AUTOMATED RESIDENTIAL ENERGY AUDITS AND SAVINGS MEASUREMENTS USING A SMART WIFI THERMOSTAT ENABLED DATA MINING APPROACH

Dissertation

Submitted to

The School of Engineering of the

UNIVERSITY OF DAYTON

In Partial Fulfillment of the Requirements for

The Degree of

Doctor of Philosophy in Engineering

By

Abdulrahman Mubarak Q. Alanezi

Dayton, Ohio

May, 2021

University of Dayton

AUTOMATED RESIDENTIAL ENERGY AUDITS AND SAVINGS MEASUREMENTS USING A SMART WIFI THERMOSTAT ENABLED DATA MINING APPROACH

Name: Alanezi, Abdulrahman Mubarak Q.

APPROVED BY:

Kevin P. Hallinan, Ph.D.
Advisory Committee Chairman
Professor
Mechanical Engineering

Rajan Rajendran, Ph.D.
Committee Member
Vice President
Climate Emerson Technologies Inc.

Andrew Chiasson, Ph.D., P.E.
Committee Member
Associate Professor
Mechanical Engineering

Jun-Ki Choi, Ph.D.
Committee Member
Associate Professor
Mechanical Engineering

Robert J. Wilkens, Ph.D., P.E.
Associate Dean for Research and Innovation
Professor
School of Engineering

Eddy M. Rojas, Ph.D., M.A., P.E.
Dean, School of Engineering

ABSTRACT

AUTOMATED RESIDENTIAL ENERGY AUDITS AND SAVINGS MEASUREMENTS USING A SMART WIFI THERMOSTAT ENABLED DATA MINING APPROACH

Name: Alanezi, Abdulrahman Mubarak Q.
University of Dayton

Advisor: Dr. Kevin P. Hallinan

The building sector has been identified as one of the biggest contributions to electricity and natural gas consumption in the U.S. These findings have necessitated the need for the development of energy saving initiatives in the sector, which will aid in reducing greenhouse gas emission needed to reduce the risk of climate change. However, despite several efforts by state agencies, such as the implementation of Property Assessed Clean Energy (PACE) and On-Bill Repayment or On-Bill Financing of energy efficiency investments, there are significant challenges to achieving energy efficiency in the building sector. Fundamentally the question is "How do we find the most cost effective energy efficiency measures present in the world?" Conventional energy audits, the typical way to discern, struggle from high cost, inconsistency in audit recommendations, and a lack of people trained to deliver. Thus, the approach just is not capable of "at-scale" identification of the measures to address first, then second, and so on.

Additionally, it is essential that the savings from any investment and/or even behavioral changes be capable of being measured with accuracy in order to improve the ability to find the most effective energy reduction measures existing in the broader building sector and in order to communicate the relative economic benefits from upgrades to

building owners. At this time, unless there are short-interval energy meters in buildings, the ability to measure savings with accuracy is just not there. As a solution, this dissertation investigates utilizing smart Wi-Fi thermostats data to conduct visual energy audits and predict energy savings with improved accuracy from any energy systems upgrade and any behavioral modification.

The study leverages data from 101 residences owned by the University of Dayton. In 2015 prior University of Dayton researchers completed energy audits of these; documenting the geometric and energy characteristics and occupancy, as well as documenting any unique energy consuming device such as washers/dyers/dishwashers in the residence. These houses provided a diversity of size, age, insulation, and energy effectiveness. Additionally, historical energy consumption data, as well as smart WiFi thermostat data with corresponding weather data, were collected for these houses. The archived thermostat measured temperature data was used to develop unique power spectrums for the measured interior temperature for each residence. The binned power spectral density is shown to be an effective signature of the energy effectiveness of the various energy characteristics associated with a residence. Moreover, the outdoor temperature for each meter period was binned into histogram groupings.

This research utilizes an AutoML H2O package to determine the best machine learning algorithm for predicting both the energy characteristics and energy consumption, as well as complete the tuning needed to determine the best model hyperparameters. Machine learning models were trained to predict attic and wall R-Values, furnace efficiency, and air conditioning seasonal energy efficiency ratio (SEER) using smart WiFi thermostat measured temperature data in the form of a power spectrum, corresponding historical weather and energy consumption data, building geometry characteristics, and occupancy data. The models validation coefficient of performance (R^2 values) were respectively 0.9408, 0.9421, 0.9536, and 0.9053 for predicting attic and wall R-Values, furnace efficiency, and AC SEER. This research helped lift up the possibility of conducting low-cost, large-scale, data-based energy auditing of residences that rely only on data that could easily be collected for any residence.

Similarly, a power spectrum derived from the measured thermostat indoor temperature is combined with outdoor temperature data and known residential geometrical and energy characteristics in order to train a singular machine learning model capable of predicting energy consumption in any residence. The best model obtained had a percentage mean absolute error (MAE) of 8.6% for predicting monthly gas consumption. This result indicates that the best model is effective to estimate energy savings from upgrades in residential buildings. Specifically, when it is applied to real residences in which attic insulation upgraded, the energy savings estimation uncertainty was less than 7%. This is a significant improvement over the ASHRAE recommended guidelines for estimating building energy consumptions and savings, which has been termed capable, at best, of resolving savings only greater than 10% of total consumption, and, in many cases, unable to resolve any savings at all.

I dedicate this to those who spend their lives in the pursuit of knowledge and achieving a dream/goal.

ACKNOWLEDGEMENTS

First, I am grateful to Allah The Almighty for my success in my life and for having a beautiful family. Allah inspired me with rough patience and helped to make this step possible and successful. Then, I would like to deeply express my thankfulness to my parents, who encouraged my enthusiasm for science and were endlessly generous with their time, advice, and pure love. Also, I am thankful to my brothers and sisters who were always present in my life with their great support and love. Great thanks to my wife and children, who not only made my studies possible with their patience, tolerance, daily love, and support. Lastly, I owe thanks to many people including my friends and relatives for their unconditional support.

I owe a great many thanks to my advisor, Professor Kevin P. Hallinan, who has been an inspiration and role model for me, inside and outside the university. Our meetings gave me energy and encouragement to keep working be on the right track towards my goals. His door was always open at any time I ran into any kind of difficulties. I am deeply indebted to him, and I will never be able to thank him enough. I would also like to thank the members of my esteemed dissertation committee, Prof. Andrew Chiasson, Prof. Jun-Ki Choi, and Prof. Rajan Rajendran for their useful comments and time reading this dissertation. I also thank all my colleagues, faculty, and staff of the Mechanical Engineering Department at the University of Dayton. A special thanks to Judy Grant for her cheerful help in administrative issues. Finally, I thank my employer, Royal Commission for Jubail and Yanbu -Saudi Arabia for the unprecedented financial support and I do not forget the Saudi Arabian Cultural Mission to the United States for administering my scholarship to the University of Dayton.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Recent survey results from various energy and climate change organizations indicate that the residential sector plays an important role in energy consumption as well as CO_2 emissions. For instance, according to the 2020 energy facts by the U.S. Energy Information Administration (EIA), the sector consumed 44% of the total natural gas and 41% of the total electricity produced in the U.S. [1], as well as accounted of 35% of the CO_2 emissions in the U.S. [2]. These findings have been echoed in the 2019 report on greenhouse gas emissions by the International Panel on Climate Change (IPCC). The organization further warns that any further increase in greenhouse does not only pose a severe risk to Earth's climate system, but also irreversible dangers to the planet's life [3]. Hence, it is critical for humans to implement measures that will mitigate against the impact of climate change. In this case, one of the proposed measures is the reduction of greenhouse gas emissions in major economic sectors including the residential sector. Therefore, there is a need for methods that can help to reduce energy consumption in the residential buildings and raise the awareness of energy savings opportunities for homeowners and other occupants in their households.

Capitalism presents a major challenge in the implementation of efforts to reduce carbon emissions by government authorities. An analysis of the economic impact of carbon reduction initiatives indicate that several industries such as oil and gas are not keen on implementing measures to curb emissions as such actions could be detrimental to their revenue objectives [4]. As a result, companies in these sectors are increasingly downplaying the damaging effects of climate change. Despite continuous pushback from industries threatened by carbon reduction initiatives, efforts are being implemented to develop efficient energy systems that are not only less costly to the economy, but also environmentally friendly. Estimates from the American Council for an Energy Efficient Economy (ACEEE) indicate that the current retail cost of electricity in the United States is $10.6 cents per kilowatt-hour (kWh) and on the other hand, the utility energy efficiency programs according to ACEEE range from two to five cents per kilowatt-hour [5] [6]. Thus, in consideration of the benefits, energy efficiency programs not only translate to improved environmental conditions, but also financial advantages. Specifically, according to a recently released market analysis report on the potential financial benefits indicates that energy efficiency initiatives in addition to reducing electricity use by 365 billion kWh by 2040, which translates to at least $240 billion opportunity [7]. These benefits have incentivized the adoption of energy efficient systems in the building sector.

Among the major programs that various states have adopted is the Property Assessed Clean Energy (PACE) and On-Bill Repayment or On-Bill Financing programs. Firstly, the PACE is an innovative approach that targets the financing of a wide range of energy efficiency as well as renewable energy improvement programs permanently attached to residential and commercial buildings [8]. The program is intended to lead to a decrease in electricity and gas use, increase in the adoption of renewable energy, and decrease in greenhouse gas emissions. Similarly, On-Bill Repayment and On-Bill Financing provide property owners to invest in clean energy programs through their utility [9]. These programs are innovative in that they allow customers to directly invest in energy efficient programs via flexible financial terms. In other words, the financial obligation associated with energy efficiency is transferred to the tenant or property owner.

Despite the benefits of energy efficiency in the building sector, the initiative still faces several challenges in regards to implementation. The main challenge arises due to difficulties associated with the process of performing large scale energy audits to determine which are the most energy inefficient buildings. For instance, to successfully perform energy audits in the U.S. it will require one to cover at least 352 billion square feet of commercial and residential floor space. The process is not only physically impossible, but also financially impractical as it will cost between $100 and $1,650 per house on average [10]. Additionally, the number of energy auditors is not enough to undertake such a project. Currently, it is estimated that there are 140 million homes and 4.9 million commercial building and a corresponding 14,000 certified home energy auditors. Considering the number of buildings, it will be impossible to successfully perform energy auditing in order to determine energy efficiency in buildings in all the states.

Furthermore, it is difficult to ascertain the information on energy audits. The challenge in this case arises from the techniques used to predict energy use and savings, which in some cases do not provide accurate data. For instance, in a study by Oak Ridge National Laboratory (ORNL) a comparison was performed between modeled and actual energy use in home heating. The pre-retrofit simulation data were determined to have over-predicted space heating requirements in comparison to post-retrofit measurements [11]. Similarly, several other studies have confirmed this challenge in energy auditing. For example, most energy auditing models tend to overestimate energy consumption in older and newer houses by at least 60 percent and 17 percent respectively [12]. Thus, due to challenges involved in predicting energy use in commercial and residential buildings, it becomes difficult to effectively implement energy efficient programs.

CHAPTER 2

AUTOMATED RESIDENTIAL ENERGY AUDITS USING A SMART WIFI THERMOSTAT ENABLED DATA MINING APPROACH

2.1 Abstract

Smart WiFi thermostats, when they first reached the market, were touted as a means for achieving substantial heating and cooling energy cost savings. These savings did not materialize until additional features, such as geofencing, were added. Today, average savings from these thermostats of 10–12% in heating and 15% in cooling for a single-family residence have been reported [13]. This research aims to demonstrate additional potential benefit of these thermostats; namely as a potential instrument for conducting virtual energy audits on residences. In this study, archived smart WiFi thermostat measured temperature data in the form of a power spectrum, corresponding historical weather and energy consumption data, building geometry characteristics, and occupancy data are integrated in order to train a machine learning model to predict attic and wall R-Values, furnace efficiency, and air conditioning seasonal energy efficiency ratio (SEER), all of which were known for all residences in this study. The developed model was validated on residences not used for model development. Validation R-squared values of respectively 0.9408, 0.9421, 0.9536, and 0.9053 for predicting attic and wall R-Values, furnace efficiency, and AC SEER were realized. This research demonstrates promise for low cost, data-based energy auditing of residences reliant upon smart WiFi thermostats.

2.2 Introduction

In 2018 according to the U.S. Energy Information Administration (EIA), residential buildings accounted for approximately 21% of total electricity consumption as well as 16% of total natural gas consumption in U.S. [14] [15]. The residential sector has been deemed to offer the most cost-effective potential for energy savings among all U.S. buildings [16]. The most common approach for garnering savings has been through utility rebate programs, whereby utilities offer financial incentives for residential investment in energy reduction measures. The rebated measures are generally those with the statistically best savings relative to investment among the entire residential population. In practice what this has meant is that all rate payers have effectively subsidized the investments of wealthier residents. Researchers have found that upgrading the housing of low-income residences to the median household efficiency would reduce excess energy by 68%. In other words, while residential energy reduction offers the most cost-effective potential among all U.S. buildings; the vast majority of this savings potential comes from low income residences [17] [18] [19].

Many factors impact the energy consumption of individual residential buildings, including weather conditions, building geometry, building thermal envelope materials, heating, ventilation, and air conditioning (HVAC) characteristics, and energy-use behavior of the residents [20] [21]. But identifying the energy efficiency priorities for individual residences is not automatic and can be both laborious and expensive. For example, traditional energy audits require a physical visit to a residence, whereby a technician performs air leakage tests, conducts infrared imaging, documents insulation in the walls, basement/crawlspace/sub-flooring, and attic, and assesses the efficiency of the heating/cooling/water heating systems. These audits can be costly [22]. The US Department of Energy estimates costs for detailed energy audits ranging from $0.12 up to $0.503 per square foot, depending on the size and complexity of the residential buildings [23]. In another study, the average cost to audit single-family residences in the US starts at $400 and increases dramatically with the size of the home [24]. The audit cost can outweigh the potential energy cost savings, and the recommendations made have been observed to be dependent on the auditor [22] [25]. For example, a study compared recommendations from three different contractors hired to audit the energy effectiveness of three different types of buildings; namely a large multi-family residence with a common heating plant, a primary school, and a terraced or row home. The final recommendations from the three different contractors were quite dependent on the auditors with installation cost and savings estimations respectively differing by as much as 300% and 250% relative to the lowest estimates [26]. Likewise, another study compared three energy audit reports conducted on the same building [25]. The three studies reported widely divergent results. First, the three reports employed different audit data. Second, the list of energy conservation measures (ECMs), short of three common measures, were different. Third, the initial cost and energy and cost savings for the shared ECMs varied widely between the analyses. Additionally, the energy audit cost from three the different companies ranged from $252 to $1,123. This trend has certainly contributed to a lack of faith about the value of residential energy audits [22] [27]. As importantly, low to low-middle income residents frankly will never opt to have their residence audited. The expense just cannot be tolerated.

There is a strong need for automatically auditing the energy effectiveness of residences at a substantially lower cost. Such audit-derived information could help to change the paradigm for utility rebate programs were every residence within a utility district to be audited. A 'worst-to-first' priority for utility investment in energy reduction could be established in such a way as to ensure that the investments made yield the biggest energy and energy cost savings [28] [29].

2.3 Background

In this section, relevant research pertaining to the standard calculation approaches is presented for: building energy models with sufficient granularity to permit estimates of savings from residential energy upgrades, inverse modeling approaches with sufficient granularity to identify residences in need of upgrades and quantity the resulting savings based on energy data pre- and post-upgrade, and the state-of-the art associated with virtual energy audits.

2.3.1 Building Information Modeling and Simulation for Energy Audits

Energy modeling software (e.g. eQuest, EnergyPlus, IES, and Energy-10) has been used extensively to simulate and predict building energy consumption. Generally these have required extensive detail about the geometric and energy characteristics of a building, as well as occupancy and control schedules. Examples of their use are extensive and, unfortunately despite the detail required of data inputs, the energy savings recommendations that result have been very inconsistent [30]. For example, one study evaluated the accuracy of the United States Department of Energy (DOE) developed eQuest software for predicting energy consumption and estimating savings from upgrades in hotels. Good correspondence was seen between predicted and actual savings based on the building energy efficiency retrofit (BEER) scheme [31]. But other studies have demonstrated just the opposite [32]. These tools are strongly dependent on the user and require significant engineering time [33]. Much of the time, these tools over-predict energy consumption [29]. For example, the Energy Trust of Oregon performed a study to evaluate building energy simulation programs. Three programs were compared: SIMPLE, REM/Rate, and Home Energy Saver (HES). Detailed audits were conducted, and utility bills were collected for 190 homes. The homes were simulated with the three energy modeling tools, including two levels of detail for HES. The models over-predicted gas use for space heating by an average of 41% in older homes built before 1960 and by 13% for newer homes built after 1989 [34] [35]. Likewise, the validity of the Manufactured Home Energy Audit tool was assessed in a two-part study by Oak Ridge National Laboratory (ORNL). Audit obtained and utility data were used to analyze the energy effectiveness of manufactured homes across five counties in the US North and Midwest. The predicted space heating energy consumption was compared to the actual space heating energy consumption. Pre- and post-retrofit comparisons of modeled and actual energy use were made. Results from the pre-retrofit simulations were observed to over-predict space heating energy use from 163% to 109% [36]. Lastly, a recent study by Pacific Northwest National Laboratory on seven homes with deep retrofits showed a range of predicted savings obtained by different auditors from 75% overestimation to 16% underestimation relative to the savings realized for all the homes evaluated [37].

2.3.2 Inverse Energy Modeling for Identifying Residences in Need of Upgrade and Estimating Savings from Upgrades

In 1994 ASHRAE published an Inverse Modeling Toolkit (IMT), which has been used since to estimate savings from various system upgrades [38]. This toolkit is based on a four steps process. The first step is to create statistical three-parameter models of electricity and natural gas consumption as a function of outdoor air temperature over the energy consumption period. This regression renders estimates of the sensitivity of the consumption to temperature (termed heating and cooling slopes), the building balance-point temperature, and average weather-dependent energy consumption for a meter period. The second step is to apply these to site-relevant typical meteorological year (TMY3) weather data to determine the Normalized Annual Consumption (NAC) for each type of energy. The third step is to derive a NAC for each set of 12 sequential months of utility data. The fourth step is to compare the NACs of multiple buildings to identify average, best, and worst energy performers and to evaluate how the consumption of a building has changed over time. It is this last step which permits measurement of savings post-retrofit of energy efficiency upgrades [39].

A case study of 14 Midwest hospital results showed that the NAC analysis is more stable and informative than the determined regression coefficients determined from the first step. Also, a change in NAC indicates a real change in the energy performance of the building, provided that the savings are greater than 10% (Note: ASHRAE suggests that this approach is not, in general, able to measure savings less than 10% [29]). In another study electric and natural gas historical consumption data was merged with residential building geometry, and historical weather data to determine the energy consumption intensity for each home in a Village of Yellow Springs, Ohio by using five-parameter fit for the electricity data and a three-parameter fit for the natural gas data. These researchers normalized the NAC calculations with the residential floor area. Using this normalized data, they were able to identify the most promising homes for energy reduction [40].

2.3.3 State of the Art in Virtual Energy Audits

Building geometric and energy characteristics (insulation type and amount in envelope components, heating/cooling/water heating efficiencies, etc…) have a prominent influence on energy consumption [41]. Knowledge of these characteristics is essential for estimating potential energy savings from specific energy upgrades. Ordinarily such data is collected from on-site audits. However, there have been some recent strides toward inferring energy characteristics from data alone. Table 1 summarizes research to predict the energy characteristics of buildings or to disaggregate the energy consumption into specific categories, such as lighting and appliances.

The private company Retroficiency (acquired by ENGIE Insight) claimed in the mid-2010s to have the ability to automatically audit the energy performance of commercial buildings. Their approach employed interval energy data from smart meters, occupant schedules, weather and systems control details. Their virtual energy assessment (VEA) provided recommendations for retrofits based upon the virtual audit. Included in their recommendation were estimates of upgrade costs and return on investment [42].

In 2016 Case Western Reserve University and Johnson Controls Inc. worked collaboratively to develop another version of a virtual energy audit for small to medium size commercial or retail buildings. Their approach employed 15 minute interval utility data, insulation characteristics, and weather data [43]. Lastly, the approaches by FirstFuel, Agilis Energy, and C3 Commercial, likewise employ interval meter data from smart meters and real time weather data to estimate various forms of electric consumption (lighting, cooling, etc.…).

Table 1. Summary of prior research in predicting energy characteristics in buildings

Ref.	Software / Company name	Learning algorithm (type)	Types of feature	Building type	Target
[42], [44]	Retroficiency	Proprietary algorithm (Not for public use)	Smart meters, occupant behavior, weather and systems control details	commercial	Heating, cooling, ventilation, lighting, plug loads, pumps, domestic hot water systems
[43], [45]	Case Western Reserve University, Great Lakes Energy Institute (GLEI)	Energy Diagnostics Investigator for Efficiency Savings (EDIFES) (Not for public use)	Smart utility meter, insulation information, operation schedules, weather data	commercial	Exterior lighting (e.g. 24-hour lighting and security / monitoring systems), HVAC (e.g. heating, ventilation, and air conditioning electricity consumption), and occupancy-based plug loads (e.g. computers, refrigerators, copiers, televisions, interior lighting, etc.)
[42], [44]	FirstFuel	Statistical model (Not for public use)	Hourly electricity consumption data, hourly local weather data, high level	commercial	Electric lighting, building envelope, equipment, HVAC, service hot water,

			building data from geographic information systems		operating schedule
[42], [44]	Agilis Energy	Statistical model (Not for public use)	Smart meter interval data and climate data	commercial	Operational energy performance, interval energy demand, occupancy, energy system operations
[42], [44]	C3 Commercial	Statistical model, Database for Energy Efficiency Resources (DEER) (Not for public use)	Smart meters data drives inverse modeling and uses national, state, and regional utility building stock data for benchmarks to compare energy benchmark with other buildings that are functionally equivalent (same type and floor area)	commercial	Electric lighting, building envelope, equipment, HVAC, service hot water, and operating schedule based on data driven inverse energy modeling, coupled with statistical analysis utilizing an existing energy conservation measures (ECM) list from the database for energy efficiency resources (DEER)

2.4 Objectives of Research

While smart meters have gained increasing market share [46], nationally there still is no consistent standard relative to frequency of data collection and input [47]. Their use in this study is not assumed. For many residences, only monthly interval energy consumption data is available. Moreover, smart meters are only generally capable of providing information about electricity consumption. The cost for smart gas meters is prohibitive for wide-scale use without some type of enabling subsidy.

There are two starting points for this research. First, is that the monthly metered energy consumption reflects the overall heating and cooling energy effectiveness of a residence. But this information alone is incapable of resolving specific contributions to the heating and cooling energy effectiveness. Second, it acknowledges that if the residential energy characteristics for a sub-set of residences are known, data-based machine learning based models can be tuned to predict the individual energy characteristics. If these models are derived from data collected from numerous diverse residences, theoretically they could then be used to predict the energy characteristics in residences where these are unknown.

The research question driving this study is the following: "How can the individual contributions to the heating and cooling energy effectiveness (namely the envelope R-Values and heating/cooling system efficiencies) be resolved from only remotely collected data? To date, this question has not been answered.

Fundamentally, the goal of this research is to estimate residential energy characteristics from monthly energy consumption (potentially gas and electric), coupled with other data that could remotely be collected for residences. This data includes historical weather data, residential building geometry data, and potentially occupancy data, and uniquely and most importantly, smart WiFi thermostat data. This latter data, because of the relative high frequency associated with its measurement, could potentially help to resolve the energy characteristics which control the thermal dynamics of a residence to heat gain/loss to changes in outdoor weather and to internal heating and cooling. Were it possible for these instruments to make possible remote energy auditing of residences, their prevalence in the world would guarantee wide-scale impact. In 2017 more than 82 million smart thermostats were in use in North America according to a study by Berg Insight. The same study projected that more than half (51%) of North America homes would be smart homes by 2022 [48].

To achieve the broad goal of predicting residential envelope R-Values and heating/cooling system efficiencies from the varied data types (static residence geometrical, occupancy, and energy characteristics; monthly metered energy consumption; higher frequency weather data; and high frequency ‘delta’ smart WiFi thermostat data) it is necessary to extract useable features from the higher frequency signals in order to combine with the monthly metered consumption. This first requires the creation of derived features characterizing the weather variation within the energy consumption meter periods. Average outdoor temperature during a meter period is not sufficient to characterize the exterior weather. Secondly, it requires the development of dynamic characteristics based upon smart WiFi thermostat data unique to a residence in which a smart WiFi thermostat is present. With static representations of the dynamics of the outdoor weather for each meter period and a residence’s response to dynamic changes established, the data could be combined and then used to train machine learning models on a sub-set of residences for which the energy characteristics are known. Last the developed model must be tested on residences not used in the training to demonstrate the potential for this approach to estimate energy characteristics in residences where the energy characteristics are unknown.

This paper is organized as follows. First, as the approach posed hinges on the data used, the data employed in this study is described. Next, the methodology and results, both aligned with the objectives posed, are presented. Lastly, we conclude by discussing the wide-scale implications of the approach developed to remote regional energy auditing and the needed work which is required to realize this potential.

2.5 Data

There are four main raw data were used in this study. A description and more details for each individual dataset at the following subsections.

2.5.1 Residence Geometrical, Occupancy, Monthly Energy Consumption, Energy Characteristics, and Smart WiFi Thermostat Data

This study considered 101 houses owned by a university in the Midwest region of the US. Geometrical data was accessed for all residences through the local county property database. Such data is publicly available nationally.

Second, historical monthly energy consumption and occupancy data (electric and gas meter data) from January 2016 to the present was obtained for each residence from the university owner of the residences.

Third, energy characteristics for these residences were acquired in 2015 through detailed energy audits made by one of the lead authors. As noted in a prior study, this audited subset of houses offered significant diversity in size, insulation, and energy effectiveness as shown in [29], which helps in developing a generalizable model capable of predicting energy characteristics in any residence.

Table 2 shows the minimum and maximum values for the building geometric data, energy characteristics, and residential occupancy characteristics for the 101 residences considered. Some input features included in the table might in general be a challenge to acquire (e.g., refrigerator related data), but are retained here in order to evaluate their importance.

Table 2. Ranges of residential building geometrical, energy characteristic, and residence occupancy collected during a summer 2015 audit of 101 houses

Category	Properties	Minimum Value	Maximum Value
Geometry	Floor area (m^2)	66	257
	Basement area (m^2)	None	131
	Attic area (m^2)	42	245
	Window area (m^2)	6	27
	Wall area (m^2)	54	301
Energy Characteristic	Attic thermal insulation (m^2 K W^{-1})	1.14	7.06
	Walls thermal insulation (m^2 K W^{-1})	0.68	2.43
	Furnace efficiency (-)	0.60	0.95
	AC SEER (Btu/W-hr)	10	16
	Water heater efficiency (-)	0.55	0.95
	Refrigerator efficiency (EF)	9	24
	Refrigerator size (L)	467	747
Occupancy	Number of occupants	2	12
Consumption	Monthly Electric usage (kWh $month^{-1}$)	459	2640
	Monthly Gas usage (MJ $month^{-1}$)	7610	31746

Smart WiFi thermostats data were accessible for each of the audited residences. Raw thermostat data, referred to as “delta data” was collected for each of the residences. Delta data are logged only when there is change in one of the thermostat features. In practice, this means that if the set point temperature, measured temperature and humidity at the thermostat, heating/cooling mode, or heating/cooling/fan status changes, data are recorded. For this research, smart WiFi thermostat data for these houses was continuously collected and archived from 6/1/2018 to the present. Typically, thousands of points were collected for each residence each month.

2.5.2 Weather Data

Corresponding hourly weather data (only the outdoor dry bulb temperature was used here) was been obtained from the U.S. NOAA National Climatic Data Center site [49], but could have likewise been obtained using the Weather Underground [50] resource.

2.6 Methodology

The methodology is organized as follows. In the first two sub-sections, the process for extracting features characterizing respectively the variation of the weather data in each meter period and the thermal dynamics of each residence to changes in outdoor temperature and internal heating and cooling as evidenced from the smart WiFi thermostat data is described. Then, the data-based machine learning and testing approaches are described.

2.6.1 Development of New Weather Features Characterizing Outdoor Temperature Variation During Each Meter Period

Inverse energy models have employed mean outdoor average temperature for an entire meter period as an input (often singular) to predict energy consumption [39]. However, including increased granularity to better reflect variation that occurs over a large time period may be beneficial.

The approach used here is to 'bin' the outdoor temperature data within a meter period into discrete temperature bands; determining the probability density of the outdoor temperature being in each of the discrete bands over one energy consumption meter period. The idea is that it is not just the mean temperature in a meter period that is important.

Rather, the record of temperature variation in a meter period is even more important, especially if the thermostat set point temperature is changing within the meter period.

2.6.2 Development of Dynamic Representations of Smart WiFi Thermostat Data for Each Residence

The measured smart WiFi thermostat temperature provides a record of heat gain/loss from residence from/to the outdoor environment and a record of heating and cooling. When the heating system and cooling system are on, the interior temperature is observed to warm/cool over a certain amount of time. So in effect it accounts for the time constants associated with the heating and cooling systems, which likewise depend upon the heating and cooling system efficiencies. After heating and cooling is interrupted, heat loss/gain to/from the outdoor environment is registered as a decrease/increase in internal temperature. The rate at which the internal temperature cools/warms after interruption of heating/cools depends upon the envelope heat losses/gain, and thus on the thermal capacitances (time constants) associated with the envelope components and infiltration.

Since the aim of this research is to develop single models to predict residential energy characteristics based upon data from numerous diverse residences, we looked to develop a representation of the measured smart WiFi thermostat that could potentially account for the different time constants associated with the envelope barriers and the heating/cooling systems. A power spectrum reduction of this measured temperature seemed a reasonable approach; as such a representation characterizes the strength of a signal relative to the driving frequencies.

In order to develop a power spectrum on a signal, however, the signal frequency must be constant. This was not the case for the smart WiFi thermostat data measured here [51]. "Delta" thermostat data is non-uniformly spaced in time. So, step 1 in establishing power spectrum representations of the measured smart WiFi thermostat temperature was to create a uniformly spaced signal. Linear interpolation was employed to estimate the temperature at fixed intervals based upon the measured thermostat temperatures, using Equation (2.1).

$$x_i = \frac{x_a - x_b}{a-b}(i-b) + x_b, \tag{2.1}$$

where a, b and i in this case are times associated with the collected data, x_a and x_b are collected neighbor data points at x_a and x_b ($x_i > x_a,\ x_i < x_b$), and x_i is interpolated data.

The characteristic frequency of each residence to changes in outdoor weather conditions is an indicator of the dynamic thermal characteristics of a residence's envelope elements (walls, windows, and ceiling). The power spectrum defines the 'strength' of the response (measured thermostat temperature) with frequency. The power spectral density *h(ω)* is equal to the correlation value *γ(k)* (where *k* is lag, and *t* is time) divided by the frequency span over which that peak is observed $e^{-i\omega t}$ (Equation (2.2) and (2.3)) [52].

$$h(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma(k)e^{-i\omega t} \qquad -\pi \leq \omega \leq \pi, \tag{2.2}$$

$$\gamma(k) = \frac{1}{2\pi}\int_{-\pi}^{\pi}h(\omega)e^{-i\omega t}\,d\omega \qquad k = 0, \pm 1, \pm 2\ \ldots, \tag{2.3}$$

A locally high amplitude in the power spectrum at a specific frequency means that the measured signal (thermostat temperature) owes much of its energy to dynamic phenomenon at this frequency. For example, higher efficiency houses have more energy in the signal at lower frequencies, so if something changes outside or the set point temperature changes inside, the response to change as measured by the thermostat temperature is slow.

In the power spectrum, the peak is in the low frequency band. On the other hand, lower efficiency houses have more energy at higher frequencies.

In this study, a histogram of the power spectra for each house was created for fixed period bands. A total of 500 uniformly spaced bins were set. The average signal strength in each bin was calculated. Thus, the available power spectrum binned data was available for each residence. Of these, only the first 50 bins were retained, corresponding to 48 hour periods. Almost all of the signal energy for each residence resided in these bands. In effect, this binned power spectra data is a characteristic of a residence.

2.6.3 Development of Data-Based Machine Learning Models for Each Envelope Thermal Resistances and Heating/Cooling System Efficiency

2.6.3.1 <u>Data Merging and Preparation</u>

In order to develop machine learning models for predicting the individual energy characteristics from the data described in Section 2.6 and developed in Sections 2.6.1 and 2.6.2, the data was merged. The binned outdoor temperature for each meter period and the binned smart WiFi thermostat temperature power spectra, along with the static residential geometry, occupancy, and energy characteristics, were synched and merged with the monthly energy consumption data by common address.

Additionally, in order to mitigate observation bias, very similar houses were removed by measure distances between the houses. A K-means Euclidean distance [53] was computed from the standardized static residential data only. The analysis found 14 similar houses (including 3 very similar newer houses). As a result, 9 houses were eliminated from inclusion in the model training datasets. As a result, the total number of residences included in the training dataset was reduced to be 86 houses. Then, all observations with any missing data were eliminated [54].

2.6.3.2 Model Development and Testing

Choosing the right machine learning algorithm is complicated; it depends upon data type, number of observations, number of input features, etc. Also, the second major challenge is to tune the model hyperparameters. Different machine learning algorithms have different hyperparameters which need to be optimized in order to yield the best models. For example the most critical hyperparameters in artificial neural networks (ANN) models are the number of hidden layers, dropout rate, network weight initialization, activation function, learning rate, momentum, number of epochs, batch size, etc. [55] [56]. In this research, the AutoMLH2O package [57] was used to select and tune the model and hyperparameters. Functional forms considered in this approach included Deep Neural Networks, Random Forests, Extremely Randomized Trees, Gradient Boosting Machines (GBMs), Extreme Gradient Boosting (XGBoost), and Stacked Ensembles. Table 3 shows the input features employed to predict the attic R-Value, wall R-value, furnace efficiency, and AC SEER targets. Note the R-value targets use as input features knowledge of the furnace efficiency and AC SEER; but the latter two do not leverage the attic and wall R-Values as features. Thus, the general predictive process would be to first predict the R-Values and then use these predictions as predictors for the furnace efficiency and AC SEER.

Table 3. Input features used to develop each target model

Input Features	Targets: Attic R-Value	Wall R-Value	Furnace Efficiency	AC SEER
Floor area (m^2)	X	X	X	X
Basement area (m^2)	X	X	X	X
Attic area (m^2)	X	X	X	X
Window area (m^2)	X	X	X	X
Wall area (m^2)	X	X	X	X
Attic thermal insulation (m^2 K W^{-1})		X	X	X
Walls thermal insulation (m^2 K W^{-1})			X	X
Furnace efficiency (-)				
A\C SEER (Btu/W-hr)				
Water heater efficiency (-)	X	X	X	
Refrigerator efficiency (EF)	X	X	X	X
Refrigerator size (L)	X	X	X	X
Is there a wash and dryer machine (yer/no)	X	X	X	X
Is there a dishwasher machine (yer/no)	X	X	X	X
Number of occupants	X	X	X	X
PDD bins for outdoor temperature (34 bins)	X	X	X	X
PSD frequencies	X	X	X	X
Monthly electric usage (kWh $month^{-1}$)				X
Monthly gas usage (MJ $month^{-1}$)	X	X	X	

A training dataset was used to develop a predictive model, while a validation dataset provided an evaluation of the model for model hyperparameters tuning. Next, the model was applied to an independent testing dataset. We used 10-fold cross-validation during hyperparameter tuning to avoid subset biases. We report and use, the mean cross-validation performance metrics [58] [59] [60].

The effectiveness of the models for both validation and testing datasets was evaluated using the following parameters: R-squared metric, mean square error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and root mean squared logarithmic error (RMSLE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{2.4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} = \sqrt{MSE}, \tag{2.5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|, \tag{2.6}$$

$$RMSLE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\log(y_i + 1) - \log(\hat{y}_i + 1))^2}, \tag{2.7}$$

$$R^2 = 1 - \frac{MSE(model)}{MSE(baseline)} = \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}, \tag{2.8}$$

A model is only as good as its ability to make accurate predictions on data not used in its training. Here the true quality of the models developed will be assessed through testing. A testing dataset was developed by extracting the observations from 6 houses from among the 92 houses included in the study. The six testing houses were randomly selected, but were also checked to ensure that the testing set includes high, medium, and low values of the responses (Table 4).

Table 4. Randomly selected test observations

House Num.	**Targeted Feature**			
	Attic R-Value (m^2 K W^{-1})	**Wall R-Value (m^2 K W^{-1})**	**Furnace Efficiency (-)**	**AC SEER (BTU W^{-1} hr^{-1})**
House 1	3.13	0.69	0.78	14.00
House 2	6.22	2.44	0.95	13.00
House 3	2.23	0.86	0.78	14.00
House 4	3.13	0.86	0.80	10.00
House 5	1.71	0.86	0.90	13.00
House 6	3.13	0.69	0.78	11.30

2.7 Results and Discussion

2.7.1 Development of New Weather Features Characterizing Outdoor Temperature Variation During Each Meter Period

Figure 1 shows a representative probability density distribution for the outdoor temperature were developed for a single meter period within discrete two degree °C bins. This figure shows how this binning took place for one meter period (January 1, 2018 to February 9, 2018).

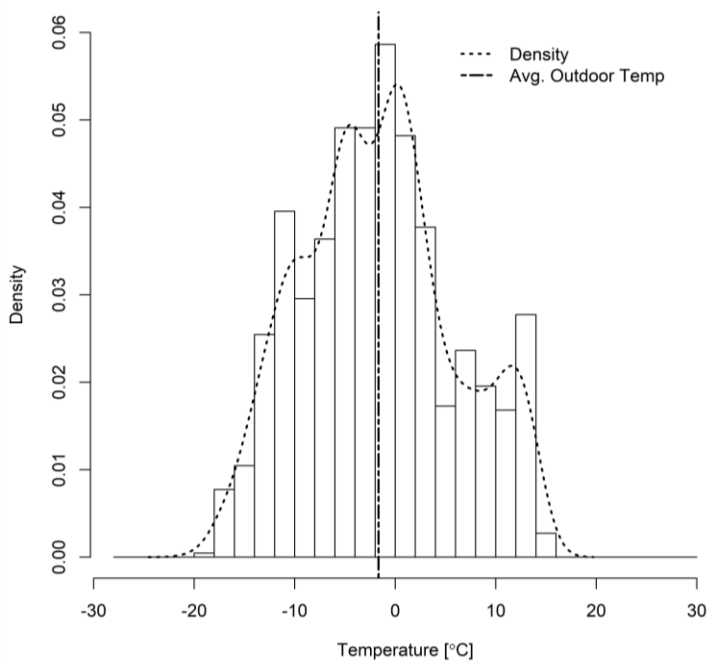

Figure 1. Outdoor air temperature histogram of one electric meter period

2.7.2 Development of Dynamic Representations of Smart WiFi Thermostat Data for Each Residence

Figure 2a shows the power spectrum for an energy effective residence with respective wall and ceiling R-Values of 2.46 and 3.16 (m^2 K W^{-1}), whereas Figure 2b shows the power spectrum for a low energy effective residence with respective wall and ceiling R-Values of 0.70 and 2.28 (m^2 K W^{-1}). Note that in the former case (a) most of the energy in the signal is at small periods; opposite of that for the low energy effectiveness case, owing to the more rapid response of high efficiency homes to heating and cooling, relative to a slower, more damped response (due to greater heat loss/gain to the external ambient) for the low efficiency residence. Most visible is that at the diurnal period (24 hr), there is little energy in the high efficiency house case, but, in comparison, the signal energy peaks at this period for the low efficiency house case. Thus, the low efficiency house 'feels' the diurnal transients far more than the high efficiency house which damps out most of the energy associated with this cycle.

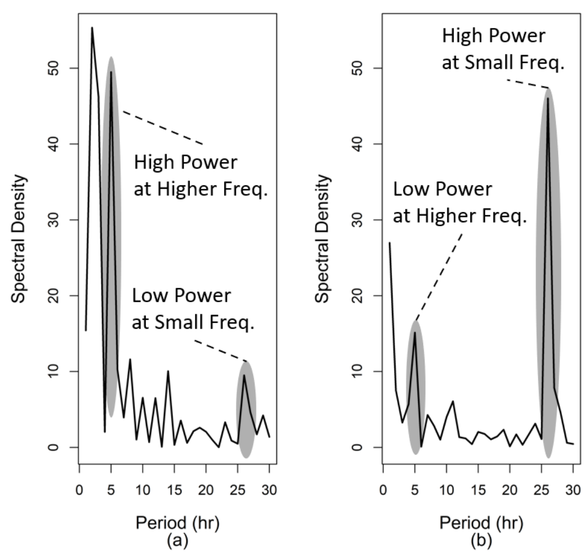

Figure 2. Power spectrum for the indoor temperature measured at the thermostat for (a) high and (b) low efficient houses

The higher energy at lower periods (higher frequencies) for the high efficiency residence in comparison to a low efficiency residence is primarily affected by the response to thermostat set point changes. The high efficiency house is able to respond quickly to indoor temperature set point changes. The low efficiency house responds more slowly. So, even the period associated with set point changes increases relative to the high efficiency house case.

2.7.3 Training and Testing of Data-Based Machine Learning Models for Each Envelope Thermal Resistances and Heating/Cooling System Efficiency

2.7.3.1 Identifying the Best Machine Learning Algorithm

This subsection aims to document how the best model was developed in predicting each of the envelope thermal characteristics. Unknown were both what model algorithm should be used and which features should be included in the model development.

First, different machine learning algorithms were applied and validated on the complete training dataset. This complete dataset included all static residential features, monthly energy consumption, binned outdoor temperature data for each meter period, and all binned smart WiFi thermostat temperature power spectrum data.

Table 5 documents the validation metrics obtained for this complete dataset for the various algorithms employed. Clear from this table is that the GBM machine learning methodology yielded the best validation performance. Hereafter, only this algorithm is considered.

Table 5. Validation metrics for model development using complete feature dataset with different machine learning algorithms

Target	Model Order	Model Algorithm	RMSE	MSE	MAE	RMSLE
Attic R-Value	1	GBM	3.39E-05	1.15E-09	1.47E-05	9.87E-06
	2	DRF	0.0021	4.39E-06	0.000291076	0.0004
	3	XRT	0.0026	6.97E-06	0.000642033	0.0008
	4	GLM	0.6587	0.4338	0.5081	0.1872
Walls R-Value	1	GBM	1.10E-06	1.21E-12	6.17E-07	3.49E-07
	2	XRT	0.0004	2.33E-07	4.56E-05	0.0002
	3	DRF	0.0014	2.16E-06	6.16E-05	0.0007
	4	GLM	0.3537	0.1251	0.2692	0.1553
Furnace Efficiency	1	GBM	3.94E-07	1.55E-13	3.24E-07	2.13E-07
	2	DRT	1.60E-05	2.57E-10	1.37E-06	8.30E-06
	3	XRT	0.0001	2.49E-08	1.22E-05	8.78E-05
	4	GLM	0.0485	0.0023	0.0389	0.0261
AC SEER	1	GBM	0.0328	0.0011	0.0046	0.0025
	2	DRF	0.1771	0.0313	0.0392	0.0134
	3	XRT	0.1828	0.0334	0.0393	0.0137
	4	GLM	1.0090	1.0182	0.7615	0.0753

2.7.3.2 Identifying the Best Thermostat-Derived Feature Set for Model Development

Figure 3 shows variable importance plots obtained from the best GBM models produced in predicting a) attic R-Value; b) wall R-Value; c) furnace efficiency; and d) AC SEER. In this figure the features labeled PSD.Freq.X refer to the average power spectrum powers in frequency bin X. Clear from this figure is that the power spectrum features are very important for predicting each of the energy characteristics. As a result, one would expect that the spectral information present in the thermostat signals to improve the prediction of the targeted energy characteristics.

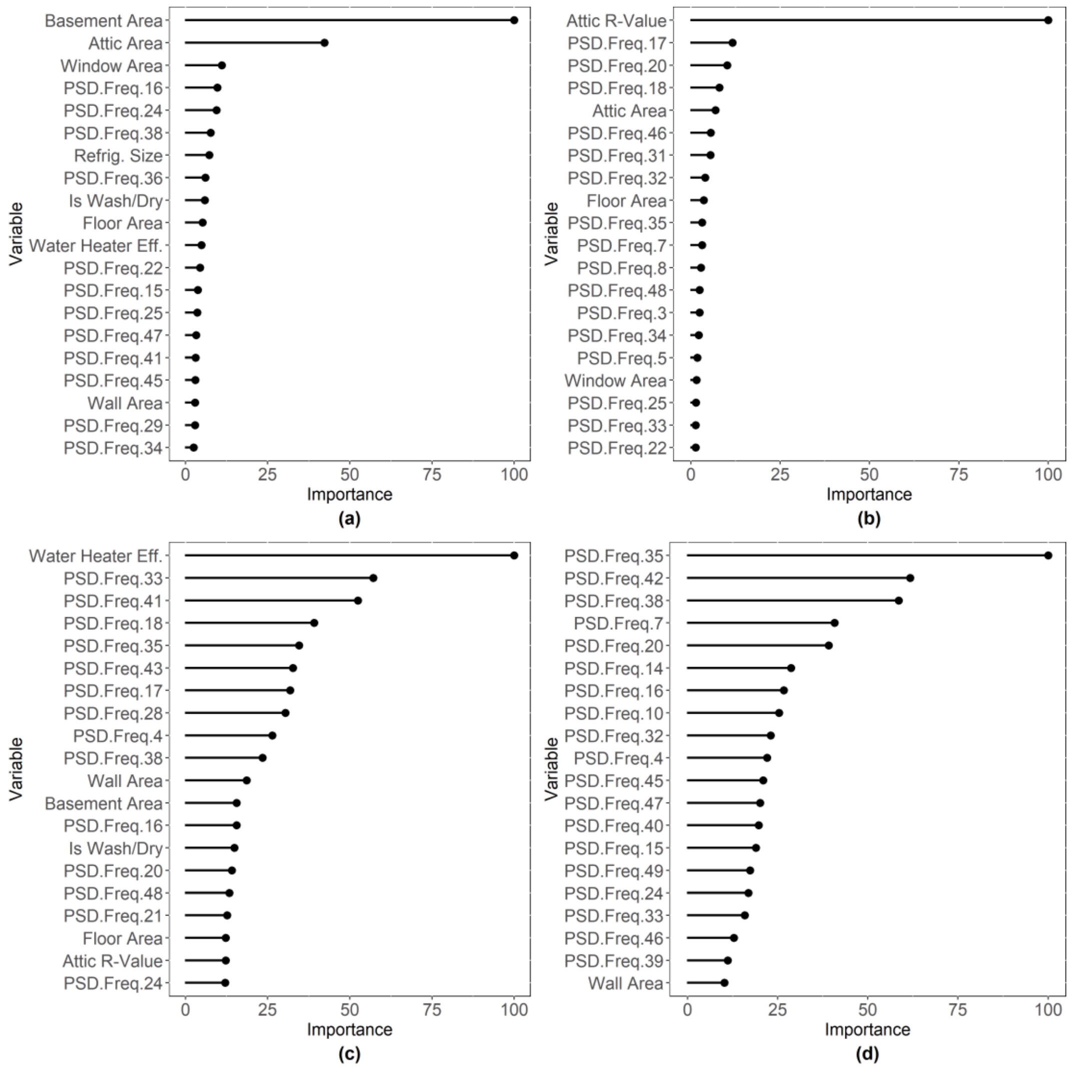

Figure 3. Variable importance plots including thermostat derived information for (a) attic R-Value model (b) wall R-Value model (c) furnace efficiency model using the natural gas dataset (d) AC SEER model using the electric dataset

We then investigated developing models using subsets of the PSD.Freq.X data. GBM models were thus developed to predict the targeted energy characteristics for the following PSD binned power subsets: a) for the first 40 frequency bins (approximately needed to capture diurnal cycle); b) for the first 20 frequency bins; c) for the first 10 frequency bins; d) for the top 10 most important frequency bins for each target obtained from a variable importance analysis using the best GBM model; e) for the top 2 frequency bins for each target obtained from a variable importance analysis; f) for the top frequency bin for each target for each target obtained from a variable importance analysis; g) for the top two frequency bins for each target obtained from an optimization to minimize error; and h) for the top frequency bin for each target obtained from an optimization to minimize error.

Table 6 shows the testing statistics for predicting the attic and wall R-Values, furnace efficiency, and AC SEER respectively for inclusion of the binned spectral powers using the same testing dataset considered in Section 2.6.3.2.

There are three main points to make. First, while some of these cases yield accurate validation metrics for individual targets, the best overall cases are those using only one or two of the optimally selected frequency bins to minimize the validation error. It is clear that use of all of the frequency bins introduces many features which have little influence on the target. Elimination of these features in general improves the model. Second, the prediction statistics for the testing dataset are improved markedly for the last three cases, cases e – h. Case e where the two top power spectrum bins based upon the GBM variable importance yielded the best model for predicting the attic R-Value. Case g, which included as predictors the two most important power spectrum frequency bins for minimizing error, yielded the best model for the AC SEER. Lastly, Case h, reliant upon a single power spectrum frequency bin based upon minimizing the predictive error yielded the best model for predicting the wall R-Value and furnace efficiency. The best MAE error in predicting attic R-Value, wall R-Value, furnace efficiency, and AC SEER was respectively been reduced from 0.5249 to 0.2752, 0.2768 to 0.1044, 0.0362 to 0.0116, and 0.7450 to 0.4245. All of these errors could be well-tolerated in virtual energy audits.

Table 6. Power spectrum density (PSD) frequencies cases with model prediction evaluation parameters for testing dataset

Case	PSD Frequency Number	Target	R^2	RMSE	MSE	MAE	RMSLE
a). 1st 40 frequencies	From 1 to 40	Attic R-Value	0.6629	0.8316	0.6915	0.6053	0.1674
		Walls R-Value	0.7721	0.2952	0.0871	0.2611	0.1374
		Furnace Efficiency	0.1097	0.0644	0.0041	0.0533	0.0352
		AC SEER	-0.2822	1.6458	2.7085	1.1239	0.1278
b). 1st 20 frequencies	From 1 to 20	Attic R-Value	0.4887	1.0241	1.0488	0.8233	0.2259
		Walls R-Value	0.7541	0.3066	0.0940	0.2659	0.1339
		Furnace Efficiency	-0.4019	0.0808	0.0065	0.0702	0.0437
		AC SEER	-0.6478	1.8658	3.4811	1.5156	0.1422
c). 1st 10 frequencies	From 1 to 10	Attic R-Value	0.8285	0.5931	0.3517	0.4712	0.1554
		Walls R-Value	0.5929	0.3945	0.1557	0.2598	0.1775
		Furnace Efficiency	-0.0214	0.0689	0.0048	0.0594	0.0376
		AC SEER	-0.3431	1.6844	2.8372	1.4900	0.1285
d). top 10 frequencies based on GBM variable importance	16, 24, 38, 36, 22, 15, 25, 47, 41, and 45	Attic R-Value	0.8028	0.6361	0.4046	0.4569	0.1318
	17, 20, 18, 46, 31, 32, 35, 7, 8, and 48	Walls R-Value	0.8400	0.2473	0.0612	0.1627	0.1154
	33, 41, 18, 35, 43, 17, 28, 4, 38, and 16	Furnace Efficiency	-0.8720	0.0933	0.0087	0.0703	0.0503
	35, 42, 38, 7, 20, 14, 16, 10, 32, and 4	AC SEER	0.1087	1.3722	1.8829	0.9489	0.1082
e). top 2 frequencies	**16 and 24**	**Attic R-Value**	**0.9408**	**0.3486**	**0.1215**	**0.2752**	**0.0688**

based on GBM variable importance	17 and 20	Walls R-Value	0.6608	0.3601	0.1297	0.2885	0.1588
	33 and 41	Furnace Efficiency	-0.7084	0.0892	0.0080	0.0774	0.0482
	35 and 42	AC SEER	0.3992	1.1266	1.2692	0.9078	0.0858
f). top single frequency based on GBM variable importance	16	Attic R-Value	0.8734	0.5095	0.2596	0.3613	0.1186
	17	Walls R-Value	0.8166	0.2648	0.0701	0.1949	0.1282
	33	Furnace Efficiency	0.0609	0.0661	0.0044	0.0570	0.0357
	35	AC SEER	0.3705	1.1531	1.3297	0.8621	0.0857
g). best 2 frequencies based minimizing error	21 and 5	Attic R-Value	0.6618	0.8329	0.6938	0.5882	0.1753
	13 and 20	Walls R-Value	0.7437	0.3130	0.0980	0.2207	0.1440
	46 and 31	Furnace Efficiency	0.7117	0.0366	0.0013	0.0336	0.0200
	6 and 23	**AC SEER**	**0.9053**	**0.4472**	**0.2000**	**0.4245**	**0.0332**
h). best single frequency minimizing error	21	Attic R-Value	0.9079	0.4348	0.1890	0.3779	0.1093
	13	**Walls R-Value**	**0.9421**	**0.1488**	**0.0222**	**0.1044**	**0.0780**
	46	**Furnace Efficiency**	**0.9536**	**0.0147**	**0.0002**	**0.0116**	**0.0079**
	6	AC SEER	0.7590	0.7135	0.5090	0.6279	0.0520

It is interesting in this table to see how the use of multiple power spectrum frequencies especially harms the models to predict the AC SEER and furnace efficiencies (cases a-d). The fact is that the ac and furnace systems for the set of residences are respectively two and single stage systems, meaning that the cooling and heating powers respectively have two and one levels. Having multiple power spectrum frequency bins to predict the cooling/heating system efficiencies is seen to actually hurt the performance of the regression. Also interesting to see is the progressive improvement in model accuracy for predicting all of the features as a result of using a reduced number of power spectrum frequencies obtained either from the variable importance characterization from the GBM model or through error minimization. This in effect says that the different features are associated with specific frequencies. For example, the best model in predicting the furnace efficiency is associated with a single binned power spectrum efficiency of 46. Given that the single-stage furnaces only are considered in this study, all with constant heating power, the time response associated with furnace on-time dictates that a single frequency should best characterize this system. In comparison, a majority of the AC systems considered in this study had two stages associated with different cooling powers. Thus, it is not surprising that two power spectrum bins capture the dynamics of these systems best. Similarly, the attic and wall R-Values control the dynamics associated with cooling of the internal environment. Again a single frequency should best characterize the dynamics of these components.

Table 7 summarizes the best model testing performance for each of the targeted energy characteristics obtained from Table 6. Table 8 shows the actual values and predicted values of these characteristics using these best models for all of the testing houses. Model performance appears strong across evaluation metrics. The errors associated with prediction of each of the energy are quite small for all of the residences. These errors could well be tolerated in any energy audit.

Table 7. Testing prediction evaluation statistics for best model case from Table 6

Target	Best ML Algorithm	R^2	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	0.9408	0.3486	0.1215	0.2752	0.0688
Walls R-Value	GBM	0.9421	0.1488	0.0222	0.1044	0.0780
Furnace Efficiency	GBM	0.9536	0.0147	0.0002	0.0116	0.0079
AC SEER	GBM	0.9053	0.4472	0.2000	0.4245	0.0332

Table 8. Actual and predicted data for the testing houses with using thermostat derived information

House Num.	Attic R-Value		Wall R-Value		Furnace Efficiency		AC SEER	
	Actual	**Pred.**	**Actual**	**Pred.**	**Actual**	**Pred.**	**Actual**	**Pred.**
House 1	3.13	3.05	0.69	0.68	0.78	0.80	14.00	13.72
House 2	6.22	5.51	2.44	2.47	0.95	0.95	13.00	12.70
House 3	2.23	2.47	0.86	1.13	0.78	0.79	14.00	14.57
House 4	3.13	2.82	0.86	0.78	0.80	0.81	10.00	10.33
House 5	1.71	1.91	0.86	0.86	0.90	0.93	13.00	13.41
House 6	3.13	3.04	0.69	0.91	0.78	0.78	11.30	11.95

Figure 4 helps to illustrate shows the most important power spectrum density (PSD) frequency for each target, and how each frequency is different from a high and low efficient house. First, the following dominant PSD frequencies: 6, 16, 23, and 46 shows high power in high efficiency houses and low power in low efficiency houses. Second, the dominant PSD frequencies, 13 and 24, show low power in high efficiency houses and high power in low efficiency houses.

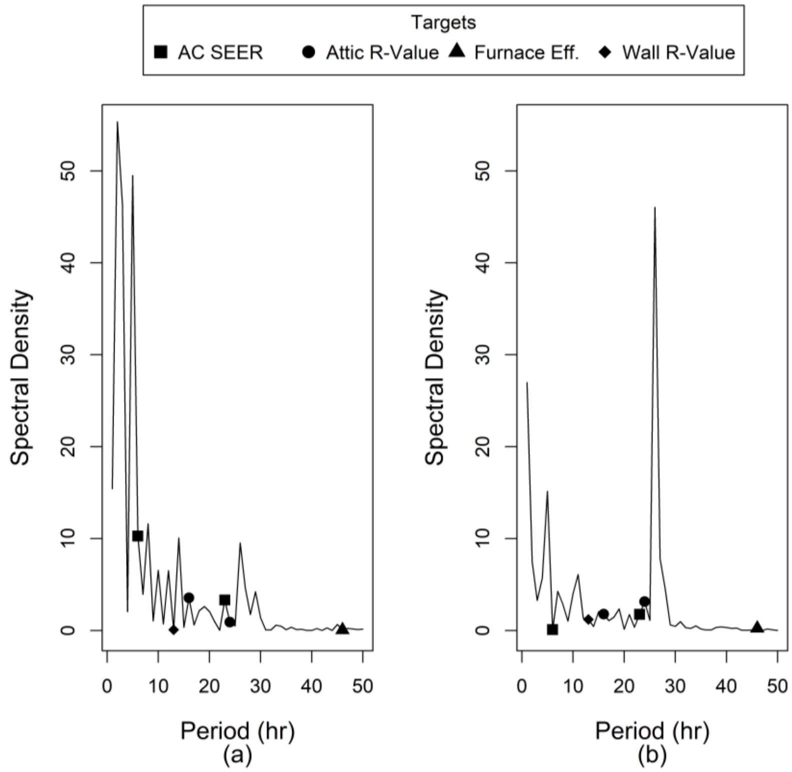

Figure 4. Power spectrum for the indoor temperature measured at the thermostat for (a) high and (b) low efficiency houses for the most important frequencies identified

2.7.3.3 Summary of the Best Model Validation Statistics and Hyperparameters

The model validation statistics for the best testing models for each target seen in Table 7 are shown in Table 9. The validation metrics are exceptional at or very close to 1 for all targeted variables. Table 10 shows the tuned hyperparameters for each of the best models.

Table 9. Models prediction evaluation parameters for validation with using thermostat derived information

Target	Best ML Algorithm	R^2	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	1	0.0007	5.36E-07	6.38E-05	0.0001
Walls R-Value	GBM	1	0.0004	1.60E-07	7.51E-05	0.0002
Furnace Efficiency	GBM	1	1.03E-05	1.06E-10	1.72E-06	5.36E-06
AC SEER	GBM	0.9978	0.0821	0.0067	0.0210	0.0062

Table 10. Model hyperparameters for all targets with using thermostat derived information

Target	Best ML Algorithm	Num. of Trees	Min. Depth	Max Depth	Mean Depth	Min. Leaves	Max. Leaves	Mean Leaves
Attic R-Value	GBM	212	6	6	6	15	57	34.87
Walls R-Value	GBM	231	6	6	6	10	64	43.44
Furnace Efficiency	GBM	225	6	6	6	15	56	34.12
AC SEER	GBM	133	6	6	6	16	62	35.86

2.7.3.4 Identifying the Value of the Thermostat-Derived Features for Predicting Energy Characteristics

Table 11 summarizes the validation metrics for predicting the targeted attic R-Value, wall R-Value, natural gas furnace efficiency, and air conditioner SEER value for the various models considered using the complete training data features, e.g., considering the case where thermostat derived power spectrum binned data is not included. From this table, it is clear that the yielding strikingly good model results, with respective R-squared values of 1, 1, 1, and 0.99 and RMSE errors of 0.0022, 0.0013, 0.0002, and 0.1513 for predicting attic R-Value, walls R-Value, furnace efficiency, and AC SEER. The tuned hyperparameters (number of trees, number of internal trees, depth, and minimum number of observations in the smallest leaf) for the best GBM models are shown in Table 12.

Table 11. Models prediction evaluation parameters for validation without using thermostat derived information

Target	Best ML Algorithm	R^2	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	1	0.0022	4.87E-06	0.0002	0.0003
Walls R-Value	GBM	1	0.0013	1.65E-06	0.0004	0.0006
Furnace Efficiency	GBM	1	0.0002	3.59E-08	8.11E-05	0.0001
AC SEER	GBM	0.9927	0.1513	0.0229	0.0427	0.0119

Table 12. Model hyperparameters for all targets without using thermostat derived information

Target	Best ML Algorithm	Num. of Trees	Min. Depth	Max Depth	Mean Depth	Min. Leaves	Max. Leaves	Mean Leaves
Attic R-Value	GBM	215	6	6	6	13	61	34.94
Walls R-Value	GBM	186	10	10	10	26	88	53.89
Furnace Efficiency	GBM	143	10	10	10	15	88	61.75
AC SEER	GBM	120	6	6	6	12	54	35.96

The hyperparameters of the best model without using thermostat derived information shown in Table 12 are compared to the hyperparameters of the best model obtained using thermostat derived information shown in Table 10. It should be noted that the number of trees and the minimum number of observations in the minimum leaf is within the recommended values which respectively are 2/3 the number of observations and 12 observations per leaf. Furthermore, there is similarity in all of the hyperparameters, providing an indication of the confidence that the models developed to predict the energy characteristics using thermostat derived data is not simply over-fit relative to the case where thermostat data is excluded.

The developed models were then applied to the testing set of houses described previously. Table 13 shows the actual values and predicted values of the targeted energy characteristics. The models were generally accurate in predicting the energy characteristics; however, the AC SEER values in the training data set did not have as much variation as desired, thus the predictions of these had the greatest associated error. The testing results were as follows (See Table 14). The R-squared and MAE values for predicting the attic R-Value, wall R-Value, furnace efficiency, and AC SEER were respectively 0.6778, 0.6474, 0.6280, and 0.5928 (R-squared), and 0.5249, 0.2768, 0.0362, and 0.7450 (MAE). These results are significantly poorer than the predictions reliant upon the thermostat derived information.

Table 13. Actual and predicted data for the testing houses without using thermostat derived information

House Num.	Attic R-Value		Wall R-Value		Furnace Efficiency		AC SEER	
	Actual	**Pred.**	**Actual**	**Pred.**	**Actual**	**Pred.**	**Actual**	**Pred.**
House 1	3.13	3.09	0.69	0.80	0.78	0.80	14.00	13.58
House 2	6.22	4.38	2.44	2.14	0.95	0.91	13.00	13.48
House 3	2.23	2.83	0.86	1.63	0.78	0.86	14.00	13.19
House 4	3.13	2.95	0.86	0.75	0.80	0.83	10.00	11.89
House 5	1.71	1.61	0.86	0.81	0.90	0.93	13.00	13.70
House 6	3.13	2.75	0.69	1.01	0.78	0.80	11.30	11.46

Table 14. Models prediction evaluation parameters for testing without using thermostat derived information

Target	Best ML Algorithm	R^2	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	0.6778	0.8130	0.6610	0.5249	0.1468
Walls R-Value	GBM	0.6474	0.3672	0.1348	0.2768	0.1668
Furnace Efficiency	GBM	0.6280	0.0416	0.0017	0.0362	0.0227
AC SEER	GBM	0.5928	0.9275	0.8602	0.7450	0.0739

2.8 Conclusions

This research has demonstrated the feasibility for utilizing available residential building data, historical energy consumption, and archived smart WiFi thermostat data to develop machine learning models to predict with accuracy the primary heating and cooling characteristics of a residence provided there is a set of residences for which the energy characteristics have been measured. Residences with known energy characteristics, if they reflect the whole pool of residences in a particular area, can be used to effectively calibrate a data-based model, which can then be used to predict energy characteristics in other residences. Uniquely, this research has shown the value of thermostat derived data characterizing the dynamic response of residential inside temperature to weather and thermostat set point changes in improving the accuracy of these predictions.

The potential implication of this research is substantial. If data for all types of possible residences could be collected, at least within the boundaries of a utility service territory, a single model could be trained to predict the most important energy characteristics that would be applicable to every residence in a region. Potential savings from upgrades of every energy characteristic in each residence could be estimated. A strategic energy (and carbon) reduction investment protocol could be established to realize the greatest savings per investment, and in a way that did not exclude low to low-middle income residences.

Admittedly there is more work to do. One, the dataset used for training must be expanded. All of the houses considered in this study were two-story wood frame houses. Data from brick, stone, single-story, duplex, etc. residences must be added to the growing database of residences. Additionally, this study only used one thermostat derived piece of information. The thermostat temperature set point history could also be considered. Finally, solar fenestration has clear impact on the dynamics of residences, especially those with large window areas. Future research should include solar irradiation dynamic inputs.

CHAPTER 3

USING SMART-WIFI THERMOSTAT DATA TO IMPROVE PREDICTION OF RESIDENTIAL ENERGY CONSUMPTION AND ESTIMATION OF SAVINGS

3.1 Abstract

Energy savings based upon use of smart WiFi thermostats ranging from 10 – 15% have been documented, as new features such as geofencing have been added. Here, a new benefit of smart WiFi thermostats is identified and investigated; namely as a tool to improve the estimation accuracy of residential energy consumption and, as a result, estimation of energy savings from energy system upgrades, when only monthly energy consumption is metered. This is made possible from the higher sampling frequency of smart WiFi thermostats. In this study, collected smart WiFi data are combined with outdoor temperature data and known residential geometrical and energy characteristics. Most importantly, unique power spectra are developed for over 100 individual residences from the measured thermostat indoor temperature in each and used as a predictor in the training of a singular machine learning models to predict consumption in any residence. The best model yielded a percentage mean absolute error (MAE) for monthly gas consumption ±8.6%. Applied to two residences to which attic insulation was added, the resolvable energy savings percentage is shown to be approximately 5% for any residence, representing an improvement in the ASHRAE recommended approach for estimating savings from whole-building energy consumption that is deemed incapable at best of resolving savings less than 10% of total consumption. The approach posited thus offers value to utility-wide energy savings measurement and verification.

3.2 Introduction

The U.S. Energy Information Administration (EIA) estimates that the total U.S. natural gas consumption was about 32% in 2019 of total energy consumption. The residential sector was responsible for 16% of this consumption [61] and 38% of the CO_2 emissions in the U.S. [62]. Reducing reliance on fossil fuels in the short term remains an existential challenge for humanity. However, as a recent analysis by Stanford University documents, getting to 100% clean and renewable energy by 2050 requires a substantial reduction in energy demand (59%) [63]. Essential in this process, as never before, is the ability to measure savings in order to validate the myriad of energy efficiency experiments which must be conducted. The most cost-effective energy reduction MUST learn from all actions. This is only possible if the means to estimate savings is certain.

Unfortunately, the state-of-the-art in measuring savings from energy improvements, short of individual real time metering, is inadequate, especially when energy consumption data is monthly. Presently, the approach recommended by ASHRAE in Guideline 14-2002, which leverages an inverse model based upon a simple three-parameter regression of monthly energy consumption with mean outdoor temperature for each meter period, suggests that savings of less than 10% cannot be resolved at best. More importantly, this savings estimation resolution depends upon the quality of the regression fit for an individual building or residence. It is likely that in most buildings, commercial or residential, this approach is unable to resolve energy savings well greater than 10% of consumption [64] [65] [66] [67].

This paper above all explores use of smart WiFi thermostats to improve both the prediction of monthly energy consumption and, as a result energy savings from systems upgrades. Such technologies are now present in an estimated 11% of residences [68]. These thermostats measure and archive indoor temperature, setpoint temperatures for heating and cooling, and the status of the heating, cooling, and fan systems at sampling periods which can be as small as 1 second. The research described herein specifically utilizes ″delta‶ smart WiFi thermostat data from individual residences described in the prior research Lu et al. [69] and Huang et al. [70].

3.3 Related Work

Data analytics techniques have become a common means to analyze energy data. There has been a wealth of prior work in this area; all significantly reviewed by Amasyali et. al. [62], Mosavi et. al. [71], Seyedzadeh et. al [72], and Villa and Sassanelli [73]. Table 15 summarizes the most relevant of the research to predict different types of energy consumption at different data collection frequencies. The frequencies associated with the energy consumption types have ranged from hourly, to daily, to monthly. Included in the table, in addition to the data collection frequency, is also information about the learning algorithm, predictors used, target or response variable, building type, and quality of the prediction.

All of these machine learning models have used as predictors different weather, indoor, building, and calendar inputs. The weather data used included dry bulb temperature ([74], [75], [76], [77], [78], [79], [80], and [81]), relative humidity, and solar radiation ([77], [78], and [79]). An hourly weather data frequency was used by Al Tarhuni et. al [74], Li et. al [77], Massana et. al [78], Kwok et. al [79], and Zhao et. al [81], whereas Özmen et. al [75], Iwafune et. al [76], and Jovanovic et. al [80] relied upon daily data.

Several researchers used building envelope data to improve the models. Al Tarhuni et. al [74] relied upon knowledge of the insulation characteristics of the walls, attic, and windows. Li et. al [82] and Ekici et. al [83] included information about the thermal inertia of building. Additionally, Li et. al [82], and Ekici et. al [83] added extra information about the residences shading and building transparency ratios.

A number of the researchers used building geometry and energy system characteristics as predictors. For example, Al Tarhuni et. al [74] used furnace efficiency, water heater energy factor, and Seasonal Energy Efficiency Ratio (SEER) value for the cooling system as predictors.

Lastly, relative to the predictors employed, a number of researchers used prior energy consumption data in various forms. Al Tarhuni et. al [74] utilized prior monthly energy consumption data to predict future consumption. Özmen et. al [75] developed a model for a specific city to estimate natural gas consumption for one-day ahead using the previous day, six, seven, and 14 days of natural gas consumption. Similarly, Jovanovic et. al [80] employed previous day consumption to forecast energy consumption for one day ahead.

In terms of approaches employed, the techniques used have been quite diverse. Most of the researchers evaluated the performance of at least one type of Artificial Neural Network (ANN). For instance, Ekici et. al [83] developed an Artificial Neural Network–Back Propagation (ANN-BP) model to predict annual building heating energy. Kwok et. al [79] predicted hourly building cooling load using only Artificial Neural Network–Multilayer Perceptron (ANN-MLP). Moreover, Li et. al [82] evaluated the performance of three types of ANN including Artificial Neural Network–Back Propagation (ANN-BP), Artificial Neural Network–Radial Basis Function (ANN-RBF), Artificial Neural Network–

General Regression (ANN-GR), as well as Support Vector Machine (SVM). Another study by Li et. al [77] developed a predictive model to estimate hourly building cooling load based on the Support Vector Machine (SVM) and Artificial Neural Network–Back Propagation (ANN-BP) techniques. Massana et. al [78] estimated hourly building electric load based on Multiple Linear Regression (MLR), Artificial Neural Network–Multilayer Perceptron (ANN-MLP) and Support Vector Regression (SVR). Multiple Linear Regression (MLR), Random Forest Regression (RF), Gradient Boosting Machine (GBM), and other algorithms were used as well. Villa and Sassanelli likewise employed a dynamic multi-step approach to predict internal temperature in a building. Their approach leverage a Support Vector Machine algorithm. Their reported accuracy was exceptional (0.1 ± 0.2 °C) [73].

A large number of studies used a static modeling approach including those by Al Tarhuni et. al [74], Özmen et. al [75], Li et. al [82], Iwafune et. al [76], Ekici et. al [83], Massana et. al [78], and Jovanovic et. al [80], while Li et. al [77] used dynamic model. On the other hand, Kwok et. al [79], and Zhao et. al [81] used a multi-step model approach.

Finally, in terms of predictive accuracy, one trend is apparent. Use of hourly information to predict energy consumption at higher frequency (e.g., sub-hourly or hourly) yields better predictive models. The best of these employed models rely upon prior consumption data to predict future consumption (Özmen et al. [75], R-squared value > 0.989, Jovanovic et al. [80], R-squared value > 0.972, Villa and Sassanelli [73], temperature prediction accuracy of 0.1 ±0.2 °C).

Table 15. Summary of prior research in predicting energy consumption in residential buildings

Ref.	Learning algorithm (type)	Predictors	Target	Building type	Model Type	Performance
[74]	Random Forest Regression (RF)	✓ Building geometrical data (e.g., floor, attic, window, and wall area) ✓ Building envelope data (e.g., attic, window, and wall R-Values) ✓ Energy system characteristics (e.g., appliances, heating / cooling systems) ✓ Energy data (i.e. historical energy consumption for each residence) ✓ Weather data (i.e., average outdoor temperature) ✓ Inverse Models (e.g., heating slope, heating balance point temperature, gas/electric baseline intensity)	Monthly natural gas energy consumption	residential	Static	94.6% (R^2), 0.00026 (MSE)
	Artificial Neural Network - Deep Learning (ANN-DL)					92.9% (R^2), 0.0027 (MSE)

		✓ Number of occupants				
[75]	Multivariate Adaptive Regression Splines (MARS)	✓ Energy data (i.e. previous day natural gas consumption) ✓ Weather data (i.e., daily maximum and minimum temperature, average wind speed, precipitation, soil temperature at 5 cm depth, moisture) ✓ Daily Heating Degree Day (HDD) ✓ Calendar data (i.e., weekdays or weekend) ✓ Number of uses	Natural gas consu-mption for one-day ahead	resident-ial	Static	99.2% (R^2_{adj}), 0.302 (RMSE)
	Conic Multivariate Adaptive Regression Splines (CMARS)					99.2% (R^2_{adj}), 0.302 (RMSE)
	Neural Network (NN)					98.9% (R^2_{adj}), 0.357 (RMSE)
	Linear Regression (LR)					98.8% (R^2_{adj}), 0.381 (RMSE)
[82]	Support Vector Machine (SVM)	✓ Building envelope data (i.e. walls and roof R-Values, building size coefficient integrated shading	Annual electric-ity consu-mption	resident-ial	Static	0.0239 (RMSE)
	Artificial Neural Network–Back					0.1446 (RMSE)

	Propagation (ANN-BP)	coefficient, thermal inert index of building walls, (E, W, S, and N) window-wall ratio, shading coefficient of (E, W, S, and N) window, and exterior walls absorption coefficient for solar radiation)				
	Artificial Neural Network–Radial Basis Function (ANN-RBF)					0.1244 (RMSE)
	Artificial Neural Network–General Regression (ANN-GR)					0.0524 (RMSE)
[76]	Multiple Linear Regression (MLR)	✓ Energy data (i.e. historical electricity load) ✓ Weather data (i.e., forecasting daily outdoor temperature) ✓ Calendar data (i.e., the day of the week)	Electri-city consu-mption for one day ahead	resident-ial	Static	12.39% (MAPE), 2.39 kWh / day (RMSE)
[83]	Artificial Neural Network–Back Propagation (ANN-BP)	✓ Geography data (i.e. orientation) ✓ Building envelope data (i.e. insulation thickness, and building transparency ratio)	Annual buildi-ng heating energy	N/S	Static	average 94.8–98.5% accuracy compared with numerical results
[77]	Support Vector Machine (SVM)	✓ Weather data (i.e., hourly dry-bulb temperature, relative humidity,	Hourly buildi-ng cooling load	Mixed	Multi-step	Jul: 0.006 (RMSE) May: 1.146 (RMSE)

		and solar radiation intensity)				Jun: 1.157 (RMSE) Aug: 1.168 (RMSE) Oct: 1.182 (RMSE)
	Artificial Neural Network–Back Propagation (ANN-BP)					Jul: 0.008 (RMSE) May: 2.302 (RMSE) Jun: 2.321 (RMSE) Aug: 2.223 (RMSE) Oct: 2.365 (RMSE)
[78]	Multiple Linear Regression (MLR)	✓ Weather data (i.e., hourly temperature, relative humidity, and solar radiation) ✓ Indoor data (i.e., temperature, relative humidity, light level) ✓ Calendar data (i.e., hour of the day, day of the week, month and working days) ✓ Number of occupants	Hourly electrical load	Non-residential	Static	4.68% (MAPE), 91.38% (R^2)
	Artificial Neural Network–Multilayer Perceptron (ANN-MLP)					0.45% (MAPE), 99.96% (R^2)
	Support Vector Regression (SVR)					0.06% (MAPE), 100% (R^2)

[79]	Artificial Neural Network–Multilayer Perceptron (ANN-MLP)	✓ Weather data (i.e., hourly temperature, relative humidity, rainfall, wind speed, bright sunshine duration and solar radiation) ✓ Indoor data (i.e., occupancy area, and occupancy rate)	Hourly buildi-ng cooling load	Non-resident-ial	Dyn-amic	12.12%-16.36% (RMSPE), 95.75%-98.56% (R^2)
[73]	Support Vector Regression	✓ Building energy management system data ✓ Detailed prior weather data	Buildi-ng internal temp. (1 min interval)	Non-resident-ial	Dyn-amic, Multi-Step	0.1 ± 0.2 °C
[80]	Feed Forward Back Propagation Neural Network (FFNN)	✓ Weather data (i.e., mean daily outside temperature) ✓ Energy data (i.e., heating consumption of the previous day) ✓ Calendar data (i.e., day of the week)	Daily heating energy consu-mption	Non-resident-ial	Static	5.24% (MAPE), 97.43% (R^2)
	Radial Basis Function Network (RBFN)					5.43% (MAPE), 97.56% (R^2)
	Adaptive Neuro-Fuzzy Interference System (ANFIS)					5.43% (MAPE), 97.48% (R^2)
[81]	Artificial Neural Network (ANN)	✓ Weather data (i.e., hourly outdoor dry-bulb	Daily energy consu-mption	Non-resident-ial	Dyn-amic	10.47% (MAPE)

Support Vector Machine (SVM)	temperature of current and previous time)	intensity of variable refrigerant volume	18.03% (MAPE)
Autoregressive integrated moving average (ARIMA)	✓ Calendar data (i.e., day type, and time type)		32.76% (MAPE)

This research builds upon the prior efforts to predict monthly energy consumption, by leveraging for the first time the burgeoning and much more readily available higher frequency smart Wi-Fi thermostat. Given that models employing to predict energy consumption where data is available at smaller periods than monthly, the additional bandwidth afforded from use of thermostat data offers hope for improving energy consumption prediction and therefore energy savings prediction in residences subject to monthly metering.

Specifically, this research combines thermostat data and derived thermostat data in the form of power spectral density data developed from the measured thermostat temperature with other data features which have already been shown to yield quality energy consumption predictions, including geometrical, energy characteristics, and occupancy, and weather data. Table 16 documents the input features used in this study, subset into features used prior and new features considered here. The new features included in this study the thermostat derived features and the binned input weather features employed previously by Alanezi et al. [84] which considered the statistical variation of the weather features developed for each energy meter period.

Table 16. Features used to predict consumption as categorized by prior use and new additions

Study	Data Title	Used
Prior	Monthly weather features	
	Indoor temperatures	
	Building geometrical	√
	Building envelope	√
	Energy system characteristics	√
	Historical energy consumption	√
	Heating Degree Days (HDD)	
	Calendar	
	Geography	
	Number of occupants	√
New	Statistical variation of the outdoor temperature	√
	Power spectrum density from thermostat temperature	√
	Questionnaire with regards to the presence of a washer/dryer	√
	Questionnaire with regards to the presence of a dishwasher	√

3.4 Methodology

The methodology employed to both estimate energy savings and predict consumption follows. Step 1 in the process is the collection and preparation of data. The data includes thermostat derived information, geometrical and energy consumption, and weather data aligned with energy consumption. Step 2 in the process involves the development and testing of machine-learning based static models to improve the prediction of monthly energy consumption of any residence (using a singular model) relative to prior work. This process above all seeks to demonstrate the value of smart WiFi thermostat derived data in predicting consumption. Finally, the last step involves application of the developed model to estimate savings in real residences. Most importantly in this step, the methodology describes how the uncertainty in estimating savings is quantified in order to validate potential improvements in resolving smaller percentage savings than achievable with the currently employed ASHRAE inverse-modeling toolkit.

3.4.1 Collection and Preparation of Data with New Thermostat Derived Predictors

This study considered 101 houses owned by a university in the Midwest region of the US. Detailed energy audits were conducted on these houses during the summer 2015 [74] and again in the summer of 2020 to validate the original assessment and to validate energy efficiency upgrades to some of these residences. As described previously [84], this set of houses offered variety in size, insulation, and energy effectiveness, which is necessary for developing a generalizable single model capable of predicting the energy consumption of any residence.

Overall, the data employed for model development includes historical monthly energy consumption data for each residence, weather data obtained via the NOAA's National Climate Data Online resource [49], geometrical data obtained from the local county auditor public data, and smart WiFi thermostat data for each of the residences. All of this data is attainable remotely. Additionally, energy characteristics associated with insulation amount in the walls and ceiling, heating/cooling/water heating efficiencies, and occupancy data were included as predictors in order to ascertain their necessity in developing accurate models. Ideally the goal of this research is to show that accurate energy consumption and energy savings predictions can be achieved WITHOUT on-site energy audit information.

In the summer of 2019, attic insulation was added to two of the included in this study. Smart WiFi thermostat data and natural gas consumption pre- and post-upgrade were available. Table 17 shows the attic R-Value before and after the retrofit for these two residences.

Table 17. Upgraded houses attic R-Value information

House Number	Attic R-Value (m^2 K W^{-1})	
	Before	**Upgraded**
House 1	1.13	3.34
House 2	3.13	3.34

Data preprocessing is necessary to develop an appropriate dataset for creating an accurate model, regardless of the application. Moreover, effective data preprocessing plays an important role in the development of machine learning models by improving the data sample quality [85]. The data preprocessing here follows that described in prior work [84]. The most critical steps are (i) creating power spectra from the uniformly spaced, measured thermostat interior temperature data; (ii) establishing histograms of the outdoor temperature for each meter period; (iii) synching data according to the time stamp and address; and (iv) elimination of similar houses to prevent model bias for such residences.

Most critical to this study is the creation of histograms from power spectra of the interior temperature obtained from the smart WiFi thermostat data for each individual residence. Effectively this data provides evidence of the thermal dynamics of the residences. Alanezi et al. [84] had shown previously the value of this processed thermostat data in the prediction of building energy characteristics. Then, this data was merged with historical energy consumption data with synched weather data, and unique geometrical and energy characteristics for each of the residences, all in one data file, thus permitting development of a singular model capable of applicability to all residences.

3.4.2 *Model Development to Predict Monthly Consumption Using Thermostat Derived Data*

The selection of an appropriate machine learning algorithm depends on data type, number of observations, and number of input features. Multiple machine learning modeling algorithms should be considered. Application of any technique also requires tuning of hyperparameters. In order to produce the best models, the hyperparameters controlling the different machine learning algorithms need to be optimized. For example, the major hyperparameters in Random Forest (RF) models are number of trees, maximum number of features considered for splitting a node, maximum number of levels in each decision tree, minimum number of data points placed in a node before the node is split, and minimum number of data points allowed in a leaf node, etc. [55] [56]. This research employed the AutoML H2O package [57] to evaluate different machine learning model performance in predicting monthly natural gas consumption utilizing the acquired and processed data described in the previous sub-sections. The considered algorithms included Random Forest, Extremely Randomized Tree, Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), Deep Neural Network, and Stacked Ensemble. Table 18 shows the input features employed to predict monthly gas consumption.

Table 18. Input features used to develop the model

Input Features	Input	Output
Floor area (m^2)	X	
Basement area (m^2)	X	
Attic area (m^2)	X	
Window area (m^2)	X	
Wall area (m^2)	X	
Attic thermal insulation (m^2 K W^{-1})	X	
Walls thermal insulation (m^2 K W^{-1})	X	
Furnace efficiency (-)	X	
Water heater efficiency (-)	X	
Is there a wash and dryer machine (yes/no)	X	
Is there a dishwasher machine (yes/no)	X	
Number of occupants	X	
Probability density bins for outdoor temperature for individual meter periods	X	
Power spectrum bins for indoor temperature (PSD Freq)	X	
Monthly gas usage (MJ $month^{-1}$)		X

The model performance for both validation and testing was evaluated using root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R-squared metric. RMSE, MAE, and R-squared parameters can be shown respectively as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} = \sqrt{MSE}, \tag{3.1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|, \tag{3.2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{y_i - \hat{y}_i}{y_i}\right|, \tag{3.3}$$

$$R^2 = 1 - \frac{MSE(model)}{MSE(baseline)} = \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}, \tag{3.4}$$

3.4.3 Measurement of Energy Savings from Improved Means to Predict Consumption

To estimate the savings from energy-efficiency upgrades, step 1 was to collect and organize new energy consumption data (E_a) for the upgraded residences post-retrofit and develop the needed weather inputs for the new meter periods. Step 2 was to apply the developed model to these residences using this weather data as inputs and the derived thermostat data pre-retrofit to predict consumption post-upgrade, *P*. Step 3 was to forecast energy consumption for the new meter periods using the developed model. The forecast energy consumption effectively represents the energy consumption were no upgrade to have been made. Lastly, in step 4 the actual energy consumption is compared to the forecasted energy consumption based upon the pre-retrofit model in order to predict savings.

$$\% \, Savings_{pred}(P) = \frac{|Predicted\ Consumption - Actual\ Consumption|}{|Precicted\ Consumption\ |} \times 100\%, \tag{3.5}$$

The derived savings from the upgrade is only dependent upon the savings in heating energy. Water heating energy should remain roughly the same. The uncertainty in the savings estimation inevitably depends upon the error associated with estimating consumption, according to:

$$\delta_{savings} = \frac{dS}{dP}\delta P = \frac{E_a}{P^2}\delta P, \tag{3.6}$$

Thus, if the uncertainty in measuring energy consumption can be estimated, then so too can the error in estimating energy savings be estimated.

3.5 Results and Discussion

In this section, results are reported to: 1) assess the value of smart WiFi thermostat derived information in the form of residence power spectra bins in improving the prediction of monthly energy consumption; and 2) demonstrate the potential of employing the developed model to improve the accuracy of energy savings predictions and the ability to resolve smaller percentage savings from energy system upgrades in residences.

3.5.1 Assessing the Importance of Thermostat-Derived Data in Improving Prediction of Monthly Energy Consumption

First, all predictors (residential building geometry, energy characteristics, and occupancy, thermostat derived power spectra data, and monthly probability density of outdoor temperature) were considered in developing a singular model representing all residences in the study using the H2O AutoML toolkit [57] to predict the monthly gas consumption for all residences. A variable importance plot was developed for the best model obtained, shown in Figure 5. Of note in this figure is that while the geometrical characteristics associated with the wall and attic areas are deemed most important, the power spectrum features (indicated as PSD Freq.X) are also very important. In fact, a number of the frequency bins are deemed more important than energy characteristic features such as the attic and wall R-Values. Most importantly, these features can be derived from the thermostat data alone; potentially mitigating the need to collect energy characteristics for the residence from on-site assessments.

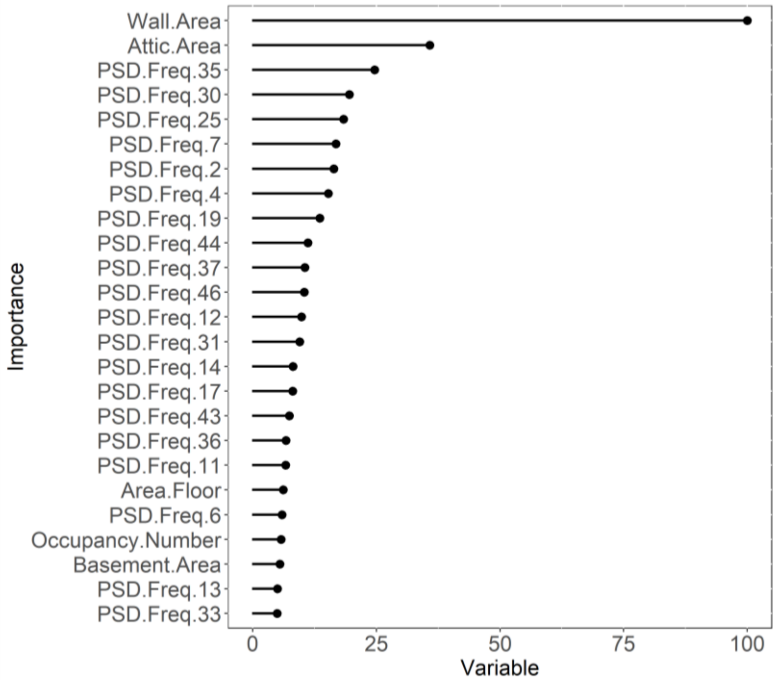

Figure 5. Variable importance plots including thermostat derived information for natural gas consumption model

3.5.1.1 Development of Best Model to Predict Energy Consumption

The GBM model showed outstanding prediction accuracy. Table 19 shows the error metrics from the testing dataset for the best models developed using this machine learning algorithm for subsets of the input features available. The predictor subsets considered for model development are documented in the table below. Additionally included are the error metrics. The MAE and RMSE error metrics are based upon energy consumption for whole year. In this table, Case (a) includes as predictors only geometrical and outdoor temperature probability density bin values. Case (b) adds consideration of both number of occupants and energy system characteristics data. It is clear that the addition of these features improved the model performance considerably. Case (c) adds questionnaire data with regards to the presence of a washer/dryer and dishwasher. The addition of this data did little to improve the model. Case (d) adds all thermostat measured indoor temperature power spectrum data. Again, there is significant improvement in the model from these input features. Thus, thermostat data conclusively improves the ability to accurately model monthly energy consumption. Case (e) considers only the top five frequency bins of the power spectra information obtained from a variable importance analysis. The model performance actually deteriorates. Case (f) adds six frequency bins used to predict energy characteristics (attic R-Value, walls R-Value, furnace efficiency, and AC SEER) by Alanezi et al. [84]. These frequencies were shown in this prior study to best enable accurate prediction of the actual energy characteristics for a residence. The model performance for this case is seen to improve markedly; the R-squared value is 0.9519 and the MAE is 996.52. In Case (g) the energy characteristics and occupancy data are removed from this best model. The model performance is noted to have declined considerably. Thus, while the goal was to develop a model that would require no on-site collected data, it is clear that such data is valuable in terms of producing an accurate model for estimating energy consumption, and likewise energy savings (see Equation (3.6)).

Table 19. Feature selection cases with model prediction evaluation parameters for the testing dataset

Case	**Feature Types**	**R^2**	**RMSE**	**MAE, Annual gas consumption (MJ)**	**MAPE**
a)	geometrical and outdoor temperature probability density bin	0.7533	2724.36	2319.08	0.2191
b)	geometrical, outdoor temperature probability density bin, number of occupants, and energy system characteristics	0.8641	1993.98	1641.50	0.1644
c)	geometrical, outdoor temperature probability density bin, number of occupants, energy	0.8646	1939.65	1602.43	0.1644

	system characteristics, and questionnaire				
d)	geometrical, outdoor temperature probability density bin, number of occupants, energy system characteristics, questionnaire, and all PSD bins	0.9109	1673.73	1413.29	0.1650
e)	geometrical, outdoor temperature probability density bin, number of occupants, energy system characteristics, questionnaire, and top five PSD frequency bins (35, 30, 25, 7, and 2)	0.8867	1770.57	1415.60	0.1561
f)	geometrical, outdoor temperature probability density bin, number of occupants, energy system characteristics, questionnaire, and six PSD frequency bins (6, 13, 16, 23, 24 and 46)	0.9519	1234.80	996.52	0.1465
g)	geometrical, outdoor temperature probability density bin, number of occupants, questionnaire, and six PSD frequency bins (6, 13, 16, 23, 24 and 46)	0.8881	1728.65	1396.56	0.1586

Overall, the best model (case f) yielded an average residential consumption over this time frame of 11,463 MJ, associated with a mean error in predicting monthly energy consumption for all of the residences considered of ±8.69%. The associated R-squared value is 0.9519. This prediction is better than the best to date in terms of predicting monthly energy consumption (Altarhuni et al.; R-squared value = 0.94, [74]). It should be noted that Altarhuni's approach used a regression of monthly energy data for each residence against monthly average outdoor temperature to derive predictors which could be used in a singular model to predict consumption of any residence. So, in effect, it used energy data to develop predictive features to predict energy consumption. The approach developed here does not do this.

3.5.1.2 Best Model Testing Results

The best model developed for Case f above, was tested on six residences not used in the training of the model. The testing results for these six residences are shown in Table 20. The R-squared and MAE values for predicting the monthly natural gas usage were respectively 0.9472, 0.9485, 0.9725, 0.9201, 0.9788 and 0.9446 (R-squared), and 1073.18, 910.01, 646.85, 1678.40, 613.37, and 1057.32 MJ (MAE). These results illustrate that the model predictive effectiveness is consistent with the validation metrics used in the training, helping to establish the generalizability of the model to new residential data.

Table 20. Model prediction evaluation parameters for testing dataset

Target	R^2	RMSE	MAE	MAPE
Test House 1	0.9472	1406.42	1073.18	0.1240
Test House 2	0.9485	1306.15	910.01	0.0842
Test House 3	0.9725	913.75	646.85	0.0729
Test House 4	0.9201	1822.71	1678.40	0.3276
Test House 5	0.9788	743.02	613.37	0.1233
Test House 6	0.9446	1216.73	1057.32	0.1470
Average	0.9519	1234.80	996.52	0.1465

A time series plot of the monthly natural gas consumption as a function of time for the six test residences is shown in Figure 6. The figure compares both the actual and predicted consumption. It is clear that the two lines representing actual and predicted consumption correspond very well. Note that the actual and predicted values for each of the testing houses are shown in Table 23 at the APPENDIX A section.

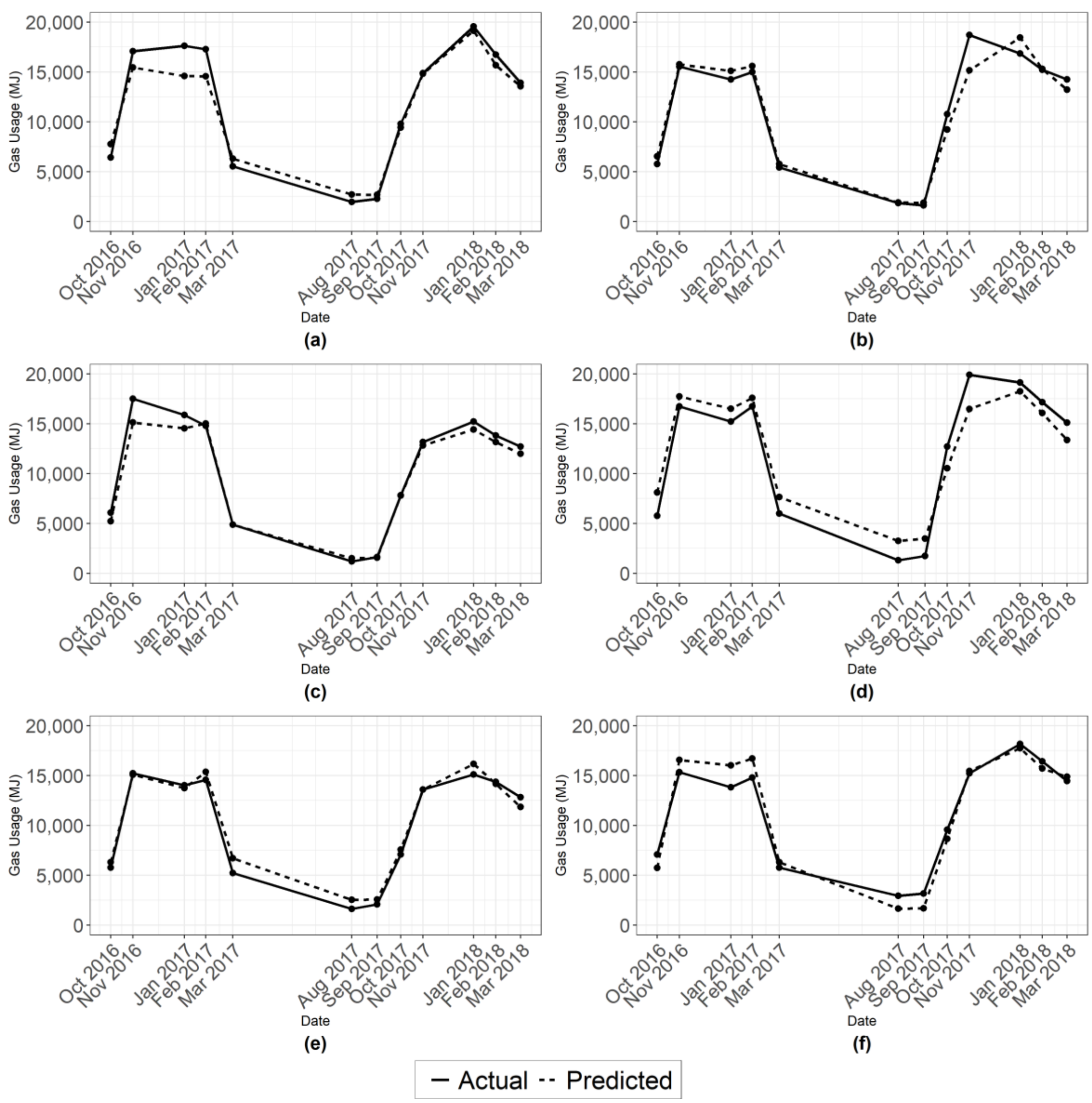

Figure 6. Time series natural gas energy consumption plots for each of the testing houses: (a) House 1; (b) House 2; (c) House 3; (d) House 4; (e) House 5; and (f) House 6.

3.5.2 Estimating Savings and Quantifying Uncertainty in the Savings Predictions

As noted previously, two of the residents included in the study received upgrades in terms of attic insulation. The estimated energy savings for one month of these two residences using equation (3.5) are shown in Table 21. The results indicate the natural gas consumption savings from attic insulation upgrade for House 1 and 2 are respectively 21.5% and 15.3%. Improvement to attic insulation in House 1 show significantly superior energy savings relative to House 2. The results are consistent with expectation, because House 1 no insulation prior to the upgrade; while House 2 had a very small amount of insulation. The uncertainty in the reported savings is respectively for House 1 and 2 ±4.18% and ±6.2%.

Table 21. Savings percentage and uncertainty for an attic retrofit

House Num.	**Bill month post-retrofit**	**Measured natural gas usage (MJ)**	**Predicted natural gas usage assuming no upgrade (MJ)**	**Uncerta-inty in estimati-ng usage (MJ month^{-1})**	**% Savings**	**Uncerta-inty in estimati-ng saving (%)**
House 1	Dec. 2019	14677.20	18712.95	±996.52	21.57	±4.18
House 2		11415.60	13476.24		15.29	±6.26

In an effort to generalize the results, the following questions are posed. What-if the energy savings is less? What percentage savings could we resolve? What percentage savings can be resolved?

Figure 7 shows a plot of the predicted savings (MJ) versus percentage savings for House #1 above were the actual savings to be less than that reported in Table 21. Error bars are shown to represent the uncertainty in predicting the savings (from Equation (3.6). It is clear from this figure that as the percentage savings declines, the uncertainty in estimating savings increases slightly. It is also clear that accuracy in estimating savings declines. In fact, no savings can be resolved for savings percentages of less than roughly 5% based upon this approach. At this cut-off the uncertainty in estimating savings is approximately equal to the estimated savings. This savings resolution is valid for any residence, given that it derives from a model based upon a large number of residences. In comparison, the ASHRAE guideline for estimating savings from whole-building energy consumption at best renders an estimation of savings no less than 10% of total consumption. Thus, there is certainty that this approach renders substantial improvement in both the estimation accuracy of savings and the percentage savings which can be resolved.

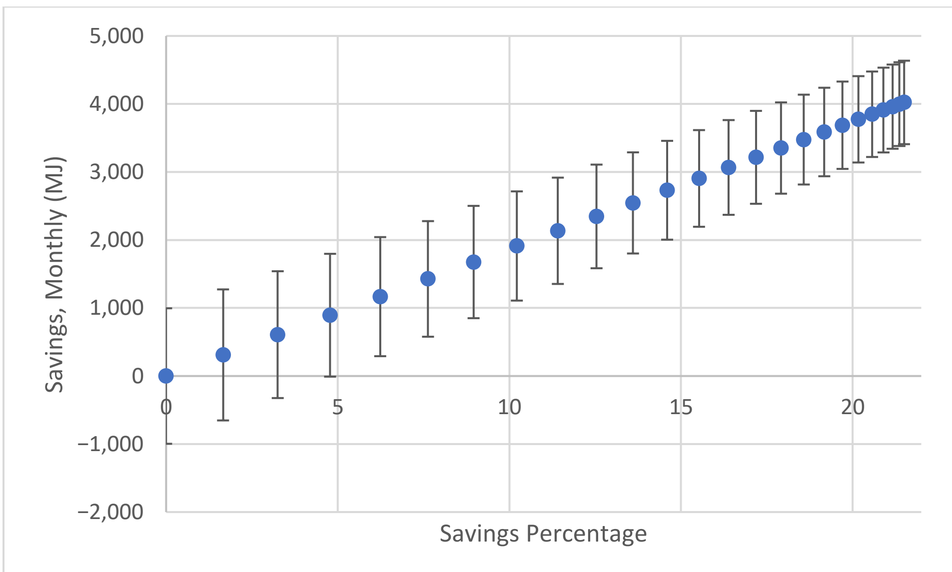

Figure 7. Plot of savings (MJ) versus percentage savings for House #1 with error bars associated with the uncertainty in estimating savings

3.6 Conclusions

This research presents an improved accuracy approach to predict monthly natural gas consumption for residential buildings from accessible residential building information, historical weather data, and archived smart WiFi thermostat data utilizing a machine learning-based approach. The singular model developed using data from a collection of residences can be used to accurately predict consumption and savings from upgrades or changes in behavior for any residence with geometrical and energy characteristics represented within the minimum–maximum bounds of the features of the residences included in the training. Specifically the approach employed, because of the use of data derived from high frequency smart WiFi data, yielded a mean error rate of ±8.69% for predicting annual consumption. Most significantly, for two houses for which insulation upgrades were implemented during the study period, savings estimation uncertainty was less than ±7%. This result shows the promise of the approach used here in estimating HVAC and envelope upgrades in any residence where monthly energy consumption is known, and smart WiFi thermostats are available. In fact, results are shown which demonstrate the ability to resolve energy savings of less than 5% for any residence. This is a big improvement upon the ASHRAE recommended guideline for estimating savings from whole-building energy consumption, where at best energy savings no less than 10% of total consumption can be resolved. It is expected that model improvement and therefore improvement in estimating both energy consumption and savings is possible through the addition of additional residential data.

With this technique, there is significant potential for implementing utility-scale programs to estimate consumption and measure savings from energy efficiency upgrades and/or behavior-based changes with accuracy. Precise savings estimates can help to validate value from all energy measures implemented in any house. The knowledge derived could help to inform more strategic energy reduction programs at a utility scale. Investment could be focused on measures having the potential for measurable savings.

Unfortunately, the results did not show that only remotely obtainable data were sufficient to yield high accuracy estimations of consumption and savings. The results showed a need to document wall and attic insulation amount and heating/cooling system efficiencies prior to an upgrade. This data likely requires on-site inspection.

Additionally, there are several notable limitations of this research and it can be future work to improve the study. First, it is necessary to expand the training dataset to contain a greater number of residences and more variety in the residences included. The current training data did not include very large and very small residences. Nor did it contain any stone, stucco, or brick residences. Second, the training data should use more behavioral information derive from smart WiFi thermostat including thermostat temperature set point history. Lastly, this approach was tested only in a single climatic region. In order to develop truly generalizable models applicable to anywhere, it is essential to broaden the location of the residences included in the singular model training data.

CHAPTER 4

CONCLUSIONS AND FUTURE WORK

4.1 Conclusions

This dissertation has examined the feasibility of uniquely using smart Wi-Fi thermostat data with available residential building data to develop machine learning models to conduct data-based energy audits and improve the prediction of residential energy consumption. This improvement enables more accurate estimation of energy savings from any energy systems upgrade.

This research had two thrusts. The first aim was to develop data-based models to predict accurately the energy characteristics which most strongly influence heating/cooling energy in a residence (e.g., attic and wall R-Values, furnace efficiency, and AC SEER). Models have been validated on homes not used for model development. R-squared values of 0.9408, 0.9421, 0.9536, and 0.9053 were obtained for the prediction of the attic and wall R-values, furnace efficiency, and AC SEER, respectively.

The second aim was to develop a singular data-based model to improve the estimation of energy consumption and savings from upgrades of every energy characteristic in any residential building. The best model yielded a percentage mean absolute error (MAE) of ±8.6% for predicting monthly natural gas consumption. The associated uncertainty of estimated energy savings was less than ±7% when applied to two houses with attic insulation upgrades.

Overall, this research, this research has demonstrated an additional value of smart WiFi thermostat data when combined with other available residential data. It has above all shown potential for conducting virtual energy audits extensively at-scale across any region if the trained model includes all types of possible residences data within that region/area. It has also shown the promise for improving estimation of energy savings from system upgrades or even behavioral savings relative to the ASHRAE standard now being used when energy consumption data is available monthly. Collectively these two contributions could be an asset to any utility company in developing targeted energy reduction investments having greatest payback and carbon reduction from investment. As well it renders the ability to predict savings, and measure with improved accuracy to validate the value of investments.

4.2 Future Work

There is more research needed. First, there is a need to expand the training dataset of residences to include different climatic zones, materials used to build the houses, and residential sizes and types. If data of all different types of residences and climatic regions could be collected, then the developed models could be generalized and make it applicable to conduct energy audits and estimating energy savings from upgrades to any residence and anywhere. Second, solar irradiation should be factored into the models as an additional predictor, as solar gains certainly impacts the thermal dynamics of residences (e.g., the spectral response of a residence). Third, include more behavioral information derived from smart WiFi thermostats, such as historical thermostat temperature set points during the meter period, which affects energy consumption. This would have been accomplished in this work had we access to thermostat records over a long period of time for each residence.

Fourth, in order to estimate savings potential for any residence, it will be necessary to develop machine learning models to predict the critical power spectrums for specific house using residential geometry, weather, and thermostat information as an input for estimating consumption and energy savings from upgrades (which invariably will affect the power spectrum). Doing this will enable not only prediction of the energy characteristics but also prediction of savings from improvement of these. This would enable regional scale prioritization of energy investment to achieve maximal carbon and energy reduction for investments made.

Fifth, there is a need develop a data-based model to predict monthly percentage cooling/heating time using daily cooling/heating percentage time from smart WiFi thermostat data for each house. Also, this model would be able to predict non-weather dependent energy (baseline) for the house. Thus, the monthly weather dependent energy (monthly cooling or heating energy) can be calculated. This approach would help to cement new ASHRAE guidelines with more accuracy and the ability to resolve energy savings less than 10%.

BIBLIOGRAPHY

[1] J. Fagerberg and A. Frick, "Smart Homes and Home Automation," Berg Insight AB, Gothenburg, 2017.

[2] "Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results," February 2015. [Online]. Available: https://downloads.nest.com/press/documents/energy-savings-white-paper.pdf. [Accessed 27 July 2019].

[3] "A review of data-driven building energy consumption prediction studies," U.S. Energy Information Administration (EIA), August 2020. [Online]. Available: https://www.eia.gov/environment/emissions/carbon/#:~:text=The%20U.S.%20residential%20and%20commercial,commercial%20sector%20(Figure%206). [Accessed 8 December 2020].

[4] W. C. Schillaci, "EIA Forecasts U.S. and Global Energy Cases, CO2 Emissions," Business and Legal Resources, 12 February 2020. [Online]. Available: https://ehsdailyadvisor.blr.com/2020/02/eia-forecasts-u-s-and-global-energy-cases-co2-emissions/. [Accessed 30 December 2020].

[5] N. Nasiritousi, "Fossil fuel emitters and climate change: unpacking the governance activities of large oil and gas companies," *Environmental Politics,* vol. 4, no. 26, pp. 621-647, 2017.

[6] L. Ungar, "A Buildings Efficiency Agenda for 2021," ACEEE, Washington, DC, 2020.

[7] N. Sönnichsen, "Average retail electricity prices in the U.S. 1990-2019," Statista, 25 August 2020. [Online]. Available: https://www.statista.com/statistics/183700/us-average-retail-electricity-price-since-1990/. [Accessed 30 December 2020].

[8] "U.S. Energy Efficiency Potential Through 2040: Update on Potential for Energy Savings Through Utility Programs Across the Nation," Electric Power Research Institute, Palo Alto, CA, 2019.

[9] A. Rose and D. Wei, "Impacts of the Property Assessed Clean Energy (PACE) program on the economy of California," *Energy Policy,* vol. 137, no. 111087, 2020.

[10] L. Mundaca and S. Kloke, "On-Bill Financing Programs to Support Low-Carbon Energy Technologies: An Agent-Oriented Assessment," *Review of Policy Research,* vol. 35, no. 4, pp. 502-534, 2018.

[11] "Home Energy Audit Costs," Home Advisor, [Online]. Available: homeadvisor.com/cost/energy-efficiency/hire-a-home-energy-auditor/. [Accessed 30 December 2020].

[12] M. . P. Ternes and M. B. Gettings, "Analyses to Verify and Improve the Accuracy of the Manufactured Home Energy Audit (MHEA)," Oak Ridge National Laboratory, Oak Ridge, TN, 2008.

[13] E. Hewitt and Y. Wang, "Understanding the Drivers of National-Level Energy Audit Behavior: Demographics and Socioeconomic Characteristics," *Sustainability,* vol. 12, no. 5, p. 2059, 2020.

[14] "CONSUMPTION & EFFICIENCY," U.S. Energy Information Administration (EIA), 26 March 2020. [Online]. Available: https://www.eia.gov/consumption/. [Accessed 15 August 2020].

[15] "Natural Gas Explained Use of Natral Gas," U.S. Energy Information Administration (EIA), 8 November 2018. [Online]. Available: https://www.eia.gov/energyexplained/index.php?page=natural_gas_use. [Accessed 11 November 2018].

[16] A. Higgins, G. Foliente and C. McNamara, "Modelling intervention options to reduce GHG emissions in housing stock — A diffusion approach," *Technological Forecasting and Social Change,* vol. 78, no. 4, pp. 621-634, 2011.

[17] J. Lin, "Energy Affordability and Access in Focus: Metrics and Tools of Relative Energy Vulnerability," *The Electricity Journal,* vol. 31, no. 6, pp. 23-32, 2018.

[18] A. G. Robertson, K. Hallinan and J. Hoody, "Achieving Energy Justice in Low Income Communities: Creating a Community-Driven Program for Residential Energy Savings," in *Social Practice of Human Rights Conference*, Dayton, 2019.

[19] A. Drehobl and L. Ross, "Lifting the High Energy Burden in America's Largest Cities: How Energy Efficiency Can Improve Low Income and Underserved Communities," American Council for an Energy-Efficient Economy, Washington, 2016.

[20] H. Do and K. S. Cetin, "Data-Driven Evaluation of Residential HVAC System Efficiency Using Energy and Environmental Data," *Energies,* vol. 12, no. 1, p. 188, 2019.

[21] S. S. Kwok and E. W. Lee, "A study of the importance of occupancy to building cooling load in prediction by intelligent approach," *Energy Conversion and Management,* no. 52, pp. 2555-2564, 2011.

[22] B. Shen, L. Price and H. Lu, "Energy audit practices in China: National and local experiences and issues," *Energy Policy,* vol. 46, p. 346–358, 2012.

[23] "A Guide to Energy Audits," U.S. Department of Energy, Washington, 2011.

[24] J. Olsen, "Department of Environmental Protection," 22 October 2008. [Online]. Available: https://www.google.com/url?client=internal-element-cse&cx=007572080359491747877:gul-_xwuyho&q=http://files.dep.state.pa.us/Energy/Office%2520of%2520Energy%2520and%2520Technology/lib/energy/docs/climatechangeadvcom/residential/energy_audits_work_plan_10100. [Accessed 4 February 2020].

[25] D. Gerlach, R. Taylor, S. Oggianu and M. Trcka, "A case study of multiple energy audits of the same building: Conclusions and recommendations," in *ASHRAE Transactions*, Atlanta, 2014.

[26] G. A. Helcke, F. Conti, B. Daniotti and R. J. Peckham, "A Detailed Comparison of Energy Audits Carried Out by Four Separate Companies on the Same Set of Buildings," *Energy and Buildings,* vol. 14, no. 2, pp. 153 -164, 1990.

[27] J. Harris, J. Anderson and W. Shafron, "Investment in energy efficiency: a survey of Australian firms," *Energy Policy,* vol. 28, no. 12, pp. 867-876, 2000.

[28] R. Brecha, A. Mitchell, K. Hallinan and K. Kissock, "Prioritizing investment in residential energy efficiency and renewable energy—A case study for the U.S. Midwest," *Energy Policy,* vol. 39, no. 5, pp. 2982-2992, 2011.

[29] B. Al Tarhuni, A. Naji, P. G. Brodrick, K. P. Hallinan, R. J. Brecha and Z. Yao, "Large scale residential energy efficiency prioritization enabled by machine learning," *P.G. et al. Energy Efficiency,* p. 1–24, 2019.

[30] A. Boyano, P. Hernandez and O. Wolf, "Energy demands and potential savings in European office buildings: Case studies based on EnergyPlus simulations," *Energy and Buildings,* vol. 65, pp. 19-28, 2013.

[31] J. Xing, P. Ren and J. Ling, "Analysis of energy efficiency retrofit scheme for hotel buildings using eQuest software: A case study from Tianjin, China," *Energy and Buildings,* vol. 87, pp. 14-24, 2015.

[32] B. Polly, N. Kruis and D. Roberts, "Assessing and Improving the Accuracy of Energy Analysis for Residential Buildings," United States Department of Energy, Springfield, 2011.

[33] A. Roth, "The Shockingly Short Payback of Energy Modeling," The United States Department of Energy (DOE), 23 May 2016. [Online]. Available: https://www.energy.gov/eere/buildings/articles/shockingly-short-payback-energy-modeling. [Accessed 22 September 2019].

[34] E. A. Institute and C. S. Group, "Energy performance score (eps) 2008 pilot," Energy Trust of Oregon: EAI/CSG, Portland, 2009.

[35] S. Pigg and M. Nevius, "Energy and Housing in Wisconsin: a Study of Single-Family Owner-Occupied Homes," Energy Center of Wisconsin, Madison, 2000.

[36] M. . P. Ternes and M. B. Gettings, "Analyses to Verify and Improve the Accuracy of the Manufactured Home Energy Audit (MHEA)," Oak Ridge National Laboratory, Tennessee, 2008.

[37] J. P. Duncan, M. Y. Ballinger, B. G. Fritz, H. T. Tilden, G. A. Stoetzel, J. M. Barnett, J. Su-Coker, J. A. Stegen, T. W. Moon, J. M. Becker, E. A. Raney, M. A. Chamness and K. M. Mendez, "Pacific Northwest National Laboratory Annual Site Environmental Report for Calendar Year 2012," Pacific Northwest National Laboratory, Richland, 2013.

[38] J. K. Kissock, J. S. Haberl and D. E. Claridge, "Inverse Modeling Toolkit: Numerical Algorithms," *ASHRAE Transactions,* vol. 109, 2003.

[39] J. K. Kissock and S. Mulqueen, "Targeting Energy Efficiency in Commercial Buildings Using Advanced Billing Analysis," in *2008 ACEEE Summer Study on Energy Efficiency in Buildings*, Pacific Grove, 2008.

[40] K. P. Hallinan, R. L. Brecha, A. Mitchell and J. K. Kissock, "Targeting Residential Energy Reduction for City Utilities Using Historical Electrical Utility Data and Readily Available Building Data," *ASHRAE Transactions,* vol. 117, 2011.

[41] O. G. Santin, L. Itard and H. Visscher, "The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock," *Energy and Buildings,* vol. 41, pp. 1223-1232, 2009.

[42] S. H. Lee, T. Hong, M. A. Piette and S. C. Taylor-Lange, "Energy retrofit analysis toolkits for commercial buildings: A review," *Energy,* vol. 89, pp. 1087-1100, 2015.

[43] "Researchers at Great Lakes Energy Institute partner with Johnson Controls to begin marketing lower-cost technology to small businesses," Case Western Reserve University, [Online]. Available: https://energy.case.edu/virtualenergyaudits. [Accessed 11 August 2019].

[44] S. H. Lee, T. Hong and M. A. Piette, "Review of Existing Energy Retrofit Tools," Ernest Orlando Lawrence Berkeley National Laboratory, 2014.

[45] E. M. Pickering, "EDIFES 0.4: Scalable Data Analytics for Commercial Building Virtual Energy Audits," Case Western Reserve University, Cleveland, 2016.

[46] "Global Smart Meters Industry (2020 to 2025) - Cellular is Expected to Dominate the Smart Meters Market," M2PressWIRE, April 2020. [Online]. Available: http://search.ebscohost.com/login.aspx?direct=true&db=nfh&AN=16PU238291088&site=eds-live. [Accessed 19 June 2020].

[47] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy,* no. 36, pp. 4419-4426, 2008.

[48] "National Oceanic and Atmospheric Administration (NOAA)," U.S. Department of Commerce, [Online]. Available: https://gis.ncdc.noaa.gov/maps/ncei/. [Accessed 16 August 2018].

[49] "Weather Underground," The Weather Company, [Online]. Available: https://www.wunderground.com/. [Accessed 19 June 2020].

[50] J. Semmlow, "Chapter 4 - The Fourier Transform and Power Spectrum: Implications and Applications," in *Signals and Systems for Bioengineers (Second Edition)*, Cambridge, Academic Press, 2012, pp. 131-165.

[51] "Power Spectral Density," 16 January 2007. [Online]. Available: https://www.mathstat.dal.ca/~stat5390/Section_4_PSD1.pdf. [Accessed 15 June 2019].

[52] A. Singh, A. Yadav and A. Rana, "K-means with Three different Distance Metrics," *International Journal of Computer Applications,* vol. 67, no. 10, pp. 13-17, 2013.

[53] H. Kang, "The prevention and handling of the missing data," *Korean journal of anesthesiology,* vol. 64, no. 5, pp. 402-406, 2013.

[54] I. Drori, L. Liu, Y. Nian, S. C. Koorathota, J. S. Li, A. K. Moretti, J. Freire and M. Udell, "AutoML using Metadata Language Embeddings," *33rd Conference on Neural Information Processing Systems,* 2019.

[55] H. Osman, M. Ghafari and O. Nierstrasz, "Hyperparameter optimization to improve bug prediction accuracy," *2017 IEEE Workshop on Machine Learning Techniques for Software Quality Evaluation,* pp. 33-38, 2017.

[56] "AutoML: Automatic Machine Learning," H2O.ai, 2020 18 June. [Online]. Available: https://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html. [Accessed 19 June 2020].

[57] R. Kohavi, "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection," in *Appears in the International Joint Conference on Artificial Intelligence (IJCAI)*, Montreal, 1995.

[58] R. Ménard and M. Deshaies-Jacques, "Evaluation of Analysis by Cross-Validation. Part I: Using Verification Metrics," *atmosphere,* vol. 9, no. 86, p. 16, 2018.

[59] R. Khandelwal, "K fold and other cross-validation techniques," Data Driven Investor, 2 November 2018. [Online]. Available: https://medium.com/datadriveninvestor/k-fold-and-other-cross-validation-techniques-6c03a2563f1e. [Accessed 22 September 2019].

[60] "U.S. energy facts explained," U.S. Energy Information Administration (EIA), 7 May 2020. [Online]. Available: https://www.eia.gov/energyexplained/us-energy-facts/. [Accessed 18 October 2020].

[61] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renewable and Sustainable Energy Reviews,* no. 81, pp. 1192-1205, 2018.

[62] M. Z. Jacobson, M. A. Delucchi, Z. A. Bauer, S. C. Goodman, W. E. Chapman, M. A. Cameron, C. Bozonnat, L. Chobadi, H. A. Clonts, P. Enevoldsen, J. R. Erwin, S. N. Fobi, O. K. Goldstrom, E. M. Hennessy, J. Liu, J. Lo, C. B. Meyer, S. B. Morris, K. R. Moy, P. L. O'Neill, I. Petkov, S. Redfern, R. Schucker, M. A. Sontag, J. Wang, E. Weiner and A. S. Yachanin, "100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World," *Joule,* vol. 1, no. 1, p. 108–121, 2017.

[63] J. S. Haberl, C. Culp and D. E. Claridge, "ASHRAE's Guideline 14-2002 for Measurement of Energy and Demand Savings: How to Determine What Was Really Saved by the Retrofit," in *Fifth International Conference for Enhanced Building Operations*, Pittsburgh, Pennsylvania, 2005.

[64] Guideline 14-2002 : Measurement of Energy and Demand Savings, American Society of Heating, Refrigerating and Air-Conditioning Engineers, June 2002.

[65] J. K. Kissock, J. S. Haberl and D. E. Clarifge, "Inverse Modeling Toolkit: Numerical Algorithms," *ASHRAE Transactions,* vol. 109, pp. 425-434, 2003.

[66] "Inverse Modeling of Portfolio Energy Data for Effective Use with Energy Managers," in *15th IBPSA Conference*, San Francisco, CA, 2017.

[67] J. King, "Energy Impacts of Smart Home Technologies," American Council for an Energy-Efficient Economy, Washington, DC, 2018.

[68] R. Lou, K. P. Hallinan, K. Huang and T. Reissman, "Smart Wifi Thermostat-Enabled Thermal Comfort Control in Residences," *Sustainability,* vol. 12, no. 5, p. 1919, 2020.

[69] K. Huang, K. P. Hallinan, R. Lou, A. Alanezi, S. Alshatshati and Q. Sun, "Self-Learning Algorithm to Predict Indoor Temperature and Cooling Demand from Smart WiFi Thermostat in a Residential Building," *Sustainability,* vol. 12, no. 17, p. 7110, 2020.

[70] A. Mosavi and A. Bahmani, "Energy consumption prediction using machine learning; a review," *Preprints,* p. 61, 2019.

[71] S. Seyedzadeh, F. P. Rahimian, I. Glesk and M. Roper, "Machine learning for estimation of building energy consumption and performance: a review," *Visualization in Engineering,* vol. 6, no. 5, p. 20, 2018.

[72] S. Villa and C. Sassanelli, "The Data-Driven Multi-Step Approach for Dynamic Estimation of Buildings' Interior Temperature," *Energies,* vol. 13, no. 24, p. 6654, 2020.

[73] B. Al Tarhuni, A. Naji, P. G. Brodrick, K. P. Hallinan, R. J. Brecha and Z. Yao, "Large scale residential energy efficiency prioritization enabled by machine learning," *P.G. et. al Energy Efficiency,* p. 1–24, 2019.

[74] A. Özmen, Y. Yılmaz and G.-W. Weber, "Natural gas consumption forecast with MARS and CMARS models for residential users," *Energy Economics,* no. 70, pp. 357-381, 2018.

[75] Y. Iwafune, Y. Yagita, T. Ikegami and K. Ogimoto, "Short-term forecasting of residential building load for distributed energy management," in *2014 IEEE International Energy Conference (ENERGYCON)*, Cavtat, 2014.

[76] Q. Li, Q. Meng, J. Cai, H. Yoshino and A. Mochida, "Applying support vector machine to predict hourly cooling load in the building," *Applied Energy,* vol. 10, no. 86, p. 2249–2256, 2009.

[77] J. Massana, C. Pous, L. Burgas, J. Melendez and J. Colomer, "Short-term load forecasting in a non-residential building contrasting models and attributes," *Energy and Buildings,* no. 92, p. 322–330, 2015.

[78] S. S. Kwok, R. K. Yuen and E. W. Lee, "An intelligent approach to assessing the effect of building occupancy on building cooling load prediction," *Building and Environment,* no. 46, pp. 1681-1690, 2011.

[79] R. Z. Jovanovic, A. A. Sretenovic and B. D. Zivkovic, "Ensemble of various neural networks for prediction of heating energy consumption," *Energy and Buildings,* no. 94, p. 189–199, 2015.

[80] D. Zhao, M. Zhong, X. Zhang and X. Su, "Energy consumption predicting model of VRV (Variable refrigerant volume) system in office buildings based on data mining," *Energy,* no. 103, p. 660e668, 2016.

[81] Q. Li, P. Ren and Q. Meng, "Prediction Model of Annual Energy Consumption of Residential Buildings," in *2010 International Conference on Advances in Energy Engineering*, Beijing, 2010.

[82] B. B. Ekici and U. T. Aksoy, "Prediction of building energy consumption by using artificial neural networks," *Advances in Engineering Software,* vol. 5, no. 40, p. 356–362, 2009.

[83] A. Alanezi, K. P. Hallinan, P. G. Brodrick and K. Huang, Interviewees, *Automated Residential Energy Audits Using a Smart WiFi Thermostat Enabled Data Mining Approach.* [Interview]. 31 August 2020.

[84] A. Chakrabarty, S. Mannan and T. Cagin, "Inherently Safer Design," in *Multiscale Modeling for Process Safety Applications*, Oxford, Butterworth-Heinemann, 2016, pp. 339-396.

[85] "How much energy is consumed in U.S. residential and commercial buildings?," U.S. Energy Information Administration (EIA), 3 May 2018. [Online]. Available: https://www.eia.gov/tools/faqs/faq.php?id=86&t=1. [Accessed 11 November 2018].

[86] Y. Lu, F. Peng, X. Li and N. Ahmed, "Coupling Feature Selection and Machine Learning Methods for Navigational Query Identification," in *Proceedings of the 15th ACM International Conference on Information and Knowledge Management*, Arlington, 2006.

[87] A. Kassambara, *ggpubr: 'ggplot2' Based Publication Ready Plots,* 2020.

[88] B. Greenwell and B. Boehmke, *Jay Cunningham and GBM Developers,* R package version 2.1.5, 2019.

[89] R. Rifkin and A. Klautau, "In Defense of One-Vs-All Classification," *Journal of Machine Learning Research 5,* vol. 5, pp. 101-141, 2004.

[90] "EIA's residential energy survey now includes estimates for more than 20 new end uses," U.S. Energy Information Administration (EIA), 5 June 2018. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=36412&src=%E2%80%B9%20Consumption%20%20%20%20%20%20Residential%20Energy%20Consumption%20Survey%20(RECS)-b1. [Accessed 11 November 2018].

[91] "Definitions, Sources and Explanatory Notes," U.S. Energy Information Administration (EIA), [Online]. Available: https://www.eia.gov/dnav/ng/TblDefs/ng_cons_sum_tbldef2.asp. [Accessed 11 November 2018].

[92] S. Alshatshati, K. P. Hallinan, A. Alrobaian, A. Naji and B. Altarhuni, "Estimating Residential Wall Thermal Resistance from Exterior Thermal Imaging," in *ASME 2017 11th International Conference on Energy Sustainability*, Charlotte, 2017.

[93] M. Knowles, "Understanding Insulation R-Values," Green Building Solutions, [Online]. Available: https://www.greenbuildingsolutions.org/blog/structural-insulated-panels-sips-r-values/. [Accessed 12 November 2018].

[94] R. S. Frazier, "The Importance of Resifential and Commercial Building Insulation".*Division of Agricultural Sciences and Natural Resources - Energy Management.*

[95] I. E. C. Code, "U.S. Department of Energy," March 2018. [Online]. Available: https://www.energycodes.gov/resource-center/training-courses/residential-provisions-2018-international-energy-conservation-code. [Accessed 16 November 2018].

[96] C. Li, Z. Ding, D. Zhao, J. Yi and G. Zhang, "Building Energy Consumption Prediction: An Extreme Deep Learning Approach," *energies,* 2017.

[97] E. Mocanu, P. H. Nguyen, M. Gibescu and W. L. Kling, "Deep learning for estimating building energy consumption," *Sustainable Energy, Grids and Networks,* no. 6, pp. 91-99, 2016.

[98] S. S. Kwok and E. W. Lee, "A study of the importance of occupancy to building cooling load in prediction by intelligent approach," *Energy Conversion and Management,* no. 52, p. 2555–2564, 2011.

[99] F. Sever, J. K. Kissock, D. Brown and S. Mylqueen, "Estimating Industrial Building Energy Savings using Inverse Simulation," in *2011 ASHRAE Winter Conference*, Las Vegas, 2011.

[100] R. Brecha, A. Mitchell, K. Hallinan and K. Kissock, "Prioritizing investment in residential energy efficiency and renewable energy-A case study for the U.S. Midwest," *Energy Policy,* vol. 39, no. 5, pp. 2982-2992, 2011.

[101] H. Sen, Z. Wangda and S. Michael D., "A BAYESIAN NETWORK MODEL FOR PREDICTING THE COOLING LOAD OF," in *ASHRAE and IBPSA-USA SimBuild 2016 Building Performance Modeling Conference*, Salt Lake, 2016.

[102] nationalgrid, "Managing Energy Costs in Colleges and Universities," E Source Companies LLC, 2003.

[103] "Higher Education: An Overview of Energy Use and Energy Efficiency Opportunities," ENERGY STAR, 2005.

[104] U. E. P. AGENCY, "Energy Efficiency Programs in K-12 Schools," 2011. [Online]. Available: https://www.epa.gov/sites/production/files/2015-08/documents/k-12_guide.pdf. [Accessed 3 3 2018].

[105] S. Uppu, A. Krishna and R. P. Gopalan, "A Deep Learning Approach to Detect SNP Interactions," *Journal of Software,* vol. 11, no. 10, pp. 960-975, 2016.

[106] M. Miškuf and I. Zolotová, "Comparison between Multi-Class Classifiers and Deep Learning with Focus on Industry 4.0," in *2016 Cybernetics and Informatics, K and I 2016 - Proceedings of the 28th International Conference*, Levoča, Slovakia, 2016.

[107] M. W. Ahmad, M. Mourshed and Y. Rezgui, "Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption," *Energy and Buildings,* vol. 147, pp. 77-89, 2017.

[108] C. Turhan, T. Kazanasmaz, I. E. Uygun, K. E. Ekmen and G. G. Akkurt, "Comparative study of a building energy performance software (KEP-IYTE-ESS) and ANN-based building heat load estimation," *Energy and Buildings,* vol. 85, p. 115–125, 2014.

[109] H. Deng, D. Fannon and M. J. Eckelman, "Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECS microdata," *Energy and Buildings,* no. 92, p. 34–43, 2018.

[110] L. Xuemei, L. Jin-hu, D. Lixing, X. Gang and L. Jibin, "Building Cooling Load Forecasting Model Based on LS-SVM," in *2009 Asia-Pacific Conference on Information Processing*, Shenzhen, 2009.

[111] R. Yang and M. W. Newman, "Living with an Intelligent Thermostat: Advanced Control for Heating and Cooling Systems," in *2012 ACM Conference on Ubiquitous Computing*, Pittsburgh, 2012.

[112] B. Roy, "All about Feature Scaling," Towards Data Science Inc., 6 April 2020. [Online]. Available: https://towardsdatascience.com/all-about-feature-scaling-bcc0ad75cb35. [Accessed 31 May 2020].

[113] "Heating and cooling no longer majority of U.S. home energy use," U.S. Energy Information Administration (EIA), 7 March 2013. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=10271. [Accessed 19 June 2020].

[114] "In 2018, the United States consumed more energy than ever before," U.S. Energy Information Administration (EIA), 16 April 2019. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=39092. [Accessed 22 August 2020].

[115] "EIA projects nearly 50% increase in world energy usage by 2050, led by growth in Asia," U.S. Energy Information Administration (EIA), 24 September 2019. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=41433#. [Accessed 22 August 2020].

[116] "International Energy Outlook 2019 with projections to 2050," U.S. Energy Information Administration, Washington, DC, 2019.

[117] "U.S. energy facts explained," U.S. Energy Information Administration (EIA), 7 May 2020. [Online]. Available: https://www.eia.gov/energyexplained/us-energy-facts/. [Accessed 8 December 2020].

APPENDIX A

Graphs Data

Table 22: Ranges of the first 24 hours of power spectrum period

Period Bin (hr)	Minimum Value	Maximum Value	Period Bin (hr)	Minimum Value	Maximum Value
Period 1	0.0079	535.78	Period 26	0.0096	7.02
Period 2	0.0211	302.25	Period 27	0.0064	10.38
Period 3	0.1754	177.83	Period 28	0.0027	11.26
Period 4	0.1842	163.19	Period 29	0.0323	8.00
Period 5	0.0265	170.60	Period 30	0.0052	11.65
Period 6	0.1263	55.03	Period 31	0.0022	6.85
Period 7	0.0820	62.02	Period 32	0.0043	8.11
Period 8	0.4016	165.33	Period 33	0.0204	7.91
Period 9	0.0590	53.93	Period 34	0.0127	4.65
Period 10	0.1251	56.29	Period 35	0.0026	5.73
Period 11	0.0209	49.24	Period 36	0.0079	5.92
Period 12	0.0161	18.75	Period 37	0.0120	3.57
Period 13	0.0449	23.33	Period 38	0.0015	12.31
Period 14	0.1046	31.88	Period 39	0.0049	9.56
Period 15	0.1137	21.85	Period 40	0.0151	9.28
Period 16	0.0239	24.81	Period 41	0.0030	28.92
Period 17	0.0132	20.87	Period 42	0.0130	53.46
Period 18	0.0263	15.42	Period 43	0.0189	9.27
Period 19	0.0178	14.37	Period 44	0.0077	6.59
Period 20	0.0643	16.02	Period 45	0.0153	9.19
Period 21	0.0046	8.93	Period 46	0.0204	13.02
Period 22	0.0494	13.36	Period 47	0.0117	5.32
Period 23	0.0041	13.83	Period 48	0.0026	7.72
Period 24	0.0488	17.52	Period 49	0.0105	7.86
Period 25	0.0049	9.89	Period 50	0.0079	535.78

Table 23. Actual and predicted data for 12 months of the testing houses using the best model

Date	House 1		House 2		House 3	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
Oct-16	6414	7757	5762	6549	6088	5229
Nov-16	17069	15463	15546	15760	17503	15136
Jan-17	17612	14589	14242	15107	15873	14537
Feb-17	17286	14580	15003	15607	14785	15031
Mar-17	5544	6321	5436	5779	4892	4881
Aug-17	1956	2721	1848	1920	1195	1516
Sep-17	2283	2682	1630	1880	1630	1565
Oct-17	9784	9424	10763	9229	7827	7796
Nov-17	14894	14825	18699	15162	13155	12821
Jan-18	19569	19127	16851	18465	15220	14417
Feb-18	16742	15693	15220	15303	13807	13157
Mar-18	13916	13578	14242	13224	12720	11980
Date	House 4		House 5		House 6	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
Oct-16	5762	8108	5762	6302	7066	5737
Nov-16	16742	17721	15220	15087	15329	16560
Jan-17	15220	16496	14024	13737	13807	16027
Feb-17	16742	17606	14568	15366	14785	16702
Mar-17	5979	7654	5218	6703	5762	6291
Aug-17	1304	3241	1630	2523	2935	1641
Sep-17	1739	3473	2065	2561	3152	1683
Oct-17	12720	10528	7066	7570	9567	8646
Nov-17	19895	16484	13590	13586	15220	15434
Jan-18	19134	18237	15112	16157	18156	17737
Feb-18	17177	16091	14351	14159	16416	15694
Mar-18	15112	13367	12828	11846	14459	14882

APPENDIX B

Publications Resulting from This Work

[1] R. Elhashmi, K. P. Hallinan, and A. Alanezi, "Roadmap for Utilizing Machine Learning in Building Energy Systems Applications: Case Study of Predicting Chiller Running Capacity for School Buildings Using Stacking Learning," *Journal of Energy & Technology (JET),* vol. 1, no. 1, p. 35, 2021.

[2] A. Alanezi, K. P. Hallinan, and R. Elhashmi, "Using Smart-WiFi Thermostat Data to Improve Prediction of Residential Energy Consumption and Estimation of Savings," *Energies,* vol. 14, no. 1, p. 187, 2021.

[3] K. Huang, K. P. Hallinan, R. Lou, A. Alanezi, S. Alshatshati and Q. Sun, "Self-Learning Algorithm to Predict Indoor Temperature and Cooling Demand from Smart WiFi Thermostat in a Residential Building," *Sustainability,* vol. 12, no. 17, p. 7110, 2020.

[4] K. Huang, A. Alanezi, K. P. Hallinan and R. Lou, "Data Mining of Smart WiFi Thermostats to Develop Multiple Zonal Dynamic Energy and Comfort Models of a Residential Building," in *5th International High Performance Buildings Conference*, West Lafayette, IN, USA, 9–12 July 2018