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Cost-Availability Curves for Hierarchical Implementation of Residential Energy-Efficiency Measures

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Key Words: community, levelized cost, energy efficiency, residential, HVAC, utility programs

Abstract

Historical residential electricity data and natural gas consumption data were collected for, respectively, 1200 and 178 residences in a small town in the U.S. These data were merged with local building and weather databases, and energy consumption models were developed for each residence, revealing substantial variation in heating and cooling intensity. After estimating approximate physical building characteristics, energy profiles for each residence were calculated and savings from adoption of the most cost-effective energy efficiency measures for each residence were estimated. Effectively, we wish to leverage commonly available data sets to infer characteristics of building envelopes and equipment, without the need for detailed on-site audits. This study evaluates the potential energy savings for the residences studied, and by extrapolation, for the entire town, as a function of cost if the savings measures were to be implemented in rank-order of cost effectiveness to show that savings penetration for the community comes with non-linearly increasing cost. The results show nearly a 32% collective savings in HVAC energy use could be achieved with a collective levelized cost for energy saving measures of $10/mmBTU saved if the most cost effective measures among the entire community are implemented first.

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Cost-availability curves for hierarchical implementation of residential energy efficiency measures

Introduction

Driven partly by climate change concerns and partly by a desire to increase energy independence, the U.S. Department of Energy has established a goal of reducing residential and commercial building site-use energy by at least 35% by 2030 (DoE - EERE 2010). This follows decades of experience, with varying degrees of consistency of implementation and of success, with programs aimed at increasing energy-efficiency, including regulations such as building codes and appliance standards, and educational and informational initiatives (Gillingham, Newell, and Palmer 2006). Energy-efficiency scenarios for the US building sector have repeatedly shown that significant savings are achievable (Koomey et al. 2001). As one example that has been widely cited, a 2009 report (Granade et al. 2009) focused on measures that could be taken by 2020 with positive net present value and finds the potential for energy-use reduction to be 20% with respect to current (2008) levels, and even higher with respect to projected business-as-usual (BAU) consumption. A recent paper by the present authors (Brecha et al. 2011) showed the value of estimating energy savings for a community based upon a measured average energy effectiveness of the stock of residences . These estimates showed that there were relatively large behavioral-based energy savings opportunities and relatively long paybacks from energy efficiency investments.

There have also been some more sober views of the costs of energy efficiency. A 2012 study documented the effectiveness of electricity energy efficiency programs (Arimura et al. 2012), concentrating on demand side management (DSM), showing 0.9 percent electricity energy savings at a weighted-average cost to utilities (or other program funders) of about 5 cents per kWh saved over an 15-year period of time, with the potential for even greater savings if programs similar to those analyzed were to be implemented more widely . A 2009 study commissioned by the Electric Power Research Institute (EPRI) suggests that the electric utility industry can only realistically expect to offset 37% of the *growth* in electricity use (in TWh) by 2030 with efficiency improvements (Rohmund et al. 2008).

It is even possible to question the existence of a real energy-efficiency gap, or from an economic perspective, the potential for reductions in energy consumption when factors such as opportunity costs and the full costs of governmental incentives are considered. (Allcott and Greenstone 2012). There is a great deal of heterogeneity in both building stock and in the response of consumers and home-owners when it comes to implementation of energy-efficiency upgrades. The current study attempts to move beyond average numbers and to evaluate potential savings based on heterogeneous building stocks.

Whether presenting an optimistic or somewhat dim view of the potential for sizeable energy reduction for existing building stock in the U.S., thus far, economic considerations have been based upon average utility results or average savings from among a collective group of buildings. In contrast, the present study utilizes a collection of residential buildings for which both energy and some limited building data are available to show the potential of energy reduction targeted at residences (or any building) with the greatest need for energy-efficiency improvements. The method starts with minimal input data, avoiding the need for time-consuming and expensive on-site audits, to evaluate energy-savings potential for a large collection of homes. The goal is to show that when the least energy-effective buildings are targeted for energy reduction first, the affordability of energy reduction achieving deep collective savings is much better.

Methodology Overview

This section describes the analysis utilized to estimate residential energy savings within a community, region, or nation as a function of simple payback and as a function of cost per mmBtu saved annually. The approach used draws from recent research by (Hallinan et al. 2011), utilizing an approach that: 1) melds energy, weather, and residential building data sets for a community; 2) calculates energy intensity for each residence; 3) disaggregates residential energy intensity into weather dependent (heating and cooling) and weather-independent (lighting/appliances/water heating) components; 4) compares individual residence performance and current energy-use patterns to available regional benchmarks to evaluate energy effectiveness of each residence relative to each energy category (heating/cooling/lighting and appliances/water heating); 5) develops individual home energy models calibrated against actual energy use; and 6) evaluates energy reduction and the costs to achieve these reductions for each home and for both individual savings measures and when two or more savings measures are simultaneously implemented. We briefly describe each of these steps in turn, with derivation details left for the Supplementary Online Material (SOM).

Melding of Databases

Five separate datasets are used in this analysis. Monthly electrical consumption data (in kWh) for 24 months are available for a total of nearly 1200 residences. Although a large database of natural gas consumption was available, these data were not address-specific, and therefore a smaller set of data from 178 residences was gathered, also for a 24-month period. County auditor real estate information was available, and include the age of the house, number of floors, type of water heating, square footage, basement and crawl space information, and more. Two types of weather data were used for purposes of normalization: Local hourly dry bulb temperature (NOAA 2013) and local hourly typical meteorological year (TMY3) dry bulb temperatures (NREL 2005). Temperature data were averaged over the billing period corresponding to the utility data for each residence, thus permitting correlation of monthly energy use to average outdoor temperature.

Calculate Energy Intensity

Both electric and natural gas energy data for each residence were normalized to the area of the residence. Also, the monthly energy use data for a particular month was divided by the number of hours in the billing period to produce for each month the average electrical power (kW/sf) from the electric utility data and average natural gas power (BTU/hr/sf) from the available natural gas data.

Disaggregation of Energy Data for Inverse Energy Modeling

Inverse energy modeling for buildings refers to use of actual data for consumption of energy to draw conclusions about the physical properties of the building envelope and energy-related equipment. Fundamentally the modeling assumes that the heat loss/gain from a building is linearly dependent upon the difference in temperature between the inside and outside of a building. We make the assumption that input heating and cooling energy also depends linearly on outdoor temperature, as shown in Fig. 1, when respectively the outdoor temperature falls below or rises above what is referred to as the heating and cooling balance point temperatures (Brecha et al. 2011, Hallinan et al. 2011). This assumption neglects the possible nonlinearities in efficiency of HVAC equipment in converting input energy to final useful energy. In creating the inverse energy models, it is assumed that the building envelope does not change seasonally and that energy use can be normalized by floor area of the building. The latter assumption works best for heating and central cooling, the focus of this study, where the interior temperature is maintained fairly constantly throughout a residence, with minimal occupancy influence.

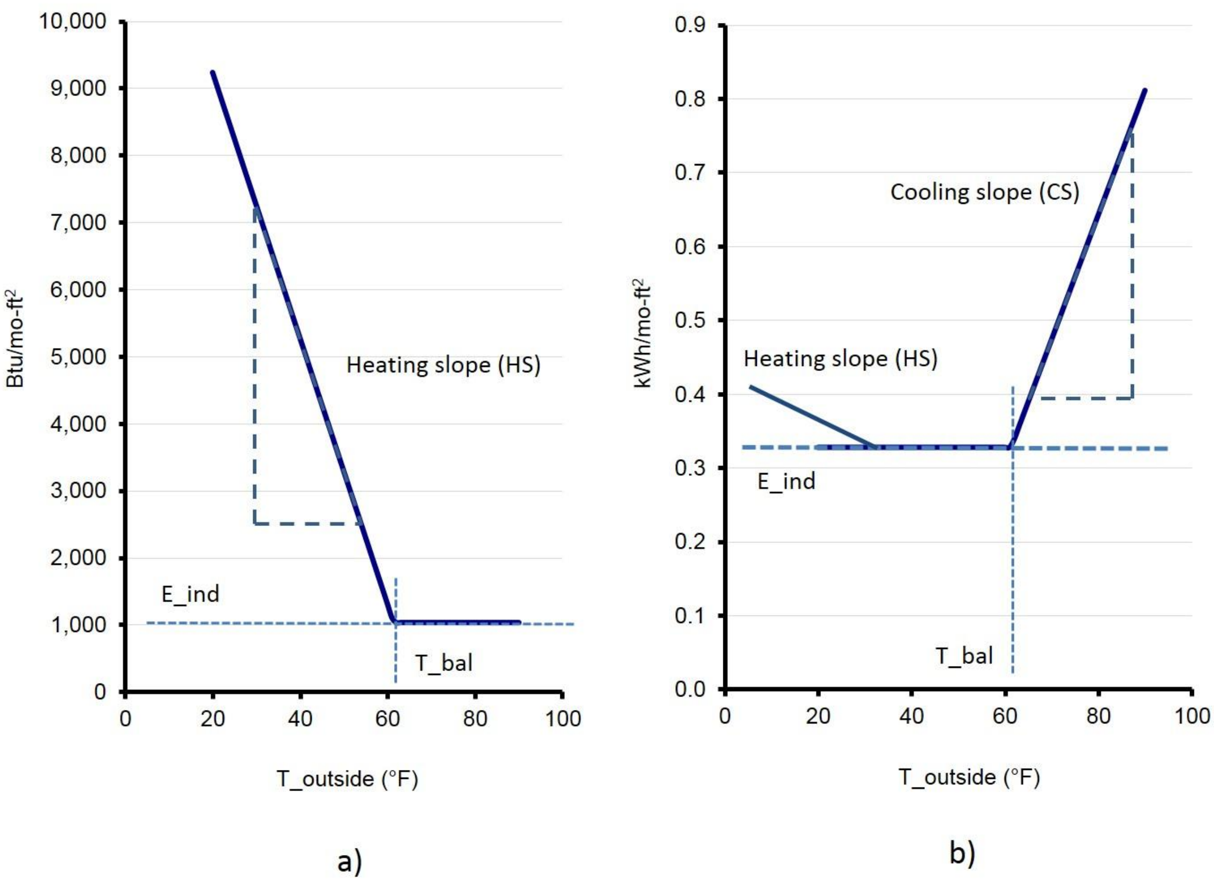


Figure 1 – Schematic representation of the inverse energy model methodology described in the text. Energy use (area-normalized) as a function of temperature leads to temperature-dependent parameters (heating and cooling slopes) and temperature-independent (baseline) consumption

To properly benchmark energy use and ultimately establish an approximate energy model for each house, the monthly energy data for each fuel type (if applicable) must be disaggregated into weather-dependent and weather-independent components. To this end, five-parameter and three-parameter regressions of monthly energy versus monthly average temperature (NOAA 2013) during each billing period are employed for electric and gas data, respectively. A swarming genetic algorithm optimization approach was used to do the regressions. Output parameters from the regressions are shown below in Table 1. The regression optimization aimed to minimize the

R-squared error between predicted actual monthly energy data, subject to an inequality constraint requiring that the annual predicted energy (from the regression) be within 1% of the actual reported energy for each house. The details of the regression are available in the Supplementary Online Material (SOM), Eqns. S1-S3, and in Ref. (Hallinan et al. 2011).

Table 1. Regression Fit Parameters

Regression Parameter	Description
CS_{e}	Cooling slope (kWh/month/˚C), electric
$HS_{\mathrm{e}}, HS_{\mathrm{ng}}$	Heating slope (kWh/month/°C), electric and gas
$T_{balc,e}$	Cooling balance point temperature, e.g., outside temperature above which there is cooling
$T_{balh,e}$, $T_{balh,ng}$	Heating balance point temperature, e.g., outside temperature below which there is heating
E_{ind}	Temperature independent energy use (kWh/month)

With regression parameters developed, the annual heating (electric and natural gas) and cooling are estimated. These are weather-normalized so that cooling and heating energy can be compared from year-to-year as the weather changes. A Normalized Annual Consumption (NAC) approach is employed (Lammers et al. 2011) to calculate cooling- and heating-degree hours (CDH and HDH, respectively) from the estimated balance temperatures and typical weather year (TMY3) temperature data, as shown below.

$$CDH_e \text{ [deg.F-hr]} = \sum_{i}^{8760} \left(T_i - T_{balc,e}\right)$$

$$HDH_{e,ng} \text{ [deg.F-hr]} = \sum_{i}^{8760} \left(T_{balh,e,ng} - T_i\right)$$

where the summation is over every hour in the year and T_i is the typical hourly temperature for a specific hour, I , in the year.

The normalized annual electrical cooling intensity (NECI), for houses where there is significant cooling energy consumption, is calculated from

$$\text{NECI [kWh/sf/year]} = CS_{\text{e}} \times CDH_e \tag{1}$$

Similarly, the normalized annual electric heating intensity (NEHI) is given by

$$\text{NEHI [kWh/sf/year]} = HS_{\text{e}} \times HDH_e \tag{2}$$

Finally, for dwellings with natural gas consumption, the normalized heating (NGHI) and baseline energy use can likewise be determined from the estimated HS_{NG}, $Baseline_{NG}$, and $T_{balh,NG}$.

$$\text{NGHI (BTU/sf/year)} = HS_{\text{ng}} \times HDH_{ng} \tag{3}$$

Benchmark

The estimated weather-dependent and weather-independent energy use in each category is then compared to the 2005 EIA typical energy-use data for residences in the Midwest North Central census region as the appropriate benchmark (EIA 2009). The annual energy intensity in each category is shown in Table 2 given as aggregate numbers.

Table 2. Midwest North Central Region typical energy use intensity (EIA 2009) and average intensities for the sample residences.

Category	Annual Energy Intensity	
	Electric	Natural Gas
Cooling	1.02 kWh/sf (EIA) 0.77 kWh/sf (sample)	-----
Heating	1.8 kWh/sf (not used for upgrade estimations)	33.9 kBtu/sf (EIA) 42.0 kBtu/sf (sample)

These data are used as reference points for determining the relative energy efficiency of each residence for heating and cooling.

Current energy use patterns

Considering only the residences for which complete energy data were known, cumulative distributions of both space heating and cooling energy intensity were developed, and are shown in Figs. 2 and 3. It is clear from both figures is that there is wide disparity in energy intensity. Interestingly, the community's heating energy effectiveness is far worse than its cooling energy effectiveness, with respectively about 1/3 and 2/3 the residences in the sample with heating and cooling intensities below typical for this climate. The most important conclusions to draw in comparing local data to EIA benchmarks are that: (i) given that the comparison is fairly close, the energy savings estimates in this study will have relevance to other communities; and (ii).the large disparity in cooling and heating intensity from the worst to best houses strongly suggests big energy reduction opportunities for the least energy effective residences. This study thus considers an energy reduction strategy which would target the worst houses for energy improvements first.

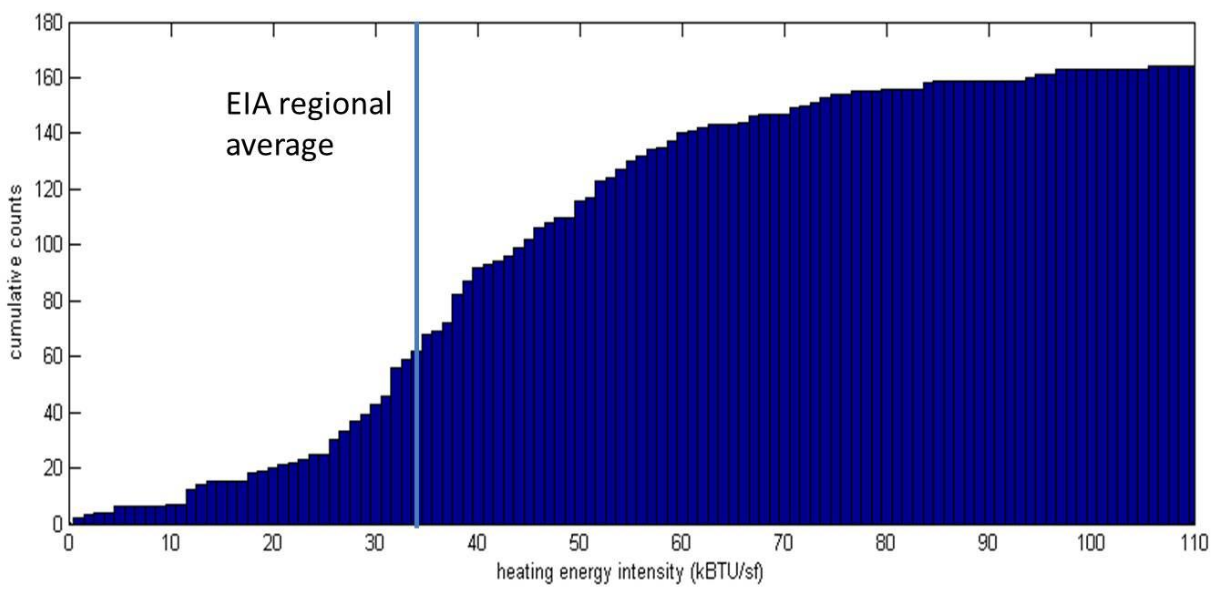


Figure 2 - Cumulative distribution of heating energy intensity.

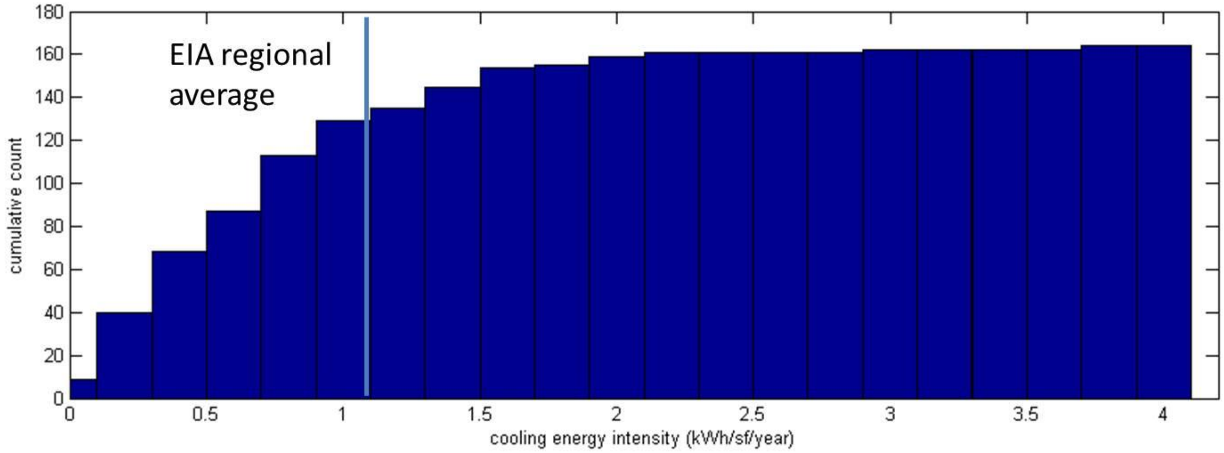


Figure 3 - Cumulative distribution of cooling energy intensity.

Residential Energy Model

The final step in the process is to develop a simplified energy model for each residence that can be calibrated against actual energy use. It is assumed that the residential building characteristics are approximately equal for the winter season as for the summer season. This means that the estimated HS_{ng} and CS_e are not independent, being related through the residential overall heat transfer coefficient, $UA_{overall}$, which is assumed the same for summer and winter seasons.

$$\begin{aligned} HS_{ng} &= UA_{overall}/\eta \\ CS_e &= UA_{overall}/\mathrm{SEER} \end{aligned} \tag{4}$$

Here, η is the efficiency of the heating equipment and SEER is the Seasonal Energy Efficiency Rating. The model developed for each residence requires estimates of physical building parameters, which must in turn be derived from the readily available building data such as square footage and number of floors. Ideally one would have data for wall area, window area, floor area, ceiling area and volume; available building databases do not generally include such information.

Thus, to construct an energy model for every residence, it is necessary to make some assumptions consistent with typical building practices for the region. The key geometrical assumptions utilized are a typical length to width ratio for houses in the area (1.4) and a typical window to wall area fraction (0.15). Based upon these assumptions, the wall, window, and ceiling area is estimable for each residence. Details of the geometrical calculations and assumptions are found in the SOM, Eqns. S4-S10.

With the geometrical properties estimated, a simplified energy model of each residence can be constructed, considering energy losses/gains through the ceiling, walls, windows, floor, and from air leakage, and neglecting solar and human gains. The simplified model for heating and cooling is given by Eqns. (5) and (6).

$$CS_{model} = \frac{\left\{\frac{A_{attic}}{R_{attic}} + \frac{A_{wall}}{R_{wall}} + \frac{A_{win}}{R_{win}} + \frac{A_{floor}}{R_{floor}} + \dot{A}\ \rho_{air} c_p \cdot \text{area} \cdot \text{ height}\right\}}{\text{SEER} \cdot \text{area}} \tag{5}$$

$$HS_{model} = \frac{\left\{\frac{A_{attic}}{R_{attic}} + \frac{A_{wall}}{R_{wall}} + \frac{A_{win}}{R_{win}} + \frac{A_{floor}}{R_{floor}} + \dot{A}\ \rho_{air} c_p \cdot \text{area} \cdot \text{height}\right\}}{(HSPF \text{ or } \eta) \cdot \text{area}} \tag{6}$$

Here, A_j is the area [sq.ft.] of the given envelope component (attic, wall, window, floor) and R_j is the corresponding R-value [°F-hr-sq.ft./Btu]. The number of air changes per hour is given by $\dot{A}$. The density and specific heat for air are given by ρ_{air} and c_p, respectively. The area and height of the rooms is also calculated and used as input. Finally, the SEER, HSPF and efficiency (η) are estimated as well. We will not consider upgrades to electric heating systems in what follows, due to their relative scarcity in the sample, and therefore the HSPF will not be used further. Since we do not have access to data on residence occupancy, we implicitly make the assumption that this does not change during the period over which data are gathered.

The constructed models for each residence rely upon estimation of the worst, typical, and best cooling and heating slopes for each residence. The worst and best values are obtained from Eqns.(5) and (6) with specification of the analogous worst and best energy performance parameters shown in Table 3 to yield a set of parameters (CS_{min}, CS_{max}, HS_{min}, HS_{max}).

Table 3. Minimum, maximum and typical values for house energy characteristics

Parameter	**Best case values**	**Typical case values**	**Worst case values**
R_{floor} (^{o}F-hr-sq.ft./BTU)	10	5	0
R_{wall} (^{o}F-hr-sq.ft./BTU)	18	12	3
R_{win} (^{o}F-hr-sq.ft./BTU)	3	1	1
R_{attic} (^{o}F-hr-sq.ft./BTU)	52	18	3
$\dot{A}$ (Air changes/hr)	0.3	0.67	2
SEER	13	10	6
Furnace/boiler[a] efficiency (η)	95%	80%	70%

[a] These values are certainly optimistic, since leaky ducts will often effectively reduce the furnace efficiency significantly

With these, worst and best normalized cooling and heating energy intensities can be calculated according to Eqn. (7).

$$\begin{aligned} NECI_{\min\, or\, max} &= CS_{\min\, or\, max} CDH_{typ} \\ NGHI_{\min\, or\, max} &= HS_{\min\, or\, max} HDH_{typ} \end{aligned} \tag{7}$$

The typical heating and cooling energy intensities are based upon the average values of homes in the area, which as observed in the presented energy intensity histograms is fairly close to the benchmarks quoted previously.

With worst, typical and best benchmarks for the cooling and heating slopes established, estimates for the residential energy performance characteristics can be made. The process for determining these estimates is shown in Fig. 4. The estimated or measured cooling energy intensity from the regression analysis, *NECI*, is compared to the maximum, typical, and minimum values estimated for the house. If the estimated normalized cooling energy intensity is high, the assumption here is that the SEER values and furnace/boiler efficiencies are likely low. Conversely, if the estimated normalized cooling energy intensity is low, then the SEER and furnace/boiler efficiencies are likely high. The same is true for all other energy performance characteristics.

Here we assume that if the measured cooling and heating energy intensities are high, all energy characteristics are poor --- and equally so. This assumption aligns fairly well with on-site assessments, where a low cooling/heating energy intensity house is generally seen to have a good building envelope and heating/cooling equipment, and a high cooling/heating energy intensity house is seen to have in general a poor building envelope and heating/cooling equipment.[1] Further, this analysis seeks only to provide gross estimates of the potential for energy savings for various improvements.

With this simplifying assumption of uniformity, a linear approximation for all energy characteristics, P_i (SEER, HSPF, η, $\dot{A}$, R_{attic}, R_{wall}, R_{window}), is made based upon a comparison of the estimated heating slope, HS_e, according to:

[1] Based on the experience of the authors' involvement with the Building Energy Center at the University of Dayton (http://www.udayton.edu/engineering/building_energy/index.php).

$$P_{i,est} = P_{i,min} + \left(P_{i,typ} - P_{i,min}\right) \cdot (HS_{max} - HS_e)/\left(HS_{max} - HS_{typ}\right) \quad HS_{min} \le HS_e \le HS_{typ}$$
$$P_{i,est} = P_{i,typ} + \left(P_{i,max} - P_{i,typ}\right) \cdot \left(HS_{typ} - CS_e\right)/\left(HS_{typ} - HS_{min}\right) \qquad HS_e > HS_{typ}$$

(8)

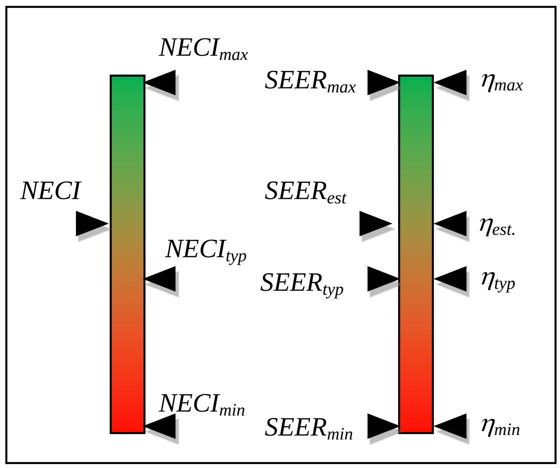


Figure 4 - Description of methodology for estimating SEER and heating system efficiency values.

Estimating Energy Savings from Adoption of Common Heating/Cooling Energy Reduction Measures

Given estimates of each of the energy performance parameters from Eqn. (8), a modeled annual energy use is predicted using Eqns. (5) and (6) and the estimated heating and cooling degree hours from the regression analysis (Eqns. (1) – (3)). The energy model developed yields a prediction for annual heating and cooling equal to that measured from the regression of actual data.

With the model calibrated against actual energy consumption, specific energy saving measures can be considered, either separately or synergistically. The savings measures considered here include ceiling, wall, and floor insulation, window replacement, infiltration reduction, and furnace replacement.

The energy savings realized from adoption of any of these measures can be calculated from Eqns. (9) and (10) below, respectively, for cooling and heating. In these equations, the improved cooling and heating slopes can be determined from Eqns. (5) and (6) with improved values of one or all energy parameters. Thus, savings from individual and synergistic measures are considered. In general, savings for each measure are based upon improvement of the relevant energy characteristic from the model value to the best value (shown in Table 2).

$$E_{saved,cooling} = \left[CS_e - CS_{improved}\right] \times CDH_e \tag{9}$$

$$E_{saved,heating} = \left[HS_{ng} - HS_{ng,improved}\right] \times HDH_{ng} \tag{10}$$

It is important to note that variations in measured heating and cooling energy intensities for each residence can be attributed to behavior influences and to errors resulting from the assumed geometrical parameters – particularly the assumed residence length to width aspect ratio of 1.4 and window area fraction (0.15). The latter error is quantifiable. A sensitivity analysis in predicting savings for the walls and windows, given estimated standard deviations for aspect ratio and window area fraction, is $\pm$15%. Uncertainty estimates for savings for the HVAC equipment is $\pm$12%. Behavior influences certainly contribute to low heating/cooling energy intensity buildings. However, the focus of this study is in showing the value of improving the worst residences first in achieving community wide energy reduction. Thus, savings from high energy intensity residences are most important. Residents who are cutting their thermostats well back in the winter and who are using their air conditioning sparingly in the summer will inevitably have low energy intensities. Clear from Figures 2 and 3 is that variation in heating and cooling energy intensity is much greater than the variation from uncertainty in the geometrical characteristics.

Methodology for implementing priority heating/cooling savings measures

To estimate the payback from individual measures, the costs to implement the measure must be estimated. Table 4 provides estimates of unit costs for implementation for each of the measures considered in this study (NREL 2010).

Table 4. Retrofit costs for heating/cooling energy reduction retrofits

Sealing home air leaks	Insulate attic	Upgrade heating equipment	Insulate walls	Upgrade windows
$0.25/sf	$1/sf	$1.76/sf	$3/sf	$21/sf

The cost savings from each measure is simply calculated by multiplying the energy savings realized by an assumed energy cost per unit energy - $0.12/kWh and $0.4/ccf for natural gas.

Results

Improvements made individually

Here we present the results of each of the savings measures in terms of the levelized cost of energy savings (Granade et al. 2009), constructing curves of cost-availability for different measures. These individual curves are essentially a version of the macro-level results presented in that report, referred specifically to a given housing stock in a particular region of the country.

Cost-availability curves for hierarchical implementation of residential energy efficiency measures

To estimate costs, a lifetime of 20 years was assumed for all weatherization improvements and 15 years for furnace replacement (Brown et al. 2010). Yearly energy savings were assumed constant over the lifetime of each measure.   The results to be presented are essentially supply-availability curves for energy efficiency measures.

Since the goal of this study is to show that the cost effectiveness of a measure depends upon the individual condition of a residence, and to show that if the most cost effective measure within an entire community is implemented first, cost effectiveness for the energy reduction is optimized. If a policy were in place to promote energy efficiency measures for a whole city, the strategy would be to first implement the savings measure having the lowest levelized cost among all potential savings measures for the entirety of residences in the community. Then, the measure with the next-best levelized cost would be implemented, and so on. Energy savings from implementation of the *i*th most effective measure can be calculated as a percentage of total energy use for that system; likewise, the collective levelized cost of energy savings for the top *i* measures can be determined, as shown in Eqn. (11) below.

$$\text{collective \% savings}_i = \sum_{n=1}^{i} \text{annual HVAC savings}_n / \text{Total HVAC energy} \times 100 \qquad (11)$$

Alternatively, one can interpret the results presented below as a description of inhomogeneity in housing stock, and as a technique for quickly identifying those residences for which upgrades can make the largest potential impact.

In each of the figures to be presented below we show levelized costs of implementation for different energy-efficiency measures. As a reference point, in each figure the estimated *average* cost of that measure as determined from (Granade et al 2009) is shown as a horizontal dashed line. The relevant point for a household to make a decision about undertaking the given upgrade is whether, for their particular home, the upgrade can be made at a levelized cost that is less than the price of energy. As we expect energy prices to increase in the future, and the lifetimes of the energy-efficiency upgrades is twenty years, we would also need in principle an estimate of future energy costs; we have chosen not to make that part of our analysis.

Fig. 5 shows results for infiltration reduction for the houses in the study benefiting from this measure. Fig. 5a presents the levelized cost for the infiltration reduction measure ($/mmBTU) for each house in ascending order. Fig. 5b shows the collective levelized cost for implementation of the infiltration measure for houses $1 \rightarrow i$. Fig. 5 clearly shows that deeper collective savings for the community come with greater cost; however, because the energy savings for the most cost effective implementations of infiltration reduction (e.g., for the poorest sealed houses) are greatest and achieved with the least cost, their effect on both the collective percentage savings of the energy used for energy and the collective levelized cost is dominant. Thus, Fig. 5b illustrates a much lower collective levelized cost than for a vast majority of houses as an increasing number of houses take advantage of the infiltration reduction measure. Of course, this curve presumes that infiltration is reduced first in the worst houses, e.g., those with the lowest levelized cost.

Fig. 5b also shows that the community could realize nearly a 10% savings in HVAC energy were all houses to adopt the infiltration measure, and with a collective levelized cost of less than $2.00/mmBTU; as a comparison, heating fuel costs are expected to be in the range of $12-$14/mmBtu by 2020 (Granade et al. 2009; EIA 2013). This implementation cost is comparatively low, driven primarily by the large savings at low costs for the worst houses. Thus, implementation of this measure for every house in the community – would have collective economic value to the community as a whole.

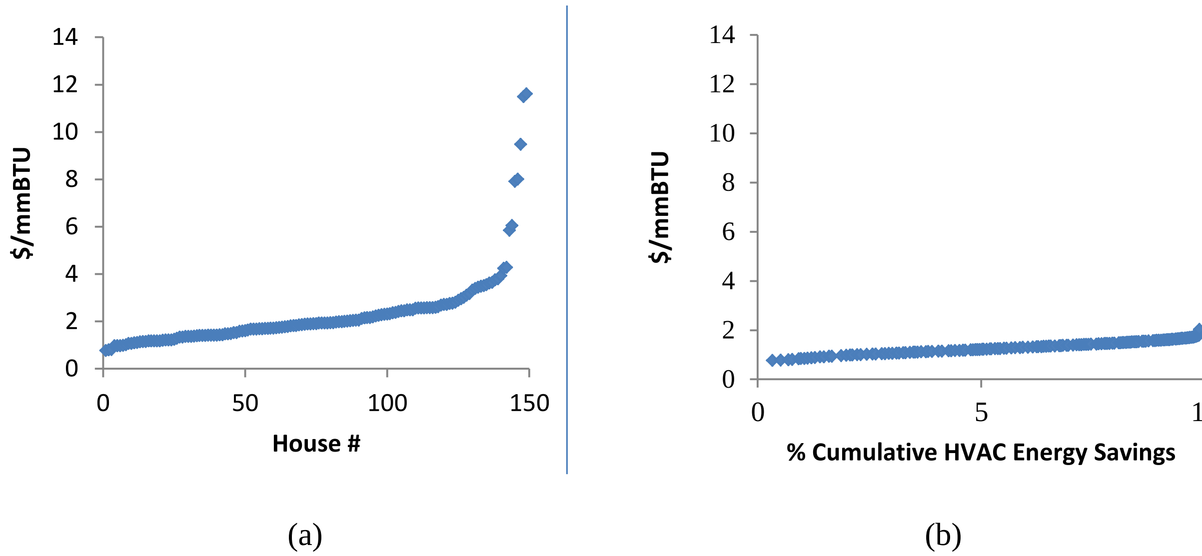
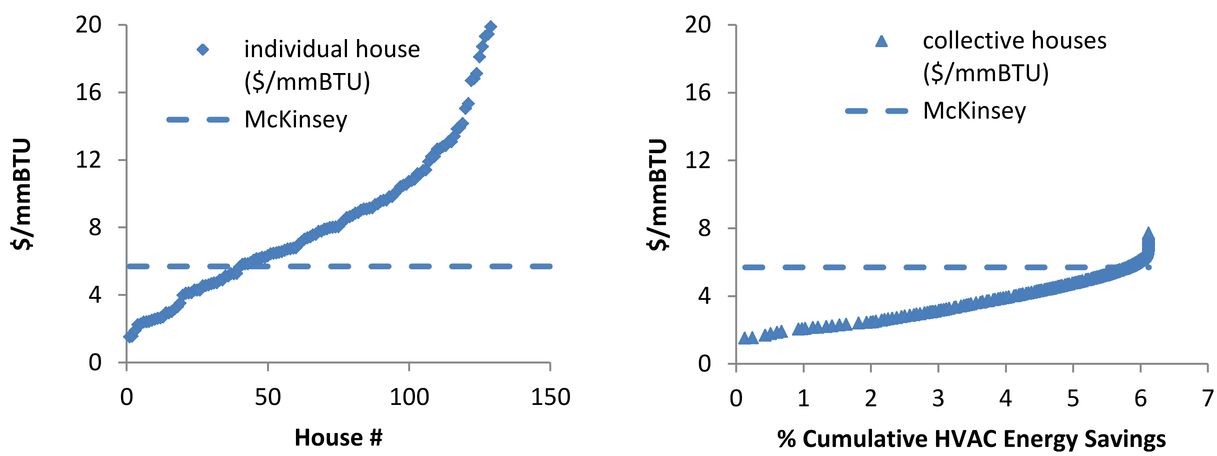


Figure 5. Levelized cost for infiltration reduction for: (a) individual houses presented in ascending order of cost effectiveness and (b) for the collective grouping of houses presuming that houses are improved in order of levelized cost as a function of percentage cumulative HVAC energy savings.

Figs. 6 – 9 present similar results for attic insulation addition, furnace replacement, wall insulation addition, and window replacement. The only difference is that a comparison is drawn to predictions of levelized cost included in McKinsey's 2009 study (Granade et al. 2009) for the attic insulation addition measure (Fig. 6), for a furnace upgrade (Fig. 7), for wall insulation addition (Fig. 8) and for window replacement (Fig. 9). As is apparent in all cases, the collective levelized cost per mmBTU for each measure is 'biased' by the lowest individual house levelized cost per mmBTU. In all of these figures the relevant decision variable for whether a given measure is financially viable is the comparison to the cost of energy (either natural gas or electricity). We have not indicated an energy cost in the figures since these will change over time.

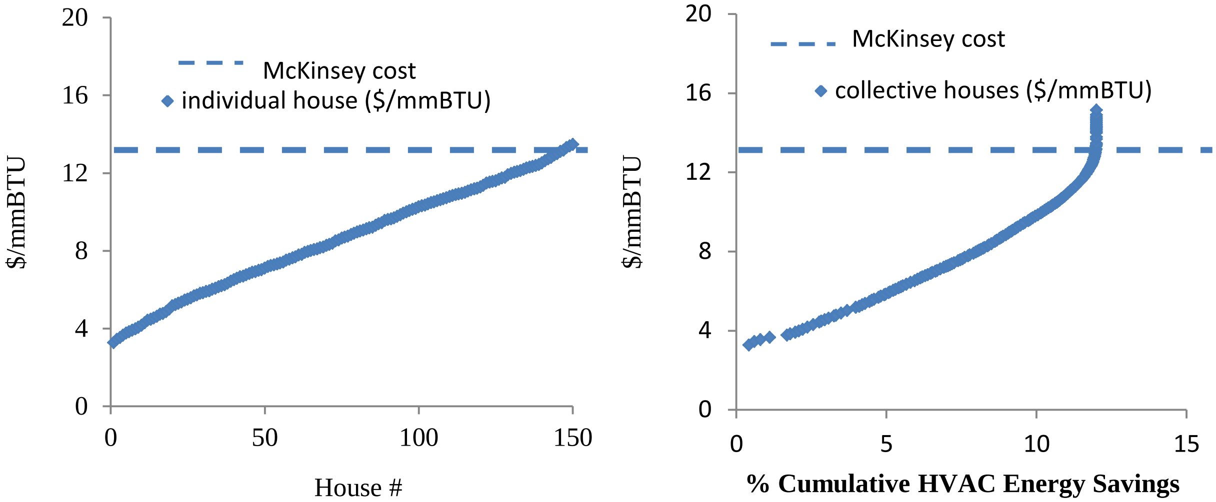
Figs. 6 and 7 illustrate the primary significance of this study. The McKinsey estimate for levelized cost for attic insulation addition and furnace upgrades are respectively \$5.7 and \$12.6/mmBtu. As apparent from Fig. 6, a majority of the homes have individual levelized costs for these measures above the McKinsey value. However, the collective levelized cost for the community of houses in the study is well below the McKinsey estimate except as the least cost effective measures begin to be adopted for houses where this is higher individual levelized cost. This result speaks to the importance of targeting energy reduction programs hierarchically; improving the "worst" houses first will achieve the highest initial savings and shortest payback times.

Fig. 8 shows analogous results for wall insulation. Fig. 8b shows that if all houses were to have upgrades to the maximum current wall insulation practices for the area, 3-4% collective HVAC savings would be realized. Thus, wall insulation impacts are clearly less than air-sealing and ceiling insulation owing to higher implementation costs. Fig. 9 shows results for window upgrades. It is clear that the levelized cost for window upgrades calculated here are well above that included in the McKinsey study. However, the NREL cost source for window upgrades (NREL 2010) seems to match up with expected window replacement costs.



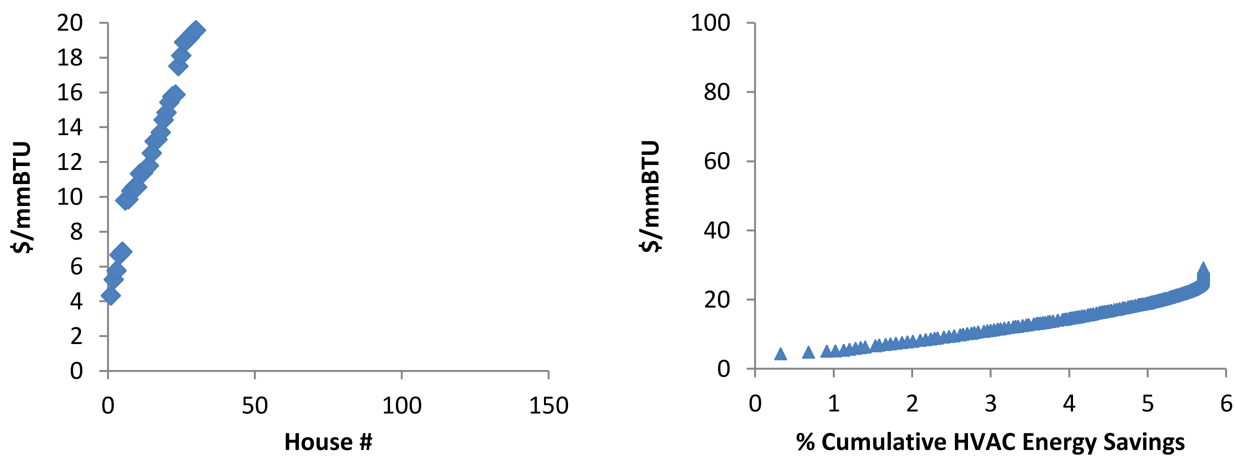
(a) (b)

Figure 6. Levelized cost for attic insulation addition for: (a) individual houses presented in ascending order of cost effectiveness and (b) for the collective grouping of houses presuming that houses are improved in order of levelized cost as a function of cumulative HVAC energy savings. A comparison to the Granade, et al. estimate is included.



(a) (b)

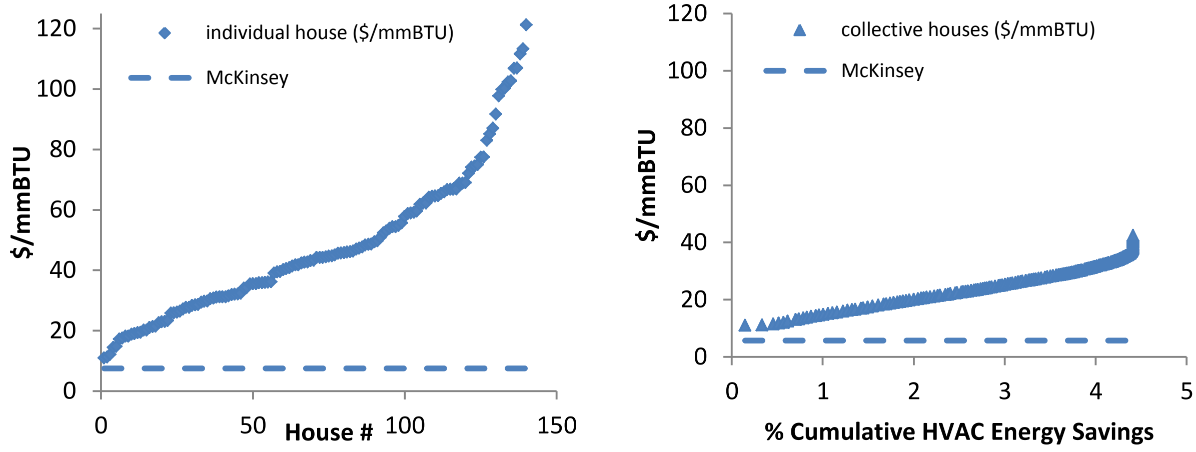
Figure 7. Levelized cost for furnace upgrades for: (a) individual houses presented in ascending order of cost effectiveness and (b) for the collective grouping of houses presuming that houses are improved in order of levelized cost as a function of cumulative HVAC energy savings.



(a) (b)

Figure 8. Levelized cost for wall insulation addition for: (a) individual houses presented in ascending order of cost effectiveness and (b) for the collective grouping of houses presuming that houses are improved in order of levelized cost as a function of cumulative HVAC energy savings.

Cost-availability curves for hierarchical implementation of residential energy efficiency measures



(a) (b)

Figure 9. Levelized cost for whole house window replacement for: (a) individual houses presented in ascending order of cost effectiveness and (b) for the collective grouping of houses presuming that houses are improved in order of levelized cost as a function of percentage cumulative HVAC energy savings.

Synergistic improvements

The most cost effective community energy savings would be derived if the measures having the lowest levelized cost from among all possible measures within the whole community were implemented first; the next best second; and so on. Thus, for example, multiple measures might be adopted in the worst house in the community before advancing to the second worst house.

Figure 10 shows the collective levelized cost for the community versus collective percentage energy savings for the entire community. It is clear from this figure that relatively low collective levelized cost for energy savings can be realized quite easily to yield relatively deep cumulative HVAC energy savings. For example, for a levelized cost of $2/mmBTU, a 12% HVAC energy reduction can be realized for the entire community. Deeper savings come with increased cost to the community. A 35% reduction in HVAC energy use can be realized with levelized costs of $10/mmBTU. This cost is still lower than projected 2020 energy costs (Granade et al. 2009; EIA 2013).

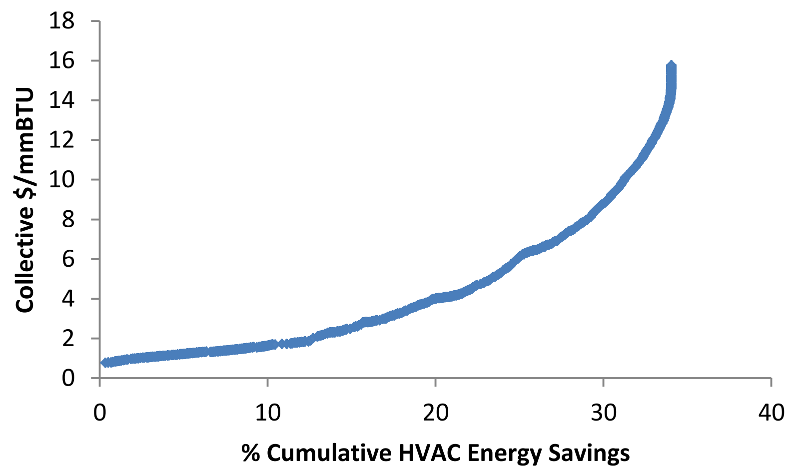


Figure 10. Collective cost as a function of percentage energy reduction for improvements for all measures considered.

Moving higher up the savings curve, at each step the marginal savings will be somewhat less; decisions on how far to ultimately progress up the curve will depend on the cost of energy compared to the levelized costs of the efficiency measures. Ideally, a homeowner would also have extreme foresight and a complete knowledge of both future energy costs and of the external social costs of energy systems to make a complete judgment of benefits to specific upgrades, but these requirements would only further complicate decision-making. In reality, however, each of these complicating factors are likely to work in such a direction as to enhance the decision to take action now.

Discussion

There is one primary observation that can be drawn from this study: a data-driven approach to increasing the energy efficiency of buildings will be a necessary part of an economically efficient program to reduce household energy costs and mitigate climate change. Aggregate data for housing stock, and thus for energy efficiency improvements is not sufficient; if the worst-performing buildings are targeted first for energy-use reduction, the affordability of energy reduction can be enhanced substantially. The techniques used in this study are general and may be extended to any group of residences where both utility and building characteristic data are available. Furthermore, having access to greater amounts of data (mainly on the physical properties of the homes) will allow refinements to the procedures presented in this work, eliminating the need for estimations to parameters for the building model.

Given that there are strong differences regionally between energy sources used for heating and electricity, and that weather-dependent utility needs vary widely across the country, an extension of this work to a national level will require a careful enumeration of the exact goals to be pursued within energy policy. Reductions in greenhouse gas emissions for climate change mitigation may not lead to the same policies as a desire to reduce oil imports or costs of energy for families. It will be necessary to determine key long-term goals for energy policy on a local or regional level, and then investigate the most economical means of reaching those goals. To the extent that energy savings can be obtained easily and inexpensively through changes that are mainly behavioral, there is little downside in pursuing policies that encourage such changes, independent of the longer-term goals. In the analysis presented here, as well as that of Ref. (Granade et al. 2009), a key point is that the measures adopted are economically sound in that they represent costs of energy savings that are for (the most part) lower than the projected or current cost of energy consumption.

A key challenge to achieving energy reduction targets is that of the implicit discount rate shown by consumer behavior. In the McKinsey analysis cited throughout this paper, a baseline discount rate of 7% was assumed in calculating the 22% potential for positive net-present-value (NPV) energy costs (with respect to 2008). In a sensitivity analysis, discount rates of 20% and 40% were also used, with the latter leading to a nearly a 50% decrease in estimated positive-NPV potential. On the other hand, other authors find that a suite of efforts that have proven successful in motivating change can be used to achieve carbon emissions reductions (their focus) of 20% in the residential sector (Dietz et al. 2009). Effectively, these efforts at changing consumer behavior are an attempt to bring implicit discount rates more in line with actual, although not "rational," discount rates chosen by consumers in other parts of their lives. While some of the measures identified in (Dietz et al. 2009) involve mechanical systems as described in our work, others are better characterized as changes in personal habits. Brecha et al. compare some of these differences within a framework similar to that of the present paper (Brecha et al. 2011). To the extent that up-front investments are needed to make energy-efficiency upgrades, it is likely that innovative financing programs will be necessary to help overcome high implicit discount rates; such programs, such as on-bill financing are becoming increasingly common (DoE - EERE 2013). The main point is that, whether one is interested in mechanical or personal behavior changes, it will be of great relevance to be able to target those homes that will benefit most from energy-efficiency upgrades.

Decarbonization of the energy system over the next several decades will remain a significant challenge, but the extent to which energy demand can be reduced will help determine the magnitude of that challenge. Lower demand and making buildings more energy-efficient can also help make the use of renewable energy more attractive in the sense that homeowners can potentially generate more of their own energy on-site. However, the challenge we face is dynamic; the cost of renewable energy is decreasing over time, while fossil-fuel costs have been rising, with the recent exception of natural gas (which has more recently begun to increase in price again). Decisions about energy efficiency measures, as well as those focusing on renewable energy, must remain flexible over time, in what might be termed an adaptive management framework. Crucial to this process is the availability of data, such as the utility data used in this study, which can be continuously updated and analyzed

Conclusions

In this paper we demonstrate a technique cost-effectively prioritizing residential building efficiency improvements based on historical billing data for individual dwellings. The benefits arise through targeting the least-efficient residences first, as determined by projections for savings estimated through an inverse-modeling of building characteristics. A 32% reduction in HVAC energy at a community-wide cost of $0.1/MMBTU is predicted. This research above all supports development of public building databases that might include envelope and heating and cooling characteristics, as well as availability of more complete energy consumption data.

Providing a methodology for determining cost-effective energy-efficiency improvements is only a first step toward actually reducing energy consumption in residences. Whereas our work expands upon that of the 2009 McKinsey report (Granade et al. 2009) in providing a more microscopic view of energy savings for a particular region and differentiating between costs for different buildings, that report provided significant detail as to potential programmatic possibilities for actually achieving results. Their recommendations apply equally well to the conclusions we draw – in fact, the goal of that report was to investigate how to unlock the known potential for energy efficiency. One point that we wish to emphasize through our work is that the data exist at the level of individual households and for a town or city to act on increasing energy efficiency in a structured and economically prudent manner.

Of course, the type of bottom-up engineering approach taken here is in many ways an idealized view of a complex socio-economic challenge that requires input from behavioral scientists, educators and policy-makers if the end goal of a double-win for economic and environmental well-being is to be achieved.

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Figure 1
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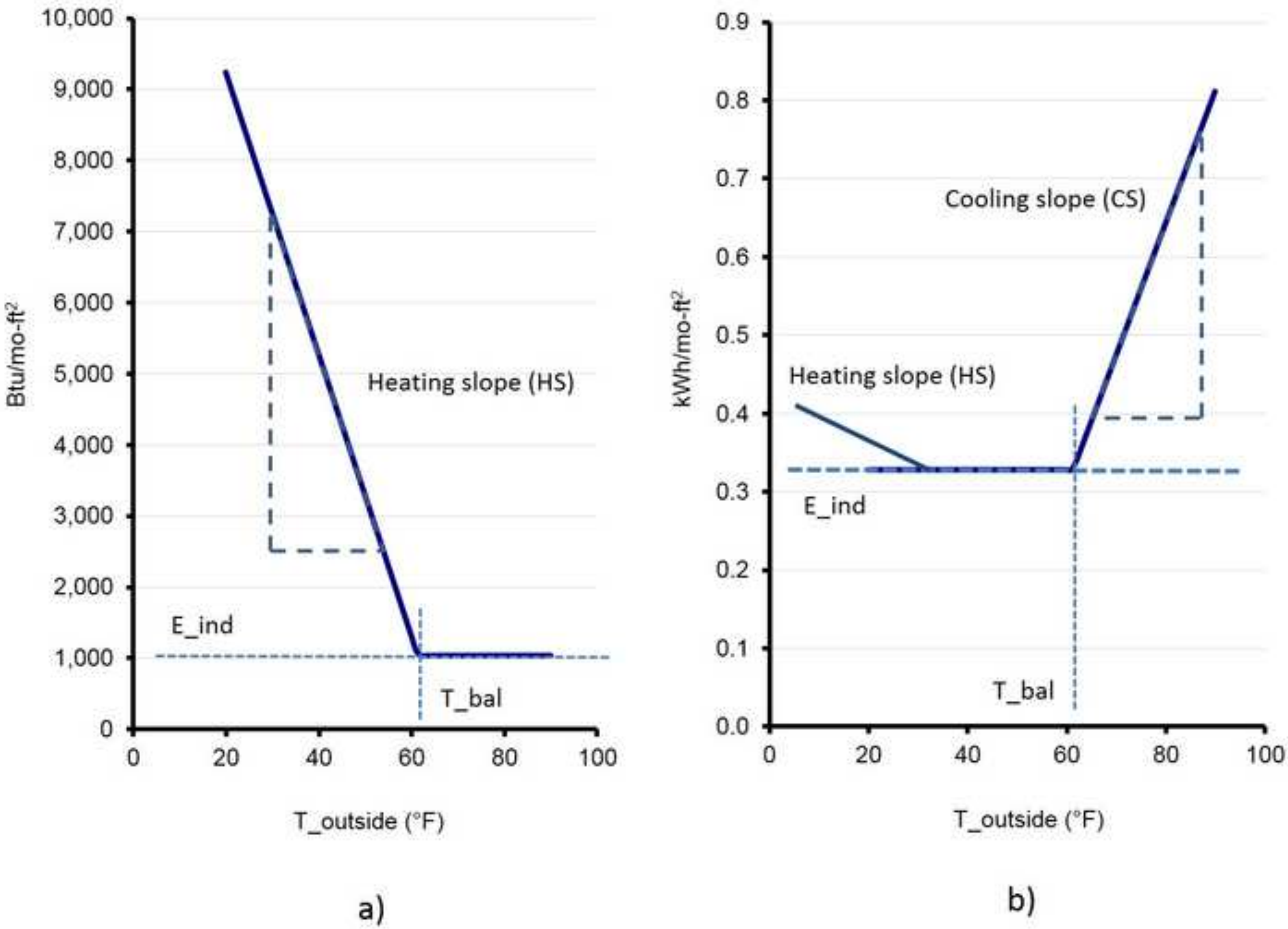

Figure 2

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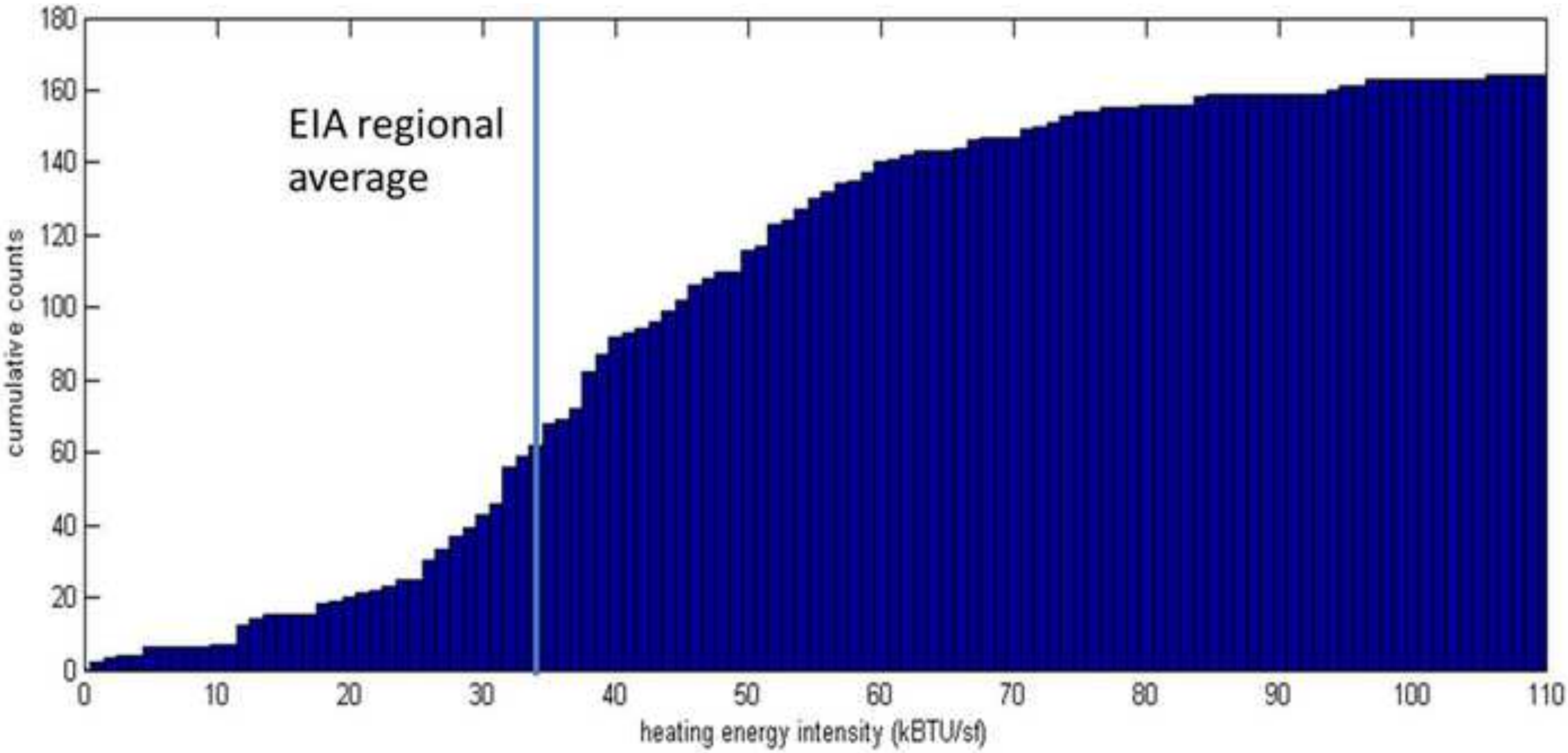

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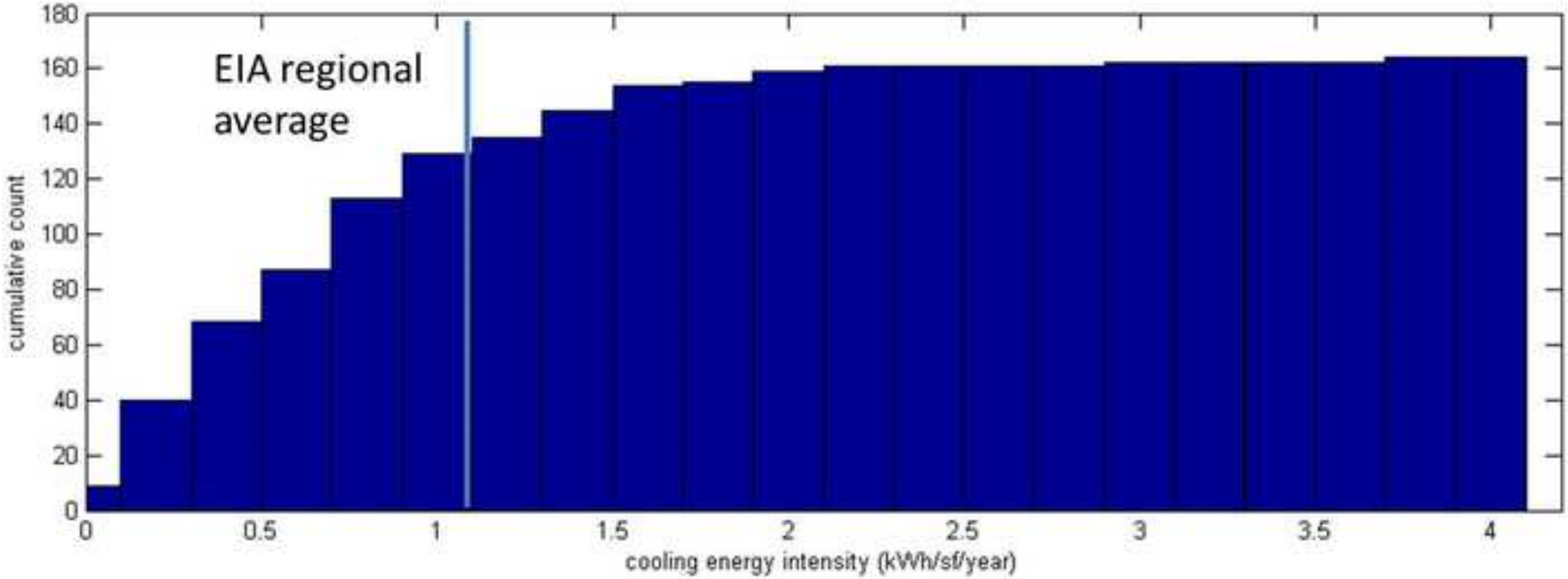

Figure 4

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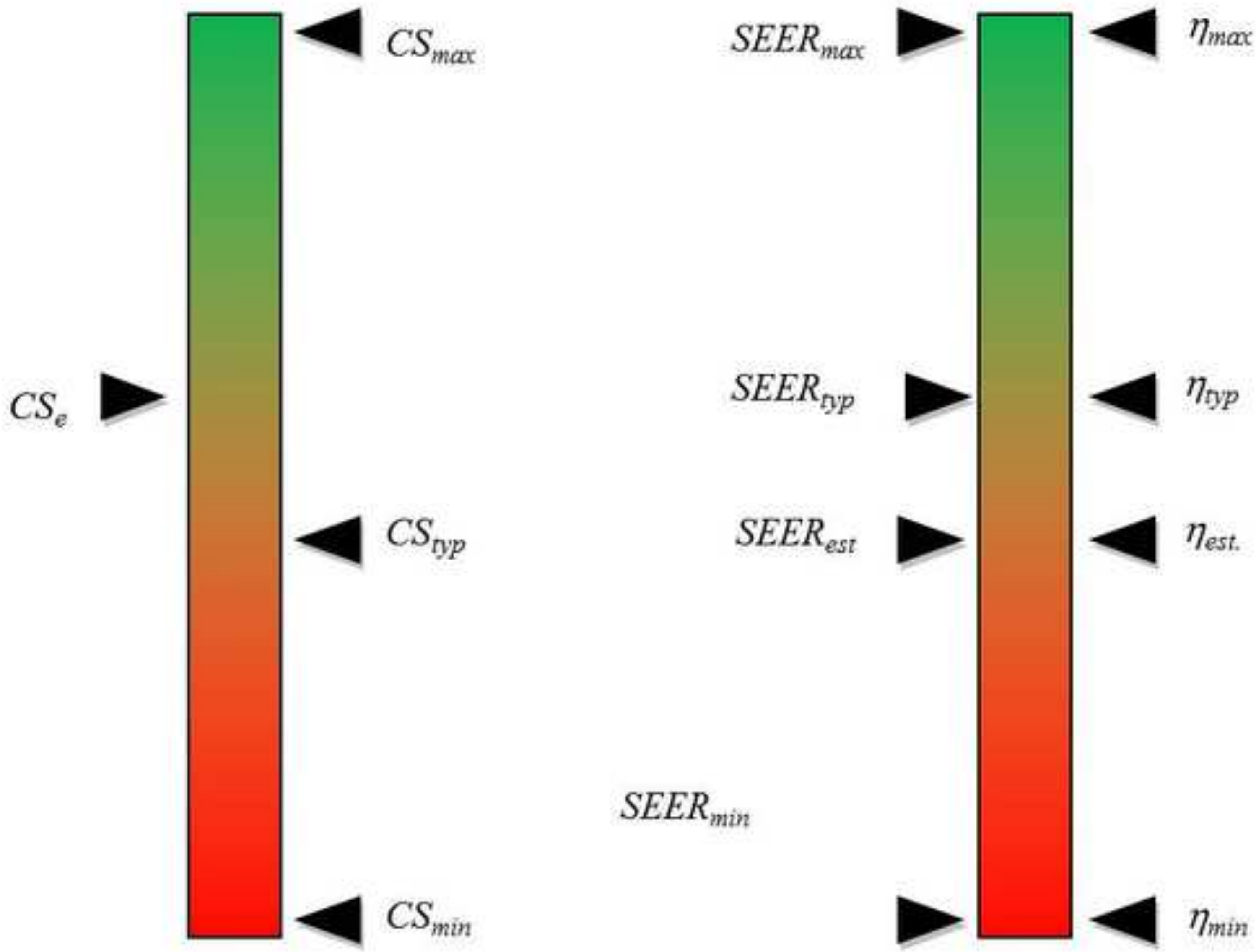

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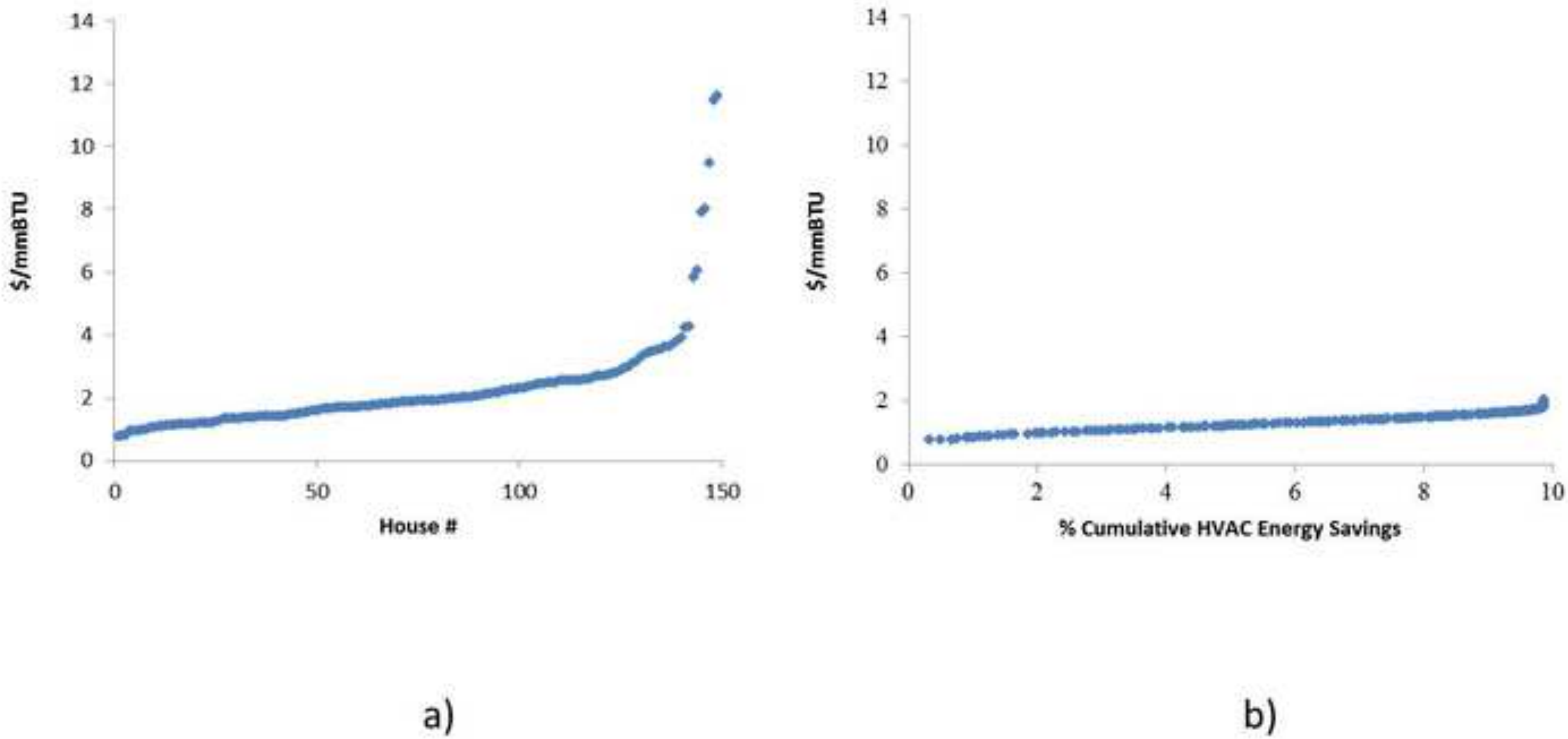

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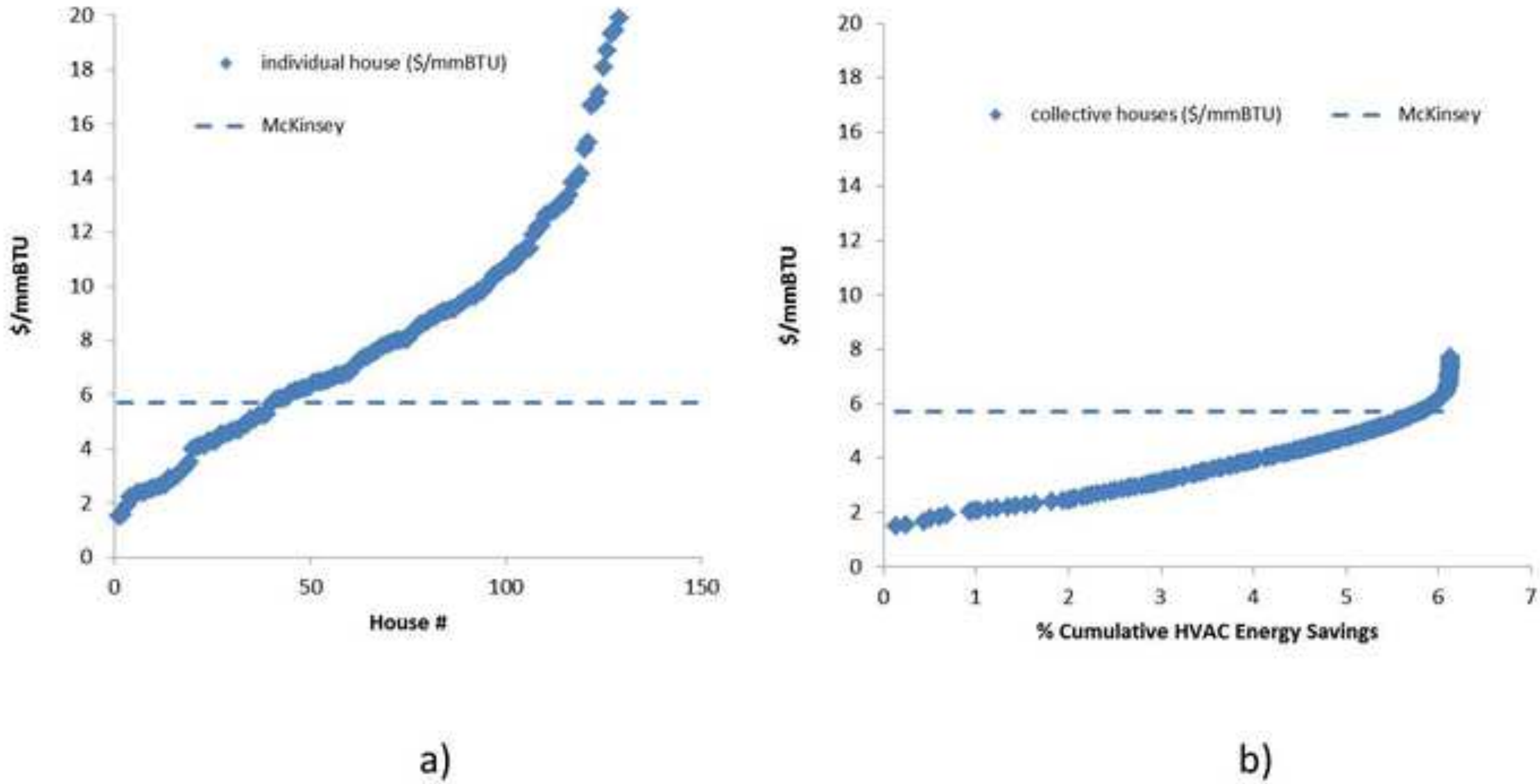

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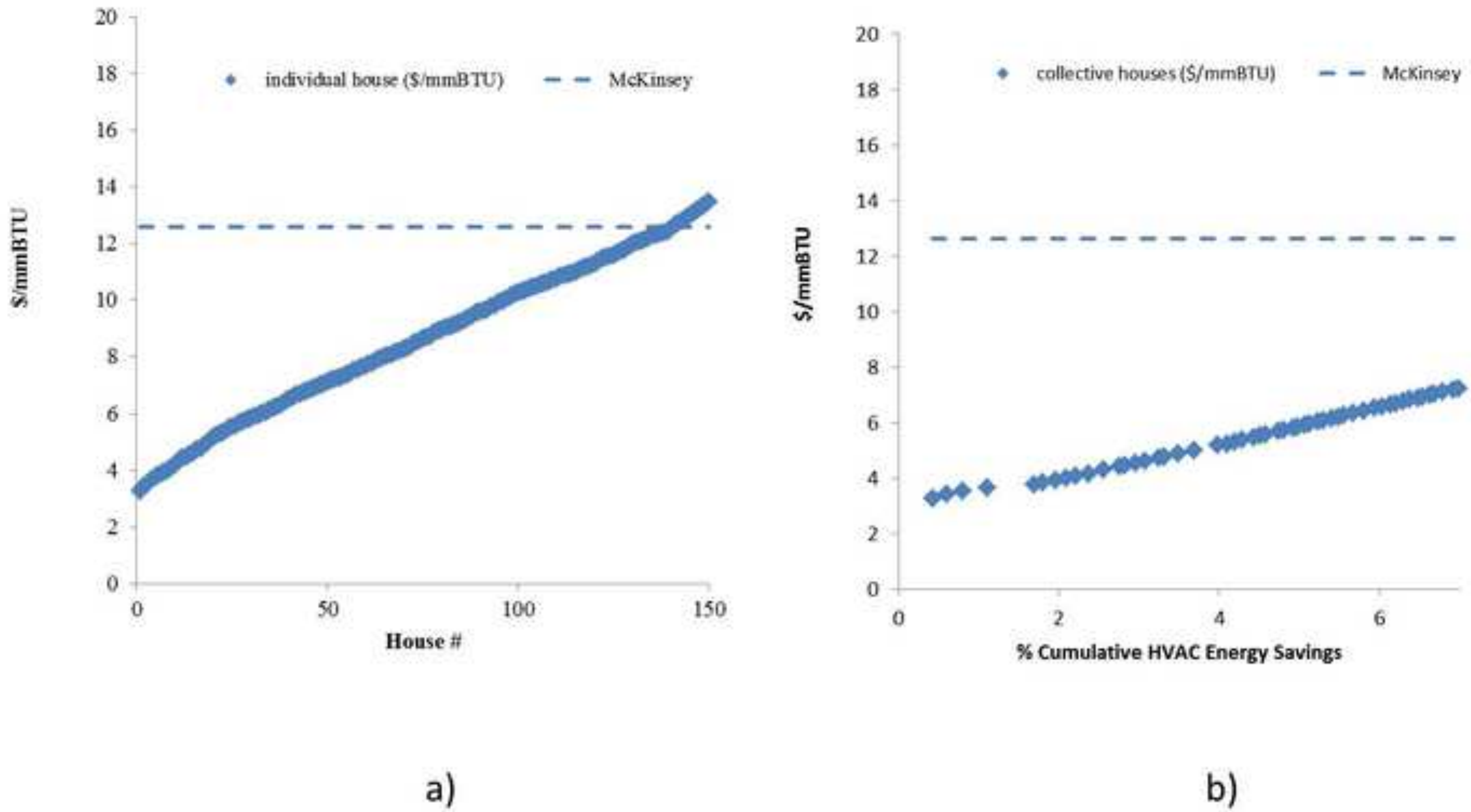

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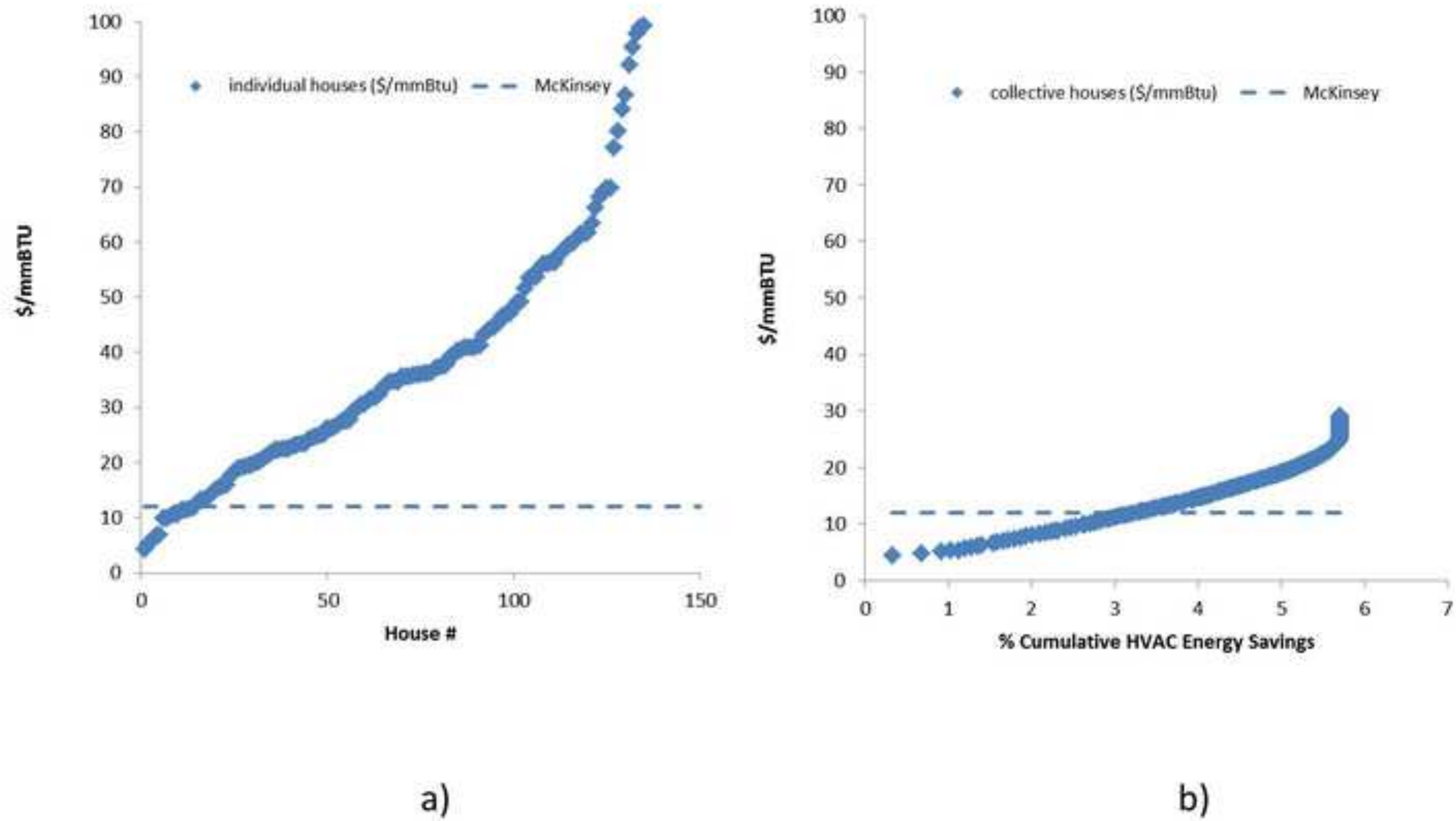

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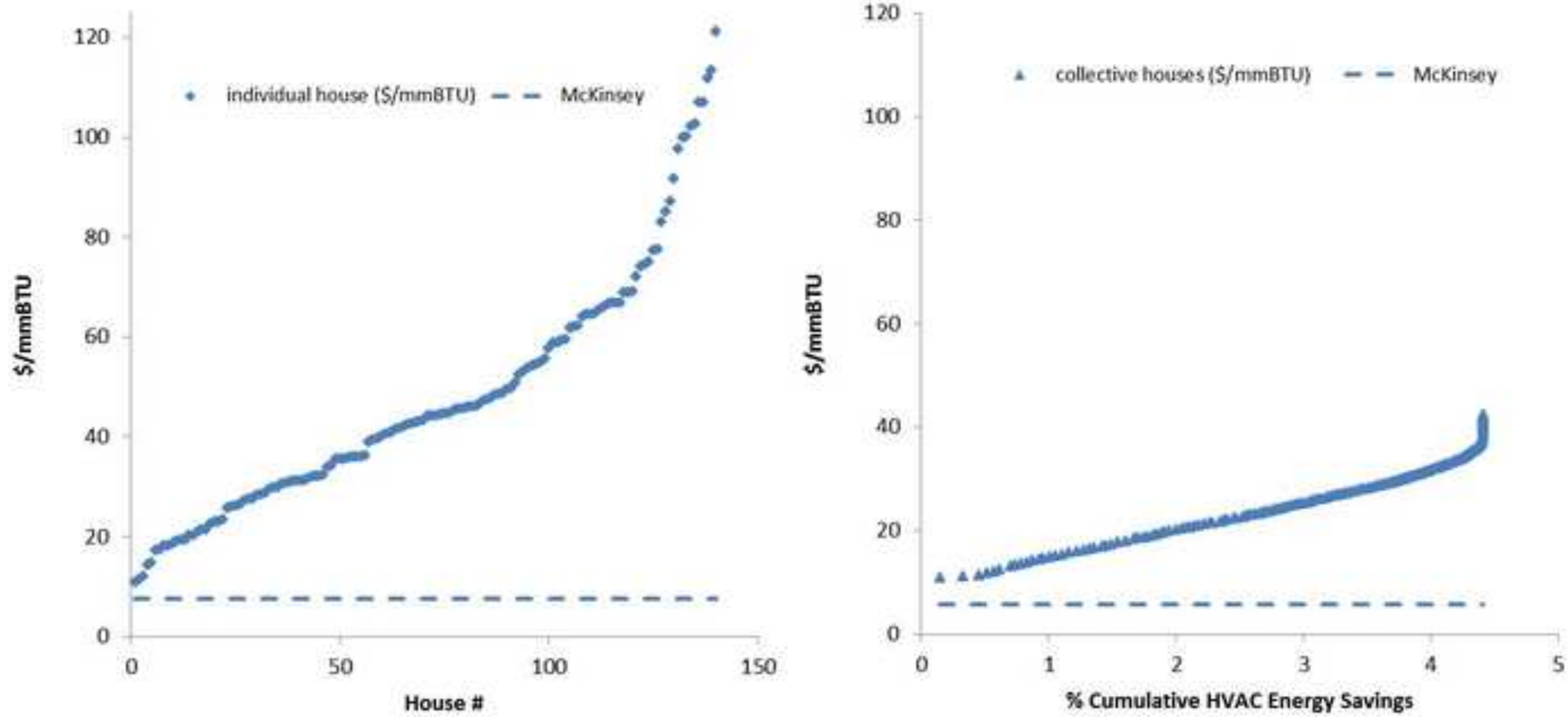

a) b)

Figure 10
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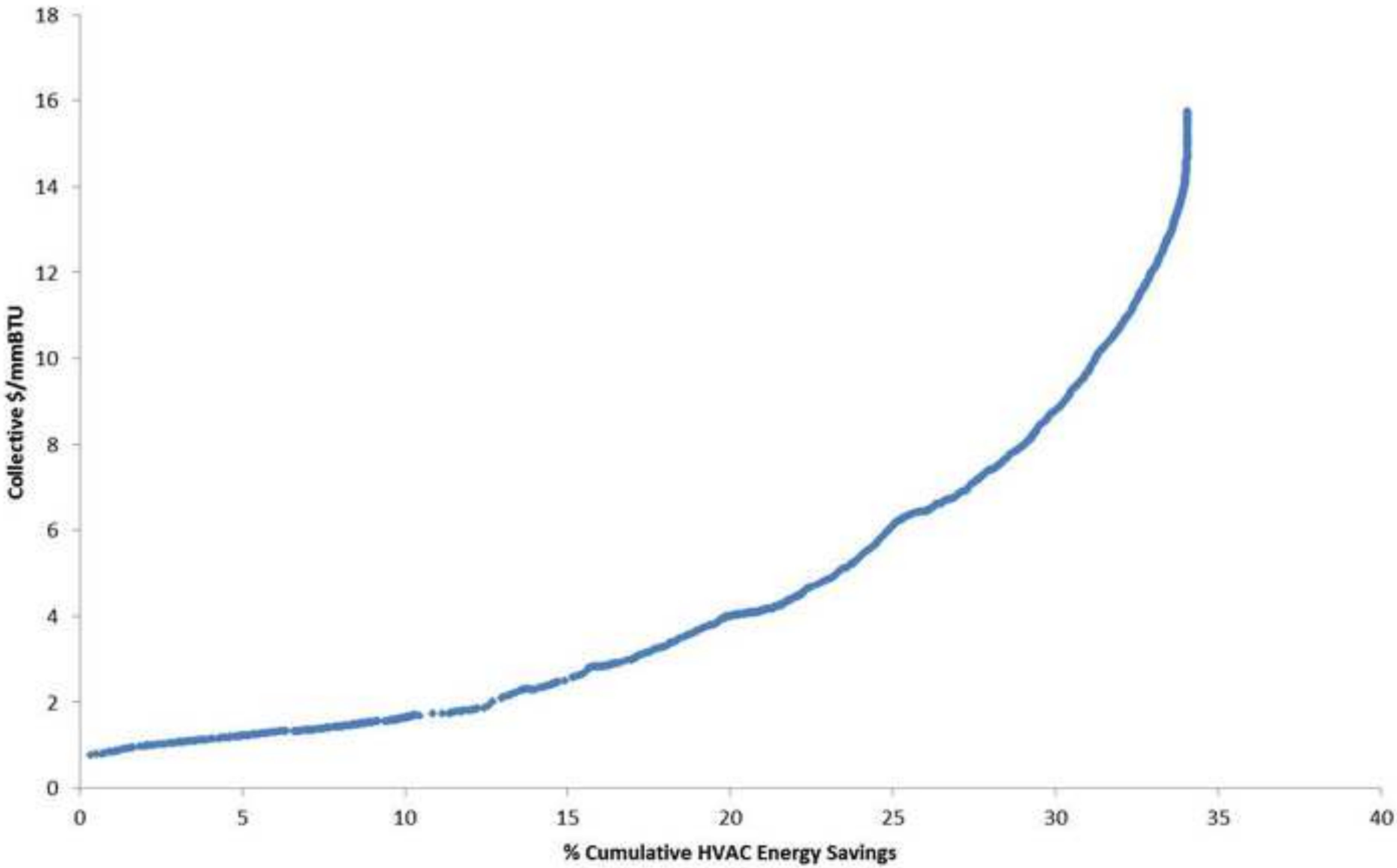

Supplementary online material

I. Fits to monthly natural gas and electric data

Given the monthly natural gas and electric data, normalized to the area of the residence, a regression fit can be performed to find the characteristics of the building. The equation describing electricity consumption as a function of temperature, T, is given by

$$\text{Monthly avg. electric power intensity [kW/sf]} = Baseline_e + CS_e \times \text{Heaviside}\left(T - T_{balc,e}\right)$$

$$+HS_e \times \text{Heaviside}\left(T_{balh,e} - T\right) \times \left(T_{balh,e} - T\right) \tag{S1}$$

This five-parameter fit describes an increase in electricity consumption with both decreasing and increasing temperatures, representing heating and cooling seasons, respectively. In addition, there is a baseline, temperature-independent consumption of electricity ($Baseline_e$). The increase in consumption for cooling starts at a balance temperature, $T_{balc,\,e}$ and with a cooling slope given by CS_e. Similarly, the increasing electricity consumption for heating starts at a balance temperature $T_{balh,e}$ and is parameterized by a heating slope HS_e. The Heaviside function is given by

$$Heaviside(x) = \begin{cases} 0 & for \;\; x < 0 \\ 0.5 & for \;\; x = 0 \\ 1 & for \;\; x > 0 \end{cases} \tag{S2}$$

For natural gas consumption a three-parameter fit suffices to describe the baseline (temperature-independent) consumption as well as the increase in consumption for heating as a function of decreasing temperature:

$$\text{Monthly avg. natural gas power intensity[BTU/hr-sf]} = Baseline_{ng} + HS_{ng} \times$$

$$\text{Heaviside}\left(T_{balh,ng} - T\right) \times \left(T_{balh,ng} - T\right) \tag{S3}$$

Baseline consumption is given by $Baseline_{ng}$ and the temperature-dependence of natural gas consumption is characterized by the heating slope, HS_{ng} and the balance temperature for heating, $T_{balh,ng}$.

In Fig. S1 we show schematically the various parameters described by equations S1-S3.

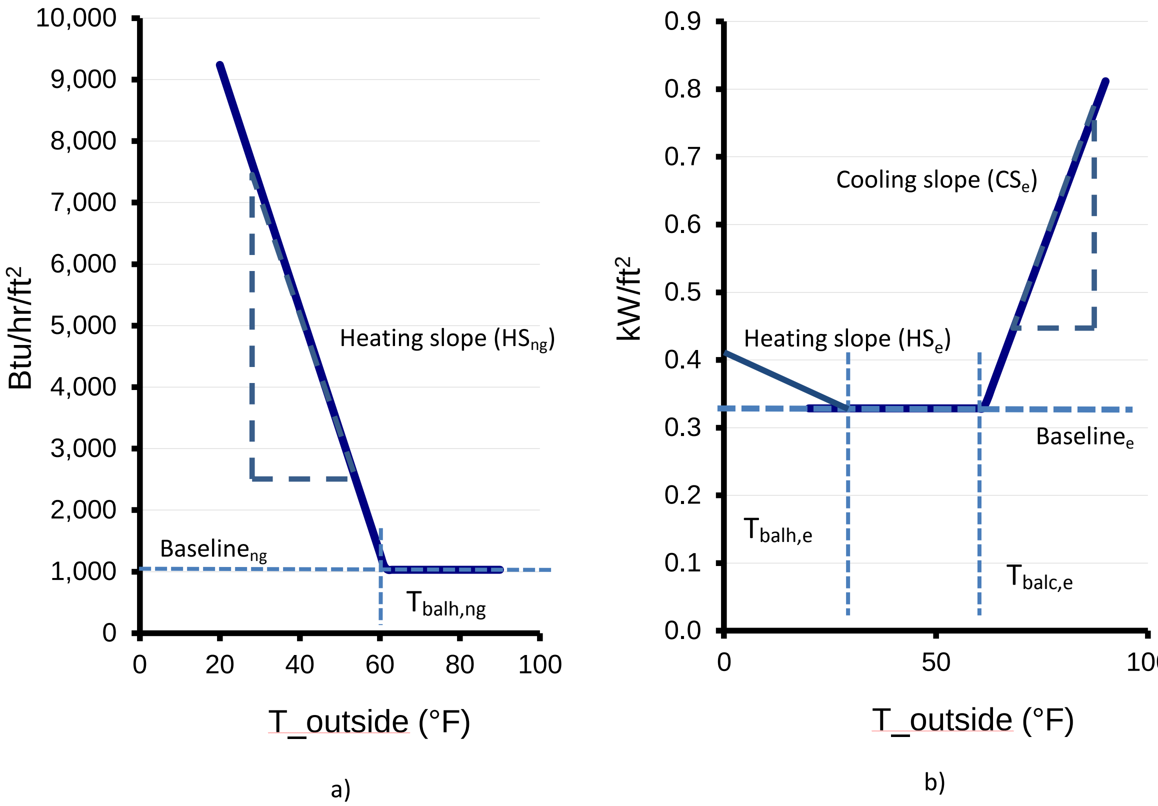

Fig. S1 – Natural gas (a) and electricity (b) characteristics for a building. For both natural gas and electricity there is weather-independent (Baseline) consumption and weather-dependent consumption for heating (HS) and for cooling (CS).

II. Geometrical calculations

The database of housing information available from the county contains only the area of the house and the number of floors. Using this information, and making some assumptions about typical building stock in the area, we derive expressions for relative attic, window, and wall areas, as well as total building volume. These parameters are then used as inputs that allow construction of the building model.

Given the total square footage of the house and the number of floors, the area of the attic is:

$$A_{attic} = \text{Square footage/number of floors} \tag{S4}$$

The area of the ground floor is assumed equal to the area of the attic. The length to width ratio of the house is assumed 1.4 (typical for all houses in the region). Finally, the width is set equal to the following.

$$\text{width=} \sqrt{\frac{\text{Square Footage/number of floors}}{\text{length-to-width-ratio}}} \tag{S5}$$

Thus, the length of the residence is determined according to:

$$\text{length} = \text{width} * 1.4 \tag{S6}$$

With these assumptions, the total wall area is estimated as:

$$A_{wall\ total} = (2 * \text{length} + 2 * \text{width}) * \text{number of floors} * \text{height of walls} \tag{S7}$$

Above, consistent with the architecture of housing in the community, the height of each floor is assumed to be 8 ft.

Lastly, the window-to-wall-area-percentage is assumed 14%, typical of residential buildings in the area, so the area of the windows is:

$$A_{windows} = A_{wall\ total} * \frac{\text{window area}}{\text{wall area}} \tag{S8}$$

With this assumption, the effective area of the wall used for heat transfer calculations is:

$$A_{wall} = A_{wall\ total} - A_{window} \quad \text{(S9)}$$

The volume of the house is then calculated as:

$$\text{volume} = \text{square footage} * \text{height of walls} \quad \text{(S10)}$$