

Energy Consumption in Campus Buildings When No One is Around

By

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THESIS

Submitted in partial satisfaction of the requirements for the degree of

MASTER OF SCIENCE

in

Energy Systems

in the

OFFICE OF GRADUATE STUDIES

Of the

UNIVERSITY OF CALIFORNIA

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2019

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Abstract

This study introduced a new methodology to estimate how often regularly-inhabited buildings are vacant and the electricity consumed during these times. In empty buildings, energy use can be greatly reduced through aggressive conservation measures, though few methods are currently available to easily estimate vacancy. The presented method uses aggregated Wi-Fi access point connection data that building operators can incorporate at almost no cost and apply to an entire portfolio of buildings.

The new vacancy inference approach was applied to 24 University of California, Davis (UCD) campus buildings using nine months of Wi-Fi and electricity data. During this period of analysis, the buildings were, on average, vacant 29% of the time with 24% of total electricity consumed during periods of vacancy. A newly proposed Vacant Building Energy Metric (VBEM) integrates the Wi-Fi inference results with an existing electricity metric to rank buildings according to their energy savings opportunity during vacancy.

Miscellaneous energy loads (MELs) are a growing portion of building energy use, but limited solutions exist to address them. As an example of a MELs application of vacancy intelligence, this study also showcased classroom audio-video (AV) equipment. Applying the new vacancy inference method with AV power monitoring data revealed that AV equipment in UCD General Assignment Classrooms accounts for approximately 270 MWh per year, with 80 MWh taking place at times when buildings are empty.

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Executive Summary

Building operations require tremendous amounts of energy to provide safe, comfortable, healthy, and productive environments for people. To address the many poor attributes that accompany excessive energy consumption, public and private entities continue to set ambitious goals for energy efficiency. In some cases, the technologies and processes needed to reach these ambitious goals are either unknown, not yet mature, or risk unfulfillment due to structural and behavioral barriers. To begin solving these challenges, it is beneficial to understand *how* and *why* people use energy, as well as detect when energy use is unnecessary.

Previous literature [1] shows that buildings can use 50% or more of their total energy at times of complete vacancy. To uncover new ways of identifying energy savings opportunities, the research presented in this study took advantage of widespread and detailed Wi-Fi connection data to estimate periods of vacancy across a portfolio of buildings. This Wi-Fi-based inference is possible due to the near-ubiquity of individuals carrying at least one web-connected device at all times.

This study applied a 24-building sample at the University of California-Davis (UCD) to test the results of this new virtual inference method. The Wi-Fi inference approach was performed using R, a programming language and free software tool, to provide an “occupied” or “not occupied” determination for each 15-minute value in the Wi-Fi dataset for all buildings (1). To identify the most likely periods of vacancy, the analysis began by determining the lowest two-hour average Wi-Fi count for each day ($\min(\{\bar{D}_i\})$). To account for fluctuating Wi-Fi counts, the model adds two standard deviations from the two-hour average period to establish a threshold for occupancy and vacancy. Anything above this value receives an “occupied” determination, and anything below receives a “not occupied” determination.”

“Occupied” is defined for all 15-minute segments where $D \geq \min(\{\bar{D}_j\}) + 2\sigma_j$
“Not Occupied” is defined for 15-minute segments where $D < \min(\{\bar{D}_j\}) + 2\sigma_j$

where...

D = Wi-Fi Demand, 15-minute Wi-Fi connection data over a one day period

n = 8, the number of 15-minute intervals in the 2-hour rolling average (1)

\bar{D}_j = The 2 hour rolling average $= \frac{1}{n} \sum_{i=(n-7)}^n D_i$

$\{\bar{D}_j\}$ = The set of \bar{D}_j within one day

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{i=(n-7)}^n (D_i - \min(\{\bar{D}_j\}))^2}$$

As Figure 1 shows, the resulting output tracks well with expected periods of building vacancy on a university campus (e.g., nights and weekends).

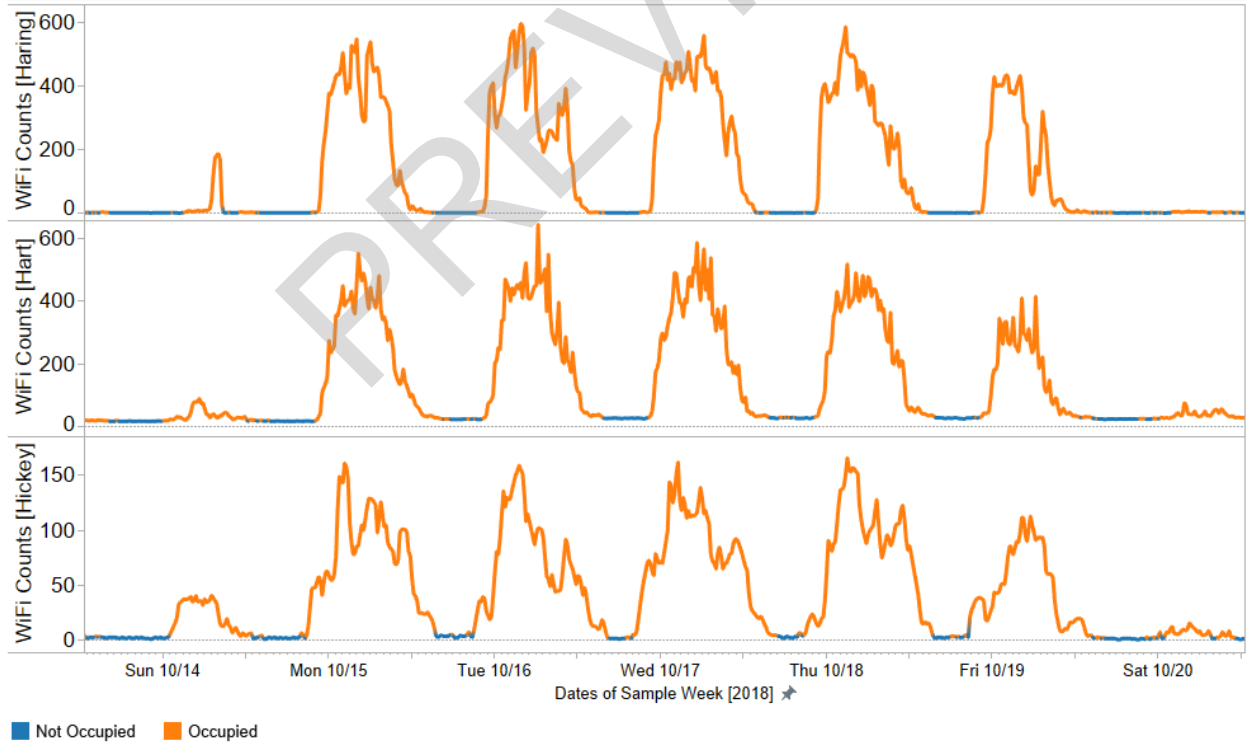


Figure 1 - Wi-Fi connection data for three buildings over one week. Blue highlights represent periods of estimated vacancy resulting from the Wi-Fi inference methodology.

When applied to 24 UCD buildings, the Wi-Fi inference approach indicates that the building sample is vacant, on average, 29% of the time and uses an average of 24% of total electricity during these times. As expected, the greatest opportunities for electricity savings occur during nightly hours—typically from 2 am to 6 am. The results also showed that weekends, holidays, school breaks, and unanticipated occurrences such as class cancellations might also provide unique savings opportunities.

In order to prioritize building retrofits based on savings opportunities during vacancy, this study also introduced a new metric—the Vacant Building Energy Metric (VBEM). This metric is a combination of the Wi-Fi inference method and an existing electricity-based ranking mechanism to arrive at a final determination for each building. The VBEM is weighted to allow for the clustering of similarly scored buildings. Ranking buildings based on this score results in a prioritized list according to each building's energy savings opportunity.

Over the next several decades, miscellaneous energy loads (MELs) are forecasted to increase while core building loads (space conditioning, lighting, & water heating) are forecasted to decrease. As an example of how the vacancy estimation framework can apply to a MELs end-use, this research also explored the energy intensity, savings potential, and institutional network of university Audio-Video (AV) equipment. To arrive at an electricity use estimate, a representative sample of the 132 AV systems installed in UCD General Assignment Classrooms (GACs) received power logging. These field measurements resulted in annual energy and cost estimates of 270 MWh and \$19,000 for all GAC AV systems. They also showed that average power during unused periods is only 16% lower than average operational power, and therefore this equipment has limited standby reductions.

Energy intensity appeared to be much higher in newer systems due to a greater number of installed components. A set of initial recommendations were suggested by the author to curtail

these barriers and spark innovation, including a UC-wide AV purchasing guideline for new AV equipment procurements. At a minimum, this purchasing guideline should specify the use of ENERGY STAR-certified equipment, set a ceiling for unused system power, and call for equipment that can communicate power states.

Existing systems can also benefit from these new purchasing guidelines through retrofit opportunities and adjustments to user behavior (e.g., powering off accessible select equipment when it is safe to do so). AV maintenance staff should integrate this practice into their regular service visits. To perform this practice automatically, staff can install power sequencers.

Future work should obtain ground truth data to determine the accuracy of the Wi-Fi inference methodology. Additionally, a mechanism capable of inferring vacancy in real-time instead of historically may unlock opportunities for automated energy savings.

Chapter 1: Introduction

1.1 Energy Consumption in Buildings

Residential and commercial buildings account for roughly 30% of global [2] and 39% of US [3] energy use. Improving building energy efficiency through innovative technologies and policies continues to be a goal for private and public entities. This is driven by the many benefits that accompany energy efficiency, including cost savings, health benefits, energy security, and decarbonization. Results of past efforts appear to be materializing with respect to the energy intensity of buildings. The IEA reports that since 2000, total floor area has grown by an average of 3% each year, while energy use per unit floor area has decreased an average of 1.6% over the same period [2].

1.2 Energy Efficiency Policy

Recognizing the past successes and future potential for building efficiency, policy makers around the world are setting increasingly ambitious energy efficiency goals. For example, the European Union's 2030 Climate and Energy framework aims to achieve a 32.5% reduction in energy consumption for the year 2030 (based on a 2007 forecast) [4]. In California, Senate Bill 350 aims to "double energy efficiency by 2030" relative to the mid-case estimate of achievable energy savings outlined in the 2015-2025 California Energy Demand Update Forecast [5]. Beyond country- and state-level goals, counties, cities, universities, and private companies are leading similar progressive efforts [6], [7]. In some cases, the technologies and processes needed to reach these ambitious goals are either unknown, not yet mature, or risk unfulfillment due to structural and behavioral barriers commonly referred to as the "energy efficiency gap" [8]–[10]. Innovations in policy, financing, technology, and organizational structuring are imperative to meeting these systematic goals.

1.3 Energy Consumption in Vacant Buildings

Successful energy reduction efforts allow building occupants to attain the full useful output of all services with less expended energy. These services change depending on building type and operational characteristics but generally focus on providing a comfortable, healthy, and productive indoor environment for human habitation. However, these environments are often unoccupied for extended periods that are difficult to pinpoint. Of the many approaches to addressing inefficient energy use (e.g., component efficiency, behavior, pricing structure), solutions that target periods of occupant vacancy are an obvious choice. Olson Hall, a classroom building on the University of California, Davis (UCD) campus, offers an illustrative example of energy waste during vacant periods (see Figure 2). This building draws an average of 75% of operational-hour (7am-11pm) power during the hours of 11pm-7am when the building is scheduled to be locked [11]. Other campus buildings—typically those with laboratories—show even less differentiation between nighttime/weekend and daytime electricity demand.

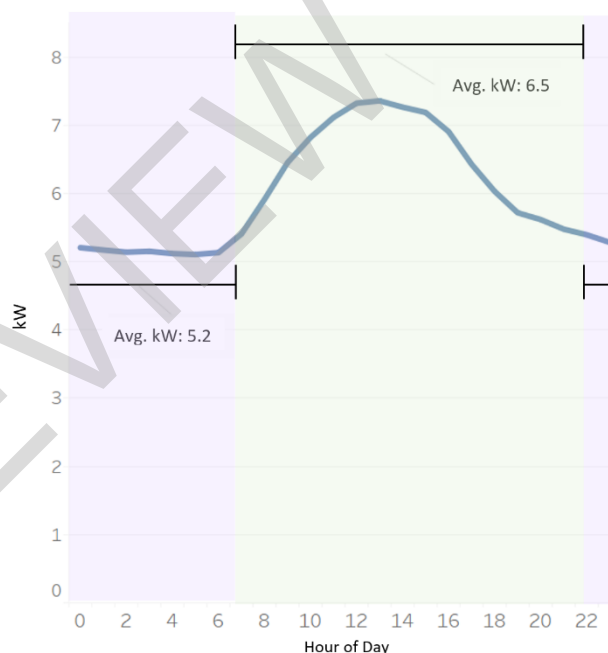


Figure 2 - Olson Hall hourly profile of average electricity consumption during operational (green) and non-operational (purple) hours

Identifying the presence and absence of occupants in these buildings provides an opportunity to turn down or power-off non-essential end-uses, allowing for considerable energy and cost savings while maintaining equal service to people. The proliferation of low-cost sensors and abundant data in buildings offer new solutions for inferring the occupancy status of a building. The Advanced Research Projects Agency-Energy (ARPA-E) recognizes this opportunity in their

Saving Energy Nationwide in Structures with Occupancy Recognition (SENSOR) program, which has an objective to develop new sensor systems that reduce heating, ventilation, and air conditioning (HVAC) energy by 30% in residential and commercial buildings [12]. This objective aligns with existing literature but leaves a gap in three notable areas—miscellaneous energy loads (MELs), wider consideration for simple binary vacancy methods, and application to large portfolios of buildings.

First, there is a strong focus on approaches that address HVAC consumption. Though efforts in this area are beneficial and should continue, MELs are a growing concern that receives little attention [13]–[15]. Second, there is a tendency to focus on occupancy over vacancy detection. Whereas occupancy is continuous ($0 \rightarrow \infty$), vacancy is binary ($0 \rightarrow 1$; vacant or occupied). The relative simplicity of binary detection of human presence (compared to occupancy) could result in a more accurate prediction, therefore allowing more end-uses (including MELs) to benefit. Lastly, most work in this space focuses on inferring human presence one building at a time [16]. Methodologies capable of assessing multiple buildings at a time can enable building operators to prioritize energy efficiency retrofits to maximize cost-effectiveness.

1.4 Study Aims

In this study, a selection of UCD's main campus buildings was used to address two primary goals. The first goal was to use Wi-Fi and electricity data to develop an estimate for how often buildings are vacant, as well as energy consumption patterns during such vacancy. Using these findings, the author also aimed to create a whole-building vacancy inference metric that allows for the ranking of buildings according to their relative energy consumption during periods of vacancy.

The second goal was to apply the vacancy estimation framework to a specific end-use by exploring the energy intensity, savings potential, and institutional network of university Audio-

Video (AV) equipment. The AV equipment represents one of the many MELs that are understudied but may enable energy savings during vacancy.

Building operators and energy managers are the intended audiences for this paper. Another aim of this paper is to illustrate the opportunity for these audiences to address excessive energy use during vacancy and provide low-cost solutions that are easily integrable into facility operations.

These study aims are part of a larger project that aims to test the concept of vacant building inference using a case study. As described in Figure 3, this larger project breaks down into three modules – modeling, measures, and post-installation efforts. The areas addressed in this paper fall under “modeling” and “measures.” The new method of identifying building vacancy and savings potential falls under “modeling,” and the AV equipment exploration serves as one example of the many measures that could benefit from vacancy information.

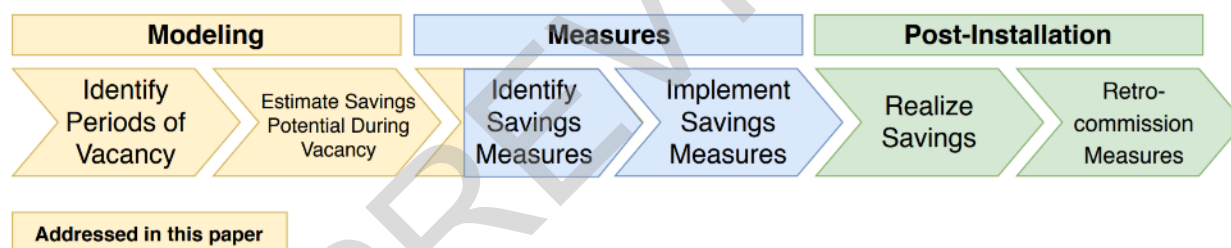


Figure 3 - Building vacancy project framework

1.5 Hypothesis Development

In order to test the objectives of this thesis, it was necessary to perform a basic analysis to provide a quantifiable baseline. To establish a reasonable estimate for how often buildings are vacant, the author first investigated building operations schedules. These schedules differed based on the building’s primary use cases, but most appeared occupied for all hours except 11pm-7am, a total of eight hours per day. To create an estimate for electricity use during vacancy, the author summed actual 2018 electricity consumption within the eight-hour