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THE OPEN SOURCE STOCHASTIC BUILDING SIMULATION TOOL SLBM AND ITS CAPABILITIES TO CAPTURE UNCERTAINTY OF POLICYMAKING IN THE US BUILDING SECTOR[1]

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Abstract

The increasing concern about climate change as well as the expected direct environmental economic impacts of global warming will put considerable constraints on the US building sector, which consumes roughly 48% of the total primary energy, making it the biggest single source of CO_2 emissions. It is obvious that the battle against climate change can only be won by considering innovative building approaches and consumer behaviors and bringing new, effective low carbon technologies to the building / consumer market. However, the limited time given to mitigate climate change is unforgiving to misled research and / or policy. This is the reason why Lawrence Berkeley National Lab is working on an open source *long range* Stochastic Lite Building Module (SLBM) to estimate the impact of different policies and consumer behavior on the market penetration of low carbon building technologies. SLBM is designed to be a fast running, user-friendly model that analysts can readily run and modify in its entirety through a visual interface. The tool is fundamentally an engineering-economic model with technology adoption decisions based on cost and energy performance characteristics of competing technologies. It also incorporates consumer preferences and passive building systems as well as interactions between technologies (such as internal heat gains). Furthermore, everything is based on service demand, e.g. a certain temperature or luminous intensity, instead of energy intensities. The core objectives of this paper are to demonstrate the practical approach used, to start a discussion process between relevant stakeholders and to build collaborations.

1. Introduction

The perception that our energy future looks increasingly uncertain, and that climate change requires us to explore radically different technology pathways has precipitated the search for new or accelerated technology research and development (R&D) and the analysis tools necessary to guide it. The work presented in this paper is part of the ongoing development of the Stochastic Energy Deployment System (SEDS), which follows in a long history of modeling in support of planning and budgetary activities at the U.S. Department of Energy (USDOE). SEDS was commissioned to better support management, research direction, and budgetary decision-making for future R&D efforts. Specifically, it will be used to comply with the Government Performance Results Act of 1993 (GPRA), which requires federal government agencies, including USDOE, to predict and track the results of their programs and report them as a part of their obligations to the U.S. Congress (Gumerman 2005). While this process may at first blush seem like a harmless bureaucratic exercise, the wider implications of research budgets and priorities being determined based on faulty or misleading forecasts are serious. At a minimum, misdirection of limited public R&D funds could result. By developing SEDS, USDOE seeks to develop a tool that will help define a range of possible outcomes rather than accepting a potentially misleading scalar prediction, and to aid in the development of robust programs to address our uncertain destiny.

SEDS is not intended to be a replacement for the Energy Information Administration's (EIA's) National Energy Modeling System (NEMS), which provides the basis for the Annual Energy Outlook (AEO), and subsequently for many energy policy studies. Rather, SEDS is an adjunct that allows modeling of economy-wide energy costs and consumption out to 2050 (NEMS currently forecasts to 2030) with minimal user effort or expertise. SEDS

[1] The work described in this paper was funded by the Office of the Assistant Secretary of Energy for Energy Efficiency and Renewable Energy, Planning, Analysis, and Evaluation section in the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

emphasizes characterizing the robustness of expected benefit streams of new technologies given the uncertain nature of energy futures, whereas NEMS is solidly rooted in historic and current conditions. To achieve fast execution, SEDS must run with variable time steps of, at a minimum, 0.5, 1, or 2 years. Also in the interests of speed and because of the belief that global equilibriums are rarely experienced in the real-world, no iterations towards solutions in one time step are allowed; rather outputs from one time step are inputs to the next.

This paper briefly describes the motivation for SEDS, but it is primarily focused on the building sector module, the *SEDS Lite Building Module* (SLBM), which is currently under review by the USDOE. This effort creates a rare opportunity to address some of the fundamental concerns that are widespread in the building energy simulation and forecasting community, such as: representing building end-use interactions, allowing competition between active and passive approaches, recognizing the key role of retrofits of existing buildings, integrating selection of on-site generation, etc. The entire SEDS project is evolving, and the motivations for reporting on the approach at this time to this audience include the hope that feedback from the building energy modeling community can guide the future shape of SLBM, which will be extended throughout this year. Note that the future direction of federal buildings energy research will rest in part upon its results.

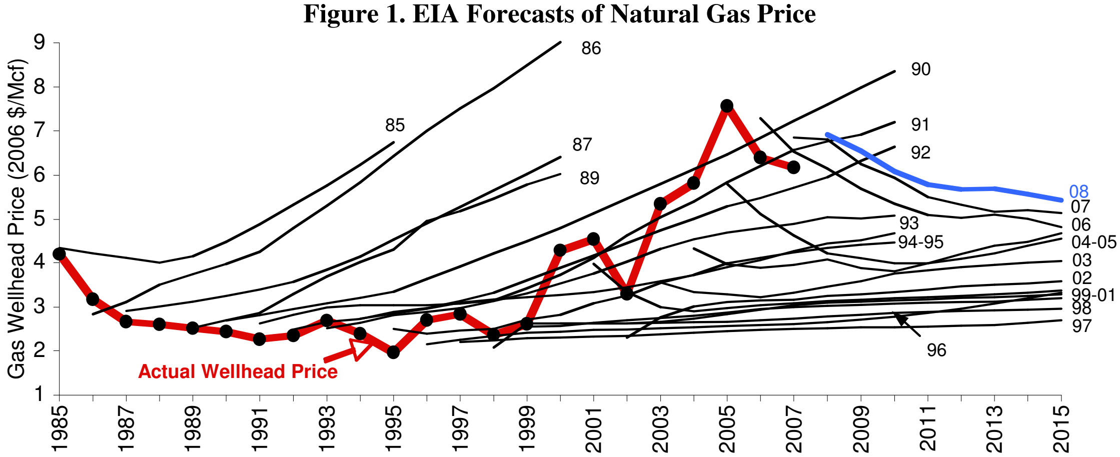
Finally, sensitivity results for photovoltaics (PV) and lighting are shown in this paper. Different measures, such as carbon cap or investment subsidies for PV, are simulated and the impact on the technology penetration as well as CO_2 emissions by 2050 are shown.

2. The Importance of Uncertainty

The type of forecasting conducted in support of policymaking and planning in the U.S. has typically paid scant attention to the significant uncertainty inherent in many aspects of such analysis. Forecasts are frequently presented as point estimates only, or as point estimates with sensitivity cases or side scenarios[2]. A preeminent example of the point forecast with side scenarios is the AEO.

Despite the obvious importance of uncertainty in any forecasting endeavor, the stability of conditions in the later part of the twentieth century fostered complacency. Figure 1 shows the AEO forecasts of wellhead natural gas prices. The years in which the forecasts were made are shown, as is the actual trajectory of prices to date. Notice that the forecasts change year-by-year towards the extrapolation of recent prices. Additionally, while some forecasts featured falling prices followed by an upswing, of the 23 forecasts displayed, only the ones made around 1990-92 came close to identifying the key turning point that occurred around 1995. Finally, conduct the mental exercise of extrapolating the outer boundary of 1985 and 1997 forecasts out to 2050. The range of possible forecasts contained in those boundaries is vast, and these are not representations of uncertainty per se; they are actual point forecasts, just made in different eras.

Figure 1. EIA Forecasts of Natural Gas Price



source: EIA 2008 & 2008a, AEO from several years

[2] In general, a sensitivity case is a rerun of an analysis in which just one input is changed, while a scenario is one with multiple variables adjusted.

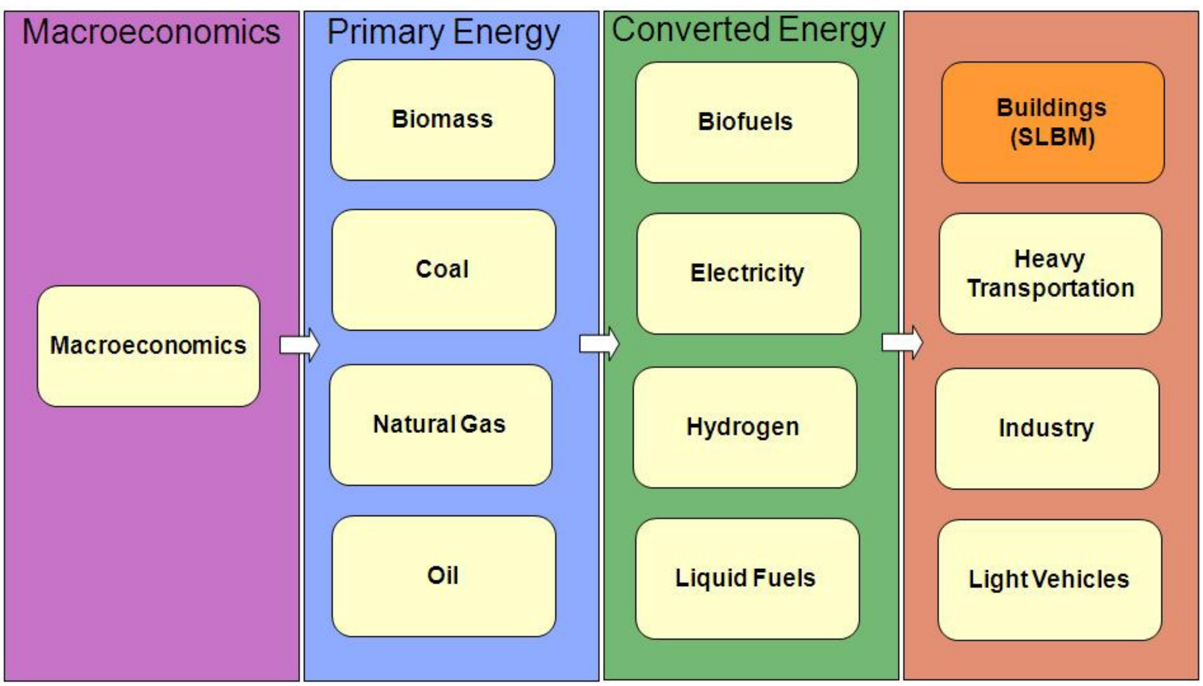
In addition to the unpredictability of technology evolution, there are several common aspects to how uncertainty enters into a forecast, and most of them are familiar and intuitive: inaccuracy of historic data, errors in methods, unexpected external conditions, price volatility, etc. All of these argue for modeling the future with key scalar variables replaced by probability distributions that reflect our level of confidence in our forecasts of their values. Such an approach is the simple principle by which SEDS is being constructed. It uses Analytica®, developed by Lumina Decision Systems[3], which is a platform intended specifically for such modeling. Analytica models are intended to be open source and can be viewed by the user.

Before exploring SLBM, it is worth noting a key aspect of forecasting that SLBM does not address. Energy history may have turned a corner around the same time the millennium turned. A long period of relative stability that lasted from the mid-1980's appears to have come to an abrupt end. Fuel prices have become more volatile and have generally increased, raising overall costs until last summer. Currently, we might also observe such a turning point. However, it is hard to predict how long the collapse of energy prices might last in the face of the current global economic crisis. Note that introducing uncertainty into certain variables does not imply that we can produce forecasts that include discontinuities, and indeed, these might be the events forecasters would be most interested in predicting. Rather, the SEDS / SLBM approach provides a wide distribution around forecasts to reflect the uncertainty of point forecasts. Nonetheless, SEDS estimates and their uncertainty bounds are still highly smoothed curves, and any "corners" can only be introduced by the modeler.

3. The Stochastic Energy Deployment System Project

Similar to NEMS, the architecture of SEDS is that all energy producing and consuming activities in the economy are modeled using a set of interconnected modules representing the key sectors, where the inputs to one module are the outputs from others (SEDS 2009). The following modules are used within SEDS at this point: Macroeconomics, Biomass, Coal, Natural Gas, World Oil, Biofuels, Electricity, Hydrogen, Liquid Fuels, Buildings (SLBM), Industry, and Transportation (Heavy and Light).

Figure 2. The SEDS Project

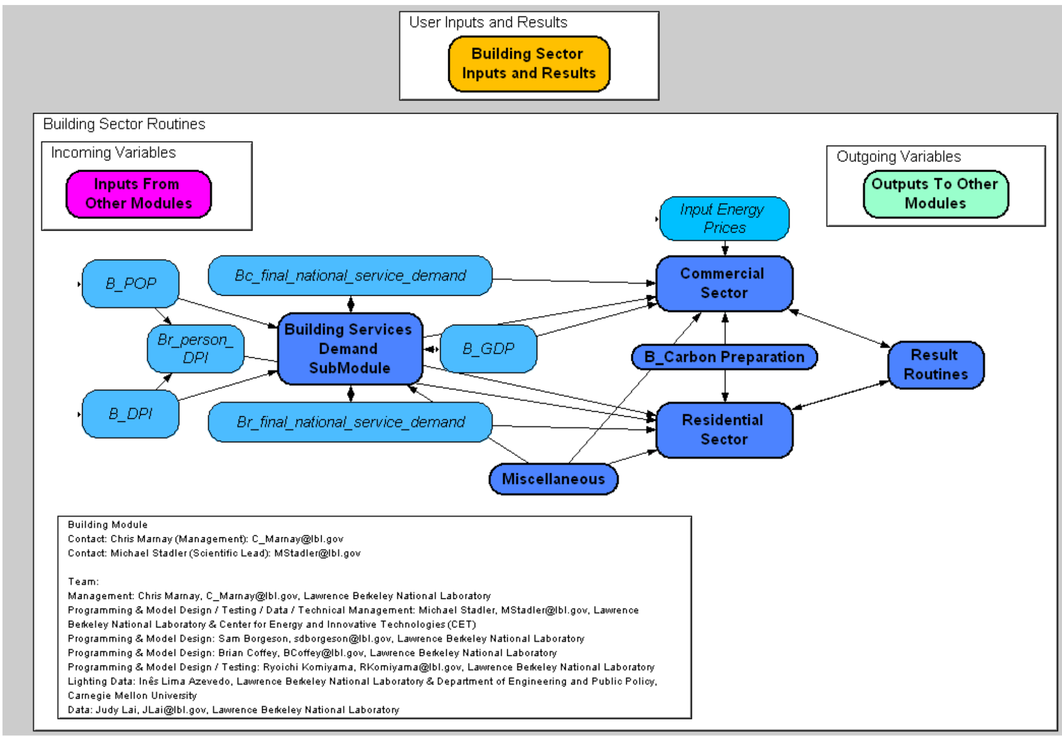


Also like NEMS, SEDS uses energy and capital costs to determine economically optimal technology adoption. The economic decision is based on a logit approach that allows modeling of market misinformation and preferences. Unlike NEMS, SEDS is designed to favor simplicity over detail, with the goal of providing a system that produces

[3] see http://www.lumina.com/

results quickly out to 2050. SEDS does not iterate towards an equilibrium, rather outputs of one time step are inputs to the next, and an effort is being made to keep the modules consistent enough for users to delve into them. Also, to allow user control over runtime, SEDS is designed around a variable user-chosen time step. Note that the emphasis on fast execution time is motivated by the need to achieve stochastic results with acceptable variance reduction. SLBM can be run in a stand alone or integrated mode that provides it with the necessary inputs, including energy prices, Gross Domestic Product (GDP), population, and other macroeconomic inputs.

Figure 3. SLBM



3.1. The Stochastic Lite Building Module

The residential and commercial sectors in the SLBM can be thought of as a series of stock models running in parallel that track equipment characteristics and market share as time progresses. The stock of equipment required is determined by the overall demand for its *services*, e.g. lum·h/a. At each time step, a series of calculations are performed that take as input macroeconomic data and fuel prices and output estimates of fuel consumption requirements for provision of a set of *building services*, i.e. lighting, domestic hot water (DHW), ventilation, refrigeration, heating, cooling, and other loads. Those calculations are performed as follows (see also Figure 4):

(1) The total demand for floorspace for residential and commercial buildings is forecasted using a simple linear multivariate econometric regression model with the following independent variables: GDP, population, a time lag, and disposal personal income (DPI)[4] (Marnay 2008b).

(2) A building stock model determines required new construction at each time step to meet floorspace demand. The floorspace stock model also tracks demolition based on average building lifetimes.

(3) Current floorspace is multiplied through by the expected service demand intensities to arrive at the total raw service demands. In the case of heating and cooling, floorspace is disaggregated by 9 climate regions so that heating and cooling degree days (HDD & CDD) can serve as appropriate service intensities.

(4) The total raw service demands are adjusted for the influence of passive technologies, such as insulation and daylighting, as well as other mitigating factors, such as internal heat gains and infiltration. At this point three

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[4] Note that SEDS has a macroeconomic module to forecast these parameters, and there is also a test harness for the standalone version of SLBM that includes the values used in NEMS.

different building quality options are considered within SLBM: 'low', 'medium', and 'high' efficiency buildings. These three different building options are characterized by different settings for U-values, daylighting, solar gains, and natural ventilation.

(5) The residual service demands are passed on to specific stock models as these must be met by active, i.e. fuel consuming, technologies.
(6) Every service-specific stock model tracks the amount of each technology available at each time step considering retirements, and calculates how much new equipment will be needed.
(7) The amount of each type of new equipment put into service and its market share is determined by an engineering-economic calculation using a logit function.
(8) Fuel type, efficiency, and technology market share are then used to determine total fuel consumption.
(9) Fuel consumption is then offset by on-site generation, e.g. PV.
(10) Fuel consumption is summed across all demand-specific stock models to yield total fuel demands.
(11) Finally, residential and commercial fuel demands are summed to total SLBM fuel consumption.

After the sequence defined above has been executed for each time step, the projections of floorspace, service demands, technology market share and quantities, energy consumption and fuel use are available for examination and interpretation; however, if any of the macroeconomic or other inputs are based on a probabilistic distribution rather than scalar values, the model will run multiple times with Monte Carlo draws.

The most promising future building efficiency developments rely on improving system integration and passive designs; therefore, much of the challenge and effort in SLBM development was the creation of a framework that could capture these alternative paths while still providing quick run-times and a transparent structure for users. Two particular objectives were crucial in shaping the SLBM:

(1) to accommodate technologies that do not consume fuel, e.g., windows or building shell, but strongly affect multiple other energy consuming technologies; and
(2) to recognize interactions between end-uses, in particular that heat gains from lights and electrical equipment are sometimes more important than envelope losses in determining the heating and cooling requirements of commercial (and more and more, residential) buildings.

Figure 4. Main SLBM Calculation Steps

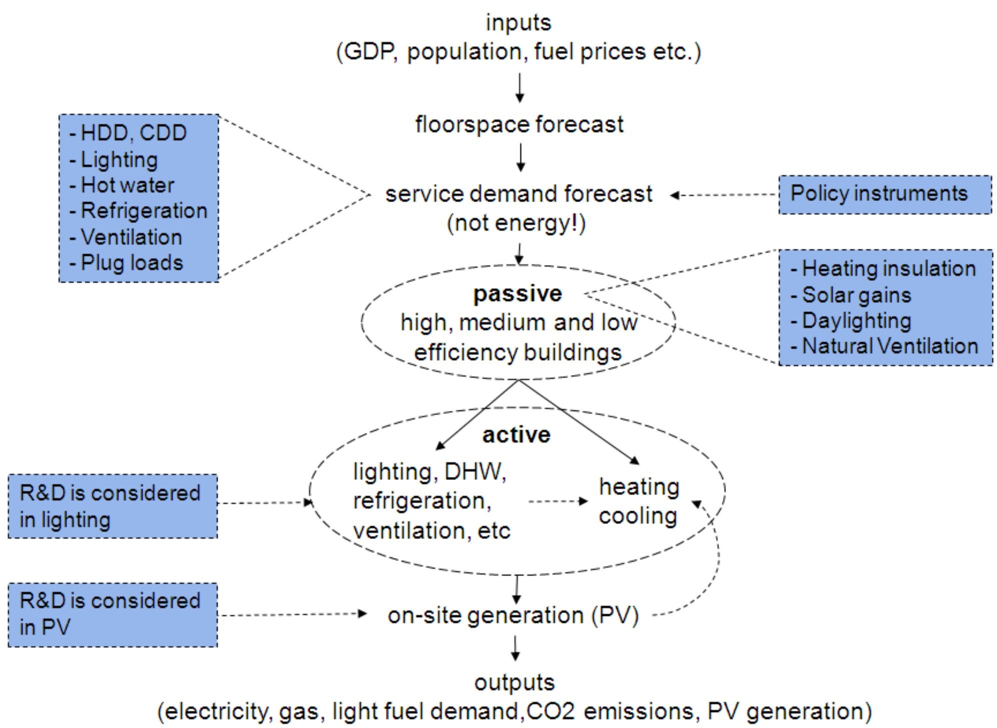


Figure 4 shows the basic structure that is used in both the residential and commercial sub-modules. Based on the floorspace forecast a service demand forecast is made and policy instruments targeting behavioral changes can be applied and change the service demand. An example of this can be demonstrated by domestic hot water. Driven partly by policies and by water shortages (such as in California), people tend to take showers instead of baths. Such behavior can be modeled by SLBM and change the service demand forecast. The *passive attributes* sub-module considers the aspects of the building shell that meet, mitigate, or intensify the heating, cooling, ventilating, and lighting service requirements. The elements in this sub-module are special in that they do not consume any fuel, and in that they are described by a vector of properties, e.g. daylighting effectiveness, natural ventilation effectiveness, solar gain intensities in heating and cooling seasons, and the envelope heat-transfer intensities in the heating and cooling seasons. The *active* technologies sub-module that follows determines equipment choice between available technologies for each service, with each technology meeting a single service. The *lighting, DHW, ventilation, refrigeration, and other* sub-modules address technologies meeting these end-uses, and calculate the internal heat gains generated by them. The *heating and cooling* sub-modules use these internal heat gains, along with the passive attributes of the building shell to determine the heating and cooling load that must be met by active technologies. This also considers options for buildings to self-provide for some of its energy requirements, e.g. with PV. At this point in our research, R&D uncertainty has been applied to lighting and PV, which reduces the net macrogrid electricity demand. Future work will consider combined heat and power (CHP) that also influences heating and cooling. Ongoing work considers R&D for window technologies and results will be available soon.

3.2 Market Shares: The Logit Function

As already mentioned, the penetration of technologies is determined by a logit function that considers the competition of consumers' options (Ben-Akiva and Lerman 1985 and Anderson et al. 1992). The principles of the logit approach are shown using the PV sub-module of SLBM. The logit function within the PV sub-module considers the competition of consumers' choices between macrogrid electricity and onsite PV generation[5]. In other words, the logit function determines the market share *MS* for PV and electricity purchased from the electric utility.

$$MS_{i,t} = \frac{\upsilon_{i,t}}{\sum_i \upsilon_{i,t}} \quad (1)$$

$$\upsilon_{i,t} = e^{(-\alpha * LCOE_{i,t})} \quad (2)$$

$$LCOE_{PV} = \frac{Costs_{PV}}{CF} \cdot \frac{r(1+r)^n}{(1+r)^n - 1} \quad (3)$$

$$LCOE_{el} = Price \quad (4)$$

where[6]

MS	market share [1]
$LCOE_{i,t}$	levelized cost of energy [$/kWh]
$Costs_{PV}$	specific system costs for PV, specific capital costs [$/kW]
$LCOE_{el}$	levelized costs for purchased electricity equals price of electricity (*Price*) [$/kWh]
CF	capacity factor PV, assumed to be roughly 1050 hours
υ	utility [1]

[5] The logit function within the PV sub-module is designed as a two step decision making process. The first logit function determines the market share for PV and macrogrid electricity and the second logit function determines the market shares for the different PV technologies within the total PV market share. The second logit function is not shown in the equations above.

[6] The shown units can change based on the considered service within SLBM. For example, α for lighting is in klumen.hr/$ and *LCOE* in $/klumen.hr.

α scaling factor [kWh/$]
i technology types, $i \in$ {el, PV}
t time [a]
r interest rate
n lifetime of equipment[7]

In our PV case, the utility υ is determined by the levelized cost *LCOE* for the various generating technologies, i.e. macrogrid electricity (el) and PV. The scaling factor α determines how sensitive the logit function reacts to differences in *LCOE*. If the scaling factor α equals zero, then equal market share will be given to each technology; whereas, if the scaling factor is much greater than 0, technologies with the lowest levelized costs of energy supply will gain most of the market share. As the reader might already suspect, the selection of α is a very crucial step within SLBM and influences the results considerably. Some services within SLBM show α close to zero and others much greater than 0 depending on the market and market participants. α can be determined based on historic market shares and historic prices (see also Marnay 2008b). However, since SEDS / SLBM is intended to deliver simulation results by 2050, changes in α are very likely, and therefore, we also can model future values for α within the PV module of SLBM.

Different mathematical descriptions for α can be considered within SLBM and were tested against other forecasts, e.g. AEO (Komiyama et al. 2009). For example, a possible "with time lag" approach for α within the PV sub-module of SLBM is shown in the following Equation 5.

$$\ln(\alpha_t) = b \cdot \ln(p_{el}) + c \cdot \ln(\alpha_{t-1}) \tag{5}$$

where
α scaling factor [kWh/$]
p_{el} electricity price in the commercial or residential sector [$/kWh]
t time [a]
b price elasticity
c exponent for time lag

The maximum likelihood estimation of α for each historic year delivers the estimation of the customer *LCOE* sensitivity and market information / sensitivity in that year. This means that Equation 1 is solved for alpha to obtain the observed historic market shares. Many different parameters can influence the decision making captured by alpha. The simplest approach one can think about is that the price of electricity influences the price sensitivity regarding PV. This hypothesis was tested using a regression approach.

Table 1. Regression Results for alpha in the Commercial Sector

	b	c
commercial sector, adjusted R^2=0.90	-0.211628	0.844749
t-value	-2.32	9.57

As shown by Table 1, the most significant parameter for α_t is α_{t-1} (t-value is very high). However, the most interesting dependency is the negative electricity influence on α. The higher the electricity price climbs, the more the costumer switches to PV as an alternative. Please note that $LCOE_{PV}$ was always above the electricity price in the considered observation years and PV was installed despite the higher cost. As long as electricity from PV is more expensive than electricity from the macrogrid, people need to act in terms of lower α (closer to 0) to increase the market penetration of PV.

Of course, this observation just might mean that investors received subsidies or other incentives to install PV systems, both of which are hard to track. Also, an increasing number of investors are thinking about the environmental impacts of their investments and are installing PV, even with the higher *LCOE* for PV. Another big problem is that only 13 years of observation data was available for this research and this is not sufficient for forecasts

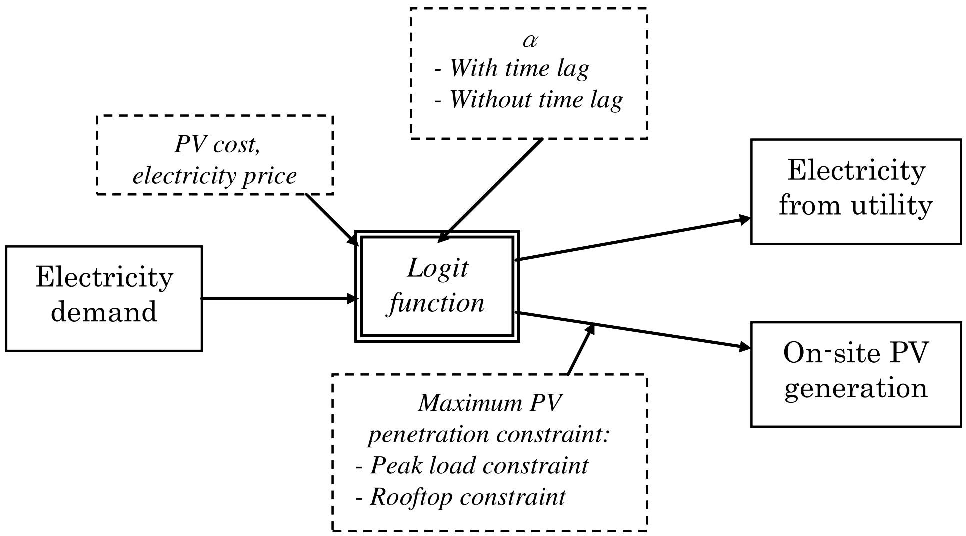
[7] Please note that the lifetime could be replaced by an investor's payback time < lifetime.

ranging to 2050. All these uncertainties show that it is very hard to find a reliable description for α, one that captures market information and price sensitivities over time, especially in times when adoption sensitivity changes due to higher energy prices. Many different approaches have been tested and some are shown at Komiyama et al. 2009.

Finally, it is possible to replace *LCOE* by a sum of weighted multiatributes. It is possible to account for the "greenness" of costumers or the anticipated future risk of the energy supply. All these multiatributes need to be weighted, summed up and multiplied with the scaling factor α. The major problem is the determination of the weight factors, which might also change over time. However, thoese multiatributes do not account for sensitivity changes in the decision making captured by α. So far, no multiatributes have been considered in SLBM. The major focus was on capturing the changes in market perception modeled by a time variable α. However, the next research step will be to capture different attributes that will influence the decision making.

Following figure shows the principle function of the PV logit function within the SLBM. To make sure that the chosen market share based on the logit function can be realized, a rooftop and a peak load constraint is used with the model (Komiyama et al. 2009).

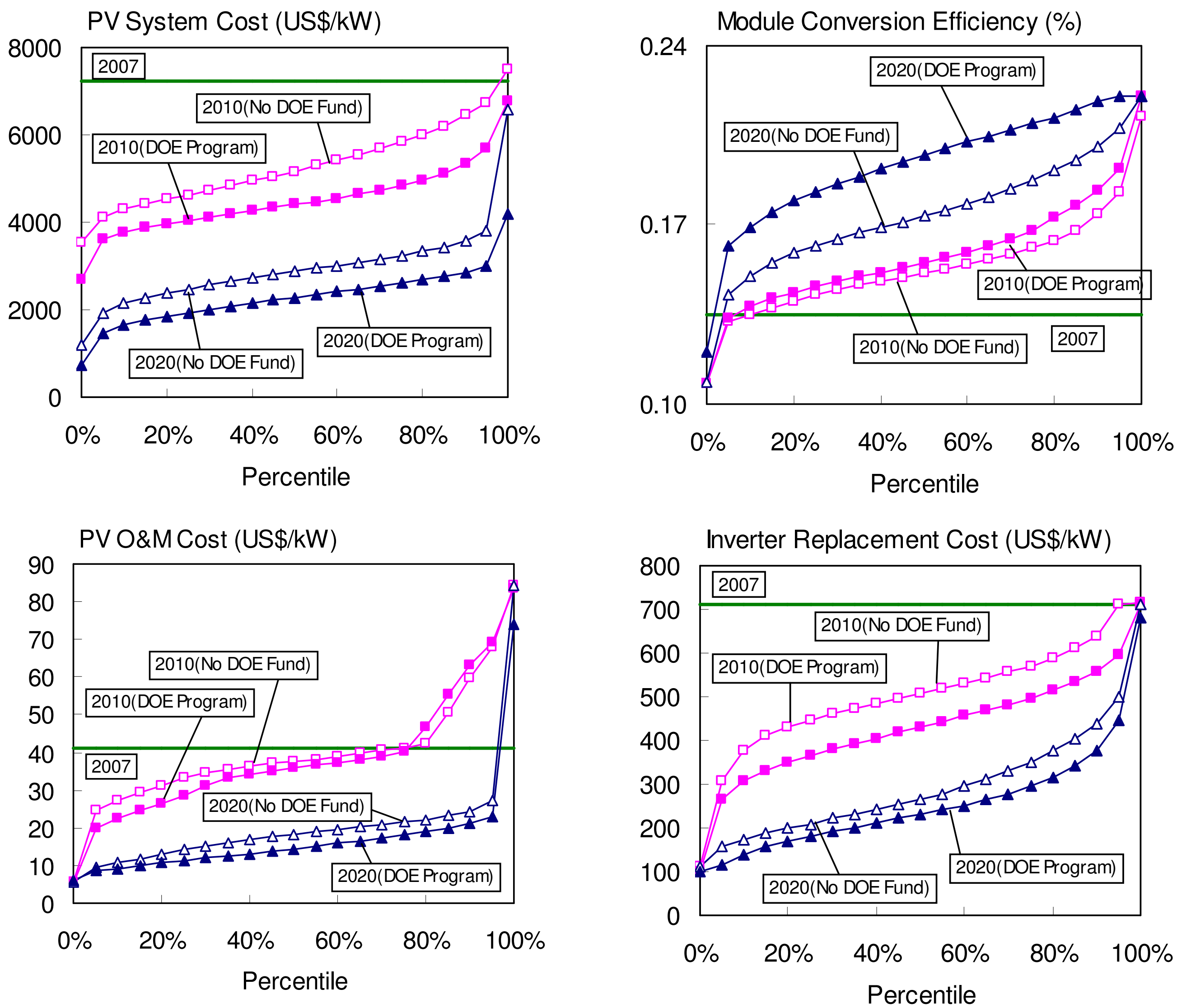
Figure 5. Logit Function for PV



3.3. Uncertainty: Expert Forecasts

The most important feature within SEDS / SLBM is the possibility to capture technology uncertainty. A major goal of this work is to identify the impact of different levels of research money dedicated to different technologies. Photovoltaics and solid-state lighting (SSL), which is designed to help light emitting diode (LED) penetration, are technologies being pursued by the various technology programs within USDOE Energy Efficiency and Renewable Energy (EERE) and are shown in this paper. The stochastic input data for SLBM are expert elicitations, which show the range of expected performance for the considered parameters. For PV, the range of system costs, module conversion efficiency, O&M costs, as well as inverter replacement costs are gathered from the different experts and merged. Figure 6 shows the outcome of those expert elicitations for PV. For example, the PV system costs for 2007 were around $7 500 (IEA PVPS USA survey report 2007) and expected costs in 2010 and 2020 will be lower than in 2007 with almost 100% chance. However, experts always expect higher PV systems costs without USDOE R&D efforts as can be seen in Figure 6. In 2020, with USDOE R&D, PV system costs should be less than $4 000 with 100% probability (blue line 2020(DOE Program)). The chance that PV systems costs will be less than $2 000 in 2020 is ca. 50%, considering USDOE R&D.

Figure 6. Expert Forecasts for PV in the Commercial Sector



The same procedure as for PV was used for SSL. Experts were asked about their expectations for the investment costs of LEDs in $/klumen and for the efficacy (lumen/W). As the reader might recall SLBM is using service demands instead of energy demands and this can be demonstrated by SSL. The experts need to estimate how much the service in $/klumen will cost in 2010, 2015, and 2020. The second estimation targets the efficacy, which accounts for the service demand to energy demand conversion. SLBM uses both projections to calculate the electricity demand distribution.

Expert forecasts for the investment costs and efficacy are shown in Figure 7 and Figure 8. For example, it is expected with 20% probability that costs in 2015, considering R&D from USDOE, will be less than the DOE point projection for 2015. Also, efficacy forecasts show that we might not reach more than 180lumen/W for LEDs, considering USDOE funding for research in SSL.

Based on that stochastic input, SLBM finds mean values, mid values, standard deviations, etc. for the technology penetration as well as CO_2 emissions by 2050. Figure 6, Figure 7, and Figure 8 suggest that the uncertainty of the technology adoption as well as CO_2 emissions might be vast. For example, the investment costs for LEDS can vary between $2/klumen and $35/klumen in 2020, according expert forecasts.

Figure 7. Expert Forecasts for SSL, Investment Costs

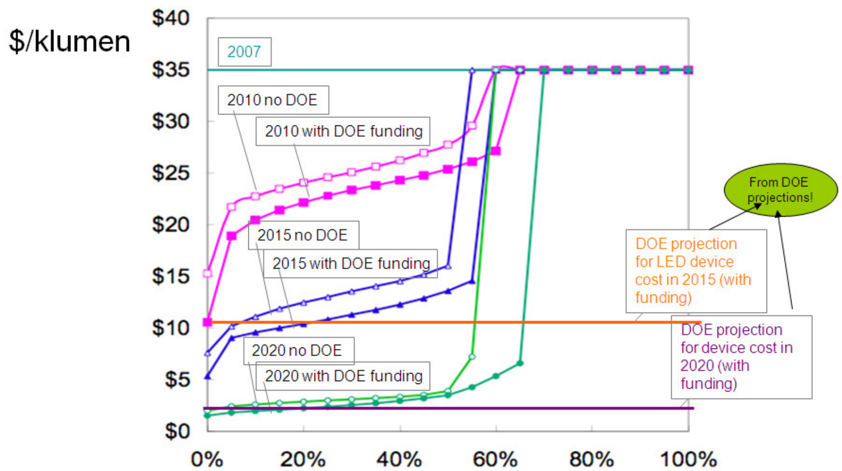
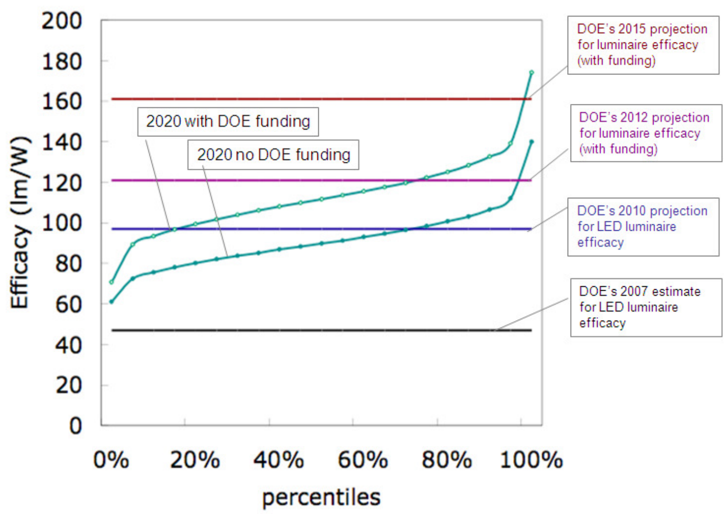


Figure 8. Expert Forecasts for SSL, Efficacy



4. Results

The latest integrated version R170 of SLBM, where SLBM interacts with all other 12 modules, was used for the simulations shown in this section.

The mid value of the total electricity demand is expected to reach 2 200TWh in 2050 (blue line in Figure 9). This demand forecast already considers SSL under USDOE R&D funding as shown in the figures above. Based on the expert forecasts, PV does not make much difference in the net electricity demand of the building sector (green line in Figure 9). In other words, the PV penetration is limited and cannot offset much of the electricity consumed in the commercial sector. If anticipating USDOE R&D funding for research, then the impact is considerably different. The total electricity demand in the commercial sector is reduced to 1 800TWh in 2050 (red line in Figure 9). For Figure 9 a constant α of 26.5 was used, which corresponds with the observed α in 2005. To see the impact of different price sensitivities as discussed in section 3.2, a sensitivity run was performed with a higher α of 35. As already discussed, a higher α results in less PV adoption (Figure 10).

Figure 9. Total US Commercial Building Sector Electricity Demand (mid value), using USDOE funding for PV. α = 26.5 constant[8]

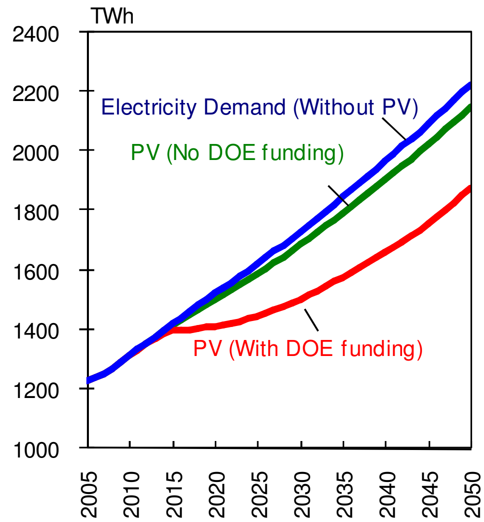
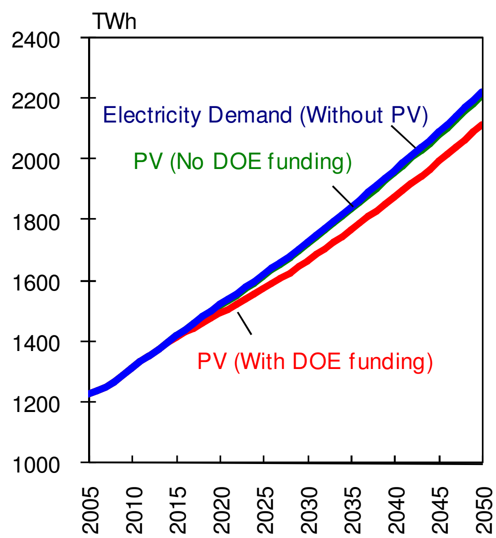


Figure 10. Total US Commercial Building Sector Electricity Demand (mid value), using USDOE funding for PV. α = 35[9] constant[10]



Since the major objective of this research is to estimate the impact of uncertainty, mid values just give a limited picture about the possible technology penetration by 2050. The uncertainty in PV generation is vast as can be seen in Figure 11. The generation can vary between almost 0 and 500TWh in 2050 (see probability picture in Figure 11). Of course, the probability to reach numbers above 250TWh is very limited, and therefore, just the 90th percentile is shown in Figure 11. However, the probability density, shown in *Figure 11 at the top left*, still gives small probabilities for generation numbers above 250TWh. Generation levels around 70TWh show the highest probability.

[8] SLBM can run as standalone version or integrated with the other modules. The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170.

[9] Adding a logarithmic trend to the historic observed α-values results to a α of ca. 38 in 2050.

[10] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170.

Figure 11. Commercial PV Generation in 2050, no USDOE R&D funding for PV. α = 26.5 constant[11]

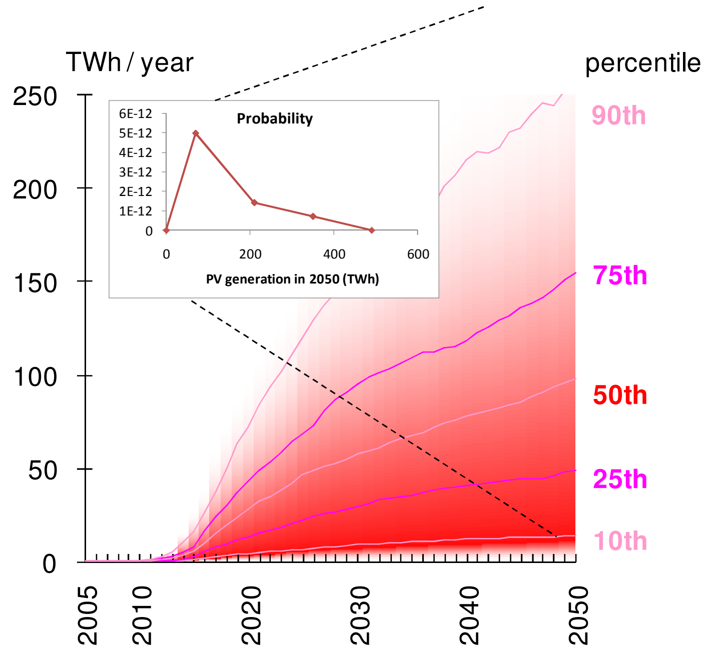
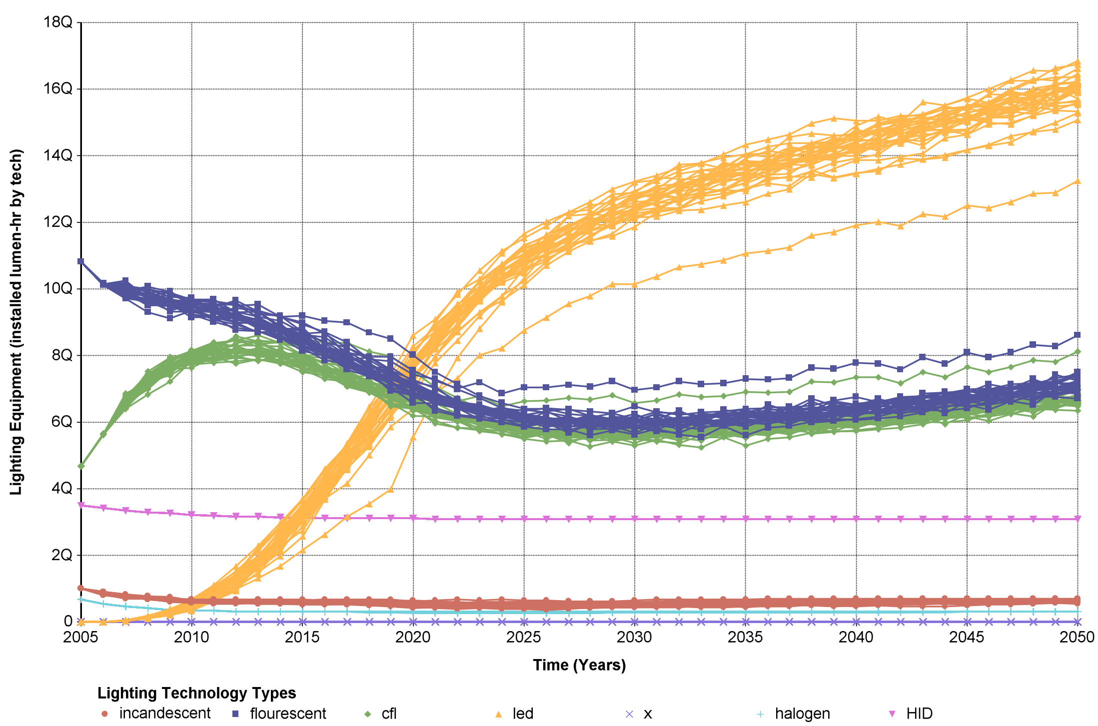


Figure 12. Commercial Lighting Equipment Adoption in Service Units, USDOE R&D Funding Case[12]



[11] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170.

[12] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170.

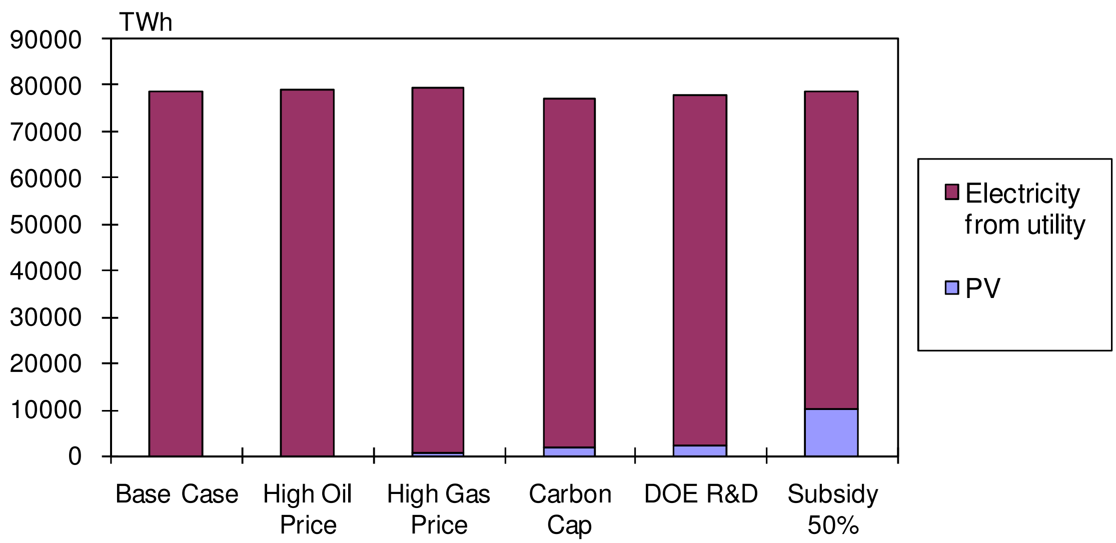
The impact of the expert elicitations on the lighting technology adoption is shown in Figure 12. It shows the Monte Carlo sample paths[13], which are based on the distributions provided by the experts. Every line represents a possible path and an accumulation of paths means that those paths show a high probability. The biggest uncertainty is shown for LEDs. The service provided (lumen-hr) can range from ca. 13Q to ca. 17Q in 2050 as shown in Figure 12. Although, the path which hits ca. 13Q in 2050 seems to be very unlikely since all other paths are centered between 15Q and 17Q. Different graphs are possible within SEDS / SLBM and Figure 12 could be shown with percentiles as Figure 11. The runs shown in Figure 12 are based on the Energy Independence and Security Act of 2007 and reflect he high hopes for LEDs. Based on the expert elicitations and Energy Independence and Security Act of 2007 it can be expected that in 2020 LEDs constitute the biggest single market share in the commercial building sector.

SEDS / SLBM is basically designed to show the impact of different policy measures as well as the impact of different energy price levels on technology adoption and CO_2 emissions. The following *abstract* scenarios are shown in Figure 13:

a) base case: no carbon regulation, no forcing of prices, no USDOE R&D funding
b) high oil price: \$100/bbl in 2005, ramps linearly to \$500/bbl by 2030, and stays at \$500/bbl for the rest of the simulation
c) high natural gas price: \$8/MMBtu in 2005, ramps linearly to \$50/MMBtu by 2030, and stays at \$50/MMBtu for rest of simulation
d) carbon cap: starts at 5902 million metric tCO2/yr in 2010, ramps linearly down to 4000 million metric tCO2/yr by 2035 (roughly 80% of 1990 levels), and stays at 4000 million metric tCO2/yr for the rest of the simulation
e) USDOE R&D program: improvements associated with USDOE R&D funding for PV and SSL
f) Subsidy 50%: 50% of PV cost is subsidized.

The cumulative comparisons of these six sensitivity runs are shown Figure 13. The biggest impact in terms of energy demand reduction and environmental friendly onsite energy generation can be reached by direct subsidies for PV adopters. Surprisingly, the impact of a carbon cap is less than the impact of USDOE R&D funding. Also, high oil and natural gas prices do not influence much the PV adoption in the current version.

Figure 13. Cumulative Electricity Demand and Cumulative PV Contribution in the Commercial Sector (mid values) by 2050, α=35 constant[14]



[13] In our case 30 samples were selected.
[14] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170.

For the frequently discussed carbon cap approach, the carbon emissions as well as energy demand reduction for the entire building sector are shown in following figures. The vast majority of carbon reduction in the carbon cap case is based on CO_2 reductions in the electricity sector. As the reader might recall, SLBM and the other 12 SEDS modules are integrated in one tool to model interactions between different parts of the US economy. The carbon cap sensitivity results in limited demand reduction in the building sector, but reduces the carbon intensity of the electricity sector considerably (see Figure 15, right bars).

Figure 14. Net Energy Demand Building Sector and Demand Reductions Compared to Base Case (mid values)[15]

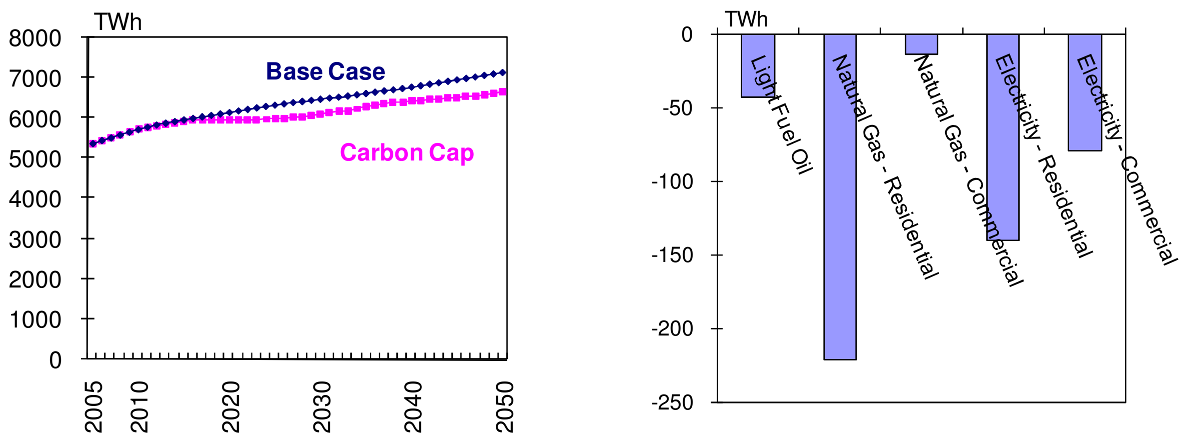
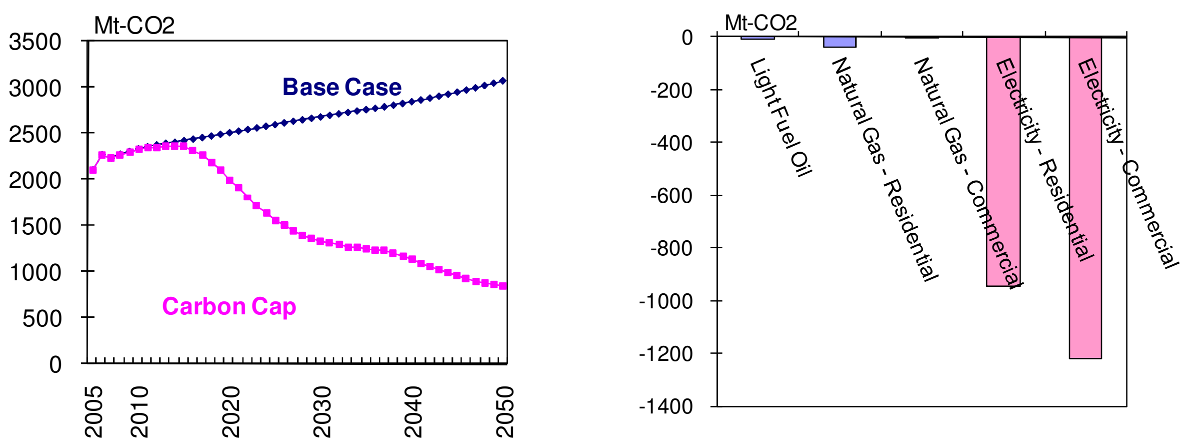


Figure 15. Carbon Emissions in the Building Sector and Reductions Compared to Base Case (mid values)[16]



5. Conclusions

Anticipating how current R&D should be directed to robustly meet the climate change challenge, especially given wide uncertainty about our evolving energy system, creates a formidable modeling challenge. USDOE is attempting to respond through the creation of an uncertainty based forecasting tool, SEDS. The buildings aspect of this tool will be a mixture of innovation and tradition. Floorspace forecasting is based on a regression of macro variables against historic floorspace requirements. Downstream of this calculation, the model attempts to use building service requirements rather than energy-based metrics of services as the basis of equipment adoption and energy use

[15] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170. Also α in the building sector is assumed to be 35 and in the residential sector 19.5.

[16] The results shown are based on the integrated version of SLBM that interacts with the other modules. SEDS model version R170. Also α in the building sector is assumed to be 35 and in the residential sector 19.5.

forecasts. These service requirements are in turn connected to the composition of the existing and new building stock. The goal is to represent decision-making such that active, passive, and on-site energy conversion options are evenhandedly considered in a way that might allow for radical rethinking of building design, and therefore, R&D objectives and investments. As demonstrated in this paper, the decision making of technology adopters will change over time in the face of radical changes and possible price spikes. Since we are living in a world that is currently rapidly changing, the prediction of future energy systems is going to be a challenging task, as shown by the SLBM results. Specifically, technologies with little history, e.g. PV are hard to model and different approaches for the decision making (logit function) are considered and compared. The PV example demonstrates the vast uncertainty by 2050 and shows that point estimates without consideration of the possible range of outcomes is meaningless. The mid value for the expected PV generation in 2050 is around 70GWh, but considering technology expectations and their probabilities PV generation can range from almost 0 and 500TWh without any USDOE R&D funding.

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