

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.

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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

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 an 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,

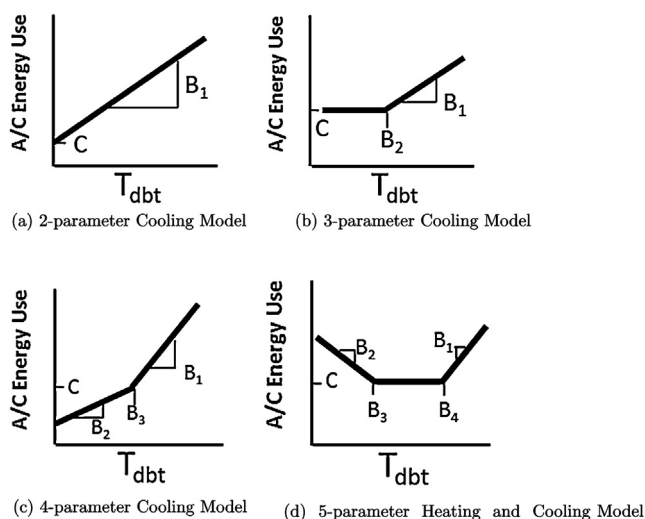


Fig. 1. Change-point models for various scenarios as given by ASHRAE. T_{dbt} is the ambient air temperature. AC energy use in our study most closely follows the 3 parameter model [8,9].

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