Multi-stage stochastic optimization of a simple energy system

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Abstract
We utilize a newly developed framework called Tools for Energy Model Optimization and Analysis (Temoa) to perform multi-stage stochastic optimization of a simple energy system. The system consists of 27 technologies used to supply primary energy resources, refine petroleum products, generate electricity, and serve end use demands. The model considers stochastic crude oil and natural gas prices over 4 time periods, resulting in a total of 256 scenarios. Model results indicate that future changes in oil price may have a larger effect on system cost than natural gas prices, but overall the system configuration requires little recourse as fuel price uncertainty is revealed over time. This analysis represents an early step towards our goal of applying stochastic optimization in a high performance computing environment to develop robust, near-term hedging strategies for energy system management.

1. Introduction

Energy economy optimization (EEO) models provide a structured and self-consistent framework that can be used to generate insight related to climate change mitigation and energy system planning. Given the expansive system boundaries and necessarily long timeframes for analysis, large, irreducible uncertainties preclude precise prediction of future outcomes. A set of projections or scenarios produced with EEO models should, to the degree possible, account for the underlying uncertainty. The sage advice that modelers should focus on generating robust insights rather than point estimates is not new (e.g., Huntington et al., 1982; Peace and Weyant, 2008; Craig et al., 2002), though it has often gone unheeded. There is growing recognition that uncertainty analysis is a key area for in-depth investigation (Haurie et al., 2012).

Parameter uncertainty is usually addressed in analyses with energy and integrated assessment models by running a few scenarios (e.g., EIA, 2009; Clarke et al., 2007; Nakicenovic, 2000). The scenarios are often highly detailed, owing to the wide range of model input assumptions that can be affected, from high level economic and demographic trends that drive energy demand to the assumed performance of new technologies. While the purpose of scenario analysis is to extend our thinking about how the future might unfold, a few scenarios, each with a high degree of detail, can actually have the opposite effect by creating cognitively compelling storylines that obscure other equally plausible alternatives and betray the true underlying uncertainty (Morgan and Keith, 2008). In addition, if scenarios are not mutually exclusive and exhaustive and are not assigned subjective probabilities, they are of limited benefit to decision makers who must take action before uncertainty is resolved.

Stochastic optimization embeds the probability of different outcomes within the model formulation via specification of an event tree (Loulou and Lehtila, 2007), which yields a hedging strategy that accounts for future uncertainties. The complexity of event trees is often limited by the computational difficulty in solving the extensive form of the problem specification with classical solution methods. For example, Kanudia et al. (1998) implemented 8 scenarios across 3 time stages, Loulou et al. (1999) implemented 4 scenarios across 2 time stages, Labriet et al. (2008) implemented 8 scenarios across 2 time stages, Bosetti and Tavoni (2009) implemented 3 scenarios across two stages, and Babonneau et al. (2012) implemented 4 scenarios across two stages.

In this paper, we utilize Tools for Energy Model Optimization and Analysis (Temoa) to perform multi-stage stochastic optimization of a simple energy system. Temoa was initiated in 2010 to meet two critical goals: develop a set of open source models and datasets, which will be archived online with free access for all interested parties; and design a modeling framework for rigorous uncertainty analysis. At the heart of the Temoa framework is a newly created technology explicit EEO model. The surrounding computational framework was designed from the beginning to support rigorous uncertainty analysis by linking an EEO model created in an algebraic modeling environment with high performance computing resources. We demonstrate the capability of the Temoa framework by applying stochastic optimization to a simple energy system. The rest of the paper is organized as follows: Section 2 provides a brief overview of the Temoa framework, Section 3 describes a test energy system representation and provides results for the base case, Section 4 describes the setup of the stochastic optimization, Section 5 presents the results from the stochastic optimization, and Section 6 draws conclusions.

2. The Temoa framework

The TEMOA model is technology explicit, and the algebraic formulation is strongly influenced by the TIMES model generator (Loulou et al., 2005). The energy system is described algebraically as a network of linked processes that convert a raw energy commodity (e.g., coal, oil, biomass, uranium) into an end-use demand (e.g., lighting, transport, water heating, conditioned air), often through a series of one or more intermediate commodities (e.g., electricity, gasoline, ethanol). Each technology has a set of engineering, economic, and environmental characteristics (e.g., capital cost, efficiency, capacity factor, emissions rate) associated with converting an energy commodity from one form to another. Technologies are linked to one another via model constraints representing the allowable flow of energy commodities. The model objective is to minimize the present cost of energy supply by deploying and utilizing energy technologies and commodities over time to meet end-use demands. The model formulation includes the following features: Flexible time slicing by season and time-of-day; variable length model time periods; technology vintaging; separate technology loan periods and lifetimes; global and technology-specific discount rates; and commodity flows balanced at the timeslice level.

The Temoa model is implemented in Python Optimization Modeling Objects (Pyomo) package developed at Sandia National Laboratory, which is built in the Python scripting language and strongly influenced by the design of AMPL (Hart, 2009). Pyomo is part of a larger package called COmmon Optimization Python Repository (Coopr), which contains Python-based Stochastic Programming (PySP), a modeling and solver library for generic stochastic programming. To utilize PySP, modelers need to provide two files: the serial (non-stochastic) version of the model and a text file defining the subjective probabilities and parameter values associated with each branch in the event tree. PySP can solve the extensive form of the stochastic model by creating and solving a single representation of the entire system. Solving the extensive form; however, quickly leads to problem size limitations dictated by the amount of physical memory. To help alleviate the memory requirements, PySP includes an implementation of progressive hedging (PH), a solution technique that employs a horizontal decomposition method to solve stochastic problems (Rockafellar and Wets, 1991). It decomposes a stochastic program by scenarios (i.e., pathways through the event tree) instead of time stages. PH calculates scenario-specific solutions and proceeds in an iterative manner by updating the scenario-specific solutions for a modified objective, combines them to form a unified solution, and repeats the process until convergence is reached (Watson et al. 2008). PH possesses theoretical convergence properties in the case of continuous decision variables and can be also used as an effective heuristic in model formulations that include discrete decision variables (Watson et al. 2008). The scenario-specific solutions required at each iteration can be evaluated in parallel on a compute cluster.

3. Test case description and base case results

In order to test the functionality of the Temoa framework, we have chosen to model a simple test system developed for this purpose, which we call Temoa_Island. The system map is presented below in Figure 1. For simplicity, Temoa_Island contains no pre-existing capacity.

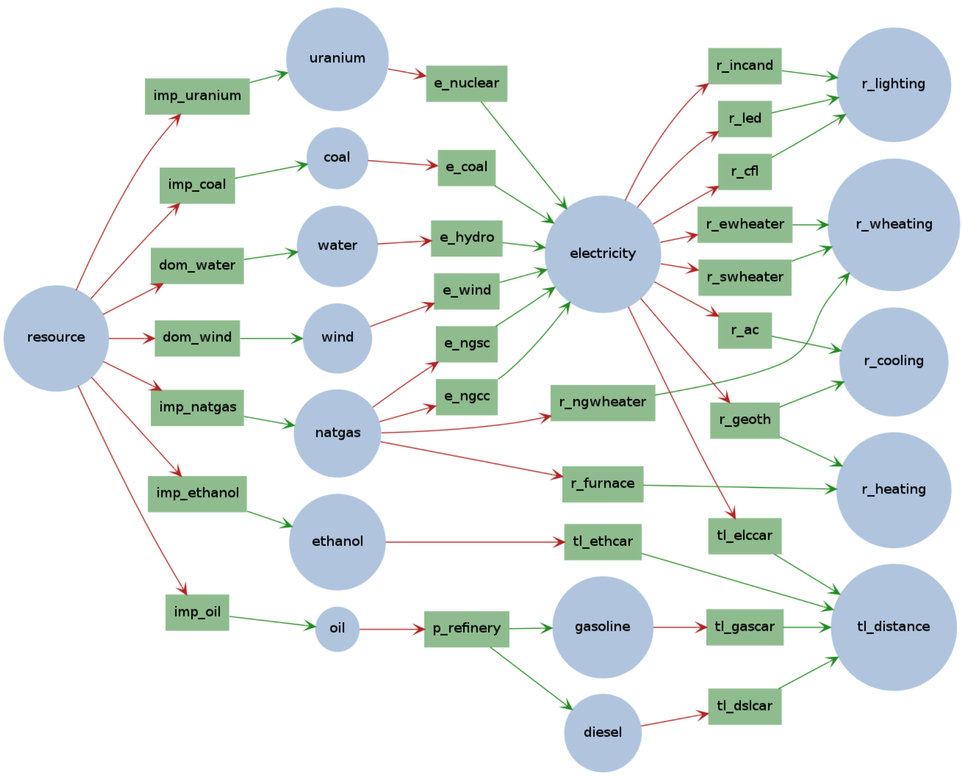

Figure 1 — Representation of Temoa_Island, a simple energy system created for testing purposes. Commodities are represented as blue circles, and processes are represented as green boxes. The abbreviation 'imp' indicates import, 'dom' indicates a domestic resource, 'e' represents an electric generator, and 'p' represents a process. Select demand technologies and end-use demands are represented in the residential ('r') and light duty transportation ('tl') sectors. In addition, 'ngcc' refers to natural gas combine-cycle, and 'ngsc' to natural gas simple-cycle.

The model time horizon spans 2010 to 2035 in 5-year increments. Six annual time slices are included (the number in parentheses represents fraction of the year): summer-day (0.125), summer-night (0.125), winter-day (0.125), winter-night (0.125), intermediate-day (0.25), and intermediate-night (0.25). Total residential and light duty transportation demand is 0.63 Quads in 2010, growing to 0.83 Quads in 2035. Annual growth in residential lighting, space heating and cooling, and water heating demand is 0.86%, which is based on the annual growth in U.S. residential primary energy demand from 2001 – 2010 (EIA, 2011). Likewise, annual growth in light duty transportation demand of 0.002% is based on the growth rate in U.S. transportation petroleum demand from 2001 – 2010 (EIA, 2011). The estimated commodity prices as well as technology cost and efficiency estimates are derived from U.S. data sources: Commodity prices are drawn from EIA (2012), energy generation data is taken from EIA (2010), and demand technology from EPA (2008). The base case produces the results shown in Figures 2 and 3.

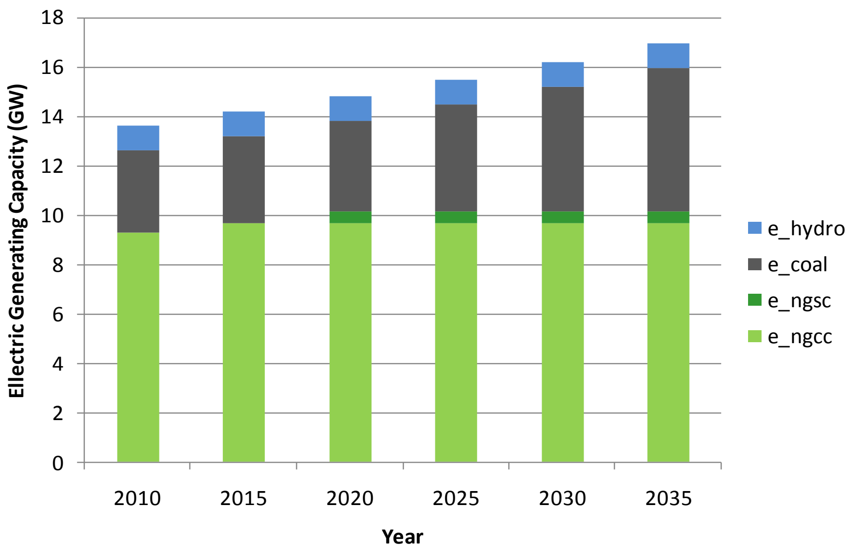

Figure 2 — Installed electric generation capacity in the Temoa_Island base case. There is no pre-existing capacity in the system, and e_hydro is limited to 1 GW each model time period.

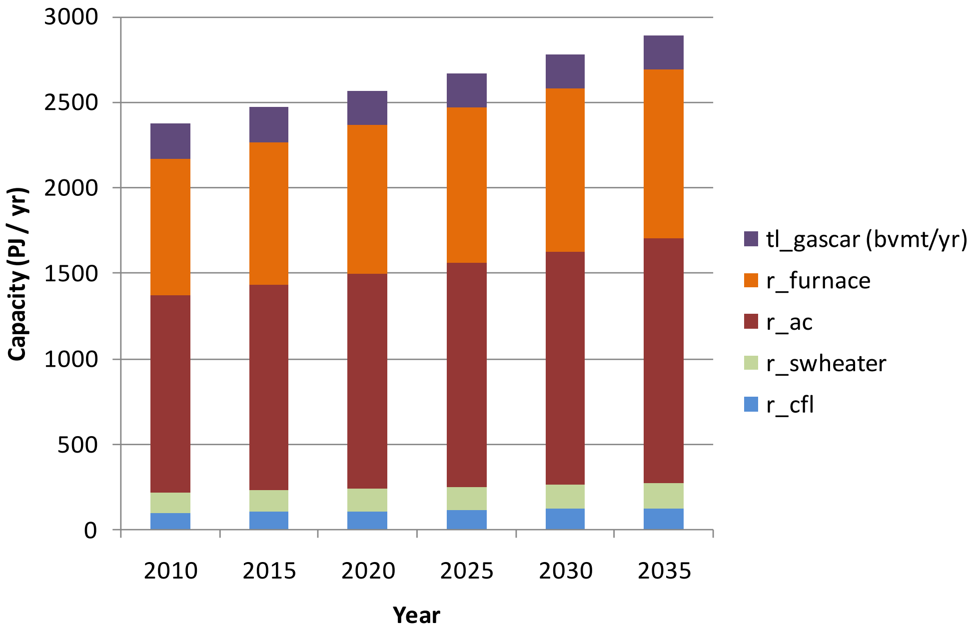

Figure 3 — Installed demand technologies in the Temoa_Island base case. Note that the output units for all demand technologies are PJ/yr, with the exception of light duty transport, which is in billions of vehicle-miles traveled/yr.

As noted above, there is no pre-existing capacity in the system. Figure 2 indicates that electricity demand is met with hydroelectricity (e_hydro), coal-fired power (e_coal), combined-cycle gas turbine (e_gtcc), and simple-cycle gas turbine (e_gtsc) capacity. A shown in Figure 3, light duty transportation demand (tl_distance) is met exclusively with gasoline vehicles (tl_gascar); space heating (r_heating) with natural gas furnace (r_furnace); space cooling (r_cooling) with central air conditioning (r_ac); lighting demand with compact fluorescent lights (r_cfl); and hot water demand is met with solar hot water heaters (r_swheater). All model source code, data, and results used in this analysis are archived online at http://temoaproject.org.

4. Stochastic problem formulation

PySP is used to perform a stochastic optimization of the Temoa_Island system described in Section 3. The stochastic model run incorporates uncertainty in two parameters: natural gas price and crude oil price. At each stochastic stage (2020, 2025, 2030, 2035), both the crude oil and natural gas prices can increase or decrease, leading to 4 branches per node as shown in Figure 4. Results from the non-anticipative periods (2010, 2015) constitute a hedging strategy, which provides a single course of action based in part on the expected value of later, uncertain time stages.

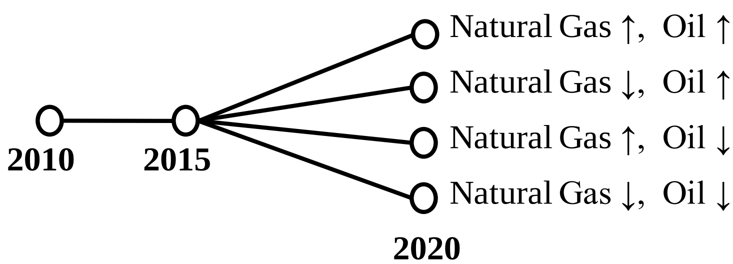

Figure 4 — Event tree showing the resolution of natural gas and crude oil price uncertainty beginning in 2020. Since there are 4 time periods with modeled uncertainty and each node has 4 branches, there are a total of 256 (4^4) scenarios. The up arrow (↑) indicates a price increase and the down arrow (↓) represents a price decrease.

Annual fuel price data from 1968 to 2010 drawn from EIA (2011) were used to calculate branch-specific probabilities and growth rates. Each joint observation of year-to-year change in natural gas and crude oil price in the historical record is categorized according to the branches in Figure 4. The subjective probability for each branch is calculated by dividing the number of historical observations in each category by the total number of observations in the record. For simplicity, the branch-specific probabilities are not updated from one model time period to the next, but instead remain constant through time. The growth rates for both stochastic parameters are determined by the average historical growth rate in each category. Table 1 below provides the growth rates and probabilities used in the model.

Table 1 – Subjective probabilities and parameter-specific growth rates for each possible outcome

Category	**Subjective Probability (%)**	**Parameter**	**Growth Rate**
Natural Gas ↑, Oil ↑	38.10	Natural Gas Crude Oil	0.075 0.25
Natural Gas ↑, Oil ↓	19.05	Natural Gas Crude Oil	0.088 -0.095
Natural Gas ↓, Oil ↑	19.05	Natural Gas Crude Oil	-0.050 0.17
Natural Gas ↓, Oil ↓	23.81	Natural Gas Crude Oil	-0.060 -0.18

In order to solve the stochastic form of the model with PySP, it is necessary to specify the baseline version of the Temoa model and the event tree information provided in Table 1 above.

During the non-anticipative stages, fuel prices remain constant at current market values and demand increases at the business-as-usual rate of 0.86%. The result is a hedging strategy for the non-anticipative stages (2010, 2015) with recourse actions beginning in 2020 as uncertainty is resolved.

5. Results

The stochastic run of Temoa_Island with 256 scenarios was conducted on a single node of Cygnus, an 11 node, 88-core compute cluster located at NC State University. The model consisted of 2,985,047 constraints and 2,169,015 decision variables and was solved using CPLEX. The CPLEX pre-solver reduced the number of constraints and variables to 636,264 and 355,032, respectively. The model took 7 hours, 42 minutes to solve and required approximately 4.5 gigabytes of memory.

The effect of stochastic fuel prices on total system cost is shown below in Figure 5. The figures show the price of natural gas and crude oil in 2035, the last model time period. The vertical spread in total cost when plotted versus natural gas price (left panel) is due to the effect of oil prices, which are varying at the same time as natural gas prices. The right panel suggests a strong correlation between crude oil price and total system cost. For example, it is possible to have a low system cost with a high natural gas price in 2035, but not a low system cost with a high crude oil price in 2035.

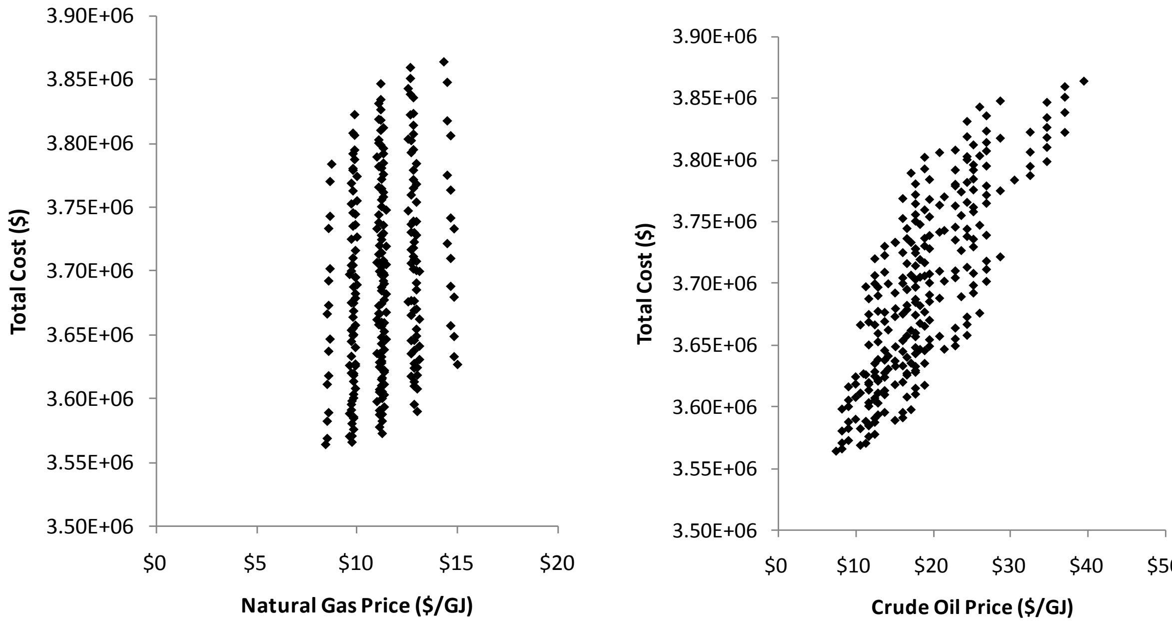

Figure 5 – The effect of stochastic natural gas prices (left) and crude oil prices (right) on the objective function value, which represents the total discounted system cost to supply energy. The results suggest that crude oil price has a larger effect on total system cost than natural gas price. Note the suppressed zero in both plots.

Figure 6 below provides capacity results from the two most extreme scenarios: fuel prices rise monotonically from 2020 to 2035 (top row), and fuel prices decrease monotonically from 2020 to 2035 (bottom row).

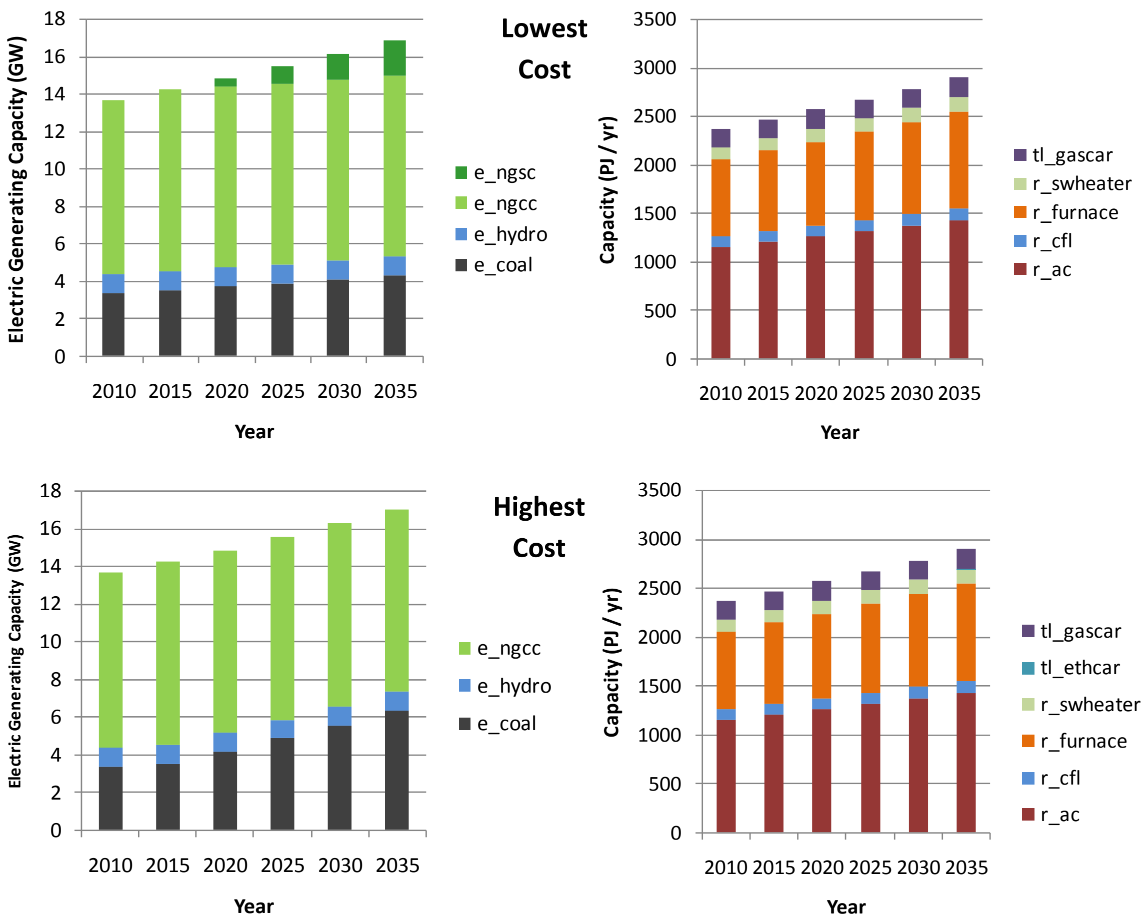

Figure 6 – Installed electricity capacity (left column) and demand technology capacity (right column) in both the lowest cost scenario in which natural gas and crude oil prices decrease monotonically (top row) and the highest cost scenario in which natural gas and crude oil costs increase monotonically (bottom row).

The results shown in Figure 6 demonstrate that the simple modeled system is relatively robust with regard to future uncertainty in crude oil and natural gas prices. In the non-anticipative stages (2010 and 2015), the stochastic optimization yields a unified hedging strategy. In the first decade, the model chooses to build coal, hydroelectric, and combined-cycle natural gas capacity in order to meet electric demand. In the scenario where natural gas prices decrease monotonically over time beginning in 2020, the model chooses to meet growing demand with simple-cycle natural gas turbines, which are less efficient but have a lower capital cost compared to combined-cycle. The results for demand technologies show little change across the two scenarios, suggesting that the technology options selected in the base case are robust to changes in fuel price. In the high fuel price scenario, the modest deployment of ethanol-power cars in

2035 (0.4 billion vehicle miles) suggests that the model is close to a tipping point that could favor ethanol over gasoline.

6. Discussion

Uncertainty analysis with EEO models is often limited or cursory, in part because it is an afterthought in the model development and application process. Temoa represents an open source EEO modeling framework specifically designed to conduct rigorous uncertainty analysis in a high performance computing environment. Unlike previous efforts to apply stochastic optimization in a limited way to existing, complex EEO models, this paper exercises the Temoa framework by solving a stochastic version of a simple energy system, which serves as a tractable computational testbed. Despite the simplicity of the Temoa_Island system tested here, the introduction of two stochastic parameters over 4 model time stages resulted in a stochastic formulation with 256 scenarios and over 350,000 decision variables. The model took roughly 7.5 hours to solve using CPLEX and required approximately 4.5 gigabytes of memory.

The results indicate that the total system cost is more sensitive to the oil price than to natural gas price as shown in Figure 5. This is due largely to the estimated growth rates associated with crude oil price, which are derived from the historical data record that includes the large fluctuations in oil price associated with the oil embargos. In general, the system is robust, with future uncertainty in crude oil and natural gas prices having only small impacts on technology deployment. Immediate future work includes the implementation of progressive hedging and Bender’s decomposition as alternative solution methods, both of which can decompose a stochastic program into pieces that can be solved in parallel on a compute cluster. Our intention is to scale to larger systems after we further develop the capability to conduct uncertainty analysis in a parallel computing environment.

Acknowledgments

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