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# Application of a Novel Optimization Technique to Produce Maximally Different Energy Futures

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**Abstract**

Over the next half century, effective climate change mitigation will require carefully crafted policy that brings about fundamental changes in the way energy is produced and consumed. Energy optimization models have emerged as an important tool to explore different energy futures using a structured and self-consistent set of assumptions. Addressing future uncertainty in these models is a critical challenge. This paper classifies uncertainty in two categories: structural and parametric. Structural uncertainty refers to the imperfect and incomplete nature of the equations describing the system, and parametric uncertainty refers to uncertainty in the model inputs. 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 large and inflexible models used to produce analysis that offers little insight into the energy challenge at hand. Yet energy models are at their most useful when they stimulate creative thought and suggest new options. 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 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 suggesting creative alternatives to the problem under consideration. A simple model of the U.S. electric sector is presented to demonstrate the utility of MGA as an energy modeling technique.

## 1. Introduction

Over the next half century, 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. Both partial and computable general equilibrium models have emerged as an important tool to explore different energy futures using a structured and self-consistent set of assumptions. Such models have been used at the international, national, and regional levels to examine 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, 2000; Yeh et al., 2006). While models can inject critical insight into the planning process, they also have the potential to produce misleading results.

A critical challenge associated with using optimization models to examine future energy systems is dealing with large future uncertainties. This paper raises concerns about the current treatment of uncertainty in energy models and introduces a technique borrowed from operations research as a partial solution. 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[1]. 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 solve the problem at hand (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 (i.e., uncertainty associated with model inputs) 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, 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 capital cost for new technologies. While the purpose of scenario analysis is to extend our thinking about how the future might unfold, a

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

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).

While conventional scenario analysis ties exogenous assumptions about the larger world to energy and environmental outcomes produced by the model, it does not adequately quantify future uncertainty. Even if all parameter uncertainty were eliminated such that the future could be encoded in a single set of scenario 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. If we accept that these models are incapable of delivering accurate long range predictions, attention should be focused on a rigorous exploration of the decision space. While conventional scenario analysis attempts to outline future possibilities, it does not go far enough. A more useful approach would systematically flex models in order to stretch our thinking, challenge our preconceptions, and suggest creative alternatives to the problem under consideration. A technique called modeling to generate alternatives (MGA)—developed nearly 30 years ago and applied to land and water management problems—can be of significant value in energy and climate policy analysis (Brill et al., 1982; Brill et al., 1990). This paper reviews the concept of MGA and suggests how it can be applied to energy optimization models. A very simple and transparent linear optimization model was created as a test case to illustrate the utility of MGA, which provides insight without the detailed explanation required of a larger model. The model optimizes the installation of new electric sector capacity to replace all existing U.S. fossil-based generation by 2050.

## 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 modeling today (Brill et al., 1979; Brill et al., 1982; Brill et al., 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). Figure 1 illustrates how 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 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.

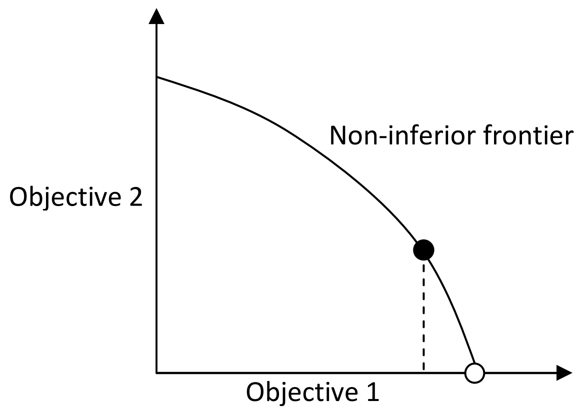



**Figure 1:** Suppose a single objective model returns an optimal solution at the point represented by the open circle. If a second unmodeled objective exists and is explicitly considered, the desired optimal solution may be represented by the closed circle on the non-inferior frontier. The projection of this optimal solution to the horizontal axis indicates that it is a feasible but suboptimal point when only Objective 1 is considered. This insight suggests it is worth exploring the feasible space around the optimal solution to find alternatives. Figure adapted from Brill et al. (1990).

Some planning problems are sufficiently complex such that there will always be unmodeled objectives, and this is particularly true of multi-decadal energy planning requiring energy optimization models. Accepting that there are unmodeled objectives 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 world are incomplete. In the author's opinion, this issue has not received adequate attention in the energy modeling community.

MGA can serve as an important tool in addressing structural uncertainty in energy models. The purpose of MGA is to efficiently search the feasible region surrounding the optimal solution to generate alternative solutions that are maximally different. The steps associated with the Hop-Skip-Jump (HSJ) MGA method are 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, (3) encode the adjusted objective function value as an additional upper bound constraint, (3) formulate a new objective function that minimizes the 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 (Brill et al., 1982). 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:

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

,

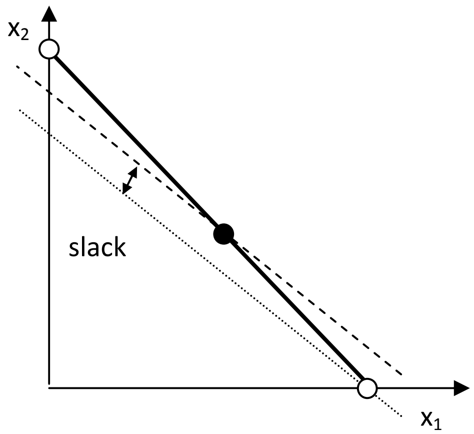
where $K$ represents the set of indices of decision variables with nonzero values in the previous solutions, $f_j(\vec{x})$ is the $j^{\text{th}}$ objective function, $T_j$ is the target specified for the $j^{\text{th}}$ modeled objective, and $X$ is the set of feasible solution vectors. Note that $\vec{x} \in X$ 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 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 (2007). In addition, the reformulated objective function that seeks to minimize the appearance of decision variables from previous solution 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 heterogeneity of costs, (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 that can be identified but not modeled quantitatively. For example, in a simple cost minimization model such as the one presented below, unmodeled objectives may include considerations such as risk aversion, equity, and public opinion.

Even if the user acknowledges that unmodeled objectives exist and is willing to accept the MGA solutions as equally plausible alternatives to the least cost solution, it might still be useful to quantify the changes in the original model formulation that would need to be made in order to reproduce the MGA solution. More specifically, does there exist a modified set of objection function coefficients in the original non-MGA model formulation that could reproduce the results from an MGA solution? An affirmative answer suggests there is a bridge between solutions generated by MGA and parametric sensitivity analysis of the original model. This should be of interest to energy modelers, who are accustomed to modifying input assumptions to generate different outcomes. The following discussion focuses on linear optimization for simplicity; however, the interpretation of MGA applied to nonlinear models is analogous.

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 non-extreme points in the original model formulation, a set of coefficients in the original problem formulation does not exist that can *uniquely* reproduce the MGA solution. This conclusion is demonstrated with a very simple example in Figure 2.




<u>Original Formulation:</u>
Minimize: $c_1x_1 + c_2x_2$
Subject to: $x_1 + x_2 = 1$
$x_1, x_2 \geq 0$
where: $c_1 < c_2$

<u>First MGA Iteration:</u>
Minimize: $x_1$
Subject to: $x_1 + x_2 = 1$
$c_1x_1 + c_2x_2 \leq c_1 \cdot \text{slack}$
$x_1, x_2 \geq 0$

**Figure 2:** 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. In this linear optimization, the model 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 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 Figure 2 can be generalized to more complicated cost-based linear 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 other technologies. Thus MGA has two equally valid interpretations: (1) it accounts for unmodeled objectives and (2) it represents a targeted form of sensitivity analysis of the objective function coefficients.

Note that the goal of the HSJ MGA method is to generate maximally different solutions in 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 the context of energy optimization models, the user may wish to maximize the deployment of a particular set of technologies within the cost-effective region surrounding the least cost solution. The MGA technique 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 models by allowing users to interact in a more meaningful way. An example of such possibilities is provided in Brill et al. (1990).

## 3. Wedge Analysis of U.S. Electric Power Sector

At the time of this writing, the *American Clean Energy and Security Act of 2009* (H.R.-2454), sponsored by representatives Henry Waxman (D-CA) and Edward Markey (D-MA), is pending before the U.S. Congress (U.S. House, 2009). Title III of the bill creates a national cap and trade program with the following economy-wide reductions in $CO_2e$ emissions: 3% below 2005 levels in 2012, 20% below 2005 levels in 2020, 42% below 2005 levels in 2030, and 83% below 2005 levels in 2050. This policy seeks aggressive reductions in $CO_2e$ emissions, and if passed, would radically transform the electric power sector by 2050. This analysis examines a simplified version of this proposal: a fixed 83 percent reduction in electric sector $CO_2$ emissions below 2005 levels in 2050, without the availability of offsets. A simple cost minimization model was created to optimize the installation of new capacity in the electric sector in order to displace existing fossil fuel-based generators and meet growing demand. The model does not account for the retirement of existing nuclear, hydro, or renewables. MGA is applied to the model in order to identify feasible alternatives to the least cost solution. The $CO_2$ mitigation challenge posed by the cap-and-trade scenario is shown below in Figure 3.

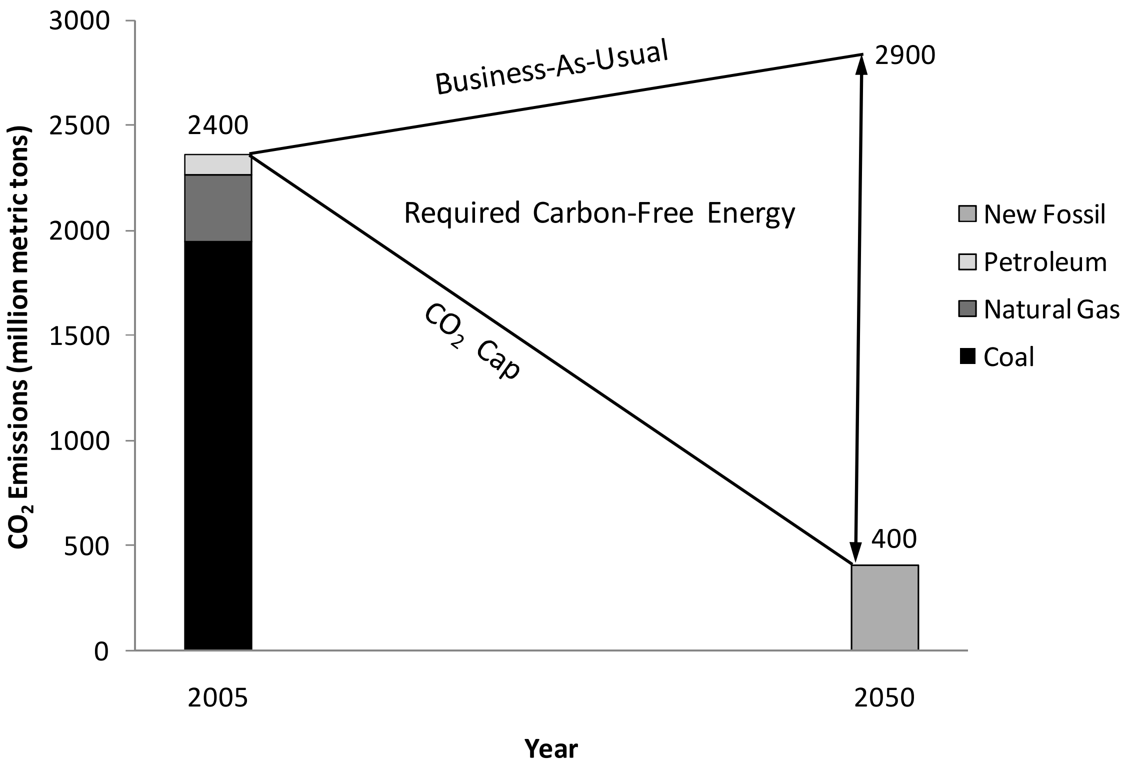



**Figure 3:** Diagram showing prescribed electric sector emissions reductions under a simplified version of a pending U.S. cap and trade proposal. The projection of business-as-usual electric sector $CO_2$ emissions is based on a linear extrapolation of $CO_2$ emissions projected in the *Annual Energy Outlook 2009* reference case (EIA, 2009a). The emissions cap forces electric sector $CO_2$ emissions to be 83 percent below 2005 levels in 2050.

Assumptions about the retirement of existing power plants are complicated and highly plant-specific. For the purposes of this simple modeling exercise, it is assumed that existing fossil capacity is retired at a constant linear rate, with enough capacity remaining in 2050 to serve as a reserve margin for reliability purposes, set at 20 percent of the new capacity. The objective then is to deploy energy technologies to replace existing fossil-based generation and meet growing electricity demand under the increasingly stringent constraint on $CO_2$ emissions. The model takes the approach outlined in Pacala and Socolow (2004), using wedges to replace all existing fossil generation. In this case; however, the number and size of technology wedges are selected to minimize the system cost of electricity. The model calculates the optimal capacity installations in 2050 and assumes linear increases from 2010 to 2050 to reach this optimal configuration. 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 intuitive 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). The input data and assumptions are provided in the Appendix. All costs and performance characteristics are assumed to remain constant through time. The model formulation can be written as follows:

Minimize:

$$C = \sum_{i=1}^{n} c_i \, x_i$$

Subject to:

$$\sum_{i=1}^{n} a_i x_i = P_{av}$$

$$\sum_{b \in B} a_b x_b \le P_{av-baseload}$$

$$\sum_{p \in P} a_p x_p \le P_{av-peak}$$

$$\sum_{f \in F} e_f x_f \le E_{2050}$$

Where $c_i$ is the annualized cost, $a_i$ is the capacity factor[2], and $e_f$ is the $CO_2$ emissions factor associated with each technology. *B* represents the set of baseload technologies, *P* the set of peak technologies, and *F* the set of fossil-based technologies emitting $CO_2$. Note that natural gas combustion turbines (GT), combined-cycle turbines (GTCC), and hydropower can serve either baseload or peak demand. The cost coefficients ($c_i$) above represent the annualized cost and are calculated as follows:

$$c_i = [\text{capital cost}]\frac{r}{1-(1+r)^{-T}} + [\text{variable O\&M}] \cdot 8760 \cdot [\text{capacity factor}] + [\text{fixed O\&M}] + \frac{[\text{Fuel Cost}]}{[\text{Efficiency}]} \cdot \frac{1\ \text{GJ}}{278\ \text{kWh}} \cdot 8760 \cdot [\text{capacity factor}]$$

[2] Capacity factor is defined as the annual electricity production normalized by the maximum theoretical production over the year.

where $r$ is the discount rate and $T$ is the technology lifetime. Note that items in square brackets are inputs taken directly from the table in the Appendix. The model is iterated until no new combinations of decision variables are present.

In the following analysis, the optimization described above is executed, followed by several MGA iterations using the HSJ method described in Section 2. The amount of slack used in the MGA runs was set to 25 percent 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 percent increase in electricity price would raise the average monthly residential bill by roughly $20, which is a potentially acceptable increase. As the base price of electricity increases, for example under cap and trade, the monthly residential expenditures for electricity become larger in absolute terms. However, this effect can be partially offset by policymakers if income from auctioned permits is used to assist lower income households. For example, a plan to reimburse low income households is part of the Waxman-Markey cap and trade proposal (House, 2009).

## 4. MGA Electric Sector Analysis

Before examining the response in the electric sector to the Waxman-Markey cap and trade proposal, results from a business-as-usual (BAU) case are presented with unconstrained $CO_2$ emissions. While one might expect slower retirement of existing fossil capacity under a BAU scenario than a stringent $CO_2$ cap, it is nonetheless illustrative for comparison to the $CO_2$ constrained analysis. Figure 4 below presents the least cost solution and the first MGA solution for comparison.

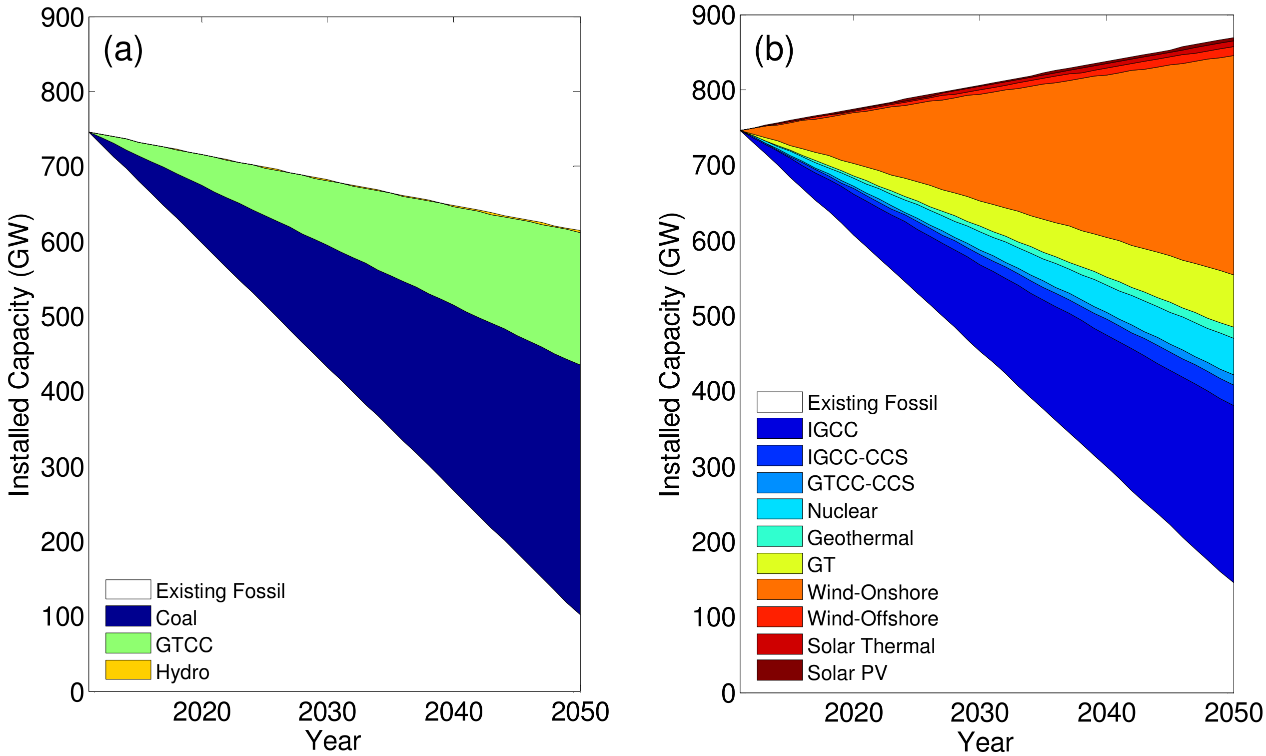



**Figure 4**: Installation of new capacity to replace existing fossil generators and meet growing demand in (a) the original BAU case and (b) the first MGA solution of the BAU case. Note that the MGA procedure was able to force out coal, GTCC, and hydro from the solution using the 25 percent slack.

Note that the BAU case in Figure 4a 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 forces out the three technologies that appeared in the BAU least cost solution, which indicates that the costs of competing technologies are close enough for them to enter the solution, given the specified slack in the MGA formulation. The comparison between the BAU original and MGA runs also demonstrates the ability of MGA to account for unmodeled objectives: although there is no limit on $CO_2$ emissions, the MGA solution produced emissions that were 42% lower in 2050 compared with the original least cost solution. This result is largely a consequence of the fact that most 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. Figure 5 presents additional MGA results for the year 2050. As mentioned above, the MGA procedure was terminated when no unique combinations of technology were generated. All 6 MGA runs resulted in carbon emissions lower than the least cost solution. Therefore, given the technologies considered in this analysis, there are several plausible combinations of electricity generation technologies that result in lower emissions, but none that raise emissions compared to the least cost BAU solution.

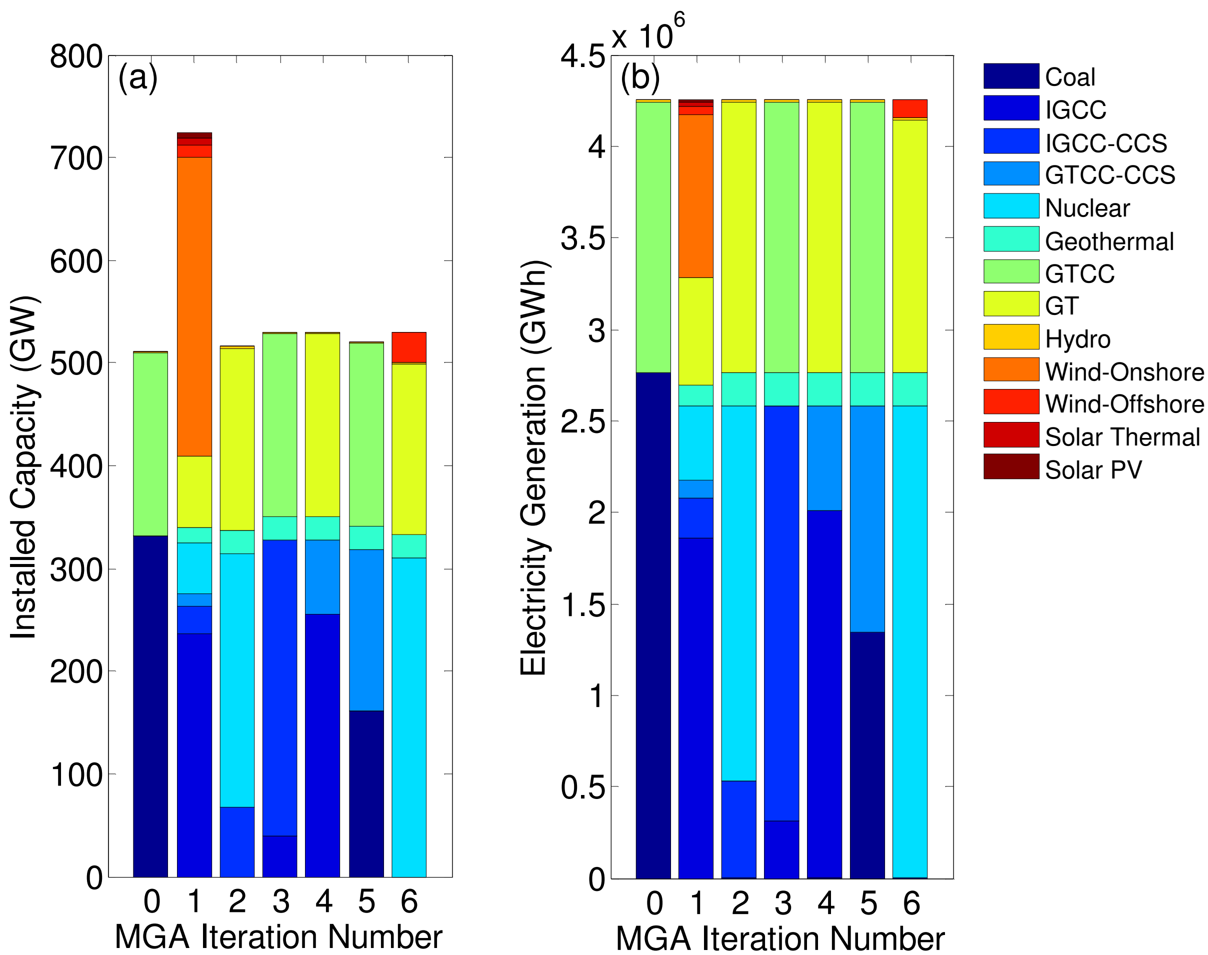



**Figure 5**: Installed capacity in GW (a) and electricity generation in GWh (b) to replace existing fossil capacity and meet growing demand under the BAU case in 2050. The original least cost solution (Iteration 0) is followed by 6 MGA solutions. In all MGA runs except the first, the upper bound constraint on system cost is binding. Note that the amount of installed capacity in each scenario varies despite fixed demand because each technology has a different capacity factor.

Moving to the simplified Waxman-Markey $CO_2$ cap requires an explicit upper bound constraint on emissions as outlined in Figure 3. Note that the availability of offsets is not considered.

The optimized wedges corresponding to the least cost and first MGA solution are presented below in Figure 6. Note that in this case, the model was not able to push GTCC, hydro or onshore wind out of the first MGA solution.

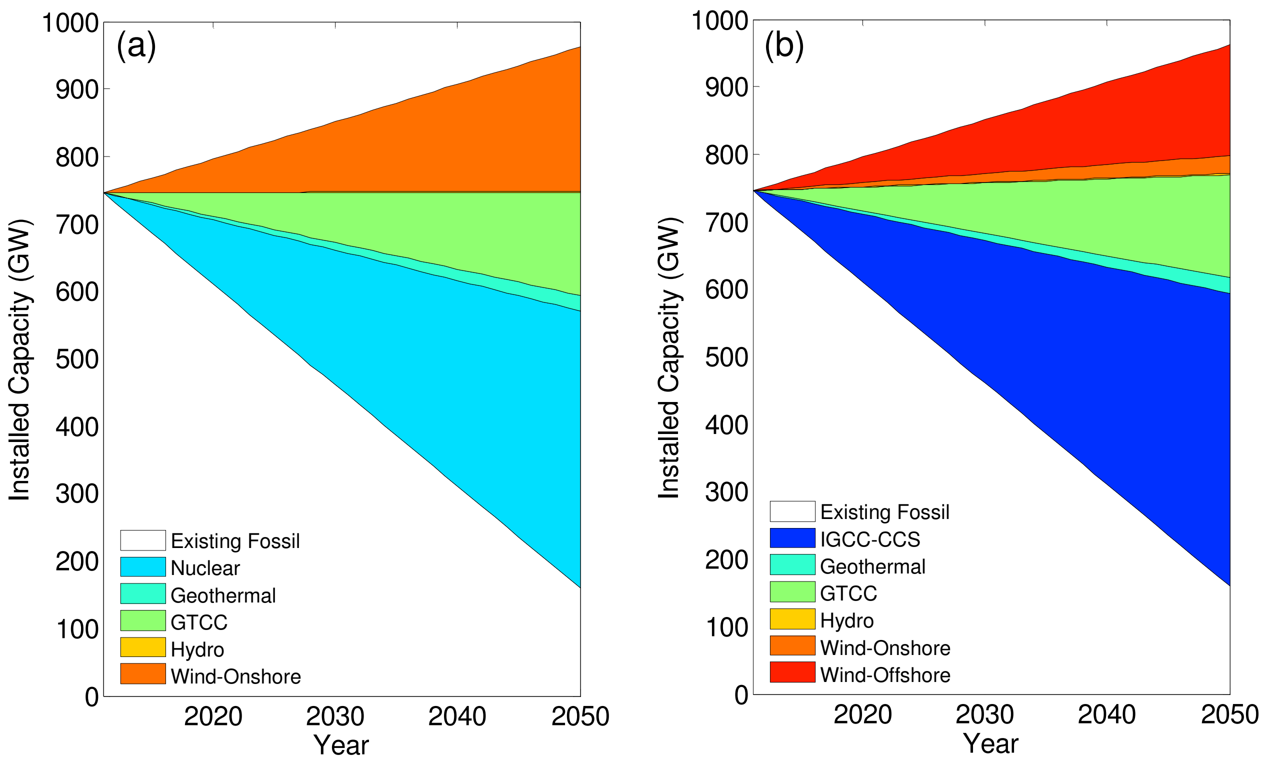



**Figure 6**: Installation of new capacity under the simplified Waxman-Markey $CO_2$ cap in the original least cost solution (a) and the first MGA solution (b). Note that the MGA solution replaces nuclear and hydro with IGCC-CCS and offshore wind.

Figure 7 below shows the original least cost solution as well as the first 4 MGA solutions. Since the $CO_2$ cap-and-trade scenario is more constrained than the BAU scenario, there are fewer feasible, unique MGA solutions. Interestingly, though perhaps 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. The constraint on system cost is binding in all 5 MGA scenarios, driving the average generation cost of electricity from 0.058 $/kWh in the original solution to 0.0725 $/kWh in the MGA solutions. Comparing the original least cost solutions in the BAU and $CO_2$ constrained scenarios (Figures 4a and 6a), the average generation cost associated with the new installed capacity is 0.050 \$/kWh and 0.058 \$/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 marginal costs between the least cost BAU and $CO_2$ constrained solutions is 0.014 \$/kWh, which results in an implicit carbon price of ~25 \$/mt$CO_2$, owing strictly to differences in generation cost associated with new capacity installation. In Figure 7 below, solar thermal at 0.17 \$/kWh sets the marginal cost of electricity in two of the four MGA cases. In these cases, the implicit carbon price between the BAU and $CO_2$ cases is ~200 \$/mt$CO_2$.

In the least cost $CO_2$ constrained case below in Figure 7, nuclear power constitutes all of the baseload capacity. While greater diversity in baseload generating technologies would clearly be expected under real circumstances, 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 most modelers would be 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 another approach by searching the feasible decision space near the optimal solution. 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 percent 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 2 in Figure 7 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 (0.066 \$/kWh compared to 0.086 \$/kWh), so some portion of GTCC-CCS can be replaced by IGCC-CCS, with no impact on emissions but lower cost. Such mixing and matching of scenarios makes the user an active participant in the modeling process, which is more likely to stimulate new ideas.

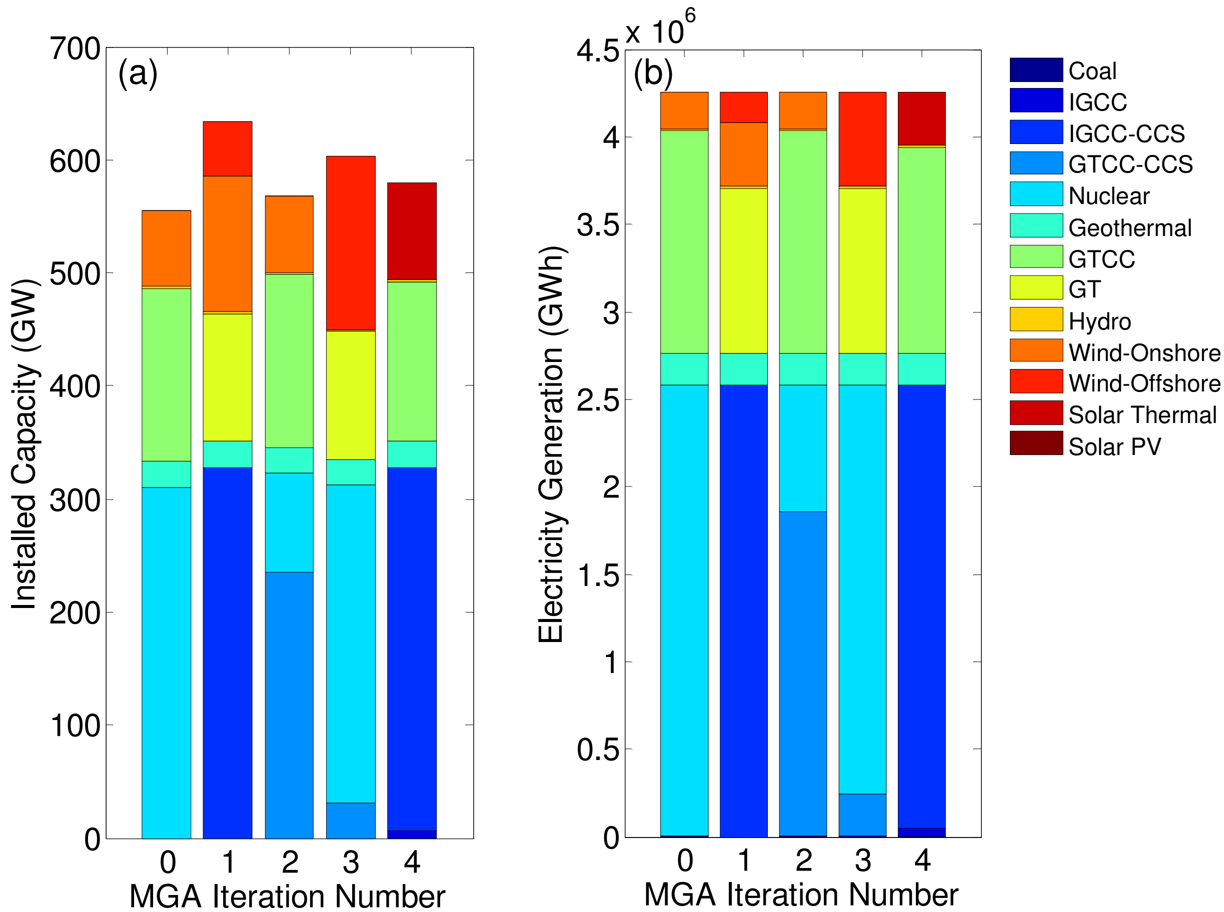



**Figure 7**: Results in 2050 from a scenario in which $CO_2$ emissions are capped according to the simplified Waxman-Markey proposal. Installed capacity (GW) is given in (a) and electricity generation (GWh) is given in (b). The original least cost solution (Iteration 0) is followed by 4 MGA solutions. The upper bound constraint on system cost is binding in all MGA solutions. Nuclear, combined-cycle gas, and onshore wind play a critical role in most of the solutions.

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 determine which technology options appear to be the most robust across different scenarios. Figure 8 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 Figure 8 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 percent 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.

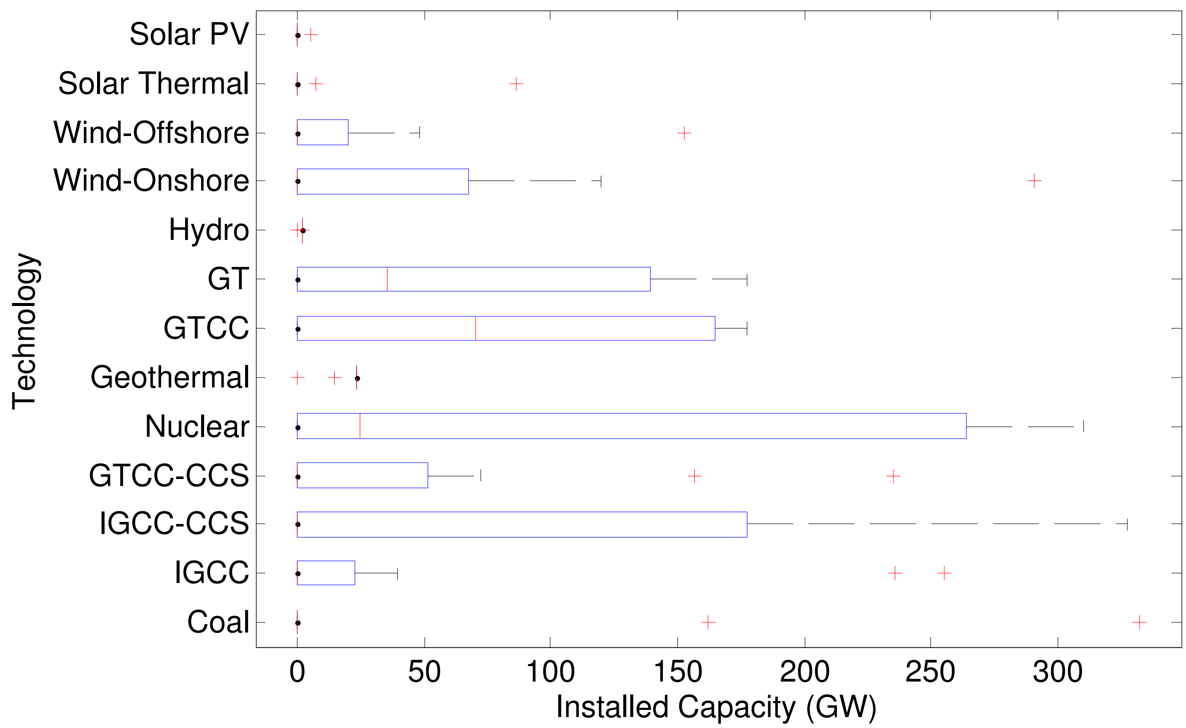



**Figure 8**: Boxplot of installed capacity by technology across all BAU and $CO_2$ constrained scenarios presented above. No technology was present at significant levels (> 50 GW) across all model runs.

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. Figure 9 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 simply be changed to maximize pulverized coal use, or that of any other technology.

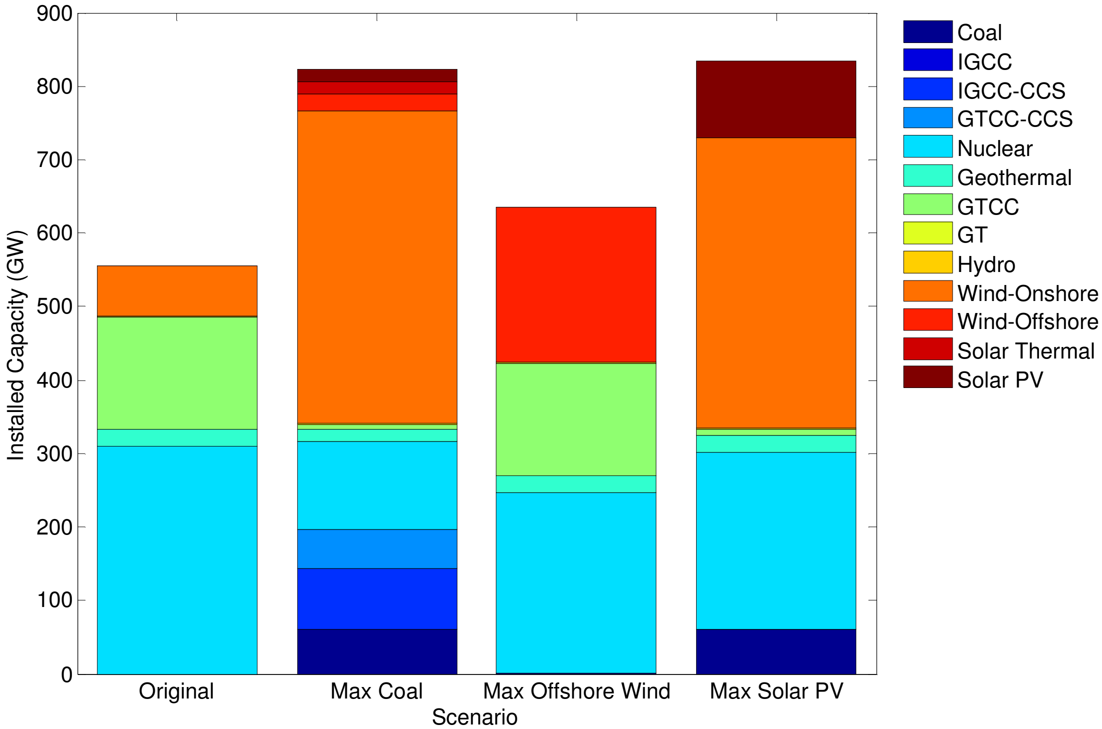



**Figure 9**: Alternative MGA objectives under the $CO_2$ constraint. The objective function in the MGA iteration can be modified to probe the system in specific ways. The plot shows the result when the objective is to separately maximize coal, offshore wind, and solar PV. The least cost solution is reproduced on the left hand side for comparative purposes.

The results in Figure 9 demonstrate the utility of MGA beyond simply generating a set of maximally different solutions. MGA can be used to probe the system within a user-defined cost-effective space around the optimal least cost solution. In this way, a suite of MGA tools along with sensitivity and uncertainty analysis can be used to create a decision support framework for energy optimization models that allows the user to explore the decision space and flex the model.

## 5. 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. If modelers accept the fact that optimization models cannot provide "the answer" because the world is too complex to condense into a set of deterministic mathematical equations with accurate parameterization, then we need to rethink how energy such models are used.

Rather than providing forecasts of future energy system development under a few detailed scenarios, the models should be flexed in a way that allows users to quickly and efficiently probe the decision space in order to identify plausible alternatives that stimulate creative thinking. Modeling to generate alternatives (MGA) has been developed as a way to do this, but has not been rigorously applied to energy models yet. 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 given that structural uncertainty exists, and (2) sensitivity analysis of the objective function coefficients in the original model formulation.

Application of MGA to the BAU electric sector returned several solutions with significantly lower $CO_2$ emissions than the original least cost solution. This result demonstrates the ability of MGA to meet unspecified objectives by searching a portion of the feasible region. MGA can address unmodeled issues that are difficult to identify, much less quantify—particularly ones that relate to human behavior or attitudes. Again, the purpose of MGA is to efficiently elucidate alternatives, it is up to the decision-makers to decide if the alternatives have desirable characteristics beyond what is explicitly modeled.

The wedge analysis presented here serves as a first application of MGA to a simple and transparent energy model. 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.

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. While parametric sensitivity analysis and Monte Carlo simulation remain valuable tools for sensitivity and uncertainty analysis, large models require significant computational resources to obtain the appropriate number of iterations for meaningful analysis. However, the power and utility of MGA increase as the model size grows, and application to larger models such as MARKAL is already in progress.

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## Appendix

Technology cost and performance data are taken from EIA (2009b). Relevant information is reproduced in the table below.

| Technology[a] | Capital Cost ($/kW) | Fixed O&M ($/kW·yr) | Variable O&M ($/kWh) | Efficiency (%) | Capacity Factor (%) | Average Cost ($/kWh) | Baseload / Peak (B/P) | Capacity Constraint (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 | Either | |
| GT | 634 | 10.5 | 0.0317 | 40 | 95 | 0.076 | Either | |
| Hydro | 2242 | 13.6 | 0.0243 | 34 | 65 | 0.047 | Either | 2 |
| Wind-Onshore | 1923 | 30.3 | 0.00 | 34 | 35 | 0.076 | P | 8000 |
| Wind-Offshore | 3851 | 89.5 | 0.00 | 34 | 40 | 0.14 | P | 800 |
| Solar Thermal | 5021 | 56.8 | 0.00 | 34 | 40 | 0.17 | P | 100 |
| Solar PV | 6038 | 11.7 | 0.00 | 34 | 30 | 0.25 | P | |

[a]The following abbreviations are used: IGCC = integrated coal gasification combined-cycle, CCS = carbon capture and sequestration, GTCC = gas turbine combined-cycle, GT = gas combustion turbine.

### Other Assumptions:

The $CO_2$ emissions factors used for coal and natural gas are 91 kg $CO_2$ / GJ and 53 kg $CO_2$ / GJ, respectively (EIA, 2008a).

The fraction of electricity supply constituting baseload was estimated by construction a load duration curve from PJM (Pennsylvania-New Jersey-Maryland) data covering the years 1997-2001 (PJM, 2002). Baseload was defined as the portion of power supplied that remained constant throughout the year, which is estimated to be 65 percent for PJM.

Fuel costs for coal, natural gas and uranium were obtained from EIA (2008b). A coal price of 25 \$/short ton was drawn from Table 7.8, natural gas price of 7 \$/$10^3$ $ft^3$ was drawn from Table 6.8, and a uranium price of 34 \$/lb uranium oxide was drawn from Table 9.3.

A 10 percent discount rate was applied uniformly to all capital investments and a lifetime of 30 years was assumed for all technologies.

No existing policies or tax incentives related to energy technology were included in the model. It was assumed that the $CO_2$ constraint would be the dominant driver of change in the electric sector.