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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 of the correlation. This work provides a screening tool to compare energy demand patterns of houses and target houses with the largest magnitude of energy slopes for future energy audits.

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 70 MW 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 33 MW 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

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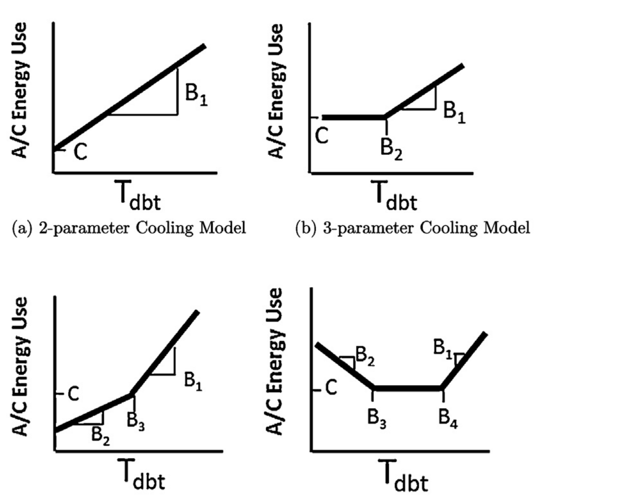
influence energy demand patterns. Consequently, energy providers will be able to forecast residential AC use for individual houses, determine which houses are excessive contributors to grid load, trigger energy audits and eventually provide mitigation techniques to change those energy load profiles.

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. Fig. 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



(a) 2-parameter Cooling Model (b) 3-parameter Cooling Model

(c) 4-parameter Cooling Model (d) 5-parameter Heating and Cooling Model

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

can be described as an “energy slope” and varies between houses. The researchers in [10] give a physical explanation for the general trend. Previous research regarding change-point models has been focused on monthly data for commercial buildings with regards to the effects of retrofits, largely because data for residential homes were previously expensive and rare.

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

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

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

In [16], the authors used change-point models in order to disaggregate AC loads from overall energy loads. They created a algorithm to identify which loads in the overall energy demand profile were influenced by weather. They then used this as a technique to separate weather-dependent loads for further study on a large number of residential homes. In [17], the authors created an approach to predict when consumers are at home based on the characteristics of 15-min smart meter data. By understanding which consumers are home, they identify which energy use patterns are behaviorally driven.

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

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

In all cases, researchers are concerned with providing models of energy use and anticipating the consequences made of changes in weather, building characteristics or occupant behaviors. Rather than applying change-point models to commercial buildings or aggregate communities, our research focuses exclusively on disaggregated AC smart meter data from residential houses. In our research we show the appropriateness of describing daily residential AC use as a three-parameter change-point model. The result of fitting these change-point models to the data is a number of energy slopes (the marginal increase in energy consumption (kW) as a result of increases to outdoor temperature (°C)). With this information, we then make comparisons between energy slopes to identify high-impact energy users. Furthermore, energy audit data adds a dimension to analyzing overall trends in residential energy consumption. We thus perform a statistical analysis on the energy slopes using 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).

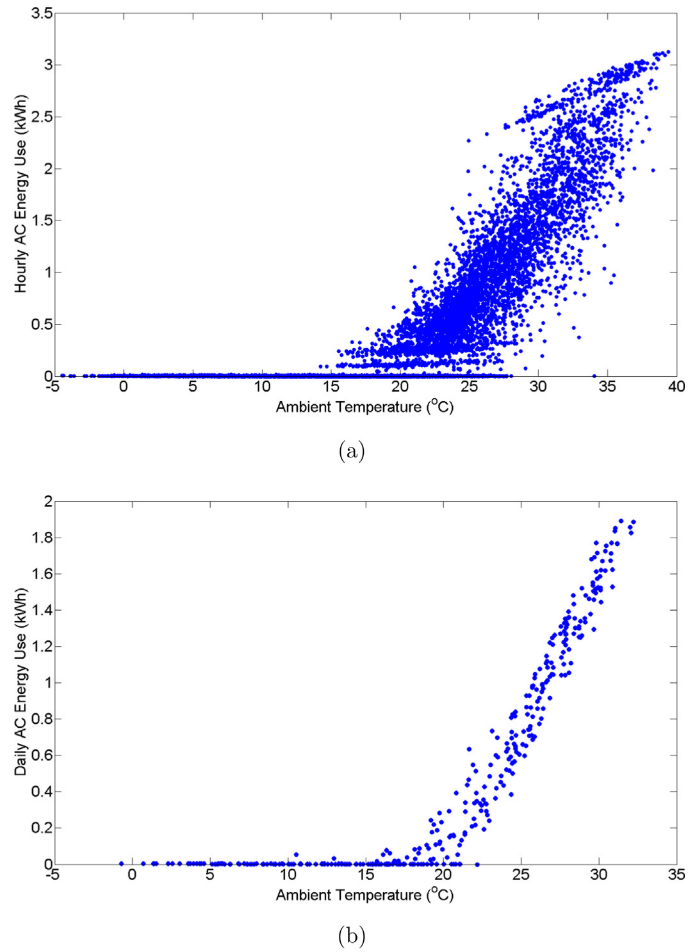


Fig. 2. AC electricity demand vs. temperature for single house for 2015, (a) hourly average and (b) daily average.

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-h 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 AC 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.

3.2. Energy slopes

In our investigation, we quantify the marginal increase in energy consumption of an individual house with respect to increasing ambient temperature. Fig. 2a and 2b plots the hourly and daily dry-bulb temperature vs. AC energy consumption data. As can be seen from the data, both the hourly and daily plots indicate increased energy use as outdoor air temperature increases after a certain change-point. While these figures represent one house, the change-point, spread and angle of increase for each house varies. In other words, for some houses, the AC energy use with respect to temperature followed a very strict and predictable line while other houses had larger variation. It is unclear if the variation is due to behavioral characteristics, like occupancy schedules, or building characteristics. The vast majority of houses, like this example house, showed daily AC energy consumption that had characteristics more similar to the three-parameter change-point model (Fig. 1b). The only exceptions were three houses within the data set that had an electric heater and followed a pattern more similar to the 5-parameter model as seen in Fig. 1d. However, based on the distribution and trends in the data, a three-parameter change-point model was determined to be the best fit for the AC systems in this neighborhood at the daily scale. For those houses with electric heaters we only considered the region in which electric cooling was required when regressing the model parameters. Eq. (1) is the mathematical model that describes the piecewise linear model.

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

The parameter C is the baseline energy use for the AC system. $B1$ is the change-point after which energy use increases linearly with an accompanying energy-slope parameter $B2$. The parameters C, $B1$ and $B2$ were determined using a segmented linear regression

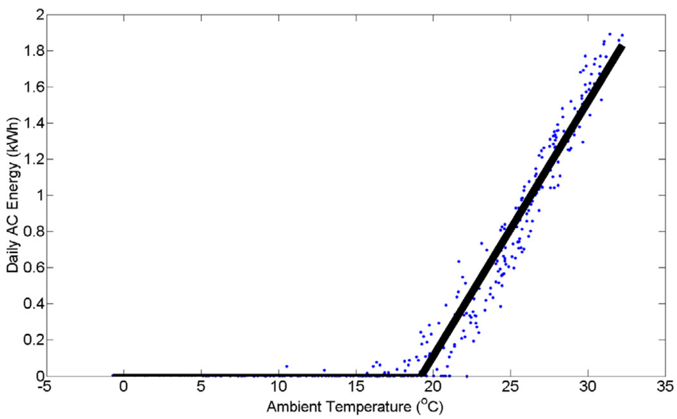


Fig. 3. AC change-point regression for a single representative house in the data set. The R^2 value for the sloped section was 0.93.

where a least-squares method was applied separately to fit each section of the piecewise linear model. The parameter $B1$ for each individual model is found by iteratively determining the change-point that has the lowest residual mean squared error or best fit. Similar direct search methods were found to be optimal in [8]. Although a quadratic fit for the energy slope was considered, the resulting accuracy was not better than the linear model.

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

A three-parameter change-point model was regressed for each of the 45 houses following the procedure described above. On average for the group of 45 houses, the R^2 value was calculated to be 0.79 with a standard deviation of 0.10. The maximum and minimum R^2 values were 0.94 and 0.57. ASHRAE Guideline 14 "Measurement of Energy and Demand Savings" states that computer models must have a Coefficient of Variation of the Root Mean Square Error (CV(RMSE)) of 15% and a normalized mean bias error (NMBE) of 5% relative to monthly calibration data in order to be considered adequate for energy retrofit analysis [23]. The average monthly CV(RMSE) value for the homes for time intervals during which AC was used was 3.5% with 0.7% and 14.5% for the minimum and maximum values. Likewise, the average monthly NMBE value for the homes was 0.33% with 0.04% and 3.9% for the minimum and maximum values. The fits of the models are therefore within the boundaries specified by ASHRAE. Though R^2 values for these houses have a wide range, as mentioned before, some houses have very repeatable and consistent AC energy use patterns with little deviation from a strict slope, while other houses have a larger spread in behavior. Fig. 4 demonstrates the spread in energy use with respect to temperature for four different houses. Those observations notwithstanding, all houses exhibited an identifiable energy slope.

3.3. BEopt model development

In order to confirm the dependency of energy slopes on house characteristics, a parametric analysis on BEopt v.2.5 [24], a residential energy model simulator, was conducted. BEopt, which stands for Building Energy Optimization, is a graphical user interface developed by the National Renewable Energy Lab programmed to use EnergyPlus [25], the flagship energy simulation engine of the U.S. Department of Energy, to predict and optimize energy use

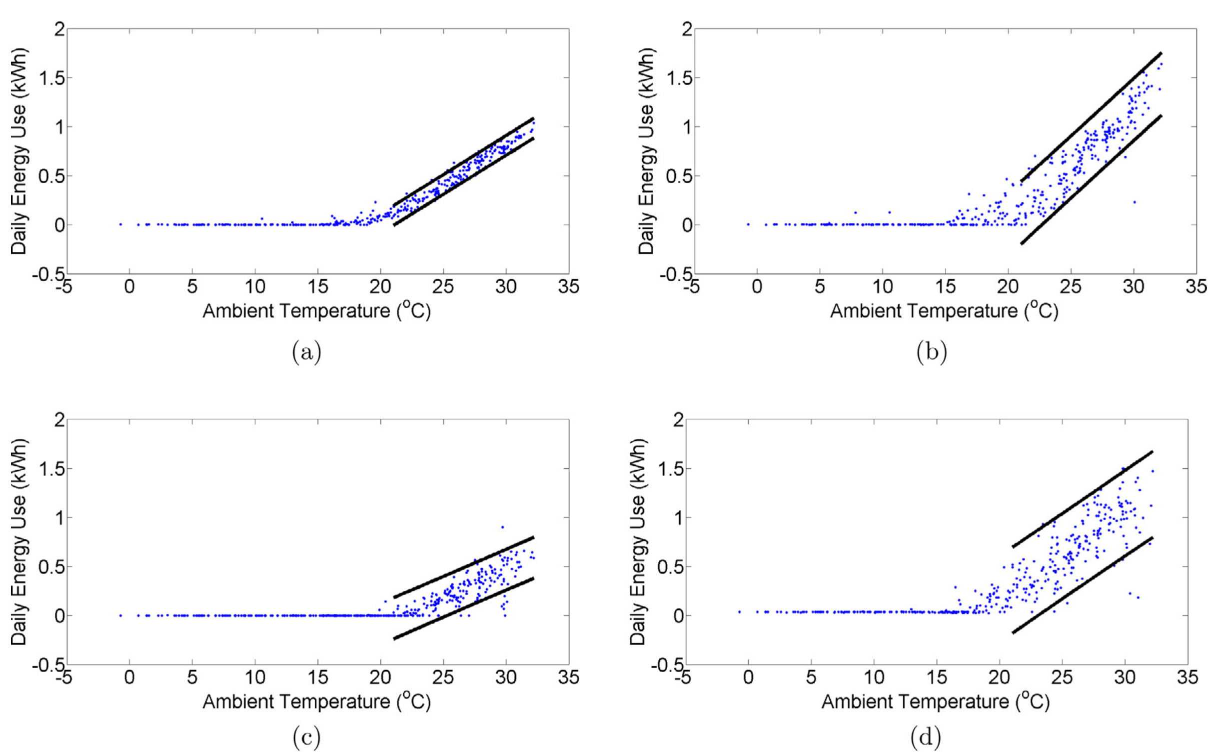


Fig. 4. Energy use for four different houses. Black lines represent 95% confidence intervals on regression of energy change-point models. R^2 values for the houses were (a) 0.953, (b) 0.814, (c) 0.662 and (d) 0.566.

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	19,000
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 °F h/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	35,000
Seasonal energy efficiency rating		14

of residential buildings. It is typically used to sequentially analyze building designs to determine retrofits or new construction features that minimize cost and energy use. The accuracy of BEopt in modeling actual houses has been validated in previous research such as [26], where the authors evaluated how closely BEOpt was able to accurately predict actual energy use of group of homes that had building information and smart meter data available. Their results indicated that the modeling software was able to estimate aggregate annual electrical energy usage within 1% (for groups of homes).

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

4. Results and discussion

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

Using this technique and simple clustering would allow an electricity provider to identify and target houses for energy efficiency improvements. Likewise, it would be feasible to encourage consumers to change their own behavior if they can be shown their ranking in regards to their overall neighborhood. Studies have shown that competition and comparison is a motivator for consumers [27]. The computational effort to obtain and compare

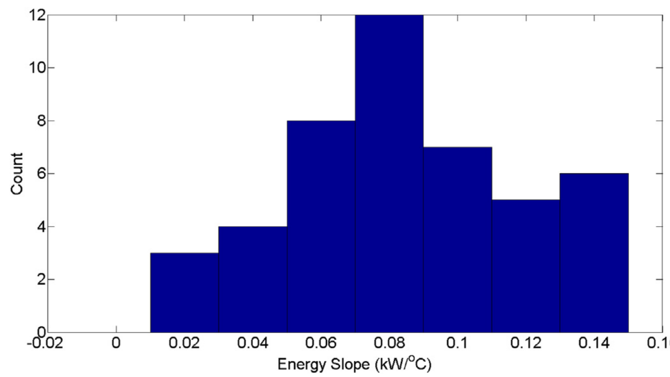


Fig. 5. Histogram plot of energy slopes for 45 houses. Slopes center around 0.08 kW/°C.

parameters in this system is minimal (after automating the acquisition and storage of smart meter data) since the models are linear.

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

Fig. 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.

Fig. 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

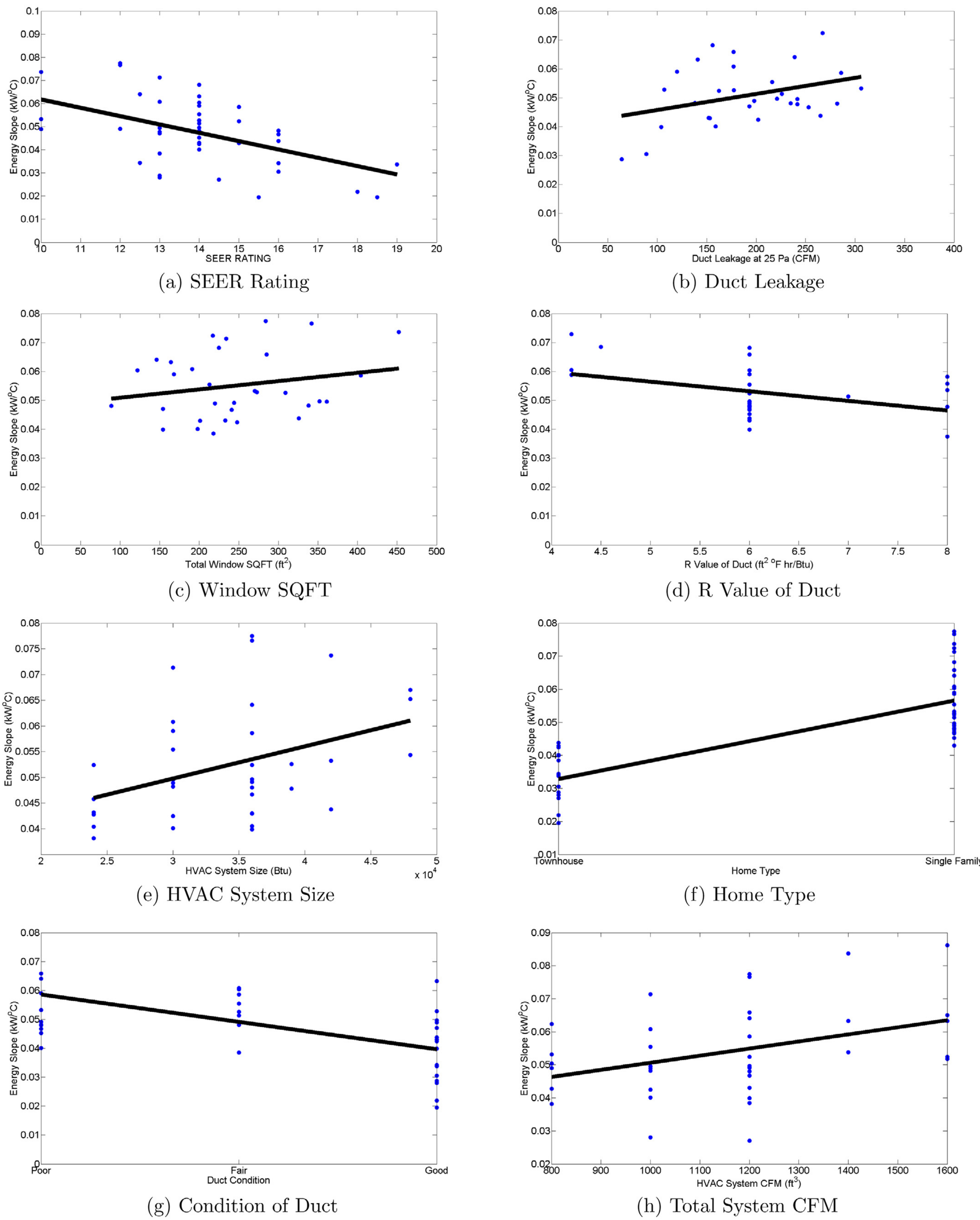


Fig. 6. AC energy slope in kW/°C plotted versus audit variables. Energy audit variables for which the regression model had a positive or negative slope with a 95% confidence interval. Points are for individual homes and the solid line in the linear regression.

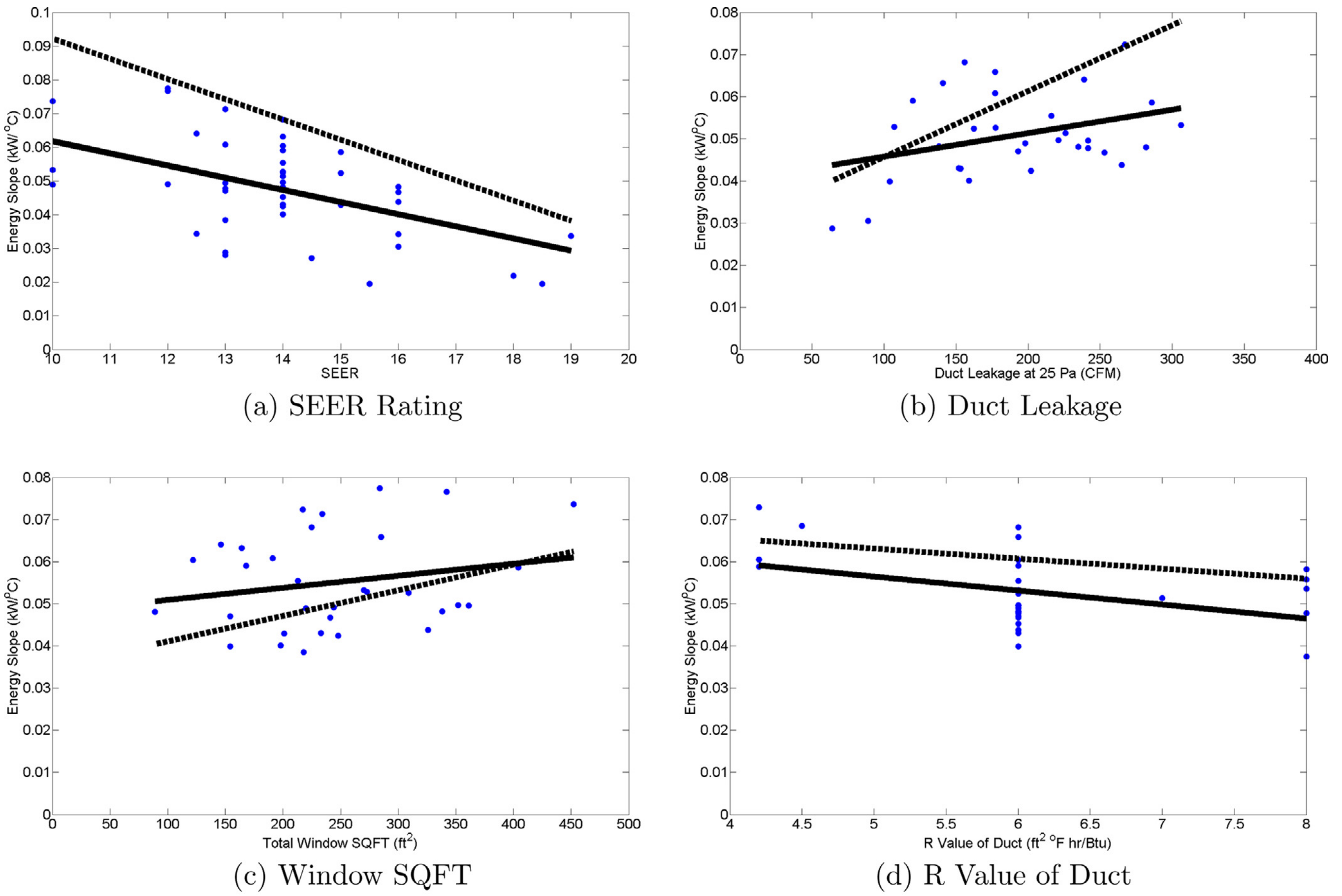


Fig. 7. AC energy slope in kW/°C plotted versus audit data. Points are for individual homes and the solid line in the linear regression. The dashed line represents the slope and values predicted for an "average" home in the BEopt model. Interactions between multiple house characteristics may account for the difference between the predicted and actual measurement. However, overall slope and direction are similar validating actual house data observations.

again plotted versus a house characteristic to determine non-zero slopes.

Fig. 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.

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

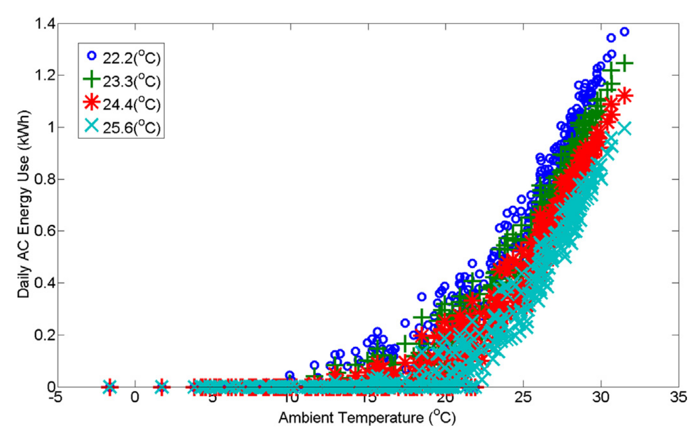


Fig. 8. Daily AC energy use in kWh plotted versus fixed ambient dry-bulb temperature in °C using data from BEopt model.

While diagnosing energy efficiency opportunities is of interest, another avenue for reducing loads is in demand-response programs where the mechanical operation of the AC system is influenced either by economic price signals or direct control. In AC systems this has typically been accomplished through smart thermostat control programs or direct load control, such as radio transceivers that can trigger compressor system shutdown during peak times based on a command issued by the utilities. We are interested in determining if the fixed thermostat setting during the cooling season has an effect on the energy slope. Recognizing that the actual house

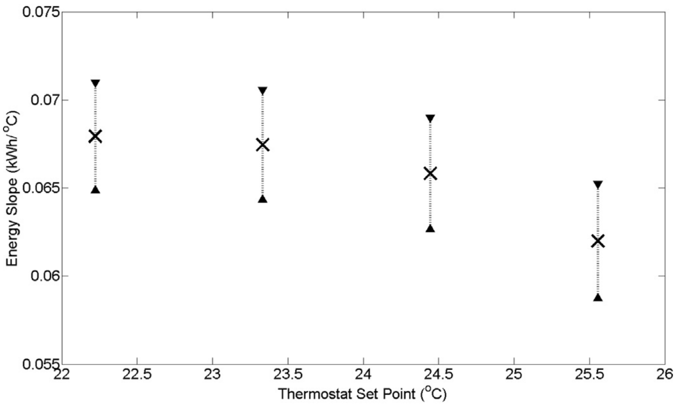


Fig. 9. AC energy slope in kWh/°C plotted versus fixed thermostat set-point settings using BEopt model. Solid cross markers represent the determined energy slopes. Dashed lines represent the bounds on the 95% confidence interval of the energy slope.

data and the BEopt data agreed in the previous analysis, we performed an additional parametric analysis on thermostat set-point regressed versus daily energy demand using simulation outputs from a house model in BEopt. The overall plot is seen in Fig. 8.

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 Figs. 9 and 10 where the cross 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.

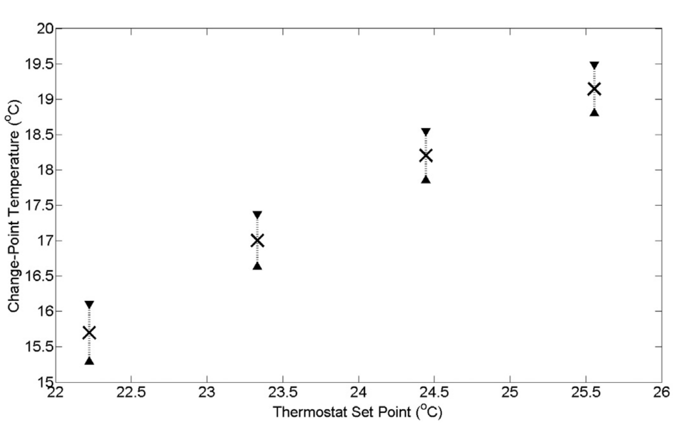


Fig. 10. Temperature change-point °C plotted versus fixed thermostat set-point settings using BEopt model. Solid cross markers represent the determined change-point temperature. Triangles represent the bounds on the 95% confidence interval of the energy slope.

5. Conclusions

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

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

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

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

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

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