Using BEopt (EnergyPlus) with energy audits and surveys to predict actual residential energy usage

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Abstract

Simulations of building energy use can give insights into how energy efficiency retrofits and operational changes can influence a building's total and temporal energy use. However, before those models are used to generate recommendations, it is important to understand how accurately the simulations predict actual energy use. This paper seeks to determine model accuracy by considering 54 homes in Austin, TX that are part of a smart grid demonstration project. Data about the homes were collected with energy audits then converted into energy models using BEopt (version 2.0), a residential building-focused graphical user interface (GUI) front-end for EnergyPlus de-

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veloped by NREL. Actual meter reads (kWh) were compared to simulation results for four cases: 1) energy model output with typical meteorological year (TMY) weather data, 2) output with an actual meteorological year weather (AMY) file created using real weather data from a year during which actual energy use measurements were made, 3) model output with thermostat user behavior data, and 4) output using a simplified home geometry. The purpose of this analysis was to evaluate how well this model, as it is, could be expected to predict energy usage using varying levels of inputs that might be included on an energy audit and survey. Results indicate that the modeling software was able to estimate aggregate annual electrical energy usage within 1% (for groups of homes) but might vary up to 28% (absolute) for an individual home. Using AMY weather data (Case 2) yielded results within 2.4% of measured (aggregate) energy use, while using a TMY3 weather file for Austin yielded results within 9% of (aggregate) actual usage. Using a simplified home geometry did not appreciably change the results of the model or its ability to simulate real usage. Results show that while the model does a reasonable job predicting usage for homes with average usage, the model has trouble predicting usage of homes with low or high consumption, particularly homes below 5 kWh/ft²/year (0.47 kWh/m²/year) of average energy use or above 10 kWh/ft²/year (0.93 kWh/m²/year), likely due to unknowns about the home when BEopt defaults were used.

Keywords: residential buildings, energy audits, measured electricity data, energy models

1. Introduction

In the United States, buildings are responsible for 40.36 Quads (40.36×10^{15} BTU), or about 40% of total primary energy consumption per year, 22.15 Quads or about 22% of which are used in residential buildings [1]. Also, the United States residential sector is responsible for about 20% of United States carbon emissions or about 4% of the world's total [2]. While there are over 130 million residential units in the United States, only 0.1% of all R&D is spent in the residential sector [3]. This lack of R&D means the residential sector represents an underinvested opportunity for energy savings.

Residential structures are unique in form, build, and use. Even tract homes built by the same builder in the same time period can be similar in outward appearance, but vary greatly in terms of efficiency and energy use. Residential air-conditioning systems are particularly disruptive to the electric grid and create significant swings in demand. In Texas, 7.7 million households (both single-family and multi-family units) use approximately 43 TWh of electricity for air-conditioning annually [4] – about 13% of total electricity use in Texas. The percentage of electrical load on the Electric Reliability Council of Texas (ERCOT) electric grid attributed to residential users increases from about 20% in the spring to 48% in the summer of 2010 (400% real increase, 6,139 vs. 30,735 MW in 2010), mostly due to the operation of residential air-conditioning systems [5]. So much heat is removed from buildings by air-conditioners that it can have an impact on the local ambient air temperature in some places [6]. Furthermore climate change might increase building energy use in hot climate zones [7].

Numerous studies have evaluated the energy savings associated with in-

creasing the energy efficiency of the United States residential building stock [8–
22]. Many studies have focused on various aspects of residential buildings
such as heating, ventilation, and air-conditioning (HVAC) equipment, façade,
air tightness, insulation levels, duct leakage, and construction type. Evidence
suggests that there is significant value in continuous energy commissioning
(actually verifying that a building is performing to the prevailing energy
code) and monitoring of buildings [23] and that significant numbers of resi-
dential buildings built to energy codes are non-compliant [24, 25]. Although
many residential efficiency standards exist [26, 27], few studies [13] can es-
timate residential resource consumption and savings for a large, statistically
significant portion of a local residential building stock because of a lack of
data.

Many different building energy simulation models have been developed
over the last 50 years to help users predict specific building performance
characteristics [28]. Recently, residential energy use modeling has become
popular to provide homeowners feedback about their homes’ energy perfor-
mance [29]. One platform for building energy simulation, EnergyPlus was
developed by the US Department of Energy (DOE) and was released in 2001,
with a focus on commercial buildings. Recently, a residential front-end to
EnergyPlus, BEopt (version 2.0 is used in this analysis), was developed by
the National Renewable Energy Laboratory (NREL) to provide easier and
better modeling of residential homes [30]. However, modeling residential
buildings can lead to systematic errors that need to be understood to evalu-
ate the applicability of the model’s results in the real world [29, 31–34]. Many
studies of building energy modeling have small sample sizes [35, 36], focus on

51 benchmarking methodologies [37], work to simplify current models [38], or do
52 not focus on residential buildings. Also, human behavior affects residential
53 energy use [39, 40], and thus more realistic building occupant schedules can
54 lead to more realistic models [41]. Generally speaking, calibration helps the
55 accuracy of models [42], but the information to perform calibration is seldom
56 available.

57 Thus, it is valuable to assess the accuracy of modeling programs. This
58 work seeks to assess the ability of EnergyPlus (via BEopt) to simulate resi-
59 dential energy use in a hot and humid climate by use of 1) a database of resi-
60 dential home energy audits, 2) data from a smart grid demonstration project,
61 and 3) modeling. Understanding how these models predict actual energy us-
62 age in Austin’s hot and humid climate under different design considerations
63 can lead to better simulations and retrofit recommendations [43, 44].

64 **2. Datasets used in this analysis**

65 This analysis considers a group of 54 single-family homes with energy au-
66 dits and metered electricity use data. These datasets were provided by Pecan
67 Street Inc., a smart grid demonstration project that is based in Austin [45],
68 and Austin Energy, the local electric utility. The Pecan Street smart grid
69 demonstration project is administered by a 501(c)(3) non profit organization
70 that has the stated goal to “re-imagine Austin’s energy distribution system
71 in a way that could support and accelerate the installation and management
72 of smarter and cleaner electricity services” [46]. The project collects high-
73 fidelity sub circuit electricity data (1 second or better) from hundreds of
74 homes in Austin, TX and has begun satellite programs in Colorado and Cal-

ifornia. A smaller group of the homes also have water and natural gas data (2 gallon and 1 cubic foot measurements, respectfully) monitored a stored for research. The program also collects yearly surveys of the research participants and has a database of energy audits on most homes in the project. The audits are similar to a citywide program, The Energy Conservation Audit and Disclosure (ECAD) ordinance in Austin, which mandates that homes over 10 years old must have an energy audit before they can be sold [8, 9, 47]. However, the audits used in this analysis contain additional house information, such as areas and locations of windows and ACH50 values [45]. Table 1 summarizes the key audit data fields that were used to build the models.

In addition to the data on residential home characteristics, electricity use data were also retrieved from Pecan Street (hourly whole home electricity use data) and Austin Energy (daily whole home electricity consumption readings). Daily data were available for all homes, while hourly data were only available for a subset of the homes. Also, demographic data about the occupants were also available for this analysis from surveys administered by Pecan Street for each of the 54 single-family homes. In part of our analysis, we also compared the outputs of models that used Typical Meteorological Year (TMY) weather data along with real measured weather data for Austin in 2011, a particularly hot year for Austin. TMY data are weather data files that are curated by NREL and represent a year’s worth of typical weather for a given location citeWilcox2008. The 2011 weather date were obtained through a commercial weather file source [48]. Austin’s weather is characterized as ‘humid subtropical with hot summers and mild winters’ [49]. Table 2 below shows a summary of Austin’s average weather [50].

Table 1: The following characteristics from the 54 homes were utilized for the energy simulations in this analysis, where BTU is a British Thermal Unit, COP is the coefficient of performance ($\text{kW}_{thermal}/\text{kW}_{electric}$) of the air-conditioning systems, AFUE is the annual fuel utilization efficiency of the furnace (the percent of useful heating energy over total energy input), and ACH50 is the air changes per hour in a space when the pressure difference between the space and the ambient is 50 Pa.

Parameter	Unit	Mean	Standard Dev.	Median
Year Built	–	1965	18.3	1964
Conditioned Area	m^2	167.3	85.2	150.4
House Volume	m^3	430.8	253.5	367.7
Window Area	m^2	20.5	12.3	19.2
Attic R Value	$\text{hr}\cdot\text{ft}^2\cdot^\circ\text{F}/\text{BTU}$ [$\text{m}^2\cdot\text{K}/\text{W}$]	23.2 [4.1]	10.9 [1.9]	23 [4.0]
Duct Leakage	%	14.8	9.7	12.6
Duct R Value	$\text{hr}\cdot\text{ft}^2\cdot^\circ\text{F}/\text{BTU}$ [$\text{m}^2\cdot\text{K}/\text{W}$]	4.3 [1.9]	1.9 [0.6]	4.0 [1.8]
AC Capacity	kW	10.8	3.4	10.5
System Efficiency	COP	3	2.3	2.9
Furnace Capacity	kW	19.6	6.3	19.9
Furnace	AFUE	80.3	1.7	80
ACH50	–	11.7	5.2	10.8

Table 2: Summary of Austin, TX monthly average temperatures ($^{\circ}\text{C}$).

Month	High	Low	Mean
Jan	17	5	11
Feb	18	7	13
Mar	22	11	17
Apr	27	15	21
May	31	19	25
Jun	33	22	28
Jul	36	23	29
Aug	36	24	30
Sep	33	21	27
Oct	28	16	22
Nov	22	11	17
Dec	17	6	12

100 **3. Methods**

101 *3.1. Construction of the models.*

102 This analysis was conducted for 54 home energy models for 4 different
103 scenarios (228 total model runs). The main performance criterion in this
104 analysis was a comparison of the model’s predicted yearly electricity use to
105 measured utility and smart metered electricity use. The process for develop-
106 ing the 54 home models for the four scenarios is shown in Figure 1. The home
107 models were constructed using BEopt, a graphic user interface that provides
108 functionality to build a residential home’s geometry and indicate specific fea-
109 tures of each individual home (e.g. home insulation values, duct leakage, AC
110 efficiency, etc). The software can use either the DOE2/TRNSYS [51] or the
111 EnergyPlus simulation engine, and for this analysis, we utilized the Energy-
112 Plus engine because it includes more flexibility in simulations. Furthermore,
113 the program contains three main interface screens to enter information used
114 by the simulation engine to calculate a home’s energy profile: the geometry
115 screen, the options screen (insulation levels, window types, etc.), and the site
116 screen (location, weather files, utility rate structures, etc.).

117 Information on the specific functionality for each screen can be found in
118 prior literature [30]. The program default values were used in cases where
119 the energy audit did not provide specific details of the building (e.g. wall
120 insulation, miscellaneous electric load, floor insulation, refrigerator, cooking
121 range, dishwasher, and lighting information). The variables that were up-
122 dated due to availability of audit data were: building orientation; neighbor
123 spacing; exterior finish; unfinished attic type and insulation; roof material;
124 radiant barrier; window areas; window type; home air leakage; clothes dryer

Figure 1: Flowchart for creating and analyzing the 54 residential homes using BEopt and EnergyPlus.

125 and water heater fuel; central AC and furnace type, efficiency, and size; duct
 126 insulation; and duct leakage.

127 3.2. Scenarios considered for analysis

128 In total, four different model scenarios (Figure 1) were developed to com-
 129 pare the 54 homes in different situations to monitor the effect of different
 130 parameters. The first scenario used TMY3 weather data and the second
 131 scenario used actual Austin 2011 weather data. Although comparing model
 132 output that used TMY3 weather input to actual use data could be considered
 133 an ‘apples to oranges’ comparison, it was included to show a progression of
 134 model outputs. No home properties were changed between these two sce-
 135 narios. The third scenario included thermostat set-point information that
 136 was obtained from the homeowner surveys. This scenario was developed to
 137 observe the effect of thermostat behavior on the model’s overall performance.

138 The fourth scenario simplified the geometry of the homes to test the effect
 139 of geometry on the home electricity use. In total, nine generalized geome-
 140 tries existed (in the original home layouts) before modification for the 54
 141 modeled homes. These geometries are shown in Figure 2. To determine the
 142 extent to which complicated geometries influence electricity consumption,
 143 each complex home geometry was simplified to geometry A while maintain-
 144 ing the other characteristics such as square footage, duct leakage, etc. For
 145 comparison purposes, special attention was given to ensure that the percent
 146 change of the new square footage to the square footage of the original model
 147 remained within 1%.

Figure 2: Nine floor geometries were used to estimate energy consumption of the 54 residential homes for scenarios 1-3. Scenario 4 used only geometry A while keeping other characteristics the same.

148 To observe the effect of the different scenarios, the model output was
 149 compared to actual electricity use data. First, electricity use measured by
 150 the local utility was compared to simulated electricity consumption from the
 151 model over an entire year. Error was calculated for each individual BEopt

152 model by Equation 1:

$$Relative\ Error = \frac{E_{BEopt} - E_{Utility}}{E_{Utility}} \times 100 \quad (1)$$

153 where *relative error* is the percent difference between the BEopt-modeled
154 and utility-measured consumption data, E_{BEopt} is the electricity consump-
155 tion predicted by the BEopt model for one home (kWh), and $E_{Utility}$ is the
156 electricity consumption provided by Austin Energy, the local utility company
157 (kWh).

158 To assess the model’s ability to predict electricity consumption in a com-
159 munity, (in this case, an aggregated relative error for the 54 homes) each
160 model’s electricity consumption in kWh over the entire year was summed
161 and compared with the summation of each home’s utility data in kWh over
162 the entire year via Equation 2:

$$Aggregated\ Relative\ Error = \frac{\sum E_{BEopt} - \sum E_{Utility}}{\sum E_{Utility}} \times 100 \quad (2)$$

163 where *Aggregated Percent Error* is the error when the modeled consump-
164 tion for all 54 homes’ are summed and compared with the sum of the utility
165 data for the 54 homes. Thus, Equation 2 is a measure of the performance of
166 a group of homes as a whole.

167 The same methods were applied to monthly real and simulated values of
168 energy use for a subset of the homes.

169 Finally, hourly temporal profiles produced by the BEopt model were com-
170 pared with hourly electricity use data to determine whether certain time
171 periods throughout the day or seasons throughout the year affected the per-
172 formance of the BEopt model. These simulations were run with actual 2013

173 weather data in order to compare output with the actual temporal home
 174 demand – the actual temporal home data were only available for 2013. To
 175 generate the temporal profiles in BEopt, modeled electricity demand data
 176 for August 30, 2013 were averaged for 5 homes. This average profile was
 177 compared to an average profile generated from the same homes’ actual usage
 178 on August 30, 2013. The same procedure was followed to produce a winter
 179 temporal profile comparison using actual and simulated data for February
 180 12, 2013.

181 4. Results

182 During the construction of the models, the pool of available homes for
 183 each scenario changed due to availability of data. Fifteen homes did not
 184 have thermostat set-point data, and therefore, only 39 homes of the available
 185 pool of 54 homes were modified with temperature set-point information for
 186 scenario 3. Furthermore, 12 of the 54 homes were initially modeled with a
 187 type A geometry, and therefore, only 42 homes of the available pool of 54
 188 homes were analyzed for scenario 4 since they were the only homes for which
 189 simplified geometry was relevant.

190 4.1. Yearly electricity usage comparison: modeled vs. measured

191 Figure 3 presents the histograms of the 54 individual homes’ relative error
 192 values for scenarios 1, 2 and 3. Scenario 4 was not included in this analysis
 193 since it was not being compared to measured electricity data but rather to its
 194 deviation from an original model due to a modification of geometry param-
 195 eters. The average relative error (Equation 1) for the individual homes was
 196 3.29% (s.d. 32.5%), 18.3% (s.d. 36.5%), and 16.0% (s.d. 31.8%) for scenario

1, 2, and 3 respectively. While a decrease from scenario 2 to 3 is expected due to the improved data quality with temperature set-point information, the increase from scenario 1 to 2 was unexpected. We hypothesize that the BEopt model might over predict HVAC energy usage in the shoulder seasons (see Section 4.2). Thus, when the actual 2011 weather data were used for Austin, the model increased its over-prediction because 2011 was a much hotter year than the average TMY3 data. However, since we did not have sub circuit data from the measured homes, we are not able to test this hypothesis.

Figure 3: Histograms of relative errors for scenarios 1–3 of model construction showing changes in predictability of model with TMY3 weather data for Austin (Scenario 1), Austin 2011 weather data (Scenario 2), and Austin 2011 weather data including temperature set-point data for 39 homes (Scenario 3) with one outlier (the same home) removed from each scenario for clarity.

To explore the hypothesis that the simulation model over predicts electricity consumption for certain homes, we looked at Energy Information Agency (EIA) data on residential homes’ energy consumption normalized over square footage. The EIA data indicate that the average value is 8.1 kWh/ft²/year (0.75 kWh/m²/year) for Texas [4]. However, a number of the homes modeled in this study exhibited smaller values for their site energy consumption per square foot with an average value of 6.99 kWh/ft²/year (0.65 kWh/m²/year). This analysis might suggest either that some of the utility data may be miss-

213 ing some values, the homes are more efficient than the average Texas home,
 214 or that the model has difficulty modeling homes that consume less energy
 215 on average per square foot. For example, 28 homes had average utility con-
 216 sumption values below 7 kWh/ft²/year (0.65 kWh/m²/year), and when these
 217 homes are removed from the calculation, the relative error for each individual
 218 home drops significantly for scenarios 2 and 3 and increases for scenario 1 to
 219 -16.2% (s.d. 22%), -3.7% (s.d. 24%), and -2.6% (s.d. 23%) for scenarios 1, 2,
 220 and 3 respectively. These results follow the expected progression from sce-
 221 nario 1-3 as data quality improved, and this analysis is graphically depicted
 222 in Figure 4.

223 However, simple relative error calculations on individual homes might
 224 unjustifiably put more weight on the relative errors of smaller homes that
 225 consume less electricity compared to the aggregate electricity consumption
 226 of the 54 homes. Thus we consider the aggregated relative error for the
 227 54 homes (Equation 2). This type of aggregated error is an appropriate
 228 tool to use for studies where modeled communities are used for analysis
 229 rather than individual homes [52]. For the 54 homes, the aggregate errors
 230 were -10.93%, 2.70%, and 2.41% for scenario 1, 2 and 3, respectively. As
 231 the input data quality increased from scenarios 1 to 3 so did the models'
 232 performance. These results are summarized in Table 3. Also given in Table 3
 233 is a break down of the absolute relative error, for which the absolute value
 234 of each homes relative error was taken before the values were averaged in
 235 each scenario. Further improvements could most likely be made by more
 236 information about the behavioral patterns of homeowners. While model
 237 results for an individual home can have a wide range of significant absolute

Figure 4: Graph comparing relative errors for scenarios 1-3 to their energy consumption per square foot showing that the BEopt models perform worse over certain bounds (below 5 kWh/ft²/year (0.46 kWh/m²/year) and above 10 kWh/ft²/year (0.93 kWh/m²/year)) and that in general relative error has an inverse relationship with energy consumed per floor area. Thus it seems that the model is able to more accurately estimate the energy usage of homes that are closer to the average Texas home (8.1 kWh/ft²/year, 0.75 kWh/m²/year), but the model is less accurate for homes that use significantly more or less energy.

error values, when considered in aggregate, the model performed much better. The effect of the lack of behavioral data on BEopt model performance is best observed by analysis of the temporal consumption profiles in the next section.

Table 3: Summary of Results from Scenarios 1 – 4

Calculations	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Relative error (%)	3.29	18.33	16.03	–
w/ homes > 5 kWh/ft ² (0.46 kWh/m ²)	–5.81	7.92	7.91	–
w/ homes > 7 kWh/ft ² (0.65 kWh/m ²)	–16.17	–3.69	–2.60	–
Absolute relative error (%)	25.93	31.10	27.81	1.22
w/ homes > 5 kWh/ft ² (0.46 kWh/m ²)	21.38	23.20	22.06	–
w/ homes > 7 kWh/ft ² (0.65 kWh/m ²)	21.79	18.45	18.11	–
Aggregated relative error (%)	–10.93	2.70	2.41	–

4.2. Monthly electricity usage comparison: modeled vs. measured

Homes from Scenario 3 (2011 weather data + temperature setback data, $n = 42$) were also compared for their monthly usage. Figure 5 shows both a bar chart monthly comparison of the average of all the homes (top) and a box plot distribution of the individual relative errors of the homes for each month.

The model was able to follow the general shape of the monthly use profile. However, there were some months, particularly those in the shoulder seasons, that were more off (greater average percent difference) than others. These greater differences can also be seen in the box plot distributions on the lower graph – note that the solid black lines in the individual boxes are median

Figure 5: Double graph showing, on top, the 2011 average monthly energy usage of the 54 homes as compared to the 2011 average modeled monthly consumption of the same homes. The bottom portion of the graph shows a box plot distribution of the individual monthly relative errors (Equation 1) of each home for each month. The model is able to predict the general shape, but seems to be predicting high during the shoulder (spring and fall) seasons, which is shown in both figures. The dashed gray line in the lower figure represents a zero relative error and is included for ease of relative comparison between the months and the solid black line in each box plot is the median for that month. The homes in this section are from Scenario 3.

values. The months of September and October have the greatest differences and could be due to some homes with rather high percent differences having changed their thermal comfort settings (stopped using their air conditioner) whereas the model still deemed it necessary. Also, the differences in the shoulder months could be from other thermostat behavior such as not heating homes on days with chilly mornings where the weather is expected to require cooling in the afternoon.

4.3. Hourly electricity profile comparison: modeled vs. measured

In this section, hourly consumption data were taken from the model hourly output file and compared with hourly data taken from a smart grid demonstration project in Austin, TX. There were only 5 homes that had audits and temporal energy usage, which limited this section of analysis to those 5 homes. These homes had an average build year of 1968, size of 152 m², house volume of 388 m³, window area of 20.3 m², attic insulation of R-20 (RSI-3.52), duct leakage of 11.8%, duct R-value of 3.8, air conditioner size of 10.7 kW, air conditioner efficiency of COP 2.7, furnace capacity of 19.7 kW, furnace AFUE of 80, and an ACH50 value of 12.4. Figure 6 shows the differences between the metered data and the model generated daily consumption profile for the summer and winter seasons. In the summer month (Figure 6, bottom), this analysis shows that the model under predicted average electricity demand in the early morning and late afternoon for these five homes. Behavioral patterns, such as times of leaving/returning home, that were not reported by homeowners could be driving the homes' differing energy consumption compared to the model. Newer versions of BEopt (2.2+) now include a specific schedule builder. It also could be the case that the

277 model has trouble simulating home performance in a hot and humid climate
278 such as that of Austin.

279 The winter graph (Figure 6, top) shows that the BEopt model did a fairly
280 good job following the consumption profile for the 5 smart metered homes
281 selected for analysis with the exception of a higher morning spike when people
282 are typically starting their day. While it does appear that the model over
283 predicts consumption between 9 AM and 5 PM, the overall trends aligns
284 reasonably well. Figure 7 shows a more detailed look at the hourly analysis
285 by showing box plots of the actual and measured values side by side.

286 Figure 7 shows how assumptions built into the models can lead to similar
287 use between homes (tighter blue box plots), while actual home use can be
288 highly variable (larger red box plots). However, as Figure 6 showed, as groups
289 of homes are averaged, the results are better. In all, spikes and offsets are
290 still present and suggest that BEopt will continue to have difficulty predicting
291 temporal profiles due to the fact that behavior becomes such an important
292 factor once the model is analyzed at the daily time scale. For this reason, this
293 energy model, in its current form, ought to be used sparingly to predict exact
294 daily electricity demand profiles for individual homes. However, seasonal
295 average curves might be acceptable, but data limitations did not allow us to
296 consider this, but could be the topic of future work.

297 *4.4. Geometry modification analysis.*

298 Scenario 4 involved the modification of home geometry of the scenario 2
299 models to determine whether home geometry characteristics were a major
300 driver of simulated energy use. Overall, the analysis showed that a simplified
301 geometry does not change model performance significantly. In total, 32 home

Figure 6: Temporal graph comparing hourly consumption patterns between simulation and measurement for an August day and a February day showing that the model is generally in good agreement with measured data most of the day in the summer time and slightly over predicts electricity consumption in the middle of the day in the winter but follows trends relatively well. Note that the data in this figure are only for 5 homes due to data availability.

Figure 7: Temporal graph comparing hourly consumption patterns between simulation and measurement for an August day and a February day showing the variability of measured data as compared to modeled data. Note that the data for Figure 6 and Figure 7 are the same.

geometries were changed from a complex geometry (B–I in Figure 3) to the A geometry type. Of the 32, 13 of the homes were modified from a combination of complex two-storied construction to a two storied construction with different A geometry shapes placed on top of each other. Twelve of the models already were constructed with the A geometry shape and therefore were excluded from this analysis.

Overall, for the one-story changes, the homes only deviated by 1.31% on average from the original model values, and the two story changes only deviated by 1.07% on average from their original models. Furthermore, since square footage could not be maintained precisely when the simplified geometries were created, some of these differences could be explained simply by the change in area. On average, the one-storied models in scenario 4 changed by less than 5.1 ft² (0.47 m²), and the two-storied models changed by 7.5 ft² (0.7 m²). Thus, results indicate that even without accurate geometry information for a real home, the model can produce plausible results. If the home was simplified to be more square than rectangular, the simplified geometry model deviated noticeably more from the original model than if the original model’s square footage was only added to one side of the home, making a more rectangular shape and maintaining the surface area to volume ratio. See Figure 8 for a depiction of the suggested method to take (the one ultimately used by the authors) when simplifying a model to a rectangular shape.

When using the rule of thumb above, the simplified geometry models only deviated by 1.3% on average from the original models. However, when the homes were simplified to make a home more square, the simplified models deviated by 2.3% on average from the original models. This result might

Figure 8: Example of a geometry simplification from type B to type A showing that, as suggested by this analysis, it is more appropriate to add floor space to one side of the home rather than on two sides.

327 become more important if home modeling is automated and extended to a
 328 large number of homes and complex home geometries need to be simplified
 329 for the automated process. Confirming that model output is not affected
 330 significantly should allow energy modelers to simplify their geometries or
 331 select geometries from a pre-defined list.

332 5. Conclusions

333 Given the integration and close comparison of two unique data sets in-
 334 cluding information about single-family homes and their hourly and yearly
 335 consumption data, we were able to quantify the accuracy of the BEopt simu-
 336 lation software under various conditions in Austin, TX. While model results
 337 for an individual home can have a wide range of error (up to 30%), when
 338 considered in aggregate with actual weather data, the model performed much
 339 better (within 3%). Furthermore, the analysis indicates that models of small

340 homes or homes that have low values of energy consumed per square foot,
341 do not perform as well, especially for homes well below the EIA average.
342 Comparisons of temporal patterns of energy consumption showed that the
343 model might be able to predict temporal energy use trends in the summer
344 and winter times, though it has difficulty predicting exact values at specific
345 times of the day. Finally, we determined that geometry adjustments do not
346 significantly contribute (about 1%) to a home's overall energy results, at least
347 within the BEopt model framework. Thus, model building might be able to
348 to streamlined for auto generation of energy models from energy audits.

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354 **7. Disclosure of Affiliation**

355 In addition to research work on topics generally related to energy systems
356 at the University of Texas at Austin, some of the authors are equity partners
357 in IdeaSmiths LLC, which consults on topics in the same areas of interests.
358 The terms of this arrangement have been reviewed and approved by the
359 University of Texas at Austin in accordance with its policy on objectivity in
360 research.

361 8. References

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