A FRAMEWORK TO SIMULATE DIVERSE OCCUPANCY AND PRESENCE SENSING TECHNOLOGY TO REGULATE HEATING AND COOLING ENERGY IN RESIDENTIAL BUILDINGS

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A FRAMEWORK TO SIMULATE DIVERSE OCCUPANCY AND PRESENCE SENSING TECHNOLOGY TO REGULATE HEATING AND COOLING ENERGY IN RESIDENTIAL BUILDINGS

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LIST OF SYMBOLS AND ABBREVIATIONS

HPB	High Performance Buildings
BPS	Building Performance Simulation
HVAC	Heating, Ventilation, and Air Conditioning
ATUS	American Time Use Survey
BEM	Building Energy Modelling
NREL	National Renewable Energy Laboratory
ASHRAE	American Society of Heating Refrigerating Air-Conditioning Engineers
DOE	Department of Energy
PDF	Probability Distribution Function
CDF	Cumulative Distribution Function
CPS	Current Population Survey
MST	Motion Sensor Timeout
PTHP	Packaged Terminal Air Conditioner Heat Pump
TMY	Typical Meteorological Year
PSR	Pressure State Response
DPSIR	Driving Force Pressure State Impact Response
DPSEA	Driving Force–Pressure–State–Effect–Action
DPSEEA	Driving Force Pressure State Exposure Effect Action

SUMMARY

With the rapid progression of human sensing technologies, High Performance Buildings (HPB) are inevitably moving towards the wide scale automation of occupancy detection for energy efficiency purposes. Occupancy patterns influence energy consumption in buildings by governing the Heating, Ventilation and Air Conditioning (HVAC) systems to regulate indoor conditions for human comfort. The integration of emerging sensing systems in residential buildings requires low-cost, low-resolution alternatives that might be subject to inaccuracies and result in errors.

In Building Performance Simulation (BPS), occupancy schedules act as proxies for human presence patterns in buildings. This thesis develops a simulation-based workflow to examine the impact of system sensing errors, like human false sensing, using occupancy schedules to quantify energy loss. A Markov-Chain analysis of the 2018 American Time Use Survey (ATUS) is used to extrapolate transition matrices and generate probabilistic driven occupancy schedules.

The aims of this thesis are threefold: i) investigate the evolution and current state of BPS occupancy schedules and their connection to sensing technologies, ii) examine the effect of different human detection system configurations on total energy consumption in false sensing scenarios, and iii) introduce occupancy schedules as a new factor in the decision analysis process of sensing systems. The simulations evaluate the impact of false positives in binary occupancy modelling scenarios using Honeybee as a front-end software and EnergyPlus as a backend Building Energy Modeling (BEM) engine.

Results highlighted the role of sensing configurations, like scanning frequency, on the percentage of weekly energy loss per false positive, with an increase from 0.51% to 1.49% corresponding to the 10-60-minute scanning frequencies. The standard deviation of the percentage of energy lost per error ranged from 0.53-0.74, indicating that the time of error also influenced the amount of energy lost. The number of errors that would result in a significant amount of energy loss (assumed as 30%) was 22 in the 60-minute error duration scenario. The high threshold was dependent on the scanning frequency and eluded to the viability of using low-cost sensing technologies.

The annual false positive impact on total energy consumption was examined under various environmental conditions. For the United States, climate zones ranging from 1 to 6, the cities of Miami, Houston, Atlanta, Albuquerque, Chicago, and Milwaukee were selected as representatives. The distribution of the annual investigation passed the Kolmogorov–Smirnov test for normality and were fitted to a normal distribution to gauge the ranges of energy loss. Results indicate an approximate mean of 0.5% weekly energy loss per-hourly error across the 6 chosen climate zones. The large range of occurring errors was shown to be attributed to prior occupancy, seasonal and daily climatic variations, and countermeasures were proposed for the reduction of such error effects. The potential energy savings by the implementation of the system varied between different climate conditions. The projected savings ranged from 20.1% for the city of Miami to 11.0% for Milwaukee. The potential of a city was governed both by the severity of the climatic conditions and the occupancy pattern corresponding to peak impact times.

Seasonal investigations showcased the benefit of full HVAC system usage in short absence periods in winter months. Critical system scanning points for the reduction of average error durations were established at 8:30 AM and 7 PM for weekdays, and 9:30 AM and 6 PM for weekends. The incorporation of additional scanning points is also encouraged for the reduction of overall error duration but must be evaluated based on inherent sensing system energy consumption.

An integrated approach combining occupancy schedule and sensing technology is finally described for the mutually beneficial enhancement of their performance. Overall, the results indicated that with recommended guidelines and criteria for system configurations, the use of low-cost, low-accuracy sensing technologies is warranted. The thesis provides an overview of the implications of integrating future sensing technology in building thermal energy regulation, from an error evaluation perspective, that must be considered before emerging technologies are eventually deployed across United States residential buildings in the future.

CHAPTER 1. INTRODUCTION

Significant advancements were made in the field of HPB in the past decades in terms of simulating and designing for the effects of geometrical attributes and physical phenomenon on the built environment. Contextual factors, like accurate climate modeling, are now investigated with increasing accuracy and precision. Building inhabitants and their influence on energy use, represented in BPS through occupancy schedules, on the other hand, are comparably less developed (Mahdavi and Tahmasebi 2019).

The impact of occupants on energy use in buildings has been recognized as far back as 1978 by Sonderegger, who stipulated that occupant behavior may influence 71% of the variation in building energy demands (C.Sonderegger 1978). It has also been established that household size and occupancy patterns are the main contributors to electrical loads in residential buildings (Richardson, Thomson, and Infield 2008). The influence of those inhabitants is expected to grow in the future, with a predicted decrease in misused energy attributed to building characteristics as a result of enhanced regulation guidelines and improved building thermal properties (Guerra Santin, Itard, and Visscher 2009).

A higher degree of accuracy in capturing human presence in buildings can create savings not only in future structures but can also be integrated to manage and conserve energy in the proportionally larger current building stock. Occupancy schedules have and will undoubtedly play a key role in regulating energy consumption by tightly managing and matching mechanical system usage to human presence patterns. The drastic improvement in sensing technologies in the last decade, on the other hand, has made them a definite candidate for regulating the consumption of energy in the future. For sensing technology to have a significant impact in the energy regulation process, they must be employed beyond their current restricted use in high-end building typologies and become more integrated in the larger fabric of the built environment.

A comprehensive evaluation of the current state and gradual progression of occupancy schedules through time is key towards understanding the diverse components of occupancy patterns. The modern representation of human presence in space can also be wielded as a means of evaluating and testing both the potential and limitations of sensing technology. The HPB community would then be prepared to answer questions regarding the integration of these systems, which would in turn pave the way for future interventions.

1.1 Research Purpose

1.1.1 Research Goal

To understand both past and current methods for occupancy informed energy regulation in buildings, and develop a simulation-based workflow that evaluates sensing technology integration from an energy conservation perspective.

1.1.2 Research Hypothesis

If sensing technology is going to replace our current occupancy representational tools, then how can occupancy schedules be used to evaluate, simulate, and explore the potentials and limitations of sensing technology integration in future residential buildings?

1.2 Research Motive and Structure

1.2.1 Significance

The research assumes the inevitable integration of sensing technology in future homes. Therefore, it investigates how wide-scale adoption of sensing technology would, in turn, create considerable energy savings for both existing and future buildings.

1.2.2 Research Objectives

- Formulate an understanding of the development of occupancy representation in buildings;
- Identify the intersection points between occupancy schedules and sensing technology;
- Develop thresholds and benchmarks for the evaluation of sensing technology integration in residential buildings from an energy regulation perspective; and
- Investigate the properties of system error in terms of total energy consumption.

1.2.3 Research Questions

1) How can the existing body of knowledge on occupancy schedules be integrated with emerging sensing technologies to enhance their mutual capacity for building energy regulation?
2) How can sensing technology's management of residential energy consumption, given errors, be evaluated and improved through our understanding of the parameters influencing its regulatory performance?

1.2.4 Target Audience

The thesis enhances our current understanding of sensing system configurations and should encourage wide-scale implementation of sensing systems. The primary target audiences are both energy modelers and technology developers. The finding can also help architects and engineers make informed decisions concerning the implementation of these emerging technologies.

1.2.5 Thesis Overview

The first chapter introduces the thesis and underlines its goals and objectives. The second chapter investigates the mutually beneficial relationship between occupancy schedules and sensing technology through a literature review. The third chapter is an examination of sensing technology's impact on energy consumption through a simulation-based experimental workflow. The fourth chapter demonstrates the results of the experiment. The fifth and final chapter is an evaluation of the findings and conclusion for the thesis. Figure 1 demonstrates the general thesis breakdown and workflow.

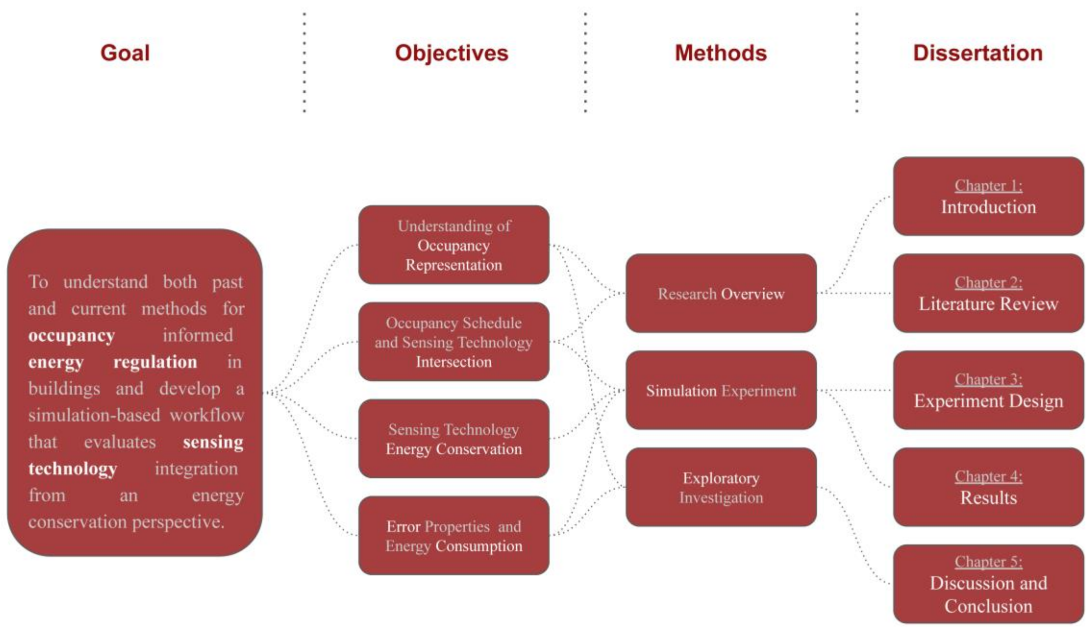

Figure 1 - Research Process Flowchart

1.2.6 Contributions to Knowledge

- Evaluation of the current relationship between occupancy schedules and sensing technologies, as agents of regulating energy consumption in buildings.
- The establishment of the terminology needed to evaluate emerging sensing technologies from an energy conservation perspective.
- Providing suggestive guidelines for sensing technology settings and configurations to achieve enhanced overall performance from an energy conservation perspective.

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CHAPTER 2. LITERATURE REVIEW

This chapter aims to investigate the evolution and development of occupancy schedules as agents of building energy regulation. The intersection between occupancy schedules and sensing technology is then explored and critical examination topics for sensing systems are highlighted.

2.1 Occupants in Buildings

Understanding and reproducing the complex impact of occupant behavior in buildings can be a challenging task. Occupants can affect the building through two main behavioral categories. People influence the building either passively by their presence, or actively through their interaction with building systems to control their environment and ensure their comfort (Hong et al. 2017). In BPS, occupancy schedules are used to give a better understanding of the passive presence of individuals in buildings. They feed more importantly into models that depict how individuals are expected to respond to changing environmental circumstances such as interaction with windows (Fritsch et al. 1990), air-condition systems (Tanimoto, Hagishima, and Sagara 2005) and lighting (Reinhart 2004).

Developing the behavioral patterns required to determine and regulate the energy consumption of a building is, therefore, highly dependent on the fidelity of the occupancy schedule (Yao and Steemers 2005). While the passive impact of occupants can be calculated, the issue lies primarily in the input that feeds those calculations. The depiction of human presence in buildings faces multiple obstacles. First, there are challenges in obtaining the necessary observational data that is critical to generate an empirically grounded presence model. Furthermore, the data that is available usually fails to describe the full range of occupant diversity and is not accurate in terms of temporal representation (Mahdavi and Tahmasebi 2019). Any generated occupancy schedule, therefore, relies primarily on various means of data interpolation, that aim to describe actual human patterns as accurately as possible. The representation of occupancy schedules has evolved in the literature over time, with both our understanding of human behavior and the discovery of more analytical tools that capture the patterns of that behavior.

2.2 Deterministic Occupancy Schedules

While different approaches are currently used to represent occupant behavior in BPS (Crawley et al. 2008), one of the oldest and most widely adopted are deterministic schedules. The method adopts logical assumptions to create different patterns based on time of the week and type of the building. In these schedules, the number of occupants that are expected to be present at any point in time is represented through a percentage of the peak building occupancy. The expected percentage of occupancy is then transmitted to the HVAC systems that expends the proportional amount of energy to regulate the indoor air conditions to the desired temperatures.

The simplicity of these initial schedules does not capture the complexity and diversity of human behavior in buildings nor take advantage of the computational potential that modern technology provides. The deterministic values of these schedules are mostly derived from codes, standards, or the intuition of experienced energy modelers (D'Oca and Hong 2015). The most referenced standard is the ASHRAE 90.1 published in 1989 that has remained relatively unchanged in the 2011 edition (American Society of Heating

Refrigerating Air-Conditioning Engineers 2011). The National Renewable Energy Laboratory (NREL) also referenced the ASHRAE Standard 90.1-1989 for office, retail, food Sales and food service buildings types, while noting that despite their belief of the flawed nature of these schedules, no better example has been established (*U.S. Department of Energy Commercial Reference Building Models of the National Building Stock* 2011). The oversimplified nature of these schedules leads to homogenous simulation results (Cowie et al. 2017) that neither captures the stochastic patterns of occupant behavior in buildings (*Annex 66 Final Report* 2018) nor is supported by empirical data. Multiple studies have indicated lower occupancy rates in the post-occupancy evaluation of office buildings than those provided by the standard (Duarte, Van Den Wymelenberg, and Rieger 2013).

An office building investigated by Sun & Hong displayed a significant 50% deviation from the standard schedules provided by the Department of Energy (DOE) when comparing them to actual observed occupancy presence (Sun and Hong 2017). The deviation of these occupancy schedules from their real-life counterparts alludes to the large quantities of energy lost due to mismanagement of mechanical systems. The inaccuracies and deviations lead to wasted energy in the form of either overheating or overcooling of vacant spaces. Occupancy schedules that depict human presence across different climate zones have also been standardized and are deterministic, while real-life observations have indicated differences due to behavioral parameters (Azar and Menassa 2012). This means that the depiction of human behavior in occupancy schedules can be further enhanced by integrating a wide variety of factors like socio-economic structure in their production. These oversimplified schedules are then incorporated in energy simulation platforms of software like REVIT and EnergyPlus, meaning that the computational potential of modern technology is lost.

To overcome this obstacle, one of the key objectives of Annex 66 was providing multiple occupancy simulation tools that can be easily used and integrated into future building performance simulations (*Annex 66 Final Report* 2018). The initiative spawned the output of multiple occupancy simulation software. ObXML (Hong et al. 2015) attempts at standardizing the behavior of occupants as an input for building performance simulation. The XML schema is based on Drivers–Needs–Actions–Systems (DNAS) ontology. Here, the environment is the driver that incites the actions performed by the building inhabitants, who control the building systems for their needs. The obXML ontology showcases occupant behavior in buildings and can be integrated by multiple BPS software. An extension of this XML schema is the software component obFMU (Hong et al. 2016). This software interprets the output of the obXML file and feeds multiple occupant behavioral models like lighting and temperature. The obFMU software has been utilized with EnergyPlus to enhance occupant behavior simulation models through co-simulation. Lastly Feng developed a software module (Online web simulator) as part of the Annex66 initiative (*Annex 66 Final Report* 2018) that helps in generating occupancy schedules (Feng, Yan, and Hong 2015). The software is capable of working as a standalone product, being imbedded in simulation tools or used in co-simulation (Feng, Yan, and Hong 2015).

These tools have the potential to improve the representation of human behavior in buildings and can subsequently enhance the fidelity of future performed energy simulations. This leaves the HPB community with the challenge of generating occupancy schedules that can be used to govern and regulate energy consumption in buildings as the complementary segment to the initially proposed initiative.

2.3 Probabilistic Models

The failure of deterministic occupancy schedules in capturing the large spectrum of human behavior led to the development of probabilistic generated occupancy schedules. Richardson et al. were one of the first to generate stochastically driven occupancy schedules that attempted to replicate human behavior. The schedules were derived from a large scale Time Use Data (TUD) survey in the UK that analyzed and divided residential behavioral patterns based on household size and day of the week (Richardson, Thomson, and Infield 2008). First Order time inhomogeneous Markov Chains were used in that analysis to generate a model in which the probability of presence at a time step is only dependent on the state of presence at the previous time step (Feller and Teichmann 1967). The resulting model provided single day occupancy schedules that accounted for differences between weekdays and weekends and the number of individuals present (Richardson, Thomson, and Infield 2008). Being driven by probability, the model generates a different schedule every time it runs, producing results more akin to human behavioral patterns. Adopting that approach, however, creates issues that relate to scarcity of data (Feng, Yan, and Hong 2015), since large amounts of detailed household inputs are required (Paatero and Lund 2006) for that analysis.

Unlike commercial buildings, collected residential data used for any model are not always based on sensor feedback but rather on surveys, which have been shown to be inaccurate (Gauthier and Shipworth 2015). In these surveys, people are asked a series of questions that pertain to their daily activities and movements. Research has shown a gap, however, when comparing actual human behavior with what people report they are doing (Gauthier and Shipworth 2015), meaning that surveys are typically not a reliable tool for data acquisition. While all stochastically generated algorithms relying on recalled memory in the form of surveys entail inaccuracies, they provide an understanding of the rationale and motivation behind human residential occupancy. Data mining approaches similar to the one proposed for office buildings (D'Oca and Hong 2015) should be considered in the future while ensuring that the privacy of inhabitants is not compromised. The TUD survey used in Richardson's study also pertained only to the UK, meaning the obtained schedules are not viable for a global audience. Page et al. believed calculating occupancy schedules based on a single day like Richardson et al. is not inclusive and attempted to reproduce an entire year in their simulations. They incorporated interruptions in the model in addition to inhomogeneous Markov Chains to account for abnormal events that result in long absences like vacations or sickness (Page et al. 2008). The schedules developed by Richardson et al and Page et al. were both critiqued, however, on their shortcomings in being calibrated according to individual characteristics of inhabitants. This is important since diversity has been shown to influence a deviation of 46% than the recommended ASHRAE standard in office buildings (Duarte et al. 2013). Research also indicated that a variation of 150% in energy consumption could be expected, depending on the values used to represent occupant behavior (Clevenger and Haymaker 2006).

Realizing the importance of occupant behavior in household energy consumption (Guerra Santin, Itard, and Visscher 2009), Wilke et al. later built on Richardson et al.'s research by providing schedules that described the time, type and duration of different activities performed in a day (Wilke, Haldi, and Robinson 2011) (Wilke et al. 2013). The researchers used a high order Markov chain and Survival analysis in the generation process. Another approach to creating occupancy schedules was undertaken by Tanimoto in 2008 and then later adopted by Yohei Yamaguchi in 2011. They used TUD only to calculate Average Ongoing Minutes (AOM), Standard Deviation (SDOM), and behavior occurrence percentage (PB) of all activities (Tanimoto, Hagishima, and Sagara 2008). They used logarithmic gauss distribution as a means of obtaining the duration of any single activity (Yamaguchi, Fujimoto, and Shimoda 2011). The research was useful in emulating general human behavior in a day in terms of duration but not in creating an occupancy schedule the depicts when those activities are performed. Wang et al. advanced occupancy schedules to be movements both inside and outside of the building for office buildings (Wang, Yan, and Jiang 2011) and were able to reproduce human presence inside different zones of the building. This work was one of the first to examine the movement of occupants inside buildings and the corresponding impact. They suggested further investigation be taken to implement the same logic in residential buildings and other facilities.

While several methods have started to build on the impact of active actions, it is generally believed that research regarding occupancy schedules still remains inconclusive. Other papers have also described the integration of stochastic occupancy schedules as scattered and isolated (Cowie et al. 2017).

2.4 Occupancy Schedules moving Forward

While stochastically generated occupancy schedules are better suited for annual evaluation of energy consumption, they fail to represent short term occupant behavior. Mahdavi and

Tahmasebi argued that predicted behavior by probabilistic models and their monitored daily counterparts are usually not compared on a one to one basis (Mahdavi and Tahmasebi 2015). In the case of Page et al.'s stochastically generated absence periods (Page et al. 2008), the frequency of days is accurately depicted, but the periods are randomly scattered across the year and do not match the actual absences.

Stochastically generated occupancy schedules, therefore, fail to accurately govern energy regulation on a day to day basis. A study conducted on a high rise commercial building recommended the use of probabilistic occupancy schedules for annual investigations rather than day-repeated schedules when trying to assess the model (Carlucci et al. 2016). Stochastically generated schedules can help us understand long term trends and represent human diverse patterns but are insufficient in producing short term predictions. The role of sensing technologies becomes apparent in enhancing the fidelity of those day to day predictions. Although occupancy schedules and sensing technologies are both means of depicting occupant presence in space, the interplay between those two elements have rarely been studied in spite of the capability of the latter in significantly managing the impact of occupants (Dounis and Caraiscos 2009).

The work performed by Mahdavi and Tahmasebi is one of the first to appreciate the value of that connection. Surprisingly, non-probabilistic predictive models that are driven by onsite observations performed better in the short term than their probabilistic counterparts (Mahdavi and Tahmasebi 2015). The reliance on sensing technologies for post-occupancy evaluation is also critical since stochastically generated occupancy schedules entail within them a 5% spatial and 10% temporal uncertainty (Carlucci et al. 2016). A study conducted on 18 design phase energy models in Canada indicated that revising the initial assumptions related to occupancy behavior can reduce the energy estimation error by an average of 32% (Samuelson, Ghorayshi, and Reinhart 2015).

Calibration of simulations also enhanced the accuracy of depicting actual energy use in the case of a high rise commercial building in Shanghai (Pan, Huang, and Wu 2007). In order for calibrations to be a realistic solution, however, the currently undeveloped evaluation process of occupancy schedules needs to be tackled (Yan et al. 2015). Research must be conducted on a large scale to compare the simulations of occupant behavior against their real-world counterparts. Sensing technologies can, therefore, be used in the post-occupancy evaluation of initially generated schedules and assist in calibrating those schedules to produce more accurate results.

Post occupancy evaluation is also required in residential buildings, where calibration at the apartment level has been encouraged to accurately gauge the energy requirements of the different building users (Carlucci et al. 2016). There have been various examples in the literature where building performance data is used to generate occupancy schedules. In one study, occupancy schedules have been produced using hourly building electricity consumption rates as a proxy for human presence in buildings (Yang-SeonKim and JelenaSrebric 2015). Occupancy schedules in non-residential facilities have been developed by using personal location meta-data. Results from meta-data generated occupancy schedules were 10% more accurate in calculating cooling loads and 50 % more accurate in calculating heating loads (Parker et al. 2017). This means that the generation of accurate occupancy schedules must be considered an ongoing process.

From the energy conservation perspective, if occupancy schedules are going to continue their regulatory role, they must transform their current static state to become dynamic and constantly be modified over time in response to new information. Occupancy schedules should utilize post occupancy data and continuously change to accurately represent the behavior of humans in buildings. The relationship between occupancy schedules and sensing technologies is not only favorable, however, for enhancing occupancy schedule accuracy. Sensing technology performance can also be improved by their integration with occupancy schedules.

A sensing technology is by nature a means of capturing current events through sensory observations. As a standalone mechanism, sensing systems do not retain information regarding prior occupancy behavior. Given that building specific occupancy schedules are generated based on prior data, they represent a history of behavioral patterns of building inhabitants in that particular unit. The probability that an occupant is present, entailed in occupancy schedules, can provide a second evaluating metric that improves the performance of sensing systems. Most visual human detection mechanisms use confidence indices to indicate the certainty that a tracked object is human (Benezeth et al. 2011). When a certain percentage or threshold is met, the system recognizes an object as a person. The probability of presence offered by occupancy schedules can therefore act as a supporting mechanism for either increasing or decreasing that percentage threshold based on prior observational data that relate to that particular time of the day. This mechanism becomes more viable with single use building typologies, that do not exhibit multiple behavioral patterns. Concerns are also raised regarding the security of preserving the autonomy of such data for ensured privacy protection. An integration and cross-validation process between sensed information and simulated results can create enhanced energy savings, a topic that has not been thoroughly researched.

2.5 Residential Human Sensing Technologies

The importance of sensing technologies is apparent in building types where occupancy schedules are either not obvious or a large uncertainty in the results is evident (Clevenger and Haymaker 2006). Unlike commercial facilities where the general behavioral trend is governed by the functionality of the building, schedules of residential buildings are greatly influenced by the nature of the occupant in terms of their work, socio-economic status and habits. Occupancy schedules have, therefore, been proven unreliable in governing day to day energy regulation in buildings (Mahdavi and Tahmasebi 2015). This further amplifies the role of sensing technology as the sole mean of regulating energy consumption in those typologies. Relying on onsite installed sensing systems is essential to ensure occupant data is collected and processed correctly.

The rapid advancement in sensing accuracy coupled with the steady decrease in necessary capital for integrating such technologies has also made them a viable solution for building energy regulation. A clear understanding of the potential and limitations of these technologies must be evaluated, however, before wide-scale implementation can be considered. A focus was, therefore, placed on developing occupant sensing technologies, and the annex 66 final report provided a framework of multiple sensing mechanisms that can be used separately or in tandem.

Human sensing technologies can generally be divided into either radio frequency signal technologies or infrared (IR) and video technologies (Yang, Santamouris, and Lee

2016). Infrared occupancy sensors have been used to count the movement of people, both exiting and entering the building and tracking them inside the buildings itself (Gul and Patidar 2015). Passive IR sensors have also been used frequently to measure occupancy in different spaces. Video imaging is currently an emerging field that enables us to accurately track individuals in space, which is important since the presence of multiple occupants has been shown as a behavior impacting trigger (Haldi and Robinson 2010). The large amounts of data that are the characteristic problem of video image-based sensors have also been constantly tackled by the progression of compressed sensing (Jung and Ye 2010). In the case of Computer Vision (CV), high accuracy has been shown but with the downside of requiring extensive computational effort (Lam et al. 2009). The fusion of multi-layered data gathering techniques has successfully increased the viability of detecting behaviors and drastically improved energy consumption in high-performance buildings (Dodier et al. 2006; Dong et al. 2010). Although the accuracy of sensing technologies is gradually improving, they are still susceptible to error caused by inactivity, airflow, or sunshine triggering a sensor. Even with the best accuracy rates for human detection through video image sensors, an error of 3% is usually expected (Benezeth et al. 2011).

A major concern in the evaluation of such problems, from an energy conservation perspective, pertains to the methodological approach that should be adopted to experiment with their general behavioral tendencies. The interplay and combination of simulation and experimentation has been recognized and called for as one of the key factors that can be used to inform and tackle such problems (Khosrowpour et al. 2018). A simulation based workflow can adopt occupancy schedules to test both the implications and parameters of integrating sensing technologies in building energy regulation. The findings can provide a comprehensive understanding of the problem and would subsequently lead to persistent energy savings in the long term (Khosrowpour et al. 2018). The results can also support energy forecasting models that are developed for the insufficiently addressed residential sector (Jain et al. 2014). The fact that human behavior seems to exhibit response relapse patterns in household electricity use (Peschiera, Taylor, and Siegel 2010) further encourages the utilization of sensing technologies in the energy regulation process rather than relying on occupants altering their HVAC usage practices. Sensing technologies can also be integrated with behavioral learning algorithms (Khosrowpour, Gulbinas, and Taylor 2016) that have been developed for the commercial sector. The fusion of those two methods for data driven occupant prediction can be wielded to enhance overall energy efficiency in buildings.

One of the underlying problems with current sensing systems is their limited application to commercial and public facilities. To encourage the widespread application of sensing technologies in the residential sector, a low-cost system must be established. Additional considerations, however, would also have to be made to ensure the privacy of individuals in their own homes is not compromised. There are currently efforts underway to develop a low-resolution camera that aims to only capture pixelated frames and helps preserve individual privacy. The low-cost target coupled with the low resolution required for residential application suggests higher levels of inaccuracies and mistakes. In order to evaluate the viability of that widespread application, a better understanding of the impact of these errors is required.

2.6 False Positive Measures

Research on sensing systems has primarily operated under assumptions of perfect accuracy for the implemented technology. The potential value brought by integrating those sensing technologies in terms of energy savings is then weighed against the cost of production and the scale of their application. 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, Firth, and Allinson 2017) and BPS (Gunay et al. 2014), a lack of research regarding the impact of errors on building energy consumption is identifiable.

An incident where the detection sensor falsely indicates human presence in his absence is generally referred to as false positive sensing. False-positive sensing can result from a wide variety of factors like the failure of the system to distinguish between pets and humans (Benezeth et al. 2011). The link between sensing technologies and building performance elements means that these errors result in the activation of household systems like Heating, Ventilation, and Air Conditioning (HVAC), consequently leading to energy loss. For a holistic examination of the topic, a general investigation on the potentials and disadvantages of relying on sensing systems needs to be conducted. The relationship and impact of false-positive errors on total energy conservation need to be examined. While a sensitivity analysis has rarely been undertaken to evaluate the impact of false human sensing, it has been applied to various other building elements relating to occupants. Blight and Coley conducted a sensitivity analysis to evaluate the impact of occupancy behavior on total energy consumption, while observing lighting and appliance use (Blight and Coley 2013). The same classical format and methodology used by conventional references

(*Sensitivity analysis* 2000) and other reviewed studies (Blight and Coley 2013) can, therefore, be extrapolated to evaluate false occupant sensing.

The impact of a false positive reading of human presence can only be calculated, however, with a developed understanding of how human sensing systems work. Differences can be found between sensing systems (*Annex 66 Final Report* 2018) based on their software configuration and limitations, so a process for breaking down system configuration and rules and extrapolating their effect is critical. The workflow of the sensing technology needs to be carefully examined for key elements like Motion Sensor Timeout (MST) intervals that form the base of simulation inputs. These inputs dictate the response of the sensing system to any detection of presence, whether true or false. Their implications would influence both the probability of a false positive occurring and the speed at which a false positive reading of human presence can be amended. Responses of simulated energy performance in modeling software like EnergyPlus can only then studied with respect to simulation variations (Ioannou and Itard 2015). In these software simulations, all inputs are kept constant, while changes are being tested for the chosen element. Sensitivity analysis concerning occupancy behaviors is usually performed with Monte Carlo analysis (Lomas and Eppel 1992) (Ioannou and Itard 2015), and regression techniques can also be used to understand the relationship between any number of factors in the form of an equation (Blight and Coley 2013). Given that creating energy savings is the main driver behind sensing technology integration, maximum allowable error rates that sustain the inherent potential must also be established.

To conclude, the increasing accuracy of sensing systems due to technological advancements makes its future widespread use in energy consumption management highly likely. Raised uncertainties regarding the impact of errors like false positives on total energy conservation must be addressed. A comparison and evaluation must be performed before the current reliance on preset occupancy schedules is removed. Questions regarding the potential of currently available occupancy schedules in sensing technologies evaluation are also raised. The focus of this thesis is the general investigation of the qualities and ramifications of detection errors in sensing systems. Error frequencies, that would differ between sensing systems is therefore not the main target of this thesis. The acquisition of observational data that establish error frequencies in regard to specific sensing systems becomes the role of technology developers. The findings of this thesis can be used to quantitatively evaluate the impact of false positives on energy consumption and accordingly set benchmarks and thresholds that sensing systems should adhere to for optimal general performance.

CHAPTER 3. EXPERIMENT DESIGN

This chapter aims to enhance the understanding of sensing technologies as agents of regulating energy consumption in residential buildings. The focus is placed on the examination of the potential and limitations of integrating sensing systems in terms of total thermal energy savings.

3.1 Experiment Goals and Objectives

The unique properties of sensing systems create uncertainties for the HPB community that need to be addressed before wide-scale integration can be considered. Some of the more pressing questions include:

1) What are the potential energy savings as a result of sensing technology integration in residential buildings?
2) How does the amount of energy being conserved vary by false-positive readings?
3) How do environmental, operational scenarios influence the amount of energy being lost due to errors?
4) What is the impact of system configurations on wasted energy amounts?
5) Can household occupancy patterns assist sensing technology in thermal energy regulation?

The examination of these questions would help assess the parameters of integrating detection systems in buildings and can assist decision-makers in evaluating the viability of relying on sensing technologies as the sole means of regulating energy consumption in future buildings. The findings can also inform the configuration of future sensing technology for optimal performance in terms of energy regulation.

3.2 Experiment Design

Figure 2 showcases the experimental workflow:

1) Using a TUD set to develop an extensive occupancy behavior database.
2) The dataset is analyzed, and a probabilistic occupancy schedule generating model is established.
3) Simulations for both the initial and the error embedded occupancy schedule are conducted.
4) The results are compared to estimate the impact of a false positive reading in terms of total energy consumption.

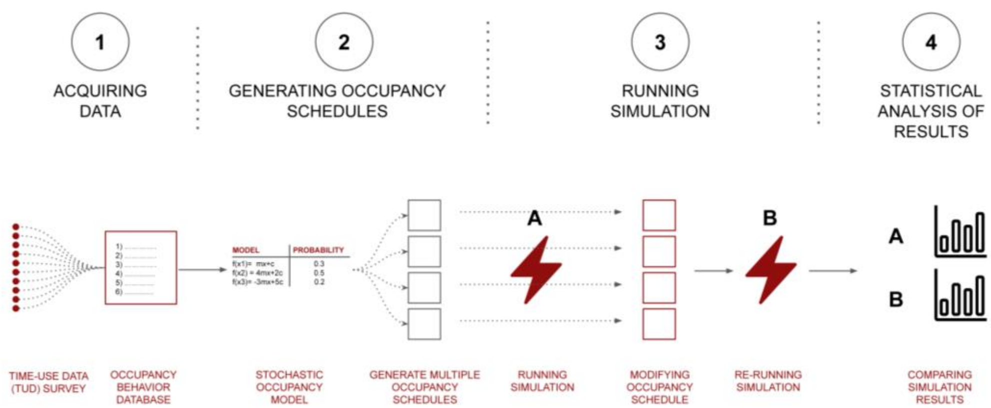

Figure 2 - Experiment Workflow

The workflow establishes the general system for all conducted experiments. The necessary number of simulations for representative result are designated on a case by case basis depending on the output. The main research findings and their output categorizations are illustrated in Figure 3. The diverse outputs of this thesis, are organized in respect to chapter 4 sections 1-5:

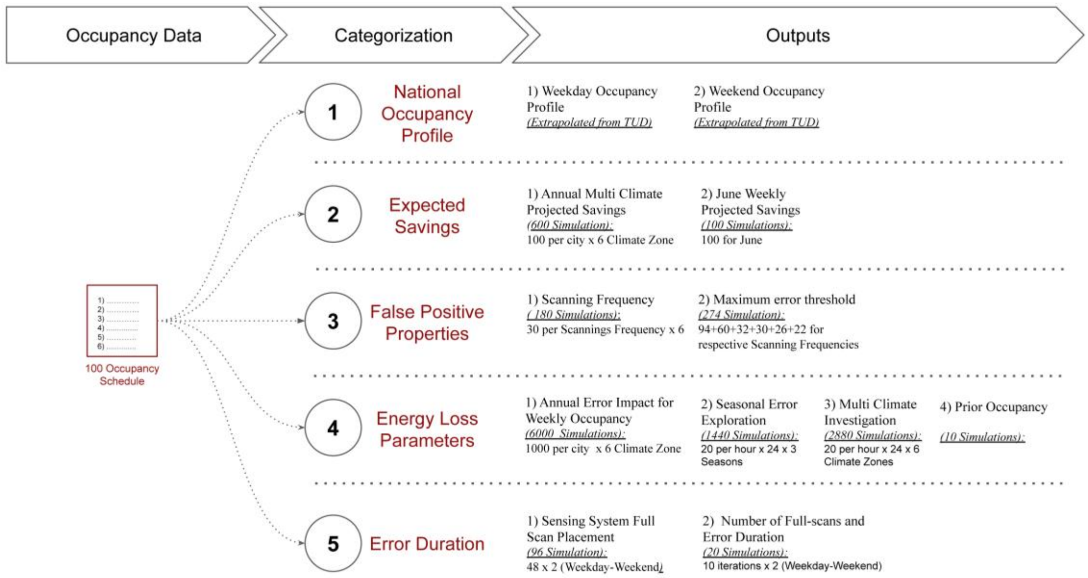

Figure 3 - Experiment Outputs

3.3 Data Breakdown/Constraints/Limitations

For this thesis, the 2018 American Time Use Survey (ATUS) is used (Statistics 2018). The main objective of the survey is the development of a nationally representative estimate of how Americans spend their time. The survey is sponsored by the Bureau of Labor Statistics and conducted by the United States Census Bureau. The ATUS sample population is a subsample of the Current Population Survey (CPS) households. The distribution of the survey respondents across different states is governed by the proportion of the national population that each state represents, respectively. The data is collected on a month by month basis and included 9592 households in the 2018 Survey (Statistics 2018). Each person provided demographic information including age, sex and marital status.

Individuals also gave a breakdown of duration, location, and timing of activities that were conducted on the day before the questionnaire. The recorded data on the location of activities were disregarded, however, due to problems of inconsistency and incompleteness in the output entrees. Assumptions, therefore, had to be made regarding the different activity types to align the data outputs with the research objectives. The survey lexicon helped categorize the wide range of activities in a simple binary representation of household and non-household activities. Household designated categories included things like sleep, personal care, home situated relaxing and leisure. The location of each person throughout the day was then aligned with that categorization.

Challenges with the data sample included significant differences in the fidelity of activity timings. While some individuals provided a detailed minute by minute breakdown of their daily activities, others gave a general summary of their prior day. Duration and timing of activities were also generally rounded up to the nearest hour for convenience and ease. Concerns regarding the reliance on recalled memory for prior events also questions the accuracy of the data.

The output is, therefore, not a true representation of how people generally occupy their residence but rather a portrayal of that process. The survey does, however, provide a general understanding of household occupancy trends on a national scale and can thus be used to extrapolate inherent patterns. The transformed survey data, in its binary representation, would form the basis for the assembled national occupancy profile and all subsequent occupancy investigations.

Future expansions on this research might include comparisons of annual ATUS outputs for different years. The examination can give insights into the evolution of household use over the years and allow us to speculate how things might develop further in the future.

3.4 Occupancy Schedule Generation

This thesis employed the previously established workflow for generating probabilistic driven occupancy schedules. The proposed method was first introduced by Richardson in 2008 in the context of UK residential buildings. The method used a Markov chain analysis approach of the TUD surveys in the creation of occupancy schedules. The governing logic is adopted here for the 2018 ATUS survey. The 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 activity patterns. The timeline of the day is then divided into 5-minute increments, with each increment being considered a separate state in 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 Figure 4 the next state is only dependent on whether the current condition is absence or presence and the transition probabilities for this time increment.

$$P\ (\underbrace{X_{n+1} = j}_{\text{Future State}} \parallel \underbrace{X_n=i,}_{\text{Current State}}\ \underbrace{X_{n-1}= k_{n-1},\ldots}_{\text{Past States}}) = p(i,j)$$

Figure 4 - Markov Chain Definition for Transition Probabilities

Analysis of the data is then performed to extrapolate binary transition probabilities from the national survey. There are two primary states that can exist for any current time corresponding to either presence (1) or absence (0), respectively. For each state, two outcomes represent the possibilities of its future development. The four possible transition possibilities illustrated in Figure 5 are accordingly established for every time increment.

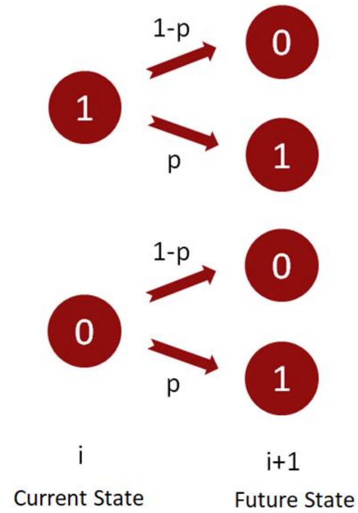

Figure 5 - Transition Scenarios for Time Increments

Being driven by probability, the model generates a different occupancy schedule every time it is run. Once the transition probabilities had been established, a sample 100 occupancy schedules were generated, using the model, for testing purposes. This is conducted in the grasshopper interface using a random seed selection process that is based on the generated transition probabilities.

While the main critique of probabilistic schedules is their incapability of informing short term predictions and use for energy regulation purposes, this thesis utilizes their potential for recreating diverse human activity patterns. Each of the generated probabilistically driven occupancy schedules, depicted in Figure 6, is considered a sample alternative of how people occupy their residence. The probabilistic model is thus only used to recreate diverse occupancy presence/absence schedules as part of a holistic investigation of the topic.

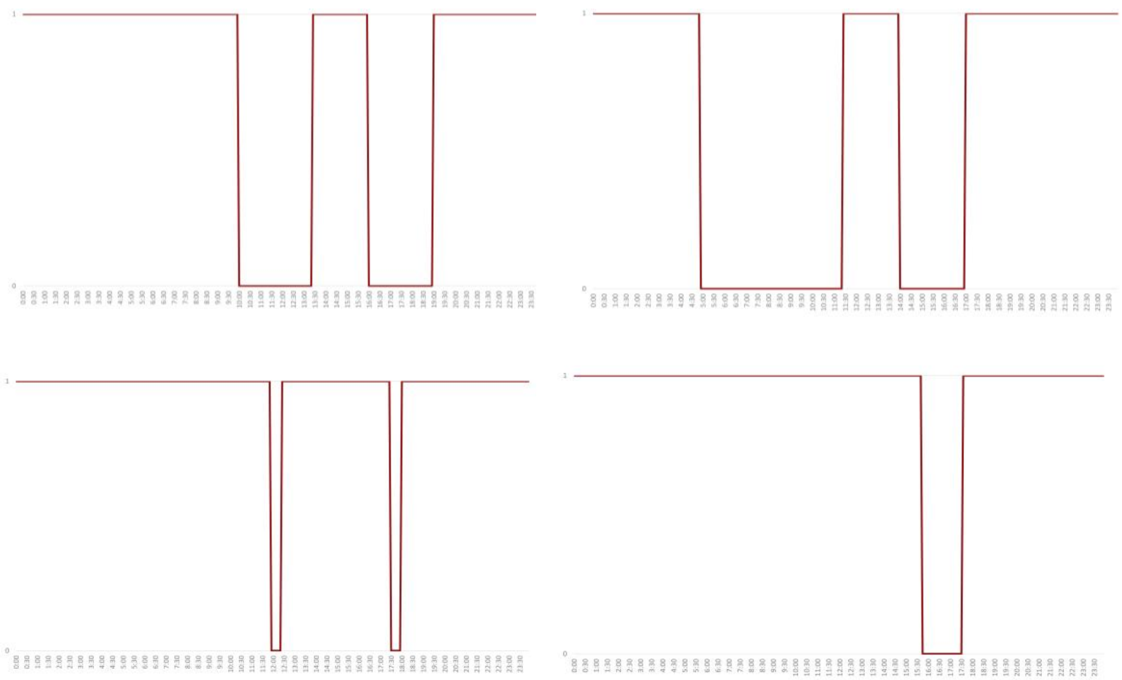

Figure 6 - Sample Binary Residential Occupancy Schedules

3.5 Experiment Logic

The thesis aims at understanding the impact of a false positive reading on total energy consumption. A false positive reading is an incident in which the presence of a human is falsely detected by a building's sensing technology, and the HVAC systems are activated accordingly. The occurrence of a false positive is represented in this experiment on the previously generated occupancy schedules. The workflow showcased in Figures 7 and 8 illustrate the changes made in occupancy schedules to emulate a false positive.

First, an initial schedule is used as a substitute for real on-site observational data and is assumed to be a true sample of a binary inhabitance pattern of a space. The original 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, any deviation or change is accordingly analogous to a false positive reading registered by the system.

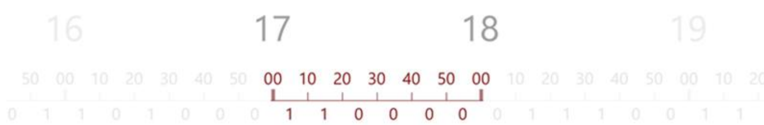

Figure 7 - Initial Occupancy Schedule Segment

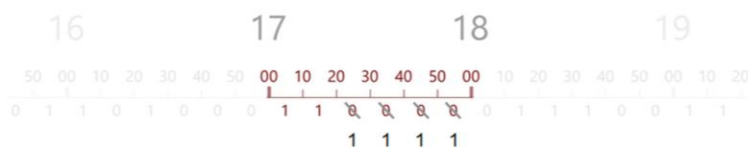

Figure 8 - Modified Occupancy Schedule Segment

The example presented in Figures 7 and 8 showcases how an initial occupancy schedule is altered to emulate a false positive occurring at 5 pm. The schedule is changed to reflect human presence at those hours due to the error. This framework is adopted for all conducted simulations in this experiment.

For holistic investigations, errors were considered random occurring events that are liable to occur at any time increment given the absence of humans in the household. The degree of change in the initial occupancy schedule due to an error and accordingly, the amount of time the HVAC systems are operating in the absence of people is then determined by the succeeding full-home scan. The scan following a false positive is where the system can rectify an error and shut down the operating HVAC building systems.

In this experiment, various types of configurations are explored for the logic that governs household full scans. In some studies, the implementation of a consistent scanning frequency is examined. The scanning frequency is the interval of time that a detection system leaves between routine consecutive scans of the interior surroundings after human presence has been detected. Scanning frequency is, therefore, used as a measure of the duration of a false positive and assists in quantifying how the occupancy schedules are modified.

Other scenarios explored the explicit placement of a restricted number of daily scans as a means of reducing system inherent energy consumption. In all examined scenarios, the difference between the total HVAC thermal load given the initial occupancy schedule and that of the modified one is the impact of a false positive reading.

3.6 Simulation Model

The residential setting depicted in Figure 9 was modeled in the Grasshopper interface for Rhino3D CAD software. The area of the modeled room is 20 m^2 (5m(L) x4m(W)), with a height of 3m. The module has a southern facing façade window located at the narrow end with a 40% window-to-wall ratio. Context modules are placed adjacent to the focus room to shelter from direct sun radiation exposure from all sides.

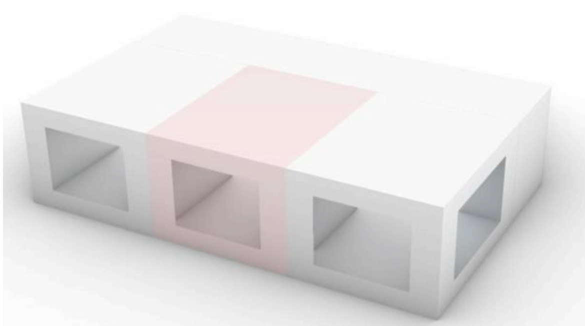

Figure 9 - 3D Rhino Model for the Experiment

The exterior walls and roofs have an R-Value of 1.94 m2-K/W and 3.53 m2-K/W, respectively. All interior surfaces were considered adiabatic. The ladybug HVAC system used for the household simulations is the Packaged Terminal Air Conditioner Heat Pump (PTHP). The number of occupants was set to one, while lighting and equipment loads were kept constant for all simulations. The stochastically generated schedules were used as the occupancy baseline for space. Equipment, lighting, and HVAC schedules were then matched to that schedule. The simulations were performed with Typical Meteorological Year (TMYx) weather files for various climate zone cities. The targeted temperature range in the simulated model was 22-25 °C.

The output being monitored was specifically the thermal load (Heating/Cooling) in any specified period. The energy consumption was simulated through EnergyPlus using Ladybug and Honeybee. These environmental open source tools act as plugins for grasshopper and facilitate the interaction with EnergyPlus for energy modelers. EnergyPlus is a building energy simulation platform that was developed by DOE and is commonly used by various disciplines for energy consumption calculation purposes(DOE 2013).

The simulated model should be considered a prototype for residential units that can be used to speculate on the behavior of diverse context scenarios. A broader focus is therefore placed on the behavioral trends of results and the existing relationships between different system configurations and their impact on total energy consumption, rather than specific numeric energy consumption values that might vary for different household contexts. These relationships can form the basis of understanding the impact of errors and the means through which they can be both minimized and controlled.

CHAPTER 4. RESULTS

This chapter aims to present the simulation and experiment findings. A simulation-based validation process evaluates the result accuracy and future developments are suggested.

4.1 National Occupancy Profile

The first output, depicted in Figure 10, is the assembled national profile for binary occupancy representation of residential units. The percentages are extrapolated from the ATUS with a 5-minute increment fidelity. The weekday occupancy pattern shows consistently high levels of occupancy between 12 AM and 4 AM, where people are most likely asleep. The occupancy then starts to decline as a result of people either going to work or conducting daily necessary trips between 4 AM and 2:30 PM, reaching a low of 37.0%. A gradual increase is then observed from 12:30 PM until the end of the day.

Figure 10 - Weekday National Binary Occupancy Profile

The weekend profile presented in Figure 11 exhibits the same occupancy trend between 12 AM to 4 AM. The decrease in occupancy that starts at 5 AM, however, is much more gradual than that of the weekday. The two dips in the occupancy percentages reflect people choosing to go out in the morning or afternoon and reach 56% and 65%, respectively.

Figure 11 - Weekend National Binary Occupancy Profile

On a holistic note, the weekend occupancy pattern experiences a generally higher level of overall residential presence in comparison to its weekday counterpart.

4.2 Potential Savings

It is important to understand the energy savings achieved by integrating a sensing system in a residential unit, as both a product of occupancy, as well as the human HVAC usage in practice. This investigation entailed an attempt to capture the maximum amount of energy that can potentially be saved by the implementation of the system. The simulations therefore presume inefficient human habits in relation to the HVAC operation in the residence. The assumption being made here is the full usage of the HVAC systems in the absence of any sensing platform as a way to mimic occupants leaving the HVAC system continuously working throughout the year. The potential energy savings are accordingly a measure of the maximum energy percentage that can be conserved by the integration of a human detection platform. In Figure 12, the markers represent the necessary annual energy consumption of the experiment module for different sample occupancy schedules. These results were then compared to the energy consumption if full HVAC operation occurs. The simulated example for the city of Atlanta, depicted in Figure 12, indicate average potential yearly savings of 19.58%. The noticeable deviation between the simulation results can be attributed to the varying general occupancy habits of the residential units. The potential energy savings are consequently different for the various occupancy modules. The higher the overall occupancy of a household throughout the year, the lower the potential savings regardless of human HVAC usage practice.

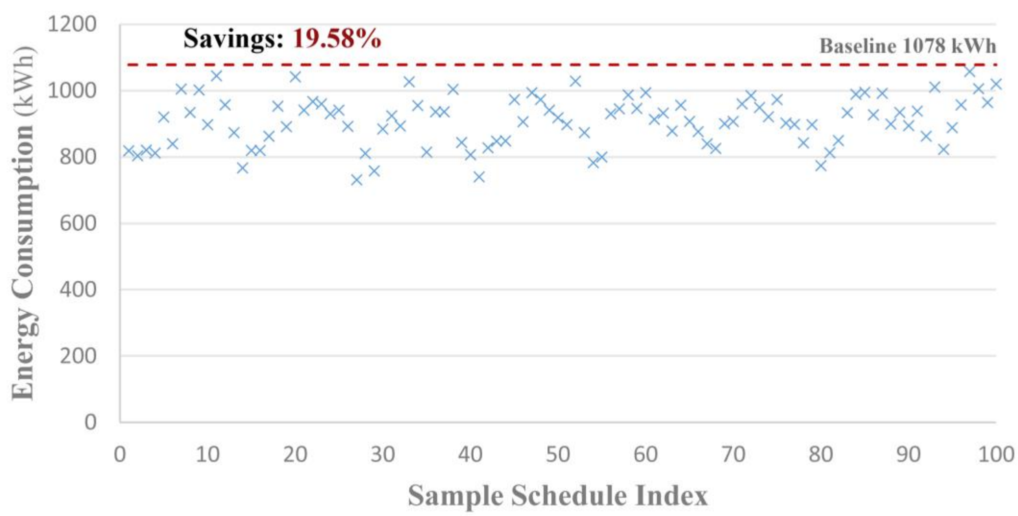

Figure 12 - Annual Energy Consumption for Diverse Occupancy Schedules in Atlanta

The investigation of the weekly energy savings potential, however, is different than its full yearly counterpart. The expected savings in June, depicted in Figure 13 were much higher than the yearly average. This highlights that potential energy savings at any given week are a function of the location of that week throughout the year.

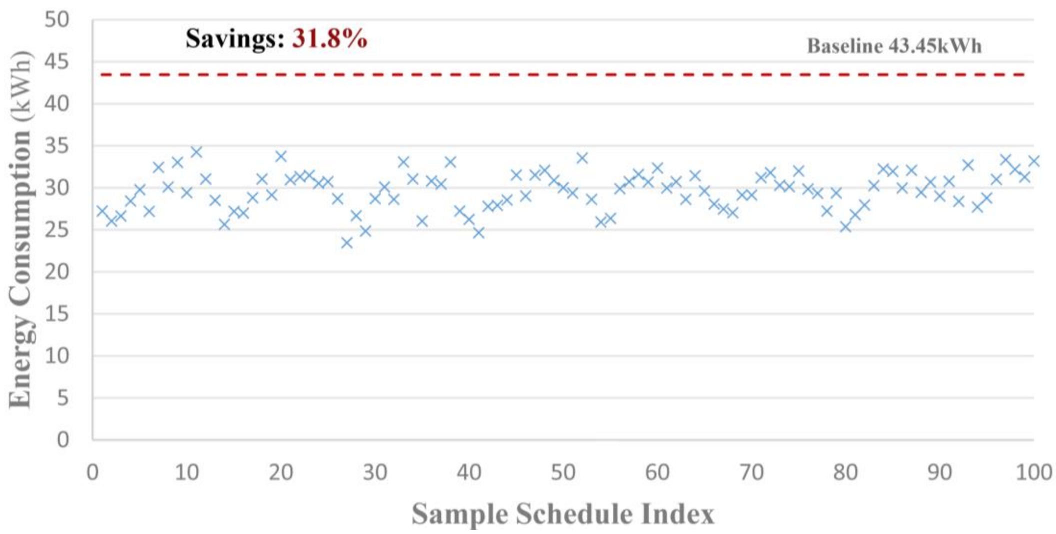

Figure 13 - Weekly Energy Consumption for Diverse Occupancy Schedules in Atlanta for the Month of June

The potential yearly savings calculated for different climate zone cities are compared in Figure 14. The average potential energy savings varied from 10.98% for the city of Milwaukee to 20.188% for the city of Miami. It is essential to understand potential savings as both a function of the context climate severity and the prevailing occupancy pattern at peak climate severity. This stipulation indicates that occupants in Miami are absent in peak climatic conditions. The energy savings that can be achieved by integrating a sensing system follows that governing logic if we normalize human HVAC usage practices.

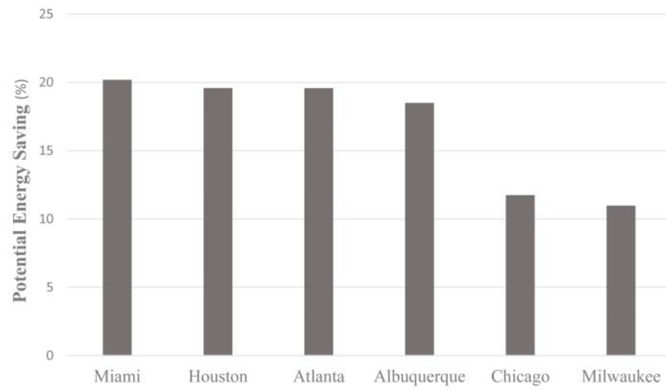

Figure 14 - Potential Energy Saving Percentages for Selected Cities

4.3 False Positive Properties

The focus was subsequently shifted to the analysis of errors and their impact on overall energy conservation. The first experiment demonstrated in Figure 15 was a general investigation of error qualities of June for the city of Atlanta. The monitored factor was the scanning frequency defined as the interval between consecutive full-home scans, where an error would potentially be rectified. In this experiment, a total of twenty false positives were randomly inserted in the weekly occupancy schedules. The results of the experiment revealed that shorter time intervals between consecutive scans produced, on average smaller percentages of energy being lost per false positive. A 60-minute scanning frequency accounted for a 1.49% loss of energy, while a 10-minute scanning frequency resulted in an average 0.51% weekly energy loss per error. The percentages can potentially contribute to significant amounts of energy being lost cumulatively, as six false positives in the case of the 60-minute interval can have an approximate 9% weekly loss ramification. While higher time periods between consecutive scans result in more significant percentages of energy loss, it does they do not follow the same ratio. The additional amount of lost percentage per added minute between scans falls off with higher error durations.

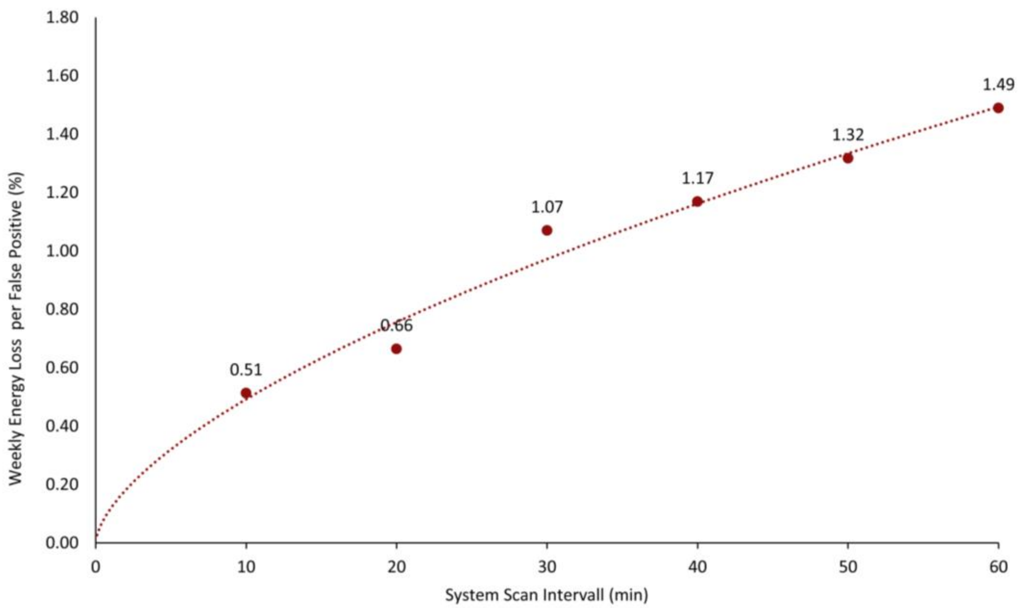

Figure 15 – Scanning Frequency’s Effect of False Positive Impact

The relationship between the weekly percentage of energy lost and the time interval of the scanning system can be best described by a power function indicated in the graph. The standard deviation from the average percentage of energy lost for all scanning frequencies, as shown in Table 1, is noticeably significant. Occurrences of false positives resulted in small quantities of energy being lost in some cases and large quantities in others. This warranted, in turn, an investigation on the factors driving energy loss.

Table 1 Standard Deviation of False Positive Impact for Diverse Scanning Frequencies

Scanning interval (min)	**60**	**50**	**40**	**30**	**20**	**10**
Weekly energy lost per false positive (%)	1.49	1.32	1.17	1.07	0.66	0.51
Standard Deviation(%)	0.74	0.8	0.7	0.77	0.49	0.53

To understand the number of errors that would contribute to a significant energy loss for the system, a simulation experiment was devised to measure the number of weekly false positives that resulted in a 30% energy loss threshold. The numbers and the subsequently required time, serve as a measure of the maximum energy losses that are liable to occur. The threshold as shown in Figure 16, is relatively substantial. In the case of the 60-minute interval, a weekly 22 hours were required to result in the 30% energy loss benchmark. These results provide boundary limitations that need to be avoided if any energy savings by the integration of a sensing system are to be expected.

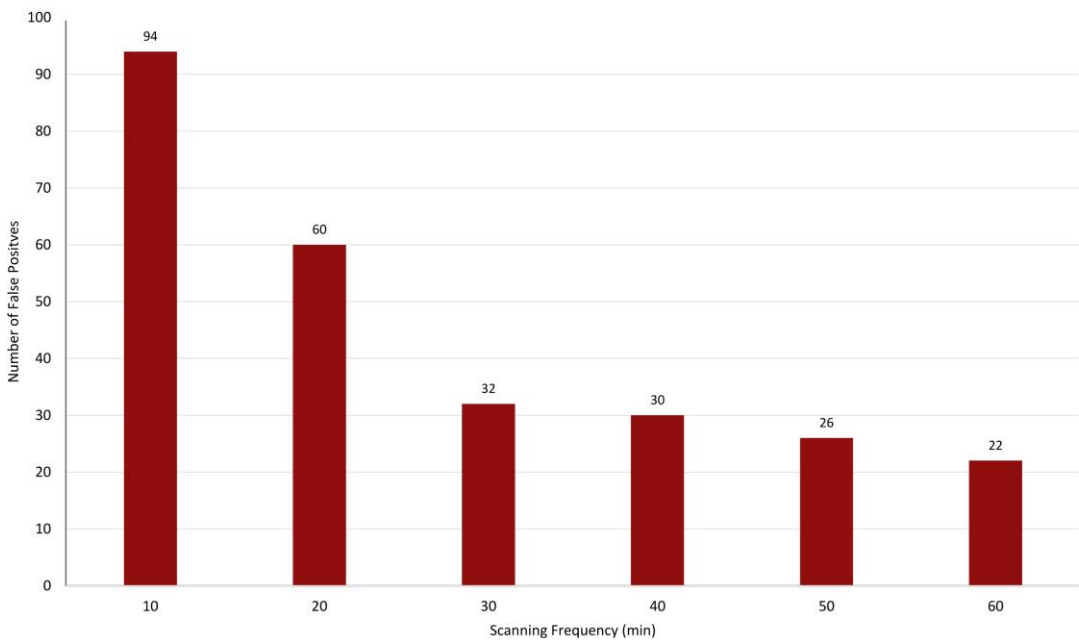

Figure 16 - Number of Weekly Errors that Result in 30% Energy Loss in June

4.4 Energy Loss Parameters

Having established some basic false-positive properties in relation to scanning frequency, a holistic examination of their impact was conducted for the city of Atlanta. For this study, each error was situated randomly in both a different time of the year and a different time of the day and assigned a stochastically generated occupancy schedule.

The simulation outputs were then organized in histograms in Matlab as depicted in Figure 17 and the distribution of the results was plotted. The sample distribution was then compared to the normal reference as illustrated in Figure 18. The distribution successfully passed the Kolmogorov-Smirnov test for normality. This meant that the effect of errors followed a normal distribution. Finally, the confidence interval was determined by integrating the area under the probability distribution function (PDF).

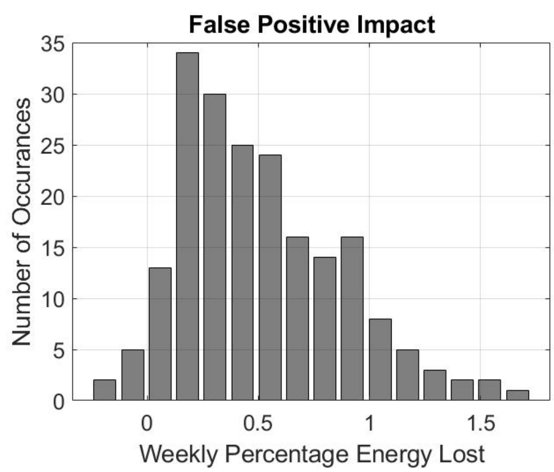

Figure 17 - Distribution of the Percentage Impact of Errors for Atlanta

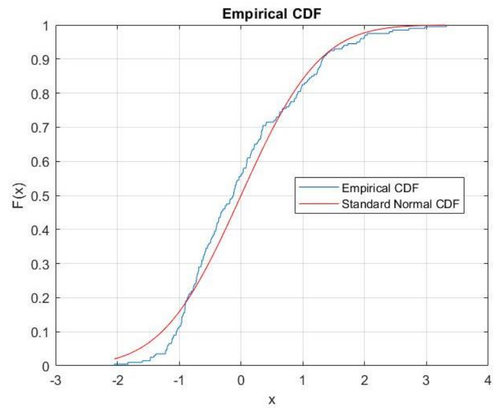

Figure 18 Visual Comparison in Kolmogorov-Smirnov Test

Confidence intervals are means of saying, with a certain percentage of certainty, that a result should lie between two points. A process of optimization and numeric integration depicted in Figure 19 was conducted in Matlab to receive the 95% desired area under the curve. The upper and lower bounds for the 95% confidence intervals contributed to -0.53% and 0.939% of weekly energy loss per error, respectively. The significant deviation between results can be inferred here by the wide shape and consequently, the broad range of the confidence interval.

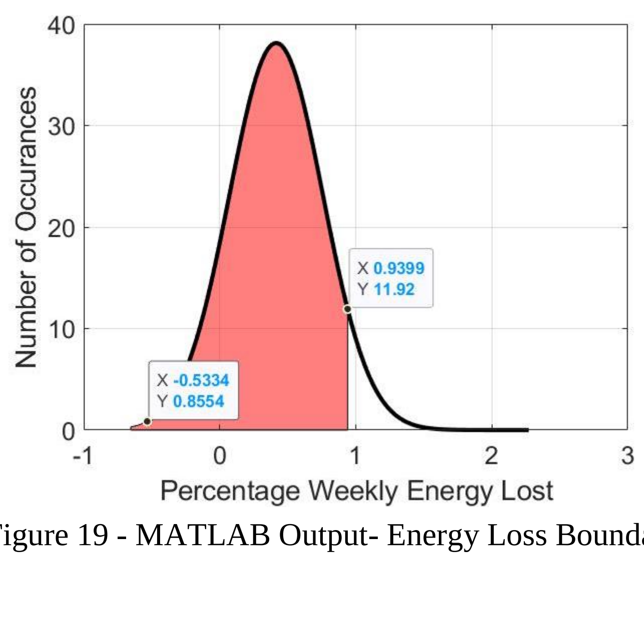

Figure 19 - MATLAB Output- Energy Loss Boundaries

The simulation process was repeated for 6 chosen cities, that corresponded to US climate zones 1 to 6. The outcomes allowed a holistic understanding of how errors impact energy consumption in different climates. The percentages are calculated in relation to a weekly consumption to provide tangible context to the impact of a single hour and allows us to establish benchmarks in relation to that impact.

Figure 20 illustrates the range for the average percentage energy loss due to an error, evaluated across the year. The 95% confidence interval exhibited a broad range across all climate zones. This wide range highlights again the variation in simulation results in relation to the timing of the error. The city of Miami exhibited the smallest range, while the largest range was experienced by the city of Albuquerque.

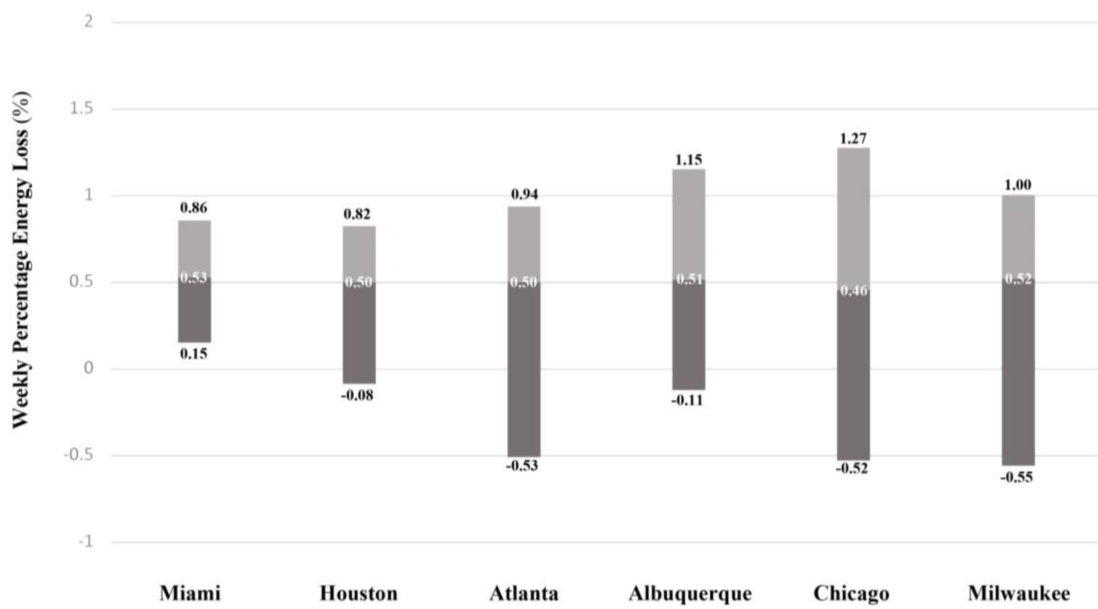

Figure 20 - Weekly Energy Loss Range and Mean for Selected Cities

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 loss 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 errors occurring in Miami should accordingly have a more substantial impact on total percentage energy loss than those of its Albuquerque counterparts. 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 climate zone cities.

These findings allude to errors in particular cases, conserving energy cumulatively by the activation of the HVAC systems in the absence of the building occupants. These highlighted particular cases, however, represent a small percentage of all occurring possibilities. The distribution for the city of Houston, illustrated in Figure 21, shows that these types of errors occurred in 15 cases out of the 200 randomly sampled simulations. The findings needed further investigation to identify specific occurrence examples.

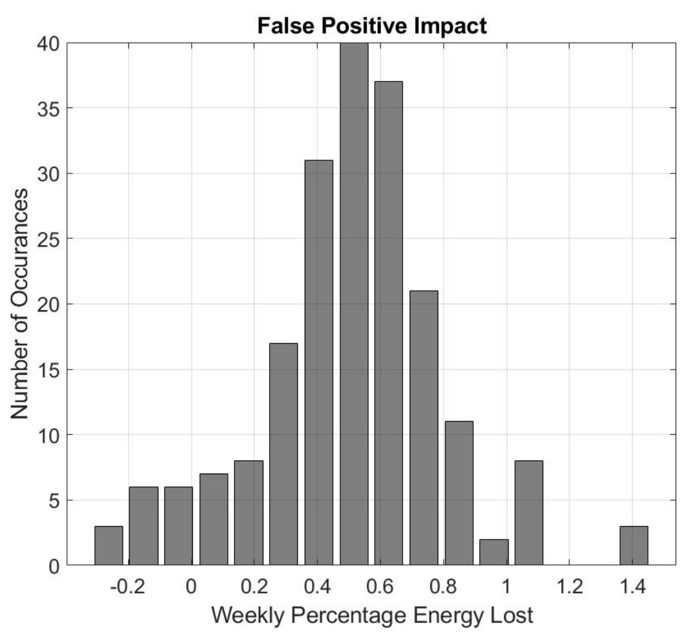

Figure 21 – Occurrence Number of the Percentage Impact of Errors for Houston

To understand the cause of the previously mentioned deviations in the error results, the impact of false positives was examined at different time increments along the day. Twenty simulations were performed for each hour to measure the impact of an error occurring in Atlanta in June. The simulations were performed for both different days in June and different occupancy schedules. In Figure 22, each dot represents the error impact,

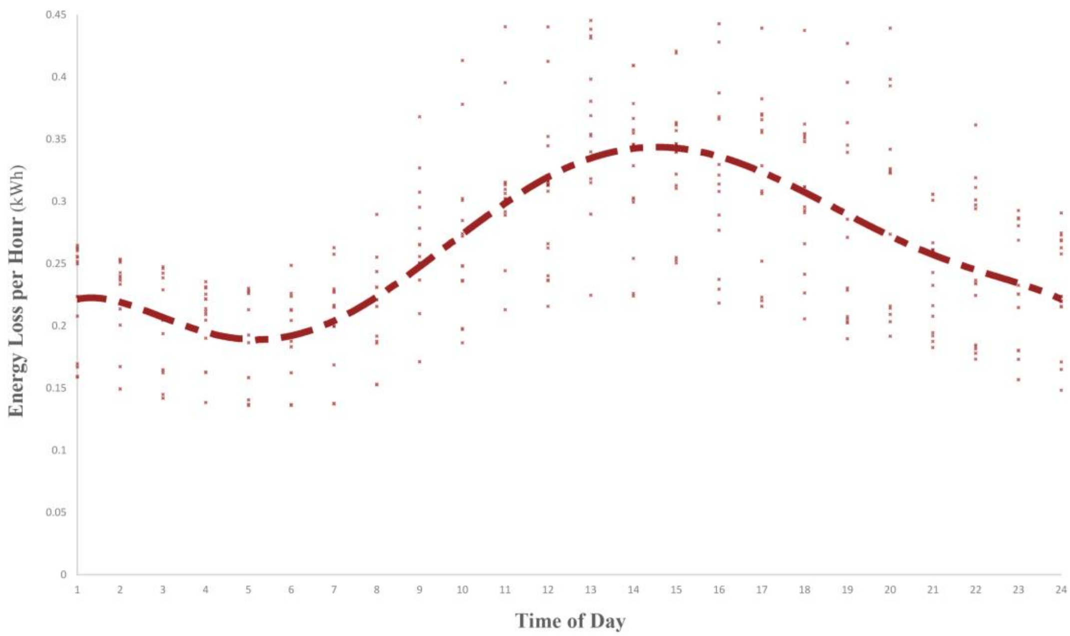

Figure 22 - Atlanta Moving Average Error Impact in June

in terms of kWh, of a simulation run output in that particular hour. The dotted line is a representation of the moving average for those conducted simulations throughout the day. The average increases from 0.198 kWh, with the emergence of the sun, starting at 5 AM, to reach a peak of 0.352 kWh at 2 PM. The impact then gradually falls off, starting at 2 PM for the remainder of the day. The moving average outline forms a gradually connected shape and does not experience any hourly anomalies. The deviations in the results for a single hour, however, are relatively high and correspond to the different conditions that are experienced in June.

Preceding occupancy also impacted the amount of energy lost due to an error. The examination entailed errors being situated at particular hours and simulated for various preceding occupancy patterns in June. The observed times, depicted in Figure 23, were incrementally distributed along the day at 10 AM, 12 PM, 2 PM, 4 PM, and 6 PM respectively. An error occurring at noon with a prior 4 hours of absence contributed to a larger amount of energy being lost than an error occurring at the same time with only 2 hours of prior absence. The observed times all displayed the general pattern of more significant amounts of energy loss following more prolonged periods of absence. The general relationship between the various observed hours was also retained throughout the simulations.

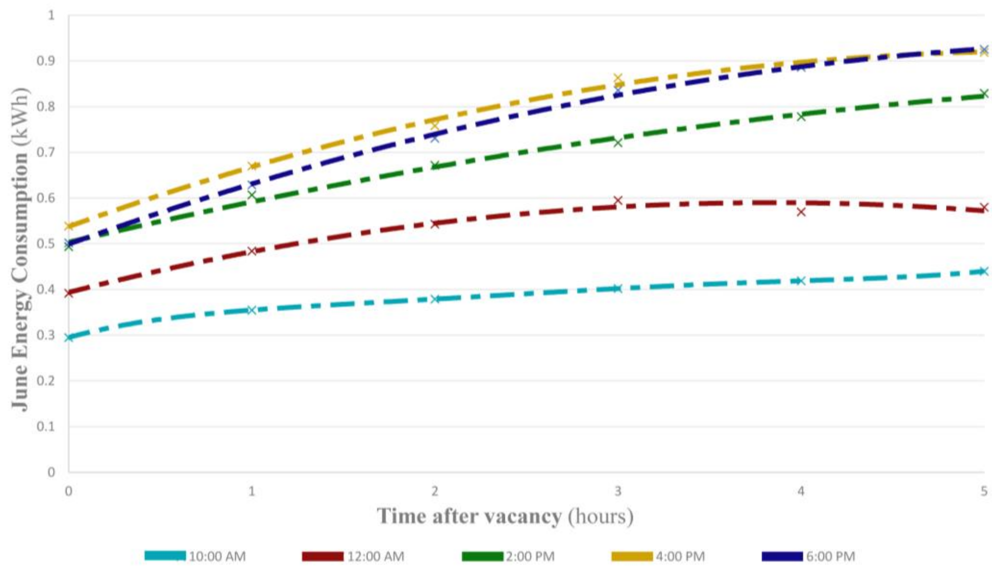

Figure 23 - Impact of Preceding Occupancy on Energy Loss in Atlanta

The underlying causes for errors contributing to energy savings were observed to dissect the logic behind their occurrence. A higher frequency of those results manifested themselves in months 11-2. The Figures 24, 25, 26 depict a recurrent example of both the occupancy schedule and the overall energy consumption relating to that particular error type. The illustrated Figures are specifically for February the 18th.

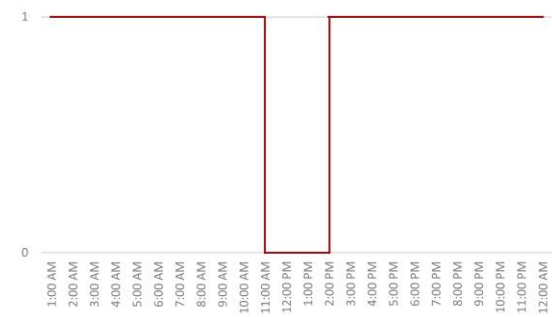

Figure 24 - Original Occupancy Schedule

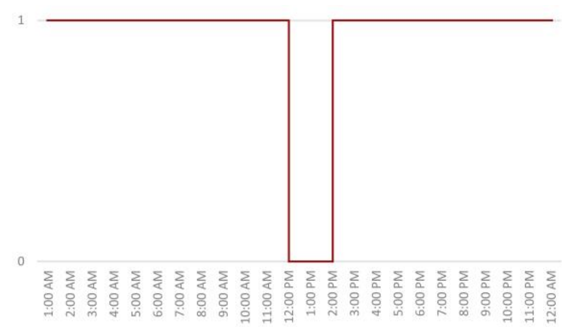

Figure 25 - Modified Occupancy Schedule

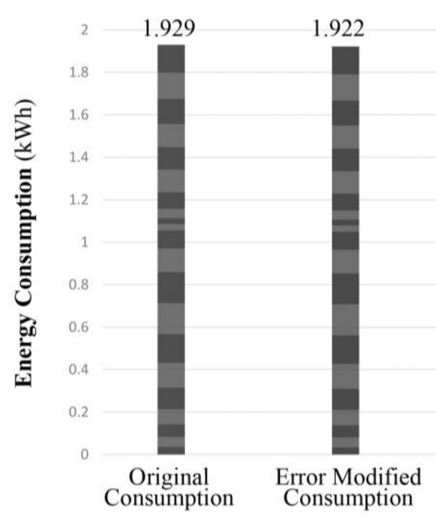

Figure 26 - Stacked Hourly Simulated Consumption

The original schedule usually experiences a generally high level of overall occupancy with a small absence period near peak noon. Given that outdoor conditions are close to the comfort level at that time, due to the heating effect of the sun, the energy consumption for the HVAC system is low for that hour. The activation of the system and the internal heating effect of the building, however, have a generally positive contribution to the energy consumption of hours following the error. The cumulative consumption of all hours for that particular day is accordingly positively influenced.

The next examination, illustrated in Figure 27, was a seasonally oriented observation of the hourly impact for the city of Atlanta. June, September, and December were observed as proxies for the Summer, Fall, and Winter, respectively. Each dot represents here again the error impact, in terms of kWh, of a simulation run output in that particular hour. The line is on the other hand, is a depiction of the moving average of the conducted simulations. A large deviation in the impact of errors was evident for 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.

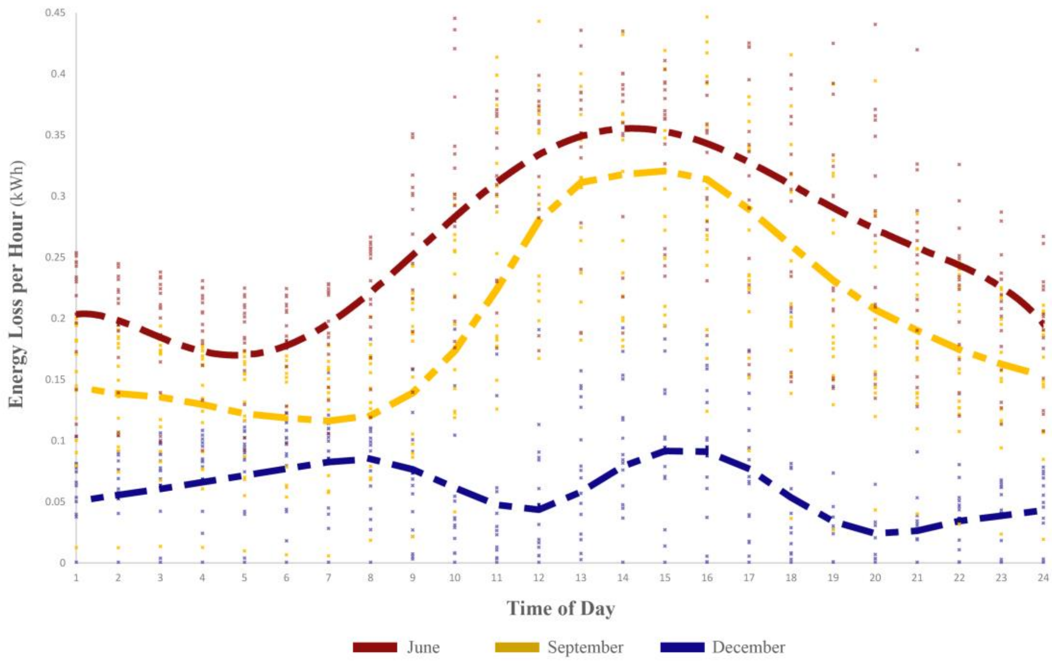

Figure 27 - Atlanta Seasonal Moving Average of Error Impact

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 nighttime averages. The average impact of December, on the other hand, formed a relatively flat curve with two dips in impact at 12 AM and 8 PM respectively. 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, the month of December experienced a second peak of 0.85 kWh at 7 AM.

The focus is then shifted towards a holistic examination of climate zones to provide insight regarding the general characteristics of multiple cities. For United States, climate zones ranging from 1 to 6, the cities of Miami, Houston, Atlanta, Albuquerque, Chicago, and Milwaukee were again selected as representatives. The same adopted logic pertaining the dots and the moving average were adopted from the previous investigations. The examination depicted in Figure 28 was performed for June with the same simulation process for each hour as the previous studies. 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.

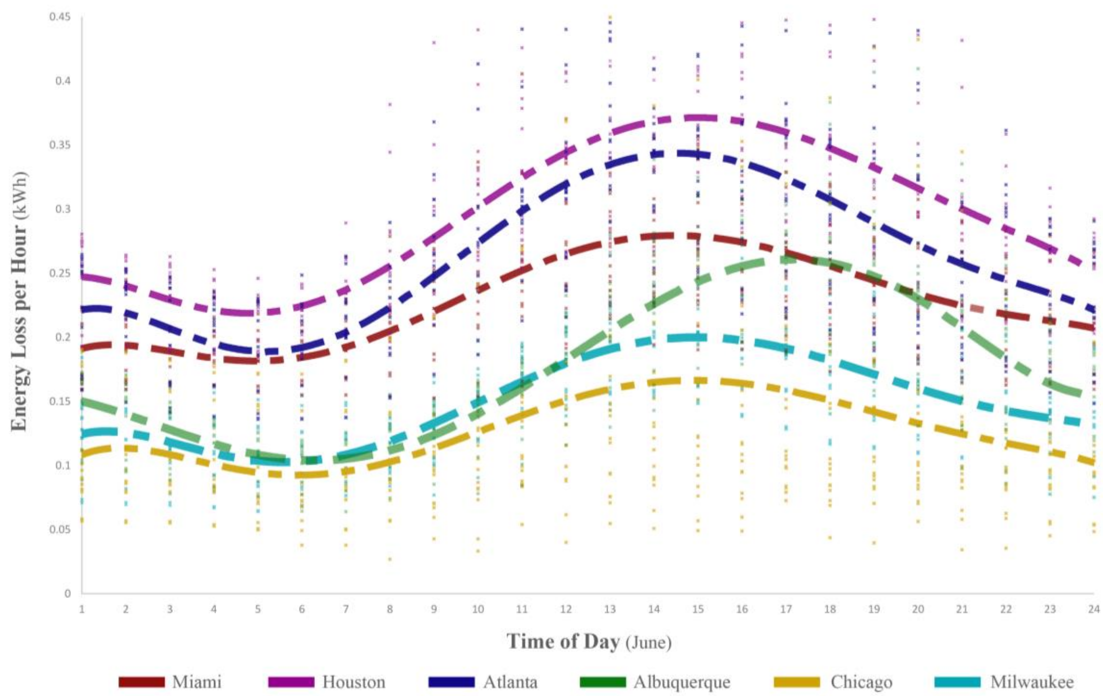

Figure 28 - Moving Average Error Impact for Diverse Climate Zones

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 between day and night values. The peak averages of the respective climate zones occurred in distinct times of the day between 2 PM and 7 PM. The minimum values on the hand occurred relatively simultaneously between 5 AM and 6 AM.

4.5 Error Duration

The focal point of this section is the minimization of error durations. The goal is to reduce the average span of errors by the strategic placement of full-house sensing system scans. A maximum number of two additional scans per day is placed as a constraint to ensure long battery life. The most efficient placement of those scanning points is accordingly determined for weekdays and weekends. The full-house scans serve here as the ending point for errors that occur after occupants leave their household. As seen in Figures 29 and 30, if scans are placed significantly later in the day, the average duration of errors would be excessively long.

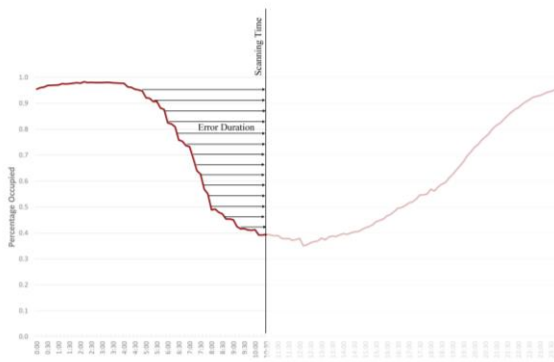

Figure 29 - Scanning Placement Alternative1

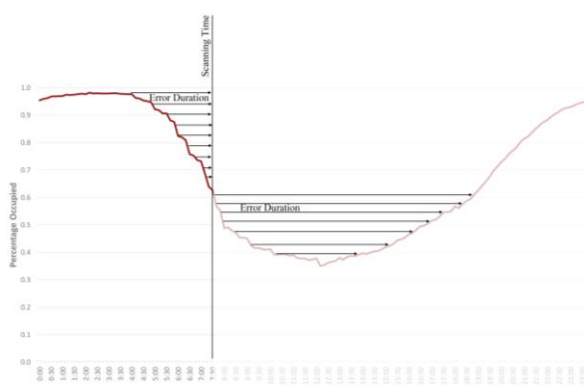

Figure 30 - Scanning Placement Alternative 2

Alternatively, if placed prematurely, errors that occur after the scan would be left unchecked until occupants return home. In this thesis, 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.

Two hundred simulations were conducted for each of the 48 time increments to calculate the average error duration. The strategic placement of the scanning point, as seen in Figures 31 and 32`, had a critical impact on the duration of errors. The worst corresponding error duration for a midnight scanning point placement 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 to situate them at 9:30 AM and 6:00 PM.

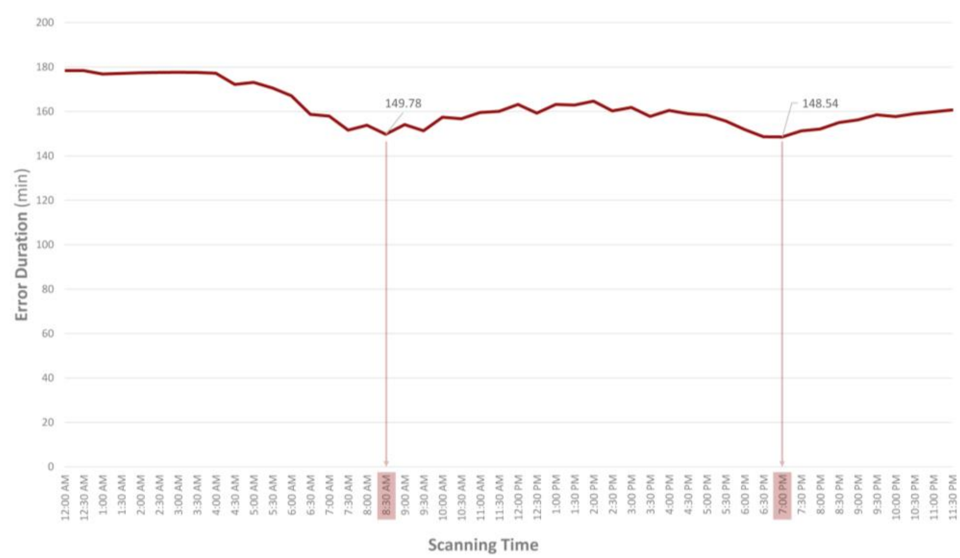

Figure 31 - Weekday Average Error Duration for diverse Full-Scan Placements

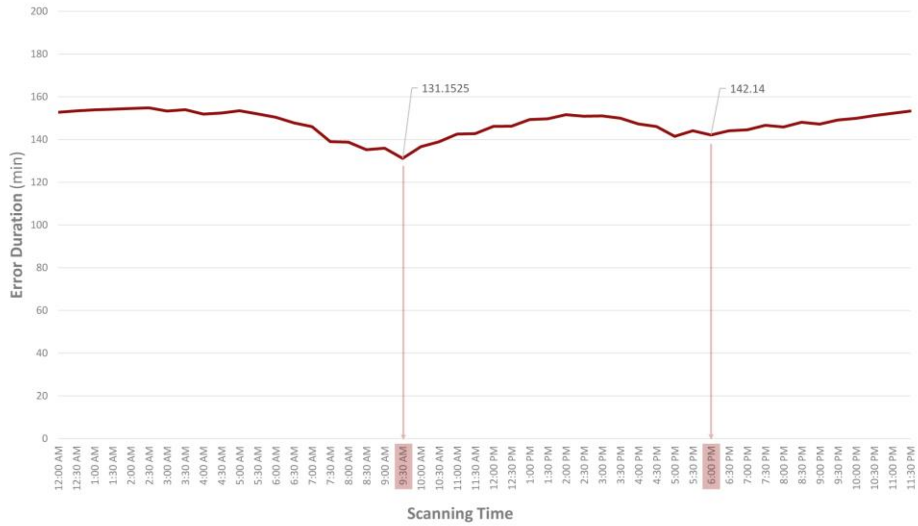

Figure 32 - Weekday Average Error Duration for diverse Full-Scan Placements

Finally, the relationship between additional daily scans and the average error duration was examined. The goal is to explore whether a higher number of scans are favored over the longevity of the sensing system battery. The relationship in Figures 33,34 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 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.

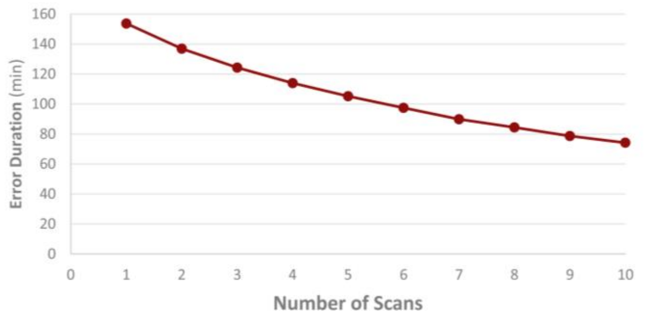

Figure 33 – Weekday Average Error Duration

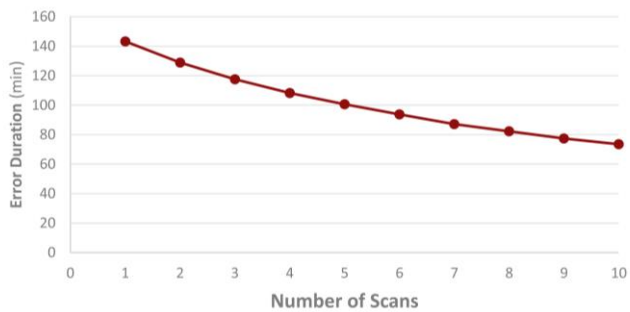

Figure 34 - Weekend Average Error Duration

4.6 Results Validation

The validation of the results was performed through a simulation-based workflow. The probability generating model was used to produce 4 new occupancy schedules as a representative test sample. The schedules were situated randomly across the year, and 5 weekly errors were consecutively embedded in each occupancy schedule. The average energy loss due to an error is then measured for the respective examples. Each test sample is simulated 6 times, corresponding to climate zone cities 1-6. The results, showcased in Table 2, are subsequently compared against the original findings of this thesis.

Table 2 Sample Validation Results

City	Percentage Impact	Sample 1	Sample 2	Sample 3	Sample 4
Miami	0.15 to 0.86% (mean 0.53%)	0.64%	0.90%	0.67%	0.61%
Houston	-0.08 to 0.82% (mean 0.50%)	0.33%	0.57%	0.50%	0.64%
Atlanta	-0.53 to 0.94% (mean 0.50%)	0.52%	0.76%	-0.19%	0.74%
Albuquerque	-0.11 to 1.15% (mean 0.51%)	0.08%	1.10%	0.03%	1.19%
Chicago	-0.52 to 1.27% (mean 0.46%)	-0.01%	0.65%	0.91%	0.06%
Milwaukee	-0.55 to 1.00% (mean 0.52%)	0.50%	0.88%	-0.11%	0.13%

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 the city of 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.

4.7 Occupancy Schedules Calibration

The future integration of sensing technology on a residential household level would provide opportunities for occupancy schedule advancements. The sensing system would become a storage unit that is continuously gathering occupancy live feed information. Safety measures regarding the ensured privacy of the gathered data would naturally be considered as part of the sensing system configuration. The data can then be used to create daily, internally calibrated occupancy schedules. The advantage of those schedules is their ability to escape the main critique of occupancy schedule use in energy regulation. The schedules would be independent and unique to the household they manage. In the long-term calibration of those schedules, patterns will inevitably begin to emerge. Occupancy patterns in response to fixed commitments like work should immediately be observable.

The next phase of investigation would entail the system's start to interpret inherent patterns that the occupant might be unaware of. A tested time threshold for system calibration must first be established as a fundamental step. Transition probabilities would be established for the different time increments of the day that are based on prior occupancy behavior. Once the system is calibrated, speculations can be made given current occupancy schedules regarding future behavior. The current knowledge provided in this thesis on the impact of errors in those predictions should help assess and weigh the risks of future occupancy speculation. The fact that errors occurring prior to occupancy arrival can sometimes have positive effects on total building energy consumption as showcased for the February example also supports this argument. It means that sensing technology predictions do not necessarily have to exhibit a perfect representational accuracy.

In some cases, even with a 30-minute prior activation of the HVAC systems, an overall positive outcome can be expected in terms of overall energy consumption throughout the day. This can be attributed to building thermal memory and its ability to store retain stored energy for long periods of time. Situations where short absences, due to behavioral patterns, are expected, can be taken advantage of to reduce energy consumption. Occupancy predictions can also be used to regulate indoor conditions prior to the arrival of household inhabitants. The reliance on system future prediction can then both reduce the energy consumption of the household as well as provide added comfort measures for the occupant.

CHAPTER 5. DISCUSSION, FUTURE RESEARCH & CONCLUSIONS

This chapter asses the implications of the findings of this thesis. It gives context to simulated results, raises questions for future research and concludes the work done in this thesis.

5.1 Discussion and Future Research

The assembled national profile for the binary residential occupancy pattern provides insights as to how and when people use their homes. The pattern follows a predictable shape with higher expected occupancies at night and varying dips in occupancy along the day, depending on whether people either have a workday or a vacation day. A false positive, by definition, is an instance where an individual leaves the residence and is falsely assumed by the system to be still present. The national pattern accordingly allows the interpretation of the times where errors are more liable to occur. False positives are more likely to happen in the daytime due to high-frequency transitions between presence and absence. The national profile also provides the times where potentially the most energy can be saved by the implementation of the introduced system and the regulation of the HVAC energy consumption. A more significant number of performed full scans should accordingly be prioritized in those periods to help rectify occurring errors. The sensing system should not be continually conducting full scans at night, where people are with a high probability expected to be present. Even if an absence is recorded in a regular system scan, pattern recognition should help the system automatically correct that error rather than proceeding to turn off the system.

While the current generated national occupancy patterns examine the TUD holistically, future research might also investigate seasonal impacts on occupancy behavior. Exterior environmental conditions such as cold and heat corresponding to winter and summer months are bound to influence residential occupancy behavior, particularly activities performed on vacation days. Accurate depictions of changing seasonal patterns can provide more accurate representations of how people occupy their residence.

The investigation on potential savings points to the prospect and viability of integrating sensing systems from an energy conservation perspective. These savings are highly dependent, however, on the occupants of the house. The added 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 newly added system. 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 purely energy conservational, non-operational perspective, the integration of the 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 made on the behavioral pattern of individuals towards the HVAC systems. This would provide valuable insights into how people regularly operate in their own homes. It can also help the acquisition of more accurate estimations of the expected energy savings by the integration of a sensing system.

Scanning frequency of the sensing system and the subsequent duration of the error had a significant impact on the percentage of weekly energy being lost. It is important to note, however, that the additional percentage energy loss per error is not directly proportional to the time of the scanning frequency. This can be attributed to HVAC systems requiring a significant amount of energy to regulate the environment when first operated in relation to the following amount of energy required to maintain that desired temperature. The HVAC systems accordingly requires a lower energy consumption per minute for large error durations where the intermediate “maintain” periods are significant in relation to smaller error durations. A lower average percentage impact can, therefore, be expected with both larger instances and duration of errors displaced in a week.

The holistic year-round examination of errors displaced 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 loss 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 itself. First, there is a need to consider the environmental climate at the occurrence time of the error. The examination of the hourly energy amount being wasted due to an error showed that energy loss is predominately dictated by the environmental context of the building. More energy was required to regulate an error occurring at peak noon in the hot climate of Atlanta in June, than an error occurring at 8 pm. The outdoor environmental conditions at peak noon require the HVAC systems to consume more energy to regulate the interior space to the desired conditions. The general June daily energy loss pattern indicates maximum energy loss between 10 AM and 4 PM. This information becomes problematic when observations from the produced national profile for residential binary occupancy patterns are considered. The time experiencing peak energy loss coincides with the dip in residential occupancy due to people either being at work or conducting necessary morning trips. The results examining the impact of prior occupancy on lost energy also supports the same argument. Errors occurring after long periods of absence experienced larger amounts of energy loss in relation to their short counterparts. The HVAC systems required 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 ranging from 1-4 PM.

Given that the regular working schedule of individuals starts at 8 or 9 AM, errors occurring between 1 to 4 PM are more liable to happen following multiple hours of absence. The period where most energy could potentially be lost is, therefore, also the time at which errors are more likely to occur. This information can be successfully used in the configuration of sensing systems. A full scan conducted by a sensing system of the interior context is considered a way of correcting errors and reducing their duration. To do a full system scan, however, requires the use of energy and can therefore not be done on a minute by minute basis. This understanding of the impact errors at different times can helps in the distribution of those scans to achieve peak performance by the system. Scans should be predominantly placed between 10 AM and 4 PM to reduce the impact of energy being consumed by the system.

The next investigation entailed a seasonal investigation on the impact of false positives. Wasted energy amounts resulting from errors in Atlanta, Georgia are expected to be much higher in Summer months like June, July, and August as opposed to December, January and February. The distribution of the number of scans across the year should accordingly be governed by that logic. The location and corresponding climate nature also played a key role in the impact of errors with large deviations in results being apparent along different climate zones. Cities in the heating dominated climate zones like Chicago and Milwaukee experienced lower impact per error in June than Houston and Atlanta. The most impactful errors in those cold climate cities, on the other hand, manifest themselves in the winter, where heating systems have to offset the substantial temperature differences between the indoor condition and the outdoor climate. Wasted energy due to errors is expected to decrease in the morning with climate temperatures increasing due to the heating effects of the sun. The integration of any scanning system should, therefore, include configurations that indicate the location of the residential unit as a way of optimizing system usage. Given the location, a sensing system should align itself with the understanding of errors in that particular climate to reduce the impact of errors on total energy consumption.

The next step included an investigation of the expected duration of errors. Logically, the placement of daily additional scans resulted in a further reduction of the duration time. Since HVAC energy consumption in buildings is high in relation 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. While the results of this experiment elude to the notion that smaller periods between consecutive scans result in lower energy loss figures, the lowest sensing frequencies might not necessarily provide the holistically best results in terms of total energy consumption. A tradeoff relationship should be established that weighs the benefits of short scanning frequency periods against the amount of energy consumed for the consequently higher number of scans performed by any particular system. This can help guide designers in adjusting the parameters of these sensing systems to provide the most efficient results in terms of overall energy consumption.

It is important to note that current findings are extrapolated from the examination of a small module unit. While larger settings should theoretically reproduce the same pattern, future research should investigate larger, multiple occupant contexts as a more representative proxy for typical residential apartments.

The impact of errors in different environmental climates should be evaluated not only in the context of the amount of energy loss but must also be tied to the possible compromised occupant comfort by the occurrence of an error. The notion of a false negative should, therefore, also be considered. A false negative is an instance where the sensing technology falsely indicates the absence of individuals, and the HVAC systems are turned off accordingly. The extent and speed by which the comfort inside a room deteriorates is then a function of building characteristics and the environmental context. The duration of the error would determine whether the system shutdown is perceived by the occupant or not. If the error persists for an extended period of time, a sense of discomfort might be experienced inside the household. A high frequency of those errors can result in distrust and removal of the sensing system. Higher standards and configurations should accordingly be established for false negatives than those of false positives to rectify any occurring errors. It is important that a compromise is found that sustains relatively good comfort levels in the event of an error to ensure continual usage of a system.

It is vital to consider how sensing systems can be integrated with previously developed technological means of regulating indoor conditions and subsequently energy consumption in buildings. The most commonly utilized products include Google Nest, Amazon Echo and other emerging technologies of the same nature. These products are used for entertainment and leisure purposes and can also be linked to smart home appliances. Built-in routines have been incorporated for the performance of multiple consecutive tasks and are used to adjust smart house systems in relation to various operational scenarios. Products like the Nest Thermostat however, have only made the control of the HVAC systems more accessible with a current reliance on voice commands in the action taking process. This workflow requires conscious decision making by the occupant in both the setup and continuous use in the house. The potential for these integrated technologies can be further amplified by a connection to human detection platforms. Human comfort and accordingly the desired temperature inside of a residence is highly dependent on the activities performed by the occupant such as cooking, reading or exercising respectively. Human detection technologies can be used to trigger built in routines and subsequently change indoor temperatures in relation to the type of activity and the relative preference of the occupant. The system's ability to control smart home appliances like Google Smart Light can be paired with the ability of the sensing system to detect individuals leaving a room, for zonal control of not only HVAC systems but also lighting and equipment. The cross-integration between sensing technologies and smart home systems can create energy savings and enhance the capacity of individuals in the customization of their household control.

As sensing technologies become increasingly integrated in our daily lives, we have to consider the implications of their wide scale use. The current gap in the literature regarding the regulations that govern those emerging technologies must first be addressed. To ensure that findings of this thesis become applicable in practice, policies must be generated to manage the quality of new sensing products that are used in building energy regulation. Previous studies have assessed the large array of frameworks that are used in informing policy in terms of application intensity (Meyar-Naimi and Vaez-Zadeh 2012). The evaluated frameworks are Pressure State Response (PSR) (Kelly 1998), Driving Force Pressure State Impact Response (DPSIR) (Niemeijer and de Groot 2006), Driving Force Pressure State Effect Action (DPSEA) and Driving Force Pressure State Exposure Effect Action (DPSEEA) (Waheed, Khan, and Veitch 2009). The PSR policy had the highest application intensity, while the DPSEEA had the lowest (Meyar-Naimi and Vaez-Zadeh 2012). The PSR framework is accordingly encouraged for a larger overall impact effect. A deeper analysis of the shortcomings and strengths of those frameworks in relation to the desired outcomes of the policies however still needs to be considered. Once a policy framework is adopted, rules must be established to ensure the overall performance of the sensing systems. Accuracy thresholds must be set, that emerging sensing technologies need to pass before they are integrated in the market. The findings of this thesis can be used to set reasonable thresholds that balance cost and overall performance given our established knowledge on errors. Guidelines for security checks also need to be set to ensure that the information of occupants is not compromised.

Finally, while some results of this experiment are self-explanatory, like the average percentage of energy being lost due to a false positive occurring, others require observational data to give more context to the results and make them better grounded. The frequency of false positives occurring should be tested using observational data from a real-world setting. These data can provide a baseline against which results can be compared and help evaluate if the occurrence of 40 false positives in a single week is something to be expected or a low figure when compared to empirical data. That context can consequently help us understand the threat that false-positive poses on the amount of energy being conserved. To improve both the accuracy and validate the findings of this thesis, a comparison should be made between simulated results and actual energy measurements. The validation could include a real-life testbed, where energy consumption is monitored, and the impact of occurring errors is measured. The model developed for generating occupancy schedules should also be calibrated using larger data sets to ensure the accuracy of the results. Empirical measurements, like that of the ECOBEE dataset (Ecobee 2020), can be used for the future development of this research. This would utilize currently employed sensing technology and gathered data to inform future developments in that field of work. The ECOBEE dataset, predominantly based on household occupancy, can help alleviate the current reliance on time use surveys and create more accurate representations of individuals in their households. The daily occupancy representation for each household can also be used to extrapolate behavioral patterns across the year. This can help future researchers understand the seasonal changes in human household occupancy. The primary concern in using these data, however, is their ability to comprehensively represent the socio-cultural diversity of society. The notions of multilayer representative sampling that are embedded in the national survey sampling selection might not be accurately conveyed through the equipment data set. The sample could, therefore, not be representative of the total population behavior. The dataset findings could be integrated with its survey counterparts to create a holistic, accurate image of the population. An agent-based approach analysis should also help identify the various prototypical behavioral patterns that emerge from observations.

5.2 Conclusions

Human behavior, represented through occupancy schedules in BPS, is considered one of the only elements that inform human energy consumption in buildings. Probabilistic driven occupancy models are our current best tools for replicating the intricate behavioral patterns of humans in buildings but are only accurate for long-term trend identification and fail in informing most short-term governing of energy. Technological advancement, on the other hand, has led to the partial integration of developing sensing technologies in building typologies but is still lacking in terms of widespread use. The wide-scale implementation of sensing technologies in our daily lives, however, requires new low-cost systems that entail inaccuracies in their use. This research has provided some insights into the impact of sensing systems detection errors. The mean percentage amount of energy loss per false positive seems to be particularly low across various climate zones, which encourages the use of relatively low-cost sensing technologies for wide-scale implementation at the sacrifice of some accuracy. The claim, however, remains to be supported by real-life observational data of average false-positive frequencies for different sensing technologies. The potential energy savings introduced by the system, coupled with increasing mechanization of tasks for human convenience, highlights the applicability of the system in energy regulation. The performance of sensing systems and the impact of errors can be further optimized by our understanding of parameters that influence the impact of errors. The mutually beneficial relationship between occupancy schedules and sensing technologies also needs to be utilized, where sensing technology can work in the calibration process of 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.

Alternatively, occupancy schedules can inform and reduce the errors experienced by sensing technologies and make predictions for optimal HVAC system operation. In conclusion, low-cost sensing technologies are on the brink of replacing preset occupancy schedules in buildings. Initial results indicate the benefit of the wide-scale integration of sensing technology in regulating energy consumption in United States residential buildings. Further expansion and examination of the impact of false positives, however, can provide, together with the social and economic dimensions of sensing technologies, better insights on the feasibility of fully integrating sensing systems in our everyday lives. The BPS community will then be prepared for the inevitable widespread integration of sensing technologies in the future by having a grasp on all of its associated parameters.

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