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Small business electricity disaggregation: Where can we improve? Towards increased transparency of appliance modal parameters

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ABSTRACT

Small commercial buildings (<50,000 ft^2 in floor area) consume 44% of all U.S. commercial primary electricity, with plug loads accounting for 31% of that portion and growing. In response, a bottom-up building energy assessment resource (BEAR) was previously developed as a practical approach to disaggregating building energy use, including plug loads. This article examines the performance of BEAR in estimating plug load consumption, specifically appliance energy consumption, through use of smart meters in two building types, food service and office.

Results of the analysis reveal that BEAR is capable of providing building stakeholders with meaningful energy information. Accuracy of BEAR's energy consumption estimates could be improved by 25% to 59% through better data on modal (i.e. appliance operating mode such as standby mode) usage and power demand, respectively. These results stress the importance of detailed modal information, because when modal power information was available the median difference between BEAR and the smart meter measured data was 36% compared with 223% in appliances where modal data was not available. In response to these findings, this study develops and presents energy contour plots, a visual tool for plotting modal usage and modal power in a two-dimensional form of energy consumption contours. Moreover, it is the recommendation of this study that increased transparency of modal power be implemented at the manufacturer label or specification to achieve increased accuracy of targeted energy improvements.

1. Introduction

Commercial buildings account for nearly one fifth of U.S. annual primary energy consumption [2], making them a critical component of national energy reduction goals. While large commercial buildings have greater financial opportunity to hire consultants or dedicated personnel to perform energy efficiency analysis, small commercial buildings (<50,000 ft^2 in floor area) lack the financial and institutional support necessary to make informed energy efficiency investments [3–5]. In recent years, some focus has shifted toward the small commercial building (SCB) sector, in part because reports have highlighted SCBs collective energy use. SCBs are accountable for roughly 16% of national primary electricity consumption and 5–20% reductions in energy demand are achievable through simple operational changes [5,6].

One approach to realize energy reductions in SCBs are energy audits, which may be used as an antecedent informational campaign intended to guide energy efficient decisions. Energy audits provide personalized information to building owners and occupants and have proven effective in demand-side energy reductions in commercial buildings [7,8]. However, energy audits are time intensive and require building sciences knowledge and advanced tools to complete, making them an ill-suited approach to engage the estimated 5.2 million SCBs in a timely manner [6].

Recognizing the potential for energy reductions in SCBs along with the limitations of energy audits, the building energy assessment resource (BEAR) was developed as a publicly available energy disaggregation resource that can provide an under-served small commercial building sector with meaningful energy information leading to the appropriate allocation of limited resources in reducing energy consumption and costs [9,10]. Assembling established energy estimate resources with annual energy consumption algorithms, BEAR disaggregates building energy profiles through a bottom-up approach, providing stakeholders with tailored information for targeted improvements. Results of a multi-building case study demonstrated BEAR's accuracy in estimating building-level electricity and natural gas consumption (weighted average absolute

Abbreviations: BEAR, building energy assessment resource; SCB, small commercial buildings.

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difference with utility bills equal to 4.7% and 13.3%, respectively), while also exhibiting the capacity to accurately evaluate food service enterprises, which are lacking in other resources [11,12]. However, an examination of BEAR's quantification mechanics is needed to identify the sources of uncertainty and the magnitude of their effect on energy consumption estimates, and to validate BEAR's efficacy in delivering appliance-level energy efficiency information.

The purpose of this study is to evaluate BEAR's mechanisms for quantifying energy consumption of appliances, in turn assessing BEAR's ability to provide targeted energy improvements. The contributions of this study are also recommendations to industry for improved data transparency and the development of energy contour plots as a visual resource with potential applications beyond those examined in this study.

To achieve these results, a network of wireless smart meters was installed at appliance outlets in two commercial enterprises, one food service and the other an office. Energy consumption of appliances attached to a wireless smart meter was recorded in 5-minute intervals over the course of 15 days at the food service tenant and 75 days at the office tenant. A combination of bootstrap statistical method and cumulative distribution functions was used to evaluate smart meter data organized by weekday and weekend. This study aimed to examine one aspect of BEAR's efficacy through a comparative analysis between BEAR's energy estimates and smart meter measurements of appliances.

In the following section, a review of energy metering studies is provided, including protocols for collecting data through wireless smart meters. In Section 3, a summary of the participating enterprises, statistical methods used, and genesis of energy contour plots is presented. In Section 4, results are presented and discussed in the context of uncertainty in appliance parameters and magnitude of effect on BEAR's energy estimates. Finally, conclusions show that the bottom-up approach to energy disaggregation employed by BEAR is as accurate as the information provided from energy estimate resources and manufacturer specifications. Future work will explore the function of energy contour plots as an alternative method for disseminating power and usage data to consumers.

2. Review of smart metering studies

To evaluate electricity use in buildings, a wireless smart meter network can be used to record time-series energy data of appliances. The review that follows will discuss existing smart meter studies and their methods used to analyze data, followed by a review of energy metering protocols used in this study [13].

2.1. Appliance-level metering studies

While building activity may offer a level of expectation towards end-use energy profile, a buildings' energy use is a function of its occupants and the appliances with which they interact [14,15]. In response, research has evaluated this interaction through appliance-level smart metering studies, documenting power demand and occupant usage for an array of appliances, including but not limited to: computers, office equipment, refrigerators, and audio/video equipment [16–18]. With appliance-level data collected, research evaluates appliance parameters (e.g. modal power and usage) to characterize electricity consumption patterns of building spaces or appliances [15,17–21] and to describe the influence of occupant behavior on electricity consumption [14,22–25].

For the purpose of this paper, the term modal refers to the distinct operating modes of an appliance, which include active and off and sometimes a low power mode. Additionally, modal power refers to the power demand in watts of an operating mode and modal usage refers to the time in hours spent in an operating mode.

To make sense of the smart meter collected data, appliance-level studies employ histograms, cumulative distribution functions (CDF), and power demand profiles. Histograms and CDFs describe appliance usage patterns through frequency of power demand values, revealing modal power levels [17,23,26]. Using a refrigerator as an example, Camilleri, Isaacs and French [17] defines standby power to be the "value that occurs most often," and is identified at 17 W, while active mode power is defined as the spike in frequency at the highest metered power, identified between 190 and 200 W. While histograms and CDFs provide limited information on the use of an appliance, they benefit from pairing with power demand profiles, which plot metered power readings over a 24-hour period depicting user influence on energy consumption, such as decreased power demand during lunch or over nights and weekends [26]. Together, these plots provide detailed energy data on modal power and modal usage, enabling evaluation of energy consumption patterns in consideration of user interaction, and are employed in this research article.

To ensure the collection of representative samples of appliance energy data, this study adopted smart metering protocols outlined by Lanzisera, Dawson–Haggerty, Cheung, Taneja, Culler and Brown [13].

2.2. Smart metering protocols for effective collection of data

Lanzisera, Dawson–Haggerty, Cheung, Taneja, Culler and Brown [13] defines three key protocols for the effective collection of appliance-level data useful to this study, including: (1) the smart meter technology necessary to record data, (2) the length of the study sampling period (preferably around 2 months), and (3) the sampling interval of appliance data (preferably 5-minute intervals). A summary of protocols used in prior smart meter studies is provided in Table 1, including the purpose for collecting the smart meter data. From Table 1, it is apparent that studies attempting to assess appliance parameters have used a host of study period lengths (spot measurements to one year) and sampling intervals (30 s–60 min).

This study used the existing body of literature to design a smart meter experiment that contributes to the greater building science research community. A network of Plugwise® smart meters using Zigbee protocol wireless networking were installed sampling at 5-minute intervals over a permissible timeframe determined by the enterprise owners; 2 weeks (food service) and 11 weeks (office). The limitation of the 2-week study length in the food service tenant is discussed in conclusions; however, the 2-week study length, in conjunction with bootstrap sensitivity analysis, fits within previously published smart meter studies (Table 1).

3. Methods

The intent of this article is to examine the efficacy of BEAR by identifying sources of uncertainty and measuring the magnitude of their effect on BEAR's mid-point energy estimate. BEAR's mid-point estimate is the calculated energy consumption of an appliance before reconciliation with energy bills, allowing it to serve as a benchmark for BEAR's accuracy [9]. This section describes the physical and operational characteristics of the participating tenants, outlines the implementation of smart meters, presents the statistical methods used to analyze collected data, and describes the development of energy contour plots.