A Stochastic Occupancy Modeling Approach to Enhance the Energy Efficiency of Residential Heating and Cooling through Occupancy Sensing Technology

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Abstract
Occupancy schedules are used in Building Performance Simulation (BPS) to act as proxies for human presence. However, they were not previously used to explore the potentials and limitations of human sensing systems. In this paper, we develop a simulation-based approach to support advances in occupancy sensing to specifically examine the impact of sensing errors, such as false positives, of human presence detection systems, by using occupancy schedules to quantify residential building heating and cooling energy use. The aim is to examine varying effects of human detection system configurations on thermal energy consumption in false sensing scenarios, and to introduce occupancy schedules as a means to inform processes of such sensing systems. To extrapolate stochastic transition matrices and generate reliable probabilistically driven occupancy schedules, a Markov-Chain analysis of the 2018 American Time Use Survey (ATUS) is used to develop presence schedules. We then evaluate the impact of false positives in binary occupancy modelling scenarios using Honeybee as a front-end interface in Rhino/Grasshopper, and EnergyPlus as a backend engine. Overall, the aim of this work is to recommend guidelines for various system configurations in which the use of low-cost sensing is justified for heating and cooling regulation.

Key Innovations
- Development of a stochastic approach to examine the role of low-cost sensing configurations, such as scanning frequency, in an integrated way for a symbiotic relationship between sensing and simulation schedules.
- Demonstration of relevance to residential building sectors, where such sensing technologies can be deployed on a large scale and showcasing how BPS can now evaluate the negative energy impacts of false positives (falsely sensing presence when space is vacant).

Practical Implications
The findings of this work aim to advance the state-of-the-art in occupancy modelling to guide practitioners in developing probabilistic occupancy simulation frameworks that focus on emulating residential presence as related to sensing technology performance. As occupancy sensing technologies become more widespread, practitioners would understand the impact of falsely detecting people’s presence in households. The findings can also be used to evaluate the viability of low cost sensing systems for wide-scale building integration.

Introduction
The field of high performance building witnessed critical advancements over the past few decades in how to employ simulation to understand the impact of geometrical and physical phenomena on the built environment. Accuracy and precision continue to increase for most contextual factors, such as climate modeling. Building inhabitants and their influence on energy use, on the other hand, are comparably less developed (Mahdavi and Tahmasebi 2019). Occupant impact on building energy use has been a topic of interest since the late 20th century, when the literature recognized that people’s behavior may influence 71% of the variation in building energy demands (C. Sonderegger 1978). In addition, household size and occupancy patterns were recognized as primary contributors to electrical loads in residential buildings (Richardson et al. 2008). The impact of household dwellers is expected to grow in the future, with expectations that enhanced building regulatory guidelines and improved thermal performance will decrease energy use attributed to characteristics other than people’s presence and their behavior (Guerra Santini at al. 2009). Such enhancements include occupancy sensing, which is linked to controlling building systems, and lowering energy use when people are not present. In this paper, we explore the methods of simulating people in buildings and their relation to advances in sensing technologies that autonomously detect occupants.

Occupancy Schedules and Sensing Technologies
Varying approaches exist and are employed to represent occupant trends in BPS (Crawley et al. 2008). The industry standard and most widely adopted method is the use of deterministic schedules. These schedules derive the proportion of people that are present in a building at any particular time based on codes, standards and the intuition of experienced energy modelers (D’Oca and Hong 2015). Their adoption leads however to homogenous simulation results (Cowie et al. 2017) that fail to capture the stochastic occupant patterns exhibited in buildings (Annex 66 Final Report 2018). Previous work has demonstrated how lower occupancy rates were observed in the post-occupancy evaluation of office buildings than those provided by the deterministic standard (Duarte et al. 2013). In response to the limitations of deterministic
occupancy schedules in capturing the ways humans inhabit their household, probabilistically generated occupancy schedules were developed. Earlier investigations include schedules derived from a large-scale Time Use Data (TUD) survey in the UK, which used household size and day of the week analysis to infer residential trends (Richardson et al. 2008). A model that generated probability at each time step depending on the presence state at the previous time step was developed using first order time inhomogeneous Markov Chains analysis (Feller and Teichmann 1967). Single day occupancy schedules were provided, and they aimed to account for differences between weekdays and weekends, as well as the number of individuals present (Richardson et al. 2008). The model generates varying schedules every time it runs, producing results more akin to human behavioral patterns being driven by probability. However, scarcity of data that supports the population of probability matrices becomes a challenge that needs to be addressed (Feng et al. 2015), since a significant amount of detailed household inputs are required for the process to be reliable for that analysis (Paatero and Lund 2006).

Occupancy sensing techniques are a means of capturing an instance of presence through sensor inputs. As standalone systems, occupancy sensing solutions may not typically retain data regarding prior occupancy. There is an opportunity to utilize that historical data to inform sensing system energy use, given that building specific occupancy schedules are generated by estimating the probability of an occupant’s presence. Occupancy schedules can be employed as a secondary method that improves the performance of sensing systems by estimating if occupants are expected to be present. Most visual human detection mechanisms use confidence indices to indicate the certainty that a tracked object is human (Benezeth et al. 2011). Occupancy schedules can add a new layer to the estimation of that confidence index. An integration and cross-validation process between detection results and simulation outputs can create enhanced energy savings at the scale of the sensing device and overall building energy use.

Residential Human Sensing and False Positives

The potential value brought by integrating sensing technology is usually evaluated against production costs and application scalability. While many studies have attempted to capture the impact of stochastic occupancy schedule implementation on energy consumption and its components like lighting (Zhou et al. 2015), electrical appliances (Yilmaz et al. 2017) and BPS generally (Gunay et al. 2014), there is a gap in knowledge regarding the impact of human sensing errors, more specifically false positives, on building energy consumption. A false positive output is defined as the incident where the occupancy sensing system falsely indicates human presence when the space is not occupied. False positive sensing can result from a wide variety of factors, such as the failure of a system to distinguish between pets and humans (Benezeth et al. 2011). Such errors in the context of building performance may result in the initiation of a household system, such as Heating, Ventilation, and Air Conditioning (HVAC) and leads to additional energy use. With the expectation that the increasing relevance of sensing systems will make their future widespread deployment, to curtail energy consumption, highly likely, uncertainties regarding error impacts, such as false positives, on total energy conservation must be addressed. The development of low cost and privacy preserving tools can change sensing systems’ current restricted adoption in high-end building typologies. The efficacy of these systems can only be evaluated after understanding the impact of their limitations. Probabilistic occupancy schedules can be used to evaluate the impact of false-sensing, and consequently inform when sensing systems should be activated to anticipate human presence. This paper investigates the consequences of false positive detections of sensing systems on energy use. It establishes a probabilistic occupancy simulation workflow combined with calculations of false positive detection rates, which allow an acceptable level of energy savings, and thus justify the use of sensing systems. The findings of this paper can accordingly set benchmarks and thresholds that sensing systems should adhere to for efficiency expectations.

Research Methods

Figure 1 showcases the experimental workflow in 4 steps:

- Using output from a TUD survey to develop an occupancy presence database.
- Analyzing the dataset and generating probabilistic occupancy schedules.
- Simulating an initial schedule output and an assumed error embedded occupancy schedule.
- Comparing results to estimate false positive reading impacts on total energy consumption.

As a demonstration of the proposed methodology, this paper uses the 2018 American Time Use Survey (ATUS) (Statistics 2018). This survey’s primary objective is to develop nationally representative profiles of how Americans spend their time. The data is collected on a month-by-month basis and included 9592 households for the 2018 Survey (Statistics 2018). The information provided included age, gender and marital status.

To generate probabilistically driven occupancy schedules, this paper employed the established markov chain analysis workflow that was first introduced in the context of UK residential buildings (Richardson et al. 2008). The ATUS survey was first analyzed by categorizing activity types by whether they were household or non-household based. The responses were then organized into two categories according to the day of the week to differentiate between weekday and weekend activities. The day timeline is then divided into 5-minute increments, with each increment being considered a separate state in and of itself.

In a Markov chain, a future state is only dependent on the current state and its transition probabilities. Therefore, under the Markov Chain assumption presented in Equation (1), the next state is only dependent on whether
the current condition is absence or presence and the transition probabilities for this time increment. \[
P(X_{n+1} = j \mid X_n = i, X_{n-1} = k, \ldots) = P(X_{n+1} = j \mid X_n = i) = p(i, j),
\]
where \(X_{n+1}\) is the future state, \(X_n\) is the current state, \(X_{n-1}\ldots\) for \(n\geq 1\) are the past states and \(P(i, j)\) is the probability that a Markov Chain moves from \(i\) to \(j\).

TUD analysis is performed to extrapolate binary transition probabilities from the national survey. Two primary states can exist for any current time step in the analysis, and they correspond to either presence (1) or absence (0). The four possible transition possibilities, illustrated in Figure 2, are accordingly established for every time increment. A random seed selection process is conducted in the grasshopper interface, based on the generated transition probabilities and accordingly a different occupancy schedule is generated when the model runs. To capture this variety, we assume and employ 100 occupancy schedules as output from the model for experimentation purposes. (Figure 3).

Simulation Parameters
The residential shoebox, depicted in Figure 4, was modeled in the Grasshopper interface for Rhino3D CAD software. The area of the modeled room is 60 m² (5m (L) x 4m (W) x 3m (H)). The shoebox has a southern facing façade window with 40% window-to-wall ratio (WWR). Adjacent rooms were placed to reduce direct solar exposure. Assemblies were chosen for the walls, roofs, floors and windows that followed the ASHRAE 90.1-2010 standard for climate zone 3, corresponding to the city of Atlanta. The assembly of the exterior walls consisted of Metal Siding, Insulation and Gypsum Board with an R-Value 1.94 m²·K/W, while roofs had an R-Value of 3.53 m²·K/W. All interior surfaces were considered adiabatic. The ladybug HVAC system used was the Packaged Terminal Air Conditioner Heat Pump (PTHP). Lighting and equipment loads were kept constant for all simulations. Stochastically generated occupancy schedules were used as the baseline to which, equipment, lighting, and HVAC schedules were matched. The targeted comfort temperature range was 22-25 °C. Thermal (Heating/Cooling) loads were observed in any period by simulating energy consumption using EnergyPlus via Honeybee in Grasshopper.

Error Modelling
The applied error modelling approach is formulated around current sensing system workflows. Sensing systems can discern human presence through “Full scans” that are initiated either by human detection through sensors, or designed as a periodic event. In the event of an error occurring, due to the failure of the human detection system, the error remains unchecked until the periodic designed event is initiated. The ensuing increased HVAC operational time in the absence of people results in additional energy consumption. The developed workflow, showcased in Figures 5 emulates that process. It illustrates the changes applied to occupancy schedules to emulate a false positive error in our simulations. First, an initial schedule is used as a substitute for real observations of binary inhabitance patterns. Baseline dataset, consisting of 0 and 1 that correspond to the absence or presence of individuals at particular time periods, is then altered. Since sensing technologies should theoretically recreate the initial occupancy schedule in the absence of errors, deviation from not present to present is accordingly analogous to a false positive reading. Errors were
considered random occurring events and their placement was dictated by a random seed selection process. The objective of the simulation was the evaluation of errors in terms of total energy consumption and their temporal qualities. The scan following a false positive, where the system can rectify an error and shut down the HVAC building systems is constrained by the number of daily scans.

Simulation Results
To gain confidence in the developed simulation workflow, outputs for 200 simulated cases in the City of Atlanta were organized in a Matlab histogram and the distribution of the results was plotted (Figure 6). In each simulation case, a weekly occupancy schedule was randomly placed along the year. Five 1 hour false positives were then embedded in that weekly schedule and subsequently their impact averaged. The distribution of the results was then compared to the normal reference as illustrated in Figure 7. The Cumulative Distribution Function (CDF), established for the simulation outputs, successfully passed the Kolmogorov-Smirnov test for normality. This meant that the effect of errors followed a normal distribution in terms of the additional weekly percentage of energy used due to an error. The shape of the Probability Distribution Function (PDF) was accordingly plotted and the confidence interval was determined by integrating the area under the curve.

A process of optimization and numeric integration depicted in Figure 8 was conducted in Matlab to receive a 95% confidence in the results range. The upper and lower bounds for the error impact contributed to -0.53% and 0.939% of weekly energy use, respectively. The significant deviation between results can be inferred by the wide shape and consequently, the broad range of the confidence interval.

Simulation Across Climate Zones
The simulation process was repeated for 6 chosen cities, which corresponded to U.S. climate zones 1 to 6. The outcomes allowed a holistic understanding of how false positive errors impact energy consumption in different climates. The percentages were calculated in relation to a weekly consumption to provide a tangible context to the impact of a single hour, and to establish benchmarks in relationship to that impact. While diverse impacts were eluded to by initial energy results, the mean of the distribution followed the same pattern across all climate zones. Figure 9 illustrates the range for the average percentage energy use due to an error, evaluated across the year. The 95% confidence interval exhibited on the other hand a broad range across all climate zones. This wide range highlights the variation in simulation results in relation to the timing of the error. Miami exhibited the smallest range, and the largest range was in Albuquerque. Expected higher energy usage in cooling dominated climates did not translate to a larger outcome.

The smaller range for Miami indicates a comparatively constant error impact across the year. The city of Albuquerque, in comparison, experienced vast differences in response to the timing of the error. The large variation warranted further investigation to
understand the key components of both low and high impact errors. The mean percentage energy use per error, on the other hand, was comparable across the chosen cities. The mean values ranged from 0.46% in Albuquerque to 0.53% in Miami, respectively. The mean of Albuquerque might be influenced, however, by errors that affected overall energy consumption positively. The positive effects of some errors, indicated by their inclusion in the range, is experienced by multiple cities.

Simulation Across Seasons

To understand the temporal properties affecting errors, the next examination, illustrated in Figure 10 (left), was a seasonally oriented observation of the hourly impact for the city of Atlanta. June, September, and December were used as proxies for the Summer, Fall, and Winter seasons, respectively. Each dot represents the error impact in kWh output in that particular hour. The curve is a depiction of the conducted simulations' moving average. A large deviation in error impacts was evident between those months in Atlanta. The average impact for June was significantly larger than that of December, with an approximate factor of 4 or larger across the entire day. The September moving average was the second highest and followed a similar pattern to that of June, but experienced a larger distinction between daytime and night time averages. The average impact of December, on the other hand, formed a relatively flatter curve, with two dips in impact at 12 AM and 8 PM. The peaks for the three months were 0.352 kWh for June, 0.32 kWh for September, and 0.094 kWh for December. Unlike September and June, December experienced a second peak of 0.85 kWh at 7 AM.

A holistic examination of climate zones was further pursued. The same adopted logic pertaining to the hourly dots and the moving average were employed from the previous investigation. The examination depicted in Figure 10 (right) was performed for June with the same simulation process for each hour. As a general observation, all climate zones followed the same pattern. Buildings were subject to a higher error impact in the day than at night. Cities located in cooling-dominated climates like Houston, Atlanta, and Miami tended to have a higher general profile than those of Albuquerque, Chicago, and Milwaukee.

Cooling dominated climates also experienced noticeable deviations between morning and evening values, while colder climates usually exhibited a smaller distinction along the day. The city of Albuquerque is the only exception, having the most significant deviation in diurnal values. The peak averages of the respective climate zones occurred in distinct times of the day between 2 PM and 7 PM. Minimum values occurred relatively simultaneously between 5 AM and 6 AM.

Error Duration

The minimization of error durations was investigated next. Full scans can be initiated either by human detection through sensors, or designed as a periodic event. Errors, in the first case, would remain unchecked until a subsequent full house scan is conducted. The goal was to reduce the average span of errors by the strategic placement of full house sensing system scans. We assumed a maximum number of two, sensor unprompted, additional scans per day to lower potential error duration while ensuring the battery life of the system remains preserved. The most efficient placement of those scanning points is accordingly determined for weekdays and weekends. The full-house scans serve as the ending point for false positives that occur after occupants leave their household. As seen in Figures 11 and 12, if scans are placed significantly later in the day, the average duration of errors would be excessively long. Alternatively, if placed prematurely, false positives that occur immediately after a scan would be left unchecked until occupants return home.
In this investigation, errors were randomly placed as the starting point of an absence period in an occupancy schedule. This was used to emulate people leaving their residence without the detection of the sensing system. The day was divided into 30-minute increments, with each increment considered as a potential scanning point. 200 simulations were conducted for each of the 48 time increments and the average error duration calculated. The strategic placement of the scanning points, as seen in Figures 13 and 14, had a critical impact on the duration of errors. The longest error duration corresponded to the midnight scanning point placement. The average duration was 178 minutes in the weekday and 158 minutes at the weekend. The weekend experienced a lower duration of errors for all scanning points as a result of its general higher occupancy levels throughout the day. The best scanning times for the reduction of the average error are determined to be 8:30 AM and 7:00 PM for the weekdays. On the other hand, the best scanning times for the weekend would be situated at 9:30 AM and 6:00 PM.

Finally, the relationship between additional daily scans and the average error duration was examined. The goal was to explore whether a higher number of scans are favoured over the longevity of the sensing system battery. The relationship in Figures 15 and 16 shows that additional scans decrease the general error durations. The decrease is, however, not linearly proportional and seems to fall off with a larger number of additional scans. The weekday average duration of errors can be reduced from 155 minutes, corresponding to 1, sensor unprompted additional scan, to 78 minutes in the instance of 10 additional scans. The weekend again displayed a lower error duration than that of the weekday. The general trend was similar, however, with the average error duration falling from 142 minutes to 78 minutes with the placement of 10 additional scans.

Results Validation

The validation of the results was performed through a simulation-based workflow. The probability driven, occupancy generating model was used to produce 4 new occupancy schedules as a representative test sample. The occupancy schedule for a week was assembled and randomly situated in the year. A total of 5 errors were embedded in these weekly schedules with each constituting a 1 hour false positive. Each test sample is simulated 6 times, corresponding to climate zone cities 1-6. The results, showcased in Table 1, are subsequently compared against the findings.

The simulation results are all primarily situated in the expected ranges for their respective cities. A 10% overall deviation percentage from the original results can be expected due to outliers. The only outliers are the second sample result for Miami and the fourth sample result for Albuquerque. The deviation of those simulated results from the originally established ranges, however, is relatively small. The variance should also be amended by the scanning time placement and the corresponding
reduction in projected single hour impact. The ranges do, however, convey the generally expected performance due to errors across the year. Future advancements of this research can find the maxima and minima of error impact to give context to the established range boundaries.

Table 1: Validation results.

<table>
<thead>
<tr>
<th>City</th>
<th>Percentage Impact</th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>Sample 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>-0.18 to 0.3%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
</tr>
<tr>
<td>Miami</td>
<td>-0.52 to 0.2%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>-0.11 to 0.5%</td>
<td>0.09%</td>
<td>0.09%</td>
<td>0.09%</td>
<td>0.09%</td>
</tr>
<tr>
<td>Atlanta</td>
<td>-0.55 to 0.2%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
</tr>
<tr>
<td>Milwaukee</td>
<td>-0.33 to 1.0%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.05%</td>
</tr>
</tbody>
</table>

Discussion

It is important to note that the economic and environmental viability of integrating sensing systems for energy regulation is highly dependent on the occupants of the household. A sensing system has the potential to conserve more energy in residential units whose occupants are absent for large portions of the day, rather than households with stay-at-home parents and a relatively constant HVAC system usage throughout the week. This becomes apparent when considering the primary two modes through which energy can be saved by the cooling/heating. Either occupants have been operating the system continuously throughout the day, even in their absence, or occupants regularly fail to shut down the HVAC systems when leaving. From a conservational non-operational energy perspective, the integration of a sensing system is more advantageous for small household residences that are subject to long periods of complete absence and a high frequency of household state transitions. For future research, a comprehensive study needs to be undertaken on the behavioral pattern of individuals towards their HVAC systems. This would provide insights into how people regularly operate their own homes. It can also help in the acquisition of more accurate estimations of the expected energy savings by the integration of a sensing system.

Annual Investigations

The holistic year-round examination of errors showcased a significant variance in terms of the simulated results. The wide shape of the normal distribution and subsequently, the large range for the percentage energy use per false positive indicates a significant deviation in the amount of energy being wasted per error. The cause of this deviation can be attributed to the time at which the random occurring false-positive manifested. First, there is a need to consider the climate at the time of error occurrence. The examination of the hourly energy being wasted due to a false positive showed that energy use is predominately dictated by the environmental context of the building. More energy was required to regulate an error occurring at peak noon in the climate of Atlanta in June, than an error occurring at 8 PM. The outdoor environmental conditions at noon require the HVAC systems to consume more energy to regulate the interior space to the desired conditions. The general June daily energy use pattern indicates maximum energy use between 10 AM and 4 PM. The time experiencing peak energy use coincides with the dip in residential occupancy due to people either being at work or conducting necessary morning trips. The HVAC systems require larger amounts of energy to bring the indoor temperature to the comfort level in a space that has been uninhabited for an extended period of time, rather than a false positive occurring immediately upon the departure of inhabitants. This phenomenon seems to amplify the impact at hours between 1-4 PM. The integration of scanning systems should, therefore, include configurations that indicate the location as a way of optimizing system usage. Given the location, a sensing system should align itself with the understanding of errors in both that particular climate and season of the year to reduce the impact of errors on total energy consumption.

Impact of Error Duration

The placement of daily additional scans resulted in error duration reduction. Since HVAC energy consumption in buildings is proportionally higher in relevance to the energy consumed by the system to conduct a full scan, a higher number of daily scans are suggested to constrain possible error durations to small periods of time. The optimum placement of the scanning point differed between weekdays and weekends as a result of the changing inhabitance patterns. While the results of this experiment showcase that smaller periods between consecutive scans result in lower energy use figures, the highest sensing frequencies might not necessarily provide the holistically best results in terms of total energy consumption. The benefits of short intervals between consecutive scans should be weighed against the amount of energy consumed for the consequently higher number of scans performed by any particular system. This can help designers in adjusting the parameters of these sensing systems to provide the most efficient results in terms of overall energy consumption.

False Negatives

Error impact should not only be assessed in terms of energy consumption but must be analysed through the lens of compromised occupant comfort. The degree of deterioration in comfort due to an error will depend on building characteristics, environmental context and error duration. A high frequency of false negatives can form mistrust and contribute to the removal of a sensing system. Future research should explore system configurations to help sustain comfort levels in the event of an error.

Conclusion

People consume energy in buildings either by their passive presence indoors, which increases mechanical loads to attain thermal comfort, or by actively engaging with the building through control of said mechanical systems, as well as lighting and equipment. It is, therefore, important for individuals to engage efficiently with their building to reduce energy consumption through effective behavior and control of systems. Consequently, a high performing building aims to also engage with its users by employing human sensing technologies as a means to automate occupancy detection to reduce energy consumption and either turn systems off in their absence,
or change set points and set backs significantly. Occupancy schedules in BPS play a key role in representing human presence in buildings and its corresponding building energy consumption. Critical developments in sensing technologies over the last decade make such schedules a candidate for simulation to aid in testing and calibrating human detection systems in buildings. However, such emerging technologies may only have disruptive effects in residential building markets, specifically, if the system is significantly low in cost, easily self-commissioned, and requires minimal maintenance. These stringent constraints make them susceptible to inaccuracies. Therefore, this paper developed a stochastic approach to examine the role of low-cost sensing configurations, like scanning frequency and seasonal performance, in an integrated way for a symbiotic relationship between sensing systems and simulation schedules. The claim, however, remains to be supported by real-life observational data of average false-positive frequencies for different sensing technologies. The mutually beneficial relationship between occupancy schedules and sensing technologies also needs to be utilized, where sensing technology can calibrate occupancy schedules in buildings. Gathered data would constantly shape the ever-changing nature of human behavior, and match occupancy schedules that govern building systems to actual human patterns.

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