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Simulating a Nationally Representative Housing Sample Using EnergyPlus

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DISCLAIMER

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1. Executive Summary

This report presents a new simulation tool under development at Lawrence Berkeley National Laboratory (LBNL). This tool uses EnergyPlus to simulate each single-family home in the Residential Energy Consumption Survey (RECS), and generates a calibrated, nationally representative set of simulated homes whose energy use is statistically indistinguishable from the energy use of the single-family homes in the RECS sample. This research builds upon earlier work by Ritchard et al. for the Gas Research Institute and Huang et al. for LBNL. A representative national sample allows us to evaluate the variance in energy use between individual homes, regions, or other subsamples; using this tool, we can also evaluate how that variance affects the impacts of potential policies.

The RECS contains information regarding the construction and location of each sampled home, as well as its appliances and other energy-using equipment. We combined this data with the home simulation prototypes developed by Huang et al. to simulate homes that match the RECS sample wherever possible. Where data was not available, we used distributions, calibrated using the RECS energy use data. Each home was assigned a best-fit location for the purposes of weather and some construction characteristics.

RECS provides some detail on the type and age of heating, ventilation, and air-conditioning (HVAC) equipment in each home; we developed EnergyPlus models capable of reproducing the variety of technologies and efficiencies represented in the national sample. This includes electric, gas, and oil furnaces, central and window air conditioners, central heat pumps, and baseboard heaters. We also developed a model of duct system performance, based on in-home measurements, and integrated this with fan performance to capture the energy use of single- and variable-speed furnace fans, as well as the interaction of duct and fan performance with the efficiency of heating and cooling equipment. Comparison with RECS revealed that EnergyPlus did not capture the heating-side behavior of heat pumps particularly accurately, and that our simple oil furnace and boiler models needed significant recalibration to fit with RECS.

Simulating the full RECS sample on a single computer would take many hours, so we used the “cloud computing” services provided by Amazon.com to simulate dozens of homes at once. This enabled us to simulate the full RECS sample, including multiple versions of each home to evaluate the impact of marginal changes, in less than 3 hours.

Once the tool was calibrated, we were able to address several policy questions. We made a simple measurement of the heat replacement effect and showed that the net effect of heat replacement on primary energy use is likely to be less than 5%, relative to appliance-only measures of energy savings. Fuel switching could be significant, however. We also evaluated the national and regional impacts of a variety of “overnight” changes in building characteristics or occupant behavior, including lighting, home insulation and sealing, HVAC system efficiency, and thermostat settings. For example, our model shows that the combination of increased home insulation and better sealed building shells could reduce residential natural gas use by 34.5% and electricity use by 6.5%, and a 1 degree rise in summer thermostat settings could save 2.1% of home electricity use. These results vary by region, and we present results for each U.S. Census division.

We conclude by offering proposals for future work to improve the tool. Some proposed future work includes: comparing the simulated energy use data with the monthly RECS bill data; better capturing the variation in behavior between households, especially as it relates to occupancy and schedules; improving the characterization of recent construction and its regional variation; and extending the general framework of this simulation tool to capture multifamily housing units, such as apartment buildings.

2. Introduction

American homes were responsible for using 21.5 quadrillion British thermal units (Btus) of primary energy in 2008[1]. This energy was primarily used for home heating and cooling, but water heating, lighting, appliances, and home electronics also create significant energy demand. Home energy efficiency projects, including such structural changes as increased insulation or a tighter building envelope, and improvements in appliance efficiency, such as more efficient heating, ventilation, and air conditioning (HVAC) systems or refrigerators, can save households significant amounts of energy and commonly have reasonable payback periods.

Individual homeowners can evaluate the efficiency of their homes through energy audits and direct their resources toward the most effective changes for their homes. On a national level, however, there is a need for tools that policymakers can use to evaluate the impacts of different efficiency measures on national energy consumption that take regional weather and housing stock variation into account. For example, it would be difficult to evaluate the energy savings from increased attic insulation, more efficient windows, or improved air conditioner efficiency on both a national and regional level using only aggregate inputs.

This report describes the development of a building energy simulation tool that constructs a nationally representative sample of single-family home prototypes, while capturing the variability of American housing stock, weather, and behavior. Properly calibrated, such a tool allows direct analysis of policy options, such as appliance standards (especially standards for HVAC equipment) and home retrofit programs that focus on the building envelope, and allows comparison of national and regional impacts. In addition, the tool could be used to assess the impact of the "heat replacement effect," in which the heat from lighting and appliances helps to heat the home in the winter and increases the load on air conditioning in the summer.

The simulation tool described here traces its origins to work conducted by researchers at Lawrence Berkeley National Laboratory (LBNL) during the 1980s and 1990s, partly on behalf of the Gas Research Institute (GRI). Ritchard et al. published the first report for the GRI using these simulated home prototypes in 1992[2], and Huang et al. continued this research in a series of papers and reports[3,4,5]. By simulating prototypical homes (using DOE-2, a building energy analysis program) with variations in a single component, Huang et al. were able to estimate the impact on building gas and electricity consumption of different components within the home, such as windows, walls, roof, floor, and appliances, and also occupants. They conducted these simulations using a set of five home designs modeled in each of 16 cities with their corresponding weather. They based the home designs on data collected for the 1980, 1981, and 1982 Residential Energy Consumption Survey (RECS), which is conducted by the Energy Information Administration (EIA), a part of the U.S. Department of Energy (DOE). In order to generate national estimates of the building loads and energy consumption, they used the weighting provided by RECS to estimate the number of households similar to each prototype and then scaled the results of that prototype. These results provided valuable insights into the impact of efficiency measures undertaken to address each of the building loads, but provided little insight into the range of variability of these impacts, and the results were not calibrated to the RECS total energy use.

In this report, we describe work conducted at LBNL to update the prototype tools developed by Huang et al. to address these points and build a policy analysis tool that can evaluate the regional and national impacts of different policy options. The development of this tool began by updating the generalized prototypes developed by Huang et al. to be simulated using EnergyPlus[*], a successor to DOE-2. The generalized prototype consists of a square home with either one or two stories. It may have one of three foundation types (slab, crawlspace, or basement), and has one fourth of its windows and doors on each wall. We updated the description of HVAC systems to include performance data for air conditioners with seasonal energy efficiency ratio (SEER) ratings between 7 and 12 and a variety of heating systems including: gas, oil, or electric furnaces; heat pumps; electric baseboards; or boilers with baseboard heaters or radiators. Each home has occupants, a refrigerator, lights, miscellaneous electric or gas equipment, or both, and either an electric or gas water heater.

Our strategy was to use the 2005 RECS, the most recently published one, to develop a prototype home that corresponds to each single-family residence in the national survey and to simulate that home in EnergyPlus. The 2005 RECS collected data from 4,382 households across the country, including 3,418 single-family homes (detached, attached, or manufactured). We have not updated the generalized prototypes that previous researchers developed for multifamily buildings; we leave that for future work.

As described on the RECS web site[6], the survey "provides information on the use of energy in residential housing units in the United States. This information includes: the physical characteristics of the housing units, the appliances utilized including space heating and cooling equipment, demographic characteristics of the household, the types of fuels used, and other information that relates to energy use." RECS also collects energy use data for the sampled households directly from their utility providers (including, for example, monthly electricity and natural gas bills). EIA uses these data, along with U.S. Census demographic data, to develop weights for each household in the RECS sample, indicating that each household stands in for a particular number of other households. With approximately 100 million households in the country, each of the approximately 4,000 households stands in for about 25,000 others. The households are grouped by census division and large state (California, Texas, New York, and Florida), and the weighted aggregate energy consumption of households in each area is intended to equal the residential energy demand for that area for all fuels.

The representative nature of the RECS, when combined with the information it collects on the details of home construction, makes it an excellent source on which to base home energy simulations. However, RECS does not provide enough detail to precisely estimate the usage of miscellaneous electric and gas appliances, or even to precisely determine the efficiency of home heating and cooling systems. We therefore developed a set of probability distributions that characterize the range of possible values for these simulation inputs. This variability within the simulations of a single sampled home prevents us from recreating a high degree of correlation between the RECS measured energy use and our simulated estimate. However, it does allow us to capture a degree of variability within the national housing stock and weather conditions that would be missing if we assigned only a single value to each house. Section 3 describes in further

[*] A full explanation of EnergyPlus can be found at http://apps1.eere.energy.gov/buildings/energyplus/.

detail the process we used to map data collected by RECS to the input parameters for simulated homes.

One of the reasons why development of this improved simulation tool is possible now, while it was impractical at the time that Huang et al. developed their prototypes, is the dramatic increase in computing power available at reasonable prices. Section 4 of this report describes in detail the process we developed to run EnergyPlus simulations on the Elastic Compute Cloud (EC2) service from Amazon.com[†]. Using this "cloud computing" platform, we were able to simulate the 3,418 single-family homes in each sample in less than two hours.

Section 5 describes the statistical techniques we used to compare the energy use of houses surveyed in the RECS with the energy use of the simulated housing sample. We also discuss how we calibrated the miscellaneous loads in the simulations to better match RECS. This section concludes by showing the results of national simulations as well as simulation of subsets of the national sample (such as homes in particular climate zones or homes of different sizes).

Once we have shown that the simulation tool can produce samples almost indistinguishable from the RECS sample, we are prepared to address some of the research questions posed at the start of this report. Section 6 describes initial attempts to measure the heat replacement effect for lighting and refrigerators and discusses ways in which the simulations need to be improved in order to increase confidence in these results. Section 7 discusses the impacts of hypothetical policies, imagining a scenario in which overnight changes increased the efficiency of appliances or increased home insulation. The report concludes with a summary and discussion of ways in which this simulation tool can be further improved in order to better address policy questions.

3. Building Prototypes from RECS

This section describes the process of building a simulated home for use in EnergyPlus from the data collected by the RECS and other data resources.

3.1 Construction Characteristics

The simulated prototype homes inherit several basic construction characteristics directly from their RECS household equivalents. These are the home size, the number of floors (one or two only), single- or double-pane windows, and the type of foundation (slab, crawlspace, or basement).

Our EnergyPlus prototypes have either one or two floors. While homes in RECS may have more than two floors, we model homes with three or more floors as two-story homes. (If we were modeling multifamily housing, such as apartment buildings, such an approximation would be less justifiable. However, only 5% of single-family RECS households have more than two stories.) Our prototypes, inherited and updated from Huang et al.'s earlier work in DOE-2, can model crawlspaces, basements, or concrete slabs. Most homes in RECS specify one of these three forms of foundation. We model the few RECS homes that do not specify a foundation type as having a crawlspace, thus

[†] http://aws.amazon.com/ec2

representing the effect on HVAC loads as intermediate between that of a slab and a full basement, making this the unbiased choice.

RECS does not contain information regarding the orientation or aspect ratio of each house. We model each house as square, with each side equal to the square root of the area of a single floor of the RECS house. RECS provides several measures of a home's size, including the heated space, the cooled space, and the space including garages or carports. We use the measure RECS calls the "total home square footage". The lack of orientation information also prevents us from allocating doors and windows to the four sides of the square in anything other than an equal distribution. As a result, each side of the house has the same window area, and a single 3-foot door is distributed across the four sides.[‡]

RECS provides limited, but useful, information regarding the number of windows and their construction. For each household, RECS provides an estimate (in bins) of the number of windows in the house, and it also provides important information regarding the construction of the windows, including the frame material (we simulate either wood or aluminum, depending on the RECS response) and the number of panes and "low-e" properties. We simulate only single- or double-pane windows of simple glass. RECS homes with low-e or triple-pane windows are simulated as double-pane (these homes constitute roughly 10% of the single-family homes in RECS). We estimate the window area by assuming that each window in the house has an area of approximately 15 square feet, and apply a broad Gaussian distribution to the average window size in each home.

3.2 Occupancy and Loads

Our EnergyPlus simulations use a collection of standard schedules, based on those used by RESNET, for heating and cooling loads. We do not vary these schedules between homes, and do not vary them by date or season. We calculate several loads using schedules: occupancy, lighting, miscellaneous electrical and gas use, and hot water demand. The magnitude of each of these loads is informed by RECS, but not fixed by it (except in the case of occupancy, where the maximum number of occupants is set to the reported home occupancy).

Lighting and miscellaneous electrical use are stochastically generated for each simulation run, and the parameters of the random distribution from which they are drawn are used as calibration variables to match the aggregate simulated results for total home energy use to the data for actual homes provided by RECS. This calibration process is described in more detail later.

Miscellaneous gas use is assigned in homes that report using natural gas (or other fossil fuels) for food preparation or heating. This load has a significant latent portion to reflect the humidity introduced into the home by cooking. The magnitude of this load is used as a calibration variable to better align RECS-reported and simulated gas use. This load uses the same hourly schedule as the miscellaneous electrical load.

Hot water demand is stochastic, but the parameters of the distribution are determined by the number of occupants (based on the RECS survey response) and by analysis of the shape of the estimated distribution for water-heating end-use energy derived by RECS. This analysis of RECS shows that a Weibull distribution with a shape

[‡] We follow Huang et al.'s EnergyPlus model as our template, and it models only a single door.

parameter of approximately 2 is capable of characterizing the hot water energy use. We adjust the scale of the Weibull curve to calibrate the simulation results with the RECS total energy bill results for homes that use gas for hot water but not for space heating (which allows us to isolate this end use). We do not use the hot water energy use calculated by RECS itself because this energy use does not allow us to capture variability (beyond the sample variability in the RECS sample).

Each simulated home contains one refrigerator, and all modeled refrigerators are the same. RECS provides much greater detail regarding refrigerators (including size, age, and number), but for simplicity we have chosen to simulate each home with the same single refrigerator. This refrigerator is modeled as a “Refrigeration:Case” plus a “Refrigeration:CompressorRack”, allowing the appliance’s energy consumption to vary with the ambient indoor conditions. (These EnergyPlus components are intended for use to model larger refrigeration systems of the sort found in grocery or convenience stores, but they can be adapted to simulate a home-scale appliance.) This appliance uses approximately 600 kWh per year under typical indoor conditions, but individual appliances may use as little as 300 kWh/year or as much as 1,200 kWh/year in cooler or warmer homes. It is modeled without a restocking or defrost schedule, so the energy use is only that due to heat penetration of the case.

3.3 Simulating Realistic HVAC Systems

RECS reports the primary home heating and cooling equipment present in each home; our simulations attempt to reproduce this equipment. On the heating side, we simulate electric, gas, or oil furnaces; heat pumps; electric baseboard heaters; and boilers with hot water baseboard heaters. On the cooling side, we simulate central air conditioners, heat pumps, and window air conditioners. We also developed models for the flow and static pressure in duct systems for homes with forced-air systems and applied this model to adjust the airflow through heating and cooling coils, as well as to adjust the energy required by HVAC fans.

3.3.1 Central Air Conditioners and Heat Pumps

EnergyPlus models direct expansion (DX) coils for air conditioners and heat pumps. The critical inputs required for these models are: the rated cooling (or heating) capacity, rated sensible heat ratio, rated airflow, rated coefficient of performance (COP), and a set of fixed performance curves. The performance curves modify the rated performance for a system not operating under the rated conditions. Two curves modify the cooling capacity as a function of the indoor and outdoor temperature (using a biquadratic functional form) and as a function of the air flow fraction (quadratic). Two curves modify the energy input ratio (the inverse of the COP) with respect to the temperatures and flow fraction. These four performance curves may vary significantly between air conditioner and heat pump models. A fifth curve accounts for compressor cycling during a simulation time step when the load does not require the compressor to run all the time. We use the EnergyPlus recommended default form for this part load fraction correlation curve:

part load fraction = 0.85 + 0.15×part load ratio,

where "part load ratio" is the fraction of time the compressor runs during the time step.

We assigned SEER values to the air conditioners installed in the simulated homes based on the average SEER values for the era in which the appliance was built. For example, for air conditioners built between 1996 and 2000, the average SEER is approximately 10.7.[7] Homes with such air conditioners have the most chance of having SEER 11 systems, with a significant probability of having SEER 10 systems instead. A smaller fraction has SEER 9 or 12 air conditioners. The proportions of each efficiency level are balanced so that the average value is 10.7.

We used published performance data for commercially available residential air conditioners and heat pumps to determine the rated COP and the four curves that modify the capacity and energy input ratio (EIR) as functions of temperature and flow fraction. Published performance data include the capacity and EIR at a range of operating conditions, and we fit quadratic and bi-quadratic curves to this data. In particular, for SEER 10, 11, 12, and 13 air conditioners, we fit functions to the performance data for 3-ton Carrier units. We used the performance curves derived for the SEER 10 system for SEER 7, 8, and 9 systems. Table 3.1 describes the air conditioning products used to derive the performance curves at the various SEER levels.

Table 3.1. Air Conditioning Products Used to Derive Performance Curves

SEER	**Outdoor Section Model**	**Indoor Section Model**
10	38TKB036	CD5AA036
11	38TMA036-30	CC5A/CD5AA036
12	38TR036	38TR036
13	25HPA336A30	FY4ANF042

Heat pumps require similar performance curves, for both heating and cooling performance. Table 3.2 describes the heat pump products used. It is possible to design systems with various heating seasonal performance factor (HSPF) ratings for a given SEER, and vice versa. However, we used the following equation to link these two characteristics: HSPF = 3.2 + 0.4×SEER.

Table 3.2. Heat Pump Products Used to Derive Performance Curves

SEER	**HSPF**	**Outdoor Section Model**	**Indoor Section Model**
10	7.2	38YKB036-30,50,60	FB(4,5)AM(A,F)036
11	7.4	38YMA036-30	FB4AN-042
12	8.0	38YR036-31	FB4AN042

To assess the energy savings from advanced, multi-speed air conditioning and heat pump systems (see Section 6), we used the performance data of a SEER 16 cooling system and an HSPF 10 heating system. On the cooling side, we based our performance curves on a 25HNA636A30 outdoor section combined with an FE4AWB006 indoor section. For the heating performance of a multi-speed heat pump, we used a 25HNA948A30 outdoor section with an FE5ANB006 indoor section.

3.3.2 Window Air Conditioners

We modeled only a single type of window air conditioner, which we modeled as a SEER 10 system with a COP of 3.0, and with the same performance curves as the SEER 10 central air conditioner system described above. We modeled each unit as having one ton of cooling capacity,[§] and fixed the number of units based on the answer to this question from RECS.[8] For homes with two floors, we divided the units evenly between the two floors.

3.3.3 Furnaces

Central heating systems, including electric, gas, and oil furnaces, were modeled using the Coil:Heating:Electric and Coil:Heating:Gas inputs to EnergyPlus (with oil furnaces modeled as gas furnaces with different efficiencies). Electric resistance heaters were modeled as having an efficiency of 100%, while gas and oil furnaces have lower efficiencies. We used the reported age of these heating systems, along with data collected for furnace efficiency analysis[9] to determine an efficiency distribution for each age of furnace. For example, gas furnaces between 10 and 19 years old have an 18% chance of being 60% efficient, a 13% chance of being 70% efficient, an 11% chance of being 75% efficient, a 39% chance of being 80% efficient, an 11% chance of being 90% efficient, and an 8% chance of being 92% efficient[10]. In each simulation, the selected home might have any one of these appliances.

When comparing our simulation results with the reported fuel consumption from RECS, we noticed that simulated homes with oil furnaces modeled in this way used significantly less fuel than the RECS homes they attempted to model. We attribute this discrepancy to two factors: First, we are modeling the oil furnaces as gas furnaces, with no standby or idle losses. Second, fuel oil is generally not purchased through a utility, so the oil use for these homes reported by RECS is subject to greater uncertainty. (RECS does attempt to procure the actual bills for these homes.) We corrected for this discrepancy by inserting an efficiency factor of 0.67 for oil furnaces. We have no physical or simulated model to explain this factor, only that it is necessary in order to capture these homes' reported energy use.

RECS allows respondents to report if they do not heat some fraction of their home. If the heated fraction fell below 60% for two story houses, we modeled the home as though the second floor were unheated.

3.3.4 Baseboard and Radiator Heating

[§] The room air conditioner product class that has the greatest market share has a cooling capacity of between 8,000 Btu/h and 13,999 Btu/h. One-ton capacity units (12, 000 Btu/h) fall within this class.

We modeled electric baseboard heating using the "ZoneHVAC:Baseboard:Convective:Electric" EnergyPlus model. Rather than allow such systems to be autosized, we modeled them as having 1,000W of heating capacity for every 750 square feet of heated space in the home. We determined this capacity factor by comparing the electricity use of simulated homes with baseboard heaters to those same homes in RECS and adjusting the capacity to achieve the best match in the energy use distribution.

For RECS homes that reported the use of gas or oil for heat, but no central furnace system, we modeled gas and oil-fueled boilers connected to hot water baseboard systems. We estimated the boiler efficiency in the same way we did for oil furnaces, using historical shipped boiler efficiencies in combination with a calibration factor of 0.65. This efficiency calibration factor, as in the case of oil furnaces, may reflect home construction characteristics correlated with the use of these heating systems, or it may reflect the imperfect nature of our EnergyPlus model of a boiler and baseboard system (such as not fully characterizing the additional losses in such a system). Butcher et al.[11] studied the full-year input-output efficiency of boiler systems and measured a similar factor for their baseline system, with inefficiency largely resulting from high idle losses (which are not captured in our simplistic model).

3.3.5 System Sizing and Accounting for Ducts

EnergyPlus has "autosizing" features that adapt systems specified by the user in general terms to the specific case of an individual home. For example, the user can leave the capacity of an air conditioning system to be autosized, and EnergyPlus will determine the capacity necessary to meet the sizing conditions described by the user. In our case, we used the 99% and 1% extreme cases from the TMY3 weather files. That is, these conditions describe the 99th and 1st percentiles of the temperature experienced in the location. The 99th percentile characterized an extreme summer day, and the 1st an extreme winter day. EnergyPlus determines the capacity necessary to meet this heating or cooling load, and assigns that capacity to the system (after applying a multiplicative sizing factor; 1.25 in our analysis). For this research, we began by autosizing the rated capacity, rated airflow, and rated sensible heat ratio (where appropriate) for the heating and cooling of each home. The SEER and HSPF of the home's air conditioning or heat pump system determined the COP and performance curves.

This capacity-sizing system provides a close approximation of the capacity of the physical system that would be installed in this home. However, EnergyPlus is able to assign capacities that do not reflect the restricted nature of system availability in the marketplace. For example, EnergyPlus could determine that a home should have a 3.22-ton air conditioning system. However, air conditioning systems generally only come in 3- or 3.5-ton sizes, not 3.22-ton. We applied a method that allows a calculation to intercede between the sizing stage and the full annual simulation to address this. The program calculates the capacity of the heating and cooling systems designed by EnergyPlus in the appropriate units (tons of cooling for air conditioners, kBTU/hour for heaters) and adjusts the systems to have the smallest capacity available on the market that exceeds the capacity designated by EnergyPlus. Our 3.22-ton air conditioner household is therefore assigned a 3.5-ton system. This correction allows us to better capture the real part-load behavior experienced by the installed systems.

EnergyPlus can autosize the airflow for heating and cooling systems (as well as the sensible heat ratio for air conditioning coils). This airflow autosizing targets 400 cubic feet per minute (cfm) for each ton of cooling or heating capacity. While the autosizing algorithm will not fix the flow at exactly 400 cfm/ton, the systems as sized by EnergyPlus are much closer to this ideal than installed HVAC systems in U.S. homes.

We collected data regarding airflow in home installations from Proctor Engineering[12], as well as from the Florida Solar Energy Center[13], Ecotope[14], Chitwood[15], and the Energy Center of Wisconsin[16]. Together, these sources provided data on 669 homes in 10 states. For each home, the data include the capacity of the air conditioning system and the measured maximum airflow, as well as the static pressure measured in the system under these conditions. The capacity and flow data allow us to calculate the cfm/ton in these real homes, and examine the distribution of this parameter. Figure 3.1 shows the distributions of cfm/ton for different installed system capacities. We fit Gaussian distributions to each of these measured distributions. Then, for each RECS home to be simulated, we drew a sample from the distribution corresponding to the home's air conditioning capacity to determine how that simulation's airflow would compare with the average of 400 cfm/ton in the maximum cooling mode.[**]

[**] EnergyPlus issues error warnings if the airflow falls outside of the range of 200 to 500 cfm/ton, so we limited the distribution by these values for all homes. Heat pump simulations showed some instability if the airflow varied outside of 300 to 450 cfm/ton, so we set these as the limits for heat pumps.

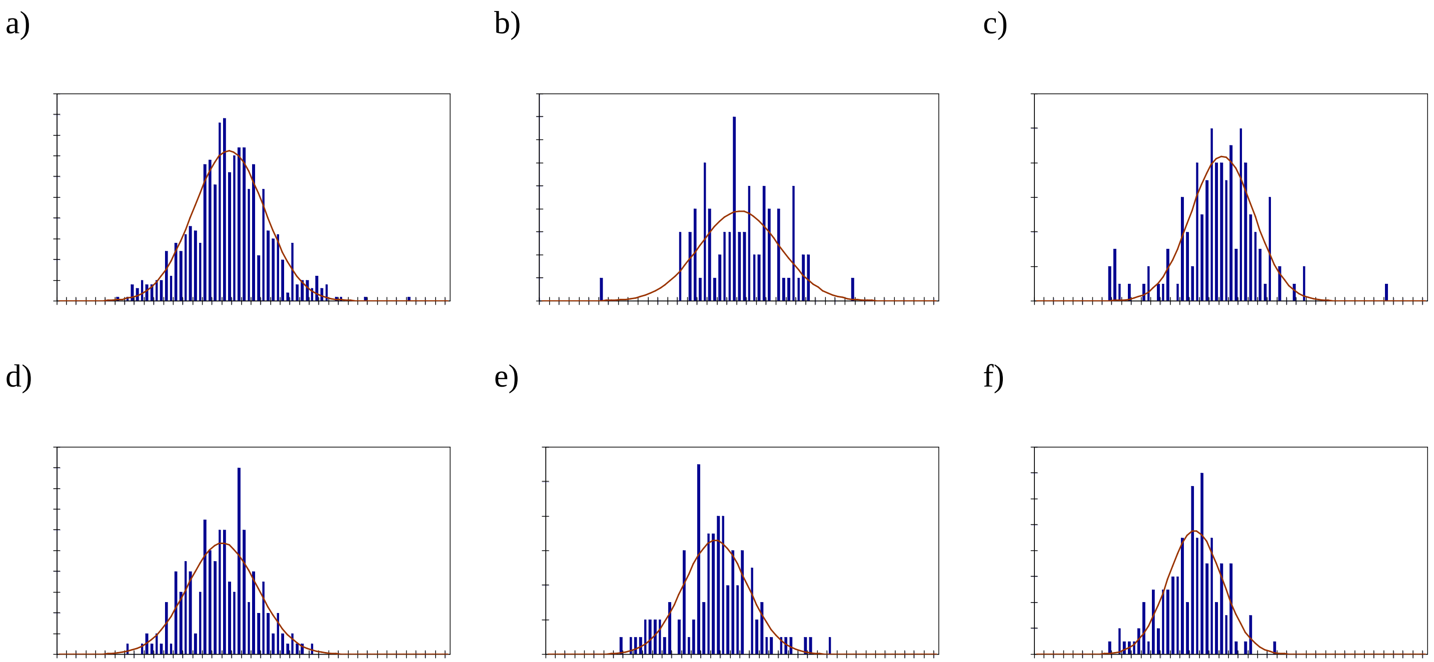

Figure 3.1. Maximum airflow as a fraction of 400 cfm/ton of cooling capacity for a) all 669 measured homes, and for subsets with different cooling capacities: b) 2 tons, c) 2.5 tons, d) 3 tons, e) 3.5 tons, and f) 4, 4.5, and 5 tons. Each plot shows the histogram of measured homes along with the Gaussian best fit to that distribution.

In order to characterize the energy consumption of the furnace fan, which is used to distribute the air for heating and cooling, we needed to determine the static pressure faced by that fan at each operating point. Generally, the airflow during heating operation is less than during cooling, resulting in different static pressure and different fan energy consumption. Based on product literature information we assumed that the airflow during heating operation was 80% of the flow during cooling, except in houses with significantly larger heating systems than cooling systems, where the airflow system design would be driven by the heating system's requirements. (If the heating capacity was between two to three times greater than the cooling capacity, then the airflow was the same for both heating and cooling; if the difference was even greater, then the heating-mode air flow was also greater.)

For each home, we needed to calculate a system curve that characterizes the home's HVAC system ductwork by relating the static pressure to the airflow. This curve usually has a roughly quadratic shape, and we assumed that it fits this form:

$$\text{Static pressure} = SCC \times flow^2,$$

where *SCC* is a parameter we called the home's duct *system curve coefficient*.

The HVAC dataset we collected allowed us to calculate the system curve coefficient of each of the 669 homes by relating the measured static pressures to maximum airflows. Some homes reported only the static pressure without the coils; for these homes we assumed that the coils added 0.3 inches of water, or approximately 75 Pascals, to the external static pressure. The data exhibit a large degree of scatter, but a plot of the SCC vs. maximum home airflow shows a definite trend (see Figure 3.2a). We smoothed the data by calculating the average SCC for homes with maximum airflow (*MaxFlow*) in each of 84 bins and fit a power law curve to this smoothed data (see Figure 2.2b). The best-fit power law function is:

$$SCC = 222.85 \times MaxFlow^{-1.6117}.$$

a) b)

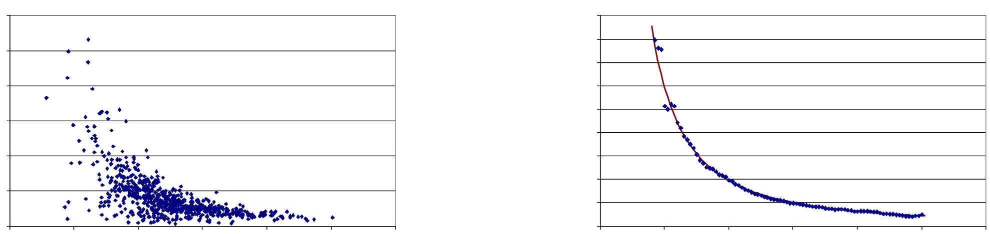

Figure 3.2. a) System curve coefficients of measured home HVAC systems as a function of maximum airflow. B) Smoothed system curve coefficient data as a function of maximum airflow, with the power law fit illustrated.

With a reference fit in hand to relate maximum flow to the SCC, we examined the residuals when this curve is compared with the SCCs of our 669 home dataset. We characterized the residuals as a multiplicative factor, rather than a shift. That is, if the average curve predicted a SCC of 300, but the home had an SCC of 600, the residual was a factor of 2. Examining the distribution of residuals, we fit the distribution with a Weibull distribution characterized by a scale of 1.10 and a shape of 3.04.

With an average function and a residual distribution, we were then able to address the SCC, and thus the static pressure, of homes in our RECS sample. For each home, we first calculated the system capacity by rounding up the capacity determined by autosizing. Then, we used the Gaussian distribution for that capacity to select a maximum airflow (on average less than 400 cfm/ton). Using that maximum airflow, we calculated the average SCC, and then drew a system curve factor from the Weibull distribution to get the SCC that determined the system curve for the home. This system curve enters the EnergyPlus simulation in the form of the static pressure faced by the furnace fan at maximum flow.

3.3.6 Characterizing Fan Energy Consumption at Different Airflows and Pressures

Accurately characterizing HVAC energy consumption requires a model of fan energy consumption that goes beyond simply applying the standard fan laws. We modeled the prototypes that have central heating or cooling systems as containing permanent-split capacitor (PSC) motors. We used data on typical PSC fan motor performance that was collected and used for the 2007 DOE efficiency standards analysis for furnaces[9]. That analysis collected data regarding the performance of hundreds of existing furnace fans and developed an average model that characterized the performance of typical fans. We extended that model by fitting the typical data to a single bi-quadratic function that calculates fan energy use as a function of airflow and static pressure.

In order to model more efficient HVAC systems (see Section 7), we also needed to develop similar models for electronically commutated motors (ECMs) under two different control strategies: a “constant volume” strategy and a “constant torque” strategy. For constant volume, we used ECM data collected and averaged for the 2007 DOE analysis, and undertook the same fitting process. Constant torque controls have been developed more recently, and we used performance data from the ECO-TECH furnace fan by Emerson[17] as our starting point for the fitting process.

Having developed functions that calculate fan energy as a function of airflow and static pressure, we were able to provide the fan performance curves to EnergyPlus that reproduce the fan energy use not only at the maximum flow condition (usually the maximum cooling mode), but also at the other flow conditions.

3.4 Assigning Location to a RECS Household

To simulate each RECS household, we had to match each household with one location from each of two different sets of locations: the weather file location and the typical building construction location. We developed a set of 272 EnergyPlus weather files, based on the set of locations for which typical heating and cooling degree day data were available from the National Oceanic and Atmospheric Administration (NOAA)[18] and standard weather files were available from EnergyPlus. Of these 272, households were matched to 218 locations[††]. Huang et al. developed a collection of typical building construction data that they used for their building prototypes in each of 16 locations for each of 4 periods of construction. This data included typical home size, number of floors, wall material, window type, and the level of insulation installed on the floor, walls, and roof (including both original and retrofit older homes). While RECS provides household-specific data that we used for most of these fields (such as home size), we did utilize the data from Huang et al. for the installed R-value of insulation.

In assigning a location to a RECS household, we used three pieces of information regarding that household: the heating degree days and cooling degree days (both with a 65 degree reference; referred to as HDD65 and CDD65) and the census division or large state. The goal of the matching process is to match each household with a construction location and weather file that most closely reflect the conditions of that household.

With only 16 construction locations, we matched the location using a simple, hand-derived method. Table 3.3 lists the 16 cities, along with their HDD65, CDD65, and census division/large state. When only one representative city was present in the census division where the household was found, we used the construction data for that city. For example, all RECS households in census division 1 (New England) have the typical construction from Boston. For census divisions with two (or more) cities, we used a threshold value of either HDD65 or CDD65 to assign households to one city or another. HDD65 was used in heating climates (e.g. to distinguish between Minneapolis and Kansas City), while CDD65 was used in cooling climates (Kansas City vs. New Orleans vs. Dallas/Ft. Worth for the West South Central census division outside of Texas). None of Huang et al.'s cities are in the East South Central census division, so we used nearby cities: New Orleans, Atlanta, and Washington, DC. The thresholds were selected so that the weighted average HDD65 or CDD65 within each area was close to the weighted average HDD65 or CDD65 of the RECS households within that area (while maintaining the thresholds as "reasonable" numbers, such as multiples of 25). Tables in Appendix A list the R-values of insulation assigned for each construction location for single-family detached, attached, and manufactured homes.

Table 3.3. Construction Locations and RECS Home Assignments

City	Census Division/Large State	HDD65	CDD65	RECS households assigned to this construction location
Boston	New England (1)	5841	646	All of the New England division
New York City	Middle Atlantic / New York (2)	5090	1002	All of the Middle Atlantic division
Chicago	East North Central	6450	749	All of the East North Central division
Minneapolis	West North Central	8003	634	West North Central with HDD65 > 7300

[††] Most of the difference is due to a number of locations in Alaska for which weather data is available, but no households were matched.

				Pacific outside California with HDD65 ≥ 10000 (Alaska)
Kansas City	West North Central	5155	1445	West North Central with HDD65 ≤ 7300
				West South Central outside of Texas with HDD65 > 3650
Washington, DC	South Atlantic	5233	1044	South Atlantic with HDD65 > 4225
				East South Central with HDD65 > 3700
Atlanta	South Atlantic	3090	1611	South Atlantic outside Florida with HDD65 ≤ 4225
				East South Central with HDD65 between 2800 and 3700
Miami	South Atlantic / Florida	141	4127	All Florida
				Pacific outside California with HDD65 < 200 (Hawaii)
New Orleans	West South Central	1464	2539	West South Central outside Texas with HDD65 < 1325
				East South Central with HDD65 ≤ 2800
Fort Worth	West South Central / Texas	2304	2415	All Texas
				West South Central outside of Texas with HDD65 between 1325 and 3650
Denver	Mountain	6083	567	Mountain with HDD65 > 3900
Albuquerque	Mountain	4361	1211	Mountain with HDD65 between 2850 and 3900
Phoenix	Mountain	1154	3815	Mountain with HDD65 ≤ 2850
Seattle	Pacific	4867	127	Pacific outside of California with HDD65 between 200 and 10000
San Francisco	Pacific / California	3839	69	California with CDD65 < 365
Los Angeles	Pacific / California	1291	470	California with CDD65 ≥ 365

Matching 3,418 RECS households with the most appropriate weather file out of more than 200 options could not be done manually. Therefore, we developed a tool (applied in a spreadsheet) that evaluates a matching function for a household with each of the weather file locations, using the HDD65, CDD65, and the census division and large state. This function places highest priority on matching HDD65 and CDD65 within the smallest geographic constraint for the household. However, it allows for the best match to be made with locations outside strict geographic constraints. The function we attempt to minimize is a product of a measure of the similarity of HDD65 and CDD65 (the sum of the absolute values of the differences between the weather file's degree days and the household's) and a measure of the similarity of the geographic location. The region factor multiplies the HDD/CDD factor by a different value depending on whether the weather file is from the same census division or large state (0.01 for an exact match; 0.03 for a match within the same division but not state), an adjacent division (0.1), or elsewhere (10). The smallest final product is assigned as the location. In this way, we allow locations that are best represented by their neighbors across state lines to use that match, but avoid matching southeastern households to California cities just because their HDD65 and CDD65 might be close.

Both the typical construction location and weather file location provide our best estimates of the location of each RECS household, but each is an approximation of the conditions and construction of each individual household. As a result, the simulated homes are more uniform than the housing stock they are meant to represent and face more uniform weather.

3.5 Retrofits of Older Homes

For homes built before 1980, we allowed for the possibility that the homes have been retrofit with better insulation than they had when originally constructed. The retrofit values of insulation are shown in the tables in Appendix A. We relied upon two sources of information to determine whether a particular home in RECS had been retrofit. First, if survey respondents reported that their homes were "well insulated," we took them at their word and modeled these homes as having been retrofit. (Our non-retrofit older home prototypes are not well insulated.) Altogether, 18.9% of our sampled households are both old and well insulated, and are therefore modeled as retrofit. Second, we derived a function relating the probability of retrofits to the sum of the heating and cooling degree days (HDD65 and CDD65). We used data presented by Huang et al.[3], derived from a presentation by A.D. Little to DOE in 1998, which show the fraction of homes which have been retrofit in each of a number of cities. We examined the retrofit fraction as a function of HDD65+CDD65, adjusted for the presence of homes we had already identified as being well insulated from the survey results, and then calibrated on home size. (We discovered that the distributions of energy use by small and large houses needed to be taken into account, because larger houses were more likely to have been already retrofitted.) Taking all of these data into account, we derived the following two formulas for the probability of non-reported retrofits of homes.

For homes built before 1950:

$$P = 0.129 + 5.08\times10^{-5}\times(\text{HDD65+CDD65}) + 0.00035\times(\textit{sq.ft.} - 1500),$$

For homes built between 1950 and 1980:

$$P = 0.312 + 3.32\times10^{-5}\times(HDD65+CDD65) + 0.00035\times(\ sq.ft. - 1500).$$

Applying this probability as a random function to each household results in 26.25% of older households being retrofit (some of which are also reported as well insulated). Combining the two retrofit functions, 35.8% of homes are both older homes and modeled as retrofit.

4. Simulating Homes in "the Cloud"

Simulating a single prototypical home, built using the methods described above, for one year using EnergyPlus takes about one minute on a 3 GHz personal computer. EnergyPlus does not use more than one processor core, even if more than one is present, so simulating a second house (in addition) can also be completed in about one minute on a dual-core 3GHz processor. RECS 2005 contains 3,418 single-family homes suitable for simulation using the tools described in this paper. On a dual-processor computer, simulating each of these homes once would take approximately 30 hours. If we would like to examine the marginal impact of a change in each house (such as increased insulation or a more efficient HVAC system), we need to simulate each house at least twice, driving the time required to about 60 hours. These time requirements make simulations of the full RECS sample onerous when conducted on a single computer.

The single-thread nature of EnergyPlus simulations makes them ideal candidates for naïve parallelization, in which each simulation is assigned to a different processor. In order to make full-sample simulations fast and straightforward, more than two processor cores are required. For example, if we had access to 100 processor cores, we could simulate each house in RECS once in under an hour. To make this performance a reality for our work, we utilized EC2 from Amazon Web Services, which is associated with online retailer Amazon.com. EC2 is a service whereby Amazon can rent its unused computer resources to other users. (Amazon needs enough computing resources to meet rush periods, but this power might sit idle or off the rest of the time. EC2 allows Amazon to utilize these resources and earn income from them.)

Amazon's EC2 makes many different computer configurations (or *instance types*) available. For our building simulations, which are CPU-intensive but not memory-intensive, we use the "High-CPU Extra Large" instance type. Each running computer is referred to as an *instance*. Each High-CPU Extra Large instance has 7 GB of RAM and 8 virtual cores, each of which is equivalent to a 2.5 to 3 GHz desktop computer processor. These cores have similar EnergyPlus performance to the cores used on our local desktop personal computers (PCs), in that a single house takes about a minute to simulate for a full year. If we use 10 of these instances from Amazon EC2, we have 80 cores at our disposal, and the time required to simulate every house in RECS using EnergyPlus falls to slightly less than an hour. In practice, the overhead time cost to launch multiple Amazon instances, upload EnergyPlus input files, download the results, and so on, adds to the total time required, making EC2 an inefficient place to undertake a handful of simulations. For large simulation sets, such as all 3,418 RECS single-family households (and in particular all of RECS more than once), the overhead is small compared with large parallelization factors. Using EC2 makes these simulations reasonable.

We found Amazon EC2 to be reasonably priced. There are two ways to launch an EC2 instance: on-demand or through the Amazon spot market. On-demand instances launch within a minute or so after they are requested and stay running until we request that they stop. The High-CPU Extra Large instances we use for simulations cost $0.68 per hour (or partial hour) when launched on demand. For a 10-instance run like that mentioned above (using 80 cores), the complete simulation run costs $6.80 (or perhaps $7.48 if the master instance, which runs for longer than the other instances, stretches past the hour mark). One user is limited to 20 on-demand instances at once without special permission from Amazon.

Spot requests are bids in the spot market that Amazon runs to auction computing resources. When we request an instance in this market, we provide a maximum price we are willing to pay for that instance. If the current price is below that maximum, instances will launch and be assigned to us. If the market price rises above our maximum, our instances will be shut down immediately, with no warning. The prices in this market are well below the on-demand price, with High-CPU Extra Large instances typically costing about $0.25 per hour. One user can own up to 100 spot instances at once, making much larger simulations possible. For example, we have simulated each single-family house in RECS eight times (with eight different HVAC configurations) in a single run over the course of less than 5 hours using 40 spot instances. We risk losing all of our simulation results if the prices rise above our maximum, but we set our maximum quite high relative to the typical prices ($0.40 per hour) so that only system-level interruptions (of the sort that occur once a month or less) are likely to cause problems.

We also take advantage of persistent storage available through Amazon's Elastic Block Store (EBS). This allows us to store EnergyPlus configuration files, scripts, and other useful files on Amazon's servers. The EBS volume can be mounted on an EC2 instance like an external hard drive, and we use this connection to transfer input files and scripts to each EC2 instance. EBS volumes cost $0.10 per allocated GB per month. That is, a 100 GB volume costs $10 per month, regardless of what fraction of that 100GB we are using.

Amazon also charges for data transfer, at a rate of $0.15 per GB downloaded (uploads are currently free). A run of 3,418 RECS households typically generates about 3 GB of downloaded outputs, costing about $0.45 for each run.

Appendix B gives a detailed description of the procedure we use to launch and run Amazon instances for EnergyPlus.

5. Comparing and Calibrating Simulated Energy Use with RECS

RECS provides the total annual energy use, by fuel, for each of the homes in its sample. This data is generally collected from the responsible utilities. RECS also provides estimates of the breakdown of this energy by end use, calculated using a regression technique, sometimes called conditional demand analysis. We compared the reported annual energy use for RECS households with the energy use of simulated households. Energy use patterns, particularly the numerous miscellaneous loads (such as lighting, home electronics, hot water demand, and cooking), vary widely by household, and RECS does not survey its respondents regarding their behavior with respect to these energy end uses. As a result, for our simulations we must estimate these uses, and use a wide distribution of possible energy demand. We cannot correlate this demand with the behavior of an individual household. We therefore cannot set as our goal reproducing the energy consumption of each household individually. Instead, we are interested in generating a national sample of model homes that looks as much like RECS as possible, when examined in aggregate, cumulative terms for the complete sample, as well as in subsamples. If we are successful, the simulation tool will generate a nationally representative sample of simulated single-family homes, with energy use statistically indistinguishable from the RECS sample.

In order to compare the energy use of a set of simulated homes with the RECS survey results, we need a statistical tool that can compare distributions. For this task, we chose the Kolmogorov-Smirnov test, or K-S test[19]. This test evaluates two one-dimensional distributions by comparing them in their cumulative form. The null hypothesis is that the two distributions are the same; the test rejects the null hypothesis with some level of confidence, depending on the data themselves. The critical statistic (generally named D) is the maximum difference between the two cumulative distributions. One may use the K-S test to compare a dataset with a known or idealized distribution (for example, to evaluate whether a distribution is Gaussian), or it can be used to compare two different samples. We use the test in the latter formulation, comparing the energy use distributions from simulated homes with the energy use distribution from RECS. If the K-S test rejects the null hypothesis with greater than 95% confidence ($Q_{KS}<0.05$), we can say with that level of confidence that our simulated sample is different from RECS, and therefore not equivalent to a national statistically representative sample of home energy use. If, on the other hand, the K-S test cannot reject the null hypothesis with confidence greater than 95%, we can say that the energy use distribution generated by our simulation tool is statistically indistinguishable from the distribution from RECS. As we used this statistic to evaluate whether our simulations were capturing the complexity of the RECS data, we generally used a 99% level as the trigger for further examination or calibration. If the K-S test could reject the null hypothesis with greater than 99% confidence, then we looked at the sample in greater depth to determine if there was a complexity we failed to take into account. In other words, we chose $Q_{KS} = 0.01$ as our threshold. If Q_{KS} is less than 0.01, we state that the two distributions are statistically distinguishable, and if it is greater than 0.01 we state that the two distributions are not statistically distinguishable. Once the simulations had been calibrated, we found that only a few subsamples approached statistical distinguishability.

5.1 Using the Cumulative Distribution Results for Calibration

RECS provides enough information to model the home heating and cooling systems, as well as to estimate the size of each home's water heater. (We assumed hot water demand is proportional to the number of occupants and apply a Weibull probability distribution based roughly on RECS end-use energy estimates for variability.) We modeled the refrigerator in a simple fashion and assumed that each home has the same refrigerator. RECS does not, however, provide sufficient information to estimate the usage of other electric and gas appliances (such as home electronics, cooking, and lighting) without taking the billing data into account.

We used the electric and gas load from these miscellaneous uses to calibrate our model with RECS. To do this, we first simulated the full RECS sample without miscellaneous electric loads and compared the annual electricity use from these simulations with the annual electricity use reported by RECS. We were then able to fit the resulting residual using a two-stage process. First, we fit a line to the residuals as a function of home size, under the assumption that some miscellaneous uses (such as lighting) should be proportional to home size. The best-fit line to these residuals is

$$\textit{misc. kWh/year} = 3{,}958 + 1.091 \times \textit{sq.ft.}$$

This fit leaves a significant secondary residual, which we fit as a multiplicative factor with a Weibull distribution (shape = 1.431, scale = 1.325). We were also able to derive a quadratic expression for the variation of the Weibull shape parameter with home size, up to a maximum of 4,000 square feet, above which the value is fixed at 0.91:

$$-7.34\times10^{-8}\times \textit{sq.ft.}^2 + 3.6\times10^{-4}\times \textit{sq.ft.} + 0.65$$

This fit is unable to capture the fact that some (about 7%) of the residuals between the no-miscellaneous model and RECS are negative. That is, even without the miscellaneous loads, the simulated energy use exceeds RECS for these homes. Once we implemented this residual in the simulations in the form of electric equipment and lighting loads, we discovered that this neglect of the negative residuals resulted in home energy estimates that were systematically higher than RECS. We achieved a final calibration to RECS by scaling these miscellaneous calibrating loads by a factor of 0.75.

We repeated this process to estimate miscellaneous gas loads (such as cooking or secondary heating) for homes that reported some fossil fuel use. In this case, there was no significant slope of these loads with home size, so we used a simple constant load (equivalent to 9.96 MMBTU/year) with a multiplicative Weibull residual (scale = 3.75, shape = 1.17). The residual again fit to a Weibull distribution without a negative component, leaving the 37% of homes with negative residuals unrepresented. (It is difficult to add a negative load to the simulation.) We were also able to derive a quadratic expression for the variation of the Weibull shape parameter for this residual distribution with home size, up to a maximum of 4,000 square feet, above which the value is fixed at 0.54:

$$-1.80\times10^{-8}\times \textit{sq.ft.}^2 + 6.07\times10^{-5}\times \textit{sq.ft.} + 0.584$$

This expression includes a scaling factor of 0.63, which achieves final calibration by accounting for the 37% of homes that would be best fit by negative miscellaneous loads.

Using the K-S test allowed us to evaluate the performance of the simulation model for subsets of the RECS sample, as well as for the full sample. This is particularly useful in evaluating the calibration of the simulation tool for non-HVAC uses. For example, we can examine the natural gas use in houses with electric heating and cooling.

For these homes, gas may be used only for water heating (in some) and for miscellaneous equipment. If the simulation tool reproduces the gas use distribution in this subset, we can have some confidence that these loads are being well captured in the full sample. Figure 5.1 shows the simulation and RECS fuel use results for homes that do not use fuel for heating. We can also evaluate the performance of our simulations of particular heating methods. We discovered, for example, that simulated homes with baseboard heaters and oil furnaces were using significantly less fuel than reported by RECS. We were able to recalibrate the efficiencies of these systems (both perhaps imperfectly modeled by our simple EnergyPlus models) in order to better match the observed fuel use distributions.

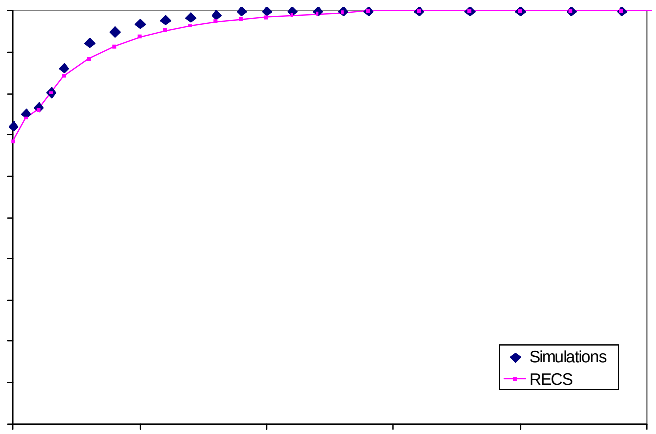

Figure 5.1. Cumulative distributions of fossil fuel use for all homes in the RECS sample that heat with electricity from simulations (blue diamonds) and from RECS (pink line). The Kolmogorov-Smirnov quality of this comparison is $Q_{KS} = 0.501$. This comparison was used to confirm calibration of gas water heating and miscellaneous gas use.

Finally, by comparing the simulations and RECS for three subsets of houses divided by size (the smallest third, the middle third, and the largest third) we have been able to evaluate two of our assumptions. First, we evaluated whether scaling miscellaneous electricity use by size is correct, and it appears to be roughly correct. Second, we evaluated whether the results are skewed by our simple assumption that we can scale the original prototype designs up and down in size while maintaining a square house shape.

Although miscellaneous electricity usage scaled with house size, miscellaneous fuel usage does not. In particular, the residual between HVAC and water-heating only fuel use and the fuel use reported by RECS shows very broad variability with no significant variation by house size. This variability is consistent with miscellaneous gas use being driven by cooking and other activities that do not necessarily increase with house size. In some simulation runs, interestingly, the best-fit slope for a linear function between the residual and house size is negative. (The fit is not robust, so we chose not to use it for our calibration.) This indicates that the heating energy in simulations may increase more strongly with house size than it does in actual homes. As described above, we fit the fuel residual as a constant value with a Weibull-distributed multiplicative factor. The Weibull distribution does show a slight variation with house size, rising as homes grow, and then falling. Taking into account all reasonable variation of the miscellaneous gas use, however, leaves the simulated fuel use slightly below the measured use for small homes and slightly above for large homes. The two fuel use distributions—for the smallest 1/3 of homes and the largest 1/3 of homes—show this trend, but the simulated curves are not statistically distinguishable from the RECS distributions (see Figure 5.9). This deviation may be a result of the simplistic model used for furnaces, which had no standby or idle losses; these losses would be roughly independent of home size.

5.2 Performance of the Calibrated Model

With miscellaneous loads adjusted to calibrate the simulated homes with the RECS single-family home sample, we find excellent agreement between the distributions produced by the simulated homes and the distributions characterizing the RECS sample. Figures 5.2 and 5.3 show the cumulative distributions for total home electrical use and total home gas use from a single set of simulations, compared with the cumulative distribution from RECS. The quality, Q_{KS}, calculated by the Kolmogorov-Smirnov test exceeded 0.01 for both electricity and fuel for the samples as a whole: Q_{KS} = 0.081 for electricity and Q_{KS} = 0.456 for fuel.

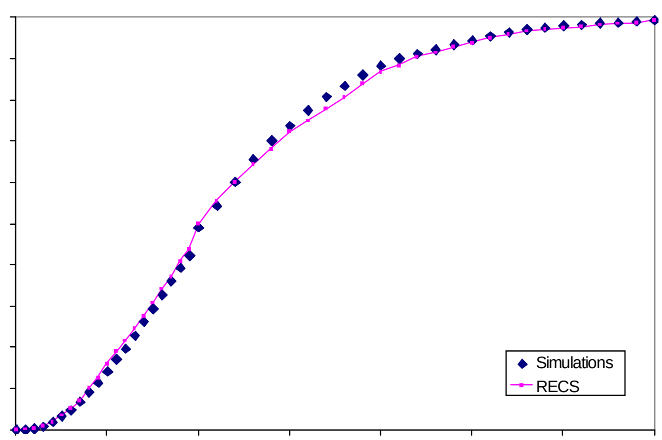

Figure 5.2. Cumulative distributions of electricity use for all homes in the RECS sample from simulations (blue diamonds) and from RECS (pink line). The Kolmogorov-Smirnov quality of this comparison is Q_{KS} = 0.081, indicating that we can say with approximately 92% certainty that the two samples are drawn from different distributions.

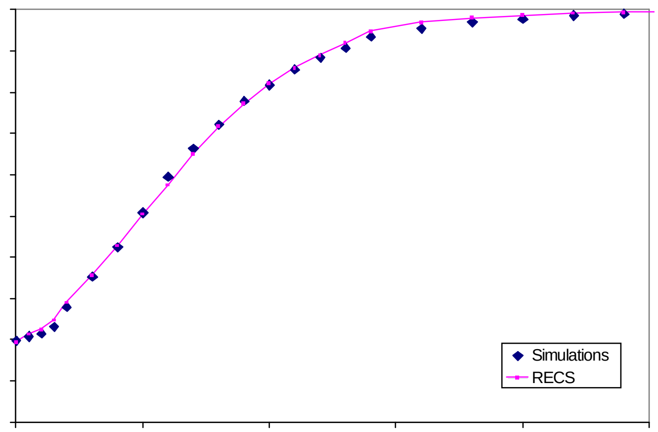

Figure 5.3. Cumulative distributions of fossil fuel use for all homes in the RECS sample from simulations (blue diamonds) and from RECS (pink line). The Kolmogorov-Smirnov quality of this comparison is $Q_{KS} = 0.456$, indicating that we can say with only 54% certainty that the two samples are drawn from different distributions.

Table 5.1 lists the Q_{KS} values for each of the subsamples we examined, for both electricity and fuel. Four subsamples have Q_{KS} values that are less than 0.01: fuel use in homes built after 1990, electricity use in homes in the South Atlantic division, homes with heat pumps, and homes in the warmest 1/3 of climates.

Table 5.1. Kolmogorov-Smirnov Test Results for Comparing National and Subsample Simulation Results and Their RECS Equivalents

Subsample	Q_{KS} for Electricity	Q_{KS} for Fuel
All homes	0.0812	0.4562
New England	0.7922	0.0256
Middle Atlantic	0.7609	0.3557
East North Central	0.6016	0.3357
West North Central	0.9909	0.9523
South Atlantic	**0.0045**	1.0000
East South Central	0.4684	1.0000
West South Central	0.2500	0.6800
Mountain	0.9148	0.6862
Pacific	0.0550	0.5884
Smallest 1/3	0.6797	0.0131
Middle 1/3	0.2048	0.9456
Largest 1/3	0.4515	0.0701
Warmest 1/3 Climate	**0.0074**	0.8157
Middle 1/3 Climate	0.6839	0.4982
Coldest 1/3 Climate	0.9811	0.1892
Central AC	0.6467	--
Heat Pump	**0.0000**	--
Window AC	0.6573	--
Electric Baseboard Heat	0.3951	0.9077
Electric Furnace	0.0340	0.1956
Gas Furnace	0.6973	0.7322
Heat Pump	**0.0000**	0.8115
Oil Furnace	0.5044	0.3095
Boiler/Baseboard heater	0.7338	0.0837
1949 or before	0.0117	0.1629
1950 to 1979	0.5235	0.4364
1980 to 1989	0.0181	0.2046
1990 or later	0.0152	**0.0095**

The failure of the simulation tool in these four cases led to closer examination, beginning with the simulation of heat pumps. Figure 5.4 shows the cumulative distribution comparison between our simulations and RECS for the heat pump sample (280 homes). Clearly, our simulations are not accurate and significantly underestimate the energy use of these homes. We compared these homes with the same homes simulated as if they had central air conditioners and gas furnaces and determined that the cooling-side performance was quite similar. The performance of the simulation tool with air-conditioned homes led us to trust these results and focus our attention on the heating side of the heat pump operation. Upon examination of the EnergyPlus algorithms for the heating-side operation of the heat pump, we identified two shortcomings of EnergyPlus that we believe result in this disparity between our simulations and RECS.

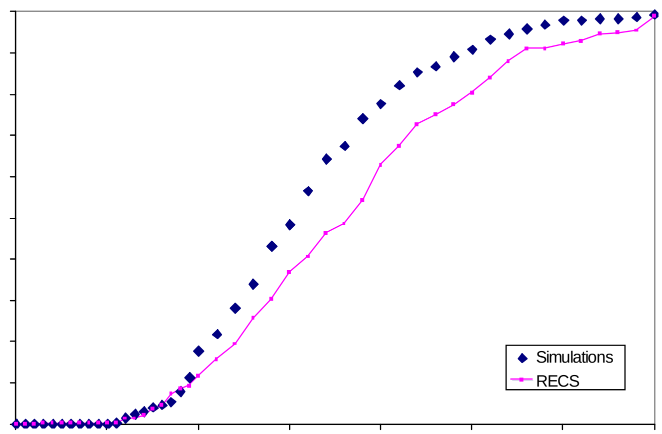

Figure 5.4. Cumulative distributions of electricity use for homes heated and cooled with heat pumps from simulations (blue diamonds) and from RECS (pink line) $Q_{KS}= 2.5\times10^{-5}$.

Both of the EnergyPlus algorithm shortcomings that we identified for heat pumps relate to the use of supplemental resistance heating. The first is that EnergyPlus turns on the supplemental heating coils only when the compressor coils are absolutely incapable of meeting the heating load. As a result, it is typical for simulated homes to use their resistance heating element only when the outdoor temperature is at or below freezing. However, heat pumps in typical operation will begin using their supplemental heating elements when the outdoor temperature is significantly higher, between 35 and 40 degrees. As a result, the EnergyPlus-simulated homes use their resistance heaters less than the equivalent real homes. Resistance heaters use much more energy than heat pumps, so this simulation algorithm results in the underestimating of the heat pump's energy use.

The second shortcoming is that EnergyPlus simulates the additional heating load due to the defrost cycle as simply another load that the compressor coils must meet. (During the defrost cycle, the heat pump usually runs as an air conditioner for a few minutes to warm its outdoor parts.) However, it is common for actual heat pumps to run the supplemental heating coils during the defrost cycle in order to prevent cold air from blowing into the home.

Once we had identified these shortcomings in EnergyPlus, which are outside of our immediate control, we focused our attention on the electricity use of only those homes that do not use heat pumps. Figure 5.5 shows the simulated and measured cumulative electricity use distribution for this set of households, where Q_{KS} = 0.459. Table 5.2 lists the K-S test results for subsamples excluding homes with heat pumps. None of the subsamples have Q_{KS} values below 0.01. Figures 5.6 through 5.9 show the cumulative distributions used to calculate the Q_{KS} values for electricity and fuel for subsamples divided by climate (Figure 5.6 and 5.8) and by home size (Figures 5.7 and 5.9).

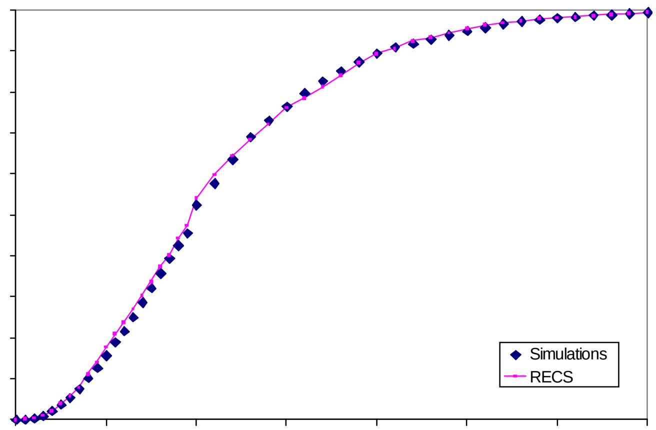

Figure 5.5. Cumulative distributions of electricity use for all non-heat pump homes in the RECS sample from simulations (blue diamonds) and from RECS (pink line). The Kolmogorov-Smirnov quality of this comparison is $Q_{KS} = 0.459$.

Table 5.2. Kolmogorov-Smirnov Test Results for Electricity Use Comparing RECS and Simulated Homes without Heat Pumps.

Subsample	**Q_{KS} for Electricity**
All homes *w/out heat pumps*	0.4588
New England	0.7922
Middle Atlantic	0.7441
East North Central	0.6614
West North Central	0.9968
South Atlantic	0.6358
East South Central	0.5440
West South Central	0.3066
Mountain	0.8976
Pacific	0.0310
Smallest 1/3	0.7214
Middle 1/3	0.3863
Largest 1/3	0.1866
Warmest 1/3 Climate	0.1493
Middle 1/3 Climate	0.9563
Coldest 1/3 Climate	0.9783
Central AC	0.6467
Window AC	0.6573
Electric Baseboard Heat	0.3951
Electric Furnace	0.0340
Gas Furnace	0.6973
Oil Furnace	0.5044
Boiler/Baseboard heater	0.7338
1949 or before	0.0148
1950 to 1979	0.4263
1980 to 1989	0.2805
1990 or later	0.2681

Once we had removed heat pump households from the subsample examination, the only remaining subsample with a Q_{KS} value below 0.01 is the one that includes the fuel use of homes built in 1990 or later, which has a Q_{KS} of 0.0095. While this value is close to 0.01, we believe this subsample deserves further exploration. The prototypical insulation values used for homes built before 1990 are based on analysis of national survey results (primarily RECS surveys conducted in the early 1980s), conducted by Ritchard et al.[2] and Huang et al[5]. However, our estimated levels of insulation for homes built in 1990 or later are based only on the work of Huang et al. We believe that these values are estimates and are not based on survey data. RECS 2005 did not survey the levels of insulation in homes, so we cannot turn there for more recent data. Based on our simulation work, we expect that surveys would show that homes built in 1990 or later have less insulation than Huang et al. estimated and less insulation than our simulated prototypes. We cannot, however, rigorously derive what the insulation values must be from the simulations and RECS alone.

With a calibrated model, including miscellaneous uses, we can simulate our national single-family home samples and derive the end-use energy breakdown by region. Table 5.3 shows the fraction of electricity and gas used within each census division for each of the listed end uses. Note that these values average over the presence or absence of particular heating or cooling technologies. For example, homes in New England that heat with electricity use far more than 0.8% of their total electricity to do so, but they are a small fraction of all households in that region.

Table 5.3. End-Use Electricity and Fuel Breakdown for Simulated Homes by Census Division

Division	Electricity Avg. Use (kWh)	Heat (%)	Cool (%)	Fan (%)	Light (%)	Other (%)	Fuel Avg. Use (MMBTU)	Heat (%)	Other (%)
1	9,006	0.8	17.7	3.3	21.0	57.2	117.0	70.9	29.1
2	10,776	6.3	24.6	4.9	18.0	46.3	102.3	67.3	32.7
3	11,364	7.0	25.9	6.7	16.4	44.0	100.1	67.3	32.7
4	12,636	9.2	31.0	6.6	14.7	38.5	80.3	57.0	43.0
5	15,689	10.7	28.6	5.2	12.6	43.0	31.8	47.6	52.4
6	15,330	13.4	28.9	5.6	11.7	40.4	38.9	50.9	49.1
7	14,508	8.0	37.7	6.0	11.6	36.7	43.5	31.6	68.4
8	11,053	7.4	26.9	5.3	16.1	44.4	64.0	43.7	56.3
9	10,104	8.8	18.0	3.6	17.6	52.1	55.2	36.9	63.1
National	**12,574**	**8.7**	**27.5**	**5.4**	**14.7**	**43.6**	**66.4**	**56.1**	**43.9**

a) b) c)

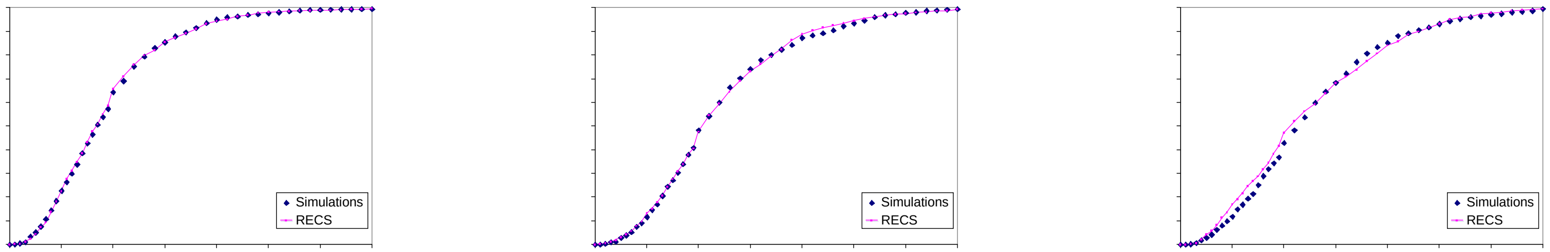

Figure 5.6. Cumulative distributions of electricity use for non-heat pump homes from simulations (blue diamonds) and from RECS (pink lines) in the a) coldest 1/3 of homes by climate (Q_{KS} = 0.978) b) middle 1/3 of homes by climate (Q_{KS} = 0.956) and c) warmest 1/3 of homes by climate (Q_{KS} = 0.149).

a) b) c)

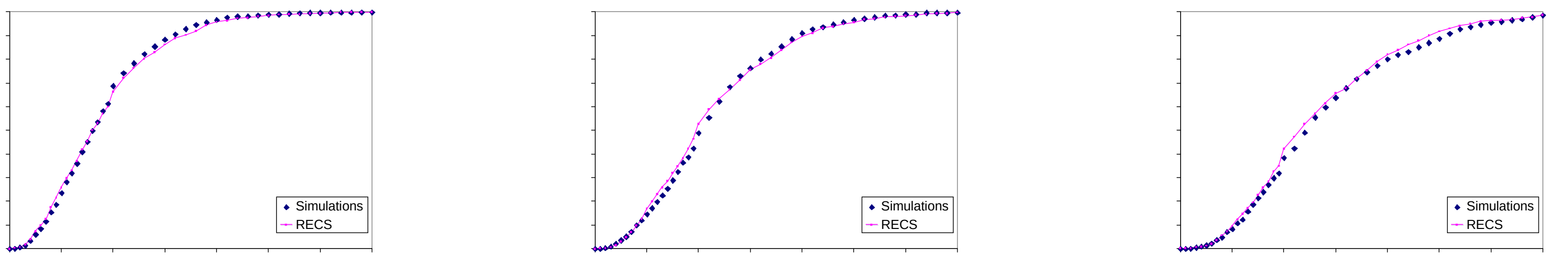

Figure 5.7. Cumulative distributions of electricity use for non-heat pump homes from simulations (blue diamonds) and from RECS (pink lines) in the in the a) smallest 1/3 of homes (Q_{KS} = 0.721) b) middle-sized 1/3 of homes (Q_{KS} = 0.386) and c) largest 1/3 of homes (Q_{KS} = 0.187).

a) b) c)

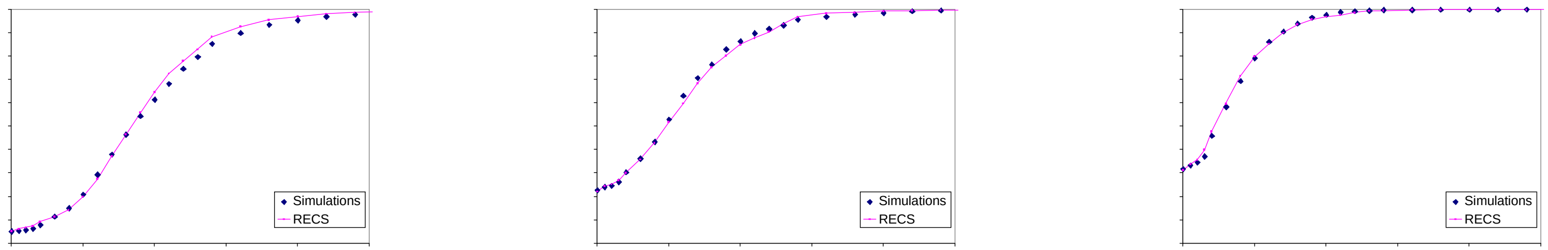

Figure 5.8. Cumulative distributions of fossil fuel use from simulations (blue diamonds) and from RECS (pink lines) in the a) coldest 1/3 of homes by climate (Q_{KS} = 0.189) b) middle 1/3 of homes by climate (Q_{KS} = 0.498) and c) warmest 1/3 of homes by climate (Q_{KS} = 0.816).

a) b) c)

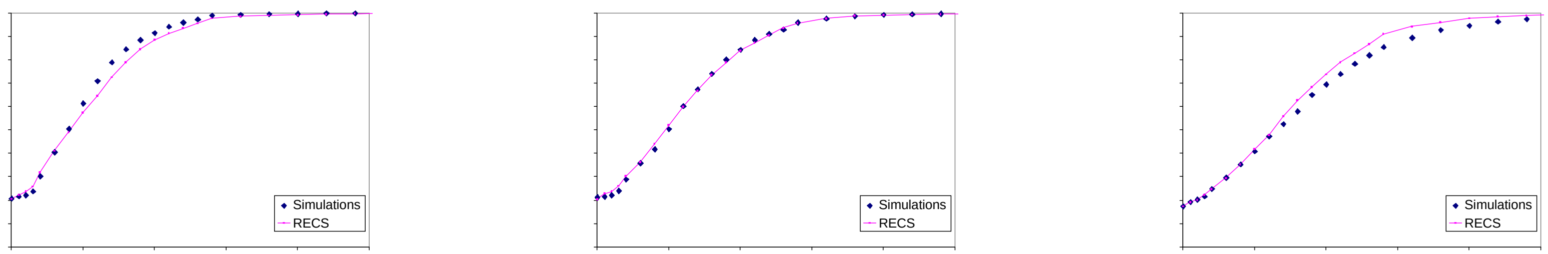

Figure 5.9. Cumulative distributions of fossil fuel use from simulations (blue diamonds) and from RECS (pink lines) in the a) smallest 1/3 of homes (Q_{KS} = 0.013) b) middle-sized 1/3 of homes (Q_{KS} = 0.946) and c) largest 1/3 of homes (Q_{KS} = 0.070).

6. Heat Replacement

The "heat replacement effect" refers to the interaction between appliance efficiency and home heating and cooling. In cool temperatures, inefficient appliances, which emit waste heat into the living space, reduce the load on heating systems, while the load on air conditioning systems is increased during warm weather. This effect has potential impacts on energy savings estimates from appliance efficiency. For example, replacing incandescent lights with fluorescent ones reduces lighting energy significantly, while increasing winter heating energy demand and reducing summer cooling demand. We expect that in cool climates (where heating dominates), appliance efficiency measures result in less overall savings than an appliance-only analysis would indicate, while the opposite is true in warm (cooling-dominated) climates. Appliance efficiency should also lead to some amount of fuel switching, where electric waste heat is replaced by fossil fuel heat. For example, a more efficient furnace fan may result in higher natural gas use.

The heat replacement effect impacts the energy savings projections from appliance efficiency programs, such as mandatory standards. As a result, it has been the subject of analysis by standards-setting agencies. The United Kingdom's Market Transformation Programme (MTP) published a set of simulation-based estimates of the effect in 1999[20]. The magnitude of the effect in these estimates is generally larger than our estimates presented below. The MTP published a revised analysis in 2010[21] in which they rejected a simulation-based approach as unrealistic for many reasons; the potential shortcomings of simulation results are discussed below. Instead, MTP developed an approach based on the coincident timing of waste heat generated from appliances with heating demand. MTP applied factors to account for the distances and heat barriers within homes; the derivation of these factors is not presented. A more complex home simulation model could be used, in future, to evaluate the validity of these factors. MTP's new estimates (for cold climates such as the United Kingdom) are smaller than those presented here by an amount consistent with the factors they present for the distance and heat barrier effects. MTP does not present a methodology for estimating the variability in the heat replacement effect by home size, climate, heating system efficiency, or any other factor. Their approach, along with the magnitude of their factors, is consistent with our conclusion that the factors we derived from our research, and present in this report, should be treated as the upper bound of potential heat replacement effects. The Canada Mortgage and Housing Corporation also examined the heat replacement effect for lighting through a simulation approach[22], and derived values similar to those presented here (although their impact results are presented in the form of cost savings, rather than energy savings).

It is difficult to calculate the heat replacement effect in a given home, because it depends on many factors. These include the level of home insulation and leakage (including the placement and characteristics of the windows), the efficiency of the home's heating and cooling systems, and the degree of temperature homogeneity within the living space. For example, an efficient lighting replacement in a room with an alwaysclosed door would have very little impact on the temperature at the location of the thermostat in a different part of the house. As a result, it would change the comfort level in the room, but not the heating or cooling energy expended for the house as a whole.

Our simulations do not attempt to take the fine granularity of these home details into account, and we believe that, as a result, we overestimate the heat replacement effect. Our simple one-homogeneous-space-per-floor prototypical houses should show more and stronger interaction between appliances and the HVAC system than real homes show.

We evaluated the heat replacement effect in our simulations through two different scenarios. In each scenario, we replaced a single type appliance within each home with an appliance using a different amount of energy. For the first scenario, we replaced the lighting mix in each home (40% fluorescent in the base case) with 100% fluorescent lighting, while maintaining the same level of light output. This reduced the lighting energy demand by approximately 42%. In the second scenario, we replaced the baseline refrigerator with a slightly larger appliance that used about 5% more energy.

In each case, we compared the change in total electricity and fuel demand to the change in appliance energy use. We expected the whole-house electricity use to change by more than the appliance-only use because of the change in air conditioning load, and the whole-house fuel use to change in the opposite direction due to changes in the heating load. The differences between the lighting and refrigeration scenarios are twofold. First, the mixtures of latent and sensible heat loads generated by the appliances are different. Second, the simulated refrigerator energy use is related to the ambient temperature of its operating environment, while lighting is not, so there is an additional correlation between refrigerator energy use and interior climate (and therefore between refrigerator energy use and the heating and cooling loads on the HVAC system).

Table 6.1 shows the results of our heat replacement simulations, for both the full national sample and for subsamples divided by heating degree days (HDD65). The results are presented as multiplicative factors which would adjust home energy use by the product of the factor and the energy savings from appliance efficiency. For example, in the warmest climates (0 to 1000 HDD65), the electricity factor for lighting is 1.16, while the gas factor is -0.04. This means that, on average, if lighting energy is reduced by 100 kWh per year, then total home electricity use would go down by 116 kWh, while fuel use would increase by the equivalent of 4 kWh of site energy. Recall that the simple nature of our home interior simulations leads us to conclude that the heat replacement effect that we calculated is greater than that which would be experienced in either real homes or by using a more complete simulation.

Assessing the overall impact of the heat replacement effect on national energy use (or on a home’s total energy use) would require combining the impacts on electricity and fuel usage. The “primary energy factor” takes into account the national average site-to-source conversion factor, which accounts for the efficiency of electricity generation and transmission, and can be used to combine electricity and fuel usages into a single measure. (Energy savings from national appliance efficiency programs, such as mandatory standards, are often expressed in primary energy units.) Applying primary energy factors to our results could help account for heat replacement, with the understanding that the factors presented here are likely to be further from unity than more realistic models would project.

It is important to note that individual homes may have heat replacement factors that differ greatly from these averages. One advantage of a simulation approach for estimating the heat replacement effect is the direct measurement of the variation of the heat replacement effect from home to home. For example, across the full sample the lighting factor for electricity varies from 0.25 to 2.0, while the lighting factor for fuel varies from -1.74 to 0. This wide variation results from different home heating and cooling equipment, including the lack thereof, different levels of home insulation, and the wide variation in climate within the United States.

Table 6.1. Heat Replacement Factors for Lighting and Refrigerators

	Lighting Factors			**Refrigerator Factors**		
Subsample by HDD65	**Electricity**	**Fuel**	**Primary Energy**	**Electricity**	**Fuel**	**Primary Energy**
0 to 1000	1.16	-0.04	1.153	1.23	-0.04	1.220
1000 to 2000	1.09	-0.38	0.965	1.14	-0.37	1.020
2000 to 3000	1.09	-0.38	0.970	1.13	-0.38	1.015
3000 to 4000	1.06	-0.38	0.939	1.10	-0.36	0.987
4000 to 5000	1.07	-0.40	0.944	1.12	-0.37	0.998
5000 to 6000	1.08	-0.39	0.953	1.13	-0.38	1.008
6000 to 7000	1.08	-0.40	0.951	1.13	-0.38	1.006
7000 to 8000	1.08	-0.43	0.941	1.12	-0.41	0.996
8000 and above	1.06	-0.41	0.927	1.08	-0.42	0.946
National average	**1.07**	**-0.40**	**0.946**	**1.12**	**-0.38**	**0.999**

7. Energy Impacts of Policies

The simulation tool described in this report could be used by policymakers to evaluate the potential energy savings resulting from policies that target the home building envelope or energy-using appliances within the home, such as HVAC or lighting systems. We examined several trial cases of such policy investigations to demonstrate this application. Each case takes the form of a single change in every simulated home. We examined the case of "overnight miracles" in which the changes were implemented on all homes in the country at once. The changes examined include:

- replacement of all home lighting with fluorescent lights,
- upgrade of central HVAC systems to efficient multi-speed systems,
- increasing all home insulation to the maximum level seen in any of the prototype homes,
- reducing leakage to 2/3 of the level seen in any of the prototypes,
- combining the insulation increase and leakage reduction,
- raising summer thermostats by 1 degree, and
- lowering winter thermostats by 1 degree.

For each imposed change, we evaluated the resulting national energy savings for electricity, fossil fuel, and a combination of these two weighted to represent primary energy, which accounts for losses in electricity generation and transmission. We also evaluated the regional differences in the impact of these changes by comparing the energy savings, on a percentage basis, in each of the nine census divisions.

7.1 Baseline Energy Use

The 3,418 simulated single-family homes, weighted by the factors provided by RECS, use a total of 1,089 TWh of electricity and 5.75 quadrillion Btus (quads) of fuel, mostly natural gas. We used the average “site-to-source” factor for the year 2005 from the 2008 Annual Energy Outlook[23], 3.18, to convert the end-use of electricity (in Btus) into Btus of primary energy, and assumed a “site-to-source” factor of 1.0 for fuel. Using this conversion, energy consumption from single-family simulated homes totals 17.57 quads, of which 11.82 quads is from electricity. The total energy use calculated by our simulation tool is within 2% of the energy use reported by RECS for the same set of households.

Table 7.1 shows the regional and national electricity and fuel consumption, as well as the combined primary energy consumption. (Note that the site-to-source factor we used to calculate the primary energy here and throughout this section is a national average. In reality, different regions have different fuel mixes and therefore have different relationships between electricity use and primary energy.)

Table 7.1. Total Energy Consumption by Single-Family Homes in U.S. Census Divisions

Division	**Electricity (TWh)**	**Fuel (quads)**	**Primary Energy (quads)**
New England	32	0.42	0.77
Middle Atlantic	111	1.06	2.27
East North Central	165	1.45	3.24
West North Central	81	0.52	1.40
South Atlantic	263	0.53	3.39
East South Central	94	0.24	1.27
West South Central	145	0.44	2.01
Mountain	73	0.42	1.22
Pacific	123	0.67	2.01
National	**1089**	**5.75**	**17.57**

7.2 Lighting

The baseline simulated homes have a mixture of incandescent and fluorescent lighting, with 40% of the light output coming from fluorescent lights. We modeled the same homes with 100% fluorescent lighting, which produces the same amount of light with less waste heat. As expected, electricity use decreased significantly, due to both the lighting itself and the reduction in air conditioning demand, while fuel use increased as a result of the heat replacement effect. On a national basis, electricity consumption fell 6.8%, to 1,015 TWh, while fuel consumption rose 1.4% to 5.83 quads. The total primary energy demand from single-family homes fell from 17.57 to 16.85 quads, a decline of

4.1%. As Table 7.2 shows, the electricity savings, fuel use, and primary energy impact vary regionally.

Table 7.2. Percentage Impact on Regional Energy Demand from a Replacement of All Single-Family Lighting by Fluorescent Lights (From a 40% Baseline)

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	-9.4%	1.7%	-3.3%
Middle Atlantic	-8.2%	1.6%	-3.6%
East North Central	-7.6%	1.4%	-3.6%
West North Central	-6.9%	1.4%	-3.8%
South Atlantic	-5.9%	1.4%	-4.7%
East South Central	-5.3%	1.4%	-4.0%
West South Central	-5.6%	0.9%	-4.2%
Mountain	-7.4%	1.3%	-4.4%
Pacific	-7.7%	1.4%	-4.7%
National	**-6.8%**	**1.4%**	**-4.1%**

7.3 HVAC Appliance Efficiency

In this policy case, we examined a fictitious case in which every single-family household replaced central air conditioners and heaters with highly efficient multi-speed systems, while making no other changes to their homes. In particular, we modeled an increase in central air conditioner and heat pump cooling efficiency to SEER 16, a heat pump heating efficiency increase to HSPF 10, and a gas and oil furnace efficiency increase to an AFUE of 92. (Electric resistance furnaces maintain 100% efficiency.) The furnace fan uses an ECM with a constant-torque control algorithm. HVAC equipment other than central systems, such as window air conditioners and baseboard heaters, was left unchanged.

The simulations leading to this result were completed as a separate run from the simulations for the other policy cases presented in this section. As a result, the baseline energy use is slightly different: 1,097 TWh of electricity and 5.71 quads of fuel, for a total primary energy use of 16.71 quads. In the high-efficiency HVAC case considered, electricity use fell 11.8% to 969 TWh, fuel use fell 9.1% to 5.19 quads, and primary energy fell 10.9% to 14.89 quads.

We also considered a policy case in which households replaced their existing central HVAC systems with systems that approximately meet the current minimum federal efficiency standards (SEER 13 and AFUE 80). If a household in the base case owned a system that exceeded this standard, it was downgraded to the minimal efficiency; this is the case for fewer than 20% of households. Under this scenario, electricity use was 4.5% below the baseline case (1,048 TWh), fuel use was 4.4% below the baseline case (5.46 quads), and primary energy use was 4.5% below the baseline (15.96 quads).

HVAC system efficiency has dramatically different impacts in different climate zones. Table 7.3 shows the percentage impact of these two HVAC-upgrade scenarios on electricity, fuel, and primary energy in the nine census divisions.

Table 7.3. Percentage Impact on Regional Single-Family Home Energy Demand from Increased HVAC System Efficiency

	SEER 13 / AFUE 80			SEER 16 / AFUE 92 / ECM		
Division	**Elect.**	**Fuel**	**Primary Energy**	**Elect.**	**Fuel**	**Primary Energy**
New England	-1.4%	-8.6%	-5.3%	-4.0%	-11.4%	-8.0%
Middle Atlantic	-3.2%	-4.4%	-3.8%	-8.5%	-8.0%	-8.2%
East North Central	-4.4%	-5.0%	-4.6%	-11.6%	-11.8%	-11.7%
West North Central	-5.3%	-3.3%	-4.6%	-13.8%	-9.5%	-12.3%
South Atlantic	-4.7%	-4.1%	-4.6%	-12.8%	-8.3%	-12.1%
East South Central	-4.9%	-3.9%	-4.7%	-12.6%	-9.2%	-12.0%
West South Central	-6.3%	-2.2%	-5.5%	-15.2%	-5.5%	-13.2%
Mountain	-4.1%	-4.0%	-4.1%	-11.5%	-8.5%	-10.5%
Pacific	-3.6%	-2.9%	-3.3%	-8.6%	-6.6%	-7.9%
National	**-4.5%**	**-4.4%**	**-4.5%**	**-11.8%**	**-9.1%**	**-10.9%**

7.4 Building Envelope Improvements

We examined three "overnight" improvements in building envelopes. The first was to increase the level of insulation to the maximum seen in any of the detached-home prototypes: wall insulation with an R-value of 19, ceilings with R-36 insulation, and floors with R-19. (Some mobile homes have floor insulation greater than R-19; these homes were left unchanged.) These improvements reduce electricity consumption to 1,040 TWh (-4.5%) and fuel to 4.51 quads (a reduction of 21.5%). Table 6.4 shows the regional and national results in percentage terms. The Middle Atlantic division experiences the greatest percentage reduction in fuel use, while the East South Central sees the largest percentage impact on electricity consumption.

Table 7.4. Percentage Impact on Regional Single-Family Home Energy Demand from Increased Insulation

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	-1.2%	-19.9%	-11.4%
Middle Atlantic	-3.3%	-28.0%	-14.8%
East North Central	-3.3%	-22.3%	-11.8%
West North Central	-3.8%	-17.2%	-8.7%
South Atlantic	-5.3%	-21.3%	-7.8%
East South Central	-6.9%	-24.0%	-10.2%
West South Central	-4.6%	-13.9%	-6.6%
Mountain	-4.9%	-18.2%	-9.6%
Pacific	-4.3%	-20.4%	-9.7%
National	**-4.5%**	**-21.5%**	**-10.1%**

The second building envelope improvement we examined was reduced air leakage. For this case, we changed the specific leakage area[‡‡] of each house to 0.0002.

[‡‡] Specific leakage area (or SLA) is an estimate of a home's leakage area under typical conditions, in square inches, divided by the conditioned floor area of the home, in square feet.

(The baseline ranges between 0.0003 and 0.001, which depended on the RECS survey response regarding the presence of drafts in the home.) On a national level, reduced leakage reduces electricity demand by 2.5% to 1,061 TWh and fuel demand by 13.9% to 4.95 quads. Table 7.5 shows the regional and national impacts in percentage terms.

Table 7.5. Percentage Impact on Regional Single-Family Home Energy Demand from Reduced Air Leakage

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	0.2%	-20.7%	-11.2%
Middle Atlantic	-1.6%	-16.9%	-8.8%
East North Central	-2.1%	-17.0%	-8.7%
West North Central	-3.0%	-13.3%	-6.8%
South Atlantic	-3.5%	-11.2%	-4.7%
East South Central	-4.2%	-9.7%	-5.2%
West South Central	-3.8%	-7.5%	-4.6%
Mountain	-1.5%	-11.7%	-5.1%
Pacific	-0.3%	-8.3%	-3.0%
National	**-2.5%**	**-13.9%**	**-6.3%**

Finally, we examined the combination of increased insulation and reduced air leakage. Combining the two building envelope improvements resulted in electricity consumption reduction of 6.5% to 1,018 TWh, while fuel consumption falls 34.5% to 3.76 quads. Note that a building simulation tool can capture the interaction effects between efficiency measures, and the savings for the two individual actions do not add up to the savings for the combined actions. Table 7.6 shows the regional and national impacts in percentage terms.

Table 7.6. Percentage Impact on Regional Single-Family Home Energy Demand from Both Increased Insulation and Reduced Air Leakage

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	-0.6%	-39.6%	-21.9%
Middle Atlantic	-4.4%	-43.7%	-22.7%
East North Central	-4.8%	-38.8%	-20.0%
West North Central	-6.3%	-29.9%	-15.0%
South Atlantic	-8.3%	-31.4%	-11.9%
East South Central	-10.6%	-32.9%	-14.8%
West South Central	-7.9%	-20.6%	-10.7%
Mountain	-6.1%	-28.8%	-14.0%
Pacific	-3.6%	-26.8%	-11.4%
National	**-6.5%**	**-34.5%**	**-15.6%**

7.5 Changing Thermostat Settings

The final change we examined in our sample of simulated homes was to change the thermostat settings. In particular, we calculated the national energy savings under two scenarios: 1) every household lowers their thermostat setting by 1 degree Fahrenheit during the heating season, and 2) every household raises their thermostat setting by 1 degree Fahrenheit during the cooling season. The weighted average heating-season thermostat settings reported by single-family homes in RECS are 70.7 degrees during the day and 68.9 degrees at night. During the cooling season, the averages are 76.5 degrees during both day and night. (For the small number of RECS households that do not report their thermostat settings, we have assumed 80 degrees in the cooling season and 72 degrees in the heating season.) We find that lowering the winter thermostat reduces electricity demand by 1% and fuel demand by 3.8%. Increasing the summer thermostat reduces electricity consumption by 2.1% and fuel consumption by 0.1%. (No homes are cooled by gas, so this fuel impact is probably a result of reduced water heating energy use.) Tables 7.7 and 7.8 show the regional and national impacts of this behavior change in percentage terms.

Table 7.7. Percentage Impact on Regional Single-Family Home Energy Demand from Lowering Winter Thermostats by 1 Degree

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	-0.4%	-4.3%	-2.6%
Middle Atlantic	-0.6%	-4.1%	-2.3%
East North Central	-0.7%	-3.7%	-2.0%
West North Central	-0.9%	-3.6%	-1.9%
South Atlantic	-1.3%	-3.7%	-1.7%
East South Central	-1.4%	-3.9%	-1.9%
West South Central	-1.1%	-3.1%	-1.5%
Mountain	-0.9%	-3.4%	-1.7%
Pacific	-1.1%	-4.0%	-2.1%
National	**-1.0%**	**-3.8%**	**-1.9%**

Table 7.8. Percentage Impact on Regional Single-Family Home Energy Demand from Raising Summer Thermostats by 1 Degree

Division	**Electricity**	**Fuel**	**Primary Energy**
New England	-1.4%	-0.1%	-0.7%
Middle Atlantic	-1.8%	-0.1%	-1.0%
East North Central	-1.9%	-0.1%	-1.1%
West North Central	-2.1%	-0.2%	-1.4%
South Atlantic	-2.3%	-0.2%	-2.0%
East South Central	-2.1%	-0.3%	-1.8%
West South Central	-2.8%	-0.3%	-2.2%
Mountain	-1.8%	-0.1%	-1.2%
Pacific	-1.5%	-0.1%	-1.1%
National	**-2.1%**	**-0.1%**	**-1.4%**

8. Conclusions and Future Work

This report has summarized our progress toward construction of a simulation tool capable of simulating a nationally representative sample of single-family homes. We have demonstrated that the tool can produce a sample of annual home energy use data that is statistically indistinguishable from the equivalent portion of RECS, a large national sample of metered home energy use. The energy-use data generated by the simulation tool successfully reproduce the distributions of home energy use for almost all the examined subsets, including subsets defined by HVAC equipment type, geographic location, climate, home size, and home age.

We also demonstrated the utility of this simulation tool, which is capable of generating a national energy use sample, for undertaking simulated experiments of potential interest to policymakers. First, we examined the heat replacement effect and evaluated the extent to which this effect might skew the results of appliance energy savings analyses. We conclude that this effect is not likely to skew national energy savings estimates by more than 5%, although its impact does show significant regional disparity.

Second, we examined a set of “overnight” transformations of home construction and equipment to measure the resulting potential energy savings. Primary energy savings from dramatic increases in home insulation, combined with much more air-tight construction, could reduce home fuel consumption by more than one third, electricity consumption by over 6%, and primary energy demand by more than 15%. Appliance efficiency also has dramatic potential to produce energy savings, as indicated by a savings of 4.1% of primary energy from the transition to fluorescent lighting, which will take place over the next few years as national efficiency standards come into force. The mass adoption of multi-speed, SEER 16 air conditioners, combined with 92 AFUE furnaces, could reduce single-family primary energy consumption by almost 11% below base-case 2005 levels.

Behavior can also have a significant impact on home energy use, without new equipment or home retrofits. We measured the energy savings resulting from energy-conserving thermostat settings and found primary energy savings of 1.9% for a degree lower winter thermostat setting and 1.4% savings from homes a degree warmer in the summer.

As we proceed to develop this tool further, we plan to evaluate its performance on other metrics and to improve its ability to simulate homes and equipment that are not accurately captured now. For example, we plan to work with the EnergyPlus community to capture realistically the behavior of heat pump systems, especially the use of the supplemental electric resistance heating element. We can also add the ability to simulate heat pump systems with natural gas supplemental heating systems.

There are four larger projects that, if undertaken, would significantly increase the value of this simulation tool and increase the range of policy questions that the tool can accurately address. The first project would be to compare the simulated energy use data with the monthly RECS bill data. We do not expect good agreement on a month-to-month basis, because the RECS houses faced the actual weather for the year 2005 while our simulated homes faced typical meteorological years. However, a comparison on a quarterly basis would allow us to better evaluate, and distinguish between, a policy’s impact on a home’s performance during the heating and cooling seasons, rather than using the variation in the national climate as our only controllable temperature variability.

The second project would be to better capture the variation in behavior between households. Currently, the tool uses only single schedules for thermostat settings, lighting, equipment, and occupancy, with the same schedules year round. A more comprehensive variability analysis would have monthly variation in lighting and occupancy schedules, and a range of possible schedules for each household, and for each simulated load or control parameter. For example, many homes are occupied by families with school-aged children, retirees, or by people who work night shifts. The lighting, occupancy, and miscellaneous electric and gas usage schedules in these homes should be different. While we believe we have captured the average behavior well, along with the breadth of the distribution, we are not taking correlations into account. This analysis could also take the RECS survey data regarding the number of electric appliances in the home into account when assigning miscellaneous loads and capture the presence or absence of second refrigerators, freezers, and other white goods. The scale of the heat replacement effect depends on the coincidence of loads and heating or cooling demand, so variation and more accurate modeling of these schedules would have an impact on estimates of this effect.

One of the major shortcomings of this research is the lack of variability in the insulation levels for different homes of the same vintage and general region of the country. This is related to the limited availability of data on the regional and temporal variability of insulation levels in general, particularly for homes constructed in the last 20 years. Ritchard et al. and Huang et al. used the early RECS surveys to develop their prototypical insulation values, but more recent RECS surveys have not included enough detail to evaluate the R-values for each surveyed home. A representative national survey, such as RECS or the U.S. Census's American Housing Survey, that included this information would be invaluable. It is possible that data on recent construction from the home construction industry could improve the characterization of recent construction and its regional variation. If RECS included this data, our simulation tool could model each house much more accurately, but any national survey that included the regional or climatic location of each sampled home could be easily applied to the RECS sample to develop a more complete model.

A related project would be to extend the general framework of this simulation tool to capture multifamily housing units, such as apartment buildings. A survey of the sort described in the previous paragraph might collect the data necessary to build these models in a way that captures regional variation in construction materials, insulation, and HVAC systems.

We hope to continue to develop and improve the tool as outlined here. Even before the anticipated improvements have been completed, the simulation tool presented in this report can address important policy questions and provide insight to policymakers regarding the relative impacts of different energy efficiency measures.

Appendix A: Insulation for Construction Locations

Table A.1. Insulation for Single-Family Detached Houses

City	Era	Not Retrofit			Retrofit		
		Wall	Roof	Floor	Wall	Roof	Floor
Albuquerque	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	19			
	After 1989	13	34	19			
Atlanta	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	26	0			
	After 1989	11	23	0			
Boston	Before 1950	0	0	0	7	22	0
	1950-1979	0	22	0	7	22	0
	1980-1989	13	23	0			
	After 1989	13	31	0			
Chicago	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	19	0
	1980-1989	13	22	0			
	After 1989	13	29	0			
Denver	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	0			
	After 1989	13	34	0			
Fort Worth	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	19	0
	1980-1989	11	22	0			
	After 1989	11	26	0			
Kansas City	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	22	0
	1980-1989	19	24	0			
	After 1989	19	30	0			
Los Angeles	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	21	0			
	After 1989	11	24	0			
Miami	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	24	0			
	After 1989	11	22	0			
Minneapolis	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	22	0
	1980-1989	19	24	0			
	After 1989	19	30	0			
New Orleans	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	22	0			
	After 1989	11	26	0			
New York	Before 1950	0	0	0	7	7	0

	1950-1979	0	7	0	7	11	0
	1980-1989	13	23	19			
	After 1989	13	30	19			
Phoenix	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	0			
	After 1989	13	34	0			
San Francisco	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	21	0			
	After 1989	11	24	0			
Seattle	Before 1950	0	0	0	7	7	0
	1950-1979	0	11	0	7	19	0
	1980-1989	11	21	19			
	After 1989	11	24	19			
Washington, DC	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	24	19			
	After 1989	11	22	19			

Table A.2. Insulation for Single-Family Attached Houses

		Not Retrofit			Retrofit		
City	**Construction Era**	**Wall**	**Roof**	**Floor**	**Wall**	**Roof**	**Floor**
Albuquerque	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	19			
	After 1989	13	34	19			
Atlanta	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	14	0			
	After 1989	11	23	19			
Boston	Before 1950	0	0	0	7	22	0
	1950-1979	0	22	0	7	22	0
	1980-1989	13	26	0			
	After 1989	13	36	0			
Chicago	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	19	0
	1980-1989	13	22	0			
	After 1989	13	30	0			
Denver	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	0			
	After 1989	13	34	0			
Fort Worth	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	19	0
	1980-1989	11	24	0			
	After 1989	11	22	0			

Kansas City	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	22	0
	1980-1989	19	24	0			
	After 1989	19	36	0			
Los Angeles	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	21	0			
	After 1989	11	23	0			
Miami	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	14	0			
	After 1989	11	16	0			
Minneapolis	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	22	0
	1980-1989	19	24	0			
	After 1989	19	36	0			
New Orleans	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	24	0			
	After 1989	11	22	0			
New York	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	13	27	19			
	After 1989	13	32	19			
Phoenix	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	0	7	11	0
	1980-1989	13	26	0			
	After 1989	13	34	0			
San Francisco	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	21	0			
	After 1989	11	23	0			
Seattle	Before 1950	0	0	0	7	7	0
	1950-1979	0	11	0	7	19	0
	1980-1989	11	21	19			
	After 1989	19	23	19			
Washington DC	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	0	7	11	0
	1980-1989	11	14	19			
	After 1989	11	16	19			

Table A.3. Insulation for Single-Family Manufactured Houses

		Not Retrofit			Retrofit		

City	Construction Era	Wall	Roof	Floor	Wall	Roof	Floor
Albuquerque	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	7	7	11	7
	1980-1989	13	26	17			
	After 1989	13	34	23			
Atlanta	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	26	17			
	After 1989	11	23	15			
Boston	Before 1950	0	0	0	7	22	0
	1950-1979	0	22	15	7	22	15
	1980-1989	13	23	15			
	After 1989	13	31	21			
Chicago	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	7	7	19	7
	1980-1989	13	22	15			
	After 1989	13	29	19			
Denver	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	7	7	11	7
	1980-1989	13	26	17			
	After 1989	13	34	23			
Fort Worth	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	19	5
	1980-1989	11	22	15			
	After 1989	11	26	17			
Kansas City	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	22	5
	1980-1989	19	24	16			
	After 1989	19	30	20			
Los Angeles	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	21	14			
	After 1989	11	24	16			
Miami	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	24	16			
	After 1989	11	22	15			
Minneapolis	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	22	5
	1980-1989	19	24	16			
	After 1989	19	30	20			
New Orleans	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	22	15			

	After 1989	11	26	17			
New York	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	13	23	16			
	After 1989	13	30	20			
Phoenix	Before 1950	0	0	0	7	11	0
	1950-1979	0	11	7	7	11	7
	1980-1989	13	26	17			
	After 1989	13	34	23			
San Francisco	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	21	14			
	After 1989	11	24	16			
Seattle	Before 1950	0	0	0	7	7	0
	1950-1979	0	11	7	7	19	7
	1980-1989	11	21	14			
	After 1989	11	24	16			
Washington DC	Before 1950	0	0	0	7	7	0
	1950-1979	0	7	5	7	11	5
	1980-1989	11	24	16			
	After 1989	11	22	15			

Appendix B. Details of Running EnergyPlus Simulations on Amazon EC2

This appendix describes the detailed process we developed to run EnergyPlus simulations on Amazon EC2, which is a service whereby Amazon can rent its unused computer resources to other users. The process begins by preparing the EnergyPlus input files specific to each house on our local PC. These files mostly consist of EnergyPlus macro variable definitions such as the house size, number of floors, insulation level, wall and foundation construction, and HVAC system parameters. The bulk of the EnergyPlus input files reside on the Amazon EBS volume, as they do not change between simulation runs.

Two other files are prepared along with the EnergyPlus files: HomeWeather.txt and Runparams.txt. HomeWeather.txt consists of one line for each home to be simulated. Each line contains the file name of the home-specific input file and the name of the weather file that corresponds with that home. Scripts on the EC2 machines use this file to prepare process-specific lists of inputs for the EnergyPlus executable. RunParams.txt consists of four lines, each with a single number. The first line contains the number of cores of the Amazon EC2 instances we will be using. This is usually 8 for the High-CPU Extra Large instances, but can also be 2, for the Large instance used for testing. The second line contains the number of Amazon EC2 instances needed for this run. The third lists the number of homes to be simulated (generally less than or equal to 3,418), and the fourth lists the number of variants of each home that will be run. For a simple marginal-impact run, this value would be 2, as we are comparing a base case of each home to a case with a single change. For the full investigation of HVAC impacts (detailed later), this value was 8.

When the local Excel spreadsheet tool is done preparing the EnergyPlus macro input files, as well as the two supplementary files just described, these files are combined and compressed into a ZIP file. At this point, the local machine has done its part, and the focus turns to Amazon EC2. (As explained in section 3, there are two ways to launch an EC2 instance: on-demand or through the Amazon spot market. On-demand instances launch within a minute or so after they are requested and stay running until we request that they stop. Spot requests are bids in the spot market that Amazon runs to auction computing resources.)

The local machine runs a Ruby script, "ec2-master.rb", which coordinates the start and stop of the Amazon EC2 simulation process. This script requests a single instance of the required type of Amazon EC2 virtual machine, uploads the ZIP file, and then starts a Perl script, "master.pl", on that single machine (referred to as the "master" instance). This machine is requested using the on-demand mechanism, regardless of whether the rest of the instances will be requested on-demand or using the spot request process, in order to avoid the delay common with spot requests, which require more user interaction. (The user must approve the connection to the master instance the first time it is made after the instance launches.) The ec2-master.rb script waits for the completion of master.pl on the master instance; at this point the results of the EnergyPlus simulations are ready for download in the form of a single ZIP file for each instance, each of which has been copied to the EBS volume, hosted on the master instance. The ec2-master.rb initiates the download of each of the ZIP files, then terminates.

The process that is coordinated by the scripts on the master instance starts with the master.pl. This script begins its work by unzipping the uploaded EnergyPlus input and parameter files. It prepares various directories and cleans up the results of previous runs. It then reads in the values in RunParams.txt in order to evaluate the number of "slave" instances to launch and the number of homes to assign to each processor core on each instance. It runs the script "distribute_imfs.pl" on the master instance; this script, which is described in more detail below, distributes the IMF files (EnergyPlus macro input files) for each processor core. It then launches the slave instances (if more than one instance was requested) using the launch_instances.rb script. This script coordinates the launch, using either spot or on-demand requests, of the required number of slave instances and records their Amazon instance identifiers in a file where master.pl can read them.

Once all the slave instances are running, master.pl begins a process to initialize and run the simulations on each slave. It first detaches the EBS volume from the master instance then attaches it to the first slave instance. It runs several commands to prepare directories on the slave and runs the "distribute_imfs.pl" script. This script takes as its inputs the parameters in RunParams.txt (describing the total number of simulation runs to be completed) as well as the identification of the machine as number *i* of *n* instances. This information allows it to calculate which homes its instance is responsible for simulating and to divide those homes among the 8 (or 2) processor cores on its machine. Each machine is preconfigured to have eight directories in the home directory of the only user (named "ubuntu"), called "1", "2", etc. Directory 1 contains all the files addressed by the EnergyPlus executable on the first processor core, so distribute_imfs.pl places the input files assigned to that core in directory 1. It also creates HomePairs.txt and HomePairs1.txt. These files are subsets of the uploaded HomeWeatherPairs.txt files. HomePairs.txt includes all of the homes (including each of the variants) and their corresponding weather files. HomePairs1.txt includes only the first version of each home, as it is used for HVAC system sizing purposes only. Each of the marginally different houses examined in additional runs of each house uses the same HVAC system sizing information. Once the input and run-parameter files have been distributed, the master.pl script detaches the EBS volume and begins the "starteplus.pl" script on the slave machine. (More details on this script are provided below). This script is run using "nohup" so that the EnergyPlus simulations are non-blocking and master.pl can proceed to disconnect from this slave entirely, move to the next, and repeat this process. Once all the slaves are running their requisite EnergyPlus simulations, master.pl returns its attention to the master instance. It mounts the EBS volume and runs starteplus.pl for the master machine, without "nohup". This ensures that master.pl continues to run until all of the EnergyPlus simulations are complete. When they are done, master.pl completes and passes control back to the ec2-master.rb script on our local PC, which can download the outputs.

The starteplus.pl script consists of 5 sections. The first four sections each have a similar form, and their purpose is to run the same commands on each of the processor cores on a given instance. Each of these sections begins by launching *n* copies of a given script, one for each of the *n* cores. These scripts are launched using the Perl "fork" formulation, meaning that they are spawned as separate processes that don't force the next process launch to wait until the first is complete. In this way we are able to fully utilize the processing power of the instance. Once the *n* copies of each script are running, starteplus.pl enters a "while" loop, waiting until all of the processes are complete before proceeding to the next section of the script. This way we can ensure that each section is complete before proceeding to the next.

The first section of starteplus.pl runs EnergyPlus using only the homes and weather files described in HomePairs1.txt, with the run_weather EnergyPlus variable set to No. This tells EnergyPlus to run the autosizing simulation, but not to simulate each house for the full year described in the weather file. The next section runs the "process_eio.rb" script. This script examines the .eio files produced by each of the sizing runs. The goal of this script is to implement changes in the HVAC system descriptions in order to make them more realistic. (These changes are described in more detail in section 2 of this report.) Once these new HVAC system parameters are determined, they are fixed in new EnergyPlus input files, which take the place of the file used in the autosizing run in which every relevant input was autosized.

The third section of starteplus.pl does the full annual simulation of every variant of every home, using the annual weather file assigned by HomePairs.txt (with the run_weather EnergyPlus macro variable now set to Yes). This section usually takes the bulk of the time used by the entire simulation process. When this section is complete, a short script called "clean_csv.rb" processes the comma separated value (CSV) outputs from the runs into a more usable and uniform format. These outputs include the hourly energy use and home temperature data. For example, the script combines the heating energy used for the first and second floors of a two-story house into a single column with

8,760 entries, one for each hour of the year, including combining natural gas used for boilers and furnaces or electricity used for heat pumps, furnaces, or electric baseboard heating.

The final section of starteplus.pl cleans up unneeded output files, copies the files we do want, such as the newly cleaned CSV files, to a standard directory, and then compresses these outputs into a single ZIP file for each instance, labeled by instance (ep_outputs4.zip for the fourth slave, for example). On slave instances, the script uses SCP to copy the ZIP file to the EBS volume attached to the master instance. Once that copy is complete, the slave instance issues the correct command to Amazon to terminate itself. On the master instance, the script simply creates the ZIP file in the correct location. It then waits until all of the slave machines are done; Amazon EC2 allows simple queries to determine whether all of the slave machines have issued their termination commands, implying that they are done and have successfully copied over their output ZIP files. The script creates symbolic links between the ZIP files on the EBS volume and files in the web server's home directory on the master instance. The files may now be downloaded over the Internet, served by the Apache web server running on the master instance. These are the files that the ec2-master.rb file, running on our local PC, downloads at the completion of the simulation runs.

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