NC STATE UNIVERSITY

Improving Model-based Scenario Analysis with Stochastic Optimization and Modeling to Generate Alternatives

IQ SCENE Workshop
University College London
26 March 2014

Joe DeCarolis, Kevin Hunter, Charles O'Connell
Dept of Civil, Construction, and Environmental Engineering
NC State University

jdecarolis@ncsu.edu; @jfdecarolis; http://temoaproject.org

Talk Outline

Discuss energy economy optimization modeling; problems with the status quo

Outline two techniques for uncertainty analysis: **stochastic optimization** and **modeling-to-generate alternatives**

Present results from a simple energy system to illustrate how the techniques work

Energy-economy optimization (EEO) models

Energy-economy optimization (EEO) models refer to partial or general equilibrium models that **minimize cost or maximize utility** by, at least in part, optimizing the energy system over multiple decades. Such models provide:

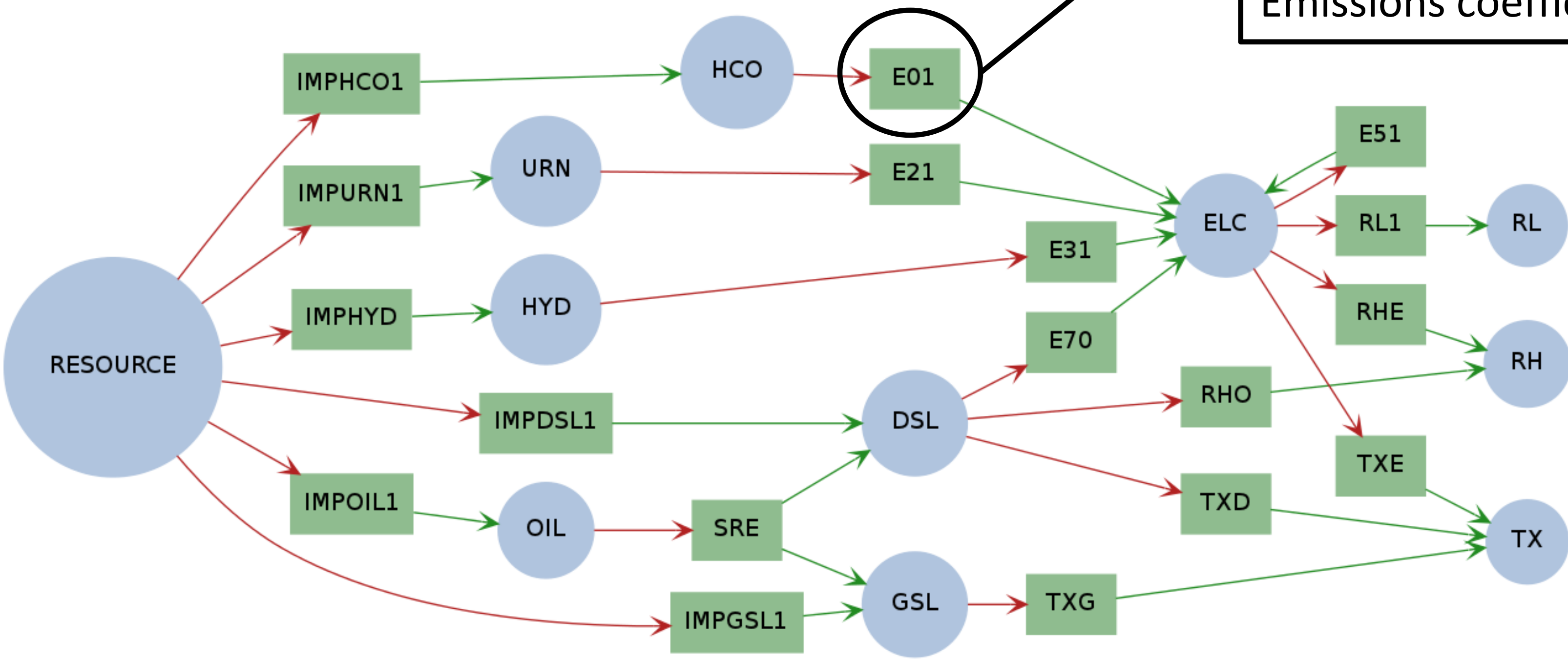
- Expansive system boundaries and multi-decadal timescales
- Self-consistent framework for evaluation
- Ability to explore how effects may propagate through a system

Model-based analysis can deliver crucial insight that informs key decisions.

What can we usefully conclude from modeling exercises where uncertainty is rigorously quantified?

Technology explicit modeling

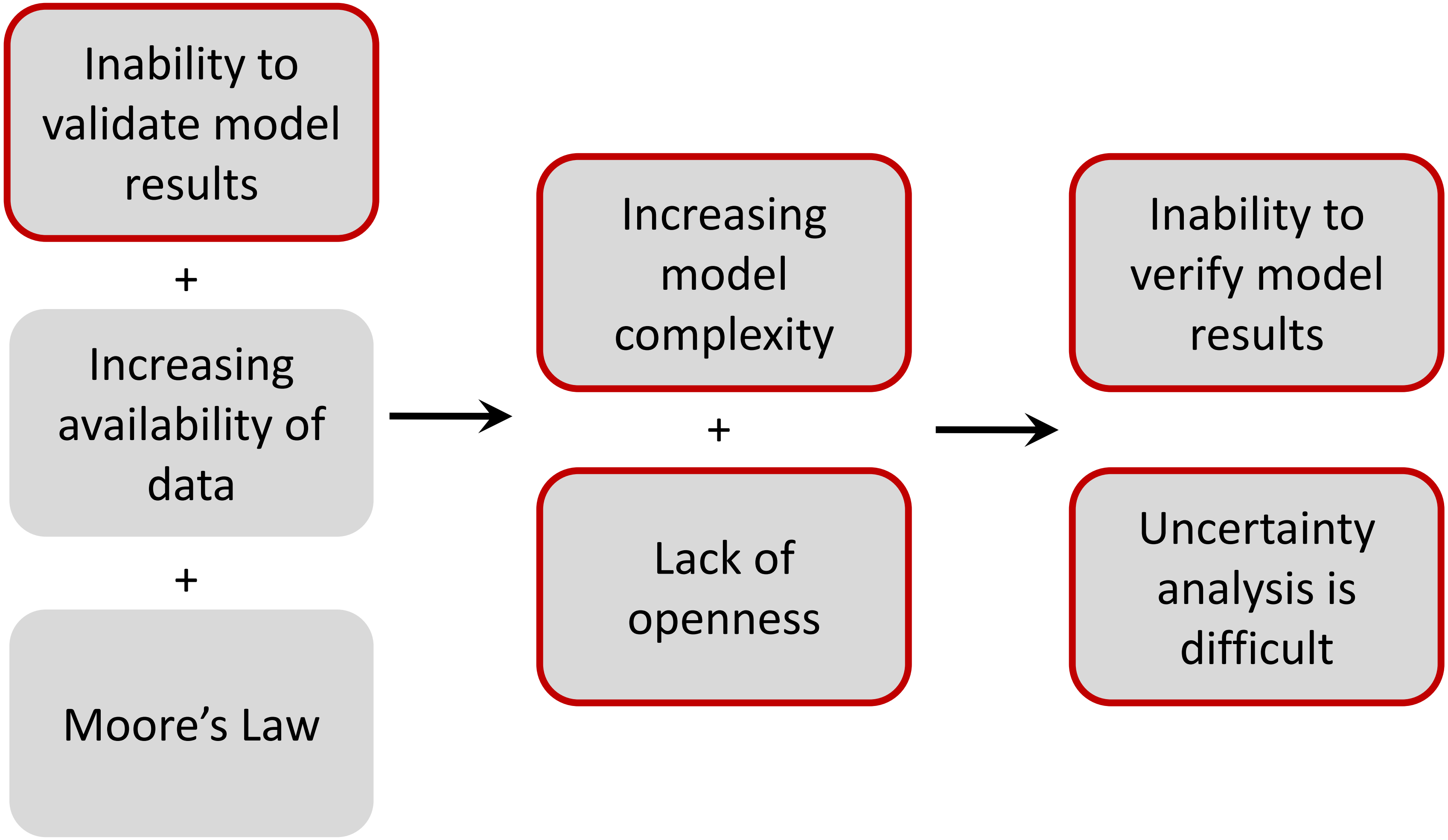
Capital Cost ($M/PJ/yr)
Fixed O&M ($M/PJ)
Variable O&M ($M/PJ)
Capacity factor
Efficiency
Emissions coefficient (kton/PJ)



Objective function: minimize present cost of energy supply over a defined time horizon

Decision variables: activity (PJ) and capacity (PJ/yr) for each technology

Problems with the status quo



Tools for Energy Model Optimization and Analysis (Temoa)

TEMOA is a **bottom up, technology explicit model with perfect foresight**, similar to the TIMES model generator.

Goals

Repeatable Analysis
- Data and code stored in a publicly accessible web repository (github.com)
- Open source software stack

Rigorous treatment of uncertainty
- Framework designed to operate in a high performance computing environment
- Capability to do stochastic optimization; modeling-to-generate alternatives

For more information: http://www.temoaproject.org

Types of Uncertainty

There are many ways to categorize uncertainty.

A key distinction:

- **Parametric**: uncertainty regarding the assumed value of model inputs.
- **Structural**: imperfect and incomplete nature of the equations describing the system

Dealing with uncertainty in energy systems

Scenario analysis

- **Uncertainty type:** parametric
- **Purpose:** characterize a small set of possible future outcomes
- **Weaknesses:** cognitive heuristics (Morgan and Keith, 2008); doesn't provide a strategy

Sensitivity analysis

- **Uncertainty type:** parametric
- **Purpose:** Identify sensitivity of key model outputs to inputs
- **Weaknesses:** computationally intensive; doesn't provide a strategy

Stochastic optimization*

- **Uncertainty type:** parametric
- **Purpose:** Develop a unified 'hedging' strategy
- **Weaknesses:** computationally intensive, curse of dimensionality

Modeling to Generate Alternatives*

- **Uncertainty type:** **structural**
- **Purpose:** Explore maximally different solutions in decision space
- **Weaknesses:** doesn't provide a strategy

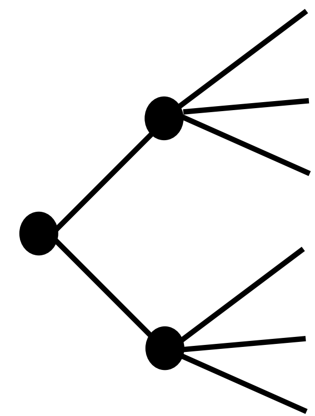
Stochastic Optimization

Decision-makers need to make choices before uncertainty is resolved.

Need to make short-term choices that hedge against future risk

Apply stochastic optimization by:

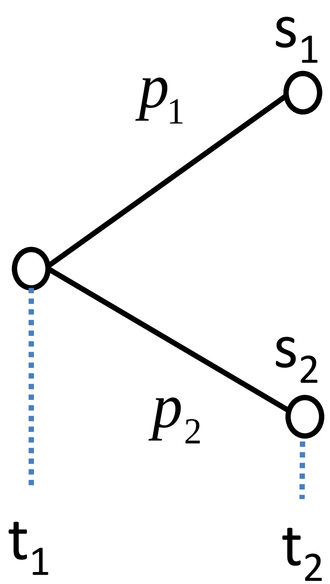
- Building a scenario tree
- Assigning probabilities to future outcomes
- Optimizing over all possibilities



The resultant solution represents a near-term hedging strategy because it accounts for alternative future outcomes.

Simple Example of Stochastic Optimization

Suppose we have two technologies, *A* and *B*. Let *x* represent the installed capacity.



Stage 1 Decision Variables:

$$x_A, x_B$$

Stage 2 Decision Variables:

$$y_{A,s_1}, y_{B,s_1}, y_{A,s_2}, y_{B,s_2}$$

$$\text{Minimize: } c^T x + \sum_{s=1}^{N} p_s \cdot d_s^T \cdot y_s$$

Subject To:

$$Ax = b$$

$$T_s x + W_s y_s = h_s \quad for \quad s = 1, \dots, N$$

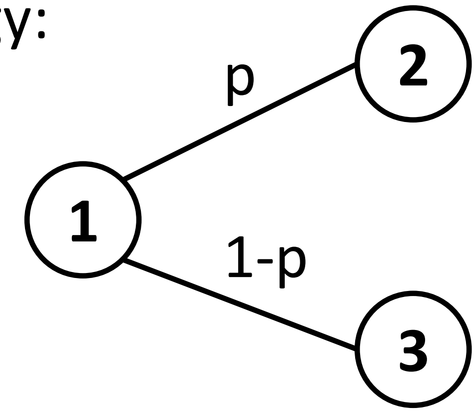
$$x \geq 0$$

$$y_s \geq 0 \qquad for \quad s = 1, \dots, N$$

How can we value the hedging strategy?

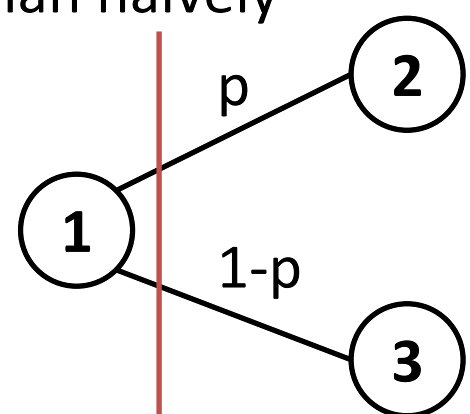
Expected value of perfect information (EVPI): The expected savings if planners knew with certainty the outcome at every stage as opposed to following the hedging strategy:

$$EVPI = C_{hedge} - \sum_{s \in S} p_s \cdot C_s$$

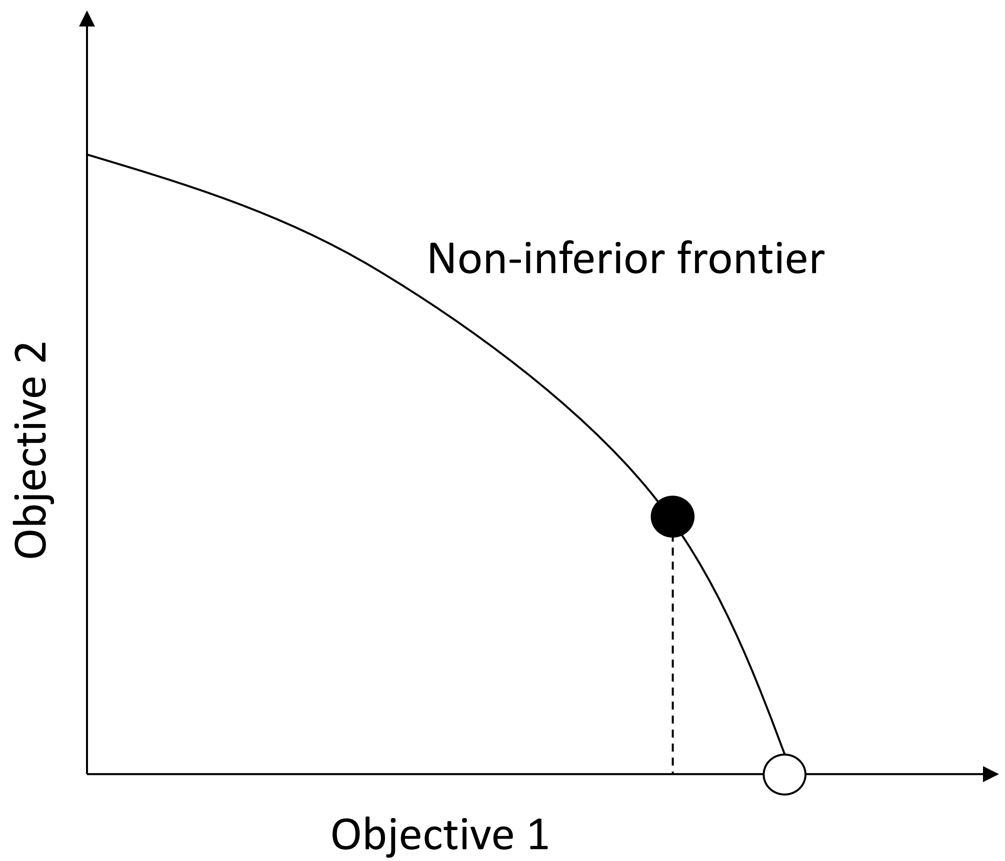


Expected Cost of Ignoring Uncertainty (ECIU): The expected savings by following the hedging strategy rather than naively guessing the outcome

$$ECIU_2 = \begin{bmatrix} C_{1|2} + p \cdot C_{2|2} + \\ (1-p) \cdot C_{3|2} \end{bmatrix} - C_{hedge}$$



What 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)

Hop-Skip-Jump (HSJ) MGA

Brill et al. (1982)

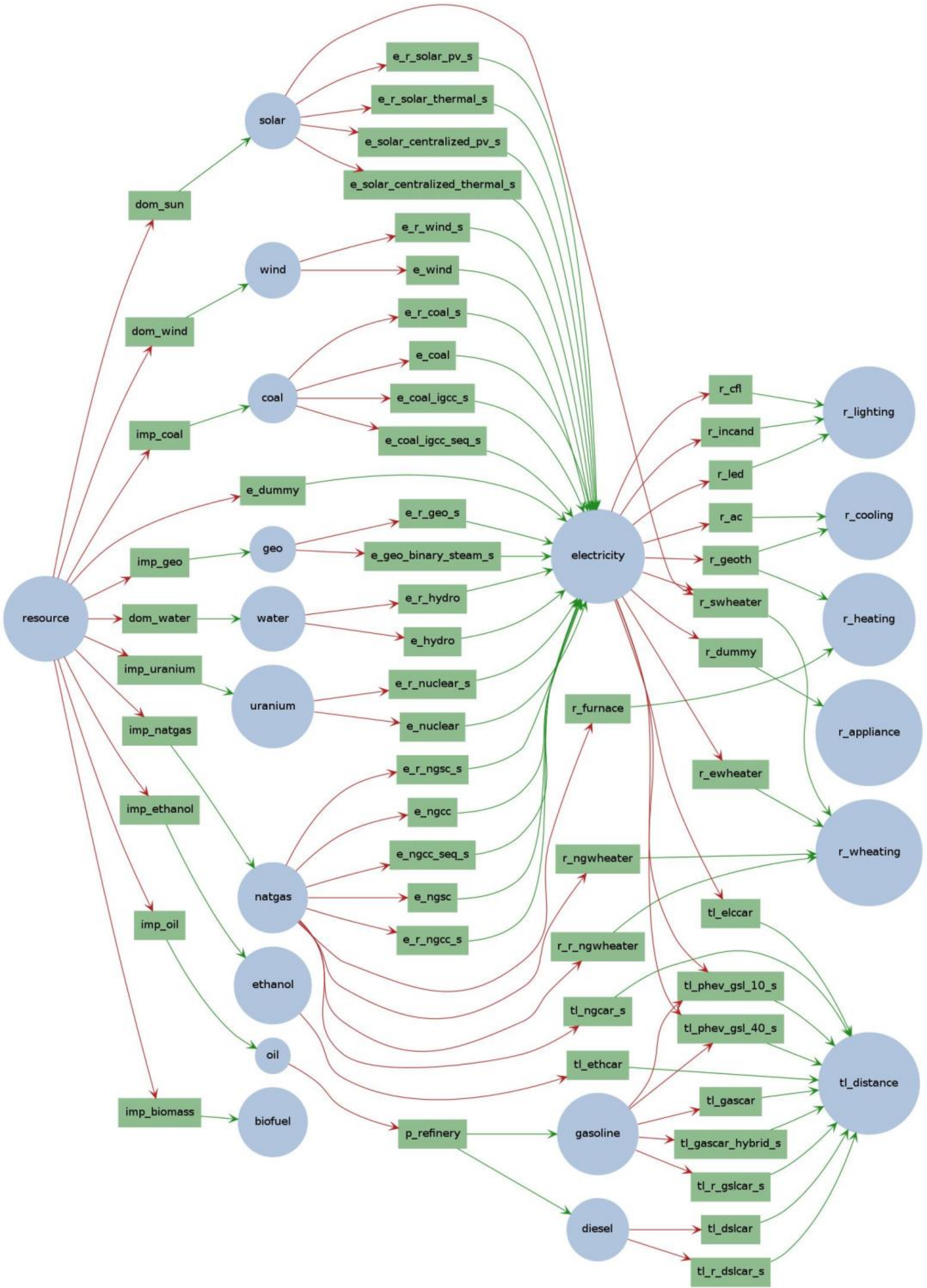
Steps:

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 that minimizes the decision variables that appeared in the previous solutions
5. Iterate the re-formulated optimization
6. Terminate the MGA procedure when no significant changes to decision variables are observed in the solutions

Case Study

‘Temoa Island’

- 10 import technologies; constant supply prices
- 54 technologies total;
- 6 end-use demands: lighting, space heating, space cooling, water heating, and light duty transportation
- 6 time slices: summer/ winter /intermediate day/ night
- 5 time periods, each 5 years long: 2010-2030.



Simple Application of Stochastic Optimization

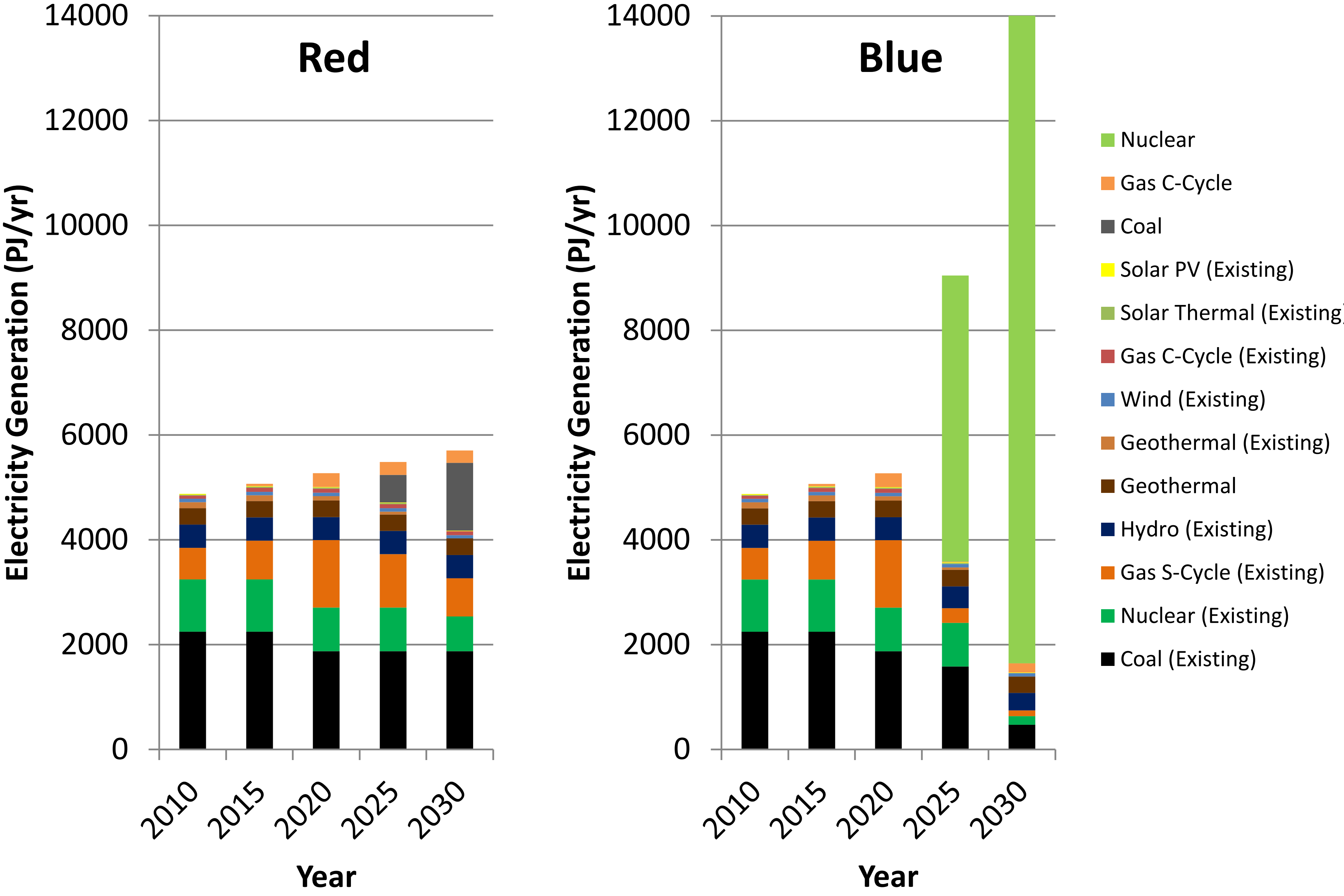
Suppose there are parliamentary elections every 5 years

- If the blue party wins the majority, they implement a 15% annual CO_2 reduction.
- If the red party wins the majority, they allow CO_2 to grow at 15% annually.
- Election outcome probabilities weighted evenly at 50% each

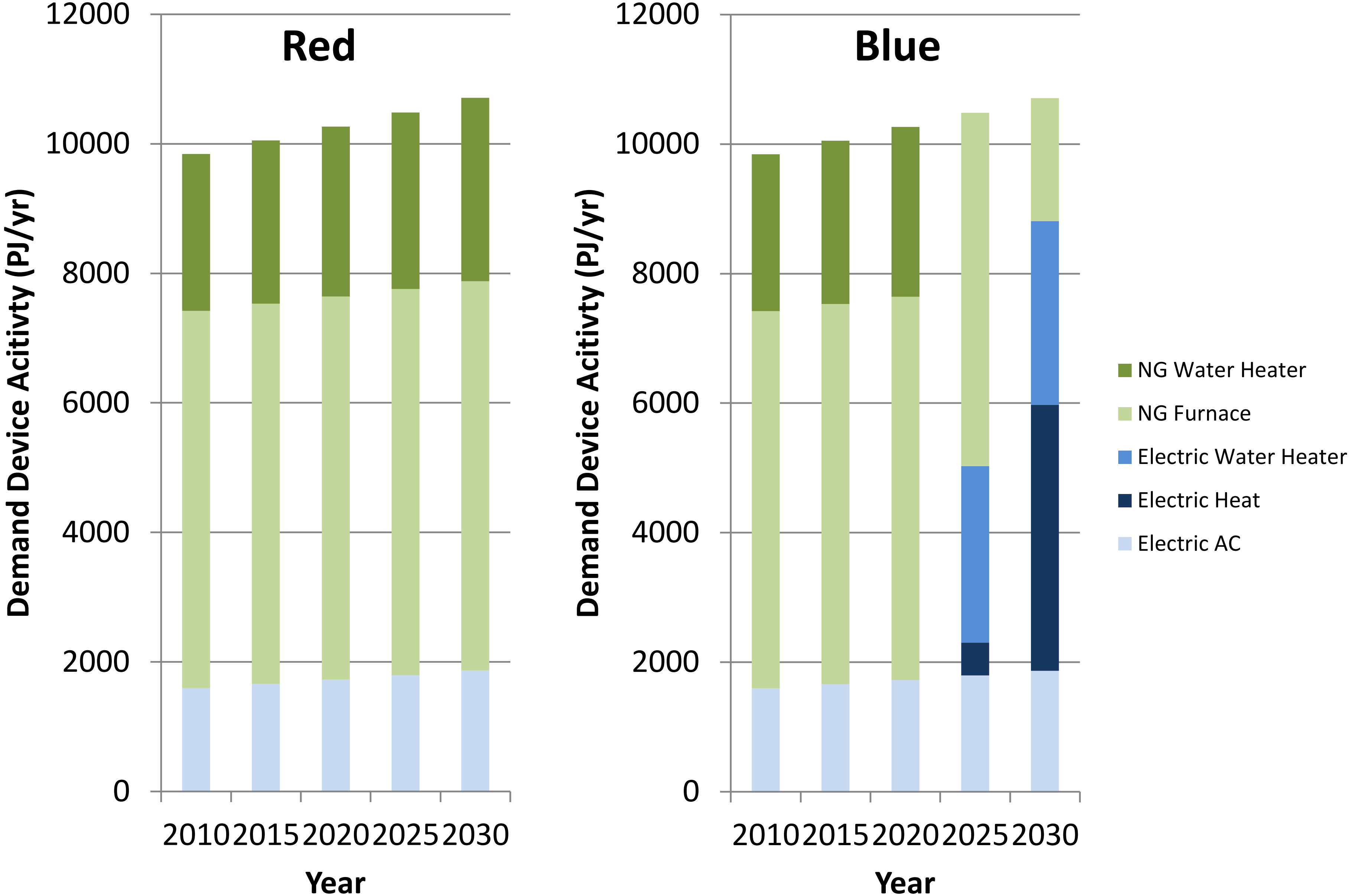
Elections begin to affect CO_2 policy in 2020; therefore we have a unified strategy in 2015

Two branches per node over 3 model time periods, so a total of 8 possible outcomes by 2030.

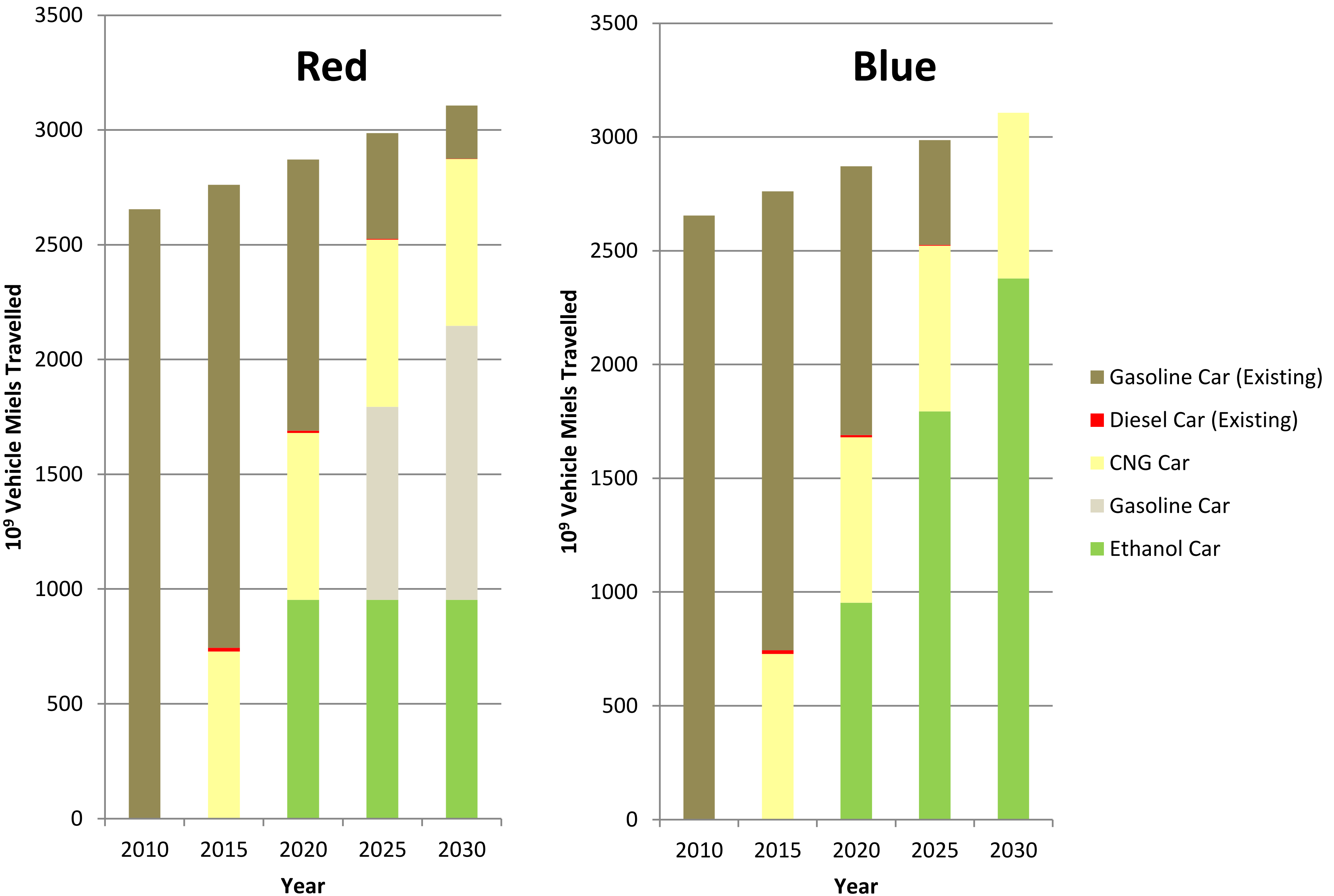
Stochastic Optimization: Electric Sector Results



Stochastic Optimization: Residential Sector Results



Stochastic Optimization: Transport Sector Results



Stochastic Results

Cost of Hedging Strategy:

$\$1.36\times10^{13}$

EVPI

0.5% (of hedging strategy cost)

ECIU

1.05% (of hedging strategy cost)

1.05%

1.05%

1.07%

1.05%

1.05%

2.10%

1.79%

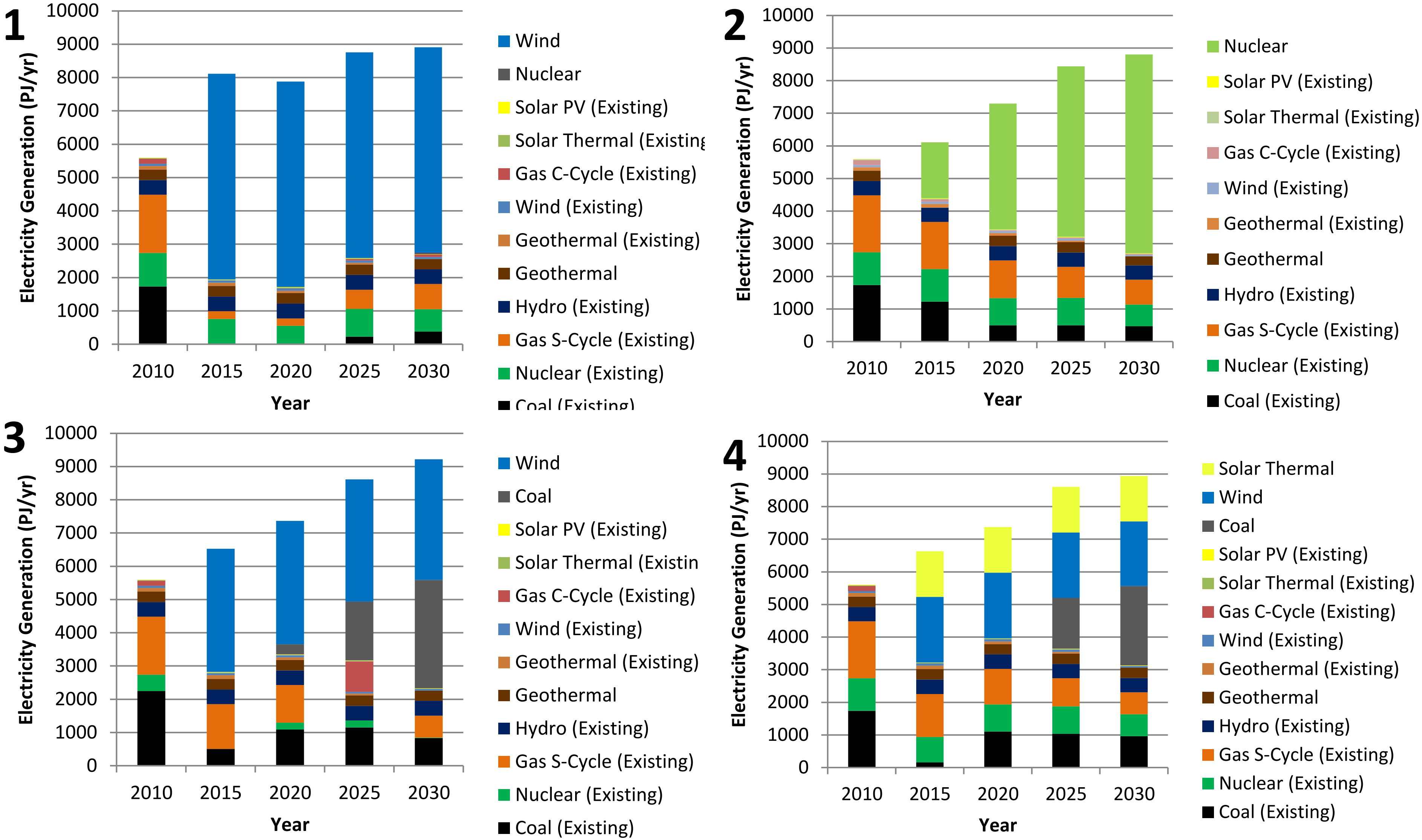
Compromise?

Suppose the red party is willing to accept a 10% increase in energy prices if the blue party drops it's demands for a CO_2 cap.

What type of system might be possible?

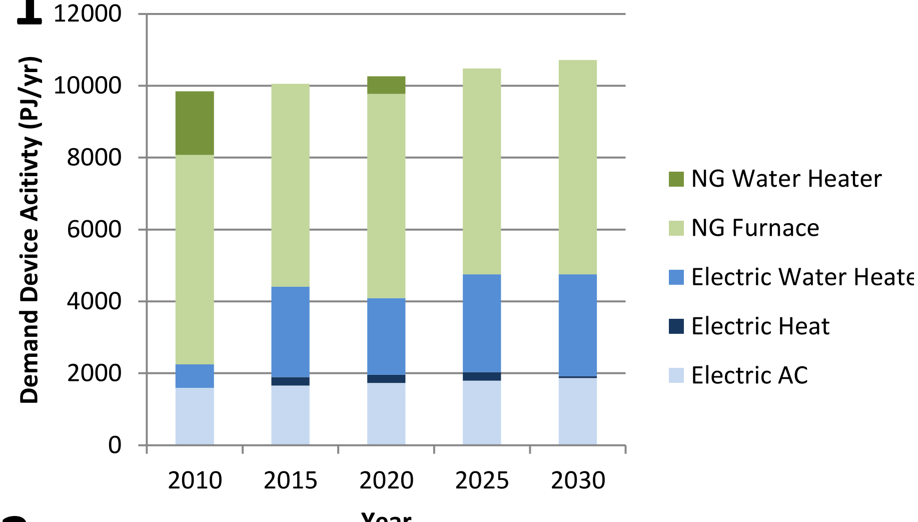
Apply MGA with 10% cost slack.

MGA Electric Sector Results

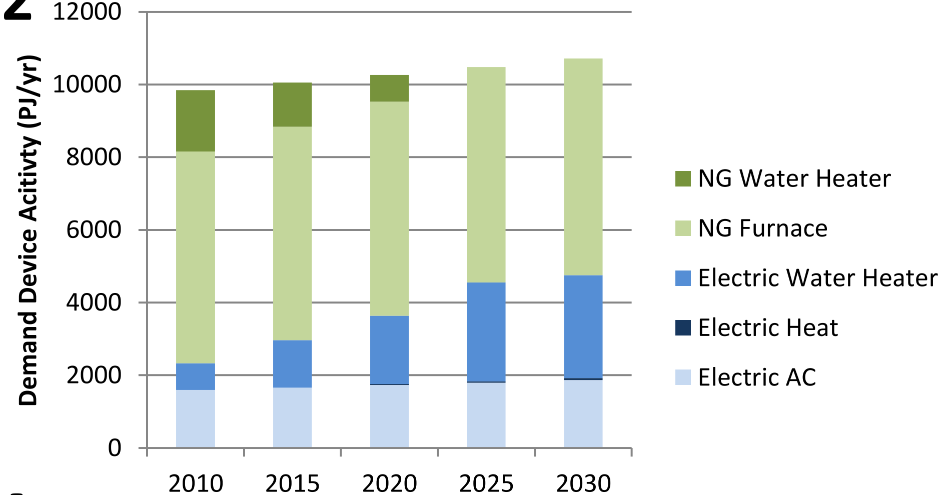


MGA Residential Sector Results

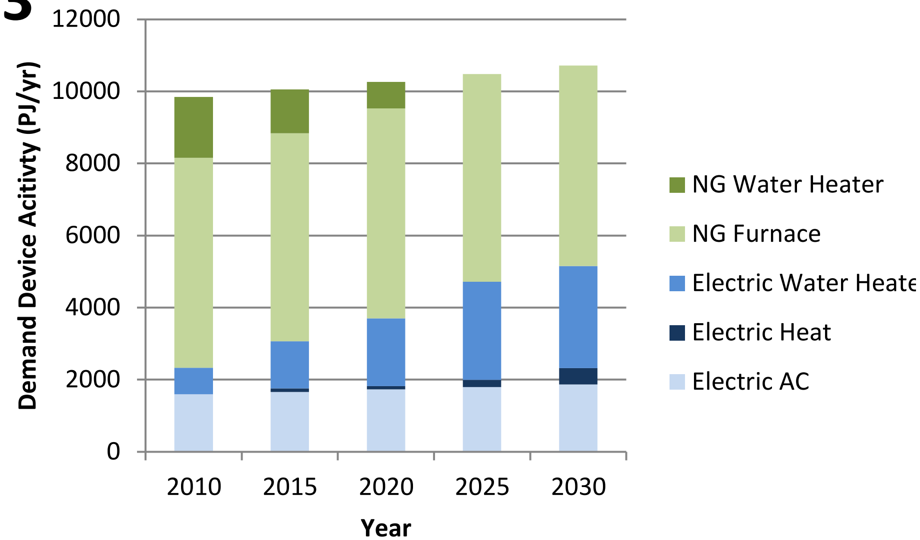
1



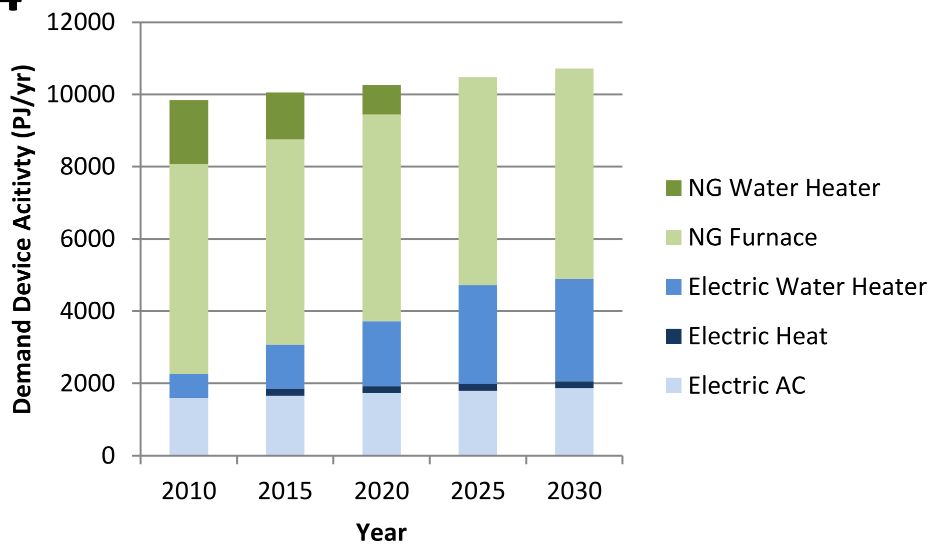
2



3

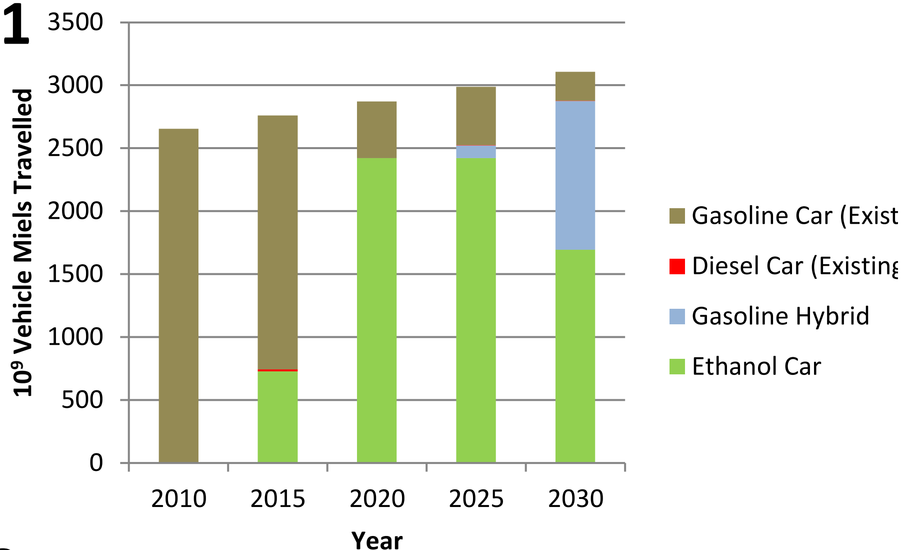


4

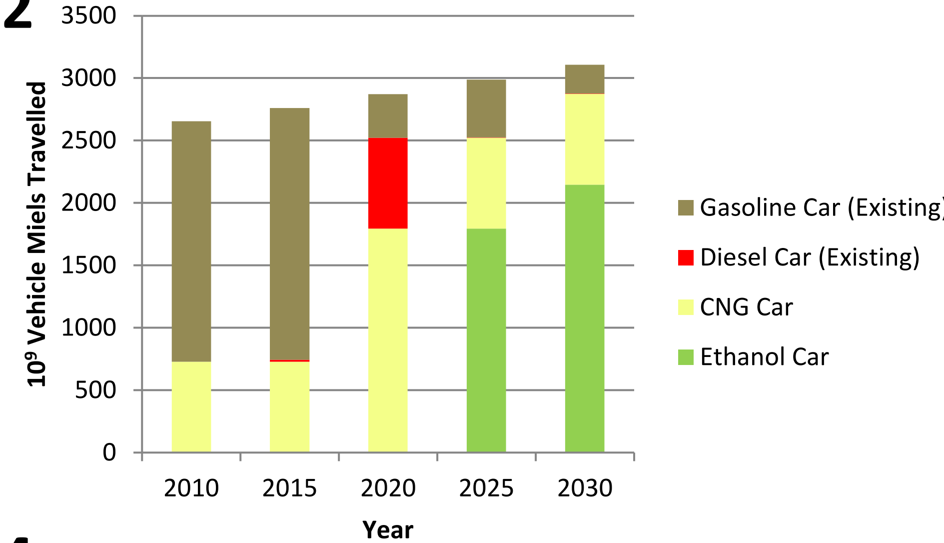


MGA Transportation Sector Results

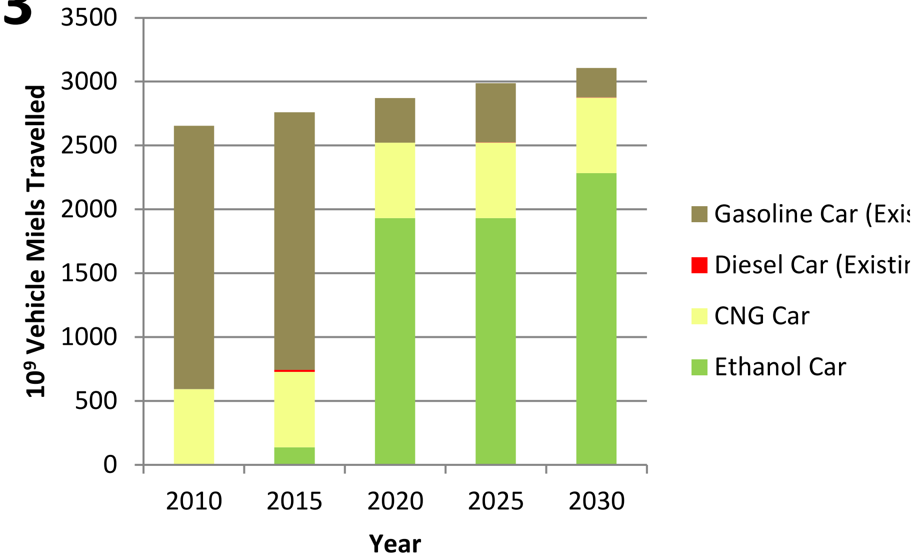
1



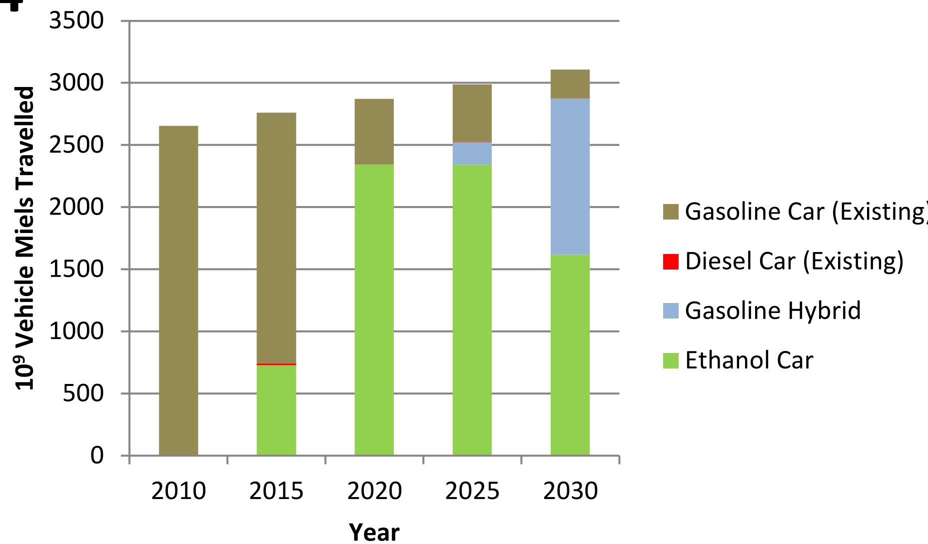
2



3



4



Discussion

Energy system planning and policy fraught with large future uncertainties

Policy relevant insight derived from scenario analysis should account for such uncertainties

Our approach:
- Use an open source model and software stack to maximize transparency (Temoa)
- Use techniques like stochastic optimization and MGA to derive policy relevant insight
- Utilize high performance computing resources where necessary

Next Step:
Build US dataset using newly developed interface and use apply uncertainty techniques discussed above

Relevant Outputs

DeCarolis J.F. (2011). Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. *Energy Economics*, 33: 145-152.

DeCarolis J.F., Hunter K., Sreepathi S. (2012). The Case for Repeatable Analysis with Energy Economy Optimization Models. Energy Economics, 34: 1845-1853.

Hunter K., Sreepathi S., DeCarolis J.F. (2013). Tools for Energy Model Optimization and Analysis. Energy Economics, 40: 339-349.

All model source code and data available for viewing and download through the project website:

http://temoaproject.org

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant No. 1055622 (CAREER: *Modeling for Insights with an Open Source Energy Economy Optimization Model*). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

National Science Foundation
WHERE DISCOVERIES BEGIN