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Using modeling to generate alternatives (MGA) to expand our thinking on energy futures

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A R T I C L E I N F O

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A B S T R A C T

Energy-economy optimization models – encoded with a set of structured, self-consistent assumptions and decision rules – have emerged as a key tool for the analysis of energy and climate policy at the national and international scale. Given the expansive system boundaries and multi-decadal timescales involved, addressing future uncertainty in these models is a critical challenge. The approach taken by many modelers 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 analysis that offers little insight. This paper introduces a technique borrowed from the operations research literature called modeling to generate alternatives (MGA) as a way to flex energy models and systematically explore the feasible, near-optimal solution space in order to develop alternatives that are maximally different in decision space but perform well with regard to the modeled objectives. The resultant MGA alternatives serve a useful role by challenging preconceptions and highlighting plausible alternative futures. A simple, conceptual model of the U.S. electric sector is presented to demonstrate the utility of MGA as an energy modeling technique.

1. Introduction

Effective climate change mitigation will require carefully crafted policy that brings about fundamental changes in the way energy is produced and consumed. While the future is highly uncertain, energy-related decisions with long-lived consequences must be made today with the best possible information, imperfect as it is. Energy-economy optimization models have emerged as an important tool to explore energy futures using a structured and self-consistent set of assumptions and decision rules.[1] Such models have been used at the international, national, and regional levels to perform integrated assessments of future energy system development and its impact on social, economic, and natural systems over the next several decades (e.g., Clarke et al., 2007; Edmonds et al., 2004; EIA, 2009a; Nakicenovic et al., 2000; Yeh et al., 2006). While models can inject crucial insight into the planning process, they also have the potential to produce misleading results.

Though often not clearly articulated, energy-economy optimization models are generally put to three broadly defined objectives: (1) prediction of future quantities, (2) prescriptive analysis for planning purposes, and (3) generation of insight related to policy design and implementation. A critical challenge associated with using energy-economy optimization models – to meet any or all of the above objectives – is dealing with large future uncertainties. A set of projections or scenarios produced with optimization models should, to the degree possible, account for the underlying uncertainty in order to produce constructive insight. The sage advice that modelers should focus on generating robust insights rather than point estimates is not new (e.g., Huntington et al., 1982), though it has often gone unheeded. This paper raises concerns about the current treatment of uncertainty in energy-economy optimization models and introduces a technique borrowed from the operations research literature to illustrate how uncertainty can be addressed more effectively.

An optimization technique called modeling to generate alternatives (MGA) was developed nearly 30 years ago and applied to land and water management problems in order to produce a set of planning alternatives (Brill et al., 1982, 1990). As explained in greater detail below, MGA 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. The purpose of this paper is to introduce MGA to energy economists as a powerful and efficient method for probing the decision space of large, complex energy-economy

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[1] In this paper, energy-economy optimization 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.

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optimization models to produce insights that might not be realized with the standard suite of tools for uncertainty analysis. Section 2 classifies types of uncertainty and describes how it is usually addressed in analyses with energy-economy optimization models. Section 3 reviews the concept of MGA and indicates how it is applied to optimization models. Sections 4 and 5 describe a conceptually simply and transparent linear optimization model that was created as a test case to illustrate the utility of MGA, providing insight without the detailed explanation required of a large model. The model optimizes the installation of new electric sector capacity to replace all existing U.S. fossil-based generation by 2050. Section 6 draws conclusions and discusses the role that MGA can play in future integrated assessments.

1.1. Characterizing uncertainty

While there are many ways to classify uncertainty, this paper draws a fundamental distinction between structural and parametric uncertainty. In this paper, structural uncertainty refers to the imperfect and incomplete nature of the equations describing the system and parametric uncertainty refers to uncertainty regarding the assumed value of model inputs.[2] Uncertainty regarding the form and structure of models is difficult to address. The conventional approach to dealing with structural uncertainty is to build larger and more complex models to account for additional dynamic processes. Because these models cannot be validated in the same way that models of physical processes can, there is little to guide the modeler and reign in efforts that do not improve model performance in validation exercises.[3] In addition, the increasing complexity of many models – ostensibly aimed at reducing structural uncertainty – makes it harder to address the parameter uncertainty through sensitivity and uncertainty analysis. As a result, many large models contribute relatively little insight about alternative ways to structure and analyze the system under consideration (Morgan and Henrion, 1990). The poor performance associated with past efforts to predict future energy outcomes supports this assertion (Craig et al., 2002).

Parameter uncertainty is usually addressed in analyses with energy and integrated assessment models by running a few scenarios (e.g., EIA, 2009a; Clarke et al., 2007; Nakicenovic et al., 2000; IEA, 2006). 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). Scenario analysis can yield greater insight into uncertainty if the scenarios represent ranges of inputs, are assigned a subjective probability, and are mutually exclusive and exhaustive (Morgan and Keith, 2008; Kann and Weyant, 2000).

Beyond scenario analysis, a more rigorous treatment of uncertainty in optimization models involves sensitivity analysis and Monte Carlo simulation of uncertain parameters. Sensitivity analysis allows the modeler to identify the model parameters that have the largest effect on key model outputs. Monte Carlo simulation yields a distribution of outputs that reflects the uncertainty in input parameters, which are represented as probability distributions. The distribution of outputs provides a quantitative measure of risk or dispersion in the model results (Peterson, 2006). Because each model realization within a Monte Carlo simulation assumes (a priori) a particular state of the world based on the input values drawn, the parameter uncertainty is propagated through the model. Resolution of uncertainty before the optimization is performed represents a “learn then act” approach (Kann and Weyant, 2000). However, the challenge of policy makers is to make decisions that are robust to uncertainty before it is resolved; that is, to take an “act then learn” approach. Decision strategies that are robust to future uncertainty can be developed by employing sequential decision-making under uncertainty, whereby decisions at specific points in time are made based on a joint distribution that describes the possible outcomes in future time periods (Kann and Weyant, 2000). The joint distribution is updated after each decision period to reflect the partial resolution of uncertainty and the effect of learning. Because decisions are made at multiple points in time over the model horizon based in part on the probability distributions associated with uncertain parameters, it is often referred to as multi-stage stochastic optimization. However, all of these techniques – sensitivity analysis, Monte Carlo simulation, and stochastic optimization – address parameter uncertainty. If there are underlying structural uncertainties associated with the model formulation, then the results produced with these methods may not accurately reflect the true uncertainty.

Even if all parameter uncertainty were eliminated such that the future could be encoded in a single set of time-dependent input assumptions, energy system and integrated assessment models would still be poor predictors of future outcomes because the set of mathematical equations describing the system are imperfect and incomplete. This point is addressed by Casman et al. (1999), who combined parametric variation of both structural and parameter assumptions in a simulation-based integrated assessment model to produce robust assessments of uncertainty in future climate change.

Similar attempts to address structural uncertainty within energy economy optimization models have been minimal. Efforts aimed at model comparison, such as the Energy Modeling Forum and Innovative Modelling Comparison Project, provide a way to identify structural differences across a set of models. Such comparison exercises are valuable; however, they occur intermittently and are focused on identifying differences across models. No sustained effort exists to evaluate, test, and improve the treatment of structural uncertainty within an individual model.

Since energy-economy optimization models are incapable of delivering accurate long range predictions, attention should be focused on a rigorous exploration of the decision space to produce insights along with robust estimates of both parametric and structural uncertainty. Alternative solutions generated with energy-economy optimization models also provide valuable insight that can be used to challenge preconceptions and suggest creative alternatives to decision makers.

1.2. An introduction to MGA

Discussion within the operations research/management science literature 20–30 years ago about the proper use of optimization models remains remarkably prescient with regard to energy-economy optimization models today (Brill, 1979, 1982, 1990). The basic insight can be summarized as follows: Because it is not possible to develop a complete mathematical representation of complex public planning problems, structural uncertainty in optimization models will always exist. As a result, the ideal solution is more likely to be located within the model's inferior region rather than at a single optimal point or along the non-inferior frontier (Brill, 1979). Unmodeled objectives – a key source of structural uncertainty – can result in an optimal solution that lies within the inferior region of the model's solution space. Conventional multi-objective optimization allows the modeler to explore the non-inferior (Pareto optimal) frontier, but not the feasible, suboptimal region. While additional objectives can be added to a model, there are two limitations to this approach: (1) it does not address remaining unmodeled

[2] Here parametric uncertainty is broadly defined to include uncertainty associated with data parameters (e.g., technology characteristics), value parameters (e.g., discount rate) and parameters that can vary stochastically over time (e.g., commodity prices).

[3] For a thorough treatment of model validation, see Hodges and Dewar (1992).

objectives and (2) tradeoff analysis among a large number of objectives becomes tedious. By contrast, MGA uses the optimal model solution as an anchor point to explore the surrounding feasible region. Policy makers often have strong concerns outside the scope of most models (e.g., political feasibility, permitting and regulation, and timing of action), which implies that feasible, suboptimal solutions may be preferable for reasons that are difficult to quantify in energy economy optimization models.

Given the complexity of most public policy analysis, there will always be structural uncertainty. This observation is particularly relevant to multi-decadal planning based on the use of energy-economy optimization models. Accepting the ubiquity of structural uncertainty implies that even if modelers had a crystal ball that allowed precise specification of all input assumptions, the optimal solution is still likely to be off the mark because the mathematical equations describing the system are incomplete. The treatment of structural uncertainty in energy-economy optimization models has not received adequate attention.

MGA can serve as a useful tool for addressing structural uncertainty in such models. The purpose of MGA is to efficiently search the feasible region surrounding the optimal solution to generate alternative solutions that are maximally different. 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), (3) formulate a new objective function that minimizes the weighted sum of decision variables that appeared in the previous solutions, (4) iterate the re-formulated optimization, and (5) terminate the MGA procedure when no significant changes to decision variables are observed in the solutions. Borrowing the mathematical formulation from Brill et al. (1982), the HSJ MGA procedure can be summarized as follows:Minimize:

$$p = \sum_{k \in K} x_k.$$

Subject to:

$$f_j(\vec{x}) \leq T_j \quad \forall j$$

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

where K represents the set of indices of decision variables with nonzero values in the previous solutions, $f_j(\vec{x})$ is the jth objective function in the original formulation, T_j is the target specified for the jth modeled objective (slack + optimal objective function value), and X is the set of feasible solution vectors. Note that $x^{\in X}$ implies that the constraints in the original problem formulation also apply in the MGA formulation.

In this way, the MGA procedure confines the model to explore a prescribed inferior region near the original optimal solution. The result is a set of solutions that perform well with regard to modeled objectives, but may be very different in decision space. Applied to energy-economy optimization models, MGA provides a technique to quickly and easily generate a set of alternative energy futures. Because the alternative outcomes are computer-generated, they do not present the same cognitive biases associated with the bottom-up construction and analysis of detailed scenarios as noted by Morgan and Keith (2008). In addition, the reformulated objective function that seeks to minimize the appearance of decision variables from the previous solutions creates a set of energy futures that are distinctly different from one another. This is a valuable feature that allows modelers and decision-makers alike to think creatively about solutions to complex energy and environment problems. The degree of difference in decision space between alternative MGA solutions will mainly depend on three factors: (1) the variance in objective function coefficients, (2) the amount of prescribed slack (i.e., the values selected for T_j), and (3) the degree to which the decision variables are constrained.

The MGA scenarios represent plausible alternatives to the model's optimal solution, and may in fact be closer to the desired optimum given that there are unmodeled objectives and other structural uncertainties that can be identified but not easily modeled. For example, in a simple cost minimization model such as the one presented below, unmodeled objectives may include considerations such as risk, equity, and public opinion. Note that MGA represents a fundamental departure from other forms of uncertainty analysis. While both Monte Carlo simulation and stochastic optimization techniques make use of probability distributions to represent uncertain parameters, an *ex post* analysis can map a specific point in parameter space to a specific point in the solution space. On the other hand, MGA involves a reformulation of the model's original objective function, so a point representing an MGA solution in the solution space is not linked to a specific point in the original parameter space. Modelers are used to a "cause and effect approach": make a change to input parameters and observe a change in the solution. While one can simply accept MGA solutions as equally plausible alternatives to the original least cost solution, it would be valuable to know if a modified set of objective function coefficients in the original non-MGA formulation can uniquely reproduce the results from an MGA solution. An affirmative answer suggests there is an equivalency between a solution generated by MGA and a specific perturbation of input parameters in the original model formulation. The following discussion and electric sector modeling exercise focus on linear optimization for simplicity. As a result, the discussion below applies directly to technology-detailed, bottom up partial equilibrium models like MARKAL and MESSAGE. While MGA can be applied to non-linear computable general equilibrium models, a detailed discussion is beyond the scope of this paper.

Optimal solutions to linear programs always lie at the extreme points of the feasible region, and extreme points always lie at the intersection of constraint equations expressed as strict equalities. However, MGA forces the model to search within a portion of the feasible region, the size of which is determined by the specified slack in the MGA model formulation. Because the MGA solutions are typically non-extreme points in the original model formulation, a set of objective function coefficients in the original problem formulation usually does not exist that can *uniquely* reproduce the MGA solution. This conclusion is demonstrated with a very simple example in Fig. 1.

The linear optimization presented in Fig. 1 will converge to one of the extreme points represented by the open circles. An objective function contour is represented by the lower dotted line, and the optimal solution is $x_1 = 1$, corresponding to the open circle on the x_1 axis. In the first MGA iteration, the new objective is to minimize x_1. For the new constraint on the original objective function, suppose that the slack introduced is positive but less than $c_2 - c_1$. The resulting new constraint is shown by the upper dashed line. This creates a new extreme point in the MGA run at the intersection of the demand constraint and the constraint on the original objective function. Because this new MGA extreme point is a

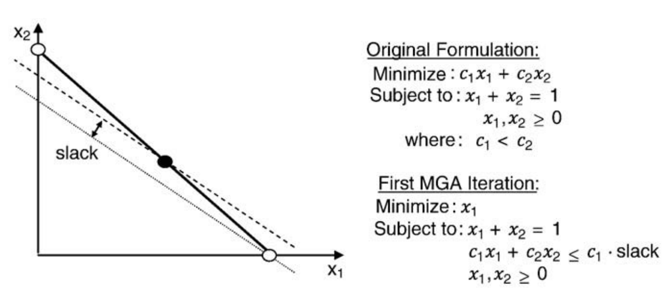

Fig. 1. Illustration of the MGA procedure in a simple linear optimization. Two technologies of differing cost must be used to meet a fixed demand. This problem is trivial and can be solved by inspection: the model will choose x_1 over x_2 unless $c_2 \leq c_1$. Nonetheless, it is a useful illustration of how MGA works more generally.

Table 1
Technology cost and performance data.
Taken from EIA (2009b).

Technology[a]	Capital Cost ($/kW)	Fixed O&M ($/kW·yr)	Variable O&M ($/kWh)	Efficiency (%)	Capacity Factor (%)	Average Cost ($/kWh)	Baseload/Shoulder/Peak (B/S/P)	Capacity Constraint[b] (GW)
Pulverized Coal	2058	27.5	0.0459	39	95	0.043	B	
IGCC	2378	38.7	0.0292	46	90	0.045	B	
IGCC-CCS	3496	46.1	0.0444	41	90	0.066	B	
GTCC-CCS	1890	19.9	0.0294	46	90	0.086	B	
Nuclear	3318	90.0	0.0049	33	95	0.054	B	
Geothermal	1711	165	0.00	11	90	0.044	B	23
GTCC	948	11.7	0.0200	54	95	0.062	Any	
GT	634	10.5	0.0317	40	95	0.076	Any	
Hydro	2242	13.6	0.0243	34	65	0.047	Any	2
Wind-Onshore	1923	30.3	0.00	34	35	0.076	S	8000
Wind-Offshore	3851	89.5	0.00	34	40	0.14	S	800
Solar Thermal	5021	56.8	0.00	34	40	0.17	S	100
Solar PV	6038	11.7	0.00	34	30	0.25	S	

[a] The following abbreviations are used: IGCC = integrated coal gasification combined-cycle, CCS = carbon capture and sequestration, GTCC = gas turbine combined-cycle, and GT = gas combustion turbine.
[b] Capacity constraint for geothermal drawn from McGowan et al. (2001) and does not include hot dry rock resources; the hydropower constraint in based on results from the High Renewables case of the Annual Energy Outlook (EIA, 2009a); wind power limits based on inputs to the NREL WinDS model (Denholm and Short, 2006), and the solar thermal limit is a conservative estimate by the author.

feasible, non-basic solution in the original model, it is not possible to manipulate c_1 and c_2 in order to uniquely obtain the MGA solution. However, if the slope of the objective contour is equal to the slope of the demand constraint (i.e., $c_1 = c_2$), then it is at least possible to obtain the MGA solution via a linear combination of extreme points from the original problem.

The insight from Fig. 1 can be generalized to much more sophisticated least-cost optimization models, assuming that demand is fixed and must be met with strict equality. In such models, the entry of a previously inactive technology into an MGA solution suggests that unmodeled objectives make the technology a desirable component of the solution despite higher cost. Alternatively, the MGA solution can be interpreted in the context of the original model formulation. In order for the original model formulation to produce the MGA solution via linear combination, the previously inactive technology must be cost-competitive with the other active technologies. Thus MGA has two equally valid interpretations: (1) it accounts for structural uncertainties such as unmodeled objectives and (2) it represents a perturbation of the objective function coefficients, though there is not a specific perturbation that can uniquely reproduce the MGA solution.

Note that the goal of the HSJ MGA method is to generate maximally different solutions within a constrained region of the decision space by modifying the objective function to minimize the appearance of previously selected decision variables. However, the MGA objective function can be modified in other ways to explore the decision space. For example, in a partial equilibrium energy system model, the user may wish to maximize the deployment of a particular set of technologies within the cost-effective region surrounding the optimal solution. The use of MGA can be incorporated into a larger energy-environment decision support framework, allowing users to explore the decision space by altering the model objectives. While important decisions should always be made by human experts rather than prescribed by a model, such a framework would significantly expand the utility of energy-economy optimization models by allowing users to interact in a more meaningful way. An example of such user interaction applied to an airline network problem is provided by Brill et al. (1990).

1.3. Wedge analysis of U.S. electric power sector

A simple least-cost linear optimization model of the U.S. electric sector was constructed to demonstrate the application of MGA. The model optimizes the installation and operation of new generating capacity in 2050 to replace existing fossil-based generation and meet growing demand. The projection of electricity generation to 2050 is based on a linear extrapolation of the EIA (2009a) reference case. Two scenarios are considered: a business-as-usual (BAU) case with unconstrained CO_2 emissions and a CO_2-constrained case. Factors affecting the retirement of existing power plants are complicated and highly plant-specific. However, for the purposes of this simple modeling exercise, it is assumed in both the BAU and CO_2-constrained case that existing fossil capacity is retired at a constant linear rate, with enough capacity remaining in 2050 to serve as reserve margin for reliability purposes.[4] To first order, this is a reasonable assumption given the aging fleet of existing plants and their expected remaining life. With all existing fossil-based generation assumed to be displaced over the next 40 years, the model calculates the optimal capacity installations in 2050 and assumes linear increases from 2010 to 2050 to reach this optimal configuration. The result is a series of technology wedges similar to those presented in Pacala and Socolow (2004); however, in this case wedges represent electric generating capacity rather than carbon mitigation. In addition, the number and size of technology wedges are selected to minimize the annual system-wide cost of electricity. While the linear changes over time associated with capacity retirement and new capacity installations represent a major simplifying assumption, the model still provides a useful, transparent framework for considering changes to the electric sector. Thirteen electric generating technologies are represented in the model, with cost and performance characteristics drawn from EIA (2009b) and presented in Table 1. Model characteristics are described below and summarized in Table 2; key model equations are given in the Appendix.

U.S. electricity production from fossil sources in 2050 is assumed to be roughly 4300 TWh, based on a linear extrapolation of data from EIA (2009a). To roughly capture the economic dispatch of electricity, a simple three-layer discretized load duration curve (LDC) – representing baseload, shoulder, and peak demand – is created. The LDC is based on historical demand data (1997–2001) from the Pennsylvania–New Jersey–Maryland (PJM) grid (PJM, 2002). See Fig. 2. The relative proportions of electricity generation and installed capacity from the discretized PJM LDC are applied to projected 2050 electricity demand. Technologies are constrained to meet demand in one or more of the three demand segments. Because intermittent renewables alone cannot be dispatched reliably for peak or baseload functions, they are assumed to serve shoulder demand only. This assumption is made for simplicity,

[4] The assumption of fossil capacity remaining to serve as reserve margin is exogenous and simplifies the modeling exercise by allowing an exclusive focus on the displacement of fossil generation.

Table 2
Model specifications.

Model domain	
Spatial scale	U.S.
Sectors modeled	Electric
Timeframe	Investment and utilization decisions made for 2050 only; assumed linear increases from 2010–2050 to form technology wedges
Key Parameters	
Fuel costs[a]	Coal: 25 \$/short ton, natural gas: 7 \$/10^3 ft^3, uranium: 34 \$/lb uranium oxide
Discount rate	7%
Technology lifetime	30 years for all technologies
Carbon cap	Unconstrained case: no reduction; constrained case: 85% reduction from 2005 levels in 2050.
MGA slack	25%
Implementation	
Modeling tools	General Algebraic Modeling System (GAMS) with a CPLEX solver
Framework	Linear programming with 39 decision variables and 33 equations
Objective	Minimize the system-wide annual cost of electricity production in 2050

[a] Costs obtained from EIA (2008).

as analyses focused on intermittent renewables such as wind demonstrate that it can serve different demand segments (e.g., DeCarolis and Keith, 2006; Greenblatt et al., 2007).

The optimization is performed under two different CO_2 emission scenarios: a business-as-usual unconstrained case and a constrained case in which 2050 emissions are limited to be no more than 15% of 2005 emissions. The magnitude of the CO_2 reduction in the constrained case is consistent with U.S. cap-and-trade proposals currently under consideration (e.g., U.S. House, 2009), though in this analysis the cap is applied only to the electric sector and the availability of offsets and financial incentives for clean energy are not considered. No attempt is made to project costs to 2050 because the result of interest is not the absolute system-wide cost of electricity, but rather the relative proportions of different generating technologies selected by the model. Note that the model makes investment decisions based on the relative costs between technologies, so the simplifying assumption that 2005 costs apply in 2050 implies that the relative cost performance of all electric generating technologies is constant through time. As a result, there is no a priori assumption of significant shifts in the cost performance of different generating technologies in the initial (non-MGA) model formulation.

Once an initial solution is obtained, MGA is applied to the model to identify feasible alternatives to the least cost solution using the HSJ method described in Section 3. The number of MGA iterations performed depends on the termination procedure, which can be defined in different ways (Brill et al., 1982). In this analysis, the MGA procedure terminates when the set of technologies appearing in the latest MGA solution repeat a prior MGA solution set, which yields a manageable set of alternative solutions.

The amount of slack used in the MGA runs was set to 25% of the original least cost solution. The slack should be set such that the resultant system cost is constrained to plausible levels. As a reality check, the current U.S. national average electricity price is 0.091 \$/kWh (EIA, 2009c) and average household electricity consumption is roughly 11,000 kWh/yr (EIA, 2001), implying a monthly expenditure of about 85 \$/month. So a 25% increase in electricity price would raise the average monthly residential bill by roughly \$20, which is a large but arguably plausible change.

1.4. MGA electric sector results and discussion

Before examining the electric sector response to a CO_2 constraint, results from the BAU case are presented. Fig. 3 presents the least cost solution and the first three MGA solutions for comparison.

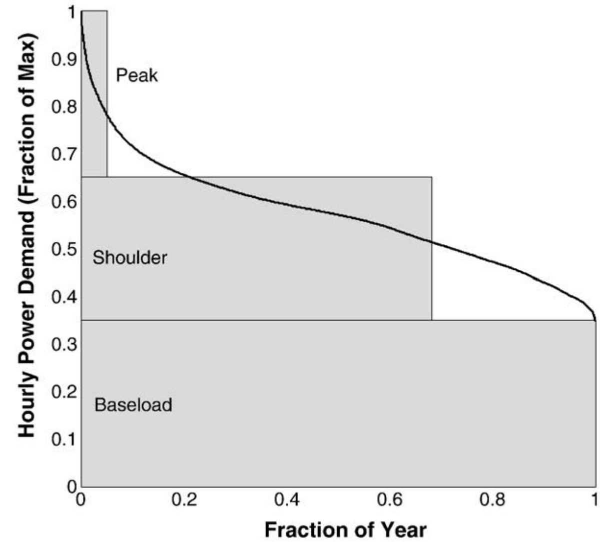

Fig. 2. Discretized load duration curve used to represent dispatch in 2050. The curve represents normalized production data from the PJM (a U.S. regional transmission organization) averaged across the years 1997–2001. This representation of load is encoded as a set of constraints on installed capacity and electricity generation, which forces the model to favor low marginal cost technologies for baseload and higher marginal cost technologies for shoulder and peak generation.

Note that the least cost solution to the original model formulation in Fig. 3 roughly agrees with other analyses that suggest combined-cycle gas turbines and new pulverized coal will dominate new installations (e.g., EIA, 2009a; EPA, 2009). The first MGA iteration replaces the conventional pulverized coal that appeared in the BAU least cost solution with IGCC and geothermal, which indicates that the costs of these competing technologies are close enough for them to enter the solution, given the specified slack in the MGA formulation. The comparison between the original BAU and MGA runs also demonstrates the ability of MGA to account for unmodeled objectives: although there is no limit on CO_2 emissions, all three MGA solutions produced emissions that were lower in 2050 – by 16%, 98%, and 68% – compared with the original least cost solution. This result is largely a consequence of the fact that the most cost-competitive technologies in the electric sector are more costly but emit less CO_2 than pulverized coal, which makes up a significant portion of the least cost solution. As mentioned above, the MGA procedure was terminated when the same combination of technologies in the solution was repeated. The MGA upper bound constraint on total system cost was binding in all three MGA cases, which is not surprising as it provides maximum cost flexibility in seeking alternative solutions.

The CO_2 constrained case requires an explicit upper bound constraint on emissions, which is set to 360 $MmtCO_2$, representing an 85% reduction below the 2005 emissions level in the U.S. electric sector. Note that the availability of offsets is not considered. The optimized wedges corresponding to the least cost and MGA solutions are presented in Fig. 4. Note that in this case, the model was not able to push onshore wind and combined-cycle gas turbines (GTCC) out of the first MGA solution. Not surprisingly, new pulverized coal does not enter any of the model solutions. Nuclear, combined-cycle gas, and onshore wind appear to play a critical role in most cases. Hydro and geothermal are present in every scenario, but their modest upper bound constraints mean that they cannot make a significant contribution to electricity generation.[5] Hydro and geothermal also highlight an important effect of the HSJ MGA approach: technologies with low upper bounds based on resource limitations never weigh heavily in the MGA objective function. As a result, technologies like

[5] Because the upper bound on new hydro is 2 GW, it was not included in Figs. 5 and 6.

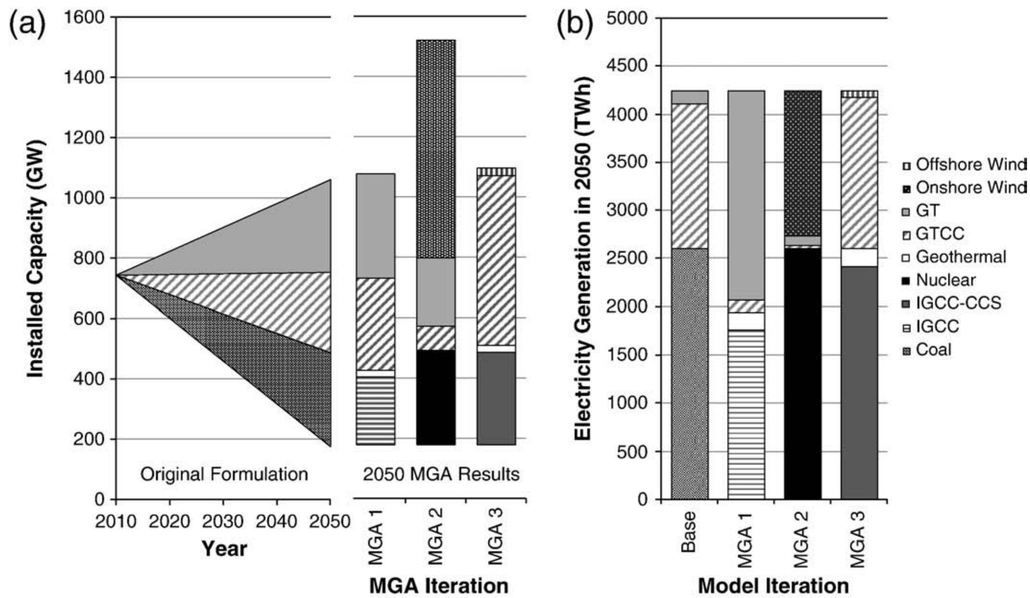

Fig. 3. Installed capacity in GW (a) and electricity generation in GWh (b) to replace existing fossil generation and meet growing demand under the BAU case. The technology wedges for the least cost solution in the original model formulation are presented in (a), along with the 2050 results for the following MGA iterations. The associated electricity generation is presented in (b) for the year 2050. The MGA procedure terminates after the same combination of technologies is observed twice in the solution set, which in this case occurred after 3 MGA iterations.

hydro with relatively low levelized cost become persistent features across the MGA solutions. The constraint on system cost is binding in all six MGA scenarios, driving the average generation cost of electricity from 0.059 $/kWh in the original CO_2-constrained solution to 0.074 $/kWh in the MGA solutions. Comparing the original least cost solutions in the BAU and CO_2 constrained scenarios (Figs. 3a and 4a), the average generation cost associated with the new installed capacity is 0.052 $/kWh and 0.059 $/kWh, respectively. The difference in estimates is low because it does not account for costs associated with upgraded transmission and distribution infrastructure and because less expensive low carbon technologies such as nuclear and combined-cycle gas turbines are unconstrained. Assuming perfectly competitive markets, the difference in the marginal cost of electricity generation between model runs – set by the deployed technologies with the highest average costs – provides a rough estimate of the allowance price. In the least cost BAU case, simple-cycle gas turbines (GT) set the marginal cost of electricity generation at 0.074 $/kWh. In Fig. 4 below, solar thermal with an average cost of 0.13 $/kWh sets the marginal cost of electricity in two of the four MGA cases. As a result, the maximum implicit carbon price between the BAU and CO_2 cases is ~90 $/mt$CO_2$, owing strictly to differences in generation cost. An allowance price of ~100 $/mt$CO_2$ is consistent with analysis generated using sophisticated CGE models to explore a pending economy-wide CO_2 cap-and-trade proposal (e.g., EPA, 2009).

The ability to automatically generate a set of feasible alternative solutions in a matter of seconds provides valuable insight at modest computational cost. For example, in the least cost CO_2 constrained case

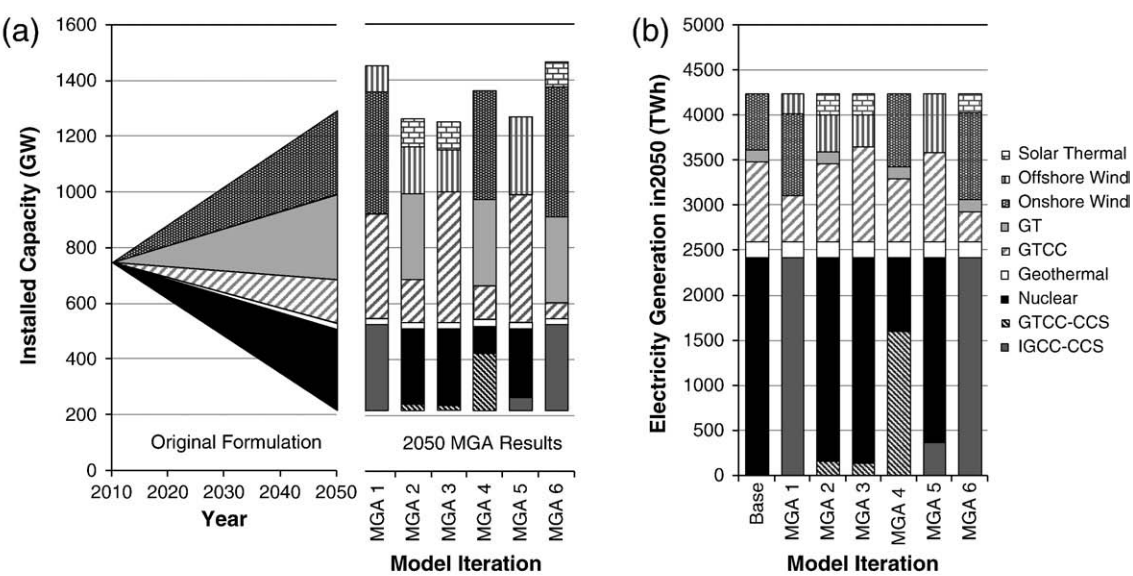

Fig. 4. Installed capacity in GW (a) and electricity generation in GWh (b) to replace existing fossil generation and meet growing demand under the constrained CO_2 case. The technology wedges for the least cost solution in the original model formulation are presented in (a), along with the 2050 results for the following MGA iterations. The associated electricity generation is presented in (b) for the year 2050. MGA terminates after 6 iterations; the upper bound constraint on system cost is binding in all solutions. Nuclear, combined-cycle gas, IGCC-CCS, and onshore wind play a key role in most of the solutions.

below in Fig. 4, nuclear power constitutes all of the baseload capacity. While such a result is clearly unrealistic, the linear optimization model nonetheless indicates that under the cost and performance assumptions given in EIA (2009b), nuclear would play a large role in a carbon constrained U.S. electric power sector. Obtaining such an unrealistic result, the first impulse of many modelers is to add a constraint to limit the penetration of nuclear based on estimates derived from the literature, or in many cases, subjective judgment. While this approach is reasonable in some instances, repetition over time will lead to a highly constrained model that simply returns the modeler's own input assumptions. An early example of this phenomenon observed in a global energy model is described by Keepin and Wynne (1984). MGA offers a different approach by returning a set of feasible, near-optimal alternatives without the need to further constrain the model. The MGA solutions that reduce nuclear installations can be interpreted as accounting for unmodeled issues related to nuclear power, such as: regulatory hurdles, public opposition, and the lack of a viable long term waste disposal option. The first MGA solution indicates that for a 25% cost premium, all nuclear could be displaced by IGCC-CCS. Again, the purpose of the MGA solutions is not to provide definitive prescriptive solutions, but rather to provide a set of plausible alternatives for further evaluation. For example, MGA Iteration 4 in Fig. 4b below implies that baseload demand can be met by a combination of GTCC-CCS and nuclear and still be within the cost-effective region determined by the 25 percent slack. However, IGCC-CCS is cheaper than GTCC-CCS (0.055 \$/kWh compared to 0.080 \$/kWh), so some portion of GTCC-CCS can be replaced by IGCC-CCS, with no impact on emissions but lower cost. Such comparisons across scenarios make the user an active participant in the modeling process, which leads to further insight.

In addition to providing modelers and decision-makers with an expanded set of different alternatives to consider side-by-side, it is also useful to assess which technology options appear to be the most robust across different scenarios. Fig. 5 presents a box plot that represents the optimized capacities for each technology from all the BAU and CO_2 constrained cases considered above. Inspection of Fig. 5 indicates that onshore wind, combined-cycle gas turbines (GTCC), gas combustion turbines (GT), nuclear, and IGCC-CCS play a significant role across multiple scenarios. However, there is also wide variability across scenarios, meaning that no single technology is indispensible in all circumstances. Of course, this conclusion is contingent on the value of the slack parameter, which was set at 25% of the least cost solution in all MGA scenarios presented above. With less slack in the system, certain technologies may clearly emerge as critical players. While such insight can be generated with conventional uncertainty analysis, the application of MGA produced these maximally different scenarios in an automated way in a few seconds.

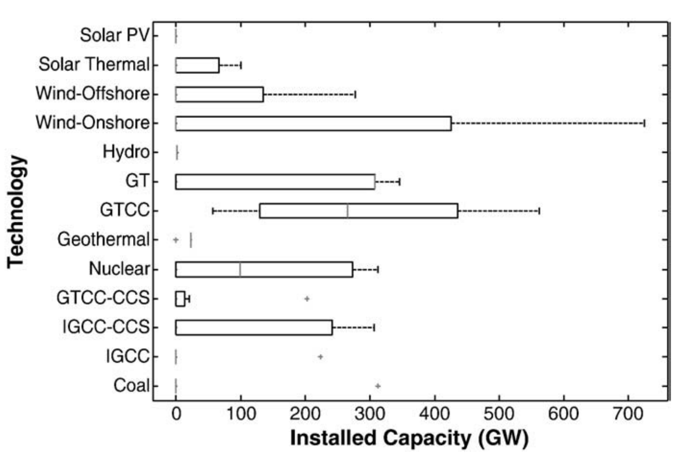

Fig. 5. Boxplot of installed capacity by technology across all BAU and CO_2 constrained scenarios presented above. No technology was present at significant levels (>50 GW) across all model runs.

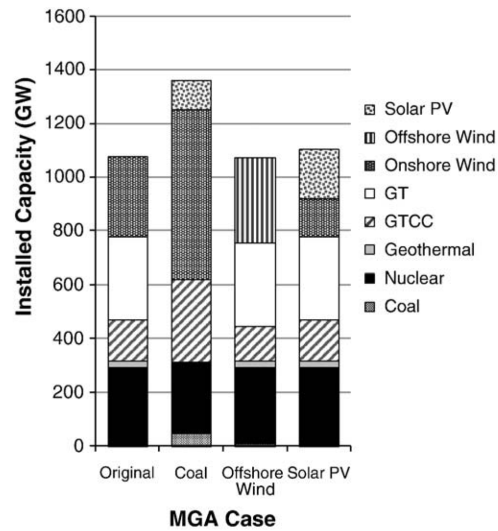

Fig. 6. Alternative MGA objectives under the CO_2 constraint. The objective function in the MGA iteration can be modified to probe the system in specific ways. The plot shows the result when the objective is to separately maximize coal, offshore wind, and solar PV. The least cost solution is reproduced on the left hand side for comparative purposes.

Finally, as noted in Section 3 above, the HSJ MGA method is only one way to explore the cost-effective region around the least cost solution. Fig. 6 presents results with different objective functions used for the MGA runs. For example, suppose an electric utility wanted to know how much new pulverized coal capacity could be built under the cap and trade system subject to a constraint on total cost. The objective function in the MGA run can easily be changed to maximize pulverized coal use, or that of any other technology. The results in Fig. 6 demonstrate the utility of MGA beyond simply generating a set of maximally different solutions: MGA can be used to probe the model decision space in specific ways defined by the user. A suite of MGA tools along with sensitivity and uncertainty analysis can be used to create a decision support framework for energy-economy optimization models that allows the user to explore the decision space and flex the model.

2. Discussion

Perfect knowledge of model inputs alone would not lead to accurate predictions because the form and structure of energy models is imperfect, owing to real world complexity and unpredictability that is difficult to model. Likewise, perfect form and structure alone do not lead to accurate predictions because of uncertainty in inputs. As a result, integrated assessments using energy-economy optimization models should rigorously account for both parametric and structural uncertainty. While most modelers concede the point, uncertainty analysis in the form of Monte Carlo simulation or stochastic optimization is often complicated by the size and complexity of many existing models.

Modeling to generate alternatives (MGA) allows modelers and decision-makers to quickly and efficiently probe the decision space in order to identify plausible alternative options. The developers of MGA realized that all models are highly simplified versions of reality, and that feasible, near-optimal solutions returned by optimization models are likely to be as useful as the optimal result. Application of the MGA HSJ method to the simple model presented here yields a set of interesting and divergent alternatives that cannot be uniquely generated by the original optimization model formulation. The MGA solutions can be interpreted as: (1) equally plausible alternatives to the least cost solution that account for structural uncertainty, and (2) a perturbation of the objective function coefficients in the original model formulation. The application of MGA can help modelers meet the three broad objectives articulated in the introduction by generating a set of results that account for structural uncertainty, thereby reducing the tunnel vision that can set in when exercising large models.

The wedge analysis presented here serves as a first application of MGA to a simple and transparent cost minimization model of the U.S. electric sector. The solutions generated by MGA in both the BAU and CO_2 constrained scenarios highlight the potential flexibility in system design, and provide analysts with a diverse set of alternatives that can be further analyzed. In addition, these alternatives were generated via a computer algorithm, and do not present the same cognitive biases as the highly detailed scenarios that must be carefully crafted by the modeler. Note that MGA takes the opposite approach to conventional scenario analysis: rather than user-generated scenarios that drive model outputs, MGA involves computer-generated results that drive scenario interpretation by users.

While MGA can help modelers account for structural uncertainty, it has its own limitations. First, choosing a value for the slack parameter is subjective and has a strong effect on the alternative solutions. Users can mitigate this effect by relating the slack parameter to key scenario indicators or performing parametric sensitivity analysis of the slack parameter. Second, as noted above, it is not possible to uniquely obtain a particular MGA solution simply by modifying the objective coefficients in the original model formulation. This makes MGA less intuitive than conventional scenario analysis, in which changes to input parameters have a direct and observable effect on model solutions. Finally, MGA does not assign subjective probabilities to alternative solutions, which means that cognitive heuristics can still play a role. Care must be taken to ensure that users do not implicitly assign equal probability to each MGA scenario. Future work includes the development of a decision framework that allows users to evaluate alternative MGA scenarios based on desirable features that are exogenous to energy economy optimization models. Another priority for future work is to develop quantitative measures of the degree of difference among alternative MGA solutions.

While similar results can be obtained through different methods (e.g., fixing technology and observing the total system cost), MGA presents a highly efficient and systematic way of exploring the feasible, near-optimal region. MGA should be viewed; however, as one among many techniques for conducting uncertainty analysis. In addition, techniques such as sensitivity analysis, Monte Carlo simulation, stochastic optimization, and MGA should not be viewed as mutually exclusive. Rather, they can be linked in series to develop robust strategies for future energy development. First, sensitivity analysis can be used to estimate partial rank correlation coefficients and identify the input parameters that have the greatest effect on the key model outputs (Tschang and Dowlatabadi, 1995; Kann and Weyant, 2000). Second, a joint distribution of the key uncertain parameters can be created for use in a multistage stochastic optimization framework. Finally, MGA can be applied to the stochastic optimization solution to test the robustness of the optimal hedging strategy. Energy-economy optimization models used in such a modeling framework would inject valuable insight into the planning process while including a rigorous treatment of both parametric and structural uncertainty.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.eneco.2010.05.002.

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