Modeling of Uncertainties in Major Drivers in U.S. Electricity Markets

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Introduction and Objective of the Stochastic Energy Deployment Model (SEDS)

The U.S. Department of Energy (DOE) and the National Renewable Energy Laboratory (NREL) are developing a new model, intended to address many of the shortcomings of the current suite of energy models. Once fully built, the salient qualities of the Stochastic Energy Deployment System model (SEDS) will include full probabilistic treatment of the major uncertainties in national energy forecasts; code compactness for desktop application; user-friendly interface for a reasonably trained analyst; run-time within limits acceptable for quick-response analysis; choice of detailed or aggregate representations; and transparency of design, code, and assumptions. Moreover, SEDS development will be increasingly collaborative, as DOE and NREL will be coordinating with multiple national laboratories and other institutions, making SEDS nearly an "open source" project. The collaboration will utilize the best expertise on specific sectors and problems, and also allow constant examination and review of the model.

Here, we present the rationale for this project and a description of its alpha version, as well as some example results. We also describe some of the expected development efforts in SEDS.

Rationale for SEDS

Today's U.S. energy situation can be characterized as complex, uncertain, and even disturbing. Oil prices are increasing as worldwide supply tightens and demand increases. Natural gas supplies appear to be limited for the near term. Climate change is heavily debated, while symptoms abound. Technology options rise to the forefront with acclaimed salvation status and recede quietly into the laboratories. Energy security is the topic of the day. Policies are proposed to address all the above.

Despite this turmoil, nearly all of our energy forecasts are purely deterministic, and offer only limited insights for policy makers. Indeed, the most prominent energy model, the DOE/EIA *Annual Energy Outlook 2006* (AEO), points to a business-as-usual energy market with 2025 crude oil import prices at two-thirds the cost of July 2006, and natural gas prices at 90% of today's cost. Of all the future possibilities, this may be the most likely scenario. But it's not probable – in fact, the authors would maintain there is less than a 50% chance that this forecast is exactly right. The EIA AEO report does include other scenarios – high and low economic growth, three different world oil price scenarios, various technology improvement scenarios, three liquefied natural gas (LNG) supply cases, etc. But, which one is a person to use? Do they cover the range of possibilities? What if several things go awry simultaneously?

The DOE/EIA is not alone in facing such uncertainties, or in using scenarios to address them. Probably one of the better known recent scenario exercises came from the United Nation's Inter-governmental Panel on Climate Change (IPCC), which produced the results shown in Figure 1. While useful for many purposes, such multiple scenarios leave a lot for the reader to determine – Which ones should I use for planning purposes? What's most likely? What's the average? What strategies would be most robust across these possibilities?

This paper describes an alternative to the use of scenarios, as well as a model under development to help answer the above questions.

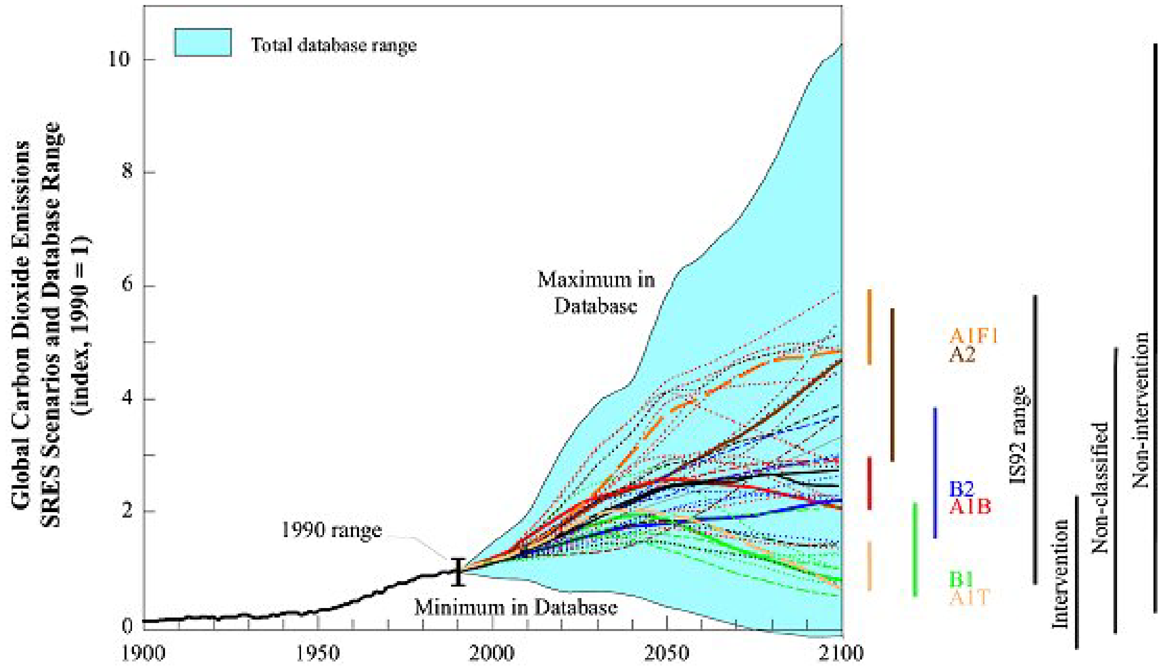

Figure 1
IPCC Scenarios

Background

One reason scenarios are developed is that often the models behind the scenarios cannot predict, with confidence, one or more of the market drivers. Consider the U.S. electric sector. As shown in Figure 2, major shifts have occurred in the types of electric capacity installed in the United States during the past 60 years. Probably the most distinguishing feature of the graph is the dominance of natural gas power plants that came online between 1998 and 2003. Although larger, this shift is typical of similar shifts in prior years: ramp-up of nuclear in the 1970s and its demise in the late 1980s; dramatic fall in new coal plants in the 1980s; decrease in gas use in the late 1970s and its rise in the late 1980s. Similar shifts have occurred in other fuels not shown in Figure 2. For example, there have been no significant oil-fired additions to capacity since the 1970s, and very little hydropower.

At the risk of oversimplifying, Figure 2 also shows the major drivers behind these shifts in the type of capacity installed. For our purposes, there are four important features associated with most of these drivers. First, many are outside the scope of most of today's U.S. energy market models. Second, most could not have been forecast with economic models as they were driven by acts of nature, human error, politics, increasing awareness of environmental impacts, resource discoveries, and technological breakthroughs. Third, most of these events were not likely enough to have been included in any prior sensitivity analysis conducted for national energy planning, even though their impacts were profound. Finally, there are a host of other driving events that did not happen that might have been included in any prior comprehensive scenario analysis (e.g., nuclear that actually is "too cheap to meter" or U.S. ratification of the Kyoto protocol).

The above would suggest that, with our current energy market models, we are at risk of missing the real drivers in planning for our national energy future. Today, as in the past, there is a host of natural, social, political, and technological drivers outside the scope of our models that are the true determinants of the future. And, as in the past, we can't simply insert them into our deterministic models because they are highly uncertain – even unlikely – but still possibilities with potentially huge consequences. There are so many of them with such a range of possible values, many of which are correlated with each other, that it is also not possible to do a comprehensive sensitivity or scenario analysis. And even if one could, no one could make sense of them all. We're left with only one viable option, which is the subject of this paper.

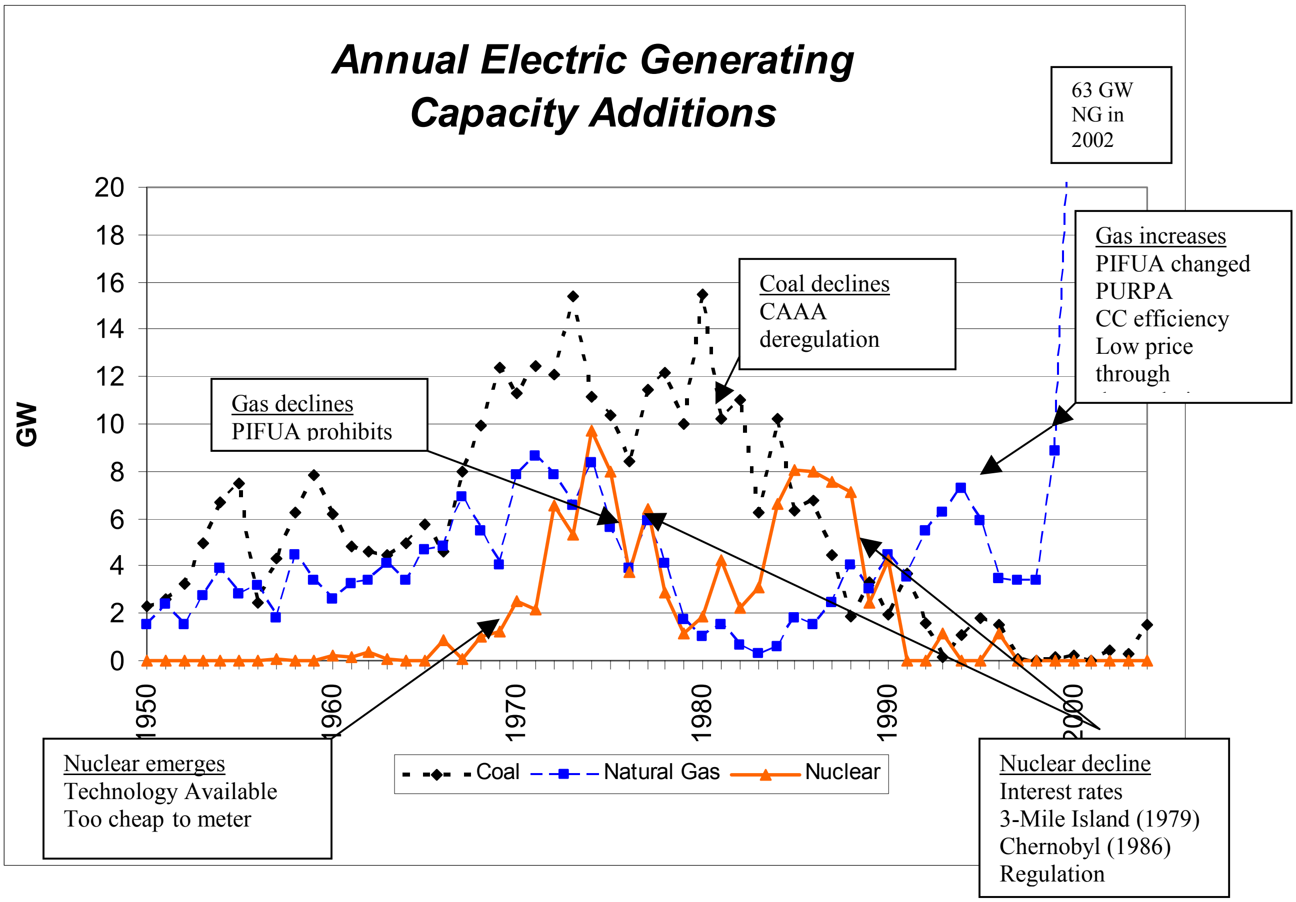

Figure 2
Major Historical Drivers in the U.S. Electric Sector

Basic Structure of the SEDS Model

Although there is no way to remove all the uncertainties associated with the future, there are alternatives other than scenarios for analyzing them. We have applied a widely known technique (Monte Carlo simulation) to SEDS, a model of U.S. energy markets. When complete, SEDS will simulate the evolution of the U.S. energy market from 2005 to 2050.   SEDS moves forward through time, simulating the U.S. energy market in one 5-year time-step after another. Its principal outputs are energy demands, energy capacity stocks, energy/fuel use, energy prices, and probability distributions that capture the uncertainty in each of those.

SEDS is being developed with a commercially available software package, Analytica, designed to facilitate the development of stochastic models. For more information on Analytica, see http://www.lumina.com.

Sectors, Technologies

As shown in Figure 3, the alpha version of the electric sector in SEDS is complete, and the transportation sector is under development. In the electric sector, SEDS estimates the type of generation capacity that will be deployed nationally in each 5-year period from now to 2050, and the generation from that capacity. To meet future loads, it considers technology, fuel, and emission costs in selecting among fossil, nuclear, and renewable electric technologies.

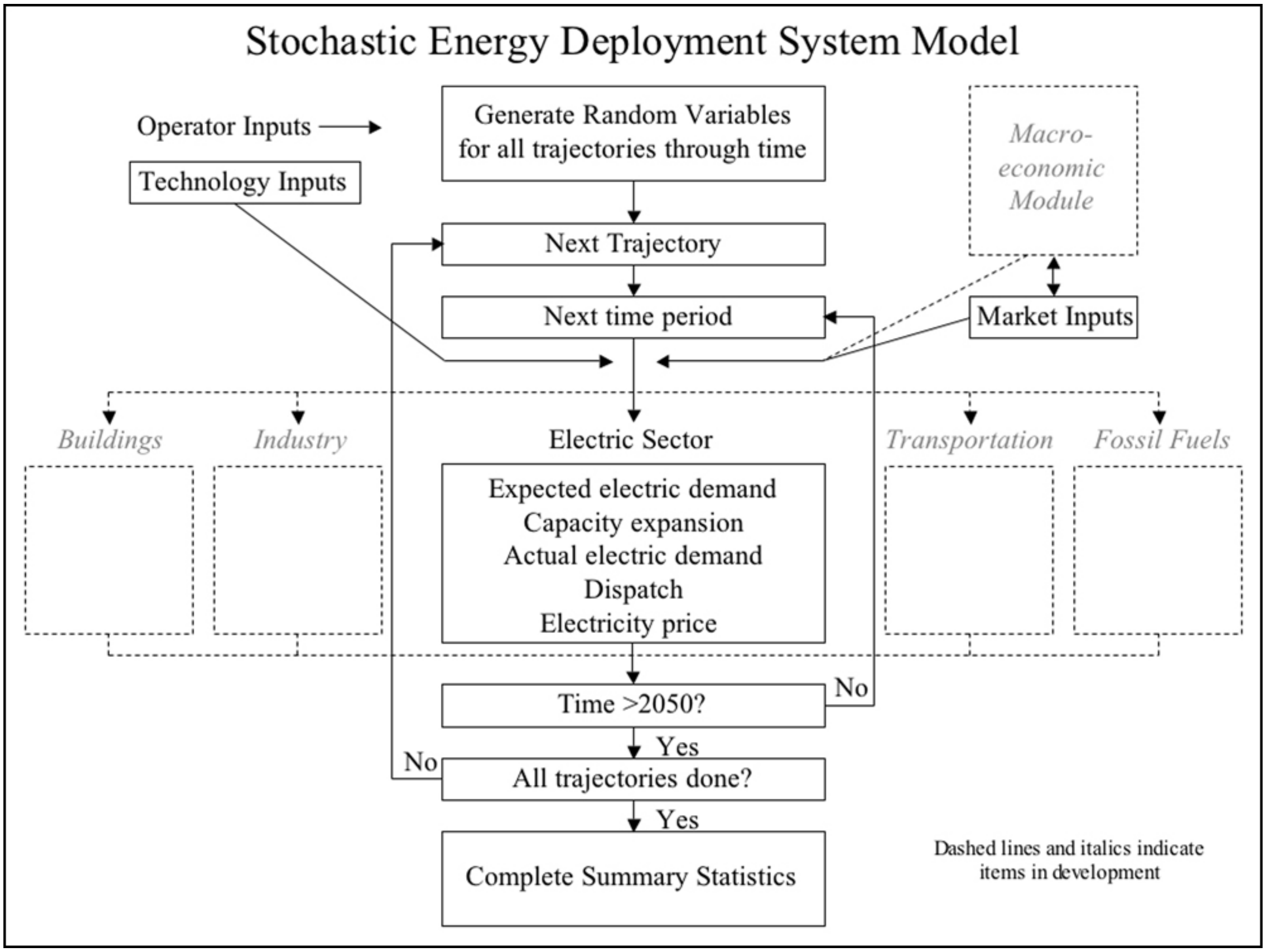

Figure 3
SEDS Logic Flow

Treatment of Uncertainty

SEDS can be operated in either a deterministic mode or a stochastic mode. When operated deterministically, SEDS uses a single value instead of the input probability distributions for the uncertain parameters. These deterministic SEDS runs can be extremely quick and informative in terms of how the model responds to different inputs and assumptions.

When operated stochastically, SEDS estimates a number of trajectories [1] through time, with each trajectory beginning in 2005 and extending in 5-year increments out to 2050. In each trajectory, the random variables are sampled using a Latin Hypercube approach, which improves on a standard Monte Carlo simulation by dividing the range of possible values for that particular random variable into bins of equal probability and selecting one sample from each of the equal-probability bins.

For each period in a trajectory through time, electricity demands and costs from the different generation options are updated, stock is retired, and a market share algorithm is employed to determine generation from existing and new generation capacity. In moving from one period to the next within a single trajectory, SEDS captures the correlation between uncertain variables in time (periods t and t+1), first by updating the value in t by simulated physical drivers; and, second, by adding to or multiplying the updated simulated value by a random variable that captures the uncertainty in the variable's value from one period to the next. For example, the price of natural gas from period t in a particular trajectory through time is first adjusted by a supply elasticity to capture resource issues, and then multiplied by a random variable intended to capture price escalation, market uncertainties, and interdependencies with other random variables (e.g., the price of oil) to yield the gas price in period t+1.

TABLE 1

PRIMARY UNCERTAINTIES in SEDS

<u>TECHNOLOGY</u>
- Rate of learning-induced improvements
- Rate and size of R&D improvements

<u>FUELS</u>
- Oil
  - Domestic resource/price
  - Time to world prod'n peak
  - Impact of peak on price
- Natural gas
  - Domestic resource/price
- Coal
  - Domestic resource/price
- Biomass
  - Domestic resource/price
- Nuclear
  - Will new plants be built?

<u>MARKETS/POLICY</u>
- Climate change - taxes
- Macroeconomics
  - Demand growth
  - Discount rate
- Wind and Geothermal Production Tax Credits

Table 1 identifies those drivers that are currently treated stochastically in the electric-sector portion of SEDS. This list will be expanded and modified as the SEDS model evolves, and as required by individual studies. We used four criteria in developing this preliminary list of uncertain market parameters. Each uncertain parameter is:
1) potentially a major driver of future U.S. energy markets
2) highly uncertain with a range of possible outcomes
3) outside the normal scope of an energy market model
4) of particular interest to the development of renewable energy

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[1] The user can input the number of trajectories through time, with more trajectories producing a more statistically accurate picture.

Many other uncertain drivers could have been included in Table 1. A SEDS user can always make any parameter stochastic, with the specification of the appropriate probability distribution for that parameter. Any parameters not included in Table 1 are currently treated deterministically by SEDS, as in any other model.

Analytica includes a large selection of probability distributions that can be used to represent these uncertain parameters. It is a simple matter to examine the sensitivity of the SEDS results to different distributions. For our default distributions, we have generally used triangular distributions, which are easily understood and visualized. There are a few examples in Table 2. The low, mode, and high columns are the lower bound, mode, and upper bound, respectively, which define the triangular distribution. In the case of a Bernoulli distribution, the "High" column is used to represent the likelihood of a positive value (0.5 means that the event has a 50% chance of happening).

Table 2 – Sample Probability Distribution Parameters

Variable name	Low	Mode	High	Shape
Carbon tax start year	2010	2015	2025	Triangular
Carbon tax phase in period (yrs)	5	10	15	Triangular
Carbon tax amount ($/ton C)	25	100	500	Triangular
Carbon Tax Allowed			0.50	Bernoulli
Coal heatrate period (years)	20	25	30	Triangular
Coal heatrate % reduction	0	0.027	0.055	Triangular
Coal cap cost period (years)	5	15	25	Triangular
Coal cap cost % reduction	0.05	0.10	0.12	Triangular

Interdependencies: Where the physical relationships between energy variables are well understood, SEDS uses explicit formulas to capture those relationships. However when there are interdependencies between variables that are outside the scope of SEDS, correlation coefficients are used. For example, in SEDS, natural gas prices are assumed to be partly correlated to oil prices.
We expand below on how these major uncertainties are currently treated in SEDS.

Fuel Prices:
Oil – Three random variables are used to capture the price of oil. The first is the percent change in the price for each year in the period before world oil production peaks. This is represented by a triangular distribution that is accessed each year, i.e. the percent change varies from one year to the next. In the SEDS base case, the mode of the triangular distribution is set to the growth rate between 2001 and 2020 in the Reference Case of the *Annual Energy Outlook 2006*. The second random variable is represented by a triangular distribution on the time at which world oil production peaks. The third is a distribution on the annual percent change in the price that covers the period after world oil production peaks. While oil is not a primary fuel for any of the electric-generating technologies in SEDS, it is included because we plan to expand SEDS to the transportation and industrial sectors – and because the price of natural gas, which is

used in the electric sector, is assumed to be partly correlated to the price of oil as described in the next paragraph.

Natural gas – There is a single distribution for the price of natural gas. The price of natural gas is assumed to be correlated to the price of oil. The price of natural gas in year t is determined from the price of natural gas in period t-1, first, by adjusting it with a supply elasticity that is a function of the cumulative demand for gas through period t-1; and second, by the random variable for the annual percent change in gas prices, which is represented by a triangular probability distribution. The distribution is correlated to the price of oil with mode set in the SEDS base case equal to the average annual increase in gas prices from the Reference Case of the *Annual Energy Outlook 2006.* We anticipate that we will eventually significantly modify the gas-pricing uncertainties to reflect uncertainties in both LNG availability/price and the construction of an arctic pipeline.

Coal – The change in the price of coal from one year to the next is captured through a random variable on the annual percent change in coal prices. The change is slightly correlated to the change in oil prices and is captured in the SEDS base case by a triangular distribution with mode equal to the average annual increase in coal prices from the Reference Case of the *Annual Energy Outlook 2006*.

Nuclear – Nuclear fuel prices are taken directly from the Reference Case of the *Annual Energy Outlook 2006*. A binomial random variable is used to represent the probability that nuclear will be allowed to be built in the future. If the random variable ever indicates that nuclear can be built, then nuclear can be built in all future years from that point forward. This single random variable is used to capture all the potential market uncertainties associated with nuclear power – proliferation, waste, accidents, financial risk, and public opinion.

Technology change:

Uncertainty in technology improvements through learning currently is captured through a triangular probability distribution on the learning parameter used in the learning curve, which is applied to a technology's capital cost. The parameter value is selected once for each technology for each trajectory through time. Currently, the following technologies have stochastic learning parameters: wind, integrated coal gasification combined cycle (IGCC), advanced combined cycle, advanced combined cycle with sequestration, and enhanced geothermal systems (EGS). Improvements due to R&D are also uncertain. Each technology's capital cost and efficiency is represented by two random variables – the amount of improvement, and the length of time it takes to achieve that improvement.

Policy:

SEDS currently includes uncertainty in two major policy drivers – carbon taxes and production tax credits (PTCs). Uncertainty as to how or whether restrictions might be imposed on greenhouse gas emissions is treated through the imposition of a carbon tax. Four random variables are used to impose a carbon tax. First, a binary distribution is used to determine whether or not a carbon tax is ever imposed. Second, if a carbon tax is imposed, a triangular distribution is used to set the time at which the tax is first imposed.

The third carbon tax random variable is represented by a triangular distribution on the size of the final carbon tax expressed in $/ton of carbon. And the fourth random variable is again represented by a triangular distribution on the length of the implementation period. The tax is assumed to grow linearly over the implementation period, starting at the initial date provided by the second distribution. The carbon tax is simply translated into the cost per kWh generated by a technology based on the fuel used and the generator heat rate.

There is considerable uncertainty as to whether the existing federal production tax credits for renewable energy will be renewed at the end of 2007, when they are legislated to expire. This uncertainty is explicitly accounted for by including a triangular distribution on the year that the PTC will expire.

<u>Time and regional disaggregation</u>:
The precision of a model with respect to specificity of results is generally improved by disaggregating over time and geography, as far down as can be supported by available input data. The tradeoff with detailed disaggregation is that computer run-time and memory requirements can be excessive. Another tradeoff that is the subject of active debate and research – and may be the subject of SEDS experiments – is the degree to which the added uncertainty, introduced with added detail, affects overall prediction accuracy. With respect to time and regions, we discuss these tradeoffs in the paragraphs that follow.

Time: As evidenced in Figure 2 for the U.S. electric sector, significant trends have formed over long periods in the type of generation selected: coal additions dominated from 1950 to 1980; nuclear penetrated between 1970 and 1990; gas was a major addition in all but the years 1975 to 1990. These additions would suggest that for the electric sector, SEDS can capture the major drivers and trends with periods as long as 5 years.

While 5-year periods might suffice to capture capacity additions, it is clear that operationally, generation changes diurnally – or even second-by-second – as load swings and generator/transmission availability dictate changes in the contributions from individual plants. In the electric-sector portion of SEDS, we simulate these varying generator-operating levels simply by expressing electric demand in terms of annual energy; and base, intermediate, and peak loads, i.e. we do not disaggregate over time within a year.

Regions: Figure 2 showed that in the electric sector, swings in market penetration from one technology are tending more and more to occur at the national level. In the 25 years between 1950 and 1975, we saw a mix of coal, gas, oil, and – in the end – nuclear penetrate the market. However, since 1975, new coal additions dominated for 10 years, then 5 years of new nuclear builds; then gas ramped up for years in the mid-1990s, before it went off the chart post-2000. Today, coal again seems to be the fuel of choice almost nationwide. Certainly there are strong regional variations, especially in the use of coal (e.g., emissions restrictions in California have largely prohibited new coal plants). However, it is clear from Figure 2, that the major drivers in market penetration for conventional technologies are not local drivers, but national factors. In the electric sector currently modeled in SEDS, we have taken advantage of this national picture to keep the model simple and quick-to-solve by using a single region. Fortunately, Analytica has a somewhat unique capability to disaggregate an existing model regionally, should that be required in the future for individual studies.

Our preliminary analysis of the transportation sector suggests that national trends far outweigh regional differences, and that we can again avoid regional disaggregation in that sector. When we develop the buildings and industrial sectors, some level of regional disaggregation will probably be required. Tradeoffs will be required between accuracy and model run-time.

Regional Treatment of Renewable Energy: The cost and performance of many energy efficiency/renewable energy (EE/RE) technologies are highly site-specific and cannot be captured by a set of average numbers at the national level. In SEDS, we use reduced-form supply curves to capture such variation. For example, SEDS assumes the cost of generation from wind is the bus-bar costs of a Class 5 resource site. SEDS adds to this an extra-generation cost associated with resource quality, site access, transmission, intermittency, and ancillary services. This extra-generation cost is presented by a supply curve derived from NREL's Wind Deployment System (WinDS) model (http://www.nrel.gov/analysis/winds/related_pubs.html). The curve presents the costs ($/kW) as a function of the amount of wind installed nationwide, as shown by the top curve in Figure 4. The three stacked curves of Figure 4 break the extra-generation cost from wind into that due to additional wind capital cost, transmission cost for wind, and the cost of conventional capacity and fuel to firm up wind resource variability. Using this curve, SEDS computes the extra-generation costs for wind as a function of installations-to-date and adds that cost to the wind bus-bar cost of generation. Whether SEDS' reduced form representations capture the appropriate heterogeneity in the electric sector will be a topic of investigation this coming year.

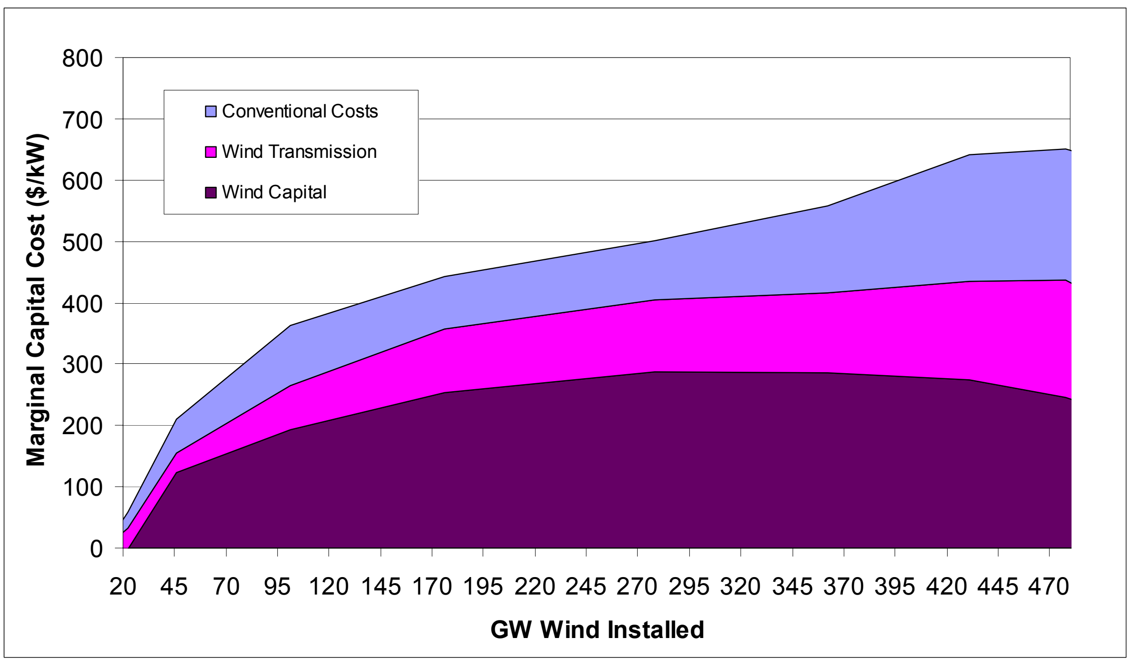

Figure 4
Wind Supply Curve for Extra-Generational Costs

<u>Electricity demand</u>:
At the start of each 5-year period, electricity demand is estimated based on the electricity price and the growth from the past two periods for the particular trajectory through time. To determine the capacity needed to meet the load, the load is divided into the fraction occurring as base, intermediate, and peak load. These demands and plant retirements are used to determine the additional capacity builds that are required. Once the capacity builds are determined, the

actual load for the period is estimated from the projected value and a random perturbation. The current stock of plants is then dispatched to meet the actual load.

Once SEDS is refined to include an explicit end-use sector representation, energy demand will be modeled as a combination of the demand for energy services and the end-use energy needed to meet that service demand. The former is driven by macroeconomic conditions, demographics, and energy prices; the latter is driven by technological change. Eventually, a macroeconomic module will be implemented to provide these macro drivers.

Capacity Expansion:
A market-share algorithm is used to allocate the demand in each 5-year period for new electric-generating capacity to different prime movers from each technology. Separate capacity expansion markets are assumed for base, intermediate, and peak loads. Different technologies compete in each of these load categories based on their levelized cost of electricity (LCOE). For example, coal, nuclear, combined-cycle natural gas, and all the renewable electric technologies compete to meet the base-load demands, while only hydro, natural gas combustion turbines, and land-fill gas compete in the peak market. The LCOE of each technology is computed based on technology costs (capital, O&M, fuel, emissions) and performance (capacity factor, heat rate, etc.) Capacity factor is assumed to be the same as that experienced by similar plants in the preceding period. The LCOE for wind is incremented by the "extra-generation" cost described above. Similarly, there are resource supply curves for biomass and geothermal that increase their costs as the best resource sites are built out.

To capture the efficiency of energy use and the need for new capital stock, SEDS tracks capital stock. Retirements are estimated through planned retirements, extrapolations of past trends, and economics. Economic retirements are more important than in most models, because SEDS must be responsive to events that, though unlikely, might arise in the Monte Carlo simulation, e.g., carbon taxes. Economic retirements are calculated on the basis of the present value of "going forward" costs for existing plants (fuel and O&M) compared to the full costs of new plants (capital, fuel, and O&M).

Market Share Algorithm:
The cost and performance of all generation technologies vary around the country. To account for this variation, SEDS uses a logit market-share model. A single-nomial logit based only on cost does not account for the status of each technology's supply industry. To prevent the growth of any particular technology from being stretched too thin, the market share is recalculated with a multi-nomial logit that considers not only price, but also the rate of growth of that technology in the marketplace.

In one sense, the use of a logit market-share algorithm is redundant with the explicit treatment of uncertainty in SEDS, because the logit implicitly assumes the competing technology attributes are random variables with Weibul distributions. Nonetheless, we have elected to use the logit for two reasons: 1) it is simple and computationally quick, and 2) the underlying probability distribution captured by the logit is assumed to represent primarily the variability in competitors' attributes, as opposed to the uncertainty in those attributes. For example, we might use SEDS' Monte Carlo capabilities to capture the uncertainties in 2020 natural gas prices, while using the logit to capture the variability around the country in that 2020 price.

Dispatch:
Based on the variable cost of operation of each plant type (fuel, variable O&M, emissions costs), a dispatch order is constructed to meet the total load. The plant type with the lowest variable cost is first in the dispatch order, and the full capacity available is dispatched. The next plant type is then dispatched, continuing until the entire load is met.

Emissions/environmental factors:
Emissions are simulated in SEDS with simple coefficients per unit energy consumed, e.g., pounds of sulfur dioxide emitted per kWh of generation from an existing coal plant. Policies to control emissions can take several forms – emission taxes, performance standards, and emissions cap (and trade). Emission taxes are easily imposed by adding the tax to the cost of energy from the technology. Performance standards are easily implemented by simply restricting technology choices to those that meet the standard at least cost and adding that cost to the LCOE. Emission caps are problematic in a model like SEDS, because they require an iterative approach to bring the emissions in line with the caps. They can also require detailed modeling of the emission-reduction technology and fuel opportunities. To avoid excessive computer run-time and complications, SEDS does not model emission caps.

Initial Results

To date, we have developed two principal forms of results – deterministic comparisons with other models and uncertainty impact estimates. We show results (below) from SEDS that can be compared with results from the DOE Energy Information Administration's National Energy Modeling System (NEMS) (EIA 2006). NEMS is used by DOE/EIA to develop the *Annual Energy Outlook* and by other offices in DOE to substantiate research progress in compliance with the Government Performance and Results Act (GPRA). The comparisons are made by operating SEDS both in deterministic mode using inputs that parallel those of NEMS as closely as possible, and also in stochastic mode to see how large the impact of uncertainty can be.

We compare results for SEDS and NEMS, published by the Energy Information Administration in its *Annual Energy Outlook 2006 (AEO06)*. Figure 5 shows the capacity of renewable, gas, and coal-fired generators over time, as projected by the NEMS Reference Case in AEO06 and as projected by a deterministic run of SEDS using the same inputs as much as possible. The results are somewhat close, because these SEDS runs have used the electricity demands and fuel prices that come from the NEMS run.

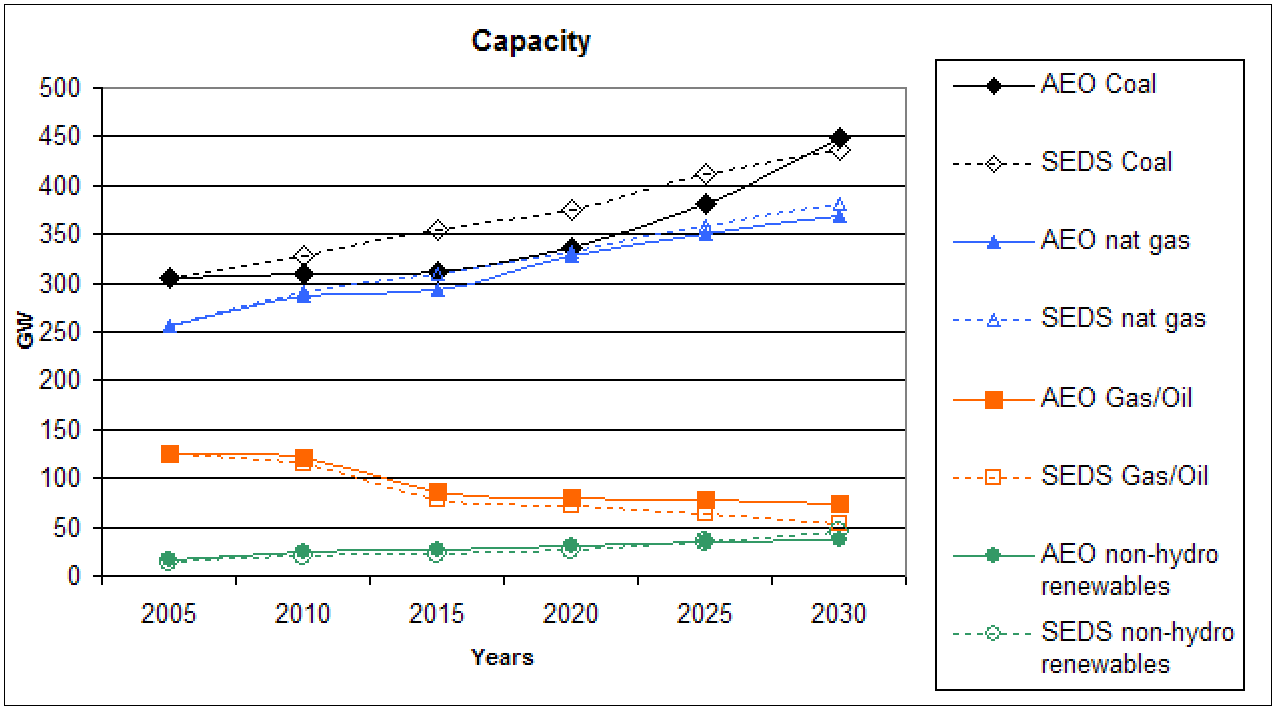

Figure 5
Deterministic Comparisons with AEO

Figure 6 presents the same deterministic capacity results from AEO 2006 for renewables, along with the expected values when SEDS is run stochastically. This figure shows the true value of SEDS. The greater level of renewables is driven by the uncertainties that we know actually exist in the U.S. energy system. It accounts for the fact that we know that carbon taxes MAY be imposed in the future; it accounts for the fact that we know that there MAY be breakthroughs in technology development of both renewables and conventional generators; it accounts for the fact that we know future fuel prices are highly uncertain. As such, it presents a more accurate picture of the value of renewable electric technologies.

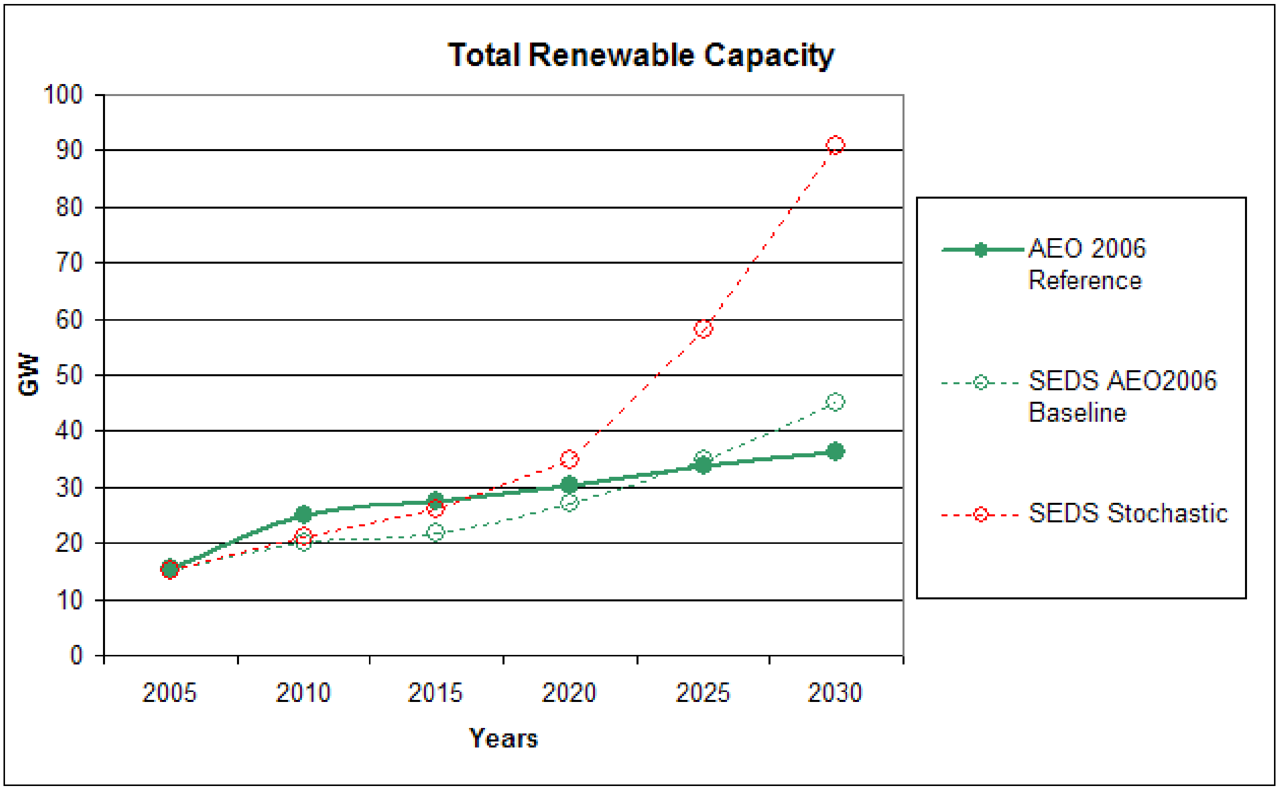

Figure 6
Renewable Energy Comparisons

Figure 7 shows that the expected values of Figure 6 are only part of the picture produced by SEDS. Figure 7 shows the probability bands around three variables within the same stochastic SEDS run: the capacity expansion of wind power, the generation of electricity from coal, and the price of electricity. This allows one to plan, not only based on a hoped-for "business-as-usual" scenario, but also for a worse-case "perfect storm" situation where several uncertainties evolve simultaneously to a critical value/position. A similar distribution can be produced for any of the outputs from SEDS, e.g., natural gas capacity, etc.

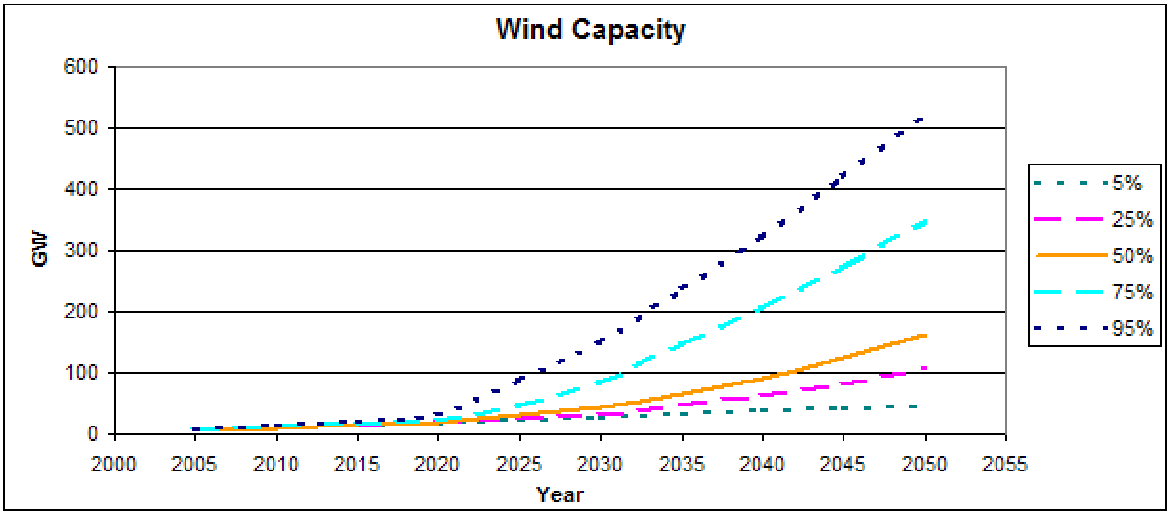

Figure 7a

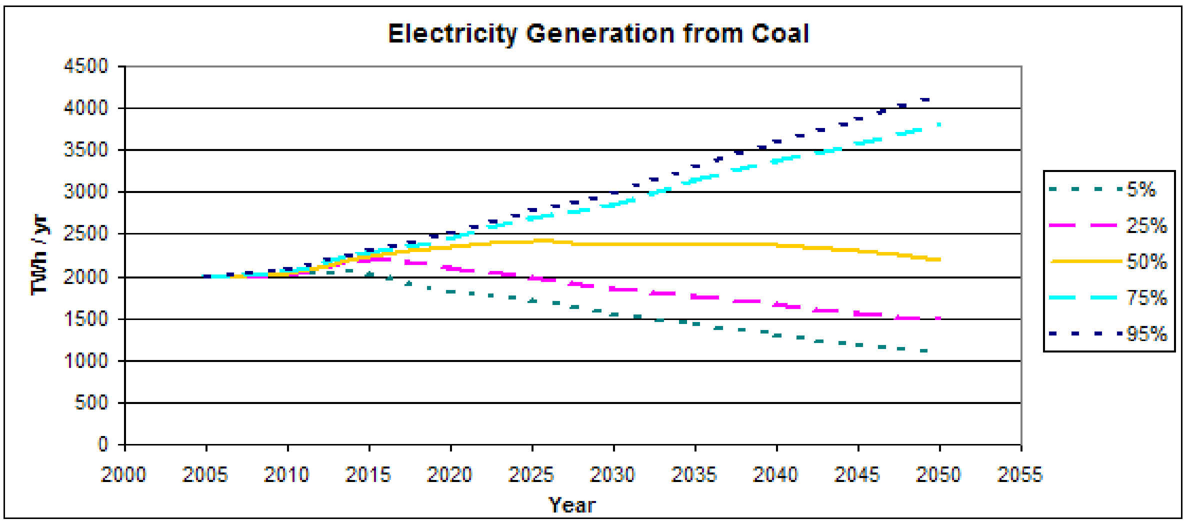

Figure 7b

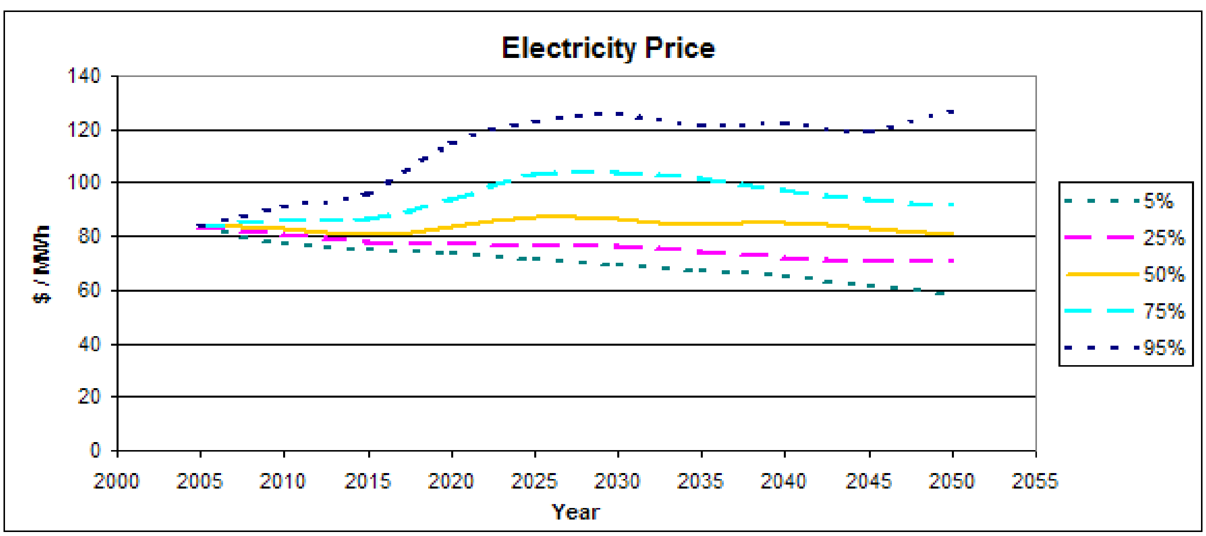

Figure 7c
Probability Bands

Figure 8 is another way to view how the results change over time; however, it provides a bit more insight than just the probability bands. Figure 8 shows the probability density function of the capacity of coal plants over time, using a different plot color for each year. One can see that, as you progress into the future, the results are more distributed (less certain) – an insight you can also glean from the probability bands. However, the probability density also provides the insight that these results become bimodal – that is, capacity values will tend toward the extreme high and low values. In the case of SEDS, this is due to a Bernoulli distribution on whether there will be a carbon tax in the future.

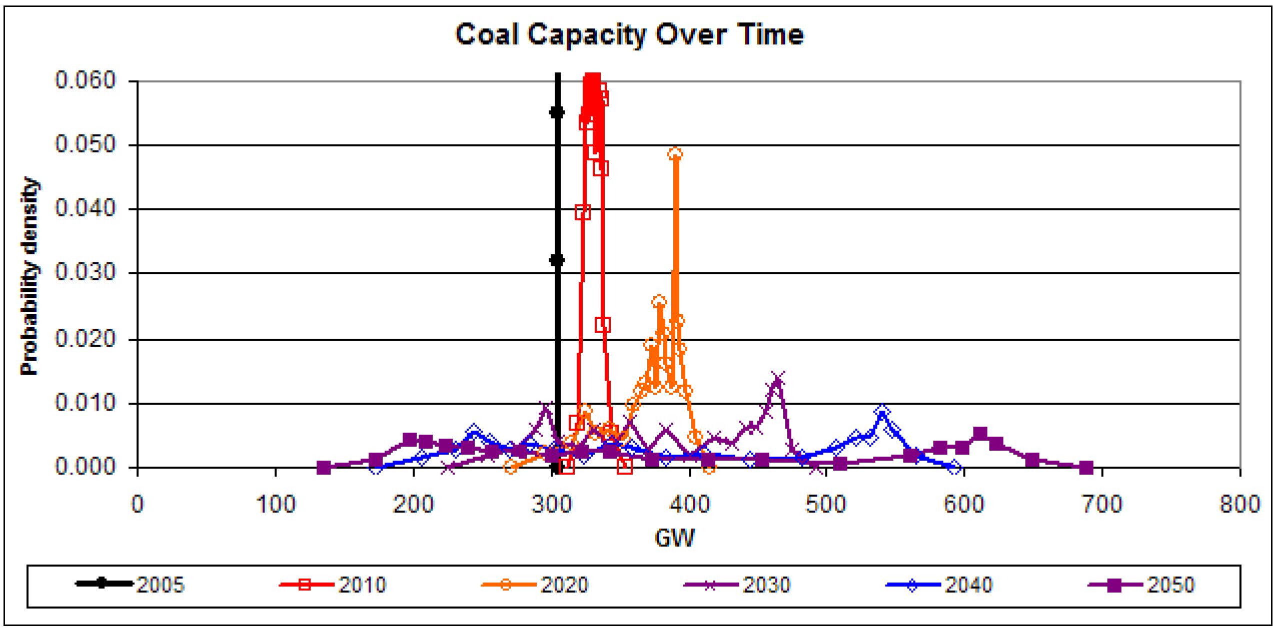

Figure 8
Distributions of SEDS Outputs

Sensitivity Analyses: In a sense, a stochastic model like SEDS automatically considers many sensitivities in its multiple trajectories through time. However, we have also investigated many sensitivities explicitly. Of particular interest are the sensitivities to the probability distributions themselves. We show (below) some sensitivities to the assumed shape of a probability distribution and to the mean of a distribution.

We have found that the results are not very sensitive to the shape of the input distributions. We tested this for most of the uncertain inputs by changing the shape from our default triangular distribution to a uniform distribution. One of the largest impacts occurred when we changed the symmetric triangular distribution on the annual natural gas price growth rate to a uniform distribution with the same mean. However, as you can see in Figure 9, the impact on the total consumer bill was still minimal.

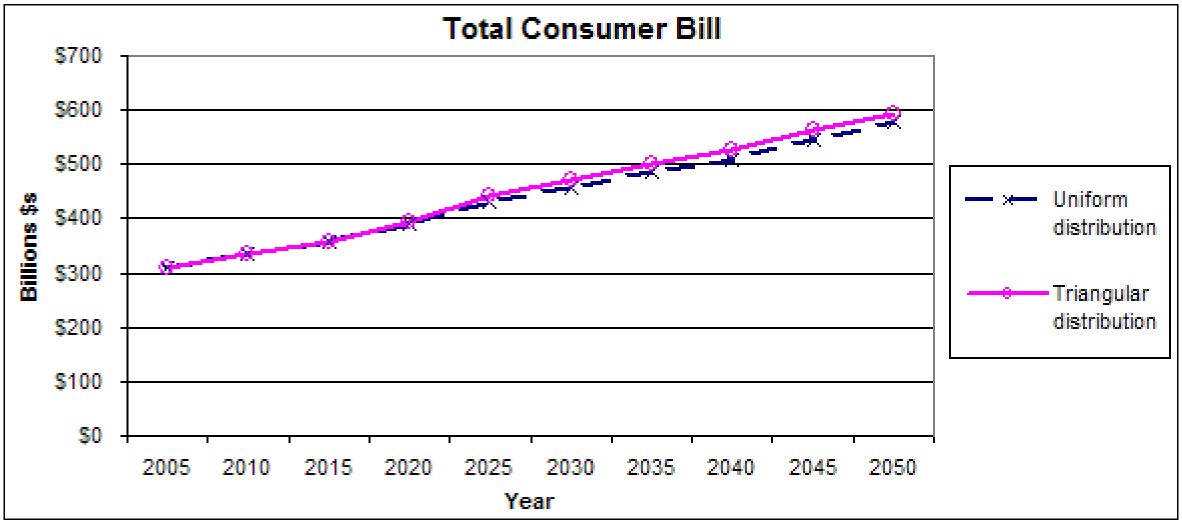

Figure 9
Insensitivity to Probability Distribution Shape

As expected, results are more sensitive to changes in the mean of a probability distribution. Figure 10 shows how the model reacts to a relatively small change in the coal-price growth rate input. The only difference in the two runs is outlined in Table 3.

Table 3 - Coal Price Growth Rate Sensitivity Inputs

Coal price growth rate (%/year)	Low	Mode	Mean	High	Shape
Run with mid = 1.008	.99	1.008	1.008	1.025	Triangular
Run with mid = 1.02	.98	1.02	1.02	1.06	Triangular

This increase in the mean of the annual growth in coal price leads on average to a 50% increase in the price of coal by 2050. The model responds to this, on average, by retiring coal plants instead of continuing to build them as show in Figure 10.

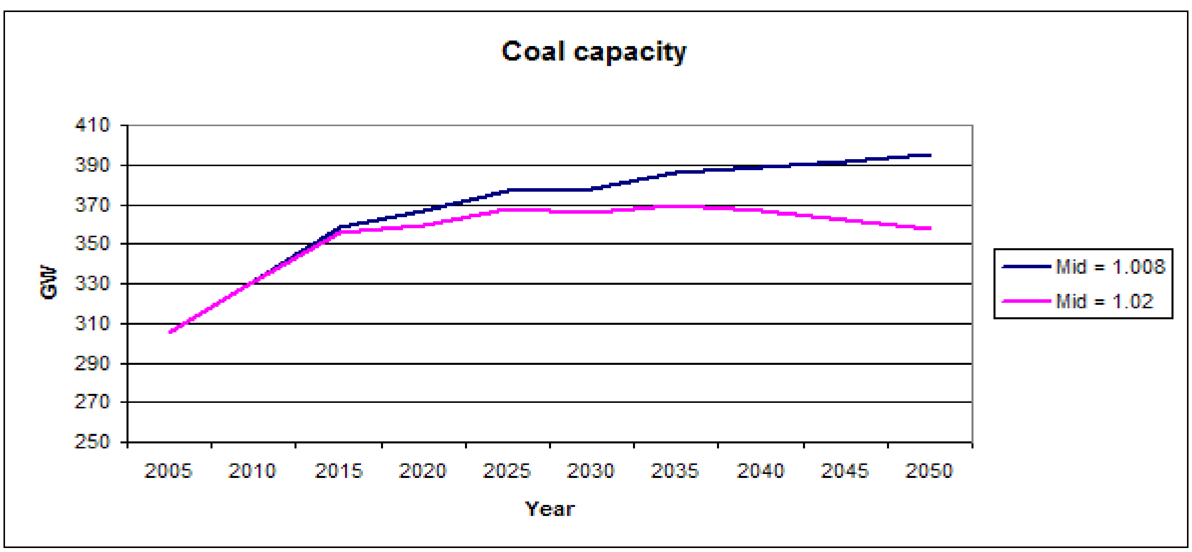

Figure 10
Sensitivity to the Mean of a Probability Distribution

NREL and the National Energy Technology Laboratory (NETL) are examining a wide range of additional uncertainties with SEDS.

Future Development

DOE is working with its national laboratories (NREL, NETL, Lawrence Berkeley National Laboratory, Argonne National Laboratory, and Pacific Northwest National Laboratory) and others to expand SEDS beyond NREL's current electric-sector version to a full representation of U.S. energy markets and their interaction with the U.S. economy. Through a multiyear development effort, the full SEDS will include the transportation, buildings, and industry demand sectors; an endogenous treatment of fossil resources; and a macroeconomic module. These will be developed with enough detail to estimate the impact of different technologies, programs, and policies under the full range of future uncertainties in primary market drivers. For example, SEDS should provide new insights into the future role of biomass fuels, hydrogen, plug-in hybrid electric vehicles, carbon sequestration, coal-fired IGCC power plants, photovoltaics for buildings, advanced lighting technologies, and advanced electric motors under a wide range of market and policy possibilities.