Development and Analysis of Residential Change-Point Models from Smart Meter Data

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Abstract

As access to residential energy use data becomes more widely available, it is possible to identify significant energy consumers and provide guidance on mitigating such large loads. In hotter climates, such as Texas, air-conditioning (AC) systems are important contributors to overall residential electricity demand. Providing a quick, simple and effective framework to describe and compare electricity demand patterns between different houses is valuable to identify potential candidates for peak load reduction and overall energy use mitigation. In this study, we evaluate the application of daily change-point models to describe the demand patterns of residential AC systems for 45 actual houses in Austin, TX during 2013. While previous research regarding change-point models has been focused on monthly data for commercial buildings, this study extends its application to daily residential energy use. The resulting models describe a behavior where energy consumption with relation to outdoor dry-bulb temperature is negligible up until a change-point, after which AC energy use increases linearly and results in an “energy slope.” An analysis of the neighborhood shows the distribution of the AC “energy slopes” is left-skewed and centered on 0.08 kW per °C dry bulb temperature. Energy audit information found eight house characteristics to be correlated with a higher energy slope. A subsequent parametric analysis using data from the energy simulation software BEopt confirmed the direction and magnitude of the correlation. This work provides a screening

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tool to compare energy demand patterns of houses and target houses with the largest magnitude of energy slopes for future energy audits.

Keywords: Smart grid, Residential Energy, Change-point Model, Energy Audit, Energy Simulation, Energy Model

1. INTRODUCTION

Residential customers are a significant part of U.S. electricity demand. In 2015, residential consumers made up 37.6% of the overall electric grid demand and 21.4% of overall U.S. primary energy consumption [1]. In hotter climates, such as Texas, the air-conditioning (AC) energy loads are of particular importance. Not only do they dominate the overall home electricity use, but they are also highly dependent on ambient temperature fluctuations. For example at 5:00 p.m. on August 10, 2015 in the Dallas, TX area, residential energy demand was 70MW or about 50% of the overall load [2]. During the same time frame on a milder day in the spring, residential energy demand constituted only 33MW or 26% of the overall electricity load. It is intuitive that residential energy consumption doubled primarily because of AC use as a result of higher ambient temperatures. Meeting such fluctuating loads is expensive. It requires electricity providers to plan their generation capacity appropriately, and to schedule its use in a way that can deal with even shorter (daily) fluctuations in demand.

In order to study and better mitigate energy demand changes, both the U.S. government and electric utilities have sponsored the wide-spread installation of smart meters. Smart meters are devices that measure electric energy consumption with relatively high frequency and transmit the data to utilities for monitoring or billing. As of 2014, around 58.5 million advanced (smart) meters had been installed, 88% of which were at residential customers [3]. By the end of 2014, 43% of U.S. homes had a smart meter installed and the number continues to rise [4]. While most practical benefits have been focused on accurate billing and the detection of power disruptions, electricity providers want computationally-efficient methods to quickly identify energy-intensive houses and, in the future, suggest which actions will decrease the electricity loads of the largest residential electricity consumers.

This study addresses the need for a simple model of residential AC electricity use built from smart meter data for quick comparisons and a statistical analysis of house characteristics that influence energy demand patterns.

Consequently, energy providers will be able to forecast residential AC use for individual houses, determine which houses are excessive contributors to grid load, trigger energy audits and eventually provide mitigation techniques to change those energy load profiles.

2. Literature Review

Researchers have modeled home energy use in a number of ways. The authors in [5] provide a literature review of the various regression methods used in dynamic and steady-state residential energy modeling. While “white-box” modeling software options are available, they are known to be time- and information-intensive. One potential option for efficient models of home energy use are steady-state change-point models as described by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) [6].

ASHRAE has investigated various inverse or data-driven models, mainly to measure the effectiveness of energy retrofits for commercial buildings. In the past, the standard for measuring the benefit of energy efficiency retrofits was the PRInceton Scorekeeping Method (PRISM) [7]. PRISM uses utility meter readings together with average daily temperatures to determine a weather-adjusted index of consumption, the Normalized Annual Consumption or NAC, for each period. Similar to the miles-per-gallon for a car, the NAC provides an estimate of energy consumption during a year normalized for the effects of weather, which is then used to quantitatively measure the benefit of a retrofit.

In 1999, ASHRAE created the Inverse Modeling Toolkit, which provides a framework for deriving regression models for energy use in buildings [8, 9]. It has been used in commercial buildings to measure savings derived from energy conservation retrofits and to identify and correct operational and maintenance problems. One tool in the toolkit is the heating ventilation and air-conditioning (HVAC) change-point regression model. In many single-zone buildings, such as small commercial buildings, space-cooling energy use increases as outdoor air temperature increases above some balance or change-point temperature. Figure 1 demonstrates four of the cooling model types [8]. As seen in the figure, all model forms are steady-state, (piecewise) linear and assume that increases in temperature have a linear effect on consumption. The linear rate of increase in AC energy use with respect to ambient temperature can be described as an “energy slope” and varies between houses.

68 The researchers in [10] give a physical explanation for the general trend. Pre-
69 vious research regarding change-point models has been focused on monthly
70 data for commercial buildings with regards to the effects of retrofits, largely
71 because data for residential homes were previously expensive and rare.

72 Recently, researchers have applied change-point models to describe gen-
73 eral energy use trends. For example, in [11], the authors forecast the daily
74 electrical cooling load of a large metropolitan city for one year by developing
75 an aggregate change-point model based on the relationship between weather
76 variables and daily-average electricity consumption. They found that both
77 temperature and humidity were significant indicators of energy use and were
78 able to accurately forecast the aggregate load. In [12], Tanaguchi et al. de-
79 rived a large-scale aggregation model for energy use of a city in Japan. They
80 revealed that turning off lights for 5% of the population could lower peak
81 load by 13 MW or 0.2%, highlighting the ability of simple models to forecast
82 potential benefits if behaviors or thermal characteristics change. In another
83 paper, Ghedamsi et al. created a bottom-up model that uses geographic
84 location information to estimate the changes in electric load resulting from
85 weather changes [13]. They were able to forecast the consequences of policy
86 decisions for building characteristics in different climate zones.

87 In [14], the authors used change-point models as a standard regression
88 tool for commercial buildings and developed an algorithm to automatically
89 identify the most appropriate model given energy use data. They verified
90 accuracy through comparing the monthly results of six different building
91 types simulated from EnergyPlus models [15].

92 With access to smart meters of residential houses, researchers are now
93 finding applications of change-point models to residential energy consump-
94 tion. There are differences between commercial buildings, which have been
95 modeled in the past using change-point models, and residential buildings.
96 For example, commercial buildings are regularly occupied and usually have
97 heavier-frame construction. On the other hand, residential buildings are typ-
98 ically a light-frame construction and are more sensitive to outdoor weather
99 conditions. Therefore, residential buildings are perhaps more appropriate for
100 use with change-point modeling techniques.

(a) 2-parameter Cooling Model

(b) 3-parameter Cooling Model

(c) 4-parameter Cooling Model

(d) 5-parameter Heating and Cooling Model

Figure 1: Change-point models for various scenarios as given by ASHRAE. T_{dbt} is the ambient air temperature. A/C in our study most closely follows the 3 parameter model [8, 9]

101 In [16], the authors used change-point models in order to disaggregate
 102 AC loads from overall energy loads. They created a algorithm to identify

103 which loads in the overall energy demand profile were influenced by weather.
104 They then used this as a technique to separate weather-dependent loads for
105 further study on a large number of residential homes. In [17], the authors
106 created an approach to predict when consumers are at home based on the
107 characteristics of 15-minute smart meter data. By understanding which con-
108 sumers are home, they identify which energy use patterns are behaviorally
109 driven.

110 In [18], Dyson et al. used change-point models to evaluate the potential
111 for residential demand response (DR) programs. They used daily energy
112 use data to determine, based on slope, which houses were using AC and
113 then fit a linear model to AC energy use. They then evaluated the DR
114 potential by assuming that a change in thermostat set point was equivalent
115 to a shift in the change-point. By looking at the timing of AC use and the
116 different house slopes, they estimated the overall impact of raising the set
117 point average over a day and in changing it instantaneously at a specific time.
118 In [19], the authors performed a sensitivity analysis for 20 house building
119 properties (using simulated energy data) in order to predict the parameters
120 in the change-point model. When compared with an actual house, they were
121 able to improve the accuracy of forecasting energy use.

122 In [20], the authors performed door-to-door surveys where they gath-
123 ered basic household information (year of construction, building materials,
124 number of appliances, etc...) and consequently clustered energy data by the
125 overall shape of the energy use. They found that physical characteristics of
126 a dwelling, HVAC ownership and occupancy profiles largely determine the
127 shape of the energy use curve or change-point.

128 In all cases, researchers are concerned with providing models of energy use
129 and anticipating the consequences made of changes in weather, building char-
130 acteristics or occupant behaviors. Rather than applying change-point models
131 to commercial buildings or aggregate communities, our research focuses ex-
132 clusively on disaggregated AC smart meter data from residential houses. In
133 our research we show the appropriateness of describing daily residential AC
134 use as a three-parameter change-point model. The result of fitting these
135 change-point models to the data is a number of energy slopes (the marginal
136 increase in energy consumption (kW) as a result of increases to outdoor tem-
137 perature ($^{\circ}\text{C}$)). With this information, we then make comparisons between
138 energy slopes to identify high-impact energy users. Furthermore, energy au-
139 dit data adds a dimension to analyzing overall trends in residential energy
140 consumption. We thus perform a statistical analysis on the energy slopes us-

ing building characteristics from energy audit data to determine significant parameters of the houses that account for the differences in energy slopes. Finally, we use BEopt, an energy simulation tool, to conduct a parametric analysis and confirm the differences in energy slopes as a function of building parameters. We also confirm, through BEopt building energy simulation models, that the gradient of the energy slope is not influenced by the thermostat set-point. The implication is that energy savings as a result of changes to thermostat set-points can be quantified and the immediate consequence of changing thermostat set-points can be determined for a large group of houses. This work provides a diagnostic tool to compare energy consumption of houses and suggests that high energy demand houses would benefit from energy audits that identify appropriate retrofits to lower energy slopes (and consumption).

3. METHODS

3.1. Data

Whole-house electricity and air-conditioning consumption data for 45 physical single-family houses in Austin, Texas were provided by the Pecan Street Smart Grid Demonstration Project in 1-hour time intervals from to January 1st, 2013 through December 31st, 2013 [21]. Each house was metered with an eGauge power monitor that reported both whole-house and air-conditioning power consumption in watts. In this case AC energy use was measured separately from overall energy use data to ensure the values were correct. However, even without direct measurement previous studies have shown a variety of non-intrusive load monitoring techniques that can disaggregate AC use data [22]. The houses were equipped with electric A/C split-system cooling units and natural gas heating systems. Weather data (dry-bulb temperatures in °C) were obtained from the KATT weather station at Camp Mabry, TX approximately 4 miles from the neighborhood. Energy audit data were collected by Energy Conservation Audit and Disclosure (ECAD) certified professionals through the City of Austin. In the energy audit, the surveyors collect information on housing characteristics such as the condition and estimated R-value of the attic insulation, percentage of air leakage from the duct system and the AC system’s age efficiency, and overall condition of the heating and cooling equipment. Energy audit data were also provided through Pecan Street.

176 3.2. Energy Slopes

177 In our investigation, we quantify the marginal increase in energy con-
 178 sumption of an individual house with respect to increasing ambient temper-
 179 ature. Figures 2a and 2b plot the hourly and daily dry-bulb temperature
 180 vs. A/C energy consumption data. As can be seen from the data, both the
 181 hourly and daily plots indicate increased energy use as outdoor air tempera-
 182 ture increases after a certain change-point. While these figures represent one
 183 house, the change-point, spread and angle of increase for each house varies.
 184 In other words, for some houses, the AC energy use with respect to tempera-
 185 ture followed a very strict and predictable line while other houses had larger
 186 variation. It is unclear if the variation is due to behavioral characteristics,
 187 like occupancy schedules, or building characteristics. The vast majority of
 188 houses, like this example house, showed daily AC energy consumption that
 189 had characteristics more similar to the three-parameter change-point model
 190 (Figure 1b). The only exceptions were three houses within the data set that
 191 had an electric heater and followed a pattern more similar to the 5-parameter
 192 model as seen in Figure 1d. However, based on the distribution and trends
 193 in the data, a three-parameter change-point model was determined to be the
 194 best fit for the AC systems in this neighborhood at the daily scale. For those
 195 houses with electric heaters we only considered the region in which electric
 196 cooling was required when regressing the model parameters. Equation 1 is
 197 the mathematical model that describes the piecewise linear model.

$$E_{AC} = C + B1(T_{DBT} - B2)^+ \quad (1)$$

198 The parameter C is the baseline energy use for the AC system. $B1$ is the
 199 change-point after which energy use increases linearly with an accompanying
 200 energy-slope parameter $B2$. The parameters C , $B1$ and $B2$ were determined
 201 using a segmented linear regression where a least-squares method was applied
 202 separately to fit each section of the piecewise linear model. The parameter
 203 $B1$ for each individual model is found by iteratively determining the change-
 204 point that has the lowest residual mean squared error or best fit. Similar
 205 direct search methods were found to be optimal in [8]. Although a quadratic
 206 fit for the energy slope was considered, the resulting accuracy was not better
 207 than the linear model.

(a)

(b)

Figure 2: AC electricity demand vs. temperature for single house for 2015, (a) Hourly average (b) Daily average

208 The change-point ($B1$) of the models was on average 19.8°C with a stan-
 209 dard deviation of 2.1°C . All 45 houses had a region for which AC energy
 210 consumption is essentially zero up to the change-point $B1$, after which en-
 211 ergy increases linearly. Therefore, every house had a parameter C value of
 212 essentially zero. Figure 3 gives a demonstration of the fit for one house.
 213 The R^2 value for this demonstration house was 0.93. ASHRAE Guideline
 214 14 stipulates R^2 values greater than 0.7 for a model to be considered well-
 215 calibrated [23]. Although the energy slope does not capture all the variance
 216 in AC energy use, it nonetheless describes accurately the overall behavior of
 217 the system.

Figure 3: AC change-point regression for a single representative house in the data set. The R^2 value for the sloped section was 0.93.

218 A three-parameter change-point model was regressed for each of the 45
 219 houses following the procedure described above. On average for the group of
 220 45 houses, the R^2 value was calculated to be 0.79 with a standard deviation of
 221 0.10. The maximum and minimum R^2 values were 0.94 and 0.57. ASHRAE
 222 Guideline 14 "Measurement of Energy and Demand Savings" states that com-
 223 puter models must have a Coefficient of Variation of the Root Mean Square
 224 Error (CV(RMSE)) of 15% and a normalized mean bias error (NMBE) of
 225 5% relative to monthly calibration data in order to be considered adequate
 226 for energy retrofit analysis [23]. The average monthly CV(RMSE) value for
 227 the homes for time intervals during which AC was used was 3.5% with 0.7%

228 and 14.5% for the minimum and maximum values. Likewise, the average
 229 monthly NMBE value for the homes was 0.33% with 0.04% and 3.9% for
 230 the minimum and maximum values. The fits of the models are therefore
 231 within the boundaries specified by ASHRAE. Though R^2 values for these
 232 houses have a wide range, as mentioned before, some houses have very re-
 233 peatable and consistent AC energy use patterns with little deviation from a
 234 strict slope, while other houses have a larger spread in behavior. Figure 4
 235 demonstrates the spread in energy use with respect to temperature for four
 236 different houses. Those observations notwithstanding, all houses exhibited
 237 an identifiable energy slope.

Figure 4: Energy use for four different houses. Black lines represent 95% confidence intervals on regression of energy change-point models. R^2 values for the houses were (a) 0.953, (b) 0.814, (c) 0.662 and (d) 0.566.

238 3.3. *BEopt Model Development*

239 In order to confirm the dependency of energy slopes on house character-
240 istics, a parametric analysis on BEopt v.2.5 [24], a residential energy model
241 simulator, was conducted. BEopt, which stands for Building Energy Opti-
242 mization, is a graphical user interface developed by the National Renewable
243 Energy Lab programmed to use EnergyPlus [25], the flagship energy sim-
244 ulation engine of the U.S. Department of Energy, to predict and optimize
245 energy use of residential buildings. It is typically used to sequentially ana-
246 lyze building designs to determine retrofits or new construction features that
247 minimize cost and energy use. The accuracy of BEopt in modeling actual
248 houses has been validated in previous research such as [26], where the authors
249 evaluated how closely BEOpt was able to accurately predict actual energy
250 use of group of homes that had building information and smart meter data
251 available. Their results indicated that the modeling software was able to
252 estimate aggregate annual electrical energy usage within 1% (for groups of
253 homes).

254 The simulation requires house characteristics such as size, occupancy,
255 insulation values, etc to be specified. In this case, a model was simulated
256 according the average characteristics of the studied houses. Table 1 shows
257 the building characteristics of the model simulated in this research. For
258 characteristics in the model not described in the energy audit, we assume
259 the default value supplied by BEopt. The simulation output provides both
260 overall energy use as well as separated AC energy data. In order to gauge the
261 influence of housing characteristics on energy slopes, a parametric analysis
262 was conducted on four variables listed in figure 7. Section 4 describes how
263 the variables in the parametric analysis were chosen.

Table 1: House characteristics for BEopt model

Characteristic	Units	Value
# of Floors		2
# of Bedrooms		3
Year Built		2000
Conditioned SQFT	ft^2	2000
Conditioned Volume	ft^3	19000
Front Door Orientation		West
Foundation Type		Slab Foundation
Type of Home		Single Family
Number of Central AC Systems		1
Number of Central Gas Heating Systems		1
Total Window SQFT	ft^2	300
Window Percentage		18%
Window Type		Double-pane
ACH50 Calculation	ft^3/min	7
R Value of Duct	$ft^2 \text{ } ^\circ F hr / Btu$	5.5
HVAC System Tonnage	ton	3
Total System Cubic Feet Minute	ft^3	1130
Duct Leakage	ft^3/min	210
HVAC System Size	Btu	35000
Seasonal Energy Efficiency Rating		14

264 4. Results and Discussion

265 After regressing the parameters for the change-point models on the 45
266 actual houses, the energy slopes were compared. Despite the houses sharing
267 similar characteristics, such as area, size and construction year, the energy
268 slopes of each house were found to vary. Figure 5 shows a histogram of the
269 energy slopes. Although this only represents a small subset of houses in
270 the entire neighborhood, one interesting trend is the slight left-skewedness.
271 Because the models are linear, it is possible to estimate an overall energy
272 slope for the group of houses. On the whole, the slope is 2.4 kW/ $^\circ$ C, ignoring
273 initial change-points. Overall, 30% of this increase is due to only 20% of the
274 homes. In other words, a subset of houses in the neighborhood with the
275 highest energy slopes contribute significantly more to overall variation in
276 energy demand.

277 Using this technique and simple clustering would allow an electricity
 278 provider to identify and target houses for energy efficiency improvements.
 279 Likewise, it would be feasible to encourage consumers to change their own
 280 behavior if they can be shown their ranking in regards to their overall neigh-
 281 borhood. Studies have shown that competition and comparison is a moti-
 282 vator for consumers [27]. The computational effort to obtain and compare
 283 parameters in this system is minimal (after automating the acquisition and
 284 storage of smart meter data) since the models are linear.

Figure 5: Histogram plot of energy slopes for 45 houses. Slopes center around 0.08 kW/°C

285 The reason for the differences in energy slopes was investigated by using
 286 energy audit data. Each house energy slope was regressed versus each of the
 287 92 house-characteristics measured in an energy audit. While most of these
 288 characteristics values were continuous, some values were binary or integer val-
 289 ues (e.g., yes/no or number of appliances). Although thermostat set-point
 290 preferences were recorded, there was no way to verify user preferences to the
 291 actual daily operation so thermostat set-points were not formally investi-
 292 gated. Variables were first normalized. For each of the 45 houses, the energy
 293 slope values were plotted versus building characteristics. A linear regression
 294 was performed to determine if any variables were statistically significant (95%
 295 confidence interval). A correlation matrix was calculated to determine any
 296 relationships between variables. For variables that were found to be highly
 297 correlated, only the variable with the highest R^2 was used.

Figure 6a gives an example of one regression analysis for the overall energy slopes plotted vs. the Seasonal Energy Efficiency Ratio (SEER) rating. The individual points represent the energy slope of each house versus the reported SEER rating and the dark line represents the linear fit of the data. In the figure, there is a negative correlation of energy slope with SEER rating, as expected. The more efficient the system is, the less power will be required to maintain the internal temperature of the house at the desired set-point when ambient temperatures increase. The R^2 value for this correlation was 0.27 which means it would be difficult to use the SEER rating to predict the overall energy slope.

Figure 6 show those variables for which the regression model had a positive or negative slope with a 95% confidence interval. Again, these are variables for which there is statistically significant positive or negative correlation with the overall energy slope of the house. Of the 92 initial variables, 8 were shown to have a strong correlation. The identified variables are essentially broken into house characteristics (house size, R-values for the ducts) and HVAC properties (size, SEER rating). In all cases, the relative direction of the slope coincided with what would be expected. For example, duct leakage, a measure of the airtightness of a building, has a positive correlation. On the other hand, increases in the SEER rating, a measure of system efficiency, result in a negative correlation with energy slope. The correlation of overall energy slopes with energy efficiency measures has shown positive and negative trends. Houses with high energy slopes could benefit from an energy audit that identifies which house property could benefit from a retrofit.

In order to confirm the general trends observed in the data, a BEopt parametric analysis was performed to compare the influence of housing characteristics on energy slope. A regression was performed on BEopt energy use data to fit the three-parameter model as described in section 3.2. Then the slopes of each house were once again plotted versus a house characteristic to determine non-zero slopes.

(a) SEER Rating

(b) Duct Leakage

(c) Window SQFT

(d) R Value of Duct

(e) HVAC System Size

(f) Home Type

(g) Condition of Duct

(h) Total System CFM

Figure 6: A/C Energy Slope in $\text{kW}/^\circ\text{C}$ plotted versus audit variables. Energy Audit variables for which the regression model had a positive or negative slope with a 95% confidence interval. Points are for individual homes and the solid line in the linear regression.

Figure 7a demonstrates the comparison between the slopes of the SEER rating versus the overall energy slope for the original data and BEopt data. The dashed line represents the slope predicted by the BEopt model and the solid from the energy data. While the slopes are not the same, the overall direction and magnitude are comparable. One of the reasons for the discrepancy is due to the fact that there are many variables contributing to the energy slope. In the BEopt model we can individually conduct a parametric analysis on isolated variables, an experiment that is not possible in a real physical system.

(a) SEER Rating

(b) Duct Leakage

(c) Window SQFT

(d) R Value of Duct

Figure 7: A/C Energy Slope in $\text{kW}/^\circ\text{C}$ plotted versus audit data. Points are for individual homes and the solid line in the linear regression. The dashed line represents the slope and values predicted for an "average" home in the BEopt model. Interactions between multiple house characteristics may account for the difference between the predicted and actual measurement. However, overall slope and direction are similar validating actual house data observations.

337 Figure 7 compares the slopes of four of the variables that can be modeled
 338 in BEopt. Here too, while the exact numbers are not the same, the overall
 339 direction and magnitudes are comparable, validating the overall observations
 340 found in the actual house data. Because both the smart meter data and the
 341 BEopt models agree, there is a case to made that the AC energy slope is
 342 affected by these behaviors. In evaluating an overall neighborhood, houses
 343 with high energy slopes may possess inefficient house characteristics that are
 344 suitable targets for retrofits. Realistically, some of the identified retrofits
 345 may not be economically feasible to mitigate high energy consumption. For
 346 example, the installation of an AC unit with a higher SEER rating, while
 347 efficient in the long run, will have a high initial cost. However, maintenance
 348 on a house AC unit or increasing insulation of ducts may decrease energy
 349 use in addition to being more economically feasible. These could even be
 350 subsidized through rebates by utilities with an interest in reducing peak
 351 loads caused by excess AC energy consumption.

352 While diagnosing energy efficiency opportunities is of interest, another
 353 avenue for reducing loads is in demand-response programs where the me-
 354 chanical operation of the AC system is influenced either by economic price
 355 signals or direct control. In AC systems this has typically been accomplished
 356 through smart thermostat control programs or direct load control, such as
 357 radio transceivers that can trigger compressor system shutdown during peak
 358 times based on a command issued by the utilities. We are interested in deter-
 359 mining if the fixed thermostat setting during the cooling season has an effect
 360 on the energy slope. Recognizing that the actual house data and the BEopt
 361 data agreed in the previous analysis, we performed an additional parametric
 362 analysis on thermostat set-point regressed versus daily energy demand using
 363 simulation outputs from a house model in BEopt. The overall plot is seen in
 364 Figure 8.

Figure 8: Daily AC energy use in kWh plotted versus fixed ambient dry-bulb temperature in °C using data from BEopt model.

On visual inspection, it appears that major difference between the different settings is the location of the change-point parameter rather than the slope. This is verified in Figures 9 and 10 where the circle markers represent the determined energy slopes and the triangles represent the bounds on the 95% confidence interval of the energy slope. For reference, the thermostat set-point settings evaluated are fixed values of 22.2, 23.3, 24.4 and 25.6°C (72, 74, 76 and 78°F). Although the slope appears to be marginally decreasing, the change in thermostat setting does not significantly (as determined by the 95% confidence intervals) affect the energy slope. The change in thermostat set-point can be quantified as a shift in the change point temperature.

The change-point models have a linear increase in kWh for each increase of temperature. Therefore, it could be assumed that lowering the temperature of the thermostat set-point by one degree would have the same effect as shifting the piecewise linear plot left by one degree. In either case, it is possible to estimate during cooling seasons the relative impact of a thermostat shift for both demand response and overall energy consumption. This analysis only assesses daily energy consumption and constant set points. Further analysis could develop hourly change-point models or consider the effect of varying set point values at finer time intervals.

Figure 9: AC energy slope in kWh/°C plotted versus fixed thermostat set-point settings using BEopt model. Solid markers represent the determined energy slopes. Dashed lines represent the bounds on the 95% confidence interval of the energy slope.

Figure 10: Temperature change-point °C plotted versus fixed thermostat set-point settings using BEopt model. Solid circle markers represent the determined change-point temperature. Triangles represent the bounds on the 95% confidence interval of the energy slope.

384 5. Conclusions

385 In this paper we used disaggregated AC data to develop and analyze of
386 change-point models for residential energy use. Change point models were
387 found to be a suitable model to describe the increase in residential energy
388 consumption. Among a group of houses sharing geographic location and
389 many architectural and mechanical characteristics, there was still a spread
390 in energy slopes, suggesting that dissimilarities or behavioral characteristics
391 of the occupants (e.g., thermostat set point preferences) play a role.

392 We evaluated the differences in energy slope when compared with energy
393 audit data. Indicators for energy slope were AC unit characteristics and
394 overall energy efficiency characteristics. Although these indicators should
395 be relatively obvious from an overall energy standpoint, this study validates
396 that energy slopes are, in fact, related to these metrics. This was further
397 confirmed by comparing the relative slopes with a parametric analysis of a
398 house modeled in BEopt.

399 The main contribution of this work is a screening tool to compare en-
400 ergy demand patterns of houses in order to target houses with the largest
401 magnitude of energy slopes for future energy audits. Based on this study,
402 the owners of a house can now compare its relative energy consumption slope
403 with other houses. If the house is in the high tail of energy slopes, the owners
404 can either consider a detailed energy audit or address the common sources of
405 these increased slopes as shown in the Figure 6. Energy efficiency measures,
406 such as increasing the thickness of the duct insulation, may be fixable at
407 lower cost with an energy audit and subsequent mitigation.

408 Lastly, through the use of the energy simulation program BEopt, we
409 confirm that the gradient of the energy slope does not appear to be influenced
410 by the thermostat set-point. Instead, a change in the thermostat set-point
411 introduces as a shift in the location of the change-point temperature. By
412 knowing the original energy slope and change-point, it may be possible to
413 estimate daily energy savings from thermostat set-point changes.

414 Change-point models provide a quick and simple method to compare the
415 heating and cooling behavior of houses. They could be used to diagnose
416 houses that are the highest fluctuating energy consumers and trigger energy
417 audits. Because they are linear systems with additive properties, they could
418 be used to provide quick estimates of anticipated energy consumption.

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