Industry R&D in a Stochastic Energy Model

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ABSTRACT

The Stochastic Energy Deployment System (SEDS) is a model that fully characterizes the energy economy, including various demand sectors and the electricity, liquid fuels, natural gas, coal and renewable energy sectors. The SEDS model is designed to account for the stochastic nature of both energy R&D and the market penetration of new technologies, some of which are developed by DOE. Two different approaches are used to incorporate R&D effects in the module. For narrowly focused R&D results that are applicable only to very specific technologies, aggregate energy savings associated with this technology are used as a primary input. R&D for this group of technologies enters the module as an aggregate improvement in the energy consumption, such that savings are applied proportionately to submodules' shares in consumption. For cross-cutting technologies associated with end-uses spanning a large subset of industries, R&D effects are reflected at the technical parameter level. These effects are characterized by improving fuel intensity and cost of these technologies through time, conditioned on a certain funding level. All R&D effects are specified as distributions to preserve the stochastic capability of the SEDS model. The paper presents results of the module simulations under various R&D levels and carbon policy scenarios.

Introduction

A new energy model is being developed by the Department of Energy's (DOE) Energy Efficiency and Renewable Energy Office. This model is designed to account for the stochastic nature of both energy research and development (R&D) and the penetration of new technologies, some of which are developed by DOE. Stochastic energy deployment system (SEDS) is a model that fully characterizes the energy economy, including various demand sectors and the electricity, liquid fuels, natural gas, coal and renewable energy sectors. The industrial sector of SEDS was constructed from an aggregate model of US manufacturing that was developed as part of the Canadian Integrated Modeling System CIMS-US framework. This paper describes the industrial module of SEDS, shows how carbon policy and uncertainty are characterized within the module, and provides results of module simulation under various carbon policy scenarios.

SEDS is being developed by a consortium of national laboratories, including Argonne National Laboratory (ANL), Oak Ridge National Laboratory (ORNL), the National Renewable Energy Laboratory (NREL), Pacific Northwest National Laboratory (PNNL), Lawrence Berkeley National Laboratory (LBNL), and the National Energy Technology Laboratory (NETL). While it is not meant to be a competitor of the national energy modeling system (NEMS), it does do what NEMS cannot do – look at the probability distributions around key parameters and variables, such as the world price of oil or effects of research and development (R&D) on energy intensity.

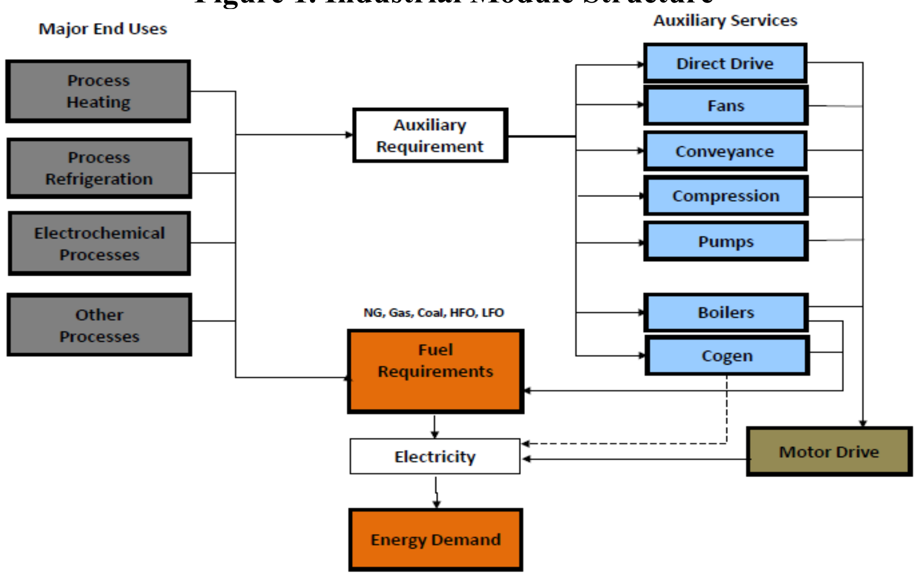
Section 2 includes an overview of the module structure, major assumptions and limitations. Section 3 provides a description of how R&D is represented in the model and includes deterministic and stochastic simulation results for several R&D funding scenarios. Concluding remarks and an outline of future model improvements are included in Section 4.

Module Structure

This module is primarily an aggregate representation of the US manufacturing sector, which could be enhanced with detailed submodules for a set of specific industries. The model is a typical engineering-economic model of the industrial sector with output, energy use and technology stocks calibrated to the 2006 Manufacturing Energy Consumption Survey (MECS) data, then simulated and benchmarked to the 2010 Annual Energy Outlook (AEO). The industrial sector is linked to the rest of the model through a set of inputs that include fuel prices (natural gas, coal, electricity, oil, light fuel oil and heavy fuel oil), the manufacturing growth rate, the discount rate for levelized cost, emissions tax/cap settings and the carbon content of various fuels. The outputs calculated by the module are energy requirements by fuel type, byproduct gas price, emissions, capital and energy expenditures, as well as the overall sector energy intensity metric. This section contains a brief overview of the module structure, while more detailed explanation with more extensive simulation results can be found in Livingston, Roop and Boyd (2010).

The industrial sector energy consumption is tied explicitly to output produced and the technologies used to produce that output. The module structure is illustrated in Figure 1. The industrial sector module is initialized based on the manufacturing output, which is attributed proportionally to the four major end uses: process heating, process refrigeration, electrochemical processes and other processes. These primary processes have two sets of requirements: a) direct fuel and b) auxiliary services. The latter group requires shaft drive provided by motors of different size classes and efficiencies. Auxiliary requirement coefficients and technological splits for size classes are derived from the CIMS-US model.

Figure 1. Industrial Module Structure



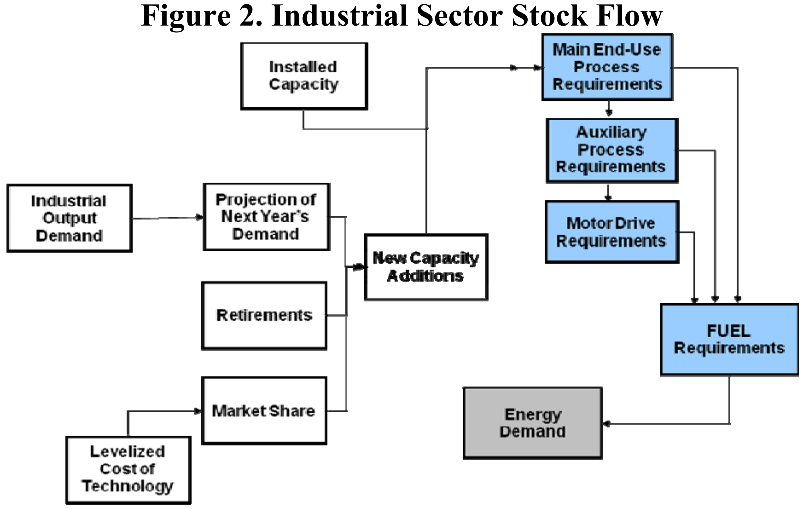
Primary processes reflected in the model are gross representations of averages of equipment contained in the CIMS data base, but themselves have no real-world technology equivalent. While the major end-use modules are not strictly technologies, the auxiliary services that are required by these major end-use modules are defined technologies such as pumps, fans, compressors, conveyors, motors, lighting, boilers and cogeneration.

After direct and indirect energy use is accounted for, the subtotal demand for electricity is lowered by the cogeneration amount. Thus, the total energy demand represents the net quantity of the purchased energy rather than overall energy consumed by the industrial sector. This leads to a CO_2 emissions calculation that is determined by the carbon content of each fuel and the amount of fuel combusted. As mentioned before, energy demand for the initialization year is calibrated to 2006 MECS manufacturing and non-fuel (feedstock) use for the total energy, as well as for each individual fuel type, and then simulated and benchmarked to the AEO 2010 reference case. The difference between MECS data and AEO totals was included in the module as non-manufacturing fuel use.

The main driver for the module is manufacturing output growth. Industrial equipment stock meeting each of the end uses is tracked in the output equivalent. After initial output is proportionately assigned to the major end-use submodules, the model simulates from the base year onward by forecasting the output quantity based on the manufacturing growth rate. Industrial stock flow logic is depicted in Figure 2.

The module tracks several vintages of stock for each technology type, so that each vintage retires subject to its expected economic life. To meet the output projection, the model adjusts the current stock for equipment retirements and then calculates necessary new capacity additions.

Figure 2. Industrial Sector Stock Flow



New equipment stock is purchased using a market share calculation that compares different efficiencies of stock and levelized cost. Capital costs, fixed and variable operation and maintenance (O&M) costs, emissions costs, tax incentives, and the expected utilization rates are used to calculate the levelized annual total cost for each technology. Fuel costs, which depend on the rate at which the fuel is used and the price of fuels, are included as well. Capital costs can be decreased as a result of R&D effects and "learning by doing" modeled with a learning curve. The effects of R&D are treated with uncertainty and can be adjusted to try to capture the level of government investment in R&D. Improvements from learning-by-doing are based on cumulative installed capacity, such that a specified percent improvement in capital costs is achieved for each doubling of capacity. Production tax credits, investment tax credits, and accelerated depreciation can be applied to appropriate technologies and will lead to lower levelized annual costs. The combination of all these factors produces a levelized annual cost that is used to determine how the market share of new capacity additions will be given to the competing technologies.

The logit algorithm is used to allocate market shares among competing technologies, and it reflects a probabilistic cost minimization process, with overlapping distributions of technology costs determining the point at which costs are minimized. Given a total demand, a list of technologies that could meet that demand (each with specified utility and capacity), the market share competition algorithm uses a logit choice function to generate the total quantity of new added capacity for each technology. In this version of the industrial sector, new added capacity for each technology is calculated based on the technologies' "utility", which is defined as levelized costs. When available, information from case studies may sometimes inform parameter selection for the logit function; otherwise, we use a parameter value that follows the rule-of-thumb that a 15% cost differential captures 80% of the new market share. If the high utility technologies cannot meet the desired demand as determined by the market share calculated above, the excess demand is allocated to the other suppliers in proportion to each technology's utility, and iterations occur until demand is met. If the proportionately scaled-up capacity mix is not sufficient to meet projected demand, then the entire capacity from every technology supplier is purchased regardless of the optimal share mix. Finally, these new capacity allocations are added to the existing stock of equipment minus that time period's retirements. The resulting stock then matches demand. Once the stock of equipment has been changed to reflect additions and retirements, fuel use is calculated.

There are three generations of technologies that compete for new stock additions: current, state-of-the-art and advanced. Current generation captures the technologies that are available now and will not be competing for new share additions after 2015. This generation has lower levelized capital cost, but high fuel intensities. The state-of-the-art (SOA) is competitive with the current stock immediately; the advanced technology becomes competitive with these two in 2025. The SOA and advanced technologies have higher capital cost and a lower fuel requirement.

Multiple fuel options, such as natural gas, electricity, coal, light and heavy fuel oil (LFO and HFO) and byproduct gas, are included for each of the technology types where fuel substitution is appropriate. This module is structured such that process heating uses electricity, coal, natural gas and byproduct gas. Only a very minor portion is serviced by LFO. Process refrigeration and cooling uses either electricity or natural gas absorption cooling. The electro-chemical processes are dominated by electricity use. Other processes, a general category that accounts for primary processes not included in the previous three categories, is serviced by coal, natural gas, electricity and byproduct gas, with a small fraction using LFO.

Just like the end-use service equipment, auxiliary services compete on the basis of costs to satisfy requirements needed by the major end-use services for the production of manufacturing goods. Capital costs, operating and maintenance costs, and performance characteristics for all the auxiliary equipment are drawn from the CIMS-US data base, and are currently being updated.

As one would expect for any attempt at modeling a complex system, this module has some limitations and simplifying assumptions, which should be explained to gain a better understanding of model results and prioritize future work. Because it is primarily a representation of the US manufacturing sector, the module is national in scope and lacks both regional and industry detail. Although no industry-specific technologies appear in the module, it does cover many of what the Industrial Technologies Program (ITP) calls cross-cutting technologies: compression, air displacement, conveyance, boilers, pumping and motor drive. In place of these industry-specific technologies, there are fuel-specific "quasi-technologies" for process heating, process cooling, electro-chemical processing, and other processes.

The use of "quasi-technologies" is one of the limiting factors of the model in part because, unlike industry-specific technologies, it is more difficult to handle fuel switching and market share competition. In addition, the technical performance of these quasi-technologies is somewhat inconsistent with industry-specific performance (e.g. the aggregate SOA technologies that replace current average performance technologies may not be nearly as efficient as industry-specific SOA technologies).

Research and Development Effects

Two different approaches are used to incorporate R&D effects in the module. For narrowly focused R&D results that are applicable only to very specific technologies, aggregate energy savings associated with the technology are used as a primary input. For cross-cutting technologies that are associated with end-uses spanning a large subset of industries, R&D effects are reflected at the technical parameter level. In this case improvements enter the model as changes in the fuel intensity and cost of these technologies through time, conditioned on a certain funding level.

Fuel intensity, operation and maintenance cost, as well as capital cost are used jointly to determine market shares for each of the a) technology groups that serve the same end-use, but use different fuels, b) technology generations (current, SOA, advanced) within each fuel group. In general, current technologies have lower capital cost, but they are also less fuel efficient. SOA and advanced technologies have significantly lower fuel intensity, but their costs are much higher. By representing the portion of R&D effects as a dynamic change in fuel intensity, the model allows immediate short-term decreases in direct fuel requirements, as well as faster penetration of fuel-efficient technologies in the future. Cost reductions result not only in higher penetration of more fuel efficient technologies, but they also induce both short-term fuel switching for a subset of technologies (for which multiple fuels are available), as well as long-term fuel substitution.

There are no explicit assumptions on the shape of the S-curves defining market penetration; it is rather a full characterization of relative costs that defines the market share competition. It is worth noting that although the current framework is driven primarily by differences in relative costs, it is flexible enough to allow for multiple factors in the technology choice algorithm. It can be adapted to represent international R&D spillover, multiple funding sources with differentiated R&D effects, or completely new R&D projects resulting in so called "black swan1" technologies. In addition, if the module is extended to incorporate regionality and to break specific industries out of the aggregate manufacturing sector, it would be possible to represent inter-industry and interregional spillover effects.

Publicly funded industrial R&D programs often have multiple narrowly defined areas of interest with highly specific end products. For this heterogeneous subset of technological advances, the R&D impacts enter the industrial module as an aggregate improvement in the energy consumption. Exogenously estimated energy savings are applied proportionately to submodules' shares in total energy requirement. This approach of incorporating narrowly

[1] Based on the "Black Swan Theory," coined by Nassim Nicholas Taleb, these are the "surprise" technologies in which the success and impact were not predicted by those working within the industry.

focused R&D effects at the aggregate level allows for the inclusion of a large list of industry-specific R&D into policy analysis without increasing complexity of the model.

All R&D effects can be specified as deterministic step-changes for a chosen number of goal years or alternatively, as probability distributions to preserve the stochastic capability of the SEDS model. It should be noted that all of the module parameters can be easily turned into random variables if relevant probability distribution information is provided. There are multiple ways to characterize these stochastic processes in the module. Currently it is done either by selecting the desired function from a large menu of built-in probability density functions (PDF), when PDF parameter estimates are available, or by using results of the outside simulations or expert elicitation.

To illustrate these analytical capabilities, as well as emphasize the importance of stochastic simulation in policy analysis, selected results of stochastic simulations are presented below. Two sets of figures illustrate changes in energy demand by fuel type, overall energy intensity of the industrial sector, as well as resulting CO_2 emission levels. Three sets of "what if" scenarios were considered: base case (no R&D funding in the future), planned (continued R&D funding at the current level), and overtarget (twice the planned level of R&D funding). The industrial module does not translate funding dollars into improvement levels at the technology level for the goal years. Instead, magnitude of intensity improvements and cost reductions for 2015, 2020 and 2025 are specified exogenously as a step change. The estimates for these step changes are obtained either from various R&D programs directly or estimated as part of expert elicitation process. However, the module does have a capability to interpolate between these set values for intermediate years. It can also interpolate magnitudes of fuel intensity and cost improvement for the budget cases bounded by the overtarget level, but it requires analysts to specify what the interpolation assumptions are for each case.

Figures 3 through 6 show deterministic results for industrial energy demand by type (coal, light fuel oil and natural gas), and CO2 emissions from total on-site combustion. Although these results provide insight regarding possible energy efficiency improvements of the industrial sector, the question about the likelihood of each improvement level remains unanswered because deterministic results do not convey information about the uncertainty around R&D outcomes. To illustrate this aspect of the analysis, stochastic simulation was performed for all of the key variables of the module. R&D impacts were characterized by distributions measuring the probability of improvement occurring (Bernoulli), and distributions describing the magnitude of this improvement if it were to occur (Triangular).

Figure 3. Industrial Demand of Coal, Quadrillion Btu/Year

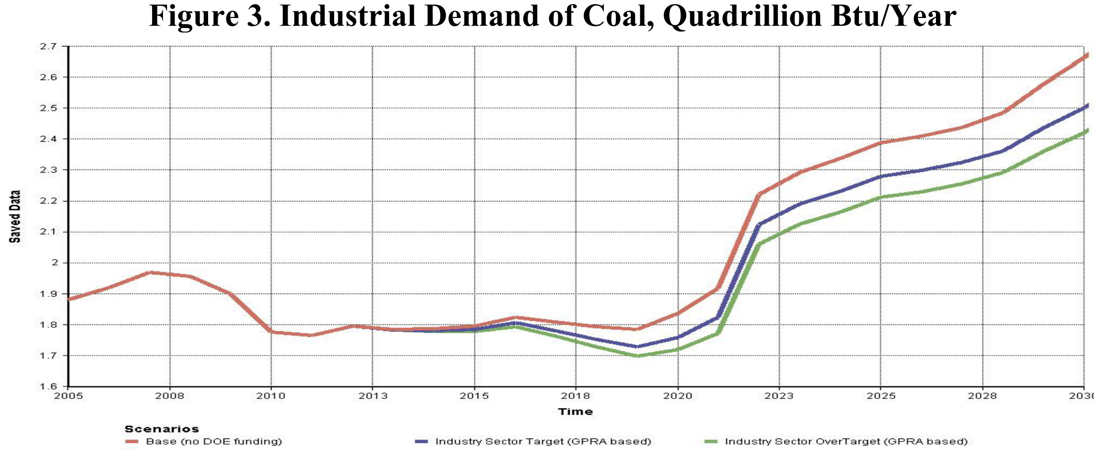


Figure 4. Industrial Demand of Light Fuel Oil, Quadrillion Btu/Year

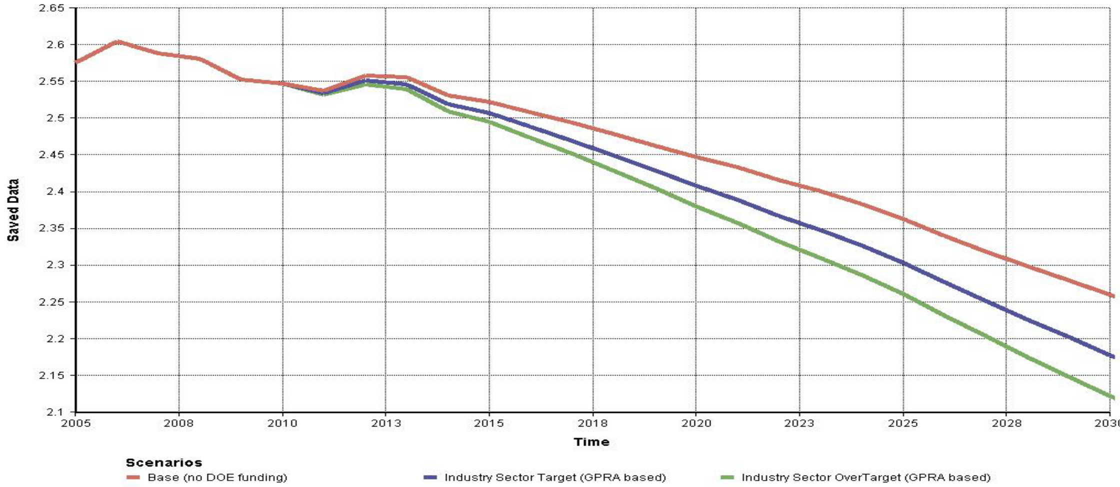


Figure 5. Industrial Demand of Natural Gas, Quadrillion Btu/Year

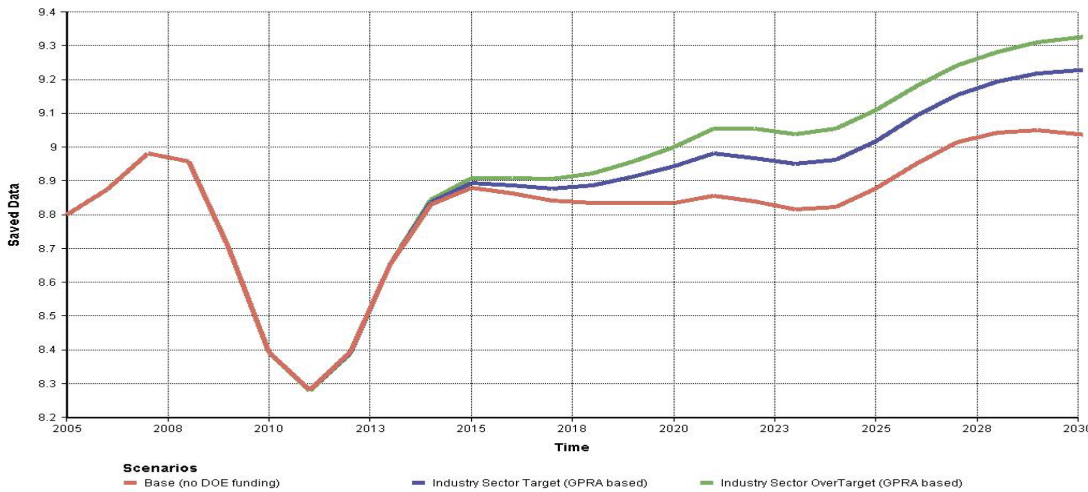
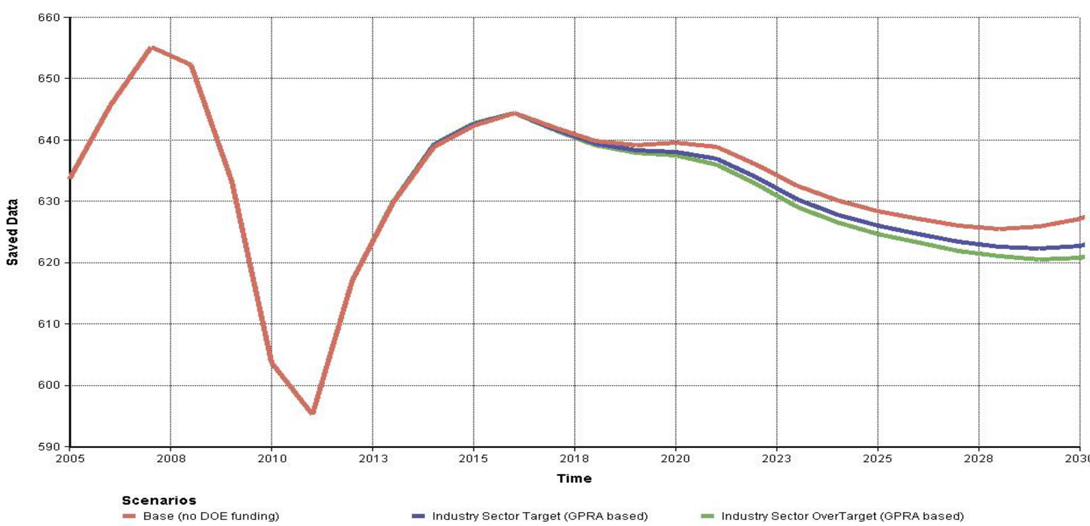


Figure 6. Industrial CO2 from All On-Site Combustion, MMtCO2



Figures 7 and 8 contain coal demand stochastic simulation results for base and target cases out to 2030. As can be observed for the base case the possible range of R&D effects at the base level is such that a large portion of the distribution is located above the levels shown by deterministic results. This implies that there is a significant chance that coal consumption will be higher than what is suggested by deterministic results. Similarly, there might be a scenario when 75% of the distribution lies above the deterministic estimate, so there is only 25% chance that this level would not be exceeded.

Figure 7. Coal Demand, Base Case, Quadrillion Btu/Year

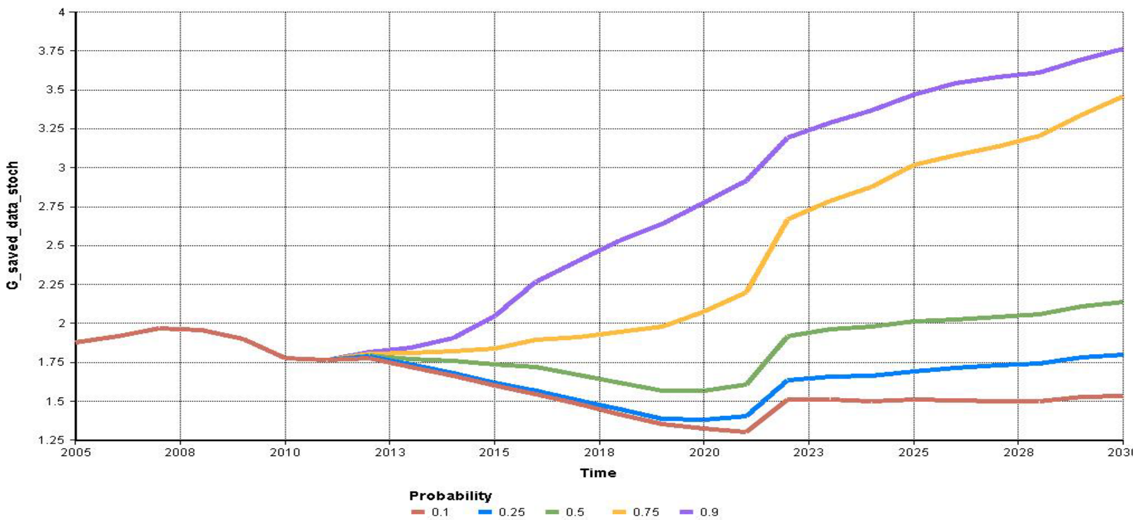
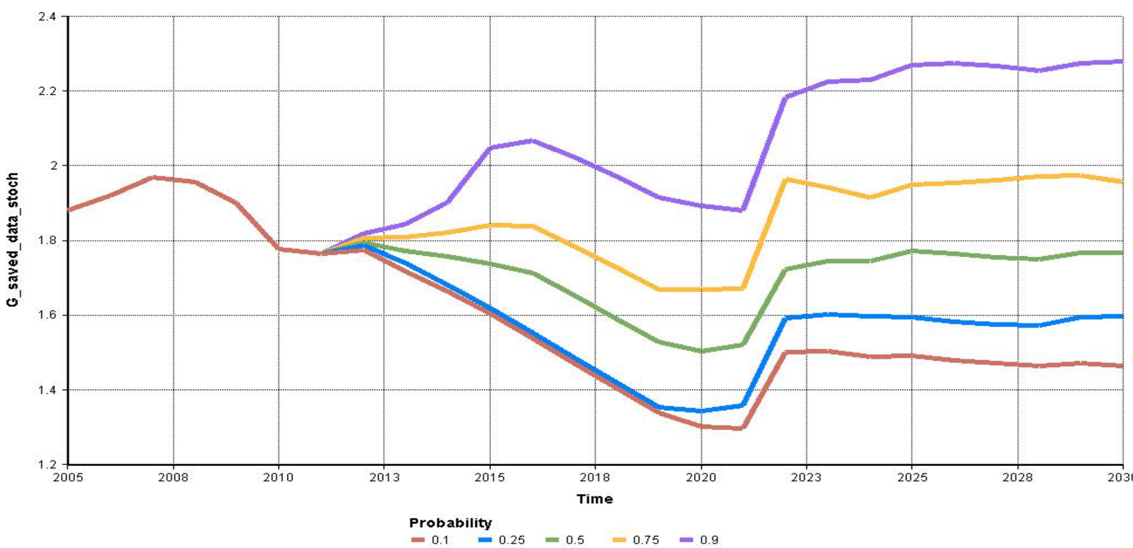
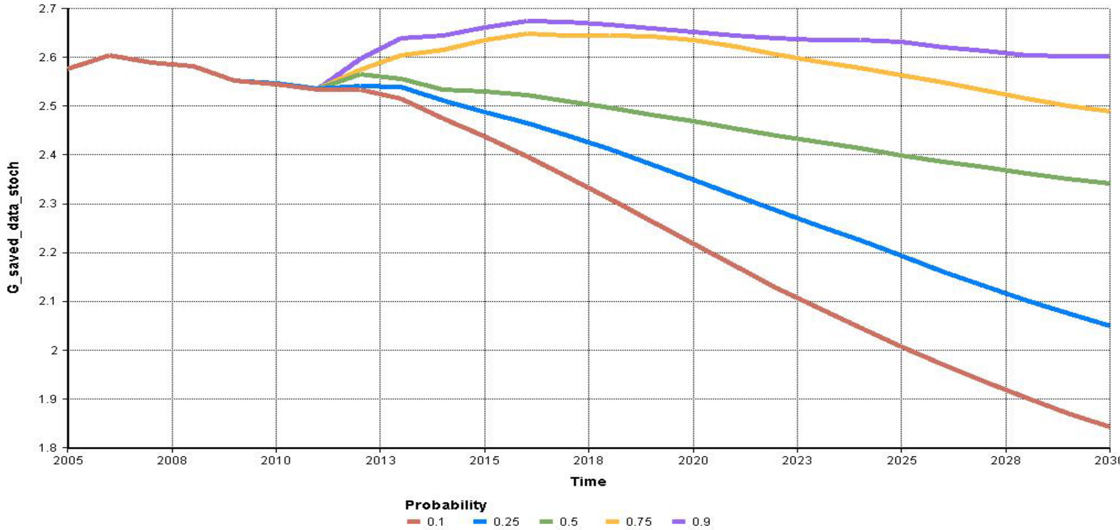


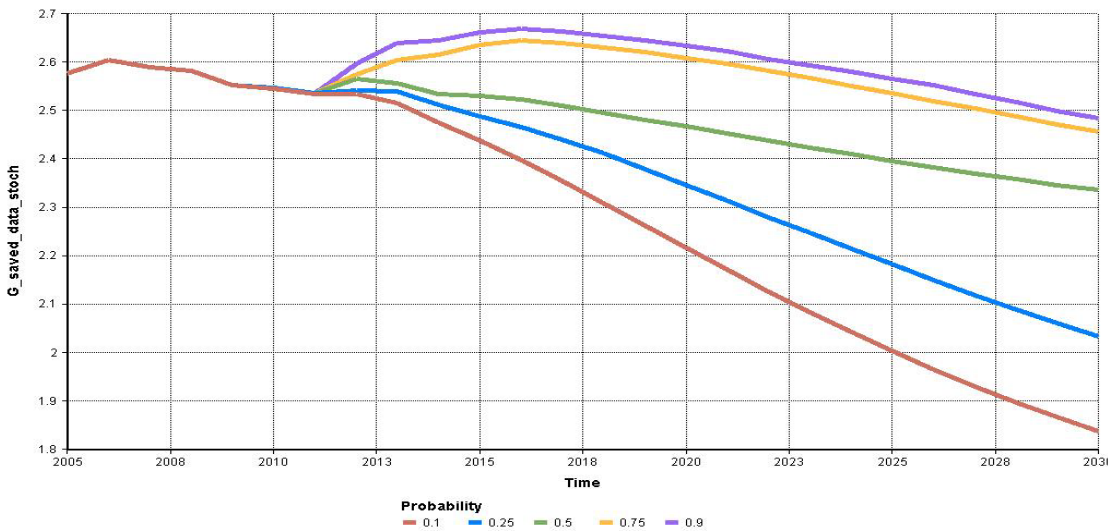
Figure 8. Coal Demand, Target Case, Quadrillion Btu/Year

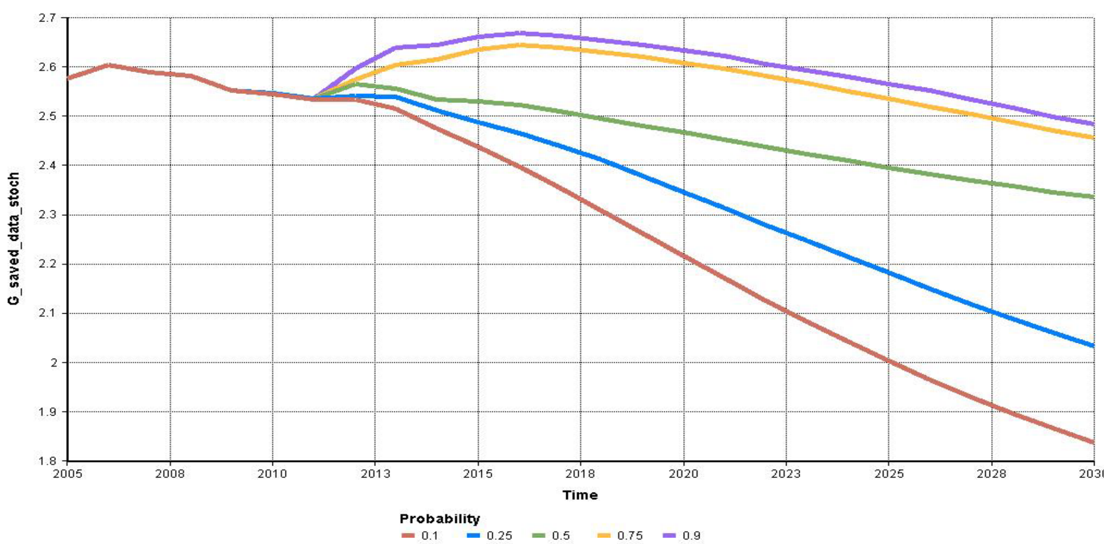


Alternatively, there could be a large overlap between distributions and a large difference in the funding scenarios. Figure 9 contains stochastic simulation results for light fuel oil demand. Although deterministic results in Figure 4 show some difference in the consumption path between the base case, target case and overtarget case for this fuel, three sets of stochastic results are nearly identical.

Figure 9. Stochastic Results for Light Fuel Oil Demand, Base, Target and Overtarget Cases, Quadrillion Btu/Year

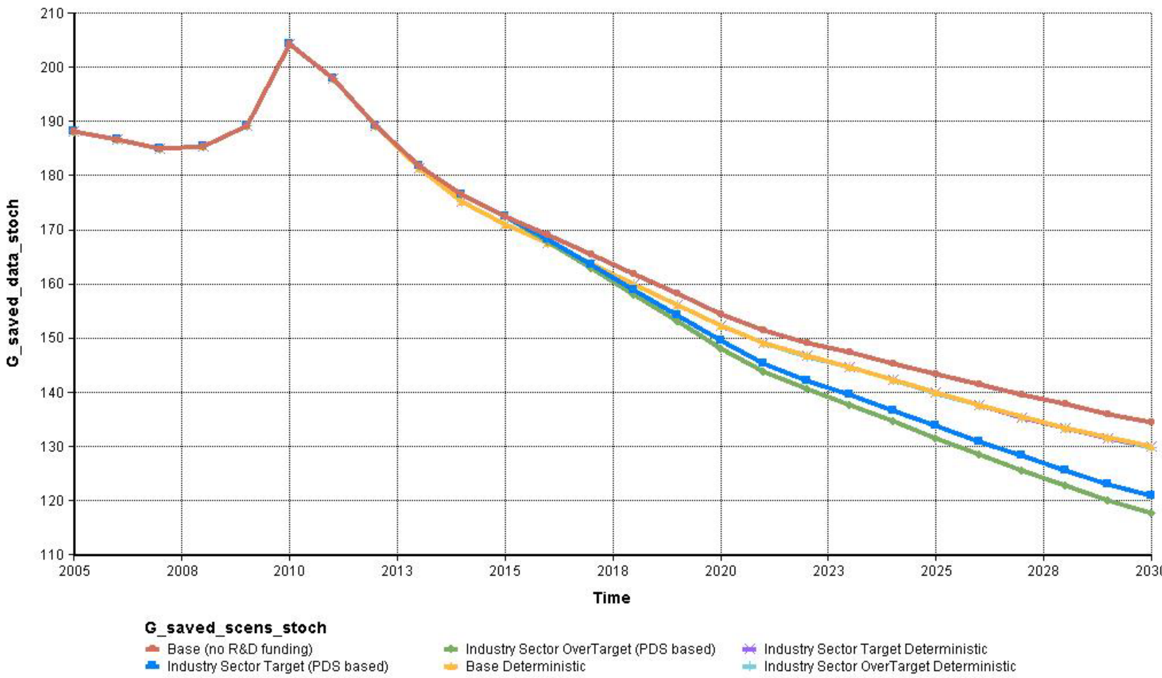






Deterministic and stochastic simulation results for overall energy intensity of the industrial sector are presented in Figure 10. Although deterministic results suggest the energy intensity of the industrial sector is identical for three cases (the paths are overlayed forming one orange line), 50th percentile of the stochastic results are different.

Figure 10. Stochastic (50%) and Deterministic Result (Overlayed Under Base Deterministic) for Energy Intensity



Default perception of deterministic paths is such that more often than not, a viewer assumes symmetry of uncertainty intervals around deterministic estimates, and there is a strong downward bias in perceived range of that uncertainty. Deterministic results contain only a portion of the answers necessary for informed decision making.

Conclusion

The SEDs industrial sector module has a capability to analyze industrial R&D impacts in several ways. For cross-cutting technologies that span a large subset of industries, R&D effects are reflected at the technical parameter level such as capital cost, operation and maintenance cost and fuel intensity. For narrowly focused R&D results that are applicable only to very specific technologies, the aggregate energy savings are used to adjust the final energy consumption.

Although the current framework is driven primarily by differences in relative costs, it is flexible enough to allow for multiple factors in the technology choice algorithm. It can be adapted to represent international R&D spillover, multiple funding sources with differentiated R&D effects, or completely new R&D projects resulting in so called "black swan" technologies. In addition, if the module is extended to incorporate regionality and to break specific industries out of the aggregate manufacturing sector, it would be possible to represent inter-industry and interregional spillover effects.

The SEDS model includes a stochastic capability for analyzing impacts of R&D on the industrial sector. As illustrated in the paper, deterministic results, although providing important information, contain only half of the answer necessary for informed decision making. SEDS structure allows for both deterministic and stochastic modeling, providing complete information regarding the likelihood of analyzed scenarios that take into account uncertainty of R&D outcomes and their impacts on the industrial sector.

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