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SIMULATION OF THE GHG ABATEMENT POTENTIALS IN THE U.S. BUILDING SECTOR BY 2050

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Environmental Energy Technologies Division

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SIMULATION OF THE GHG ABATEMENT POTENTIALS IN THE U.S. BUILDING SECTOR BY 2050

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Abstract

Given the substantial contribution of the U.S. building sector to national carbon emissions, it is clear that to address properly the issue of climate change, one must first consider innovative approaches to understanding and encouraging the introduction of new, low-carbon technologies to both the commercial and residential building markets. This is the motivation behind the development of the Stochastic Lite Building Module (SLBM), a long range, open source model to forecast the impact of policy decisions and consumer behavior on the market penetration of both existing and emerging building technologies and the resulting carbon savings. The SLBM, developed at Lawrence Berkeley National Laboratory (LBNL), is part of the Stochastic Energy Deployment System (SEDS) project, a multi-laboratory effort undertaken in conjunction with the National Renewable Energy Laboratory (NREL), Pacific Northwest National Laboratory (PNNL), Argonne National Laboratory (ANL) and private companies. The primary purpose of SEDS is to track the performance of different U.S. Department of Energy (USDOE) Research and Development (R&D) activities on technology adoption, overall energy efficiency, and CO_2 reductions throughout the whole of the U.S. economy. The tool is fundamentally an engineering-economic model with a number of characteristics to distinguish it from existing energy forecasting models. SEDS has been written explicitly to incorporate uncertainty in its inputs leading to uncertainty bounds on the subsequent forecasts. It considers also passive building systems and their interactions with other building service enduses, including the cost savings for heating, cooling, and lighting due to different building shell/window options. Such savings can be compared with investments costs in order to model real-world consumer behavior and forecast adoption rates. The core objective of this paper is to report on the new window and shell features of SLBM and to show the implications of various USDOE research funding scenarios on the adoption of these and other building energy technologies. The results demonstrate that passive technologies contain significant potential for carbon reductions—exceeding 1165 Mt cumulative savings between 2005 and 2050 (with 50% likelihood) and outperforming similar R&D funding programs for distributed photovoltaics and high efficiency solid-state lighting.

1. Introduction

The work presented in this paper is part of the ongoing development of the Stochastic Energy Deployment System (SEDS), which was commissioned as part of a long history of modeling in support of planning and budgetary activities at the U.S. Department of Energy (USDOE). Currently, it is being used as a potential tool to support compliance 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. A core feature which distinguishes SEDS from other national energy models is in how it treats uncertainty. SEDS has been constructed in Analytica®, a visually based platform which embraces uncertainty, allowing for stochastic inputs and producing stochastic results. The value of this feature will be demonstrated throughout the body of this paper. For more basic information on uncertainty and policy analysis, please refer to Morgan and Henrion 1990.

SEDS is structured such that all energy producing and consuming activities within the U.S. economy, disaggregated into key sectors, are represented as a network of interconnected modules. Further detail on the specific sectors present in SEDS can be found by referring to previous publications (Stadler 2009, Marnay 2008). The focus of this paper is exclusively on the Buildings module of SEDS, also called the Stochastic Lite Building Module (SLBM).

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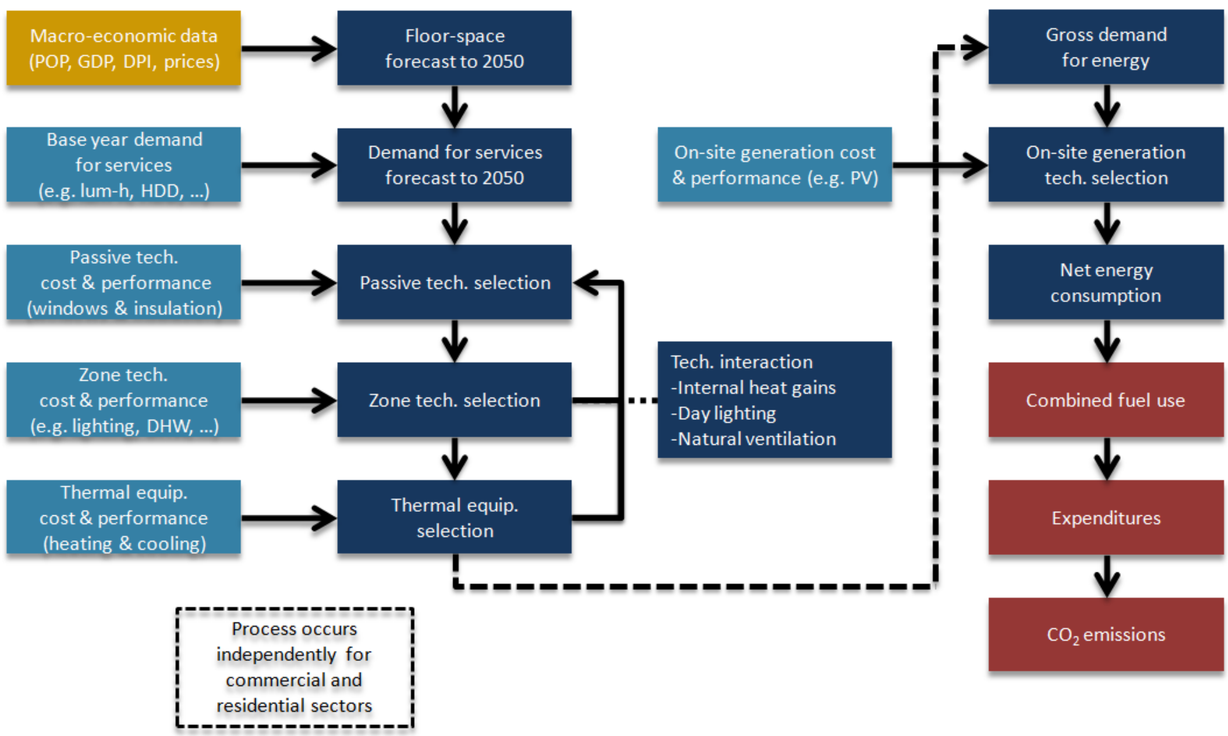
Within SLBM, the separate residential and commercial building sectors can each be thought of as a series of stock models which track cost, performance and market share characteristics at each year. This flow of data can be seen schematically in Figure 1. As the diagram shows, the key inputs to SLBM are projections of macroeconomic performance, which along with historical values are used to generate forecasts of demand for floor space. The equipment stock models are driven fundamentally by forecasts of demand for services, for instance lumen hours (lum·h) for lighting and heating degree days (HDD) for heating. Each year, retirements in existing stock and growth in floor space will produce an additional demand for services which must be met that year. The technology selection for supplying the unmet demand is determined by a logit function which considers metrics based on cost, performance and consumer behavior (Anderson 1992, Ben-Akiva 1985, Stadler 2009). In the case of passive technologies, i.e. windows and walls, the selection process is based on a comparison between investment costs and savings from interaction with other enduses, e.g. heating and cooling, a socalled multi-atribute logit function. Once every service demand has been met, a final logit selection process is used to determine what portion of the resulting gross demand for energy can be met using on-site generation. Finally, the major values determined within the buildings module—fuel use, expenditures and CO2 emissions—can be output for use in other major sectors[2] within SEDS. Additional details on the structure of SEDS and SLBM and a mathematical description of the logit function frequently employed can be found in previous SEDS related publications (Stadler 2009).

Figure 1. Schematic representation of the flow of data within SLBM. The gold box (top left) represents key input data SLBM receives from other modules within SEDS. Light blue boxes (left) represent inputs which are only utilized in the buildings module to define technology performance. Red boxes (bottom right) denote the major outputs of SLBM for use elsewhere in SEDS.



2. Passive Technologies - Windows

The addition of the new building shell submodule represents an important step forward in the on-going development of SLBM. Within this module changes in the U.S. building shell stock are managed for new and existing buildings. The module considers 12 levels of shell quality, determined by 3 options for walls and 4 for windows. Adoption rates of each shell option are determined by a multi-attribute logit approach which considers an annualize cost[3] based on investment options and energy savings due to interaction with other enduses, e.g. heating and cooling. The

[2] Major sectors modeled in SEDS include buildings, industry, electricity, liquid fuels, light and heavy duty vehicles, among others.
[3] Annualized costs for passive technologies are based on a payback period of 25 years if the technology lifetime exceeds the payback period.

key parameters which define each technology option are as follows: capital cost, durability (lifetime), U-factor and solar heat gains. It is these parameters, along with energy price forecasts, which will determine the level of achievable savings and subsequently the annualized cost of each shell type. A brief description of each window technology currently considered in SLBM is given below. First, however, it is important to understand the various mechanisms for heat transfer when considering a window's thermal performance. Convective heat transfer occurs from the building shell's exposure to outside air and results in either heat flow to or from the building. Far-infrared radiation (FIR) with wavelengths between 2 and 50 μm is the primary mechanism for radiative heat losses from buildings. Finally, sunlight in the form of near-infrared radiation (NIR) contributes to an inflow of thermal energy, or solar heat gains. Whether solar heat gains are desirable or not will depend on the specific circumstance of the building, i.e. whether it being heated or cooled. SLBM models convective and FIR heat flow simply, utilizing an effective U-factor for windows and walls, total shell area and temperature difference derived from HDD and CDD data. Solar heat gains are given in $kWh/m^2{\cdot}y$ and are added to requisite cooling loads or subtracted from heating loads.

Low Insulating Windows – This option is intended to represent the baseline thermal performance within the current U.S. window stock. Its U-factor performance of 3.1 W/m^2K (0.58 $Btu/h{\cdot}ft^2{\cdot}°F$) is calculated based on the assumption that the window stock is comprised mostly of moderate/low efficiency double paned windows, with smaller shares allotted for both low emissivity coated doubled paned and less efficient single paned windows. Given that the U-factor for a single paned window can reach as high as 7 W/m^2K, and it may comprise a larger portion of the actual U.S. window stock, this assumption may be underestimating the magnitude of heat losses and subsequently damping consumer preference for higher efficiency alternatives.

Highly Insulating Windows – As the name suggests, this window option provides a higher level of insulation to reduce unwanted heat flow to and from the environment via convection and FIR. It is characterized by a U-factor of 0.58 W/m^2K (0.1 $Btu/h{\cdot}ft^2{\cdot}°F$), the target performance for future window products necessary to meet the requirements of zero-energy homes (Arasteh 2006). This represents an ambitious step forward from the existing windows stock, utilizing many new and emerging features , such as triple paned structure, multiple low-emissivity coatings and gas filled cavities.

Dynamic (Electrochromic) Windows – The dynamic electrochromic option allows for active control of NIR inflow. Unlike highly insulating windows, dynamic windows are not well suited for combating convective and FIR losses. Its U-factor is in fact the same as low insulating windows. Instead, the variable opacity of dynamic windows can be used to tune solar heat gains in such a way as to reduce heating and cooling loads. As presently modeled, dynamic windows can provide a 30% reduction in solar heat gains on days which require cooling and a 15% increase on those which require heating.

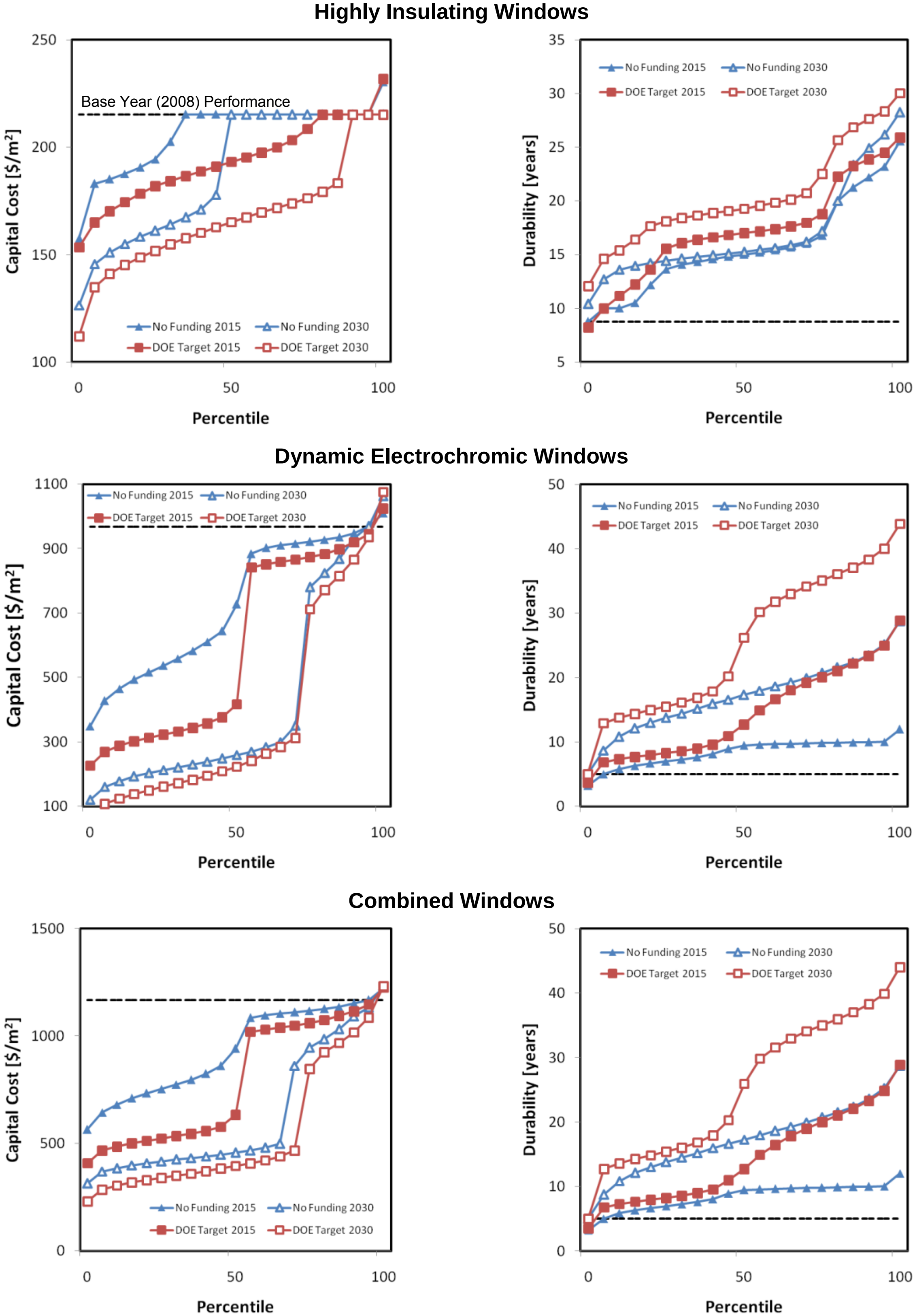
Combined Windows – This option represents the most advanced window available within SLBM. It incorporates the features of both highly insulating and dynamic windows resulting in potential for reduction in unwanted convective and FIR heat flow and optimal utilization of NIR solar heat gains.

3. Uncertainty in Window Performance

The process of forecasting the progression of each emerging window technology out to 2050 carries a significant degree of inherent uncertainty. It is therefore important to characterize these technologies in such a way as to include that uncertainty. As mentioned previously, one of the most important features of SLBM is its ability to utilize stochastic inputs when calculating forecasts. Such inputs form the basis for defining the cost and performance characteristics of many of the technologies considered in SLBM. Once passed through the logit function decision process, it is these parameters that will determine the level of market adoption for a given technology. To define them SEDS utilizes expert elicitations[4] to create distributions of expected performance levels at various points in time. Furthermore, this is done for current conditions and under proposed USDOE research funding scenarios in order to assess the impact of various R&D programs on the progression of technology performance. A pertinent example of such distributions can be seen below for windows in new commercial buildings. In each case, the two improvable parameters, capital cost and durability, are shown for both the base case (no USDOE R&D funding) and target scenario at the years 2015 and 2030.

[4] Further information about the elicitation process can be found by referring to chapter 6 of Morgan and Henrion 1990.

Figure 2. Stochastic input data for cost and durability, collected via expert elicitation, define the progression of window technology performance by funding scenario. Source: Livingston et al 2009.



There are a myriad of observations which can be derived from the above figures. Examining highly insulating windows, it appears that without funding, there is only a 35% likelihood that 2015 capital cost will decrease from the 2008 value. This increases to 50% in 2030. Conversely, with funding there is a 50% likelihood that the capital cost will fall below $\$190/m^2$ in 2015 and $\$165/m^2$ in 2030. With no USDOE funding, highly insulating windows have a 50% likelihood of achieving a durability of approximately 15 years in 2015, an improvement of nearly 60%. However, 15 years later, this value remains static. Funding produces a durability improvement to 17 years in 2015 and 19 years in 2030, with 50% likelihood. Similar observations can be drawn by examining the remaining plots. In most instances R&D funding produces a meaningful improvement over the base case. Though even without USDOE funding, moderate performance improvements occur in later years. This is expected to contribute to an uptick in adoption of higher efficiency windows in later years for both funding scenarios.

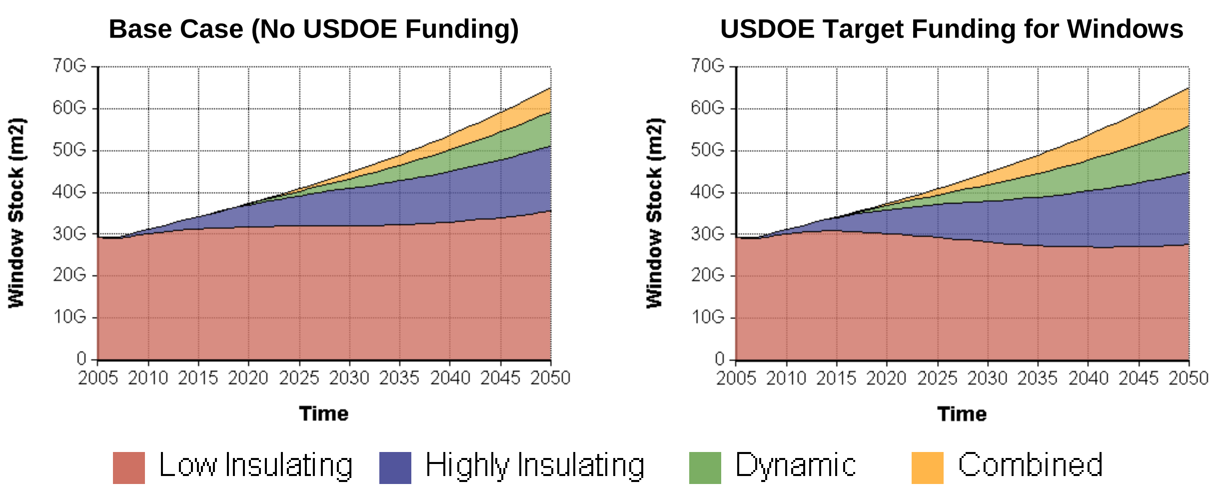
4. Results

The major findings of this investigation are presented in four parts. In the first, the expected market adoption of advanced window technologies is examined. Then, given its strong interaction with active thermal technology and energy use, the impact of passive technology adoption on heating and cooling energy use intensity (EUI) is also explored. From this point, the analysis transitions to the impact on carbon dioxide emissions. A comparison of scenarios is conducted, along with a closer look at uncertainty within the forecast. Finally, a comparison with several active efficiency technologies is conducted to determine which areas provide the highest potential for carbon savings by mid-century.

4.1 Market Penetration of Advanced Passive Technologies

As demonstrated in section 3, both time and funding improve the performance of advanced passive technologies, making them more attractive to consumers (as represented in SEDS by the logit function), subsequently increasing their levels of market penetration. However, to what extent this occurs is dependent on interactions with multiple active technologies and disparate consumer behavior in new and existing buildings. Rather than attempting to discern the exact detail of this relationship, it may be more useful to simply examine qualitatively the impact of R&D funding on the passive technology market. To do this the total U.S. floor space, summed for commercial and residential, new and existing buildings, is shown below, broken down by which window technology is employed.

Figure 3. Market penetrations of advanced window technologies for all (commercial and residential) floor space illustrate the impact of R&D funding[5].



The difference between these cases is clear, if also subtle. While under current conditions, the stock served by the least efficient window appears to grow slowly, the target scenario produces a slight decline in this windows type out to about 2040 when it begins to level off. The difference in market behavior appears to be reallocated to the most

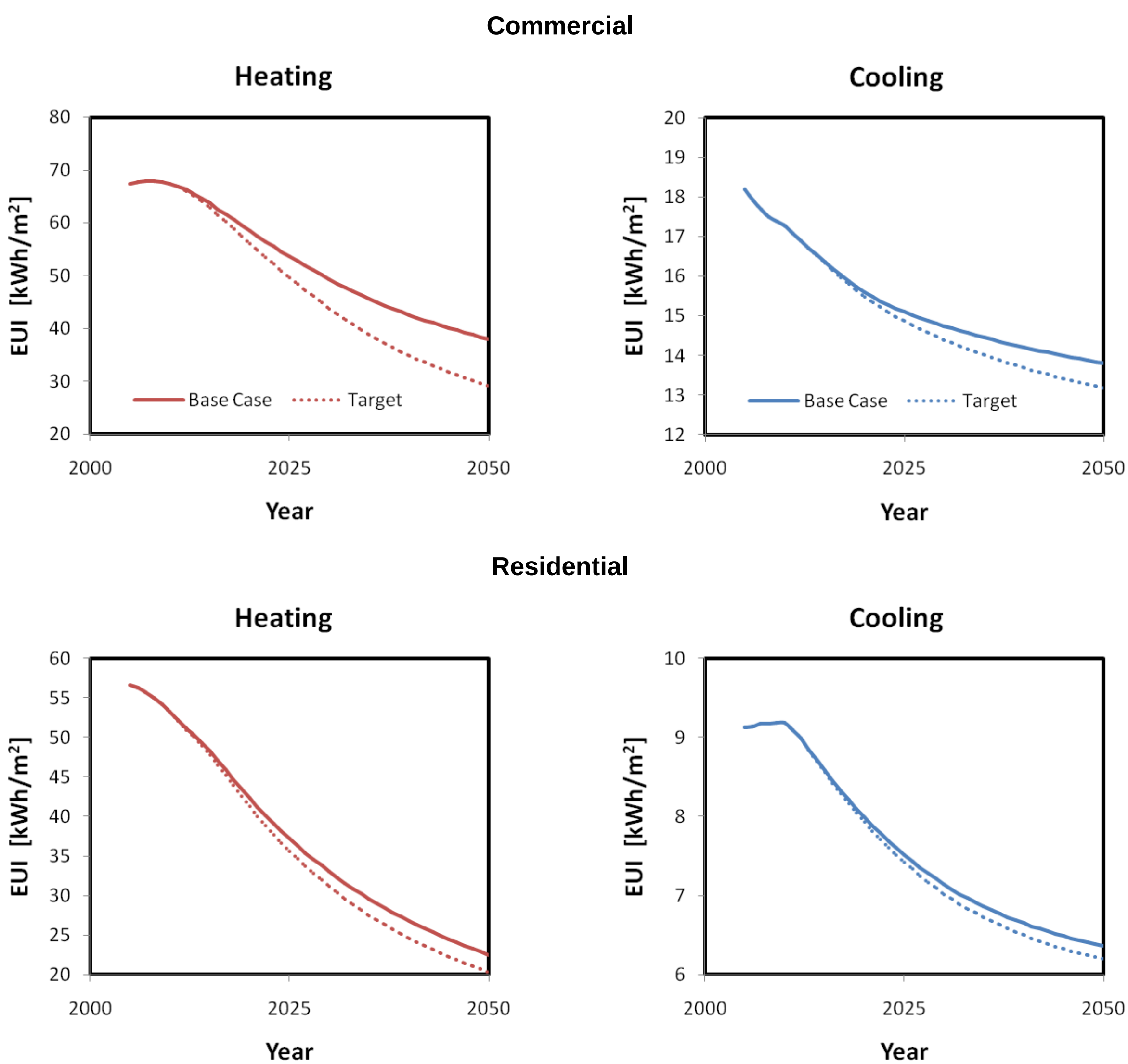
[5] Please note that these results do not show the impact of forced standards and building codes. The adoption rates are purely based on the logit approach.

advanced window technologies. At 2050, highly insulating windows see market penetration increase 10 percent between funding scenarios, while dynamic and combined windows see increases of 34 and 60 percents, respectively.

4.2 Passive Impact on Energy Use

The impact of changes to building shell quality will primarily manifest in heating and cooling loads. One way to assess this impact is by examining energy use intensities (EUI) for heating and cooling, which normalize for temporal changes in floor space. Such figures, however, do not reveal a completely isolated relationship between building shell and energy use. There are still a number of complex, interrelated changes occurring within the model. For instance, the performance characteristics of the heating and cooling equipment will also evolve over time. Also, internal heat gains will generally decline as more efficient stock is installed for enduses such as lighting.

Figure 4. Plots of heating and cooling energy use intensities (EUI) indicate that funding passive technologies produces most significant reductions in commercial heating.



With USDOE R&D funding, commercial heating sees the largest reduction in energy use – 23% from the base case at 2050 – resulting from less heat lost to the environment. The residential side sees a smaller, yet still significant, 10% reduction in the last year of the simulation. That commercial buildings have a higher average window-wall ratio (0.35) than residential (0.3) is one factor which may be contributing to this difference in behavior. Because a higher percentage of their overall shell area is comprised of windows, commercial buildings have greater potential to be improved by more efficient windows. Note that the residential heating EUI sees a much more pronounced decline than commercial under base conditions. For cooling loads, the levels of saving are clearly lower – 4.5% and 2.7% at 2050 for commercial and residential, respectively. There are many factors which could contribute to this disparate trend in heating and cooling. The presence of internal heat gains stands out as one distinct possibility. While advanced windows are capable of reducing unwanted heat flow into a building from the outside environment, they do nothing to mitigate internal gains generated from building occupants and most equipment. Since they can address only external sources of heat, their potential to reduce cooling loads is less than that for heating.

4.3 CO_2 Emission Forecasts

Reducing carbon emissions is one of the major goals of encouraging energy efficiency in buildings. It makes sense then to frame the success of a USDOE R&D program by its capacity to reduce emissions. Figure 5 shows a comparative plot for CO_2 emissions for the entire U.S. building sector. In this comparison, windows are the only technology to receive R&D funding (where specified). Other technologies, such as PV and solid-state lighting are present in the model and improve over time; however, they do not receive any funding from USDOE. Note that the trend of steadily increasing emissions results from similarly increasing projections for population and GDP, to which the floor space forecast is strongly linked. The extent of this link is further explored in Figure 6. This shows the sensitivity of buildings CO_2 emissions to various key parameters. Clearly population and GDP are the most significant driving factors. Returning to Figure 5, the target scenario appears to follow the base case trend closely, producing a maximum annual carbon emissions saving of only 2.1% (71 Mt) at 2050. While, this seems quite insignificant, one should take into consideration that the building shell generally affects only heating and cooling loads. Collectively, these end uses only represent about 15% percent of commercial energy use and 30% of residential. While it may also marginally reduce energy use for lighting and ventilation, it does nothing to abate energy use towards other major enduses. For instance, plug loads or "other", which can reach as high as 50%. So while a 2% reduction may seem low in and of itself, if building shell improvements are seen a part of a larger efficiency plan and coupled with additional measures, the overall savings become more substantial.

Figure 5. Forecasts of total carbon emissions resulting from energy use in U.S. building sector. Saving from USDOE R&D funding for advanced windows represent approximately 2% of total emissions at 2050.

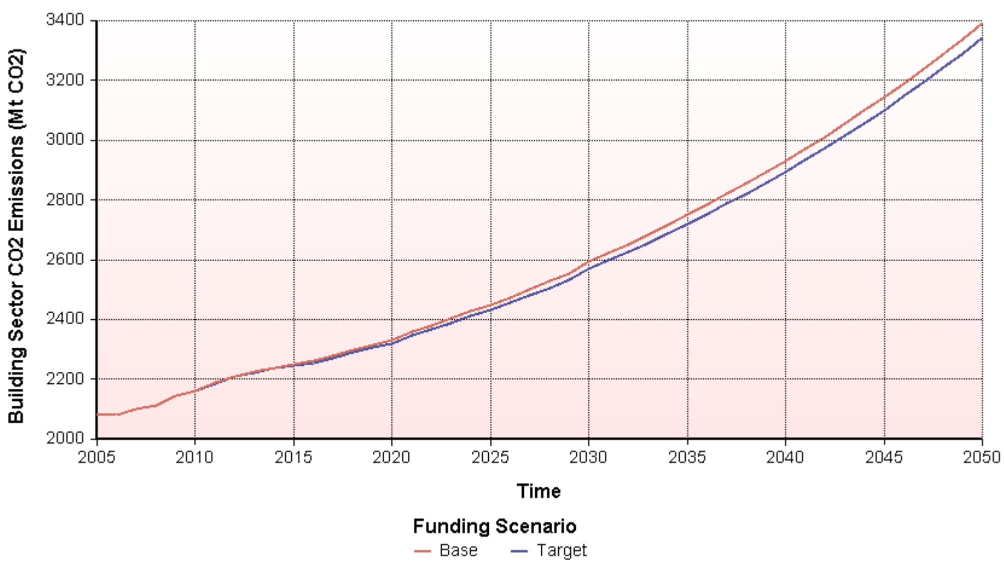
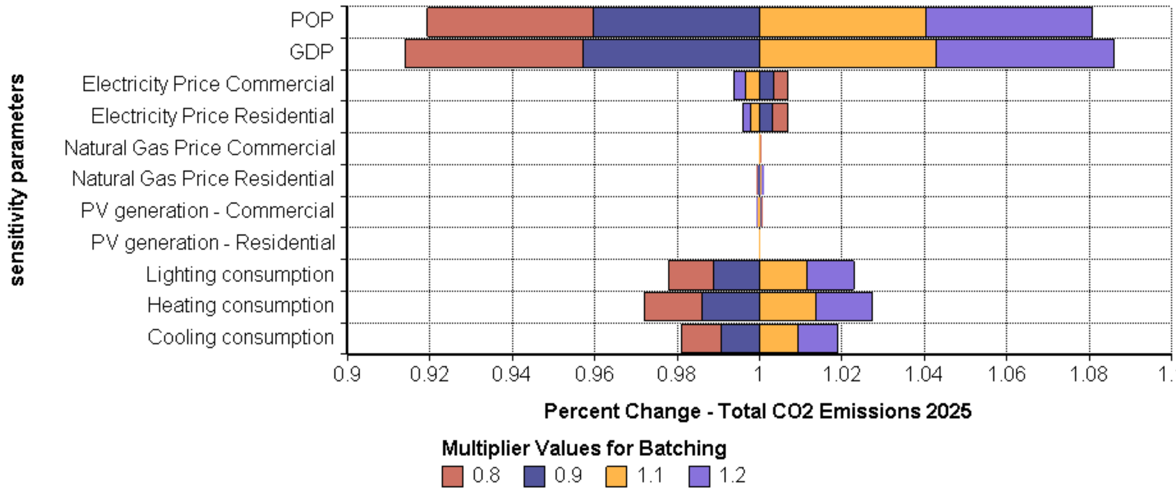


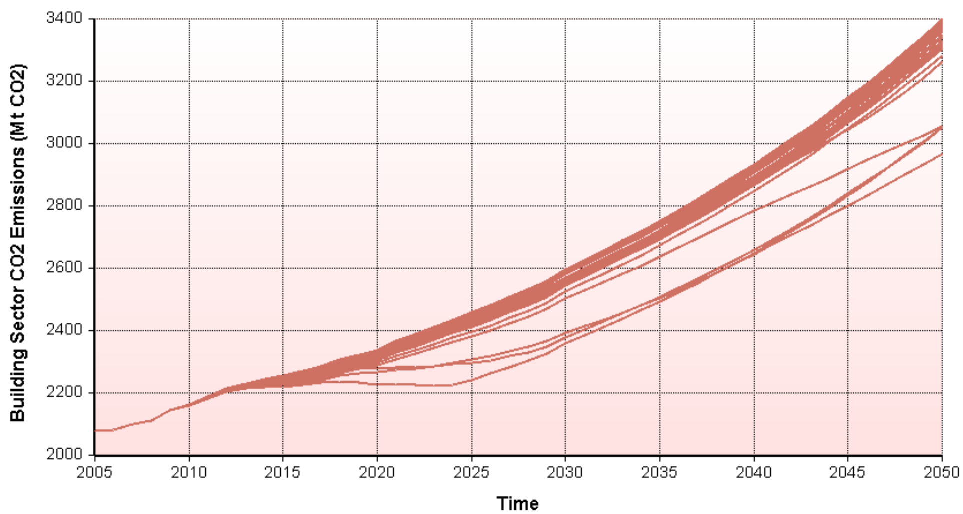
Figure 6. Sensitivity analysis of total CO_2 emissions from buildings at 2025 to various internal factors. This demonstrates the comparably immense influence of macroeconomic values on emissions results.



However, thinking of these results as a single line forecast is in reality a simplistic strategy. This paper has mentioned already several times that such forecasts come with a substantial degree of inherent uncertainty. It is therefore important to consider also the range of all possible outcomes. Because it allows for the consideration of stochastic inputs, SEDS is capable of quantifying uncertainty in every projection it makes. The result of this exercise can be seen in Figure 7. The stochastic functionality of SLBM produces a sample of 30 Monte Carlo draws, which defines the upper, lower and mid values of CO_2 emissions, giving a succinct and informative look at the degree of uncertainty in the forecast. In this specific instance, CO_2 emissions can reach as high as 3400 Mt or as low as 2960 Mt in 2050. It should be noted that this set of results incorporates uncertainty from a number of different technologies and parameters, such as PV performance and fuel prices, and not simply from windows alone. It is this compounding of uncertainty which contributes to the wide range of possible outcomes.

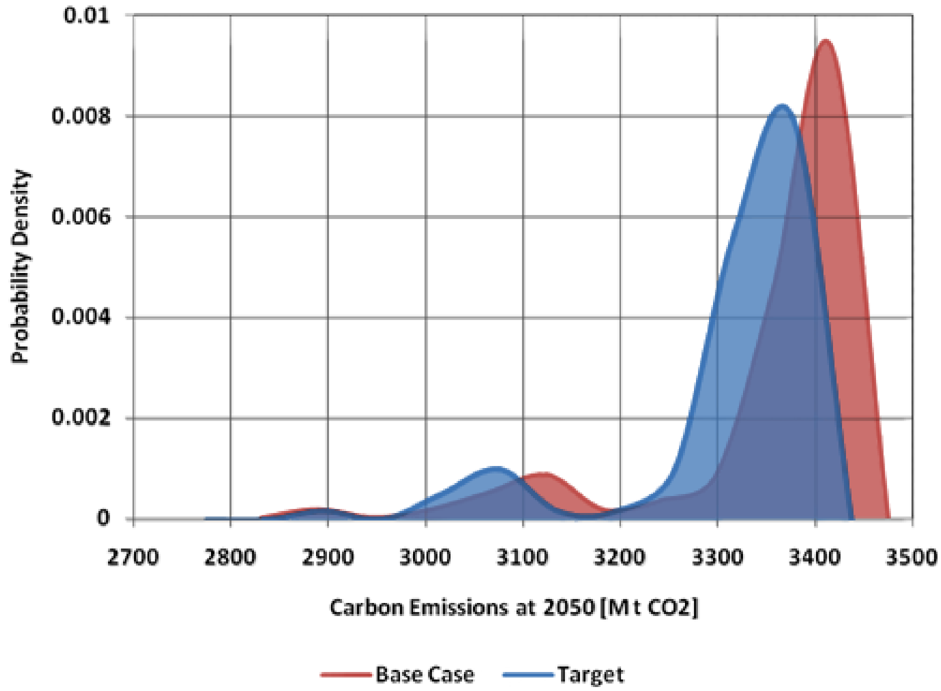
From this figure, it appears that most of the draws are clustered towards the high end, while only a few draws produce substantially lower CO_2 emissions (4 of 30). These cases likely result from a confluence of high electricity prices and competitive PV performance, which together produce high PV adoption rates and subsequent drops in carbon emissions. Better than average performance in passive technologies may also be contributing.

Figure 7. The stochastic functionality of SLBM, demonstrated here by 30 Monte Carlo draws, shows the extent of uncertainty in forecasting CO2 emissions to 2050.



Analytica® also contains the capacity to produce probability distributions of stochastic results, allowing for quick comparisons between scenarios. An example of this is Figure 8, which compares the distribution of CO_2 emissions at 2050. This figure paints a clear picture of how significant the influence USDOE R&D will be on the results. In both cases, the most probable emissions level occurs near the high end, indicated by the peaks on the right side of the plot. However, in the case of target funding, the shift toward the lower end of the emissions spectrum is clearly evident. Its most prominent peak begins to spread to the left. Additionally, its secondary peak centered at around 3050 Mt appears to have grown. All of the qualitative factors combine to indicate an increased likelihood for lower carbon emissions under the target funding scenario.

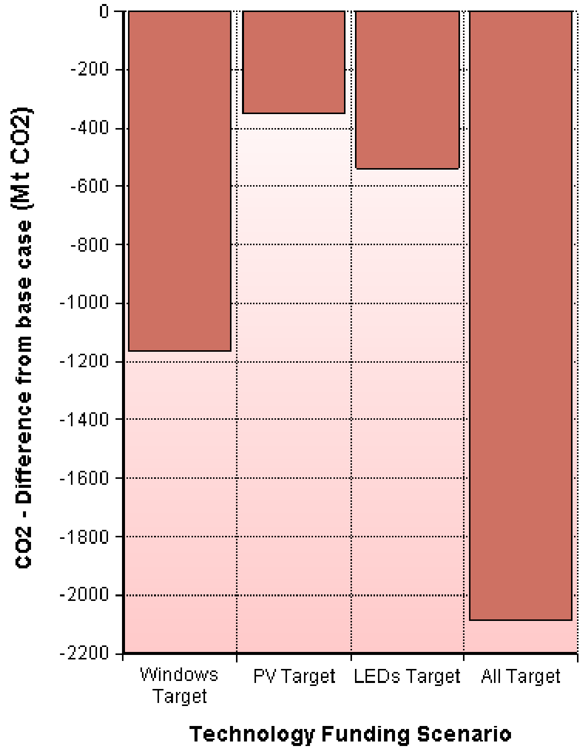
Figure 8: The probability density, or the likelihood of possible outcomes, for carbon emissions at 2050. USDOE target funding produced a clear tendency towards lower emission values.



4.4 The Value of Targeting Passive Technologies

Passive technologies represent just one of many approaches to increasing building efficiency, any of which may also be of interest to USDOE for R&D funding. In a world of limited financial resources, it is important to consider which of these areas of research is likely to produce the most significant savings. Currently, SLBM also considers USDOE R&D funding programs for LED lighting and on-site PV generation—two much hyped technologies in the sphere of building efficiency. The impacts of each program are compared, in Figure 9, by evaluating the cumulative savings in CO_2 emissions between 2005 and 2050 relative to the base case. Such a comparison gives a simple, yet important metric for determining which programs are most effective. As the preliminary results illustrate, targeting passive technologies produces the highest level of carbon reduction, more than the other two programs combined. It is important not to surmise too much from this simple comparative exercise. One point which is evident, however, is that passive technologies in general, and advanced windows specifically, represent an important piece of the efficiency puzzle and should regarded accordingly. Any approach that does not attempt to address them can be seen, at best, as incomplete.

Figure 9. Cumulative carbon savings in all U.S. buildings by technology targeted. The CO_2 reductions (compared to the base case) for windows demonstrates the importance of targeting passive technologies. Clearly there is a large potential for reductions; more so, even, than comparable programs for distributed PV generation and solid state lighting.



5. Conclusions

The U.S. building sector currently contains a number of prime targets for efficiency improvements, among which include passive measures such as advanced window technologies. This paper has assessed the effect of a USDOE program funding R&D for three such technologies. The analysis began with projected improvements in performance, then continued to market behavior and reductions in energy use intensity, finally the impact to total CO_2 emission from the U.S. buildings sector was determined. The potential impact of funding is expect to be a 1165 Mt reduction in CO_2 between now and 2050, with a 71 Mt reduction in the year 2050 alone, exceeding the combined reductions from similar programs for on-site PV and solid-state lighting. This investigation has been conducted using the Stochastic Lite Building Module (SLBM) as part of the Stochastic Energy Deployment System (SEDS). SLBM has proven to be a versatile and valuable tool for assessing the impact of emerging building technologies and the funding programs which support them. The stochastic framework of SEDS allows for the comprehensive inclusion of uncertainty analysis, an essential part of such far reaching and complex forecasts.

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