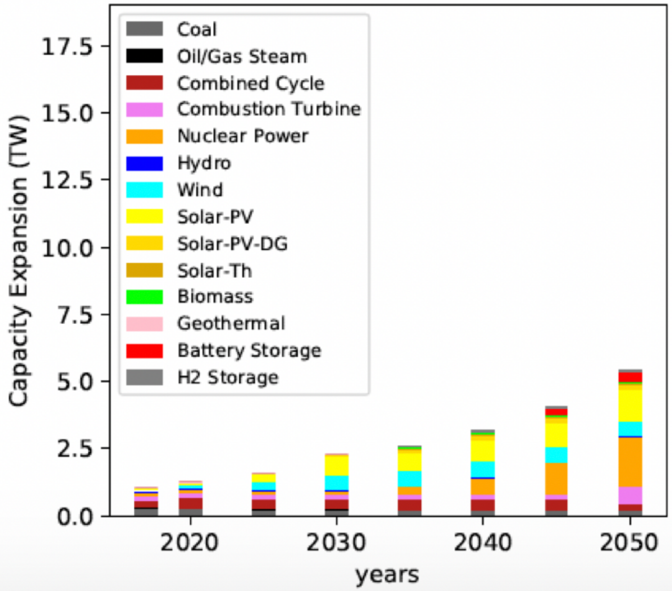
- Model time horizon: 2017 – 2050; 5-year time periods
- 12 time slices: 3 seasons (summer, winter, intermediate) and 4 times of day (morning, afternoon, evening, night)
- US modeled as a single region
- Modeled sectors: electricity, industry, transportation, residential, and commercial
- Exogenously specified fuel price trajectories drawn from the EIA Annual Energy Outlook 2019
- Electric sector cost and capacity factors largely drawn from NREL Annual Technology Baseline; other sectors from US EPA MARKAL database
- End-use energy service demands are fixed

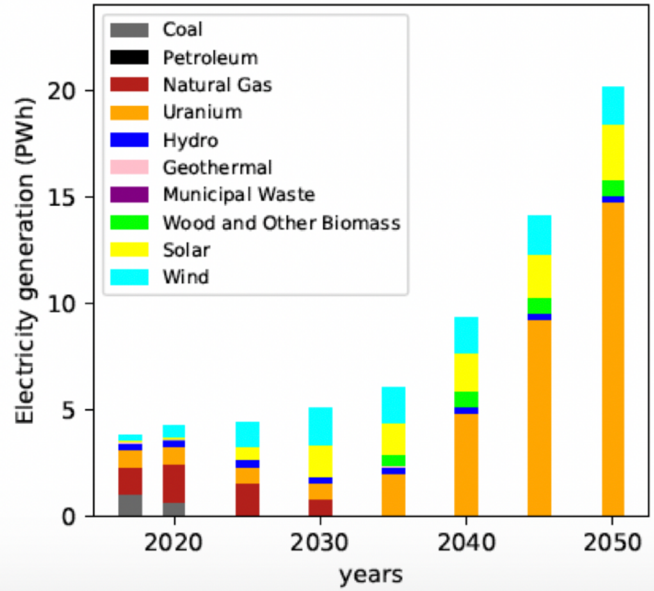
Representation of input data



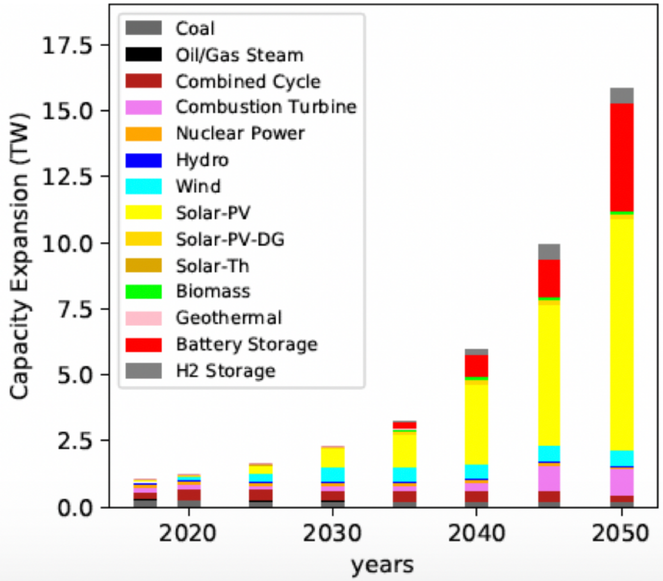
*Carbon Capture and Storage
**Integrated Gassification Combined Cycle
***Bioenergy with Carbon Capture and Storage
****Combined Heat and Power

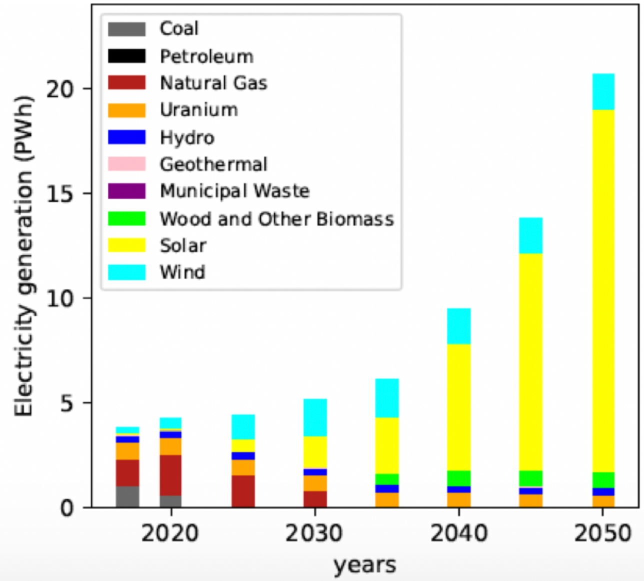
CCap results without MGA





Baseline results based on NREL Annual Technology Baseline (2019), mid-case projections





Same as above, but with cost of nuclear cost overruns drawn from Sovacool et al. (2014)

Brief Aside on Nuclear

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Applying risk tolerance and socio-technical dynamics for more realistic energy transition pathways

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[b] *Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, USA*
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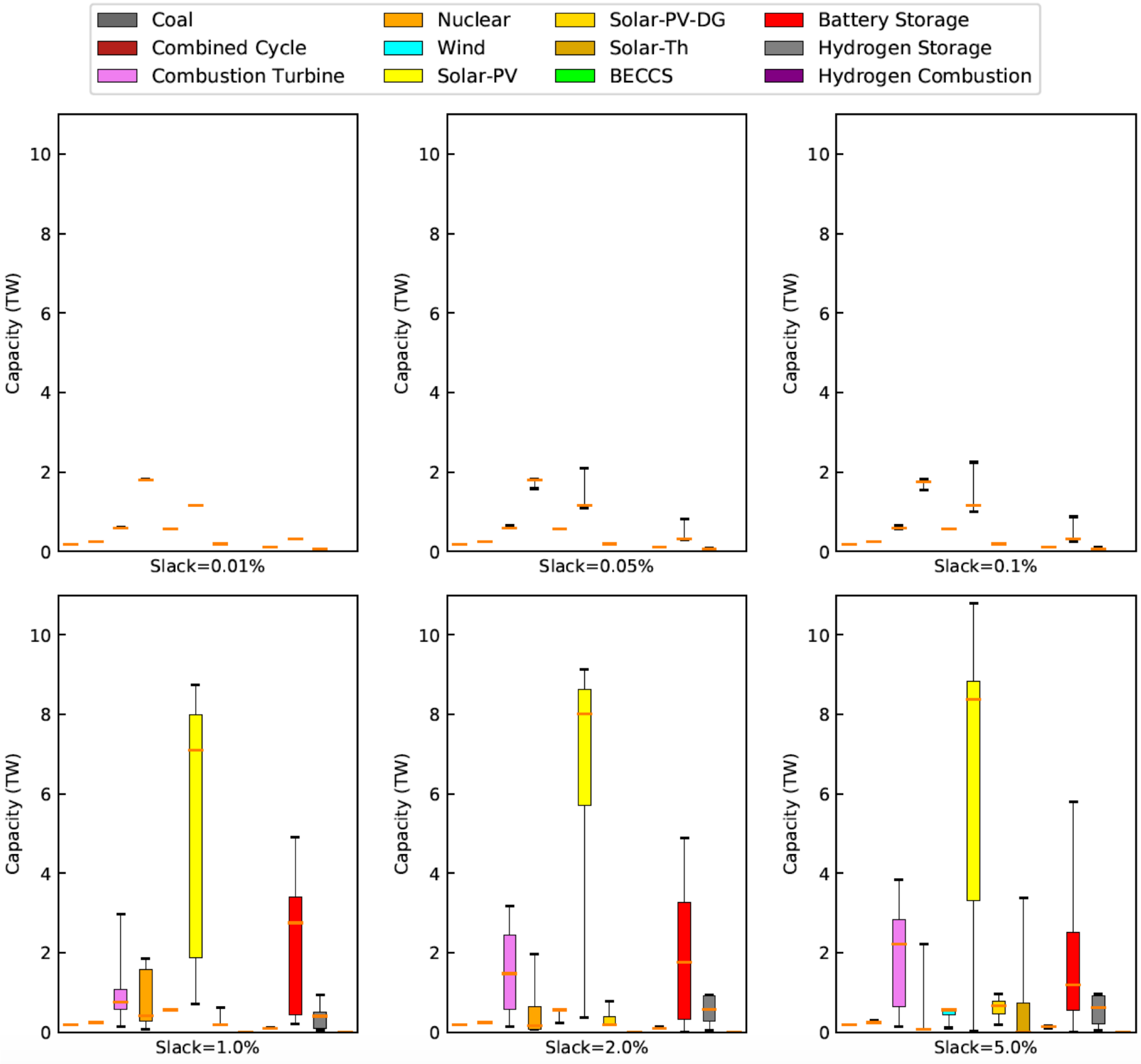
Developed a Social Risk Tolerance (SRT) model that generates a distribution of perceived accident risk and an accident acceptability threshold; used to set more realistic upper bounds on nuclear

https://www.sciencedirect.com/science/article/pii/S0306261921002609

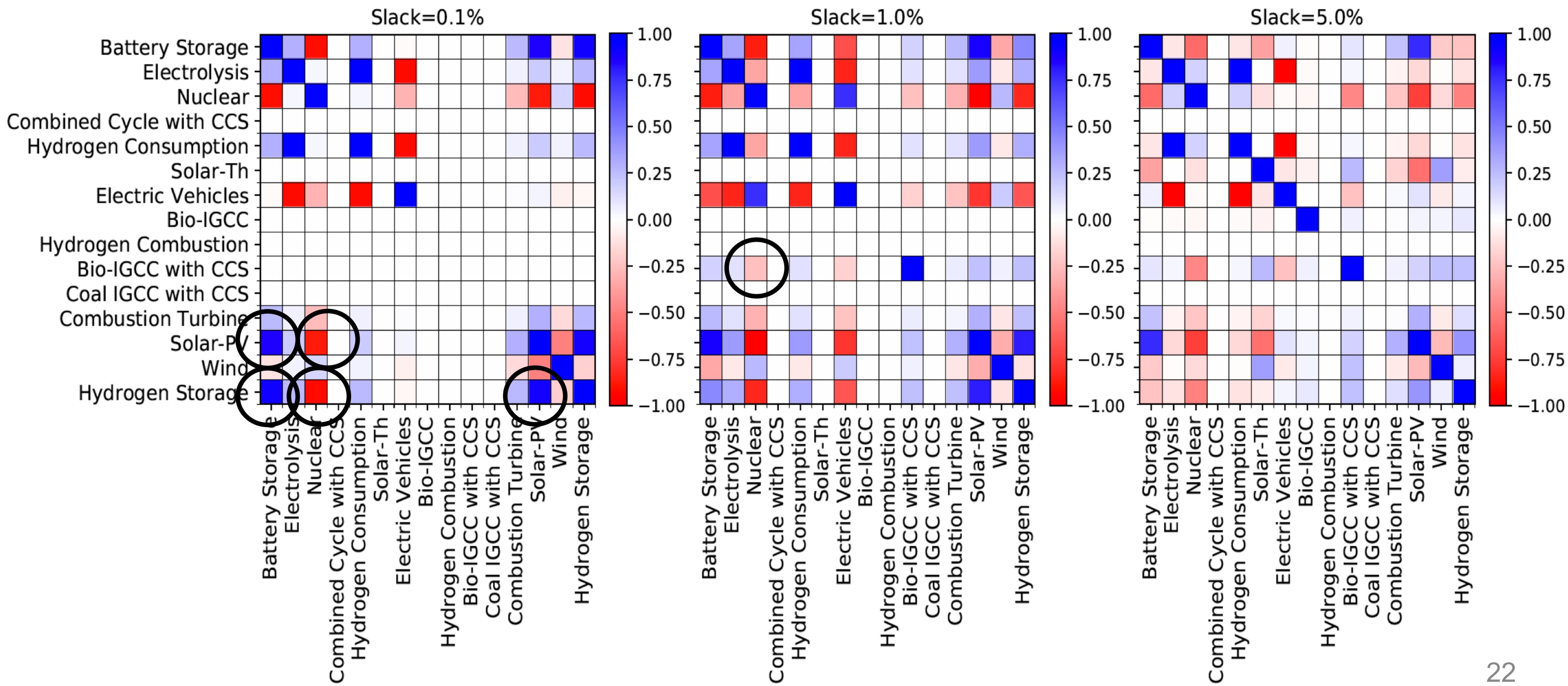
MGA electric sector results



- Perform 200 MGA iterations with random objective coefficients
- Slack values range from 0.01 – 5% of baseline CCap scenario
- Electric sector results shown here
- Boxplots represent min/max, 25/75 quartiles, median
- Tradeoffs center on nuclear, solar PV, battery and H2 storage

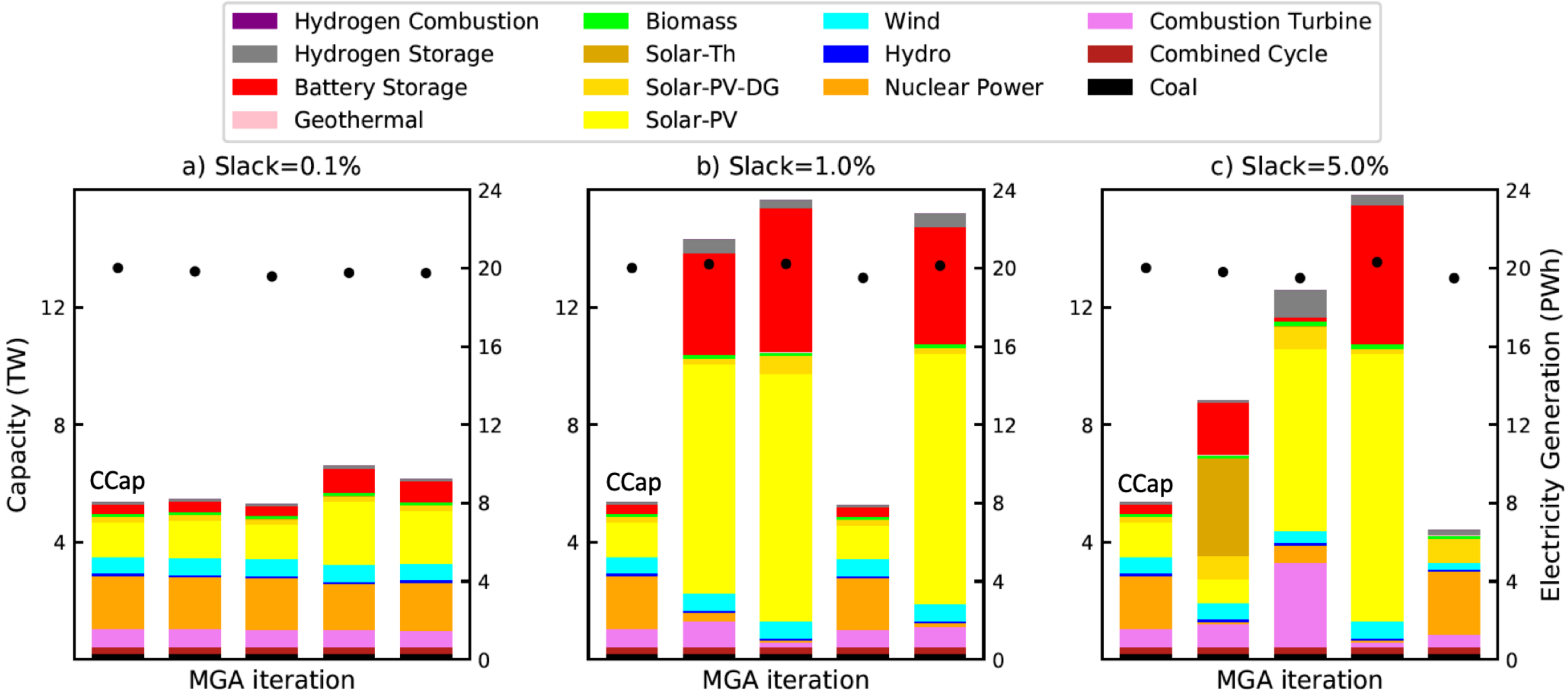
Correlation in production by technology

Across 200 model iterations, calculate Pearson correlation coefficient between cumulative production of key technologies over model time horizon (2017-2050)



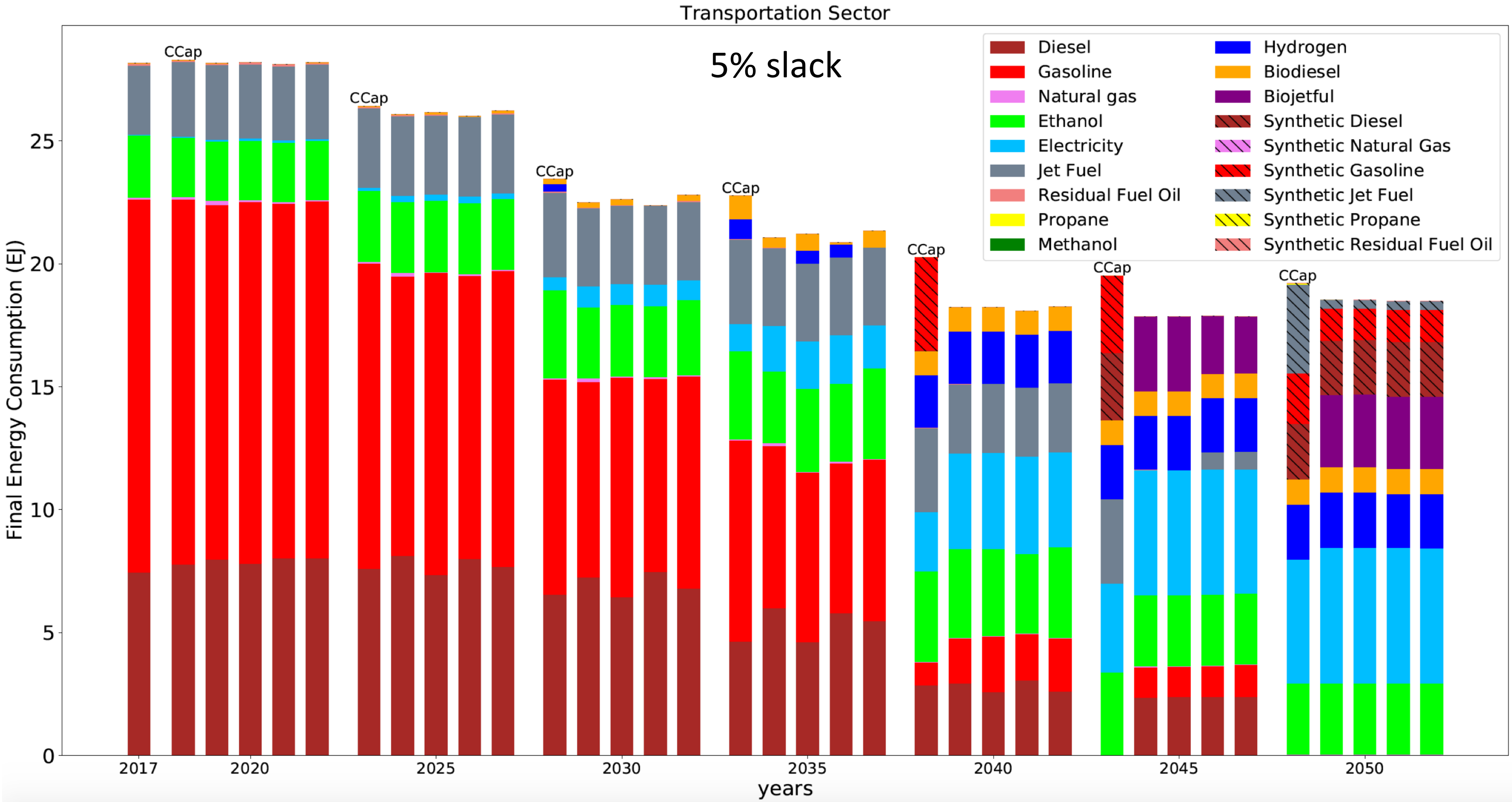
MGA results: Electric Sector Capacity

Apply distance-to-selected screening method in order to select the 4 out of 200 model solutions that are maximally different in decision space

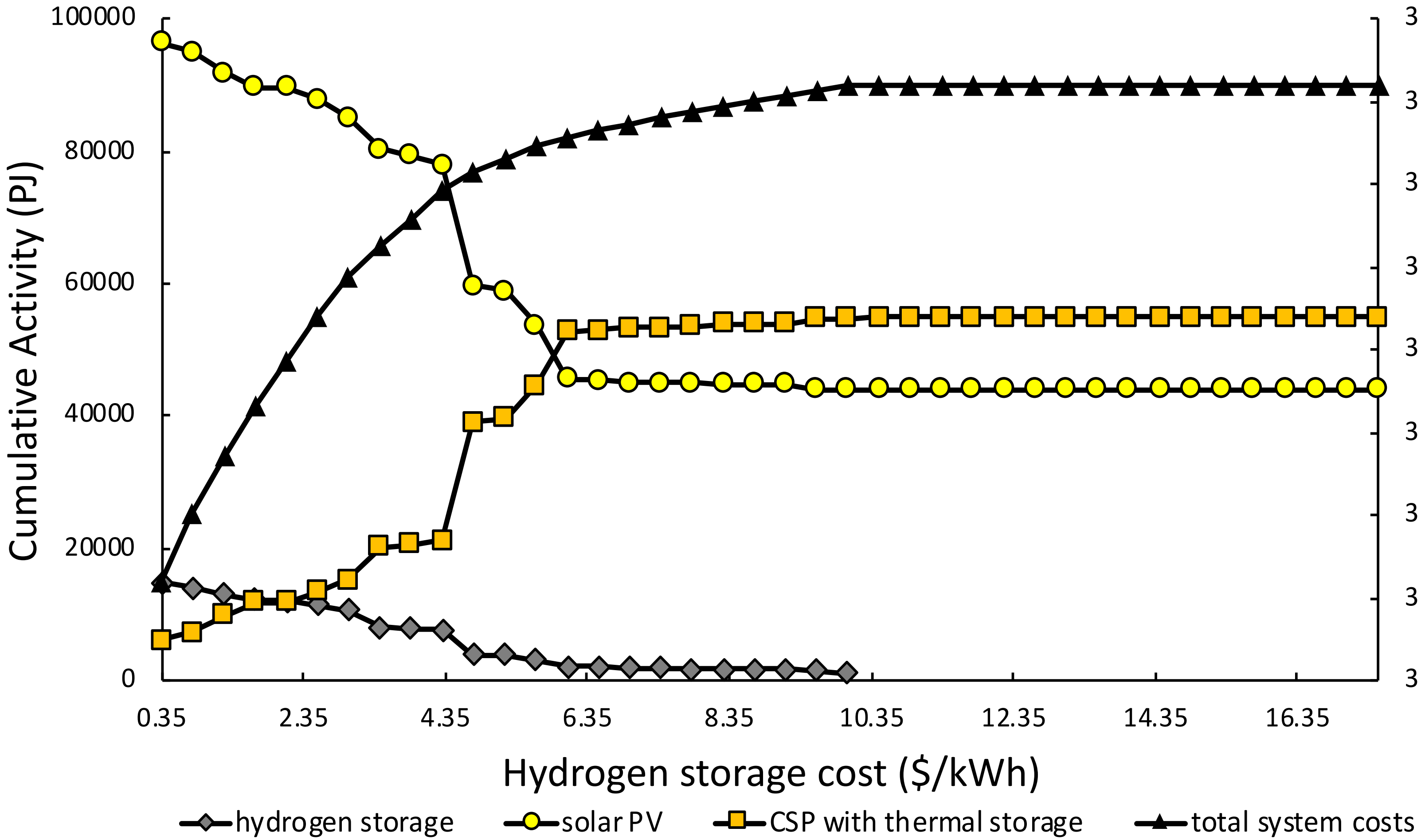


Results from 2050

MGA results: Transportation Sector Fuels



Sensitivity to H_2 storage cost



Conclusions

- Applying MGA provides a systematic way to test system flexibility and explore the decision space.
- Key tradeoff in the electric sector is between firm, carbon-free power and renewables with storage.
- End-use sectors decarbonized through a combination of electrification, biomass, and synthetic fuels.
- In next decade, we need massive scale up of wind, solar, storage, battery electric vehicles, and end-use electrification of space heating
- Post 2030:
  - Power-to-X, involving H_2 production via electrolysis and the production of synthetic fuels, is a key pathway.
  - BECCS offsets last 7% of 2017 CO_2 emissions
  - DAC captures CO_2 equivalent to 20-35% of total 2019 emissions for synthetic fuel production

Caveats

- Single region with a time sliced approach; planning to test this systematically over the next few months
  - Curtailments, ramping constraints, capacity reserve margin affected

  → Consequence is low wind deployments
- Assume exogenously specified fuel prices from the EIA Annual Energy Outlook
- Simplified industrial sector representation with non-manufacturing and manufacturing; the latter split into process heat, CHP, and 'other'
- Large cost and performance uncertainties remain

OPEN ENERGY OUTLOOK
FOR THE UNITED STATES

https://openenergyoutlook.org/

CMU Participants

- Paulina Jaramillo, co-PI
- Aranya Venkatesh, research scientist
- Destenie Nock, uncertainty; energy justice
- Costa Samaras, energy justice
- Katie Jordan, transportation

We Need a More Cohesive Community

- Much more focus on open source efforts, but we're still largely on our own islands
- Everyone creates a mental model based on experience with their own energy models.
- Hard to compare models given differences in model structure and data – so debates persist

What if we create a community platform where we can test hypotheses by starting from a familiar reference point?

Critique of the Annual Energy Outlook

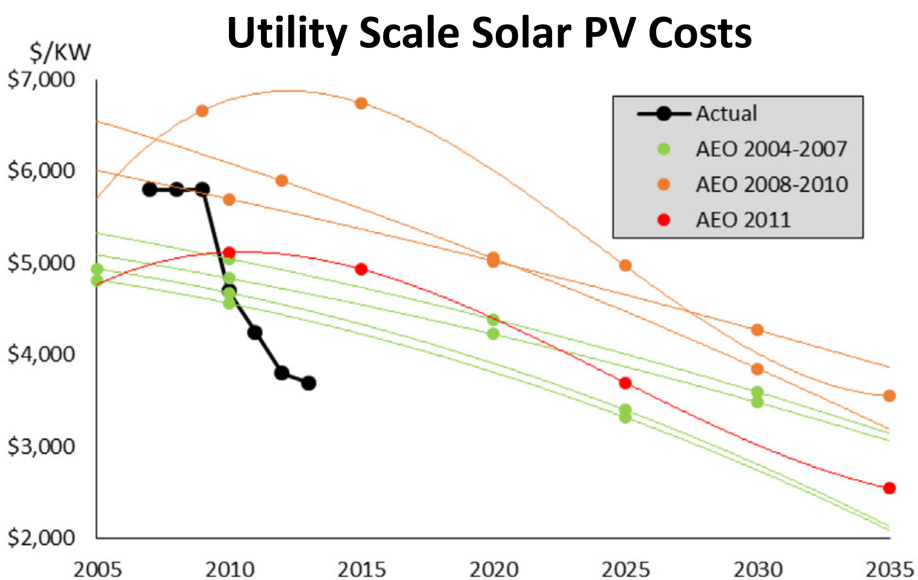
- Federal government constrained by prevailing political environment
- NEMS is a large, complex model that is difficult to run
- No community

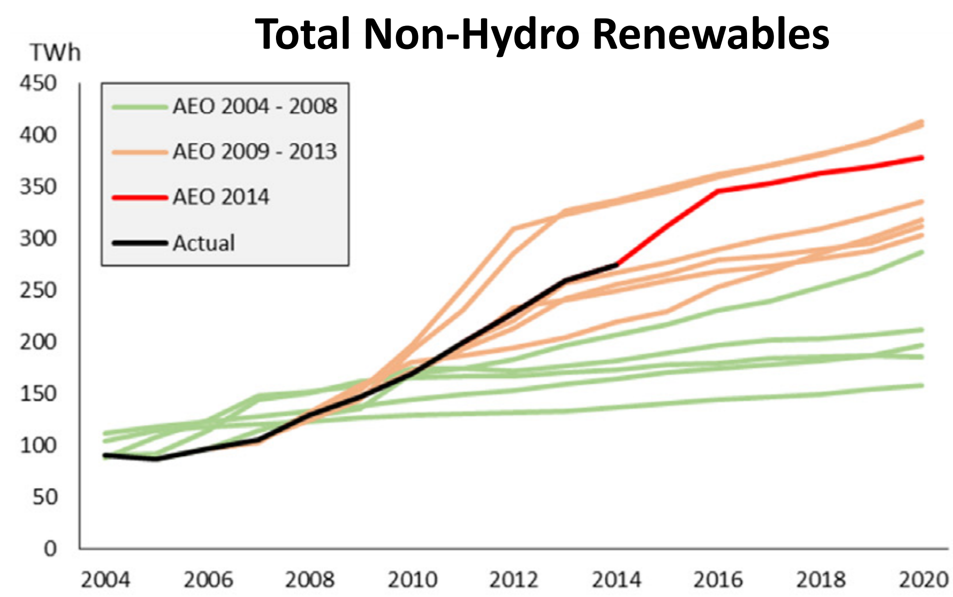
> The National Energy Modeling System (NEMS) was developed primarily for the modelers at the U.S. Energy Information Administration (EIA) and is only used by a few organizations outside of EIA. Some non-EIA users have found NEMS to be too difficult or rigid to use. For example, it is not typically used for state-level analysis and is not well-suited to be modified to analyze other countries. However, many users obtain the model for the data in its input files or for the source code. EIA developed NEMS, so most of what constitutes NEMS is in the public domain (and no licenses are required). However, NEMS does contain some proprietary components that are outside of the public domain but can be licensed as discussed below.

- Limited sensitivity and uncertainty analysis (8 total scenarios in last AEO)

Projections are overly conservative

- Projections assume no new policy; including extensions of long-time tax credits
- Renewable cost assumptions do not keep pace with reality





Gilbert AQ, Sovacool BK. (2016) Looking the wrong way: Bias, renewable electricity, and energy modelling in the United States. Energy, 94: 533-541.

An Open Energy Outlook for the United States

Project funded by the Sloan Foundation for the next three years

"Our project aims to bring energy modeling into the twenty-first century by applying the gold standards of policy- focused academic modeling, maximizing transparency, and building a team that works toward a common goal: examining alternative U.S. energy pathways to inform future energy and climate policy efforts."

- **Focus on deep decarbonization**
- **Use open source data, models, and tools**
- **Build a community around the effort**

An Open Energy Outlook for the United States

Questions to address

- How do we formulate deep decarbonization policies that are robust to future uncertainty?
- What technology pathways are critical to achieving low emissions across a wide range of scenarios?
- What are the cost and emissions implications of different policy approaches?
- How does decarbonization affect equity and justice concerns?
- What are the system-level inflection points that set technical limits or significantly increase the cost of deep decarbonization?

https://github.com/TemoaProject/oeo/blob/master/OEO_Roadmap.md

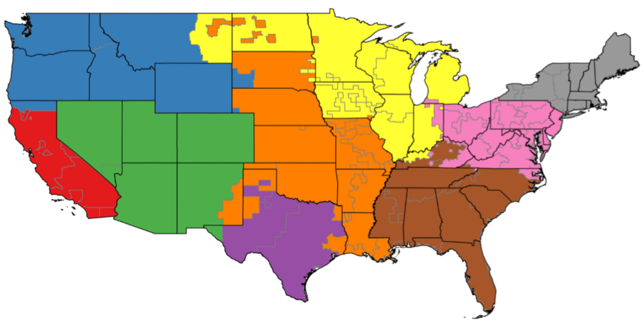
An Open Energy Outlook for the United States

Planned Outcomes

- Attract an array of scholars who can improve the model-based analysis.
- Increase the coverage of energy technologies and sectors represented in energy system models.
- Provide public access to the model's revision control system via GitHub, which gives users provenance over data and code
- Provide a platform to test hypotheses and resolve debates over data and model dynamics.
- Issue an annual report that can be used by other stakeholders to inform energy and climate decision-making.

Progress to Date

- Heavy focus on input data development
  - 9-region representation



  - Engagement with OEO teams on sector representation
  - Experimentation with representative days
  - Documentation in jupyter notebooks
- Developed a rolling horizon formulation
- Published paper on distributed collaboration

Joule

Commentary

Leveraging Open-Source Tools for Collaborative Macro-energy System Modeling Efforts

Joseph F. DeCarolis,[1,*] Paulina Jaramillo,[2] Jeremiah X. Johnson,[1] David L. McCollum,[3] Evelina Trutnevyte,[4] David C. Daniels,[16] Gökçe Akın-Olçum,[5] Joule Bergerson,[6] Soolyeon Cho,[1] Joon-Ho Choi,[7] Michael T. Craig,[8] Anderson R. de Queiroz,[9] Hadi Eshraghi,[1] Christopher S. Galik,[1] Timothy G. Gutowski,[10] Karl R. Haapala,[11] Bri-Mathias Hodge,[12] Simi Hoque,[13] Jesse D. Jenkins,[14] Alan Jenn,[15] Daniel J.A. Johansson,[16] Noah Kaufman,[17] Juha Kiviluoma,[18] Zhenhong Lin,[19] Heather L. MacLean,[20] Eric Masanet,[21] Mohammad S. Masnadi,[22] Colin A. McMillan,[23] Destenie S. Nock,[2] Neha Patankar,[14] Dalia Patino-Echeverri,[24] Greg Schivley,[28] Sauleh Siddiqui,[25] Amanda D. Smith,[29] Aranya Venkatesh,[2] Gernot Wagner,[26] Sonia Yeh,[16] and Yuyu Zhou[27]

Thank you! Questions or Comments?

Temoa:
http://www.temoacloud.com

OEO Project Links:
https://openenergyoutlook.org/
https://github.com/TemoaProject/oeo