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Ranking appliance energy efficiency in households: Utilizing smart meter data and energy efficiency frontiers to estimate and identify the determinants of appliance energy efficiency in residential buildings

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ABSTRACT

This paper offers a novel method to rank residential appliance energy efficiency utilizing energy efficiency frontiers. The method is validated using a real-world case study of 4231 buildings in Ireland. Our results show that structural factors have the largest impact on energy efficiency, followed by socioeconomic factors and behavioral factors. For example, households with high penetration of efficient lightbulbs and double-glazed windows were on average 4 and 3.5% more efficient than others. Households with the head of household having higher education are on average 1.3% more efficient than their peers. Finally, households that track their energy savings are on average 0.4% more efficient than others.

Furthermore, installing heater timers, wall insulation, and living in owned residences were correlated with higher efficiency. Generally, families with kids who have full-time employment and are highly-educated are more efficient compared to families with no kids, or families with retirees or unemployed members. This result has important implications for both targeting and messaging of energy efficiency programs.

Some behavioral factors demonstrated significant impact on appliance energy efficiency. For instance, households that expressed interest in making major energy-saving lifestyle changes scored higher efficiency ranks on average. Conversely, households that expressed doubt about their motivation to save energy ranked lower in efficiency. This finding validates the role of educational programs to increase awareness about energy efficiency and its importance.

In short, our results show that a data-driven analysis of a population is needed to develop a balanced view of the drivers of energy efficiency, and to devise a targeted approach to improve homes' energy efficiency.

1. Introduction

Residential buildings consume about 22% of total primary energy in the US [22]. Appliances account for more than 20% of residential energy consumption (US Buildings Data Book, US DOE, 2014). Thanks to improved manufacturing standards, the efficiency of newly-manufactured appliances has improved significantly over the past few decades [1]. However, this improvement has not resulted in proportionate reduction in appliance energy consumption in homes [22]. Such discrepancy can be attributed to lower than expected penetration of efficient appliances, increased use of efficient appliances (rebound effect), or keeping old appliances such as refrigerators after purchasing a new more efficient system. In fact, even across similar buildings, the energy consumption levels for similar appliance saturation levels are widely variable [2].

Utilities spend millions of dollars annually to improve appliance energy efficiency. For example, in California alone in 2013, utilities spent $80 M on appliance and plug load efficiency programs, the highest expenditure among all utility energy efficiency programs (CPUC, 2013). To improve the effectiveness of energy efficiency programs, utilities need to identify and address a group of homes

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with higher potential for energy reduction, in a process called "targeting" [3–5]. Estimating appliance energy usage efficiency is a critical step in targeting. The most widely known methods for estimating appliance consumption are: Sub-Metering [6], Non-Intrusive Load Monitoring (NILM) [7], and Conditional Demand Analysis (CDA) [8]. Sub-metering involves installing separate energy meters for appliances, and monitoring their loads individually. While highly accurate, sub-metering requires an extensive metering infrastructure that currently renders it impractical for large-scale applications. NILM methods analyze high-frequency energy consumption data (often on the sub-second frequency), and estimate individual appliance energy consumption. The high-frequency data requirements (sub-second load) and high computational power needed to analyze the data make NILM impractical for most common applications. The least data-intensive method of the three, CDA estimates appliance ownership using regression analysis of monthly bills. Due to its use of aggregate load, CDA is not able to identify the sub-monthly trends of energy efficiency, such as the difference between weekdays and weekends. There is a need for a method that could leverage 15-min or 30-min interval energy consumption data that most utilities collect using their smart meter networks.

This paper presents a method to rank residential buildings based on their appliance energy efficiency. The method is based on the previous work on Stochastic Energy Efficiency Frontiers (SEEF), a dynamic method to estimate energy efficiency using an input-output framework. To our knowledge, this is the first work that uses smart meter interval data to estimate energy efficiency of appliances, without disaggregating the load into its components. To illustrate the method in a real-world setting, we use a database of more than 4000 households in Ireland.

The following sections first introduce the experimental data, followed by the model setup, results, and insights.

2. Experimental data

A data set of 4231 households in Ireland was used to illustrate the appliance efficiency ranking method. The experimental data set includes electricity consumption (30-min interval) from July 20th, 2009 through December 26th, 2010 for a total of 525 days. In addition, the data set includes a detailed list of dwelling characteristics, as well as demographic and socioeconomic data about participant households [9]. Table 1 summarizes appliance ownership data. Figs. A1–A4 in Appendix show the summary statistics of important household variables.

No information on the location of individual homes was released. However, our analysis of weather data from weather stations across Ireland shows that the weather conditions are reasonably consistent across the geographic areas. Thus, we used the average readings from three weather stations across Ireland as an estimate of users' weather for our analyses.

Table 1
Summary of appliance ownership on CER data.

Appliance	Count (total $n=4231$)			
	0	1	2	3+
Washing machine	51	3516	25	
Clothes dryer	1136	2451	5	
Dish washer	1161	2422	9	
Instant hot shower (electric)	1085	2298	189	20
Shower pump	2529	968	82	13
Cooker	820	2761	10	1
Electric heater	2594	800	162	36
Freezer	1805	1718	65	4
Water pump	2893	684	14	1
Immersion heaters	845	2736	11	
TV	34	919	1333	1306
Computer	1867	1620	13	5
Laptops	1638	1546	296	112
Gaming consoles	2352	828	305	107

There are three sources for temporal fluctuation in energy consumption of a house over time: climate and seasonal effects, lifestyle effects, and random effects. Lifestyle effects are individual temporal patterns of energy consumption of users that are not explained by external variables such as a change in seasons or outside temperature. Lifestyle effects impact both timing and end uses of energy.

Climate and seasonal effects are outside the control of the households and should not impact energy efficiency ranking. For our purposes, we also do not include lifestyle effects in our energy efficiency ranking. Other studies with a behavioral or conservation focus might find lifestyle effects particularly interesting for energy reduction purposes. The next sections briefly explain controlling for climate, seasonal, and lifestyle effects.

2.1. Controlling for weather and seasonal effects

Fig. 1 shows the relationship of daily consumption with outside temperature and day of week in our data set. Each individual home is different in the way that it is affected by outside temperature. Fig. 1(b) shows the distribution of the correlation of outside temperature with daily total consumption for individual houses. As seen the correlations range from −0.8 (highly negatively correlated) to +0.4 (moderately positively correlated). Finally, as Fig. 1(c) shows, consumption also has a strong relationship with day of week—the total consumption on the weekends is on average 0.83 kW h higher than weekdays.

To account for weather and seasonal effects, an individual time-series regression model was fit to each house. The model covariates include temperature, day of week, and month variables. For ease of reference, we call this model the S&T model, standing for "Seasonal and Temperature" model.

$$y_i = a_i + \sum_j b_{ij} T_{ij} + \sum_j c_{ij} D_j + \sum_j d_{ij} M_j + \varepsilon_i$$

$$i = 1, 2, \ldots, K \quad \text{buildings}; \quad j = 0, 1, 2, \ldots, 525 \quad \text{days}$$

where T_{ij} outside temperature reading for building i at day j; D_j day of week on day j of the data; M_j month of year on day j.

The estimated coefficients ($\hat{b}_{ij}$) are then used to calculate normalized energy consumption, by assigning a reference temperature (10 °C or 65 °F depending on the data unit) to all households, and calculating their hourly consumption using the regression model.

$$\tilde{y}_i = a_i + \sum_j \hat{b}_{ij} \tilde{T}_{ij} + \varepsilon_i \quad i = 1, 2, \ldots, K; \quad j = 1, 2, \ldots, 24;$$

$$\tilde{T}_{ij} = 65F \quad \forall i, j$$

Fig. 2 shows total daily consumption before and after normalizing for weather components.

The coefficient of determination (R^2) of the S&T model for each household provides useful insights for energy efficiency planners. Especially, it is an indication of the ratio of the total load that goes towards electrical heating and cooling. A high value for R^2 can be interpreted in several ways: (a) high heating and cooling load; (b) low non-heating and non-cooling loads, leading to a higher ratio of total load that goes towards heating and cooling; and (c) regularly and frequently-occupied house, resulting in a significant seasonal effect. In any of these cases, houses with high R^2 values have high sensitivity to seasonal and temperature effects. Therefore, they are