Technology Prioritization: Transforming the U.S. Building Stock to Embrace Energy Efficiency

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ABSTRACT

The U.S. Buildings sector is responsible for about 40% of the national energy expenditures. This is due in part to wasteful use of resources and limited considerations made for energy efficiency during the design and retrofit phases. Recent studies have indicated the potential for up to 30-50% energy savings in the U.S. buildings sector using currently available technologies. This paper discusses efforts to accelerate the transformation in the U.S. building energy efficiency sector using a new technology prioritization framework. The underlying analysis examines building energy use micro segments using the Energy Information Administration Annual Energy Outlook and other publically available information. The tool includes a stock-and-flow model to track stock vintage and efficiency levels with time. The tool also be used to investigate energy efficiency measures under a variety of scenarios and has a built-in energy accounting framework to prevent double counting of energy savings within any given portfolio. This tool is developed to inform decision making and estimate long term potential energy savings for different market adoption scenarios.

Keywords: energy efficiency, technoloy prioritization, green buildings

1 INTRODUCTION

The U.S. Buildings sector is responsible for about 40% of the national energy expenditures [1]. This is due in part to wasteful use of resources and limited considerations made for energy efficiency during the design and retrofit phases. The projected annual energy consumption by end-use in 2030, expressed in quadrillion BTU (quads) in both residential and commercial buildings is summarized in Figure 1. The total expected buildings annual primary energy end-uses in 2030 is 42.6 quads. Recent studies [2, 3, 4, 5] have indicated the potential for up to 30-50% energy savings in the U.S. buildings sector using currently available technologies. The U.S. Department of Energy's Building Technologies Office (BTO) seeks to continually catalyze and support the development of innovative, cost-effective energy saving solutions to improve the U.S. building stock efficiency and maximize energy utility. The BTO portfolio encompasses research and development, market stimulation, and building codes and equipment standards activities. BTO has developed a prioritization tool in an effort to inform programmatic decision making based on long-term national impact of different energy efficiency measures [4, 5]. These measures represent new and existing energy saving opportunities, design guidelines, operating practices, or technologies. This prioritization tool provides an objective comparison of new and existing measures and is being used to inform decision-making with respect to BTO's portfolio of projects. Four criteria drove the tool's design at the outset of its development:

- Comprehensive. We tried to include most known energy efficiency measures proven to save energy in residential and/or commercial buildings.
- Open. We only included measures that are peer-reviewed, and subsequently solicited peer review on the tool.
- Straightforward. We limited the inputs, outputs, and applied analytical techniques to established methods.
- Objective. We devised a standard objective level for incorporating inputs in an effort to avoid bias between different measures.

The Prioritization Tool or "P-tool" builds upon a legacy of previous activities in evaluating the national and regional impact of energy efficiency measures. For example, Meier and his colleagues [6, 7] developed a similar methodology for characterizing energy saving measures according to their economic potential energy savings and the Levelized Cost of Conserved Energy (LCCE). The LCCE is the present value of the incremental investments of deploying a given measure divided by the present value of energy saved over the baseline energy use. These studies also developed the concept of an "energy accounting framework" to insure that an organization pursuing multiple measures accounts for the energy captured by each measure pursued without "double counting" any energy savings. Various studies present results in the form of economic potential energy savings, which represent the reduction in U.S. annual energy use that could be captured if 100% of the market adopts the measure that provide services at the lowest lifecycle cost rather than Business As Usual (BAU) forecast.

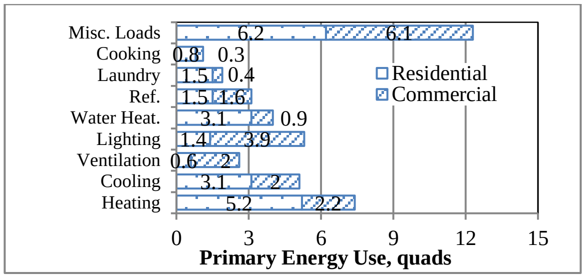

Figure 1: 2030 building primary energy end-uses [1].

2 METHODOLOGY

The P-tool is developed to estimate the long-term energy savings of different measures under various scenarios. The tool starts by comparing the measure with the baseline or BAU and then uses a stock-and-flow model to track replacements, retrofits and new installations over the period of interest. The tool then uses the available BAU and performance data to evaluate the un-aided adoption of this measure using the Bass Diffusion Model [8] and the annual percentage improvement in unit stock energy consumption. Next, the tool evaluates the annual energy savings potential for a given scenario and calculates the corresponding LCCE. Such analyses are termed as "un-staged" since the tool is analyzing the measure without accounting for interaction with other measures. The tool is also capable of performing a "staged" analysis using an energy accounting framework to develop a scenario alternate to the BAU. Staged analysis starts by ranking the measures based on their cost effectiveness and national impact and then employs the energy accounting framework to avoid double counting energy savings from measures with overlapping markets. The following sections provide a summary of the tool methodologies. Readers interested in more details are encouraged to refer to [4].

2.1 Baseline and Measure Definitions

The P-tool is primarily based on detailed energy end-use data available from the reference case of the 2011 Annual Energy Outlook (AEO) [1] and other studies such as the Residential (RECS) [9] and Commercial Buildings (CBECS) [10] Energy Consumption surveys and the 2011 Building Energy Data Book [11]. The AEO is based on detailed simulations of the National Energy Modeling System (NEMS) [12]. In this tool, the U.S. building energy market is divided into 2,510 micro-segments to ensure market granularity for different measures under consideration. This enables using the energy accounting framework to avoid double counting of energy savings from measures with overlapping market(s).

Each measure is compared to the corresponding baseline or BAU which is identified as the stock and energy consumption predicted by NEMS and other information used to further subdivide the regional predictions. As an example, consider evaluating a measure that will improve the efficiency of central air conditioning equipment in single-family housing within the US hottest two climate zones. NEMS output provides the central air conditioning stock and end-use energy consumption for different residential building types for each of the 9 US census regions. We then use RECS data on housing unit characteristics by climate zone to find the ratio of housing units within the hottest two climate zones in each census division. The tool then cross-multiplies the NEMS regional stock and energy consumption data with these ratios to establish the BAU. Furthermore, the baseline equipment is defined as being at the minimum standard efficiency (e.g. SEER 13). The measure and baseline installed cost and lifetimes are also required to evaluate the LCCE.

In order to create a level playing field for competing measures with different lifetimes and market diffusion mechanisms, we have selected our performance metrics as the annual potential energy savings in the year 2030 and the LCCE evaluated between the years 2010 and 2100. However, NEMS data are only available for a limited time frame (2005-2035) and do not provide a means to evaluate the un-aided diffusion of the measure within a given stock. Farese et al. 2012 [4] devised an approach to extrapolate NEMS data beyond the year 2035 while evaluating the un-aided diffusion using the Bass diffusion model. In this approach, the Bass diffusion coefficients are evaluated by fitting the BAU stock and energy consumption while accounting for potential stock efficiency improvements with time. BAU annual energy consumption, $U^B(y)$, can be calculated as shown in Eq. (1) where $S_e^B(y)$and $S_m^B(y)$ represent the baseline annual existing and new measure stock respectively, and $C_e(y)$ and $C_m(y)$ represent the existing and new measure unit stock energy consumption at year y. The sum of $S_e^B(y)$and $S_m^B(y)$ is equal to the overall stock for year y as shown in Eq. (2). The new measure stock diffusion is evaluated using the Bass diffusion model as shown in Eq. (3). $C_e(y)$ is calculated as shown in Eq. (4) where f is the annual reduction in existing stock unit energy consumption and $C_e(y_0) = U^B(y_0)/S_e^B(y_0)$. The 25 data points $\{U^B(y)$ and $S(y)$ for y = 2010 to 2035} can then be fit using three variables [*f*, *p*, and *q*] using Excel Solver under reasonable constraints: $0 \le p \le 0.1$, $0 \le q \le 0.25$, and $-5\% \le f \le 5\%$. The solver is used to minimize the square root error between the BAU fit and 25 available data points, and the error, slope and curvature at the last available data point. These additional terms, representing a departure from a standard least-square fit, reflect the impact of the slope second order terms on the extrapolation of our BAU case beyond 2035. The model may change the starting fit year to avoid fitting complexity due to complex changes in forecasted energy consumption.

$$U^B(y) = S_e^B(y) \times C_e(y) + S_m^B(y) \times C_m(y) \quad (1)$$

$$S(y) = S_e^B(y) + S_m^B(y) \quad (2)$$

$$S_m^B(y) = \left(p + q \times \frac{S_m^B(y-1)}{S^B(y)} \right) \times \left(1 - \frac{S_m^B(y-1)}{S^B(y)} \right) \quad (3)$$

$$C_e(y) = C_e(y_0) \times (1-f)^{y-y_0} \quad (4)$$

2.2 Stock-and-Flow Modeling

A simplified stock-and-flow model is incorporated into the tool to track the stock vintage and efficiency levels (measure under consideration versus existing BAU measure) with time. This model allows us to identify the annual competed stock due to replacement (accelerated or at end-of-life) and new addition due to market growth. The model also tracks the stock elimination by efficiency levels due to stock retirement or early disposal. The market penetration of the efficient measure within the competed stock is evaluated based on the considered scenario. The model assumes uniform vintage distribution at y_0, and that once a portion of the stock becomes efficient it will remain efficient.

2.3 Scenario Evaluation

The prioritization tool was used to investigate several market scenarios, namely: Technical Potential (TP), Full-Adoption Potential (FA), and Adjusted Diffusion Potential (AD). For any given scenario (scenario *X*), the estimated annual energy consumption is calculated using Eq. (5). The annual energy savings, $P^X(y)$, can then be calculated as the difference between $U^B(y)$ and $U^X(y)$. The LCCE under the same scenario is calculated as shown in Eq. (6).

$$U^X(y) = S_e^X(y) \times C_e(y_0) \times (1-f)^{y-y_0} + S_m^X(y) \times C_m(y) \quad (5)$$

$$\text{LCCE} = \sum_{y=y_0}^{N} \frac{\phi^X(y) - \phi^B(y)}{(1+d)^{y=y_0}} \Bigg/ \sum_{y=y_0}^{N} \frac{U^X(y) - U^B(y)}{(1+d)^{y=y_0}} \quad (6)$$

where $\phi^X(y)$ and $\phi^B(y)$ represent the cash outlays for deploying the measure under scenario X and the baseline respectively and d is the discount factor. $P^{TP}(y)$ assumes that the entire market can be switched overnight to the new measure; i.e. $S_m^B(y) = S(y)$ for all y. $P^{FA}(y)$ represents a scenario where the new measure has 100% market penetration; i.e. all the competed stock is of the efficient measure. This scenario accounts for stock-and-flow market dynamics, natural market growth of energy efficient measures, and stock growth and efficiency improvement with time. Finally, $P^{AD}(y)$ represents a scenario that simulates the impact of BTO programs on the measure diffusion. In this scenario we assume that R&D-funded activities would accelerate market introduction and increase *q*, Deployment-funded activities would increase *p*, and Standards would set market adoption to 100%. More details about this scenario can be found in [4].

Figure 2 depicts a sample implementation of the three scenarios considering the example of R-10 windows as an efficient measure for residential buildings. The FA scenario approaches the TP when the entire stock is replaced with R-10 windows. This will occur in 40 years (residential window lifetime) after market introduction. Furthermore, the AD scenario approaches the TP roughly 40 years after code enforcement of R-10 windows for residential buildings.

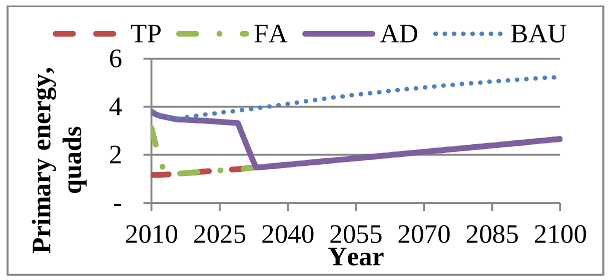

Figure 2: Primary energy consumption related to considering R-10 windows for residential buildings

2.4 Staging

Staging is an energy accounting framework that avoids double counting energy savings for measures with overlapping markets within a portfolio. It involves a 4-step iterative process that starts by sorting the measures from lowest to highest LCCE where a "tie" is broken by prioritizing the measure with the largest potential energy savings. The staging model then determines the nature of the interaction between all these measures and evaluates the overlap of each measure's market to those with a lower LCCE. The iteration ends by calculating the "staged savings" by subtracting the overlapping savings from lower LCCE measures.

There exist three primary market interaction types: independent (measures do not interact), savings reducing (a measure directly reduces the savings of another measure), and market reducing (a measure would decrease energy use another measure can address but does not affect its percentage savings of the remaining market). The staged savings of a measure ranked "N" can be evaluated as shown in Eq. (7); where $\pi_{i,N}$ = 0, 1, P_N^X/S_N for independent, savings reducing, and market reducing interactions respectively. The $\text{LCCE}_{\text{staged}}$ can be evaluated by multiplying the LCCE by the ratio of $P_N^X/P_N^{X,staged}$.

$$P_N^{X,staged} = \max\left(\left(P_N^X - \pi_{1,N} \times P_1^X - \sum_{i=2}^{N-1} \pi_{i,N} \times P_i^{X,staged} \right), 0 \right) \quad (7)$$

3 PRELIMINARY RESULTS

Figure 3 shows one realization of the “ultimate savings” supply curve as determined by analyzing measures relevant to BTO under the FA scenario and taking a snapshot of the data in 2030. The horizontal green line indicates the typical range of energy costs today. By comparing each measure’s LCCE to the cost of energy it is saving (i.e., fuel and time-of-day specific pricing) and selecting those with a lower LCCE than energy price we derive the conventional “economic energy savings potential” which shows a possible annual primary energy savings of 52% (22.1 quads) in 2030. This scenario assumes 100% market penetration of cost effective energy efficient measures. When using the adjusted adoption scenario, the “economic” potential energy savings was reduced to 27% (11.7 quads) in 2030. Furthermore, analyzing the prioritized list identified high impact measures for different BTO activities as shown in Table 1.

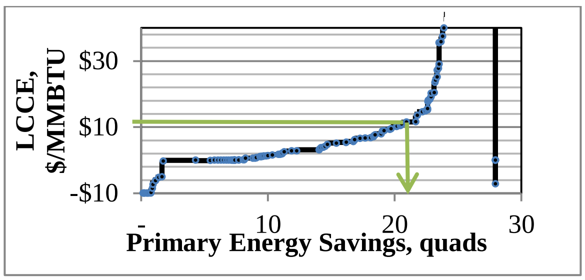

Figure 3: Efficiency supply curve using BTO-relevant measures

BTO activity*	High Impact Measure
R&D, R	Gas absorption heat pump water heater
R&D, C	Optimized whole-building controls
Deployment, R	Heat pump water heater
Deployment, C	Energy recovery ventilation

*R indicates residential, C indicates commercial.

Table 1: High impact measures for different BTO activities.

4 CONCULSIONS

A prioritization tool was developed to provide BTO with a comprehensive set of models needed to determine the long-term prospective benefits from buildings-related energy efficiency measures. It provides an objective analytic framework, a landscape of measures, and a level playing field to compare measures with different markets, end-uses, and lifetimes. The tool estimates the long-term energy saving potential under various scenarios with or without staging. Thus a portfolio analysis might use various scenarios to examine the potential effect of staging or the influence of programmatic funding on market penetration and therefore impact. The staging algorithm results in a prioritized list of measures worthy of further investigation, a catalog of opportunities that is likely of low priority and an extensive dataset with which to compare a broad range of opportunities. Preliminary results show the economic energy savings potential for over 50% reduction in annual energy use in the year 2030 compared to the BAU under the full adoption scenario. This result exceeds all recent estimates of energy savings potential because it includes technologies not currently cost effective in the market place. This highlights the important benefits of research, development, and market stimulation as these measures can be made cost effective in the future if action is taken today. This tool can be used to inform (although not form) programmatic decision.

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