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

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Extended Abstract
Energy system models are a critical tool used to evaluate the potential future impacts of energy and environmental policy. Given the expansive system boundaries and multi-decadal timescales involved in model projections, addressing large future uncertainties in these models is a key challenge. A common approach is to build larger models with greater complexity to deal with structural uncertainty, and run a few highly detailed scenarios under different input assumptions to address parametric uncertainty. The result is often large and inflexible models used to conduct limited scenario analysis that offers little insight.

Our research at North Carolina State University has focused on producing sound, policy relevant insight through improved scenario and uncertainty analysis. We have developed Tools for Energy Model Optimization and Analysis (Temoa), a bottom-up, technology rich energy system model embedded within a larger framework for analysis. Temoa includes two key features that make it unique within the energy modeling community: (1) all source code and data are publicly archived online using a modern revision control system, and (2) the model was designed to operate in a high performance computing environment in order to facilitate rigorous uncertainty analysis (Hunter et al, 2013).

We observe two critical shortcomings with the standard approach to scenario analysis. First, most model-based analyses assume a set of exogenous scenario-based assumptions to capture potential outcomes. While the resultant family of scenarios is meant to capture the range of potential future outcomes, they are of limited value to decision makers who must make a single set of near-term decisions before uncertainty is resolved (Morgan and Keith, 2008). Second, by focusing on changes to exogenous parameters, conventional scenario analysis tends to focus on parametric rather than structural uncertainty. Yet structural uncertainty, which refers to the imperfect and incomplete nature of the model, has a large influence on model results. The poor performance associated with past efforts to predict future energy outcomes supports this assertion (Craig et al., 2002). Below, we discuss our approach to address these issues.

Rather than running a set of independent scenarios, parameter uncertainty can be incorporated within the model formulation by performing stochastic optimization. This technique involves building an event tree and simultaneously optimizing over all specified future outcomes, each weighted by a subjective probability of occurrence (Loulou et al., 2004). The resultant stochastic solution represents a near-term hedging strategy that accounts for potential future outcomes and puts the decision maker in a position to take recourse action as the uncertainty is resolved. Compared to any single perfect foresight scenario, the stochastic solution is necessarily more expensive because it hedges risk by simultaneously accounting for all specified scenario outcomes rather than assuming that future outcomes are correctly guessed at all points. A critical

issue is whether the resultant hedging strategy is worth the extra cost. There are two relevant cost metrics to assess the efficacy of the hedging strategy: (1) the expected cost of perfect information (EVPI), which is the difference in cost between the stochastic solution and the expected value of the perfect foresight scenarios (Clemen and Reilly, 2004), and (2) the expected cost of ignoring uncertainty (ECIU), which can be used to value the stochastic solution relative to planning that ignores future uncertainty and may require more drastic recourse action (Birge and Louveaux, 1997; van der Weijde and Hobbs, 2012). While running the stochastic version of the model as well as calculating EVPI and ECIU is computationally intensive, Temoa was specifically designed to handle such analyses.

To address structural uncertainty, we have implemented an optimization technique called model to generate alternatives (MGA). Rather than generate different scenarios based on differing exogenous assumptions, the MGA algorithm forces an optimization model to search the feasible, near-optimal region of the solution space for alternative solutions that are maximally different in decision space. Brill et al. (1982) describe the steps associated with the Hop-Skip-Jump (HSJ) MGA method as follows: (1) obtain an initial optimal solution by any method, (2) add a user-specified amount of slack to the value of the objective function(s), (3) encode the adjusted objective function value(s) as an additional upper bound constraint(s), (4) formulate a new objective function that minimizes the weighted sum of decision variables that appeared in the previous solutions, (5) iterate the re-formulated optimization, and (6) terminate the MGA procedure when no significant changes to decision variables are observed in the solutions. MGA allows modelers and decision-makers to quickly and efficiently probe the decision space in order to identify plausible alternative options. Previous work has illustrated the utility of MGA through a simple energy application (DeCarolis, 2011).

The presentation will include a more detailed description of stochastic optimization and MGA, and also present an application to a simplified energy system using Temoa.

References

Birge JR, Louveaux F. (1997) “Introduction to stochastic programming”, Springer, New York.

Brill, ED, Chang SY, Hopkins LD. (1982), “Modeling to generate alternatives: the HSJ approach and an illustration using a problem in land use planning” Management Science 28, 221–235.

Clemen RT, Reilly T. (2004), “Making Hard Decisions” South-Western College Pub, Cincinnati OH.

Craig PP, Gadgil A, Koomey JG. (2002), “What can history teach us? A retrospective examination of long-term energy forecasts for the United States” Annu. Rev. Energy Environ. 27, 83–118.

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

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

Loulou R, Goldstein G, Noble K, (2004), “Documentation for MARKAL Family of Models” http://www.etsap.org/documentation.asp. Accessed 12 May 2010.

Morgan G, Keith D. (2008) “Improving the way we think about projecting future energy use and emissions of carbon dioxide”, Climatic Change, 90: 189-215.

Van der Weijde, AH, Hobbs, BF (2012) “The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty”, Energy Economics, 34: 2089-2101.