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Data-driven modeling for improved residential building electricity consumption prediction and HVAC efficiency evaluation

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by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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2018

DEDICATION

I dedicate this to my family for their love and overwhelming support!

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ABSTRACT

In recent years, building energy consumption has increased, accounting for approximately 40% of total energy consumption in the U.S, approximately half of which is from residential buildings. Given the environmental impacts associated with energy and electricity generation, and the importance of reducing these impacts to minimize climate change, it is important to work towards methods to reduce energy consumption. This work focuses on modeling improvements associated with two aspects of residential buildings that have a significant impact on energy consumption, namely occupants and their energy consuming behaviors, and residential heating, ventilation and air conditioning systems.

In residential buildings, as compared to commercial buildings, energy consumption is more highly dependent on occupants and their energy consuming behaviors. Behavioral energy efficiency is generally considered to be a low-cost method to reduce energy consumption by providing information and feedback to occupants that enables them to understand and change their energy-consuming behaviors. Information provided to occupants typically include energy use trends, as determined through data-driven modeling of historical energy use data to predict the performance of the building. This work improves data-driven modeling methods for residential buildings in two ways – first through improved treatment of outliers, and second, through development and use of a modified sequence of change point modeling methods.

The presence of outliers in energy use data can limit a model's accuracy, limiting the confidence in the model on the part of the owner, and thus the use of the model to

adjust energy consuming behaviors. In this work, three outlier detection methods are used to identify energy use outliers from a diversity of residential buildings. The causes and impact of these outliers are also evaluated for determination whether to keep or remove an identified outlier to improve model performance. Second, a modified sequence of development of an inverse change point model is proposed, to better fit energy consumption trends, as well as several modifications to the modeling method. This includes the addition of (a) a segmented change-point model, and (b) change-point models with relaxed prerequisite criteria in the cooling or heating season. The improved sequence and methods are evaluated across four different locations in the U.S., with results indicating that overall the resulting model fits better with the data and enables a larger range of building types and energy consumption patterns to be represented by a model.

In addition to occupant-dependent energy use, the HVAC system is generally the largest electricity-consuming end use in a residential building in the U.S. Yet despite the HVAC system being a large energy consumer, this HVAC system is not likely to be regularly serviced, as compared to a commercial building, in part because it requires the presence, engagement, and time from the homeowner to do so. The occurrence of an inefficiency in an HVAC system also can develop slowly over time and may not be noticeable to a homeowner, allowing the HVAC system to operate inefficiently over a long period of time before a failure occurs. This research works towards a non-intrusive data-driven assessment tool that uses building assessors data, HVAC energy demand data, indoor environmental conditions, and outdoor weather data to assess the efficiency of operation of a residential HVAC system. The results of this study should prove beneficial for homeowners and for service technicians to help target HVAC systems in homes in need of HVAC service or energy efficiency upgrades, ultimately motivating improved sustainability of residential buildings.

CHAPTER 1. INTRODUCTION

1.1. Research Needs and Purposes

In recent years, the energy consumption in buildings has increased, currently accounting for approximately 40% of energy consumption and 74% of total electricity consumption in the U.S., approximately half of which is from residential buildings [1-3] (Figure 1.1). This increasing energy utilization in buildings has a strong impact on the environment and climate, including greenhouse gas emissions and resulting climate change [4,5]. Therefore, it is necessary to identify methods that can help to reduce energy consumption in the residential buildings and to raise the awareness of energy savings opportunities for homeowners and other occupants in their households.

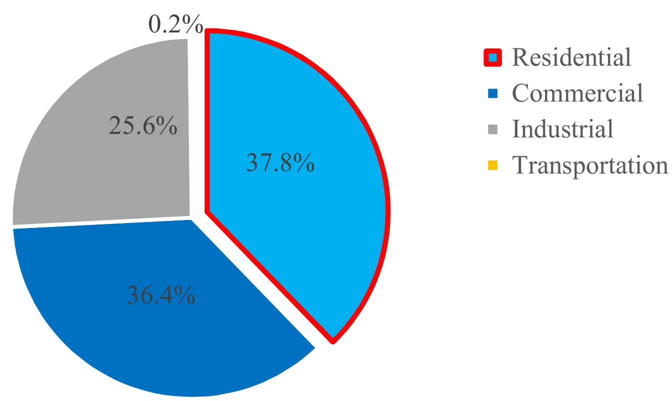

Figure 1.1 *Electricity consumption by sector in the U.S [2].*

Currently, there are many methods that can improve the energy efficiency of existing and future buildings to reduce energy consumption, including the design and construction of efficient new buildings, utility of highly energy efficient equipment and materials for retrofitting existing buildings, and application of smart control strategies in buildings [6-8] among others. However, recent studies have also shown that, particularly for residential buildings, much of this energy consumption is also highly dependent on occupant behavior and occupants' utilization of energy consuming end-uses such as plug loads and appliances [9-11]. Therefore, investigating opportunities to influence and ultimately reduce occupant-dependent energy use also represents a promising way to reduce energy consumption in residential buildings.

Occupant-dependent energy efficiency is generally consider to be a lower-cost and simpler method among other energy savings methods that require capital investment in equipment or other building retrofits [12,13]. The purpose of such methods are to, through providing information and feedback to homeowners and/or occupants in real-time or near real-time, or indirectly (post-consumption), change their energy-consuming behaviors [14]. As a result, recent surveys of the literature in this area indicate approximately 2% - 7% savings of residential energy use can be achieved [15], with the lower range of savings achieve from enhanced billing strategies, and the higher end of savings achieved through real-time feedback methods [16]. Direct feedback strategies, while shown to be more effective, require the availability of high frequency, real-time or near-real-time energy use data. In addition monthly energy use data is the only energy data that is available for approximately half of households in the U.S. [17-18]. Thus, for these homes with limited energy data, indirect feedback can be utilized to help support behavior-based energy savings. Given the significant number of homes where only monthly energy use data is available, *the first portion of this research focuses on methods to improve the prediction of whole-home energy use for such buildings with limited available data.*

For the other half of the households in the U.S., smart meters or in a smaller number of cases, home energy monitoring systems (HEMS) have been installed [19]. Smart meters provide more frequent energy use data, ranging typically from 15 minute to daily energy use data. For those homes with HEMS, often minute or sub-minute level, whole-home and end use disaggregated consumption data can be collected. As compared to monthly data, these types of data can provide significantly more insights on building and system-level performance [20]. Among the research efforts in this research field to use this more frequent data for the development of such insights, however, less effort has focused on insights related to residential heating, ventilation and air conditioning (HVAC) performance and efficiency evaluation using energy data. Given that HVAC systems are the largest energy user in residential buildings in the U.S., and the fact that recent research surveys has found that the large majority of existing residential HVAC systems have faults which prevent them from operating at optimal performance [21,22], *the second portion of this research effort focuses on the use of this more frequent data to assess the HVAC operational efficiency.*

The areas of particular focus in this proposed research are included in Figure 1.2, including the two focus areas discussed in the above paragraphs. In this figure the blue boxes represent data or information provided as inputs or developed based on outputs of this research; the white boxes encompass the proposed research effort challenges to be addressed. This information provided to occupants is typically determined through the development and use of data-driven models trained using historical data from a variety of possible sources. These insights have been shown in many studies to drive energy saving behaviors and actions on the part of building occupants and owners [22,23]. In the use of data-driven, inverse models [24-25], particularly for energy efficiency behavioral changes, the accuracy of such models is important to enable the homeowner or other end-user to trust the results and predictions of the models sufficiently to invest time and effort into understanding their results and ultimately taking actions to invest in efficiency upgrades. Data-driven modeling techniques typically use outdoor weather data, such as ambient temperature, wind speed, humidity, and solar radiation as the main predictor(s) of the energy use of a building [26,27]. These parameters all impact the heat transfer dynamics in a building and thus the need for HVAC system operation to meet the occupant-requested indoor environmental conditions. As weather significantly influences residential energy use in particular, often the use of weather data combined with historical energy data as the input into these models is sufficient to develop a sufficiently reliable model.

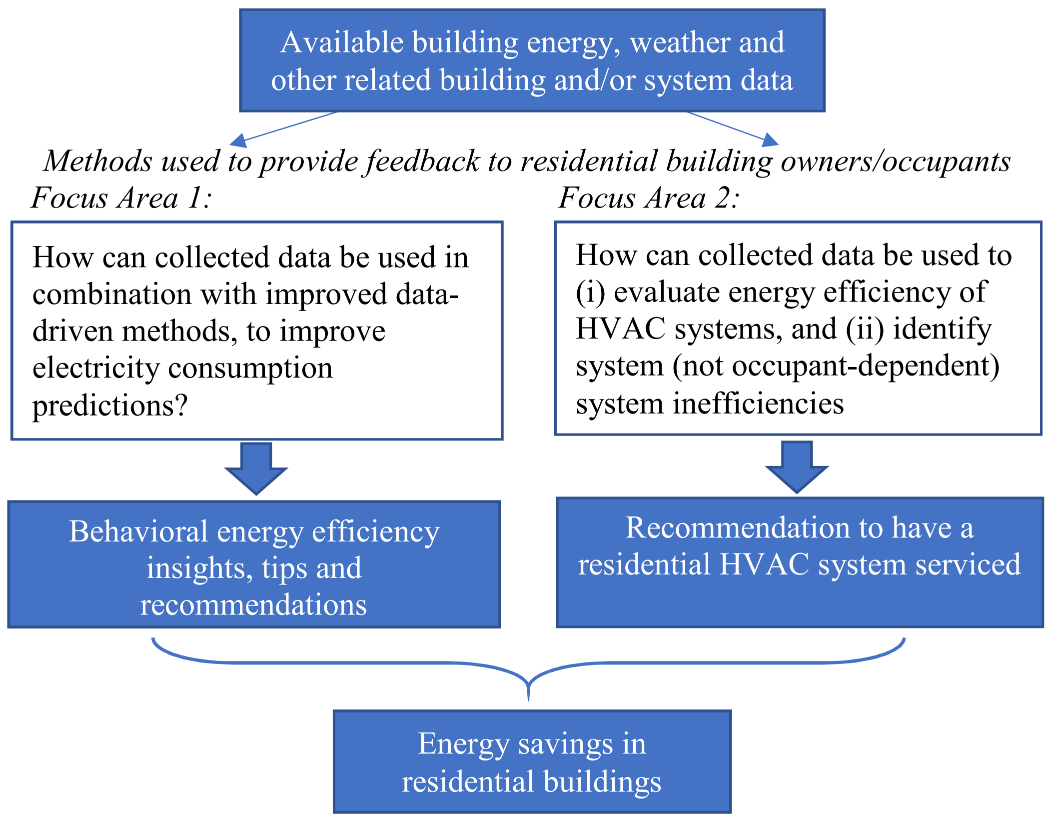

Figure 1.2 *Diagram of challenges associated with the use of energy data to develop insights on the energy performance of residential buildings and their systems*

However, for *Focus Area 1* (see Figure 1.2), one challenge that arises with these models, particularly for residential buildings, is that the prediction of energy use is strongly influenced by occupant behavior, which can be unpredictable, and also highly influential in consumption patterns, particularly for residential buildings. In particular for residential buildings where there are only a limited number of occupants, the behaviors of one occupants' stochastic behaviors can have relatively significant impacts on energy performance. By comparison, a commercial building has many occupants with varied behaviors which combined, can overall provide a more predictable impact on performance. In studying a broad range of residential building energy performance data, it should be noted that while many home's performance is consistent and can be easily predicted, for some residential buildings, energy use patterns are not consistent, limiting common inverse modeling techniques' accuracy. The challenges is that *currently, it is not known why such inconsistencies occur, nor is there any provided guidance on how to detect such inconsistencies in energy use, nor how to treat such inconsistencies if detected*. These inconsistencies, particularly in monthly-level residential energy data, include in particular (a) the presence of energy use outlier months, in which a home consumed significantly more or less than the energy use trends and data-driven model would have otherwise predicted, or (b) homes with monthly energy use patterns that are inconsistent with typically-observed residential building energy use patterns, and thus what typically used inverse modeling techniques would expect.

For example, for (a), the energy use in residential buildings in some cases was extremely low in summer months, as mentioned by Kim et al. [28]. Through contacting the owner, it was determined the owner was on vacation during that time. Therefore, in such cases, the energy use prediction might not align with the actual performance predicted using a data-driven inverse model. In such cases, an outlier occurs in predicting energy use from the developed data-driven model. In other cases, however, a seemingly outlier month of data may in fact not follow the typical trends of the house for the remainder of the year, but be consistent across multiple years of data, such as if a particular household is always gone for a particular month in the summer. In addition, in most cases, it is not possible to definitively determine the actual reasons why the energy use outlier happened in that month as suggested in Kim et al. [28]. The process to identify and remove outliers from datasets is suggested in industry-standard Measurement and Verifications (M&V) procedures [29], based on engineering judgement. However, if the decision or judgement of the modeler to keep or remove a data point outlier is made incorrectly, it could affect the accuracy of model prediction. Therefore, it is necessary to further study the occurrence of energy use outliers, including determining the possible reasons for the occurrence of these outliers and the influence on model performance.

Similarly, for (b), it is challenging to develop inverse models for some residential buildings with highly variable energy use. In these buildings, the energy use does not have a strong relationship with monthly weather data, nor does the energy follow the expected trends associated with inverse models typically used for residential building energy use prediction. In other words, these buildings can be classified as being "pattern outliers". Current the reasons for such energy behaviors of buildings are not known or well-studied in existing literature, thus their treatment when attempting to create a model to predict performance is limited. Typical model generation algorithms result in no model creation for these particular building(s). Therefore, for this type of buildings it is important to study why such varied used occurs, and also to determine if a modified version of current modeling techniques can enable development of an energy prediction model.

Besides model development to motivate behavioral energy efficiency, for Focus Area 2 (see Figure 1.2), the completion of a home energy audit is one of the most common methods to assess residential energy efficiency [30]. Among many other assessments performed, in this method, the largest energy consuming end use of a home, the HVAC system, may be checked by a service technician for system performance. Based on the results, a set of recommendations are then made to the homeowner on how to improve any identified inefficiencies of the building and, if assessed, the HVAC system operation. This is often in the form of a report. This is also often also linked to rebate programs offered by, most commonly, utility companies [31], providing incentives to purchase more efficient energy-consuming systems, or upgrade components of a home.

However, one of the main challenges and road blocks associated with achieving improved efficiency in the HVAC system is knowing, in the first place, that there are inefficiencies occurring. Many homeowners are either not aware of opportunities to assess and improve the HVAC system's efficiency in their home, or are not interested in these opportunities. This is often more broadly called the "energy efficiency gap", or the difference between what efficiency levels can be achieved given the state of current technologies, versus the actual state of efficiency of the current building stock [32]. Most often, residential HVAC systems are only serviced if there is a problem or significant failure, rather than through regular maintenance. This can lead to a lifetime of HVAC operation that is less efficient and thus more energy-consuming than designed. Therefore, a less intrusive method is needed to assess the HVAC system's energy efficiency, and to identify potential opportunities for efficiency improvements.

In recent years, as technologies and ease of connectivity have progressed, the amount of data available related to home energy performance has increased significantly; the difficulty of obtaining this data has decreased somewhat [33]. Data can be collected from various frequencies from monthly, hourly, sub-hourly, 1-minute, or even, second or sub-second intervals depending on data collection technologies and sample rates. Weather data is also available and be easily accessed from public or private sources. Indoor temperature data can be extracted from smart thermostats installed in houses or from temperature sensors. The data from the above-mentioned sources, provides the possibility of rich datasets that can be taken advantage of to better and less intrusively develop and validate data-driven methods to assess HVAC performance and efficiency. *How such data can be used to assess HVAC performance and energy efficiency is thus the focus of this portion of this research.*

1.2. Research Objectives and Questions

Based on the above-described challenges, the overarching purpose of this research is develop methods that use energy data to ultimately better predict the residential energy use and residential HVAC system-level energy demands and efficiency. More specifically, this includes development of an improved methodology for the prediction of residential energy consumption where limited electricity consumption data and building characteristic information is available, and development of a methodology to assess HVAC operational efficiency using high frequency electricity use data. There are three main objectives in this research. Figure 1.3 represents the relationship of these objectives and how they relate to the overarching purpose. The details of each objective are described below; each objective aims to address several major research questions.

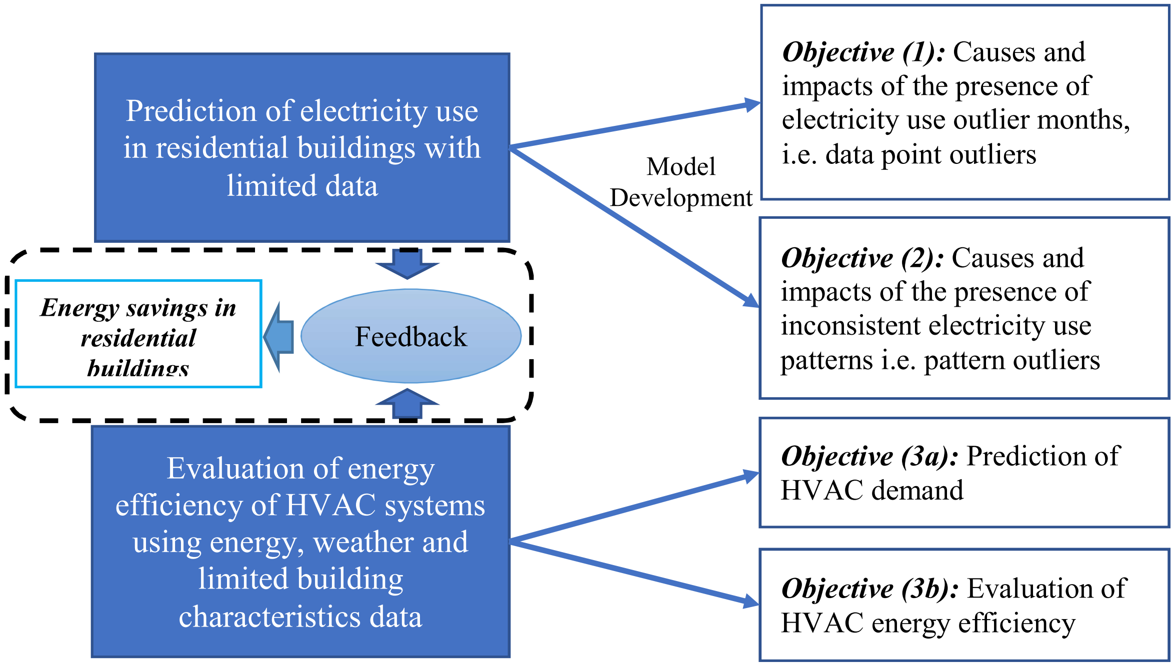

Figure 1.3 *Schematic diagram of dissertation research objectives (Note: the contents included inside the dash line represent the anticipated impacts on residential buildings, but these are not assessed in this research).*

To improve the inverse modeling of electricity use data for this type of situation, this research addresses two major issues identified as Objectives 1 and 2. For the evaluation of energy efficiency of HVAC systems using energy, weather and limited building characteristics data, this research focuses on two major and related issues identified as Objectives 3a and 3b.

1.2.1. Objective 1: Evaluation of the Causes and Impact of Outliers on Residential Building Energy Use Prediction Using Inverse Modeling

For some residential buildings, energy use patterns are not consistent, in part due to its high dependency on occupant behavior. This limits a developed inverse model's accuracy in predicting energy use of some buildings, due to the presence of energy use outliers, called point outliers. Currently there is no information available to explain the causes or reasons why these data point outliers occur. In addition, no specific guidance on how to handle this issue is available. Thus specifically, this objective aims to answer the following questions:

a) What can impact the accuracy and fitness coefficients of a data-driven electricity use prediction models?

b) What methods can be used to detect the occurrence of these data point outliers in the inverse models?

c) What is the most common cause of outliers in these models and why may households use more or less energy use than predicted?

d) Is the accuracy of these models impacted if the outliers occur in the data used to develop these models?

e) What should be done to treat outliers if detected, so as to ensure the overall model most accurately predicted energy use?

In this research, a monthly energy use data in residential buildings in Austin, TX is investigated to recognize the occurrence of outliers in inverse models by three different methods. Then, a high frequent, disaggregated energy data for these homes are used to determine the cause of the outliers, their impact on the model performance, and the final decision of keeping or removing outlier in the inverse models.

1.2.2. Objective 2: Improvement of Inverse Modeling of Energy Consumption in Diverse Residential Buildings across Multiple Climates

This objective addresses the fact that, if an inverse modeling method is used to fit models to monthly energy use data from a diverse set homes, a subset of homes do not fit the typically recommended criteria for model acceptance for this modeling type. These homes are classified as having energy pattern outliers. However it is not clear why such houses do not follow a common trend, nor if or how a model should be development to predict these types of home's performance. The following questions will be addressed in this objective:

a) Can a modified version of the inverse models be developed to better fit the energy use data in such houses?

b) How well do these models work across multiple climate zones and for a diversity of homes, including those with and without the identified inconstant energy use patterns?

In this research the datasets of residential energy use data have been gathered from four different regions of the U.S., including three ASHRAE climate zones, which will be used to assess and develop a solution to this objective.

1.2.3. Objective 3a and 3b: Prediction of Residential HVAC Demand and Evaluation of HVAC Energy Efficiency Using Limited Energy Data

This objective focuses on the development of a method and model that uses energy data to predict residential HVAC energy demands, which is ultimately used to assess the efficiency of the HVAC system itself, independent of any influence that occupants may have on operation. This research works towards an assessment tool that can be used to assess the energy efficiency of HVAC system in residential buildings without the need for more traditional methods such as a more costly and intrusive physical energy audit. The following questions need to be answered:

a) How can building characteristics, including assessors data, and weather data be used to predict the HVAC demand of a residential building, and how accurate can such a prediction be?

b) How can the relative efficiency of a residential HVAC system be evaluated in real-time using high-frequency energy data?

Detailed energy use and weather data will be collected for homes with air conditioners and/or heat pumps. A method and model will then be developed to predict HVAC energy demands (kW), which will then be used to compare the actual and predicted performance of the HVAC system. The results of this work will help homeowners and service technicians to target HVAC systems in homes in need of HVAC service or HVAC energy efficiency upgrades, ultimately motivating improved sustainability of residential buildings.

1.3. Dissertation Organization

The dissertation research is organized in six chapters as follows: Chapter 1 introduces the needs, purposes, and objectives of this research. Chapter 2 is a review paper, representing a background of energy data availability, characteristics and energy performance prediction methods for residential building energy consumption. Chapters 3 to 5 address the research questions in three journal papers, and three associated conference papers (Figure 1.4). In details, Chapter 3 demonstrates the evaluation of the causes and impact of outliers on residential building energy use prediction using inverse modeling. Chapter 4 shows the improvement of inverse change-point modeling of energy consumption in residential buildings across multiple climates. Chapter 5 represents evaluation of HVAC system energy efficiency in residential buildings. Finally, Chapter 6 summarizes the conclusions, unique research contributions, as well as research limitations and future work.

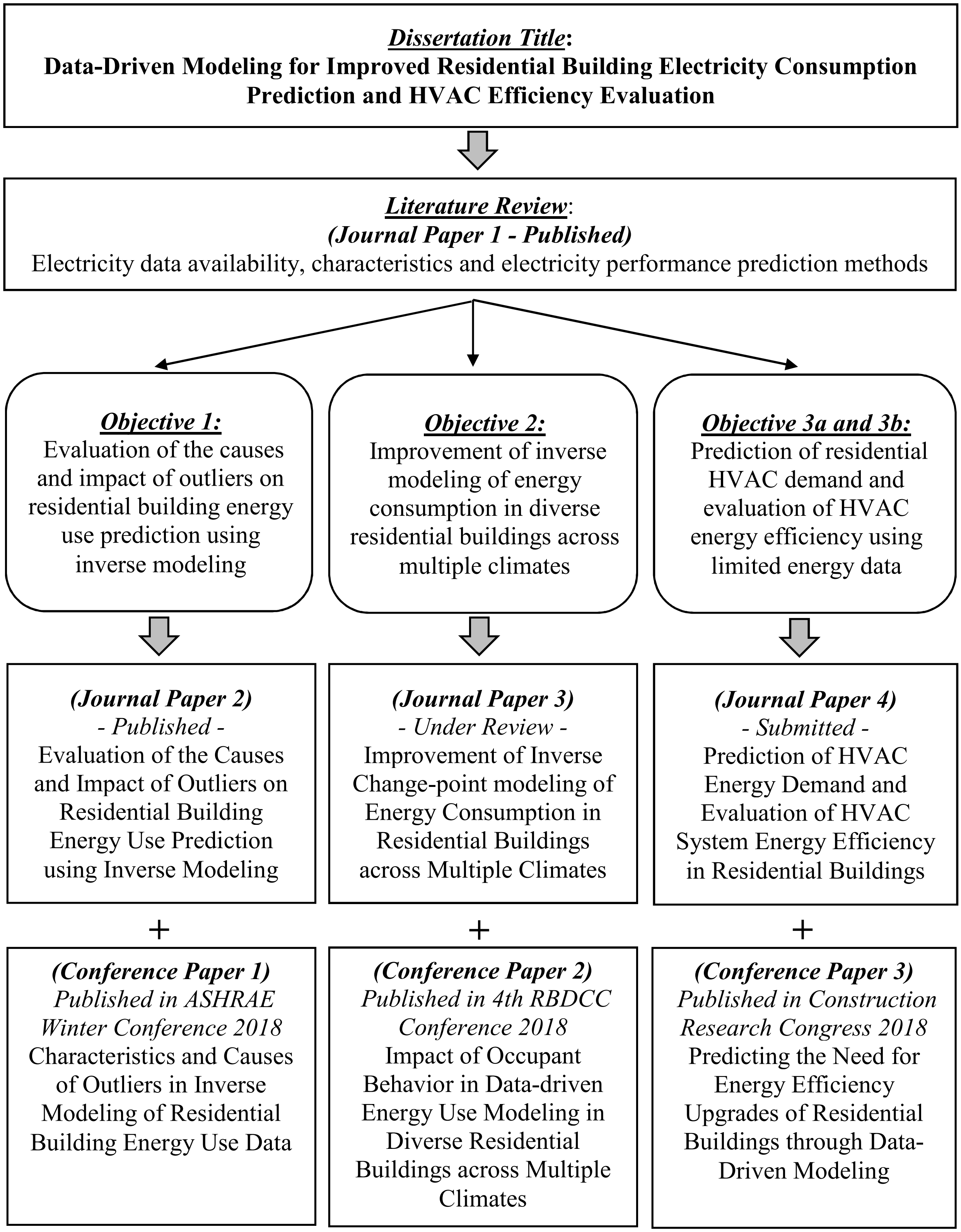

Figure 1.4 *Diagram of dissertation organization*

CHAPTER 2. RESIDENTIAL BUILDING ENERGY CONSUMPTION: A REVIEW OF ENERGY DATA AVAILABILITY, CHARACTERISTICS AND ENERGY PERFORMANCE PREDICTION METHODS

Huyen Do and Kristen Cetin, "Residential building energy consumption: A review of energy data availability, characteristics and energy performance prediction methods", Current Sustainable/Renewable Energy Reports, Volume 5, Issue 1 (2018), Pages 76-85. DOI: 10.1007/s40518-018-0099-3

Abstract

Residential energy performance prediction has historically receive less attention, as compared to commercial buildings. This likely is in part due to the limited availability of residential energy data, as well as the relative challenge of predicting energy consumption of buildings that are more highly dependent on occupant behavior. The purpose of this effort is to assess the types and characteristics of energy and non-energy data available for algorithm developed, and methods that have been developed to predict residential consumption. While there are several large residential building energy datasets, data availability is still generally very limited. Most energy prediction methods used recently include data-driven approaches, as well as combinations of multiple methods, however many methods have not been tested for residential buildings, or at a range of energy data frequencies. The literature points to the need for the availability of more residential building data sources to be able to assess and improve models, and further testing is needed including those models that have not yet been significantly use for residential buildings.

2.1. Introduction

Energy consumption has significantly increased in recent years, particularly in buildings, growing at a rate of approximately 0.9% per year in the U.S. [1]. Consistently, the residential buildings consume approximately 38% of electricity and 21% of this energy [2]. Given buildings' overall significant contribution to energy use, as well as environmental concerns and climate change, methods are needed to reduce this consumption. This is particularly the case for residential buildings, whose operation is highly dependent on occupants, and their behavior [3-6]. There are many possible strategies to reduce energy use in residential buildings, the most common of which is through retrofitting an existing building with more energy efficient systems. What retrofits are completed is often a decision made by the homeowner, based on a variety of factors [7-8]. While non-energy related factors can be influential in making such decisions [9], the most strongly cited reason is costs, i.e. the economics of the upfront costs, rebates or incentives provided, and the energy savings that the retrofit(s) will achieve over time. Another method to reduce consumption is through occupant energy behavior interventions, which aim to reduce consumption through altering the behavior of occupants, particularly how they use energy-consuming systems [10].

The ultimate decision of the homeowner to implement retrofits or change occupants' behaviors can depend on the information provided on quantification of the energy and costs savings achieved as a result of interventions, particularly if cost is the driving factor [11]. This includes (a) prediction of consumption of the building in its existing state, (b) prediction of energy consumption after interventions, as well as (c) how their relative difference translates into energy and costs savings [12]. Therefore, building energy use prediction methods, used to determine (a), (b) and ultimately (c), play a highly important role in building energy conservation [13]. The methods proposed and used in recent literature to predict energy use of buildings range in complexity and the frequency and duration of input data needed. Some methods have also been developed and tested only for specific building types. A recent review of these methods and their use for different types of data and building applications is thus needed, particularly as the availability and range of types of data to develop these algorithms is highly limited.

This work reviews two critical topics in this research area. This includes, first, a review of known available data and published information, which is relevant for use in the development of methods to predict residential building consumption. This review includes the type(s), frequency, quality, and duration of data, as well as identifies the challenges and needs in the area of building energy datasets. Second, is a review of recent published literature on the methods used to predict the energy consumption in residential buildings, as well as those developed for other building types that could be applied to residential buildings. This concludes with the limitations of existing data and methods, and future research needs in this area.

2.2. Residential Building Energy and Non-Energy Data: Sources, Availability, and Characteristics

Critical to the ability to develop, test and validate methods to predict building energy use is the availability of data for algorithm development. This includes real building energy data, as well as non-energy data, such as characteristics of the building(s) and their occupants, and/or weather data, all of which have demonstrated impacts on energy use. For residential buildings, much of this information can be challenging to obtain, particularly for a large number of buildings. This section is divided into two main subsections, including first, an overview of residential energy data, and second, residential non-energy use data. Both these sub-sections review the sources of data, data availability, and characteristics of datasets, such as frequency, quality, and duration.

2.2.1. Residential Energy Data

Historical energy use data includes electricity use, gas use, and in some cases other fuel use data collected at a regular frequency. This historical data is used in many cases, to train, test, and validate building energy use prediction methodologies. One of the greatest sources of energy data is electric and gas utilities, which maintain large sets of energy use data from their residential customers. This is collected and stored at a minimum frequency of the monthly level for all residential buildings, with some locations having higher frequency data from utilizing AMR (automatic meter reading) and AMI (advanced metering infrastructure) technologies [14,15]. However the barriers associated with the use of this energy use data particularly for residential buildings are often privacy and law-related [16]. There are a small number of exceptions such as the city of Gainsville, Florida [17,18], which provides public access to six years of monthly electricity and gas consumption data for all homes in the city, however this type and availability of energy data is not common.

This means that in many cases, methods for predicting building energy use must often be developed and tested using limited data based on energy measurements from small number of occupied homes, energy measurements from real building(s) using simulated occupancy methods (e.g. using [19]), or energy use data based on simulated buildings resulting from a building energy modeling program such as EnergyPlus. While these real residential building data provide valuable information, larger datasets of real data can encompass energy use information for wider variety of home types, locations, occupant behaviors, and other natural variations in energy consumption that smaller datasets cannot. Given the significant variations in energy and occupant patterns that can occur in residential buildings, this can be beneficial to provide a more comprehensive understanding of how well a methodology works in comparison to others.

An alternative source of the utility energy use data collection is obtaining this information directly from homeowners, who have access to utility-collected monthly data, and in some cases 15 minute or hourly data if a smart meter is installed in their home [20]. In rare cases homeowners may have minute, sub-minute, or sub-metered data from a home energy monitoring system, however these systems are not common currently. Thus, with homeowner consent, energy data can be obtained for algorithm development. However, large-scale collection of this information is time-consuming and costly. There are, however some efforts towards more open access to energy use data, some available datasets, as well as broader platforms created to enable easier sharing of datasets.

Arguably, more information is currently available on commercial building energy use than for residential buildings. For commercial buildings, there are more policies supporting the public availability of energy information, particularly in large cities and for publically-owned buildings. Large cities such as Boston [21], New York City [22], and Washington D.C. [23] among others, have enacted laws and/or ordinances requiring energy benchmarking. Under these laws, buildings must report energy consumption on a regular basis, which is compiled into databases and often made publically available. In some cases, such as Boston [21,24], this data includes larger non-residential and multi-family residential buildings. However, the data in these datasets is also only reported at the annual level which has limited use for building energy prediction methods.

Similar benchmarking efforts could also be beneficial for residential buildings, particularly if the data was at an appropriate level of frequency. For example, the ECAD Ordinance [25] requires that all residential buildings bought and sold that are over 10 years of age to have an energy audit completed in Austin, TX, the results of which are compiled into a centralize database; the city of Chicago allows for disclosure of energy use and/or costs during the sale of a home [26]. These, and other policy-enforced energy data sources could be highly valuable. Some local policy-enforced data sources are available, such as energy use by census block in Chicago [27], energy use by zipcode in New York [28-30], and aggregated annual energy use savings for homes in Austin [31]. However these datasets are also aggregated, and in most cases only at the annual level.

Other efforts collect data from a variety of sources on commercial and/or residential energy use in a common location. The Building Information Database [32], supported by the U.S. Department of Energy (DOE) consists of datasets of residential and commercial buildings energy use intensity on an annual basis, building characteristics and systems, and location. Similarly, the DOE-supported Building Dataset [33] contains information on energy use, building operations and analysis tools for buildings-related datasets, and the Energy Data Resources site [34] collects information on sources of energy data and tools from energy related projects. The types of data vary, but do include datasets with energy consumption at varying levels of frequency.

There are a small number of datasets of residential energy use information that provide higher-frequency and in some cases disaggregated end use energy data for residential buildings. A large-scale study in the Pacific Northwest in the 1980s and1990s collected whole-home and end use data for residential buildings [35]. Many research papers were written based on this dataset, and the aggregated data is available online [36]. The results of this effort are also still used today in residential energy modeling programs [37,38] for end use modeling. The most recent U.S. large-scale data collection effort for residential building data known to the authors is in Austin Texas [39]. This database provides up to 1-min interval electricity and gas consumption for a large number of homes from 2012 to present, and includes whole-home and end-use consumption. A number of recent research papers have used this to study residential energy use [40-42]. Given the current cost of equipment needed to obtain higher frequency and disaggregated data, it is unlikely that other efforts of this scale will occur frequently moving forward. However, given recent efforts to improve the ease of energy data equipment installation and collection, as well as improved abilities to disaggregate energy use data using higher-frequency whole-home energy data (e.g. [43]), lower-cost tools and/or equipment to obtain the frequency and quality of energy data for larger number of residential buildings may be more feasible moving forward.

2.2.2. Non-Energy Data

Non-energy data, linked with the energy data, also has an important role in energy use prediction. Weather data, is among the most critical non-energy factors impacting residential building energy use, and particularly HVAC systems which are used in a high percentage of U.S. residential buildings. Weather data is often available from public sources of ground-based weather station data, most commonly at airports [41,44,45]. However as some recent research efforts have found, this weather data is not necessarily representative of the conditions where studied residential buildings are located. For example, recent efforts have found variations in localized wind speeds and temperatures (e.g. [46]). The state of the art in this general area has been summarized in several recent research articles (e.g. [47,48]), and thus is not the focus of discussion herein. However, it is still important to note that while modeling methods and research efforts in building microclimates are significant, accessibility to raw weather data that well-represents the actual conditions experienced by buildings is still a challenge. More recently, some fields of study have adopted the use of publically-available satellite data-based weather data from MERRA [49], which is available world-wide on a regularly-spaced grid. The use of this dataset reduces the dependency on ground-based weather stations.

Building characteristics, such as size, fuel type, HVAC system type, age, efficiency, appliances types, thermostat preferences, air exchange rate, and building envelope characteristics can also have a strong impact on energy consumption. Thus while knowing this information can be highly beneficial, in many cases, this information is not available or linked with building-specific energy use data. The best publically available sources of building data originate from disparate sources, including assessors data, MLS data, cities' GIS databases, and LIDAR data. However if energy use datasets are anonymized for privacy reasons, this makes linking energy and non-energy datasets very challenging.

Some datasets, such as national level datasets U.S. Census data [50], RECS data [51], and American Community Survey [52] data, and localized datasets such as the Green Building Aggregate data in Austin, Texas [31], provide aggregate-level residential building and occupant characteristic data for enabling an understanding of building characteristics at a broader scale than the building level. The Better Building Neighborhood Program [53] provides a large anonymized building-level dataset representing over 75,000 building energy-related characteristics, specified by region and zip code information. This and the aggregated datasets can be useful to determine likely characteristics of a building in a specific area, or for use in community-scale energy use prediction methods (e.g. [54]), but is of limited benefit to building-level energy consumption prediction as they are not linked to specific residential building energy use data. The datasets mentioned in the previous section, including the Building Information Database [32], the Building Dataset [33], and the Energy

Data Resources dataset [34] do contain some building energy use information linked to building characteristic data.

In summary, building energy data and non-energy datasets are available, the characteristics of which range significantly. There are some promising sources of quality and higher frequency data which can be valuable for residential energy consumption prediction methods. There are also promising methods to encouraging sharing of data that can be further explored. However, significant opportunities remain to improve data availability in this field, which if done, will be highly beneficial to improvements in the capabilities of energy performance prediction methods.

2.3. Building Energy Performance Prediction Methods

Using energy data and non-energy data sources, building energy performance prediction methods range significantly in complexity and required types and frequencies of input data. Most recent efforts have followed similar methodologies for model development, including, as discussed in Wang and Srinivasan [13], first, (a) the collection of data for model development, then (b) the raw data processing is completed to ensure the data is of sufficient quality and format. The third step (c) includes using historical data to train the model to follow the patterns of use associated with the training dataset, as well as determining what of the available input data is significant and ultimately used for the model. The final step is (d) model testing. The fit of the model to input data not included in the training dataset is determined and evaluated in this step. Common metrics and statistical indices utilized for evaluation include root mean square error, coefficient of determination, coefficient of variation of the root mean square error, sum of squares error, mean squared error, and normalized mean bias error. Energy use prediction methods can either be physics-based approaches, data-driven inverse modeling approaches, or a combination of the two [55]. In this section the most recent efforts in energy performance prediction methods are reviewed, most of which are data-driven methods.

2.3.1. Change-point Modeling

Change-point modeling is among the more simple methods, which are typically single-variate models using dry-bulb temperature as the predictor. A balance point is determined which best fits the trends in the energy data, where building energy use switches between seasonal trends [55,56]. Linear regression is then used to create a multi-parameter model based on the determined level of fit criteria [56,57]. Perez et al [58] focused on its use to predict daily consumption of residential HVAC systems in Austin, TX using data from [39]. Kim and Haberl [59] used three-parameter change-point models to calibrate daily whole-building energy simulations for two single-family homes based on monthly billing data. Do et al [40,60] utilized large number of homes across multiple climate zones to study the use of change point models, demonstrating these methods can fit to a wide range of homes' use patterns. Zhang et al. [56] used it to predict hourly and daily HVAC hot water energy and Abushakra and Paulus [61-63] used a hybrid inverse change-point model to predict consumption in simulated and actual buildings, however both these efforts focused on commercial buildings.

The strength of the change-point models is the simpler development with lower computational effort in comparison to other methods [55,56]. The accuracy of prediction in change-point models depends on the type and frequency of data available, but has been shown to demonstrate similar levels of accuracy to more complex models in some situations [56]. Particularly for buildings with a limited number of data points, this method can be advantageous. However, as discussed in [40,59], some data points can be considered outliers that may significantly impact the model fit, particularly for highly occupant-dependent residential buildings. With acceptable methods to assess what data is appropriate to use for residential building models as well model improvements such as those suggested by Abushakra and Paulus [61-63], this modeling method provides a simpler but often sufficiently accurate method.

2.3.2. Artificial Neural Networks

Artificial Neural Networks (ANN) consist of an input layer, one or more hidden layers, and an output layer, and have mostly been used for more frequent, hourly or sub-hourly building energy consumption prediction in recent literature [56,64]. Input variables typically include outdoor temperature, wind speed, solar radiation, and relative humidity. These methods have been used to predict whole-home HVAC, and appliance use in residential buildings [64,65], and hot water [56], heating energy [66], total electricity [54,67], and chilled water use [68] for commercial buildings. ANN has also been combined with other methods and/or enhancements, including feed forward backpropagation neural network, radial basis function network, and adaptive neuro-fuzzy interference system [66], back-propagation algorithms [64,69], particle swarm optimization and genetic algorithms [54], principal component analysis [54,70] and hybrid lightning search algorithms [65] to improve and/or optimize performance.

ANN generally performs well with sufficient training data, and can be advantageous particularly for nonlinear electricity consumption [64,68]. Wang and Srinivasan [13] also found performance of ANN methods in short-term prediction is better than regression methods. Improvements made to ANN methods also further improve accuracy [54,71] with lower error [70]. However, the complexity of the model also increases computational time [72], and has limited physical interpretation which limits applicability outside of the training data limits [13]. In some cases ANN has also been found to perform worse than simpler models [56]. ANN has only been used in recent literature to predict whole-home consumption of unoccupied rather than occupied residential buildings [64].

2.3.3. Genetic Programming

Genetic programming is an automated computational method based on the process of biological evolution [73], and has been used in combination with other methods to predict residential energy consumption. Castelli et al [73] applied different genetic programming systems that use the genetics semantic operators to predict residential HVAC use. Jung et al [74] used genetic programming with a hybrid of the direct search optimization algorithm and a conventional real-coded genetic algorithm, with least-squares support vector machine to predict daily commercial building energy. Genetic programming has been shown to be an effective method that produces lower errors than other methods [73], and to also provide an effective approach for parameter selection and better performance in terms of convergence time and iteration than conventional least-squares support vector machine methods. However, similar to ANN, genetic programming typically requires a larger set of input data. It also has only been used in limited studies for residential buildings.

2.3.4. Bayesian Networks

Bayesian Network models include nodes that represent random variables such as outdoor temperature and energy use with statistical and probabilistic dependencies between the cause nodes and the effect nodes with a probabilistic graphical model [76]. The parameters of such models are the conditional distributions at every node using Bayes' rule. This method has been used to predict appliance energy use in residential buildings [75] and hot water HVAC use in a commercial building [76]. Bassamzadeh and Ghanem [77] also used this model to forecast the aggregated electricity demand in smart grids. In the limited number of studies that have used this method for building energy use prediction, the accuracy of the model predictions were within the recommended limits developed by ASHRAE for commercial buildings [76]. The uncertainties from input variables were also determined to be well-represented using this type of method [77]. However, similar to the ANN and genetic algorithm methods discussed above, this method requires significant input data and can be highly complex to implement.

2.3.5. Gaussian Mixture Model

Gaussian mixture model (GMM) establishes a weighted sum of Gaussian component densities based on a parametric probability density function and multivariate nonlinear regression function [56]. This method has been used in a number of recent studies for a range of buildings. Li et al [78] utilized GMM to design feasible time-of-use tariffs to minimize the electricity bills for residential customers. Also in residential buildings, and Melzi et al [79] used GMM to optimize smart meter electricity consumption, better understand consumer behavior and electricity use profiles. For other types of buildings, Zhang et al [56] applied GMM to predict daily and hourly commercial hot water energy, and Carpenter et al [80] predicted supplied energy for a range of manufacturing processes in an industrial building. The advantage of this method found in [56] was that it results in energy performance predictions that had the lowest error compared to change-point and ANN models, for commercial buildings. The GMM has also been found to capture non-linearity in simpler way than Bayesian or ANN methods [56,80] for non-residential buildings. However, its performance in comparison to other methods for residential buildings is not well studied. Studies have also found that other statistical values of fitness are also worse for GMM than change-point modeling [80].

2.3.6. Support Vector Machines

The final modeling method discussed is Support Vector Machines (SVM). This method has been shown to be effective in solving regression estimation problems and forecasting time series [72]. Jain et al [81] used a version of SVM for regression estimation, Support Vector Regression, to evaluate the effect of temporal and spatial granularity of data on the prediction of energy in multi-family buildings. SVM has also been combined with genetic algorithms to predict energy use [74]. SVM has been assessed as a highly accurate and effective method for the energy prediction [72]. However, SVM requires multi-step forecasts, implemented using various features and selected techniques [81], therefore, it is more complicated and requires more computational effort in comparison to other models discussed. Similar to other methods it can also benefit from additional evaluation for residential building energy performance prediction methods.

In summary, there are a number of different types of methods used in recent literature to predict energy consumption of residential buildings. Table 2.1 represents the summary of six main methods of building energy performance prediction. However, particularly for residential buildings, it is challenging to compare the capabilities and determine the overall "best" model for use for residential energy performance prediction, in part due to the lack of studies that compare performance of the models using residential datasets. Many of the algorithms have been developed, utilized and tested for commercial building applications, and may be well suited for residential buildings as well. Some residential building energy prediction studies have used larger datasets [77,58], however the number of studies with this size dataset is limited, for both residential and commercial buildings. The type of energy data being predicted also varies. Some studies focus on the use of methods to predict whole-building consumption [54,67], while others focus on HVAC [58], or other end uses [75].

Finally, the frequency of data and type of energy use data used to develop and test these models ranges significantly.

Table 2.1 *Summary of the building energy performance prediction methods.*

No.	Method	Most Common Data Frequency	Advantages	Disadvantages	References
1	***Change-Point Models:*** Supervised machine learning; single-variate or in some cases multi-variate steady-state model including a balance point and weather variable(s) as the predictor(s)	Monthly, Daily	Simpler; lower computational effort; easy to interpret and explain results	Outlier(s) may impact the model fit	[39,40,55-63]
2	***Artificial Neural Networks*** Supervised machine learning; Consists an input layer, one or more hidden layers, and an output layer; can be combined with other methods and/or enhancements	Daily, Hourly, Sub-hourly	Works well for non-linear consumption data	Higher computational demand, limited physical interpretation; requires significant input training data; over or under fitting	[13,54-56, 64-72]
3	***Genetic Programming*** Evolutionary algorithm; an automated computational method based on the process of biological evolution	Daily, hourly	Effective in parameter selection, convergence time and iteration	Requires significant input training data, higher computational demand	[73,74]
4	***Bayesian Networks*** Probabilistic graphical model; Includes cause nodes and effect node with a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph	Hourly, sub-hourly	Ability to assess uncertainties;	Requires significant input training data	[75-77]
5	***Gaussian Mixture Models*** Probabilistic model; unsupervised learning; a weighted sum of Gaussian component densities based on parametric probability density function and multivariate nonlinear regression function	Monthly, daily, hourly	Captures non-linearity in simpler way than Bayesian Networks or Artificial Neural Networks	The performance of GMM modeling in some studies is not better than change-point modeling	[56,78-80]
6	***Support Vector Machines*** Supervised machine learning; solves classification and regression estimation problems	Daily, hourly	Less prone to overfitting than some other supervised methods;	Higher computational effort with multi-step forecasts;	[72,74,81]

2.3. Conclusions

In summary, this review discusses both sources of energy and non-energy data, as well as methods that uses these data to predict energy consumption. This review points to the need for the availability of more residential building energy and non-energy data sources to be able to improve energy performance prediction models, and the need to more comprehensively and comparatively study the accuracy of these models for residential buildings across a range of frequencies of data, and whole-home as well as end-use consumption. More specifically the following conclusions can be drawn:

- Most available datasets provide energy or non-energy data, however these are generally not linked together or do not have the ability to be linked as they are anonymized; this limits the usability of these datasets for energy use prediction methods. Datasets that link energy and non-energy data are needed and with higher frequencies and quantities of data;
- Many available national-level and local-level datasets of energy use provide annual level data. Given that energy use prediction methods are often developed with the goal of predicting energy use at higher frequencies, this limits the data usability. There are some recent efforts to make large-scale studies' data and law-mandated data available, however more efforts is needed in this area, including those datasets associated with publications in this area, almost none of which are available for broader use. Recent efforts to improve the infrastructure, ease and motivation for energy data sharing [82,83], may help to improve this moving forward.
- Further and more comprehensive testing is needed to assess the different energy prediction methods at different data frequencies; this will help to assess which

models are most appropriate and best able to predict consumption for each frequency level, as this is currently not well established;

- Similarly, many of the prediction methods discussed have been tested for commercial buildings more than for residential, and in many cases only tested for specific end uses; testing of the possible methods across larger sets of diverse residential buildings could provide a more comprehensive picture of capabilities of these methods;
- The complexity of prediction models ranges significantly, as well as the amount of input data needed. Further clarity is needed as to the positives and negatives associated with more complex versus less computationally complex methods;

As more technologies become available that connect to the internet and are able to collect energy and non-energy data, such as through the internet of things, there is a significant opportunity to improve energy prediction methods. As energy efficiency continues to be a priority, improved data, combined with improvements in prediction algorithms using this data will help to improve the accuracy and reliability of such models, and as a result, likely drive efficiency improvements as well.

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CHAPTER 3. EVALUATION OF THE CAUSES AND IMPACT OF OUTLIERS ON RESIDENTIAL BUILDING ENERGY USE PREDICTION USING INVERSE MODELING

Huyen Do and Kristen Cetin, "Evaluation of the causes and impact of outliers on residential building energy use prediction using inverse modeling", Building and Environment, Volume 138 (2018), Pages 194-206. DOI:10.1016/j.buildenv.2018.04.039

Abstract

Inverse modeling techniques are often used to predict the performance and energy use of buildings. Residential energy use is generally highly dependent on occupant behavior; this can limit a model's accuracy due to the presence of outliers. There has been limited data available to determine the cause of and evaluate the impact of such outliers on model performance, and thus limited guidance on how best to address this in model development. Thus the main objective of this work is to link the use of outlier detection methods to the causes of anomalies in energy use data, and to the determination of whether or not to remove an identified outlier to improve an inverse model's performance. A dataset of 128 U.S. residential buildings with highly-granular, disaggregated energy data is investigated. Using monthly data, change-point modeling was determined to be the best method to predict consumption. Three methods then are used to identify outliers in the data, and the cause and impact of these outliers is evaluated. Approximately 19% of the homes had an outlier. Using the disaggregate data, the causes were found to mostly be due to variations in occupant-dependent use of large appliances, lighting, and electronics. In 20% of homes with outliers, the removal of the outlier improved model performance, in particular all outliers identified with both the standard deviation and quartile methods, or all three methods. These two

combinations of outlier detection methods are thus recommended for use in improving the prediction capabilities of inverse change point models.

3.1. Introduction

In recent years, the energy consumption in buildings has continued to increase, accounting for approximately 40% of worldwide energy consumption [1]. In the U.S. in 2015, energy use in residential and commercial buildings represented approximately 40% of total energy consumption [2]. Building energy consumption accounts for one-fifth of total global energy use [3]. In addition, the total building energy use worldwide is forecasted to increase an average of 1.5% per year from 2012 to 2040 [3]. This increasing energy utilization in buildings strongly affects the environment and climate. The energy consumption in buildings currently accounts for approximately one-third of the current greenhouse gas (GHGs) emissions worldwide [1], and 12% in the U.S. [4]. Thus, the identification and application of methodologies to decrease the buildings energy and electricity demands is important given global energy challenges as well as the impending consequences of climate change [5].

Energy efficiency improvements to the existing and future building stock helps accomplish these energy reductions. Several of these upgrades include improving the design and construction of new buildings, and retrofitting existing buildings with higher-efficiency equipment, higher-efficiency materials for the building envelope, and more intelligent and efficient controls and control strategies [6-8]. These methods do not require human intervention and are not dependent on occupant interaction with the building to save energy. However, much of a commercial or particularly residential building's energy use is also dependent on occupant behavior. Recent studies have found that 19% of energy use can be explained by variations in occupants' use of the building [9-10], and that when end-uses such as plug loads and appliances are dependent on occupant interaction they are up to 10 times more variable over time than those that are not [11]. Occupant behavior can make energy use more unpredictable, but it is also possible to influence occupant-dependent energy use as a method of energy conservation.

Behavioral energy efficiency is a generally lower-cost method to achieve energy savings [12-13]. This method's purpose it to change occupant energy-related behaviors [14] by providing feedback to customers through either a direct (real-time or near real-time) or indirect (post-consumption) method. Previous studies have found that these methods can achieve on average from 2 to 7% energy savings depending on the frequency and type of energy information provided [15], or an average of approximately 4% savings for real-time feedback programs and 2% for enhanced billing strategies [16]. However, real-time feedback strategies are not possible for many households, since for approximately half of households in the U.S., monthly energy use is the only energy consumption information available [17,18]. For these homes, indirect feedback can provide information to aid in behavior-motivated energy savings.

The feedback provided to residential customers most commonly includes information such as whole-home energy use, disaggregated end uses, future forecasted energy use, and/or comparison with neighboring homes' performance [15,19]. This information is typically determined through the development and use of data-driven models trained using historic energy data. As a result of such information, customers are better informed about their energy behaviors, and also better understand through recommendations developed through these insights, what energy savings they can achieve. These insights drive energy saving behaviors [20]. In the use of data-driven, inverse models [21,22] for energy efficiency behavioral changes, the accuracy of such models is highly important to ensure the homeowner trusts the results and predictions of such model enough to invest time and effort into efficiency upgrades. This method has advantages over calibrated building energy simulation methods, including limiting the need for detailed building information, and the ability to provide near-instantaneous results [23].

Inverse modeling techniques typically use outdoor weather data, including temperature, wind speed, humidity, and solar radiation as the main predictor(s) of the energy use of a building [24]. As weather significantly influences residential energy use, often the use of weather data as the input into these models is sufficient to provide a reliable model. A variety of inverse modeling methods have been applied for the prediction of building energy use in recent literature [25]. Change-point models [23, 24] typical use outdoor dry-bulb temperature as the independent variable to predict building energy use using a combination of regression analysis methods and the determination of a balance point between trends in energy use trends by season. Artificial neural networks (ANN) are a supervised machine learning method which includes input layers, hidden layers, and output layers to predict the energy consumption, often applied to more frequent datasets such as daily, hourly, or sub-hourly data [26-28]. Similarly, genetic programming uses an evolutionary algorithm to automatically compute data and make the prediction from biological process; this method has been applied to predict residential HVAC use or commercial building energy [29-30]. Probabilistic graphic models such as Bayesian networks [31-32], and Gaussian mixture models [23, 33-34] with multivariate nonlinear regression function have been shown to be able to predict the energy consumption in the building using monthly, daily or hourly frequency data. Recent research has also utilized other models including support vector machines (SVR) [30, 35-36], hybrid model predictive control schemes [37], or occupant behavior models [38-42] to predict residential building energy use. In these types of data-driven models, there are many factors that may affect the accuracy and computation of such models. In most models, the data frequency such as the monthly, daily, hourly, or sub-hourly data is a strong factor that has direct influence on the performance of models [25]. The requirement of significant input training data in ANN method, genetic programming, and probabilistic graphic methods increases the associated computational demand [23]. The presence of outlier data points also impacts the fitness of these models [23, 25].

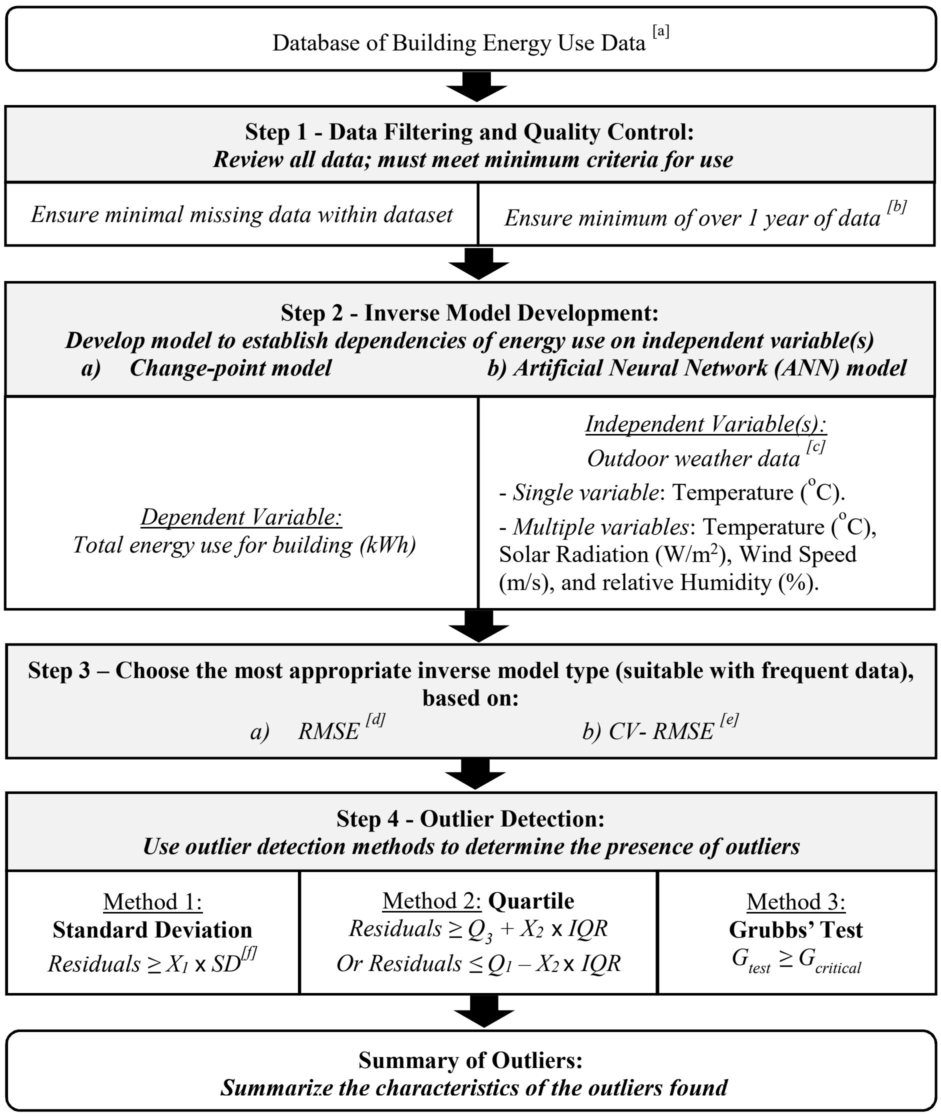
However, when applying these inverse modeling techniques, particularly for residential buildings, a variety of uncontrollable factors, including occupant behavior, can have a strong influence on building energy performance, and can also result in significant variations in use. For example, Kim et al. (2015) [43] observed that the energy use of a residential building was extremely low during the summer season, then through contact with the owner, determined they were on vacation during that period. Therefore, in such cases, the energy consumption prediction using the inverse model might not align with the actual performance. The accuracy of inverse models, thus, is limited in these households if such outlier behaviors occur, as the occurrence of an outlier can influence the model prediction. In addition, in most cases it is not possible to make contact directly with a homeowner as suggested in Kim et al [43], for better understanding the actual reasons for the energy use outlier in that month and it resulting treatment.

It is generally recommended in measurement and verifications (M&V) procedures to identify and remove outliers from datasets in the development of energy use predictions [44]. However, the decision to remove an outlier is often also dependent on the judgement of the modeler to determine, and typically requires justification beyond solely statically reasons as to why a particular data point should be removed. Without additional information to understand the causes of such outliers in residential energy use datasets, the removal of data is challenging to justify. If the decision to keep or remove a data point outlier is made through incorrect assumptions or justification, this may negatively influence the model accuracy. Therefore, it is necessary to further study the occurrence of energy use outliers in the inverse modeling techniques, including determining the possible reasons for the occurrence of these outliers and their influence of the model performance. This can help in developing a method for how to identity, assess, and treat these outliers in inverse modeling, and a stronger understanding of why such outliers occur in residential energy use. This is accomplished with the ultimate goal of better prediction of energy use in residential buildings, the results of which can also drive energy saving behaviors.

In this research a large dataset of residential buildings with highly-granular, disaggregated energy use data is investigated to determine the existence of outliers in inverse models developed from monthly energy use data, the most common type of energy data available for residential buildings in the U.S. First, three different methods including the standard deviation method, quartile method, and Grubbs' test are applied for outlier recognition in the developed inverse change-point models of residential building energy use data. Then, the specific reasons for the occurrence of the outliers are investigated using highly detailed and disaggregated data in these homes. Next, the impact of keeping or removing outliers these outliers on the performance of the inverse models are evaluated to ultimately determine the best methods for better prediction of energy use in the inverse models. Finally, the limitations, conclusions and future work are also discussed.

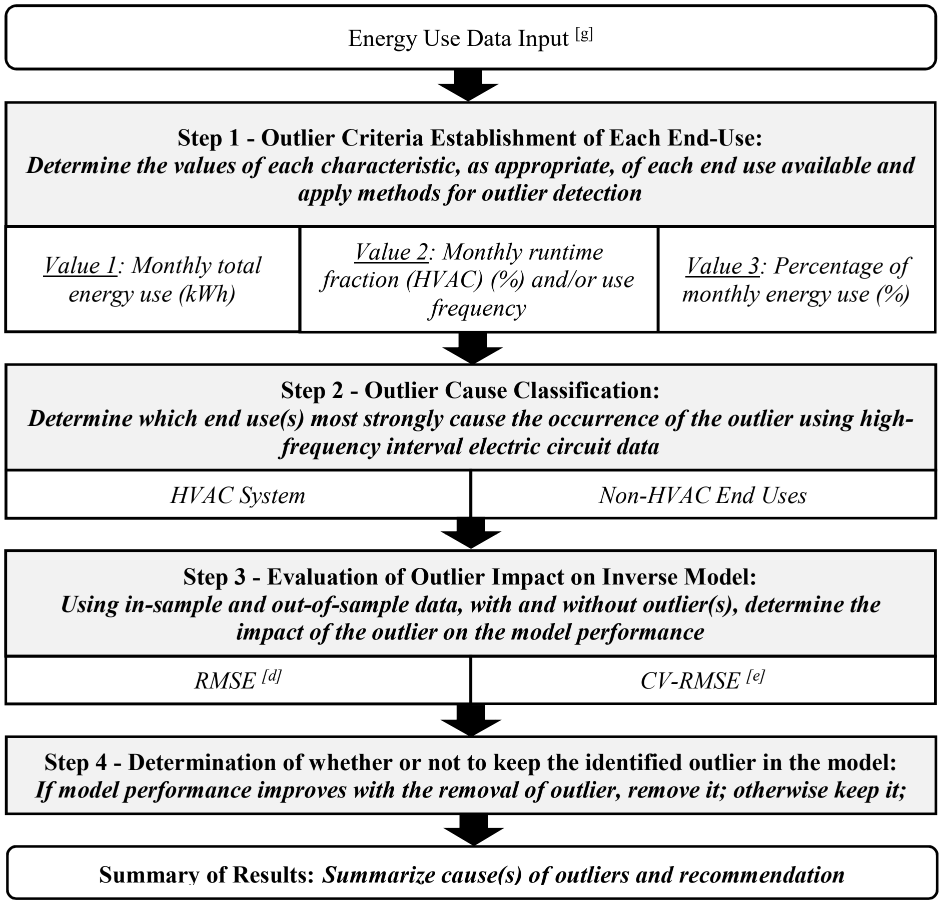
3.2. Methodology

In this study, the methodology is divided into two main stages. The first stage (Figure 3.1) develops an inverse model and detects the presence of outliers in the inverse model. The second stage (Figure 3.2) determines the causes of the outliers, whether it is recommended that these outliers be included in final models based on their impact on model performance.



[a]. Data source for this study: [28]
[b]. Data in this study was from 2012 to 2016 (5 years)
[c]. Method of determining can include: HDD (heating degree days), CDD (cooling degree days), averaging, bin method, modified bin method, etc.
[d]. RMSE = Root Mean Squared Error
[e]. CV-RMSE = Coefficient of Variation of the Root Mean Squared Error

Figure 3.1 *Methodology for outlier detection in inverse modeling of residential energy use data.*



[g]. From Figure 1. Output
[d]. RMSE = Root Mean Squared Error
[e]. CV-RMSE = Coefficient of Variation of the Root Mean Squared Error

Figure 3.2 *Methodology for determining the cause of outliers and determination of whether or not to include outlier(s) in final model.*

3.2.1. Outlier Detection Methodology

Step 1 - data filtering and quality control

This step involves the collection, processing, quality control, and characterization of building energy use data and weather data. Each house in the dataset must have at least one year of data but preferably more than one year. This is needed in order to cover the energy performance of the building throughout all seasons with some additional data for use as out-of-sample data to test the model performance, and have over a minimum threshold percent of total data used to create the monthly energy use data dataset. The focus of this work is on outliers in monthly data, thus when considering houses with monthly data values, more than three months of data were required to be available in each season at a minimum to enable model development and performance evaluation. The availability of high-frequency 1-minute level data was also quality checked. Pratt et al. [45], recommends a minimum threshold of 90% of electricity use data points for a calendar month and a calendar year should be used to determine which households have a sufficient amount of time-series data to be able to be used in this analysis.

Weather data was taken from the local Austin–Bergstrom International Airport, and used to calculate from the hourly weather data using the bin method, where hourly average data [46] is classified into bins with a bin size of 2.8°C (5°F). Compared to the simple average method, this bin method limits the influence of significant fluctuations in hourly data that might occur over the time period of study.

Energy dataset characteristics

A database of five years (Jan 1, 2012 to Dec 31, 2016) of highly granular building energy use data, building characteristics data, annual survey data, and energy audit data of several hundred homes in Austin, Texas was used, as summarized in Table 3.1 [46]. Weather data, including outdoor temperature, humidity, solar radiation, and wind speed was also collected from the Austin airport weather station. The average number of occupants, household age, number of bedrooms, and age of residents are all close to national averages. In general, the level of education and household income are higher in this dataset, however it is not anticipated that these factors will have a significant impact on the occurrence of outliers. For additional information, previous research has discussed this dataset, as well as its similarities to American Community Survey data [11,47].

Table 3.1 *Characteristics of residential buildings in dataset.*

Categories	Households in dataset [a] (n=128)	Households in the United States [b,c]	Categories	Households in dataset [a] (n=128)	Households in the United States [b,c]
Household age *(average, in years)*	11	37.4	Number of bedrooms *(average)*	3.2	2.8
Occupants (*average*)	2.6	2.6	Area (*average, m^2*)	204	183.1
Age of residents			*HVAC system*		
Under 5 years	11.3%	6.4%	Central air gas furnace	70.6%	39.0%
5 to 24 years	15.1%	27.0%	Central air electric furnace	6.6%	16.8%
25 to 34 years	12.7 %	13.5%	Heat pump	7.5%	8.6%
35 to 64 years	49.1%	39.4%	Window air conditioning	3.9%	22.8%
65 years and over	11.8%	13.8%	Others	11.4%	12.8%
Level of education			*Number of compressors*		
Postgraduate degree	60.1%	11.0%	1	65.5%	-
College graduate	35.1%	18.3%	2	16.8%	-
High School graduate	0.6%	28.0%	3	3.3%	-
Others	4.2%	42.8%	Not reported	14.4%	-
Total annual income			*Programmable thermostat*		
Under $50,000	5.4%	46.9%	Yes	57.1%	36.7%
$50,000 - $74,999	11.7%	17.8%	No	28.2%	47.7%
$75,000 - $99,999	12.3%	12.2%	Not reported	14.7%	15.6%
$100,000 - $149,999	32.4%	13.0%	*Ceiling fans*		
$150,000 and over	30.6%	10.1%	Yes	90.1%	72.7%
Not reported	7.5%	-	-	-	-

[a] Data source: Pecan Street Research Institute (2012-2016)
[b] Data source: American Community Survey (2014)
[c] Data source: Residential Energy Consumption Survey (RECS) (2015)

Energy use data cleaning

In this dataset each house is anonymized and represented by a unique Data ID, as discussed in Cetin et al. (2014, 2015) [11,47] and Rhodes et al. (2014) [48]. The whole-home electricity use as well as electricity use for up to 10-15 individual circuits was collected at one-minute intervals, representing appliances, lighting, HVAC (heating, ventilation, and air conditioning), and other plug loads. From the several hundred homes of available data, only houses that have 100% of whole-home electricity use for the time period considered at the one-minute level were used. The dataset of available data ranges includes 2012 to 2016, however, the number of houses with 100% of data in multiple years is limited, and thus, a dataset of 128 houses with 100% of whole-home energy use for a 24 months period (2014, 2015) was primarily used for this analysis.

Step 2 - inverse model development

Of different methods for inverse models [24], four methods are applied and compared to determine the most appropriate modeling method for the frequency and quantity of the dataset utilized. As with many residential energy datasets such as those collected and maintained by utility companies, monthly energy use data and weather data are the most commonly available information and little other information is known. As such the prediction of monthly energy use was the primary goal, taking advantage of the highly granular data included in this dataset to assess the reasons and causes for how well dataset fit the models.

The first set of inverse modeling method considered are a single and multi-variate steady-state model called change-point modeling [24]. This method traditionally predicts energy consumption using (a) outdoor temperature data as the independent variable; this is the more common and widely-used approach. This model can also be developed using (b) multiple weather data variables as independent variables. The modeling method determines a base temperature as the balance-point temperature at which a building does not require or only requires minimal energy use for heating or cooling [23,49]. This splits the model into multiple sections with different behaviors based on the characteristics of energy use during these different periods; differences in characteristics are often associated with different seasons and outdoor conditions. The value of the coefficients determined identifies the types of these change-point models [49]. With temperature as the main predictor, for houses with electric-based heating and cooling, typically a five- or four-parameter change-point model is most appropriate; for houses with a gas-furnace or non-electric heating, a three-parameter cooling model is best, for house with only electric-based heat a three-parameter heating model is most common. Houses may also fit a two–parameter model in which the electricity use increases or decreases with change in temperature, regardless of season.

Similarly, the multi-variate model uses monthly energy consumption as dependent variable and different parameters of outdoor weather data such as temperature, humidity, solar radiation, and wind speed as the independent variables. The heating and cooling portions of the multi-variate models were developed using stepwise regression [50]. In this study, the base temperature is determined for each house through the developed change-point model algorithm which is run in MATLAB, building off of methods outlined in [49]. Code was also developed to implement and automate the change-point model development. A unique inverse model is calculated for each building studied.

The second set of inverse modeling methods used utilizes artificial neural networks (ANN) [51], another inverse modeling technique that has been used for building energy data and performance prediction [24]. In this study, Long Short-Term Memory (LSTM), a specific recurrent neural network (RNN) architecture, is used, which is often recommended for time series data. LSTM contains special units called memory blocks containing memory cells with self-connections storing the temporal state of the network and the gates to control the flow of information [51,52].

Specifically, two different ANN models for each house are used with a different numbers of independent weather variables to predict monthly energy use. For the first, only outdoor temperature was used as the independent variable. The LSTM models were defined with 2 neurons in the first hidden layer and 1 neuron in the output layer for predicting the energy use for each house. This model was fitted for 50 training epochs using a batch size of 3. The second model used temperature, humidity, wind speed and solar radiation as inputs, with 4 neurons in the first hidden layer and 1 neuron in the output layer. The models were also fitted for 50 training epochs using a batch size of 3.

Step 3 - choose the most appropriate model

To determine the fit of the models to the data, the values of Root Mean Squared Error (RMSE) and Coefficient of Variation of the Root Mean Square Error (CV-RMSE) are assess for the in-sample and out-of-sample data. These values are commonly used methods of evaluating the fit of a set of data to a model. The RMSE value evaluates the variance of all residuals in the models [53], while the CV-RMSE demonstrates the uncertainty inherent in the models [23]. The most suitable model with monthly data of whole-home energy consumption and collected weather data was chosen if the values of RMSE and CV-RMSE were small.

Step 4 - outlier detection

Three different methodologies are used to detect outliers in the data: (1) Standard deviation, (2) Quartile, and (3) Grubbs' Test, as described briefly in this section. There are many types of possible statistical methods used for the determination of outliers, however not all methods are appropriate for datasets where a smaller number of data points are used. Based on the most appropriate model chosen from Step 3, each method of outlier detection is applied. The standard deviation method (1) is commonly used and recommended in the building energy performance field for measurement and verification (M&V) activities, such as for energy performance contracting [44]. The other methods are also accepted statistical methods to determine the occurrence of outliers. These three methods are used to enable a comparison of the detection abilities of the different methods for the specific use case of residential energy use predictions.

The standard deviation method (1) is a common method to identify outliers based on the mean value and the standard deviation of the dataset [54,55]. The standard deviation is calculated from the residual values in each residential building, the mean of these residuals and the number of observations in each inverse model. Generally, a threshold of two or more standard deviations are applied for outlier detection [54]; this is also consistent with M&V practices recommended in the literature [44]. Thus a value of 2 standard deviations is chosen as the threshold for detecting outliers in this study. The (2) quartile method [56,57] is based on box plots that identify the first quartile (25th percentile) and third quartile (75th percentile) of the data residuals. The interquartile range is computed as the difference between these values, then the range for outlier detection is established using a lower and upper fence with the value X2. If the value of the residual is less than the lower fence or higher than the upper fence, these values are considered outliers. Similar to a previous study [58], a value X2 of 1.5 is used for the lower and upper fence as a threshold. The Grubbs' test is a method that uses the approximate normal distribution to detect a single outlier in the dataset [59]. In most cases the outlier is recognized as the maximum or minimum values in the data set. Therefore, this method is also called as the maximum/minimum normed residual test [59]. This method detects outliers in the dataset through an established hypothesis with two statements – no outlier found or an outlier found in dataset. A value of Grubbs' Test is identified from mean and standard deviation of the dataset of energy use in each inverse model. The critical value of Grubbs' Test is determined from the t-distribution table. If the value of Grubbs' Test is higher than critical value, there is an outlier in the dataset.

The identified data point(s) in each house from each of the three methods are, for a comprehensive analysis of outliers, all analyzed. The number of methods (1, 2, or 3) that determined a point is an outlier is also tallied for assessment of the most appropriate type of outlier detection method for residential building energy use predictions.

3.2.2. Determining the Cause of Outliers and Impact on the Accuracy of the Inverse Models

The outputs from the first stage are applied as the input data to this stage (Figure 3.2) to determine their cause and impact on model performance. Determining the cause of the outliers is only possible to implement with the use of detailed data, such as high-frequency (e.g. 1 minute) disaggregated energy use data. If less frequent data is available, evaluation of accuracy is still possible, however, the cause cannot likely definitively be determined without additional information. The steps below assume that the data used is electricity data. The same methods could be used for natural gas data, however disaggregated gas use data is not common and is challenging to collect.

Step 1 - outlier criteria establishment of each end-use

The outlier criteria for each end-use in each house, including both HVAC and non-HVAC end uses, are established in this step. Monthly total electricity use (kWh) and monthly runtime fraction (%) for the HVAC system or use frequency (minutes) for non-HVAC loads are determined for the outlier month(s). The runtime fraction for the HVAC system depends on when the HVAC system turned on or off based on the electricity use from one-minute level data, as discussed in [47]. Similarly, the monthly use frequency of each end-use is the time which the end-use is turned on in each month.

Step 2 - outlier cause classification

The outlier causes are classified into two main categories: HVAC system and non-HVAC end uses. The HVAC is distinguished from the other end uses due to its high percentage of electricity use in residential buildings in the U.S, and since it is typically weather-dependent while other end uses may be, but to a significantly lesser extent. If additional data was available, for example indoor temperature values and/or thermostat set points, this data could also be helpful in this analysis, however these were not consistently available and thus were not used in this work. For HVAC use, an inverse model is developed for HVAC-only energy use, following methods described in previous steps. If the month considered an outlier shows HVAC use is outside 2 standard deviations (95% confidence interval) (Method 1), and/or is lower than the lower fence/higher than the upper fence (Method 2), and/or higher than the critical value (Method 3), HVAC is considered as a cause of the outlier. For non-HVAC uses, the average energy use per month is calculated for that end-use as non-HVAC loads are not found to be strongly weather dependent. Similar to process for HVAC, if the month considered an outlier shows a high or low non-HVAC use, this particular non-HVAC use is considered to be a cause of the outlier.

There are a number of possible causes of outliers anticipated, most of which are likely to be caused by occupant-related behavior changes which impact the energy use of particular end-uses. Changes in occupant behavior, including events such as changes in the number of occupants in a home, whether or not an event or gathering is being held, such as during the holidays, the types of activities occurring in the home such as significant cooking or electronics usage, changes in thermostat set points by occupants higher or lower than predicted use for individual end use(s), the underlying causes of which are in most cases due to differences in occupant behavior-based energy use.

Step 3 - evaluation of outlier impact on inverse model

To evaluate the impact of outliers on the performance of an inverse model, the model is developed with and without the identified outliers. Using additional months or years of data used in the model development across the multiple years of data in the utilized dataset, these out-of-sample data are compared as the model-predicted values. Similar to Step 3 in the first stage of model development and outlier detection, the values of RMSE and CV-RMSE are also evaluated for comparison of performance of models. In both cases, the lower values of RMSE and CV-RMSE, the better prediction is demonstrated. If the inverse model with outliers better predicts the out-of-sample data, these outliers are recommended to be kept. Otherwise, the outlier is recommended to be removed for improved model performance over time.

3.3. Results and Discussion

3.3.1. Inverse Model Development

A minimum of two years (2014 - 2015) of energy use and weather data were used to develop the inverse change-point models and ANN models, including one year for in-sample data (training) and one year for out-of-sample data (validation). The inverse change-point and ANN models are developed with single predictor (only outdoor temperature) and multiple predictors (outdoor temperature, wind speed, solar radiation, and/or relative humidity). The root mean squared error (RMSE) and the coefficient of variation of the root mean square error (CV-RMSE) are used to assess the fitness of both the change-point and ANN models using single and multiple variables. These measures follows the industry guidelines for building energy use prediction, including ASHRAE Guideline 14 [60], and International Performance Measurement & Verification Protocol [61]. The model performance results of four inverse modeling methods are shown in Table 3.2. Table 3.2 demonstrates that the inverse change-point models with both single and multiple variables have the lowest CV-RMSE of the models evaluated. At approximately 12% for in-sample data for the single variable change-point models (Table 3.4), the CV-RMSE is below the industry guideline proposed threshold of 15% for monthly data [60]. The ANN model CV-

RMSE value is higher than the change point models, and higher than the recommended threshold per the ASHRAE Guideline 14 requirements. Comparing the inverse change-point models and ANN models in out-of-sample data, change-point models perform better, with the lower RMSE and CV-RMSE than the ANN models. In addition, the change-point models require lower computation effort [23,24] to develop, making them an overall more favorable choice from both perspectives. This is in agreement with the finding of other studies that compared change point models to other more complex and computationally-intensive inverse modeling methods including ANN [23]. ANN models generally benefit from situations with more data to improve performance [24], but are more complicated and require more computational time [35], and have been found to perform better for commercial buildings with more consistent use schedules than occupied residential buildings [26]. Therefore, based on these findings, in this study change-point models are used.

Table 3.2 *The evaluation of inverse change-point (CP) and ANN models developed for studied residential buildings.*

Median values	Change-point models		ANN models	
	Single variable	Multiple variables	Single variable	Multiple variables
RMSE	160.4	154.4	386.8	321.7
CV-RMSE	17.1%	17.0%	44.0%	37.6%

For determining the change point modeling method to use for this work, Table 3.2 shows the values of CV-RMSE in the models with a single and with multiple variables are nearly identical. The RMSE values are slightly lower (5%) overall for the multiple variable modeling method than the single variable modeling method. However, in the developed change point models which considered the use of multiple independent variables using stepwise regression methods, the large majority of these homes' models (81%) were found to use only one independent variable, including 63% with outdoor temperature, 16% with solar radiation, and 2% with relative humidity as a predictor. 13% of the homes with developed models were found to have two variable predictors, including outdoor temperature and wind speed accounting for 9%, and outdoor temperature and solar radiation at 2%. In addition, approximately 50% of the homes that used multiple variables as predictors found that the weather parameters that are significant predictors in one season are not the same as the significant predictors in another season, making the model predictors non-uniform across multiple seasons. Thus although the RMSE values of single variable modeling method is slightly higher, this method demonstrates sufficient accuracy and provides predictor uniformity that enables comparison of homes' performance across all seasons with a low computational demand in comparisons with other inverse modeling methods [23]. Therefore, the single-variable change-point models are used for each residential building in this study. A change-point model requires the determination of the balance-point temperature, using methods such as those in Paulus et al. (2015) [62]. To develop the inverse change-point model for each residential building, four criteria are assessed for each portion of the model to determine if the model is acceptable, following the recommendations of [62]. This includes a shape test to ensure the magnitude and sign of the slope of each portion of the model is acceptable, a significance test which is passed if the p-value is assessed to be under a threshold level set at 0.05, an R^2 test which is passed if this value is over a set threshold level of 0.5, and a data population test which is passes if at least three data points are available for model development for each portion of the model [62]. The change-point model in which all tests are passed and which has the lowest RMSE and associated CV-RMSE value is chosen as the best fit [62].

3.3.2. Inverse Model Development Results

A total of 128 inverse change-point models were developed with one year of monthly whole-home energy use data as the dependent variable and binned outdoor temperature data as the independent variable. The number of houses determined to fit best for each type of change-point model are represented in Table 3.3. The inverse change-point model identified for each house is typically most closely related to the type of HVAC system used, particularly whether or not electricity is used as a means for heating the home, as the HVAC system typically represents the largest weather-dependent energy consumer in a residential building. The 5-parameter or 4-parameter change-point models typically best fit homes with heat pumps, while the 3-parameter cooling best fit homes with gas furnaces. This type of inverse change-point model is simpler method with lower computational demand. The accuracy of the prediction is still impacted by the limited number of data points available associated with monthly data frequency and the occurrence of outlier values.

Table 3.3 *Summary of inverse change-point (CP) models developed for studied residential buildings.*

Type of models	Number of houses (*n=128*)	Outliers (#)	Coefficients of slopes					
			Heating season			Cooling season		
			Max	Median	Min	Max	Median	Min
5-parameter CP	3	--	-7.9	-88.7	-105.8	269.8	122.7	51.0
4-parameter CP	18	2	-6.2	-111.5	-295.4	211.8	89.9	30.8
3-parameter CP cooling	102	20	--	--	--	500.8	99.7	29.3
2-parameter CP cooling	5	2	--	--	--	95.9	36.0	4.1

The distribution of models dominated by cooling models aligns with what is expected in Austin Texas (ASHRAE Climate Zone 3A), which is both a humid, cooling climate, and a location where natural gas is commonly used for heating [63]. The majority of homes were found to best fit a 3-parameter cooling model (80%), followed by a 4-parameter model (14%), and a small percent fitting a 5-parameter (2%) and 2-parameter cooling (4%). None were found to fit at 2-paramter heating model. In terms of natural gas use, over 70% of homes in this dataset use gas heat (Table 3.1). Homes with the best fit being a 3-parameter cooling model was compared to the known use of gas heating; in all cases where this information was available, these homes were found to follow the 3-parameter cooling model. Those that fit the 4-parameter and 5-parameter models (16%) likely use a heat pump or electricity for heating. This was also cross-checked with homes with known non-gas heating HVAC types (14.1% of homes) and agreed with the known building characteristics. The homes where the 2-parameter cooling model fit best indicate that regardless of season, as the temperature increases the electricity use increases, even in the heating season. Likely, these homes have non-HVAC uses that decrease with decreasing temperature consistently throughout all seasons, and also use gas or other non-electric sources of heat in the winter.

The overall model results indicate that the median change in monthly energy use per degree of increase in monthly binned temperatures is approximately 100-123 kWh/^{o}C in the cooling season, and 105-112 kWh/^{o}C. This is a similar range for both the heating and cooling season across the homes studied and is in reasonable agreement with previous residential studies on HVAC and whole-home energy use [64,65]. Those homes most impacted by temperature reached monthly energy use increases of up to 501 kWh/^{o}C in the cooling season and 295 kWh/^{o}C in the heating season. These higher slopes may be caused by homes that are inefficient, or may have high or low thermostat set points in the heating and cooling seasons respectively. The homes with energy use least impacted by temperature but still with a statistically significant relationship were as low as 6-8 kWh/°C in the heating season and 4-51 kWh/°C in the cooling season.

Examples of representative homes' monthly data with the developed inverse models are shown in Figure 3.3, including each of the different types of models. Figure 3.4 shows a distribution of the base temperatures for the studied homes, which range from 9°C-23°C. Nearly 60% of the homes in this dataset have a base temperature in the range of 14°C-18°C, which is consistent with commonly used values discussed in ASHRAE Guideline 14 [60]. A lower change-point value indicates that the homes in this dataset use the least amount of energy and lowest HVAC use at a lower range of outdoor temperatures.

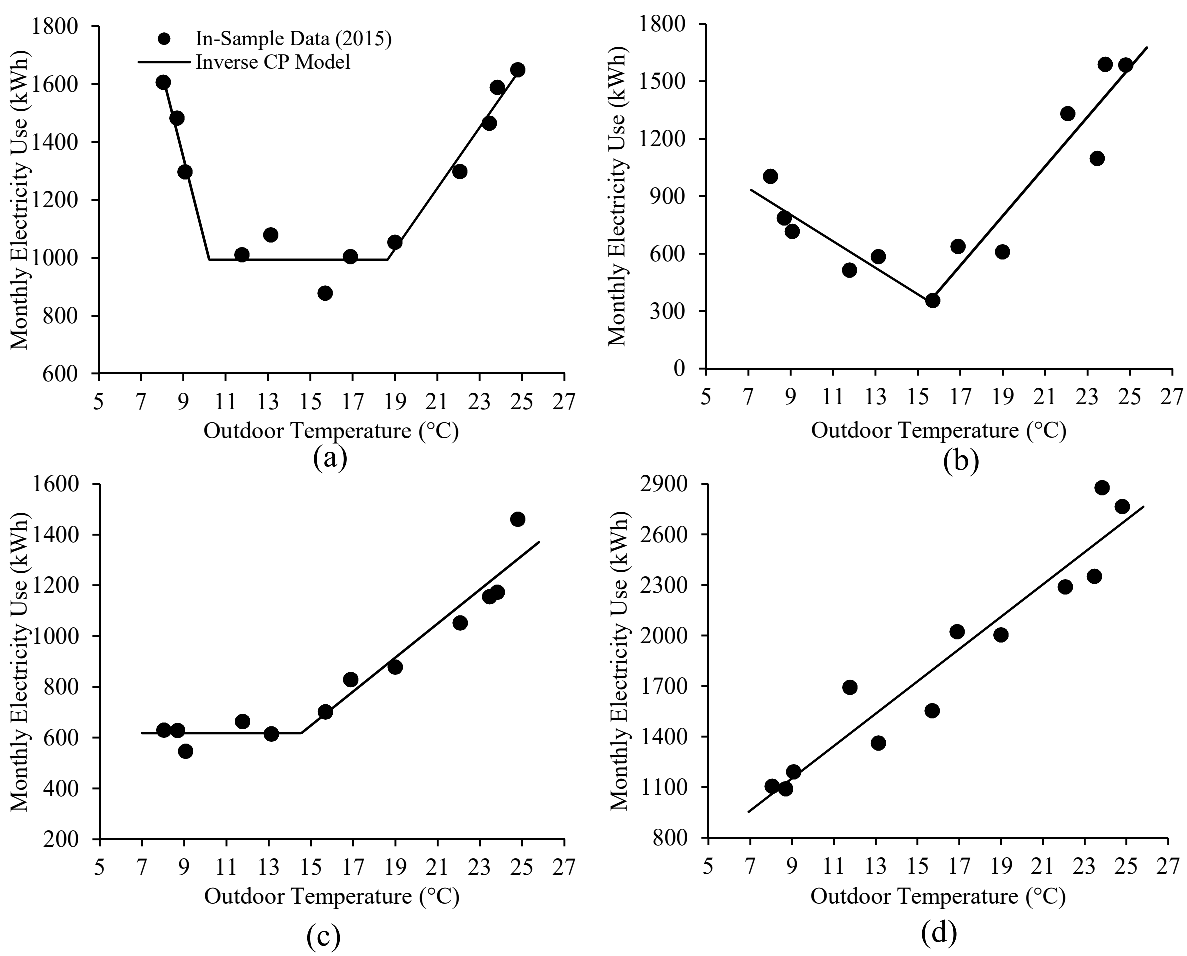


Figure 3.3 *Examples of inverse change point models of energy use developed including: (a) 5-Pamameter, (b) 4-Pamameter, (c) 3-Pamameter cooling, and (d) 2-Pamameter cooling.*

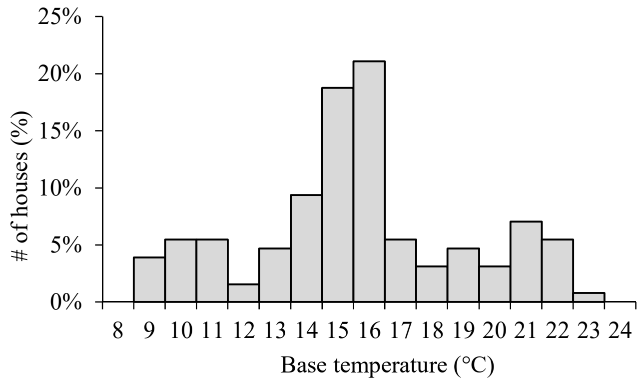


Figure 3.4 *Distribution of base temperatures of change-point models (n=128).*

The models developed using the one year of data were then evaluated to determine the quality of fit of the model for both in sample in-sample and out-of-sample monthly energy use data (Table 3.4). As expected, the fit of the data is better for in-sample as compared to out-of-sample data, however, on average the difference between the in and out of sample data was small, indicating a similar fit of the data to the model across multiple years. This information is used to compare to the performance of the models with the removal of the identified outliers. Figure 3.5 shows the distribution of the residuals of actual and predicted energy use from in-sample data (2015) and out-of-sample data (2014). Over 50% of all predicted values are within 100 kWh, and over 77% are within 200 kWh. The data points (months) on the upper and lower extremes of the data are consistent with the outliers identified through the three detection methods, which are summarized in Table 3.5 and 3.6.

Table 3.4 *Evaluation of accuracy inverse change-point (CP) models developed of residential buildings (RMSE = root mean squared error, CV-RMSE = coefficient of variation of the root mean square error).*

Values	In-sample data		Out-of-sample data	
	RMSE	CV-RMSE	RMSE	CV-RMSE
Median	98.0	11.7%	160.4	17.1%
Mean	122.2	12.9%	173.3	19.4%

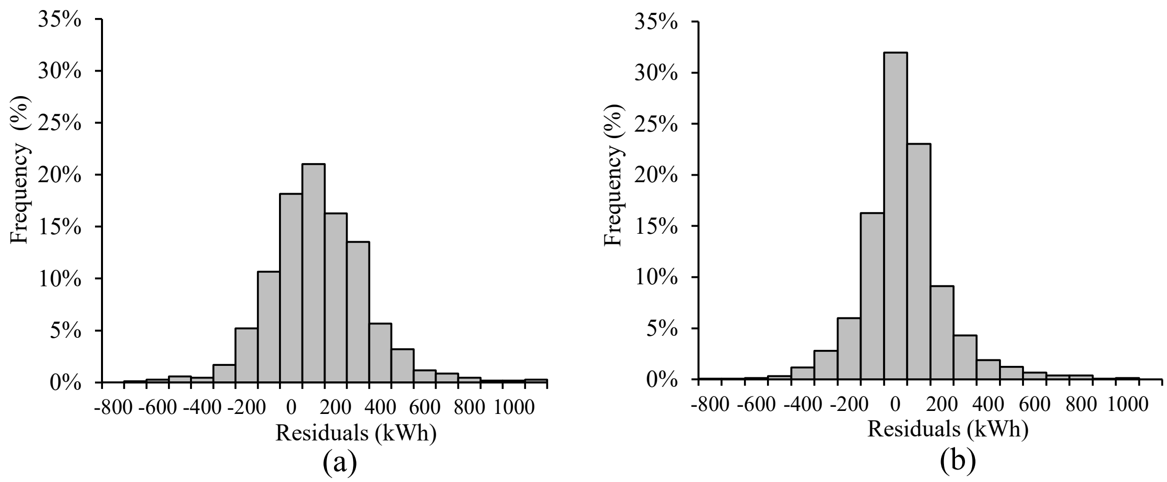


Figure 3.5 *Residuals of actual and predicted electricity use for the studied residential buildings (n =128) with (a) In-sample data (2015), and (b) Out-of-sample data (2014).*

Table 3.5 *Summary of outliers in inverse change-point (CP) models detected by one, two and three methods.*

Outlier detection methods	Type of models				Recommendation	
	5-parameter CP	4-parameter CP	3-parameter CP cooling	2-parameter CP cooling	Accepting outliers	Removing outliers
One method						
- Standard Deviation	-	-	1	1	2	-
- Quartile	-	1	6	-	7	-
- Grubbs' Test	-	-	5	-	5	-
Two methods						
- Standard Deviation & Quartile	-	1	1	1	-	3
- Quartile & Grubbs' Test		-	5	-	5	-
Three methods						
- Standard Deviation, Quartile & Grubbs' Test	-	-	2	-	-	2
Total of outliers (n=24)	0	2	20	2	19	5

Generally across all of the evaluated outlier detection methods, the number of outliers detected is similar, ranging from 5-16% for individual methods. In addition there are 2 outliers months found by all three outlier detection methods, 8 outliers found by two methods, and 24 outliers found by at least one of the three methods. Within each of the types of change point models, the 2P models had the largest percent of outliers (40%), followed by the 3P models (20%), and the lowest number of outliers were the 4P models (11%). This distribution of outliers within the model types makes sense because it follows the significance criteria and sequence of modeling development in the order of 5-parameter, 4-parameter, 3-parameter, and 2-parameter change-point models.

In many cases where outliers were detected, a different method detected these outliers. Each method detects data points as outliers that other methods do not detect, which is due to the differences in how the outliers are detected in each method. For a single-variate models, the standard deviation method takes into account the dispersion of all individual data-points of the dataset around the mean [66]. In the measurement and verification (M&V) field for buildings, this method is commonly used [44]. The quartile and Grubbs' test, however, take into account parts of the dataset; the quartile method is based on distance from median of dataset, and Grubbs' test considers one extreme data point, including either the maximum or minimum value. By assessing each method, this provides insights as to which method(s) identify outliers that should be removed to improve model performance. Table 3.5 shows the number of outliers detected by single and multiple methods in different types of inverse change-point models. The recommendation of accepting or removing outliers in the models is also demonstrated in this table. Approximately 80% of total outliers found (n=19) are suggested to be kept. Most outliers in this case come from one method of detection, or from two methods, including both the Quartile and Grubbs' Test. The outliers recommended to be removed from the models based on impact on model performance account for 20% of total outliers (n=5). The combination of methods that detect this type of outlier include (a) both the Standard Deviation and Quartile method, and (b) all three detection methods. This indicates that, based on this dataset, these two combinations of methods are the best recommended methods for identifying outliers in need of removal for overall model performance improvement benefits.

As evident from Table 3.6, the number of outliers detected in each month varies. December, January, and February are the three months that have a larger number of outliers across all methods. These months are common holiday months in which homes may be under-occupied if occupants are on vacation elsewhere and are not at home, or over-occupied if there are guests staying in the house for the holidays. This variation in occupancy would lead to increased or decreased electricity use in these outlier months due to significant increases in, in particular, internal loads such as cooking appliances, water heater use, plug loads, and lighting, as well as the use of items (e.g. oven) that were not used as frequently during other time. Several examples are included in Figure 3.6. For other months, the reasons for outliers in each house vary. Additional causes of outliers included both HVAC system and non-HVAC use deviations. For HVAC systems, these include faults in the HVAC system and increases or decreases in monthly electricity use and frequency in the HVAC. The non-HVAC loads were similar to those in the holiday months. In Figure 3.6a, the energy use of the HVAC unit from one home from Feb 23 to Mar 27 indicates that it continues to use approximately 500W continuously even when the system is not on. This may be due to the HVAC system or sensor malfunctioning or due to the system fan being left on continuously and perhaps unintentionally. As a result, the electric use of the HVAC unit is approximately 3.6 times higher than the other months (Figure 3.6b). Figure 3.6c-e represent a different home, where the outlier is cause by significant increases in the monthly use of non-HVAC appliances including a dishwasher, microwave, and oven. It is likely that this house has additional occupants during this month.

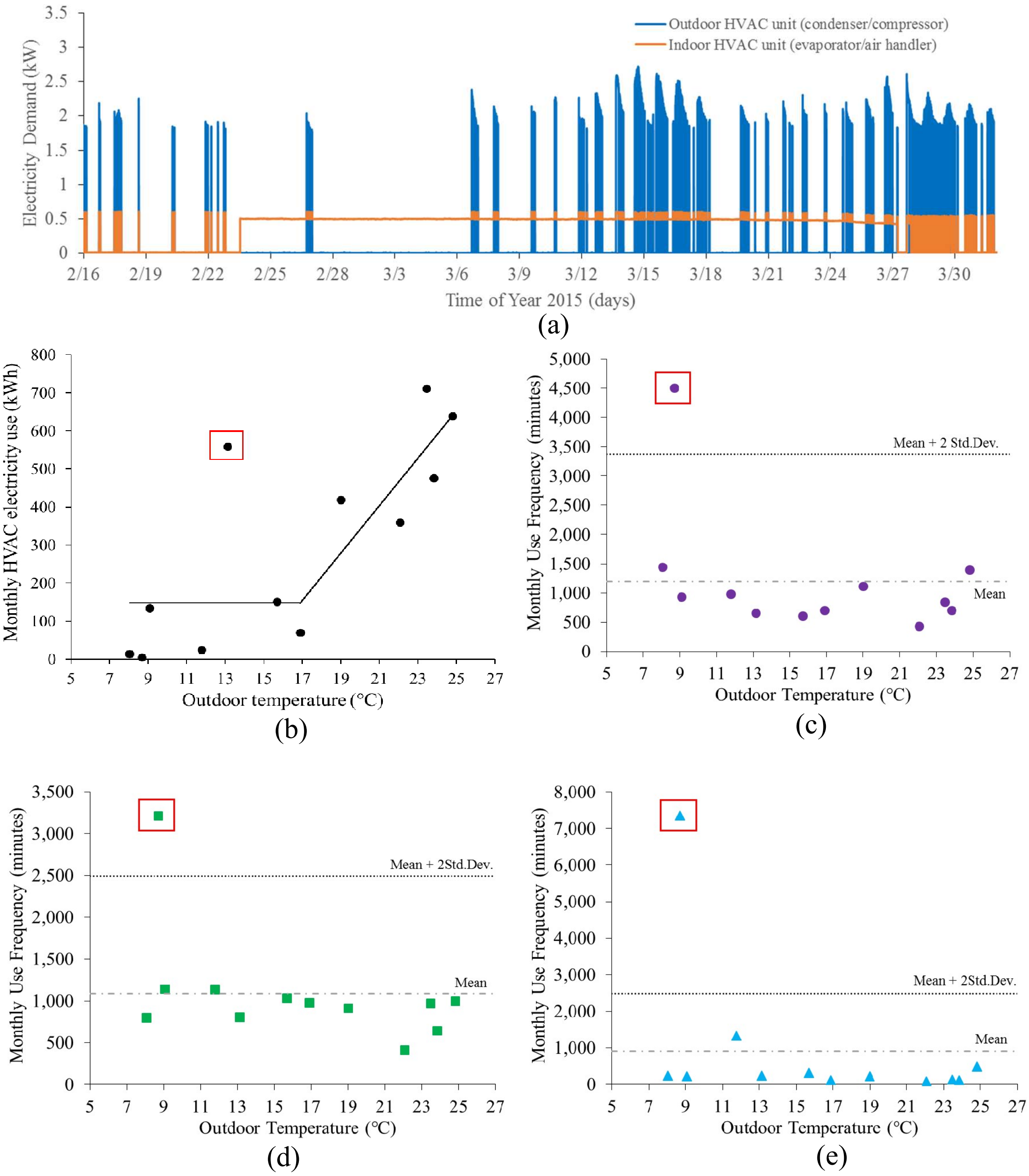


Figure 3.6 *Examples electricity end-use cases of outliers: (a) Fault in the interior unit (AHU) of the HVAC system; (b) monthly electricity use of HVAC system; monthly use frequency of the (c) dishwasher, (d) microwave, and (e) oven. (Note: red square indicates the identified outlier).*

Table 3.6 *Summary results of outliers detected using each methodology and multiple.*

Number of outliers found per months	Outlier detection methods					
	Standard Deviation	Quartile	Grubbs' Test	Two methods	Three methods	Total Unique Outliers
January	-	3	3	3	-	3
February	-	1	2	-	-	3
March	2	2	1	1	1	2
April	-	-	-	-	-	-
May	-	-	-	-	-	-
June	1	2	1	1	-	3
July	2	2	-	1	-	3
August	-	-	-	-	-	-
September	-	3	-	-	-	3
October	1	-	-	-	-	1
November	-	-	-	-	-	-
December	1	4	5	2	1	6
Total	7 (5%)	17 (13%)	12 (9%)	8 (6%)	2 (2%)	24 (19%)

In order to evaluate the impact of outlier(s) on the prediction performance of inverse models, 12 months of out-of-sample data are used to compare the performance of the model with and without the outliers. The model which provides a better prediction of the out-of-sample data is considered to be the preferred method. If the RMSE and CV-RMSE values for the inverse model using the out-of-sample data with outlier are lower than their values without the outlier, accepting outlier is recommended. Otherwise, the inverse models without outlier (i.e. rejecting outlier) is recommended to be applied to predict the future energy use in residential buildings. It was found that in most cases the outliers are recommended to be removed, however for some homes they should not as this negatively impacted the model performance. The results of four representative homes is included in Table 3.7, including homes with outliers detected with three outlier detection methods (1 home), two methods (2 homes), and one method (1 home). House #1 and House #4 are examples where the outliers are recommended to be removed. In these homes the out-of-sample data better matches the model developed without the outlier than with the outlier (Figure 3.7a and 3.7d). On the other hand, for House #2 and #3 keeping the outlier is recommended. As shown in Figure 3.7b and 3.7c, there is a lower difference between the outlier and other values of monthly electricity use in other years, therefore, original inverse models with outlier are the suitable choice. Previous works has suggested that in the case of the detection of an outlier, it should be removed or adjusted to improve model performance [43,44]. The results of this analysis indicate that while this is the case for many buildings, it is not the case for all, and thus additional consideration should be made before the removal of an identified outlier.

Table 3.7 *Impact of outlier(s) on the prediction performance of models in four representative houses*

Coefficients	Inverse CP model in 2015 with outlier	Inverse CP model in 2015 without outlier	2016 (out-of-sample)		Difference	Recommendation
			using model with outlier	using model without outlier		
RMSE						
House #1	169.8	94.9	169.3	116.9	-30.9%	Remove outlier
House #2	228.9	151.1	270.8	316.5	+16.9%	Keep outlier
House #3	240.0	142.2	445.3	470.8	+5.7%	Keep outlier
House #4	199.9	72.0	158.7	102.0	-40.5%	Remove outlier
CV-RMSE						
House #1	21.6%	12.5%	21.6%	15.4%	-28.7%	Remove outlier
House #2	12.8%	8.4%	15.1%	17.6%	+16.6%	Keep outlier
House #3	23.7%	14.6%	44.1%	48.2%	+9.3%	Keep outlier
House #4	25.9%	9.7%	20.5%	13.8%	-32.7%	Remove outlier

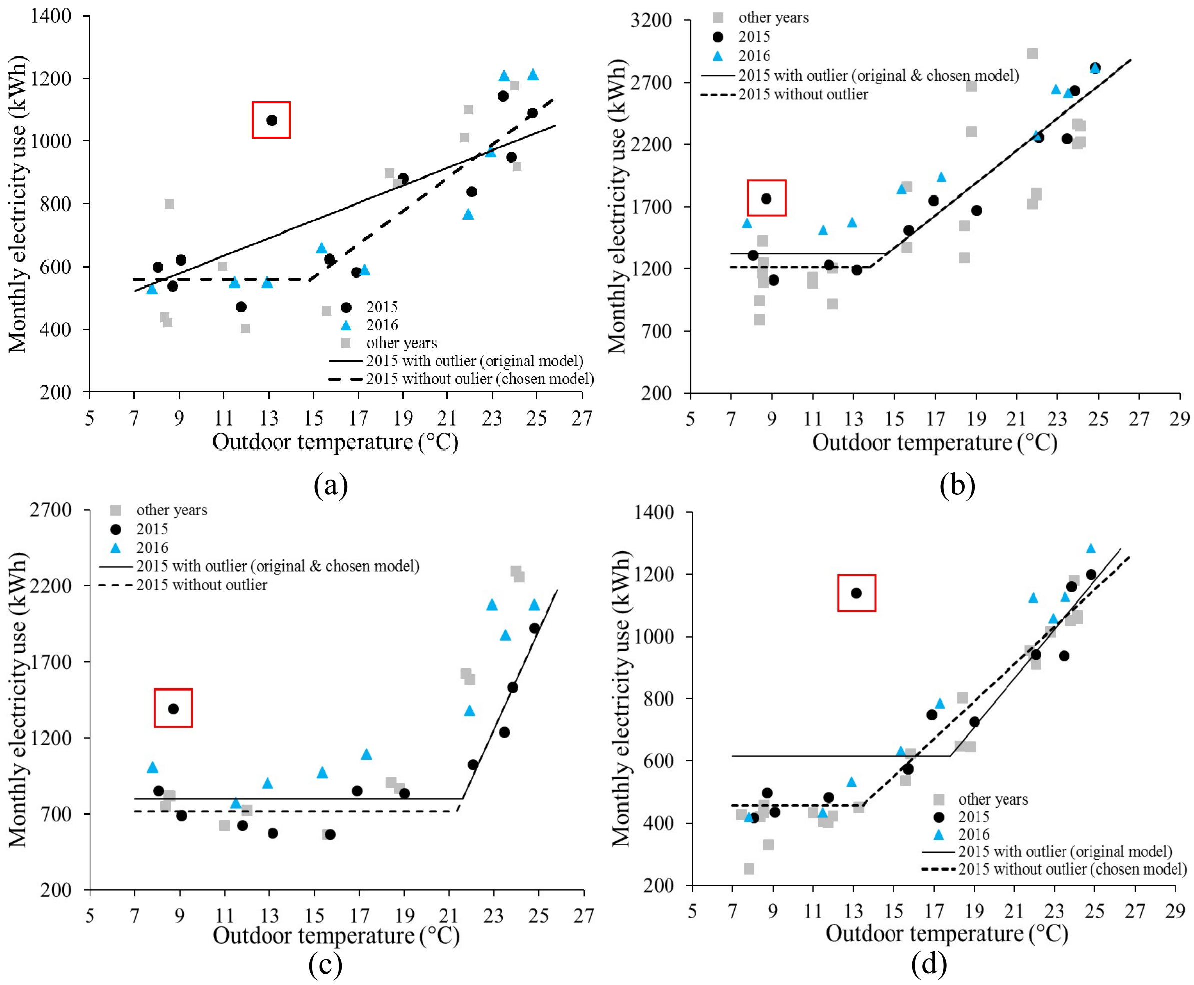


Figure 3.7 *Impact of outliers on the inverse CP models in 4 represented houses: (a) House #1, (b) House #2, (c) House #3, and (d) House #4. (Note: red square indicates the identified outlier; #1 and #4 recommend to remove the outlier, and #2 and #3 recommend to keep)*

As a case study, a residential building is considered (representative house #3 in Figure 3.7c and Table 3.7) with a 3-parameter change-point cooling model with an identified outlier in the month of December. The energy use in December is 74% higher than the inverse model-predicted, and is therefore considered an outlier, the main cause of which is higher HVAC use and large appliance use. Appliances including the dishwasher, dryer, microwave, and oven also have use frequencies in December outside of the set threshold levels including 125%, 79%, 84% and 810% higher, respectively. This is equivalent to approximately 2.30 occupants [67], as compared to an average the equivalent of 1.25

occupants in all other parts of the year. Comparing the fitness values in multiple years, the RMSE for the inverse model with the identified outlier (445) is lower than without (471). Additionally, a similar value of energy consumption occurs in this month in two other years (2016, 2017), meaning that this house has consistently high energy use in this month. Therefore, keeping the identified month in the original inverse model is of benefit, however given that this month does not follow the trends of other months in terms of consumption it may benefit from separate treatment and/or modeling as compared to other months.

Based on the analysis of the homes with identified outliers in this work, other houses (n=19) have been found to also benefit from keeping the identify outlier months. These findings indicate that the removal of an identified outlier using one of these methods is not always merited, and that an understanding of the reason why outliers occur and their associated impact on the model is important to assess.

3.4. Conclusion

When developing the inverse models to predict the energy use in residential buildings, generally for monthly data change point modeling methods were found to be best of the different methods considered and thus were used for the inverse model development. Outliers in these models occur in many of the homes, typically in the middle of the heating or cooling season rather than in the transition seasons, and can be detected using the proposed methodologies. The causes of outliers are investigated by studying one-minute interval circuit level data, which is typically not possible as high-frequency disaggregated data is typically not available for a large number of residential buildings. Understanding of characteristics of these outliers and why these have occurred helps to evaluate the impact of outliers on inverse change-point models effectively before determining whether to remove or keep these outliers. The following general conclusions are made:

- For monthly energy use data in residential buildings, the inverse change-point modeling method performs better, with a lower RMSE and CV-RMSE, and requires the lower computation effort than the ANN method considered. Thus for monthly-level frequency data across the range of homes studied, change point modeling methods appear to be the preferred method.
- Using change point modeling, the majority of homes studied (80%) fit a 3-parameter cooling change point model, indicating that most homes in the dataset use electricity for cooling and gas for heating. This was confirmed through comparison with survey data for those homes which provided this information, indicating this developed method for assigning change point model types appropriately represented the expected type of change point models for the studied homes; a smaller number (14%) fit a 4P and (6%) fit a 5P or 2P cooling model;
- The homes with the 5P and 4P had the lowest percent of homes with outliers and best fit of data to the models; the homes fitting the 2P model had the highest percent of homes with outliers. This indicates that homes may be assigned to the 2P model type due to the presence of one or more outliers. When the outlier was removed for this model type, the change point model type that best fit the data changed from a 2P to a 3P model, confirming this prediction.
- The number of outliers detected with each of the three methods considered was similar, but while in some cases all method detected the same specific months as outliers, this was not the case for all months; overall approximately 19% of homes analyzed were found to have an outlier month.

- Outliers occur most often across the three methods during the winter holiday season of December and January; analysis of the disaggregated end-use data indicates that these homes were generally over or under occupied as compared to normal operating conditions and that this over or under occupied state was not consistent throughout the different years of study. This indicates that when using monthly data to develop inverse models for residential buildings, it is important to be cautious when including these data points in the development such models – it may be preferable to treat these months separately and predict using a separate mechanism.
- In most cases the removal of the identified outlier improved the model performance and in some cases changed the model type assigned, most often from a 2P to a 3P or 4P model; however in other cases the outlier removal was detrimental to the model performance with out-of-sample data; therefore all identified outliers should not necessarily be removed.
- Occupant behavior, particularly for residential buildings, has an impact on the development and predictive performance of inverse models used to predict energy use of buildings, and can be the source of the occurrence of outliers in these models. Most of the studied residential buildings with an identified outlier month show that the outlier time period has notably different occupant-dependent energy end uses as compared to other times, i.e. there were a significant increase or decrease in loads such as large appliances (e.g. clothes washer, dryer, dishwasher), cooking appliances (e.g. kitchen appliances, microwave, range, oven), lighting, and/or plug loads. The use frequency, run time, and total electricity use in these major appliances are highly dependent on the number of occupants and their associated behaviors.

- The identification of appropriate methods for outliers detection in energy use prediction models is beneficial in that if such outliers are identified and adversely impact the ability of the model to predict energy use, as found with 20% of cases with identified outliers, the data point can be removed to improve the energy model predictions. If improved accuracy of the model can be achieved, this enables the ability of such energy model prediction methods to be more reliable and thus more trusted by the utility companies or by homeowners that may use these results to assess the energy performance of a building. This can lead to the more actionable results such as energy improvements or behavioral changes to improve efficiency. Secondly, if outliers are identified, this can also point to potential issues or inefficiencies in energy consuming systems that may need to be further investigated, such as a fault in an HVAC system.
- Most of the cases (80%) benefit from keeping the identified outlier months. These findings indicate that the removal of an identified outlier is not always merited.
- The methods that are best at identifying outliers that are detrimental to the model performance include (a) both the standard deviation and quartile method, or (b) all three methods. Therefore, these combination of methods are recommended methods for identifying outliers in need of removal for overall model performance improvement benefits.

This study focuses on residential single family homes located in the Austin, TX, a warm, humid region of the U.S. In addition, while the homes included in this dataset and occupants living in these homes have many similar characteristics to the U.S. building stock, they are not necessarily representative. Additional study is needed to understand the impacts of climate and variations in occupant characteristics on change point model development, as well as the occurrence, causes and treatment of energy use outliers. In addition, a small number of houses in the utilized dataset have a large variation in energy use, limiting the fit of the data to a change-point model and therefore the accuracy of prediction of electricity use. Further work is needed to determine if modified or alternative data-driven methods or modifications to the proposed approaches beyond those studied here may be better suitable for such homes. This effort is a strong starting point that, through further study, will help to realistically predict the presence and cause of such outliers and the likelihood that they will occur for homes even without highly detailed data.

3.5. Acknowledgements

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CHAPTER 4. IMPROVEMENT OF INVERSE CHANGE-POINT MODELING OF ELECTRICITY CONSUMPTION IN RESIDENTIAL BUILDINGS ACROSS MULTIPLE CLIMATE ZONES

Huyen Do and Kristen Cetin, "Improvement of Inverse Change-point Modeling of Energy Consumption in Residential Buildings across Multiple Climates", Energy, 2018 (Under Review).

Abstract

Inverse modeling is a common method to predict electricity consumption in buildings. Residential building electricity consumption can vary significantly due to occupants and their sporadic energy-consuming behaviors. In addition, variations in HVAC system types and characteristics across climate zones impact energy consumption patterns. This points to the need for the use of residential energy consumption data from a range of locations and homes for the assessment of the performance of inverse models and determination of model improvements. In this research, inverse change-point modeling methods are developed using monthly electricity use and outdoor weather data for 3,643 houses in four U.S. cities in three ASHRAE climate zones (2A, 4A, 5A). Approximately 40% of homes did not fit within recommended criteria for change-point model development following a common change-point modeling development sequence. Therefore, a modified version of the model development sequence is proposed, including (a) a segmented change-point model, and (b) change-point models with relaxed prerequisite criteria in the cooling or heating season. This both increases the number of homes with models from 60% to 71%, and improves the measures of goodness-of-fit by 13% (RMSE) and 8% (CV-RMSE), enabling improved prediction of energy use across a diversity of buildings and climate zones.

4.1. Introduction

In the recent past, the electricity consumption in residential buildings has increased, currently accounting for nearly 40% of total electricity consumption in the U.S. [1]. This increasing electricity use, given the current mix of generation sources in the U.S., has an influence on the environment, including the production of greenhouse gas emissions which negatively impacts climate change [2,3]. Therefore, it is of strong interest to reduce the electricity use in residential buildings as well as increase occupants' awareness of the use of energy-consuming end-uses.

The ability to develop a model that predicts the electricity consumption of a building based on historical data is an important aspect of many of common methods used to assess the impacts of energy efficiency upgrades, and methods used for energy savings performance contracting (ESPC) [4,5]. There are many types of models that have been developed in recent research to predict building electricity consumption, as summarized specifically for residential buildings in [6]. These data-driven or inverse models range significantly in complexity and input data requirements [6], including models such as change-point modeling [7,8], artificial neural networks [9,10], genetic programming [11,12], probabilistic graphic models [13-15], support vector machines [16-17], and occupant behavior models [18-19]. Most models use outdoor weather data such as outdoor temperature, solar radiation, wind speed, and/or relative humidity as the primary input data as predictors of electricity use in various data frequent levels. Among these types of model, change-point models are a simpler method that is typically appropriate with the use of monthly level data [6,7]. In comparison with other machine learning methods, this method also has lower computational effort but also has been found to be able to achieve similar levels of accuracy of electricity use predictions compared to other more complex methods [6,8].

For residential building there are often homes that have irregular use patterns of the energy-consuming building systems that make the prediction of energy consumption challenging using the above-mentioned methods. As compared to commercial buildings which typically operate on a more regular schedule, typically with a fairly predictable number of occupants and internal loads, residential buildings are highly dependent on the occupants and their energy-consuming behaviors, which are often more sporadic. For example, residential energy data collected and used in Do et al. (2018) [20] shows monthly energy use of some residential buildings ranged from 200 kWh/month to more than 1000 kWh/month for a single home (e.g. Figure 4.1), In addition, for similar weather months even where the heating, cooling, and ventilation (HVAC) energy use was similar, the energy consumption of a single home was also found to vary by more than two times. These differences are likely due to human behavior related energy consumption rather than the inherent performance of the building.

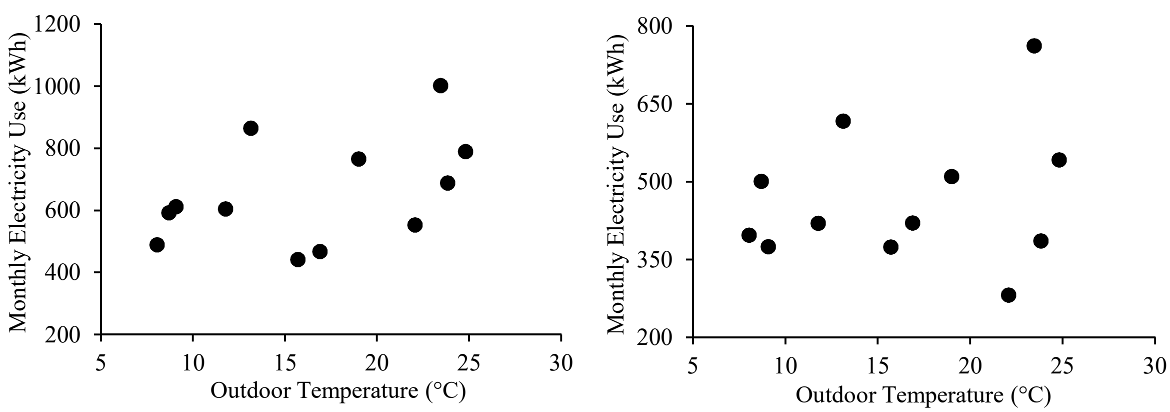

Figure 4.1 *Examples of high variable energy consumption in residential buildings (data from [20]).*

Currently, there is more publically available and/or accessible information and data on energy use in commercial buildings than residential buildings. Most previous studies on data-driven model development for energy use prediction have utilized commercial building data [8, 21-22]. This is, in part, due to the many, and increasing number of policies, laws and/or ordinances that support the public sharing of energy information, such as for energy benchmarking. This is particularly the case in many large U.S. cities, such as Boston [23], New York City [24], and Washington D.C. [25]. Energy information in residential buildings generally is associated with more privacy policies and laws on the sharing and use of this information [6]. This has generally translated to limited data availability, and thus more limited data sources which have been used to develop models for predicting residential building energy use. This limited data has translated to a less comprehensive understanding of the ability of available modeling methods for use in predicting energy consumption across the broad range and diversity of residential buildings that make up the U.S. building stock. In addition, factors such as the type of HVAC system, which significantly impact energy consumption patterns, vary significantly across regions and climate zones. This points to the need for the use of residential energy data from a range of locations in the U.S. for model development.

For approximately 50% of residential buildings in the U.S., the only available collected energy use data is monthly energy consumption [6]. Given this, this research focuses on improvements in the modeling of energy consumption of these buildings. As mentioned, for lower frequency energy consumption data, more simplified models are typically considered more appropriate for energy use prediction, one of the most common of which is change-point modeling. Change-point modeling methods are referenced in many energy performance standards (e.g. ASHRAE Guideline 14 [26], ASHRAE Standard 140 [27]). Change-point models are typically developed by using total energy consumption as dependent variable and outdoor weather data as predictor to decide the balance point in the type of five-, four-, three-, or two-parameter change-point models. To improve the ability of the existing models to predict electricity use of residential buildings, in this research a new sequence of change-point model development is proposed which includes modified versions of existing methods. These are termed a "segmented" change-point model, and a model with related requisite criteria. A dataset of electricity consumption data for a total of 3,643 residential buildings in four cities in the U.S. located in three ASHRAE climate zones is collected and analyzed to determine the appropriate sequence to better improve the performances of inverse change-point models and enhance the prediction of electricity consumption in residential buildings.

This research is organized into three main sections, including the methodology, results, and conclusion and future work. The proposed method for the improvement and evaluation of inverse change-point of energy consumption in residential buildings. The results section shows the comparisons between initial and improved sequences among the different homes and regions.

4.2. Methodology

The proposed methodology for the improvement and evaluation of inverse change-point modeling of energy consumption in residential buildings is summarized in Figure 4.2, including three major steps: (1) develop inverse change-point models using commonly-used methods [21,28,29], (2) develop the new proposed inverse change-point model method and sequence, and (3) evaluate each inverse change-point model to determine and compare the overall quality of fit of the models. The major inputs into this evaluation include energy use data from residential buildings in multiple climate zones and the corresponding weather data, enabling the evaluation of the proposed improvements across a diversity of weather conditions, locations, and buildings. In many cases in other related studies, the evaluation of such methods is limited to a small number of buildings and/or climate regions [8,21,22]. This diversity of input data is crucial to the assessment of the quality of fit of the methods as residential buildings are highly diverse [6]. The details of each major step are analyzed in following sections.

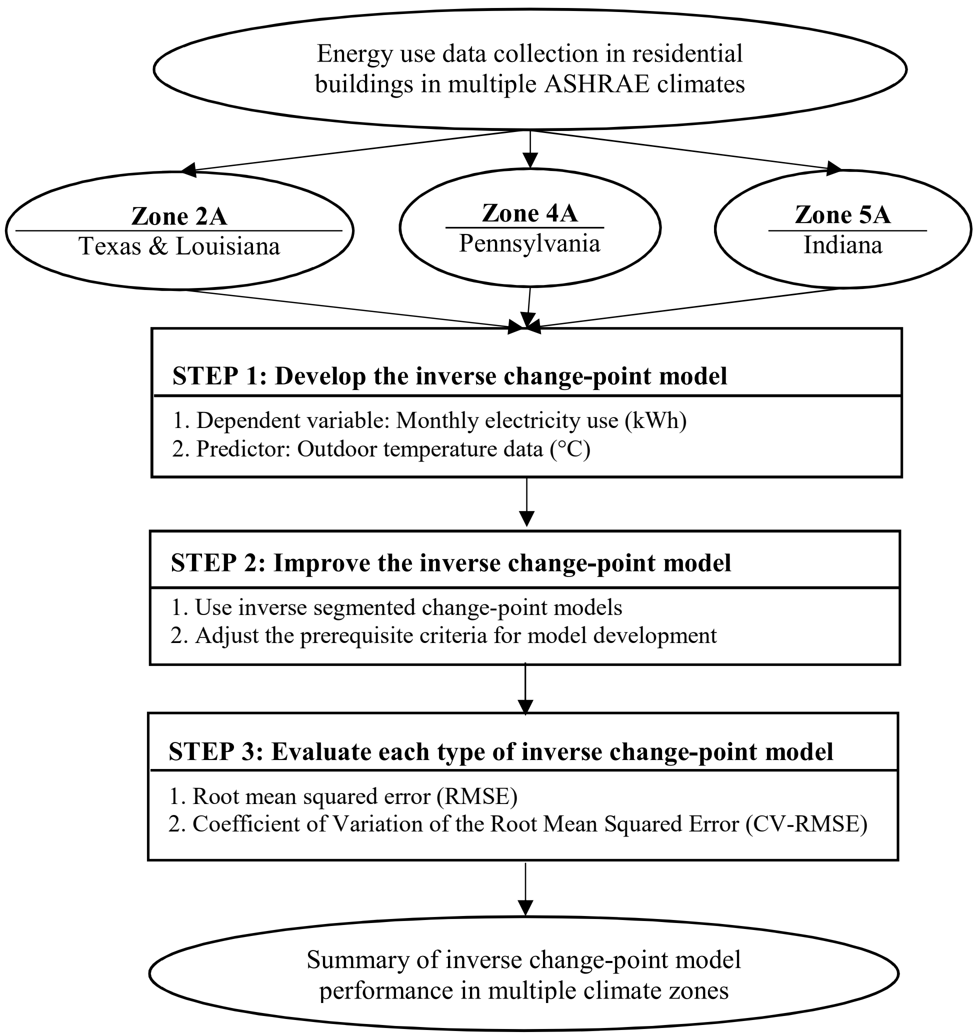

Figure 4.2 *Overview of methodology for improvement and evaluation of inverse modeling methods across multiple climate zones.*

Energy Use Data Collection in Residential Buildings through Multiple Climate Zones

The dataset of monthly electricity consumption was collected from residential buildings in four cities in the U.S., including New Orleans, Louisiana (1000 houses in ASHRAE hot-humid climate zone 2A), Houston and Austin, Texas (1,541 houses in

ASHRAE hot-humid climate zone 2A), Philadelphia, Pennsylvania (102 houses in ASHRAE mixed-humid climate zone 4A), and northern Indiana (1,000 houses in ASHRAE cool-humid climate zone 5A). In general, characteristics of residential buildings in these locations are similar [30]. An average 63%-66% of buildings are owner-occupied with an average of 2.5 people per home. The total annual household income in the four locations is also similar, including approximate 58%-61% of houses that have a household income under $60,000; 19%-24% of houses have income from $60,000 to $100,000; and 18%-22% with an income over $100,000.

Arguably, one of the most important characteristics of the studied homes that contributes to the electricity consumption in residential buildings is the type and characteristics of the HVAC system in each house. The distribution of HVAC system types in each climate region varies (Figure 4.3). ASHRAE climate zone 2A has the highest percentage of homes using air conditioning (94%) in the summer, with 65% using electricity-based heat (e.g. heat pump, baseboard heat, etc.). With the mixed climate (ASHRAE climate zone 4A), 86% use air conditioning in the summer and a nearly an equal number use electric heat (42%) and gas heat (43 %) in winter. For the cool climate region (ASHRAE climate zone 5A), most of the houses use both gas heat and air conditioning in heating and cooling seasons due to the high demand in both seasons.

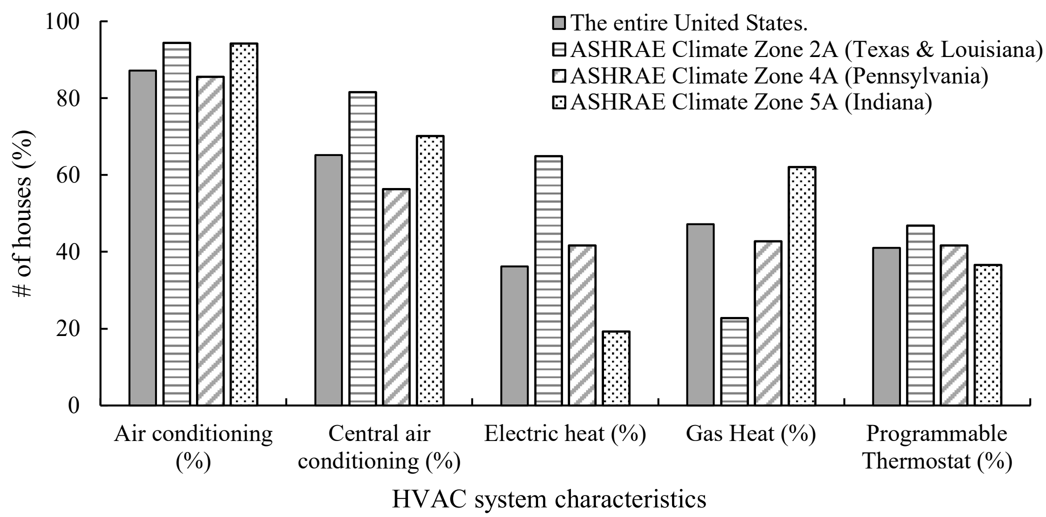

Figure 4.3 *HVAC system characteristics in residential buildings across the climate zones of studied homes.*

The electricity consumption data for residential buildings in these climate zones was controlled following the methods suggested by Cetin et al. (2015) [31]. Given that typical electricity monthly billing start and end dates are not consistent across all homes and are also often a slightly different number of days in each billing cycle, the electricity data for each billing cycle was normalized to 30 days per month across the entire dataset. The distribution of the normalized monthly electricity usage of residential buildings across multiple climate zones, including Louisiana, Texas, Pennsylvania, and Indiana is shown in Figure 4.4. Overall, the utilized data ranges from 2014 to 2016. Data is from November 2014 to December 2015 in Louisiana (14 months), from May 2014 to April 2015 in Texas (12 months), from April 2015 to January 2016 in Pennsylvania (10 months), and from January 2015 to April 2016 in Indiana (16 months) respectively. The average monthly electricity use in the studied locations varies (Figure 4.4). Pennsylvania has the highest average of 1,134 kWh/month; Louisiana and Texas have a similar distribution of monthly electricity use with an average of 1,037 kWh/month and 893 kWh/month respectively. Indiana has the lowest average of monthly electricity use among four studied locations (448 kWh/month), likely associated with the low use of electricity-based heating. Weather data utilized in this research is collected from the local airports within the vicinity of the studied residential buildings.

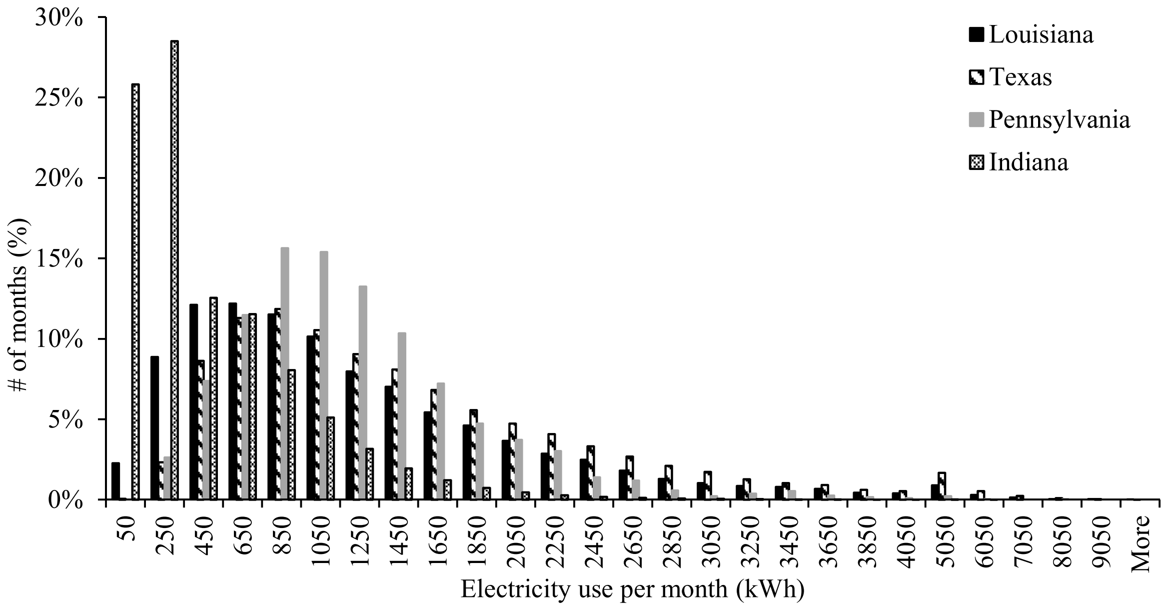

Figure 4.4 *Distribution of monthly energy usage data for residential buildings in Louisiana, Texas, Pennsylvania, and Indiana. (Note: The bin sizes utilized for electricity consumption of 5050 kWh/month and higher are larger; this is done to better show the tail of the distribution in this figure).*

Step 1 – Develop the Inverse Change-Point Model

To develop inverse change-point models for each residential building, an inverse single-variate model [7,8] is used with monthly electricity consumption as the dependent variable and outdoor temperature data as the predictor. Compared with an inverse multi-variate model or other forms of inverse models such as artificial neural networks (ANN) [9,10], genetic programming [11,12], Bayesian networks [13,15], or support vector machine [16-17], etc., an inverse single-variate model in the form of a change-point model is more statically appropriate [6], given the monthly-level frequency of data and the number of data points per home (from 10 to 16 data points for in-sample data). Previous studies' comparisons of the change-point modeling method to other models [8] have demonstrated the statistical accuracy of this model for this level frequency of data. For the predictor of the model, the outdoor temperature variable is the most commonly used and typically more statistically significant, in comparison other common weather variable such as solar radiation, wind speed, and relative humidity [6,7].

Inverse change-point models take different forms based on the number of parameters utilized each model, including the five-, four-, three-, and two-parameter change-point cooling and/or heating models [7,8]. The balance point in this model is represented by the base temperature that represents the transition between the heating and cooling seasons. The base temperature of inverse change-point model in each residential buildings was automatically chosen by custom-developed algorithm in MATLAB [21,32]. To choose the best fit of inverse model type in each house, the developed algorithm applies four prerequisite criteria that all must be passed for the final chosen model type, including a shape test, significance test, R^2 test, and data population test [21,32]. The shape test requires the appropriate slopes of the regression lines in the inverse change-point model [21]. A p-value of 0.05 is the required threshold for the significance test [21]. For the R^2 test, a coefficient of determination of 0.5 is required as an acceptable threshold to check the fit of model [21]. Finally, for the data population test, at least three data points are required in each portion of the regression line. A final type of inverse change-point model is chosen if these four prerequisite criteria are all passed. The sequence utilized to choose the best type of inverse change-point model from 5-parameter to 2-parameter is demonstrated in some previous studies [21,32]. If any of the prerequisite tests are failed for all of the change-point model types, no model is developed for the studied home and the home is considered to have no model.

Step 2 – Improve the Inverse Change-Point Model

To improve the inverse change-point model, and improve the number of inverse models developed in studied houses in each climate zones, a new sequence of inverse change-point model development is applied, including a new type of change-point model called as a “segmented” change-point model. The “segmented” model does not require the different segments of the change-point model to intersect. This new sequence also applies relaxed criteria of two of the four tests used when developing change-point models, including increasing the acceptable p-value and/or threshold of R^2. The improved sequence for development of inverse change-point (CP) models is represented in Figure 4.5. First is the development of inverse segmented/normal change-point models with 5-, 4-, 3-, and 2-parameter with all four tests checked. This step is similar to the common sequence in previous studies [6,7,21,32]. If the house does not satisfy with the criteria in the first step, the second model development is applied with relaxed two tests (significance and/or R^2 test) in the heating or cooling seasons. Several other sequences were considered, however the proposed sequence (Figure 4.5) was found to provide the most improvement in overall performance as compared to other model sequence orders.

Step 3 – Evaluate Each Type of Inverse Change-Point Model

The accuracy of each model is evaluated with the values of root mean squared error (RMSE), and coefficient of variation of the root mean squared error (CV-RMSE) with in-sample data and out-of-sample data. These values are common metrics used to assess the level of fit in prediction models, where RMSE evaluates the residual variance in the prediction model [33] and CV-RMSE evaluates the variability of the error between measured and model-predicted values, indicating the model's ability to predict the overall load reflected in the data [8]. CV-RMSE is also used in commonly referenced guidelines for building energy use predictions (e.g. ASHRAE Guideline 14 [26], International Performance Measurement & Verification Protocol (IPMVP) [34]).

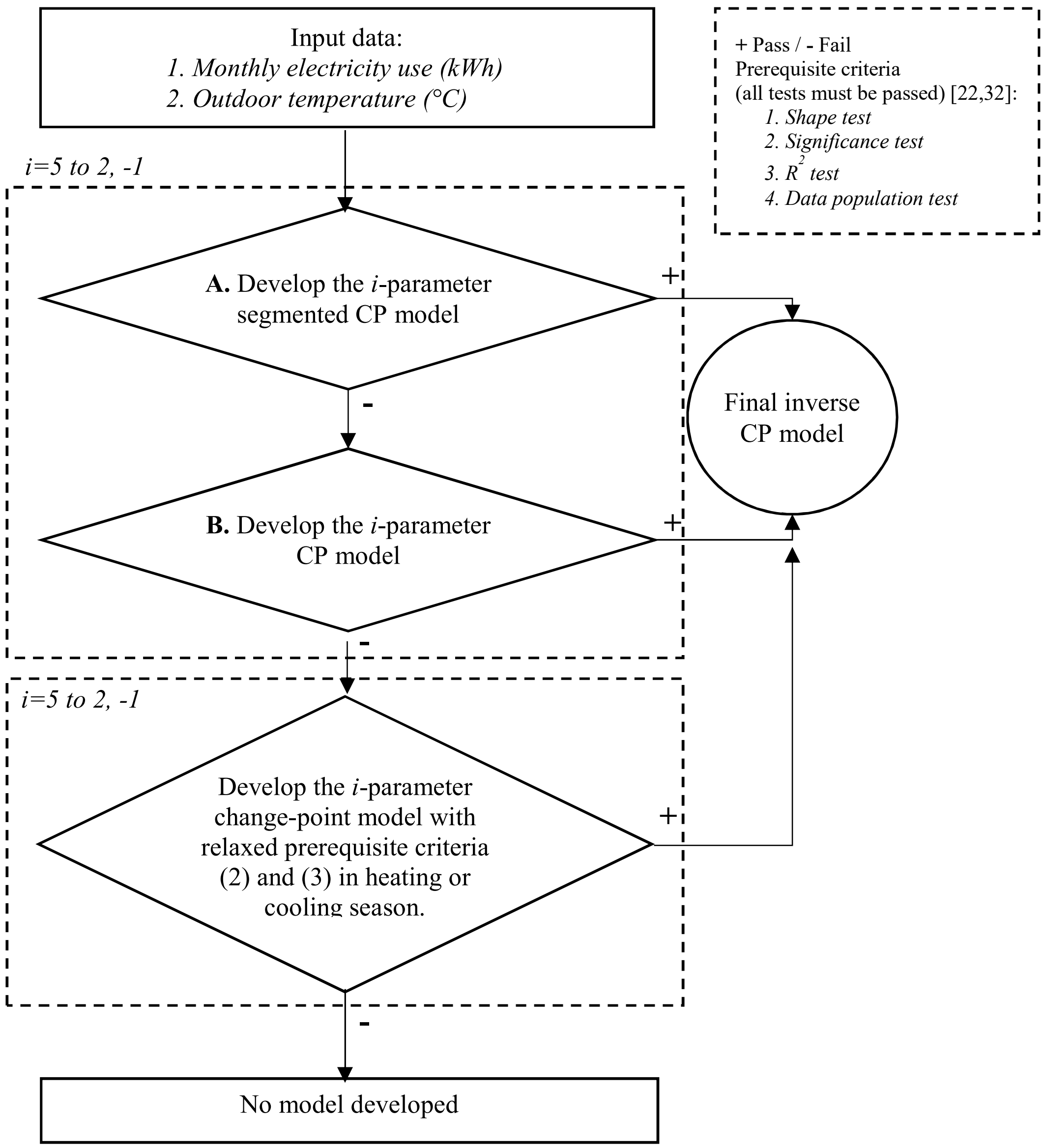

Figure 4.5 *Improved sequence for development of inverse change-point (CP) models. (Note: the "i=5 to 2, -1" indicates the number of parameters of the CP model is iterated in a loop starting with 5-parameter and decreasing sequentially to 2-parameter CP model).*

Based on these methods, the best-fit inverse change-point model is determined to be the model with the lowest values of RMSE and CV-RMSE using in-sample data. The out-of-sample data is used to evaluate the performance of prediction for each house.

Summary of Inverse Change-Point Model Performance in Multiple Climate Zones

The results are then compared among the climate zones, including the inverse model performance with the initial sequence (with only inverse change-point model) and improved sequence (with inverse change-point model, segmented inverse change-point model, and change-point model with relaxed prerequisite criteria in cooling or heating season).

4.3. Results and Discussion

Of the available data in each location of study, energy data from a total of 681 houses in Louisiana, 1133 in Texas, 68 in Pennsylvania and 301 in Indiana were used to develop the inverse change-point models using the commonly-used method [21,28,29] that includes outdoor temperature as predictor and monthly electricity consumption data as dependent variable (Table 4.1). The inverse models developed include the five-, four-, three-, and two-parameter change-point models. Examples of each type of inverse change-point model using the common sequence are demonstrated in Figure 4.6. Other houses from these locations have a high variation in monthly electricity consumption, therefore, these houses did not pass the prerequisite tests in the model development sequence. In other words, there is no model developed for these homes.

Based on these model designations, the types of HVAC systems in the residential buildings studied generally appear to be similar to that of the homes in the studied ASHRAE climate zones. Typically homes with 3-parameter heating, 4-parameter, or 5-parameter models represent homes with electricity-based heat, and 3-parameter cooling represents homes with gas-based heat. 62% of homes in the climate zone where the Indiana homes are located (ASHRAE climate zone 5A) use gas-based heat and 19% use electricity for heat, compared to 8% and 13% of inverse models developed respectively. Similarly, in Pennsylvania (ASHRAE climate zone 4A), the number of homes that have electric heat and gas heat is approximately 42% and 43% respectively, compared to 53% and 11% of the corresponding types of inverse models developed, respectively, in climate zone 4A. Approximately 48% of total homes in Texas and 20% in Louisiana have three-parameter change-point cooling models (Table 4.1). These values are slightly different from HVAC system characteristics in ASHRAE climate zone 2A where overall, approximately 23% of houses using electric heat. Given that the specific regions of study represent a smaller geographic location than the entire climate zone, some differences are expected.

Table 4.1 *Percentage of homes with different types of change-point (CP) model using the common sequence of inverse CP model development.*

Types of models	Louisiana	Texas	Pennsylvania	Indiana
5-parameter CP	8.4%	10.1%	14.7%	0.5%
4-parameter CP	28.9%	10.5%	19.6%	7.9%
3-parameter CP cooling	19.6%	48.2%	10.8%	7.9%
3-parameter CP heating	4.4%	1.0%	18.6%	4.9%
2-parameter CP cooling	6.2%	3.7%	2.9%	6.8%
2-parameter CP heating	0.6%	0.1%	0.0%	2.1%

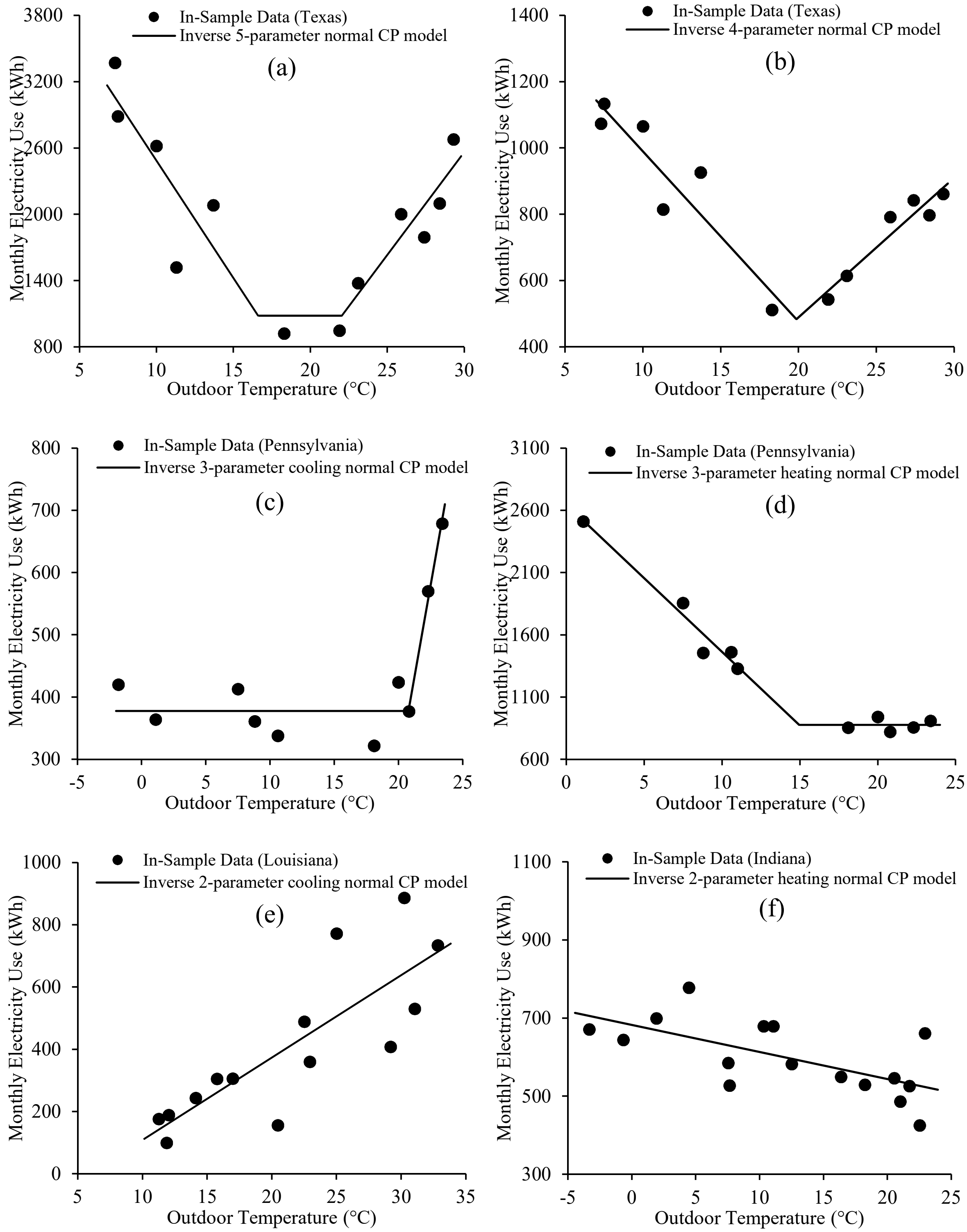

Figure 4.6 *Examples of inverse change-point models developed in each residential building with the common sequence in four locations in three ASHRAE climate zones.*

Following the proposed improved sequence of change-point modeling, the same data are then used to develop new models for these homes. Examples of inverse change-point models developed for each residential building with the proposed improved sequence in the four locations in three ASHRAE climate zones are included in Figure 4.7. In these examples, Figure 4.7a-d shows the inverse change-point segmented model; the inverse change-point model with relaxed prerequisite criteria in the cooling and heating season is shown in Figure 4.7e and 4.7f respectively. Overall, with the common sequence of model development, approximately 68%, 74%, 67%, and 30% of total of houses respectively across Louisiana, Texas, Pennsylvania, and Indiana have an inverse model developed (Table 4.1). However, with the improved sequence of inverse change-point model development, the number of houses that have models are significantly increased, including 71%, 84%, 69% and 60% respectively in each of the climate zones (2A, 4A, and 5A) (Table 4.2), or in total 71% of homes on average. Of particular improvement is Indiana (ASHRAE climate zone 5A), in which the number of homes with models increased from 30% to 60%. Using the improved sequence of inverse change-point model development, in all ASHRAE climate zones (2A, 4A, and 5A), an average of 35% of houses utilized the inverse change-point segmented model, 23% used the inverse change-point model, and 13% of houses used the inverse change-point models with relaxed prerequisite criteria in cooling and/or heating seasons. The improved sequence of inverse change-point model development enables an additional 11% of total houses to have a model with an acceptable level of fit that did not have a model with the initial sequence (Table 4.3).

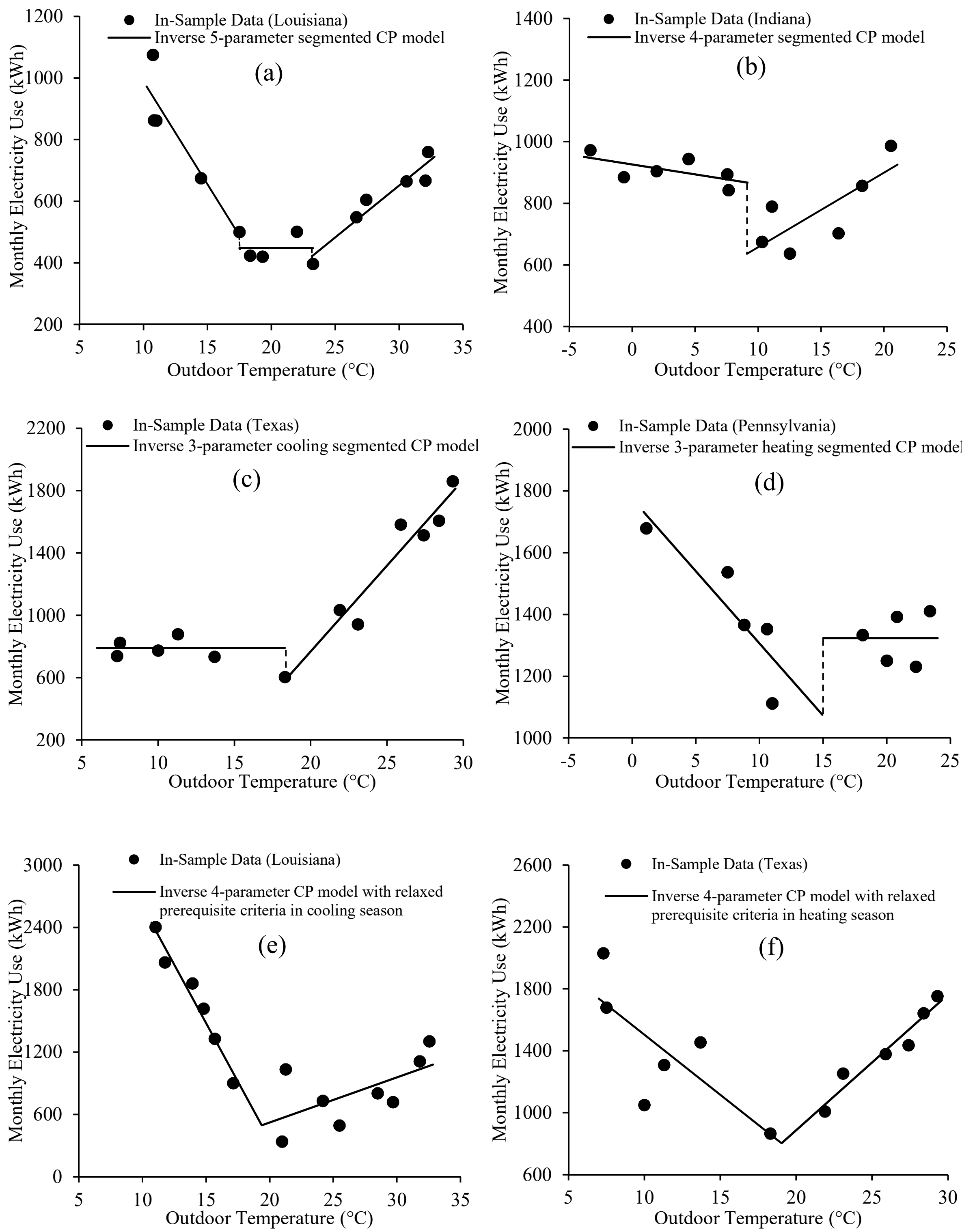

Figure 4.7 *Examples of inverse change-point models developed in each residential building with the improved sequence in four locations in three ASHRAE climate zones. (Note: Figure 6a-d: inverse change-point segmented model, Figure 6e: Inverse Change-point model with relaxed prerequisite criteria (2) and (3) in cooling season, Figure 6f: Inverse Change-point model with relaxed prerequisite criteria (2) and (3) in heating season).*

Table 4.2 *Percentage of homes with different types of change-point (CP) model using the improved inverse CP model sequence (from Figure 4.5).*

Types of models	Louisiana	Texas	Pennsylvania	Indiana
5-parameter segmented change-point	21.6%	9.9%	19.6%	22.1%
5-parameter change-point	0.8%	3.6%	3.9%	0.2%
4-parameter segmented change-point	3.1%	1.0%	4.9%	1.5%
4-parameter change-point	5.6%	2.1%	4.9%	2.5%
3-parameter change-point segmented cooling	14.8%	6.9%	7.8%	13.6%
3-parameter change-point cooling	10.9%	44.4%	2.0%	4.7%
3-parameter change-point segmented heating	1.5%	0.8%	4.9%	4.6%
3-parameter change-point heating	0.4%	0.0%	1.0%	0.1%
2-parameter change-point cooling	0.7%	2.1%	1.0%	0.1%
2-parameter change-point heating	0.0%	0.1%	0.0%	0.2%
* Change-point segmented model with relaxed prerequisite criteria (2) and (3) in cooling season	1.6%	0.3%	2.0%	1.9%
* Change-point model with relaxed prerequisite criteria (2) and (3) in cooling season	1.1%	0.2%	2.9%	3.1%
* Change-point segmented model with relaxed prerequisite criteria (2) and (3) in heating season	3.7%	2.6%	6.9%	2.3%
* Change-point model with relaxed prerequisite criteria (2) and (3) in heating season	4.7%	9.9%	6.9%	3.5%

Note: Prerequisite criteria (2) is significance test, and prerequisite criteria (3) is R^2 test.

Table 4.3 *Improvements in the percentage of homes with change-point (CP) models assigned using improved sequence.*

% of houses	Louisiana	Texas	Pennsylvania	Indiana
% of houses with no model developed from initial sequence	31.9%	26.4%	33.3%	69.9%
% of houses with no model developed from improved sequence	29.5%	16.2%	31.4%	39.6%
% of houses that have CP model using improved sequence that did not with the initial sequence	**2.4%**	**10.2%**	**1.9%**	**30.3%**

To compare the model fitness using the initial sequence and the improved sequence, both the in-sample electricity consumption data in the three ASHRAE Climate Zones and out-of-sample electricity consumption data, where available, are used (Table 4.4). As mentioned in methodology section, the values of model fitness coefficients such as RMSE and CV-RMSE are applied to compare the accuracy and performance of inverse models developed. For both RMSE and CV-RMSE, the lower the values, the better model performance. Therefore, any sequence that has the better model fitness with in-sample data and better prediction with out-of-sample data is considered to overall be the better model development sequence to forecast the monthly electricity consumption in residential buildings. The results of evaluation of model fitness quality of each type of inverse change-point model using both initial and improved sequences are shown in Table 4.4.

Table 4.4 *Evaluate the quality of model fitness of each type of inverse change-point model using both initial and improved sequences.*

Average values of coefficients of model fitness	In-sample data				Out-of-sample data		
	Louisiana	Texas	Pennsylvania	Indiana	Louisiana	Texas	Pennsylvania & Indiana
A. Initial sequence	***n = 681***	***n = 1133***	***n = 68***	***n = 301***	***n = 681***	***n = 1133***	**-**
RMSE	*176.0*	*168.3*	*146.7*	*153.7*	*268.8*	*389.3*	-
CV-RMSE	*16.4%*	*12.8%*	*13.5%*	*19.5%*	*27.1%*	*22.7%*	-
B. Improved sequence	***n = 705***	***n = 1291***	***n = 70***	***n = 604***	***n = 705***	***n = 1291***	
RMSE	*157.4*	*153.5*	*126.4*	*127.6*	*261.9*	*303.3*	-
CV-RMSE	*15.4%*	*11.7%*	*12.3%*	*18.0%*	*26.1%*	*21.1%*	-
1. CP models	*n = 184*	*n = 804*	*n = 13*	*n = 78*	*n = 184*	*n = 804*	
RMSE	128.6	142.3	140.0	101.1	236.4	276.2	-
CV-RMSE	13.2%	10.8%	*10.7%*	14.8%	21.8%	19.1%	-
2. Segmented CP models	*n = 410*	*n = 288*	*n =38*	*n = 418*	*n = 410*	*n = 288*	
RMSE	170.3	167.8	125.5	135.2	267.3	360.1	-
CV-RMSE	16.0%	12.8%	*13.2%*	19.0%	26.8%	21.4%	-
3. CP models with relaxed prerequisite criteria in cooling or heating season	*n = 111*	*n = 199*	*n = 19*	*n = 108*	*n = 111*	*n = 199*	
RMSE	187.4	189.1	148.7	156.7	284.2	374.3	-
CV-RMSE	16.9%	14.3%	*13.6%*	19.1%	30.7%	26.6%	-

Note: RMSE = Root mean squared error, CV-RMSE = Coefficient of Variation of the Root Mean Squared Error.

First, for in-sample data, with the commonly used sequence of inverse change-point model development, the values of RMSE and CV-RMSE are 161.2 and 15.6%, on average, respectively among the three climate zones. However, with the new sequence of inverse change-point model development, the RMSE and CV-RMSE are lower, at 141.2 and 14.3% respectively, representing an approximately 12% and 8% improvement in these values. In addition, the RMSE values for the change-point models, segmented change-point models, and change-point models with relaxed prerequisite criteria in the cooling and/or heating seasons in the three ASHRAE climate zones are 128, 149.7 and 170.5 respectively. Similarly, the CV-RMSE values for each type of inverse models using the improved sequence are, on average, 12.4%, 15.3%, and 16.0% across the dataset. From these results of RMSE and CV-RMSE using in-sample data, it is clearly seen that the improved sequence of inverse change-point model development enhanced the quality of model fitness in four locations in three ASHRAE climate zones.

The accuracy of prediction from inverse models using both the initial and improved sequence with out-of-sample data in two locations (Louisiana and Texas) with sufficiently longer periods of data collection is next evaluated. From the initial sequence of inverse change-point model development, the average values of RMSE and CV-RMSE are 329.1 and 24.9% respectively, while these values are lower with the improved sequence, at 282.6 and 23.6% respectively. More specifically the RMSE are 256.3, 313.7, 329.3 and the CV-RMSE are 20.4%, 24.1%, and 28.6% respectively, on average, for the change-point model, segmented change-point models, and change-point models with relaxed prerequisite criteria. Overall, improved sequence of inverse change-point model development performs better with both in-sample data and out-of-sample data.

The evaluation of the values of RMSE and CV-RMSE in this research follows industry guidelines for electricity use in buildings including ASHRAE Guideline 14 [26] and the International Performance Measurement & Verification Protocol (IPMVP) [34]. The average value of CV-RMSE under the improved sequence of inverse change-point model development is 14.3% and thus below the industry guidelines threshold of 15% for monthly data. A recent previous study of Do et al. (2018) [32] which applied the original sequence of inverse change-point model development for electricity consumption in residential buildings had average values of RMSE and CV-RMSE for the developed change-point models of 160.4 and 17.2% respectively. In this research, by using the improved sequence of inverse change-point model development, improved both the RMSE and CV-RMSE values across the datasets (141.2 and 14.3% respectively) are lower and thus demonstrate better fit on average. In addition, these values are also significantly lower than the machine learning methods assessed in the previous study [32] using monthly electricity use data; the ANN (artificial neural network) that has average value of 386.8 for RMSE and 44% for CV-RMSE. The values of RMSE and CV-RMSE using the improved sequence of model development in this study are also lower than values in other studies such as 14.96% for CV-RMSE in research of Zhang et al (2015) [8] with hourly energy use data, and 17.2% for CV-RMSE in the study of Kim et al (2015) [35]. Therefore, in other words, the model fitness for electricity use prediction are significantly improved, even with a highly diverse dataset of data, with the proposed improved sequence of inverse change-point model development.

4.4. Conclusions

Inverse change-point modeling is a commonly used method to predict the electricity consumption in buildings. For many buildings, particularly those with consistent energy consumption patterns, inverse change point modeling methods can provide sufficiently accurate predictions of energy consumption, particularly at the monthly energy consumption data level. However, with the high dependency of residential energy consumption on the potentially significant variations in occupant behavior and use of occupant-dependent loads, variations in electricity consumption patterns in residential buildings occur. Particularly across the diverse dataset utilized in this work, over 40 % of studied houses in the four cities in three ASHRAE climate zones were found to not fit the inverse change-point model development criteria following the four prerequisite tests often utilized for model development. Therefore, in this research, a modified version of the initial inverse model development sequence is proposed, improving the number of houses that have a model and enhancing the quality of prediction. This modified version, including an inverse segmented change-point model technique and an inverse change-point model with relaxed prerequisite criteria in cooling or heating season, improved the RMSE values by 13%, and CV-RMSE values by 8% across the studied dataset. This improved sequence of inverse change-point model development also reduced the number of houses in the three ASHRAE climate zones that do not have a model developed from 40.4% to 29.2%. These results demonstrate that this improved sequence works well and enables better quality prediction of energy consumption of residential buildings. There are a range of applications of this effort, such as in energy performance contracting, and energy efficiency evaluation of residential buildings. This will help both owners of residential buildings and energy contractors be able to evaluate building performance.

This research focuses on the electricity consumption in residential buildings located in four cities in three ASHRAE climate zones (hot-humid climate zone 2A, mixed-humid climate zone 4A, and cool-humid climate zone 5A). The characteristics of the homes in these dataset and occupants who are living in these homes vary, including the characteristics of the HVAC systems, therefore the types of inverse change-point models also vary. While it has proven to be challenging to gather residential energy consumption data in the U.S. due to privacy issues [6], further studies in this area would help to assess residential energy consumption patterns and change point model performance across a broader range of homes, HVAC systems and climate zones.

4.5. Acknowledgements

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CHAPTER 5. DATA-DRIVEN EVALUATION OF RESIDENTIAL HVAC SYSTEM EFFICIENCY USING ENERGY AND WEATHER DATA

Huyen Do and Kristen Cetin, "Data-driven evaluation of residential HVAC system efficiency using energy and weather data", Energy and Buildings, 2018 (In preparation)

Abstract

In the U.S., the heating, ventilation, and air conditioning (HVAC) system is generally the largest electricity-consuming end use in a residential building. The most common methods used to assess a residential HVAC system's performance are a home energy audit or regular HVAC system service check. However, as compared to commercial buildings, residential buildings are less likely to have their system serviced on a regular basis; such services also require the presence, engagement, and time from the homeowner. To overcome these barriers, this research works towards a non-intrusive data-driven assessment tool that uses a range of data sources, including building assessors data, HVAC energy demand data, indoor environmental conditions, and outdoor weather data to assess an HVAC system's operational performance and efficiency. Assessors' data on the size, location, and age of the building is used to estimate the system size for the HVAC indoor and outdoor units. This is then used to determine the electricity demand curve of the HVAC system as a function of outdoor temperature. The developed model's electricity demand prediction is compared to the energy demand predicted from a detailed HVAC modeling program, ACHP, finding strong agreement between the models. This program is then used to determine the impact of the level of HVAC system condenser airflow reduction fault on the electricity demand curves. Detailed data for 32 occupied, conditioned residential buildings in Austin, Texas are then used to determine an HVAC efficiency rating. The results of this work should prove beneficial for homeowners and for service technicians to help target HVAC systems in

homes in need of HVAC service or energy efficiency upgrades, ultimately motivating improved sustainability of residential buildings

5.1. Introduction

Residential building electricity consumption makes up approximately 40% of total electricity use in the U.S. [1,2]. Many factors impacts the electricity use in the residential buildings, including weather conditions, size of houses, building characteristics such as window and building envelope properties, air infiltration and ventilation, occupant behavior, and occupant-dependent end-uses, among others [3,4]. However, in the U.S., the heating, ventilation, and air conditioning (HVAC) system is among the largest electricity-consuming end use in a home [5]; its energy demand is associated with the amount of heat gains and losses in a building, as well as its size, efficiency, thermostat set points, and the local environmental conditions in which it operates.

The completion of a home energy audit or HVAC system tune up are among the most common methods used to assess residential HVAC system energy efficiency and performance [6], and are often completed by a service technician who comes to the residence in person for an onsite evaluation of HVAC operations. Based on the results, recommendations of how to improve inefficiencies of the HVAC system are then made to the homeowner. This is often done by or in collaboration with programs in many utility companies that provides incentives and rebates for more energy-efficient HVAC systems or other upgraded components [7].

However, the main challenge when achieving efficiency improvements for HVAC systems in residential buildings is the periodic occurrence of inefficiencies, i.e. faults, that still allow the HVAC system to run, but in a less efficient way. These faults likely go undetected, until either the system is serviced or the inefficiency is corrected, or until a more catastrophic failure occurs and the system is replaced. However, unlike commercial systems, most homeowners do not have their HVAC system regularly serviced [8,9], and rather, they service their system when something occurs that makes the system non-operational. As a result, survey results indicate that a large number of residential HVAC systems are considered to be operating in a faulty state [9]. This typically impacts both the energy demand (kW) associated with the operation of the system, as well as the cycle length (minutes) associated with the system's on-off operation. Therefore, to overcome the barrier of requiring a visit from an HVAC technician and homeowner time to assess the efficiency of operation of a system, it is beneficial to have a less intrusive method, and more frequent method to evaluate the efficiency of an HVAC system in a residential building and recommend efficiency improvements for homeowners.

Due to the development and implementation of many state-of-art technologies such as smart meters and home energy management systems [10], as well as the now ubiquitous availability of the internet and cloud storage, computing, obtaining, storing, and processing data related to the energy performance of residential systems, while still challenging, has become more accessible in recent years. This availability has also benefited from the wider spread commercialization of technologies that can collect energy data [11]. Data can be collected at different frequencies depending on the technology utilized for data collection. Frequencies vary from monthly, hourly, 15-minute, or 1-minute intervals, with some technologies providing data at the second and sub-second level. The other data that is needed to support the evaluation of the operation of an HVAC system including indoor temperature, is also more easily collected, stored, and accessed from smart thermostats. Weather data continues to be available from various public sources, from ground-based weather stations

(GBWS). Additionally, significant improvements have also been made in availability of satellite-based weather data available in more locations than GWBS (e.g. [12]).

This research focuses on the development of a methodology that uses energy data, and weather data to, first, predict residential HVAC energy demands. This is ultimately used to assess the efficiency of operation of the HVAC system itself, independent of the influence that occupants may have on HVAC operation. More specifically, when looking at the information that can be extracted from an energy use signal of an HVAC system, the energy demand (kW) depends only on the characteristics of the HVAC system itself and the environmental conditions in which it is operating. Runtime values and energy consumption also depend on the characteristics of the HVAC system, but are also dependent on the interior temperature set points set by occupants, and occupant behavior. Therefore the focus of this work is on energy demand as a proxy for evaluation of efficiency.

This research works towards an assessment tool that can be used to assess in real-time, the energy efficiency of HVAC system in residential buildings without the need for more traditional methods such as more costly, time intensive, and intrusive energy audits. The focus of this work is on developing a method that can be utilized which does not require information or engagement from the homeowner, and strictly uses data that can be obtained from energy use data and assessor's data (e.g. building conditioned area). Detailed energy and weather data, and building assessor data for 32 occupied, conditioned residential buildings in Austin, Texas are used for evaluation of this method, as well as the results of an analytical HVAC model for a case study home. The results of this work should prove beneficial for homeowners and also for service technicians to help target HVAC systems in homes in need of HVAC service or energy efficiency upgrades, ultimately motivating improved sustainability of residential buildings.

5.2. Methodology

To predict the efficiency of operation of a residential building HVAC systems, the following methodology is developed and followed in this work. This includes several stages, including, first (Figure 5.1) the utilization of data collected on basic building characteristics to determine the most probable size of the HVAC system. This is among the more challenging features to estimate without detailed system-level data, however typically HVAC system data is not typically available except through an on-site energy audit or service call. Next is the development of a model to predict the HVAC system electricity demand as a function of outdoor and indoor temperature and humidity levels. The final stage is the energy efficiency evaluation of the system (Figure 5.2).

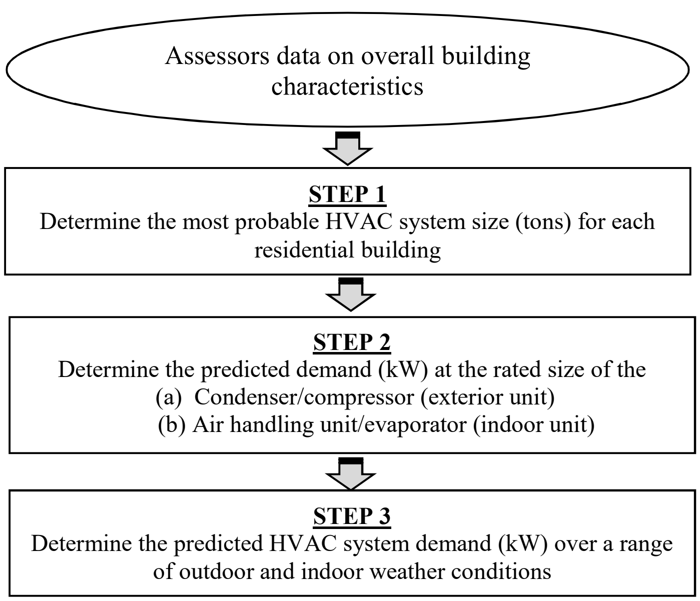

Figure 5.1 *Methodology for estimating HVAC electricity demand in residential buildings.*

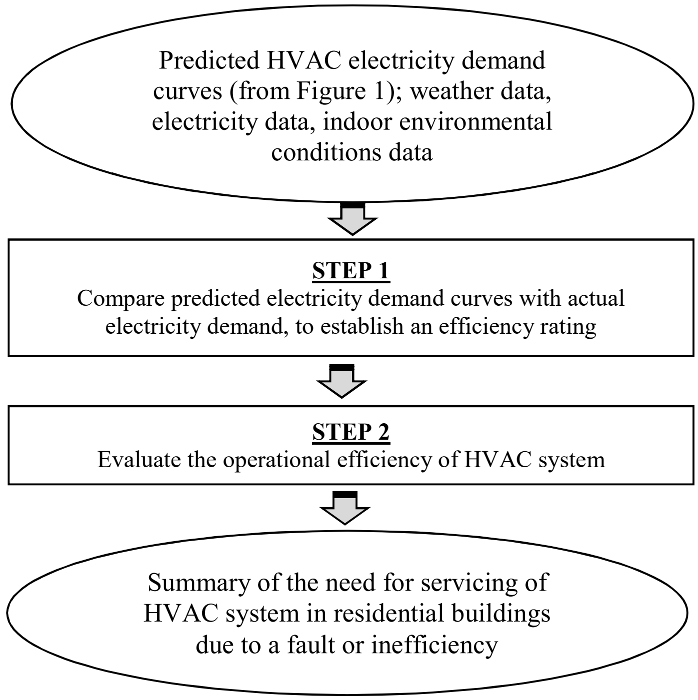

Figure 5.2 *Methodology for evaluation of residential HVAC performance efficiency.*

5.2.1. Prediction of HVAC Demand in Residential Buildings

Step 1 - determine most probable HVAC system size (tons) for each residential building

To determine the most accurate estimates of residential heating and cooling loads for the right sizing of HVAC equipment, it is generally recommended to use calculation methods in Manual J from the Air Conditioning Contractors of America (ACCA) [13]. This method utilizes information on many aspects of a building's thermal characteristics such as wall, floor, roof, windows, and door types, basement characteristics, expected indoor/outdoor temperature and humidity levels, etc... [13,14]. However the significant number of inputs and information needed to complete the Manual J calculations are not readily available for a utility company or other party attempting to assess HVAC performance of a large number of homes, without a detailed audit of the building. Assessor data (e.g. [15,16]) generally includes information such as the age of house, year of occurrence and type of any major improvement, total conditioned area, building style, exterior wall material, number of total rooms, bedrooms, and bathrooms, fuel type, HVAC system type, presence of a basement, etc. Thus assuming there is only publically-available assessors data as a worst-case scenario, this research proposes a method that uses this limited data to determine the most probable HVAC size. Several different methods are explored for estimating HVAC size. For the first method, an analysis of the 72 homes in the Austin, TX area where home area and HVAC size (Figure 5.3) is available from the utilized dataset, indicates that the average size of the HVAC system per squared-meter of conditioned area is approximately 0.016 (tons/m^2).

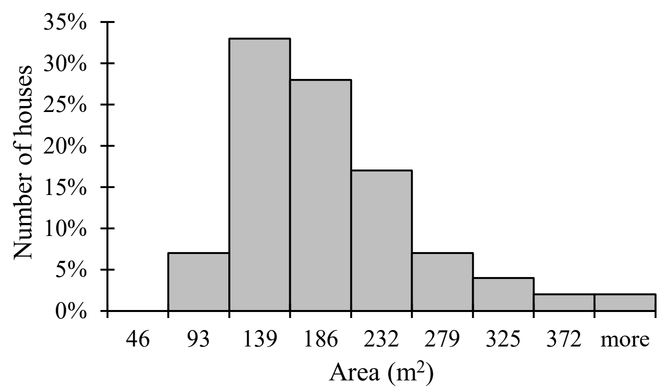

Figure 5.3 *Conditioned area (m^2) for houses in the utilized Austin, Texas dataset.*

The distribution of HVAC sizes per unit areas (standard deviation of 0.0027) indicates there is some uncertainty associated with this estimate; however of the potential predictor variables available in assessors data, the conditioned area was the most significant (p-value = 0.0007×10^{-5}, R-square = 0.678). The second method considered is an industry rule of thumb, cited in a number of publications (e.g. [17]), where the HVAC size (*S,* in tons) is approximated as follows (Equation 5.1), where *A* is conditioned area (m^2):

$$S = \frac{A \times 0.093}{400} - 1 \qquad (Eq.\ 5.1)$$

The last method is broken up generally by U.S. climate regions from the residential energy consumption survey (RECS) (Figure 5.4, Table 5.1) [18,19]. Houses in Austin, are in Zone 1.

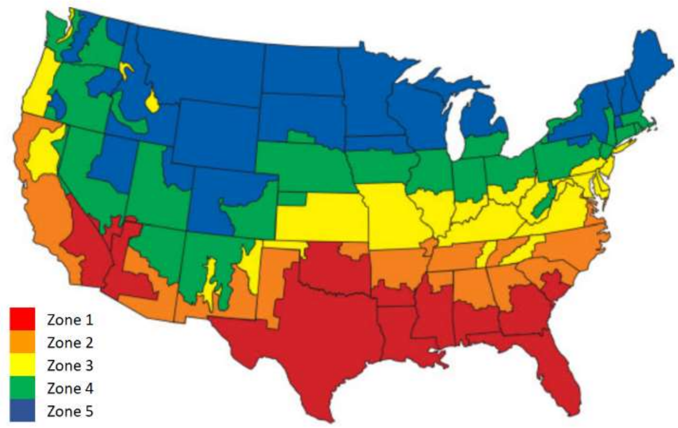

Figure 5.4 *U.S climates zones for Residential Energy Consumption Survey [19].*

Table 5.1 *ASHRAE climate zone ranges [18].*

Size	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
1.5 tons	56 – 84 m^2	56 – 88 m^2	56 – 93 m^2	65 – 98 m^2	65 – 102 m^2
2 tons	84 – 111 m^2	88 – 116 m^2	93 – 121 m^2	98 – 125 m^2	102 – 130 m^2
2.5 tons	112 – 138 m^2	116 – 144 m^2	121 – 149 m^2	126 – 149 m^2	130 – 153 m^2
3 tons	139 – 167 m^2	144 – 172 m^2	149 – 177 m^2	149 – 186 m^2	153 – 195 m^2
3.5 tons	167 – 195 m^2	172 – 200 m^2	177 – 204 m^2	186 – 209 m^2	195 – 214 m^2
4 tons	195 – 223 m^2	200 – 232 m^2	204 – 242 m^2	209 – 251 m^2	214 – 251 m^2
5 tons	223 – 279 m^2	232 – 288 m^2	242 – 297 m^2	251 – 307 m^2	251 – 307 m^2

Step 2 - determine the predicted demand (kW) at rated size of the exterior/ indoor units

The sizing and efficiency rating of the HVAC system must then be converted to a cooling capacity (kW) at design conditions. The rated capacity of an HVAC system is based on the AHRI (Air-Conditioning, Heating, and Refrigeration Institute) design conditions (Table 5.2) [20]. While there are a range of rating conditions used to evaluate parameters such as energy efficiency ratio (EER) and coefficient of performance (COP), which are then used to calculate the seasonal energy efficiency ratio (SEER) and/or heating seasonal performance factor (HSPF), of these conditions, two standard rating conditions are generally accepted by industry to be used for evaluating HVAC capacity. These include, for the cooling season, the rated value is associated with an outdoor dry bulb temperature of 35ºC; and for the heating season, the outdoor dry bulb temperature is 8.33ºC.

Table 5.2 *AHRI design conditions for indoor/outdoor units [20].*

AHRI design conditions	Air entering indoor units		Air entering outdoor units (°C)	
	Dry-bulb (°C)	Wet-bulb (°C)	Dry-bulb (°C)	Wet-bulb (°C)
Cooling	26.7	19.4	35	23.9
Heating	21.1	15.6	8.33	6.11

A SEER value must also be determined or assumed. If available, the HVAC system model numbers can provide information on the efficiency of the system [21], however this data is not always available for use, particularly in a public dataset. Per ASHRAE Standard 90.1 [22], currently a minimum efficiency of SEER 13 or 14 is required in the U.S. for residential systems, depending on the location and climate zone where the system is installed. However, this does not mean that the HVAC system being evaluated using this method will be at this level of efficiency. Previous versions of ASHRAE Standard 90.1 [22] required lower SEER ratings, thus it is likely that older systems will have a lower SEER value. For the purpose of development of the proposed methodology, in the development of the predicted HVAC electricity demand curve, it can be assumed that the SEER value is the code-required value, as the purpose of the results of this analysis method is to determine if a system is less efficient than is ideal (i.e. code-required, properly functioning system). The implications of this are, if the system under evaluation is not a SEER 13 or 14 (i.e. it is lower efficiency), the results of the use of the developed method will indicate the system is less efficient than predicted, regardless of if an operational inefficiency or fault exists. This is determined to be acceptable, as the purpose of the proposed method is to identify if the system is less efficient than desired, regardless of cause, to indicate that there are opportunities for improvement as compared to code minimum. Using the determined size (*S*, tons) and SEER value, the HVAC capacity (*C*, kW) of the exterior unit is estimated as follows in Equation 5.2:

$$C = \frac{S \times 12}{(1.12 \times SEER - 0.02 \times SEER^2)} \qquad (Eq.\ 5.2)$$

The total or net demand of the HVAC system ($\dot{Q}_{total,rated}$, *W*) at design conditions includes the electricity demand of both the indoor and outdoor units. Thus in addition to the predicted demand at design conditions for the outdoor unit, the indoor unit's fan's electricity demand must also be predicted. The indoor fan capacity is assumed at 0.365 W/cfm with the flow rate of 400 cfm/ton [23]. The 0.365 W/cfm is the AHRI default value for fan efficiency if the information about the indoor fan is unknown in ANSI/AHRI Standard 210/240 [23]. The total demand of the HVAC system is then taken to be the demand from both the indoor and outdoor units combined.

Step 3 - determine the predicted HVAC system demand (kW) over a range of outdoor and indoor weather conditions

Using these design conditions, a set of empirical equations is used to relate the estimated size and design conditions to an estimated energy demand over a range of environmental conditions. These equations follow the direct expansion (DX) model utilized in EnergyPlus [24] to simulate DX equipment. This includes several biquadratic functions, with the values of the dependent variables being the design conditions listed in Table 5.2, where T_{ewb} and T_{odb} are the entering wet bulb temperature and outdoor dry bulb temperature, respectively. These equations take the following form (Equation 5.3), where the coefficients *a* through *f* are determined based on laboratory test data of residential systems collected in [20].

$$y = a + b * T_{ewb} + c * T_{ewb}^2 + d * T_{odb} + e * T_{odb}^2 + f * T_{odb} * T_{ewb} \qquad (Eq.\ 5.3)$$

The power gross demand ($\dot{P}_{gross}$, *W*) is calculated as a function of the energy input ratio *(EIR)* and the total cooling and/or heating capacity ($\dot{Q}_{total}$, *W*) (Equation 5.4) [20]. By combining the power gross demand ($\dot{P}_{gross}$, W) and the calculated indoor fan capacity ($\dot{P}_{fan}$, *W*), the power net demand or the predicted HVAC system demand ($\dot{P}_{net}$, W) is determined. The flow fraction (*FF*) and runtime fraction (*RTF*) are assumed to be 1 for purpose of this work. The values of *EIR* and $\dot{Q}_{total}$ are calculated using Equation 5.5 and 5.6, where $EIR_{f(T)}$ and $\dot{Q}_{f(T)}$ are the normalized energy input ratio curve and the normalized total cooling and/or heating capacity curve that are calculated as a function of T_{ewb} and T_{odb} [20]. Since the flow fraction is assumed to be 1, $EIR_{f(FF)}$ and $\dot{Q}_{f(FF)}$ are also assumed to be 1, leaving the calculation of *EIR* and $\dot{Q}_{total}$ as a function of T_{ewb} and T_{odb}.

$$\dot{P}_{net} = \left(EIR \times \dot{Q}_{total} \times RTF\right)_{gross} + \dot{P}_{fan} \qquad (Eq.\ 5.4)$$

$$EIR = EIR_{rated} \times EIR_{f(T)} \times EIR_{f(FF)} \qquad (Eq.\ 5.5)$$

$$\dot{Q}_{total} = \dot{Q}_{total,rated} \times \dot{Q}_{f(T)} \times \dot{Q}_{f(FF)} \qquad (Eq.\ 5.6)$$

The values of the coefficients (a through f) in each of the equations for $EIR_{f(T)}$ and $\dot{Q}_{f(T)}$ are determined based on laboratory-collected data from a range of residential HVAC systems [20], and are summarized in Table 5.3.

Table 5.3 *The curve coefficients of the energy input ratio and total capacity as a function of dry bulb and wet bulb temperature [20]*

Coefficients	Energy input ratio	Total capacity
a	-3.3026959	3.6702707
b	0.1378715	-0.0986524
c	-0.0010570	0.0009559
d	-0.0125739	0.0065524
e	0.0002146	-0.0000156
f	-0.0001451	-0.0001319

5.2.2. Evaluation of HVAC Energy Efficiency in Residential Buildings

Step 1 - compare predicted electricity demand curves with actual electricity demand, to establish an efficiency rating

To evaluate the efficiency of a particular system, the final predicted and actual (measured) demand of HVAC system are compared. A rating of efficiency of HVAC system is determined, represented as the ratio between actual (*W*) and predicted (*W*) values (Equation 5.7).

$$\text{HVAC system rating} = \frac{\text{HVAC Demand}_{\text{actual}}\ (\text{kW})}{\text{HVAC Demand}_{\text{predicted}}\ (\text{kW})} \qquad (Eq.\ 5.7)$$

Step 2 - evaluate the operational efficiency of HVAC system

When comparing actual versus expected values, two methods of comparison may be used. The actual performance may be compared to the expected performance based on the age of the home, expected age of the HVAC system and corresponding minimum efficiency of the required HVAC system at the time of construction. This comparison's results would be a reflection on what the system operational characteristics should look like at a minimum, based on the code-minimum performance specifications. Second, the actual performance could be compared to the predicted performance based on the rated tonnage and SEER value of the system. This comparison would be a reflection of the overall system health and whether or not it needs to be serviced due to a fault or inefficiency.

If the HVAC system under consideration is operating as expected, then the energy demand of the system should be similar to that of the predicted value. If the system is not functioning properly or the system is less (or more) efficient than expected, then the system will have a higher or lower energy demand for a given set of environmental conditions. To assess whether or not a system is properly functioning or not, a distribution of HVAC efficiency ratings (Equation 5.7) is used. These values are calculated using the high frequent 1-minute interval energy dataset. Some of the most common faults in residential HVAC systems are low condenser airflow, and high or low refrigerant charge [9]. Previous research studies have found that low condenser airflow and high refrigerant charge increase the HVAC demand, while low refrigerant charge decreases the electricity demand [9]. In this work, the middle approximately 75% is considered to be average performance, where the efficiency rating value is close to a value of 1.0. The upper and lower approximately 25% are consider to be outside this average range, where there is a discrepancy between predicted and actual performance. Thus the threshold values of the average acceptable level of performance are from 0.9 to 1.0.

5.3. Results and Discussion

To assess the ability of the proposed methodology to identify the relative efficiency or inefficiency of an HVAC system, first a HVAC modeling program is used to predict energy demand of a residential HVAC system of a real home, which is then compared to the proposed method-predicted values. The home is a 10-year old single family house (111 m^2) serviced by a residential HVAC heat pump split-system with a SEER value of 13, and size of 2.5 tons, with 410A refrigerant, and 93W fan [25]. The characteristics of the HVAC system are entered into the HVAC modeling program Air Conditioning/ Heat Pump (ACHP) [25], along with a range of outdoor temperature conditions (18.3°C to 40.5°C). These are used to assess what the theoretical demand of the HVAC system should be, as shown (black line) in Figure 5.5. This is compared to the results of the proposed method for electricity demand of the HVAC system (blue dashed line). The comparison of the model-predicted values and the theoretical demand values is strong and nearly identical across the range of environmental conditions considered. To assess the theoretical impact of a common HVAC inefficiency, condenser airflow rate reduction, a reduced airflow is modeled in ACHP, at a range of 10% to 40% condenser airflow reduction. As shown in Figure 5.5, the more condenser airflow reduction, the higher HVAC demand. The HVAC system efficiency rating in these cases are different, demonstrating from 1.02, 1.03, 1.09, and 1.12, respectively for the faults from 10%, 20%, 30%, and 40%. Thus using the developed thresholds for an average versus inefficiently operating systems, a fault level of 25% and above for condenser airflow reduction is determined to be an inefficient system.

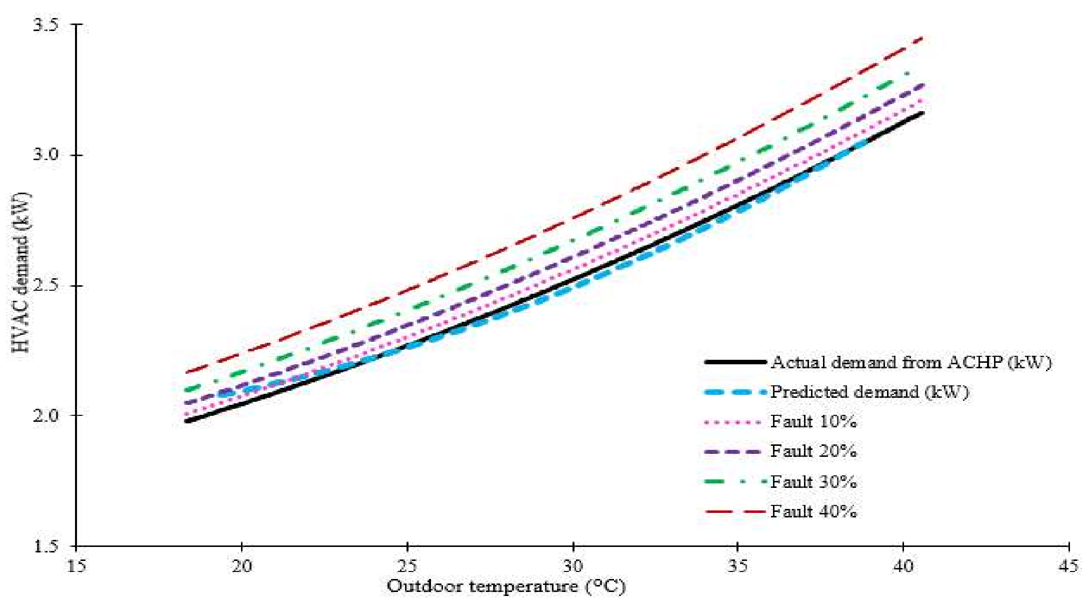

Figure 5.5 *HVAC demand curves using ACHP model and predicted data for a properly functioning and faulty HVAC system.*

Based on this analysis, the proposed method provides good agreement with physics-based model predictions of demand. Thus this method is then used with a dataset of HVAC energy demand of real homes, to understand if faults appear to be present and detectable using the proposed method with real data. Performance data in 32 residential building was collected from Austin, Texas (from 01/2015 to 12/2015) [21]. This dataset includes utility energy use (kWh) and demand data (kW) and weather data, including outdoor dry bulb and wet bulb temperature (°C). To develop the demand curves and assess overall energy efficiency of the HVAC systems, the high frequency 1-minute level HVAC energy data are used. Overall, the buildings studied are 28 years old on average, with a significant range of ages, from over 80 to less than 5 years old. The conditioned areas of the buildings also vary substantially, with an average size of 182 m^2. These residential buildings can be divided into 10 main groups based on size (tons) and SEER value (Table 5.4), including sizes of 2.5, 3, 3.5, and 4 tons, and SEER values of 14 to 19.

Table 5.4 *Characteristics of each group of residential buildings.*

Group	# of houses	Average area (m^2)	Size (tons)	SEER
1	6	165	2.5	14
2	7	190	3	14
3	5	220	3.5	14
4	5	274	4	14
5	2	159	2.5	15
6	1	166	3	15
7	2	145	3	16
8	1	221	3.5	16
9	1	200	4	17
10	2	199	3	19

To compare the average actual HVAC demands in each group, two cases are considered: first, the same size but different SEER values, and second, the same SEER value but different sizes (Figure 5.6). With the same size (3 tons) system, when the SEER values increase from 14 to 19, the HVAC demand decreases approximately from 2.8 kW to 1.5 kW at design conditions. Thus as expected, the higher SEER values have lower HVAC demands. The increase in size of HVAC systems from 2.5 tons to 4 tons also increases the HVAC demand.

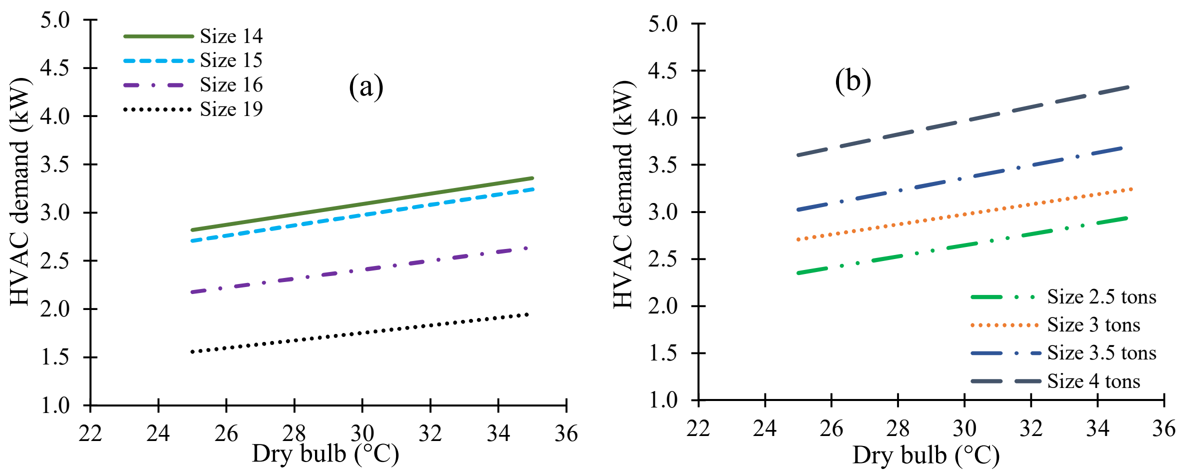

Figure 5.6 *Comparison of two cases of HVAC demand: (a) same size (size 3 tons) but different SEER values, and same SEER value (SEER 14) but different sizes.*

Using this same data of homes in Austin, TX, the predicted curve of the HVAC system demand (as dependent variable) is developed. Some examples of predicted and actual demands of HVAC systems are represented in Figure 5.7. In these figures, the actual HVAC demands are created from the actual data points of 1-minute interval electricity data (kW).

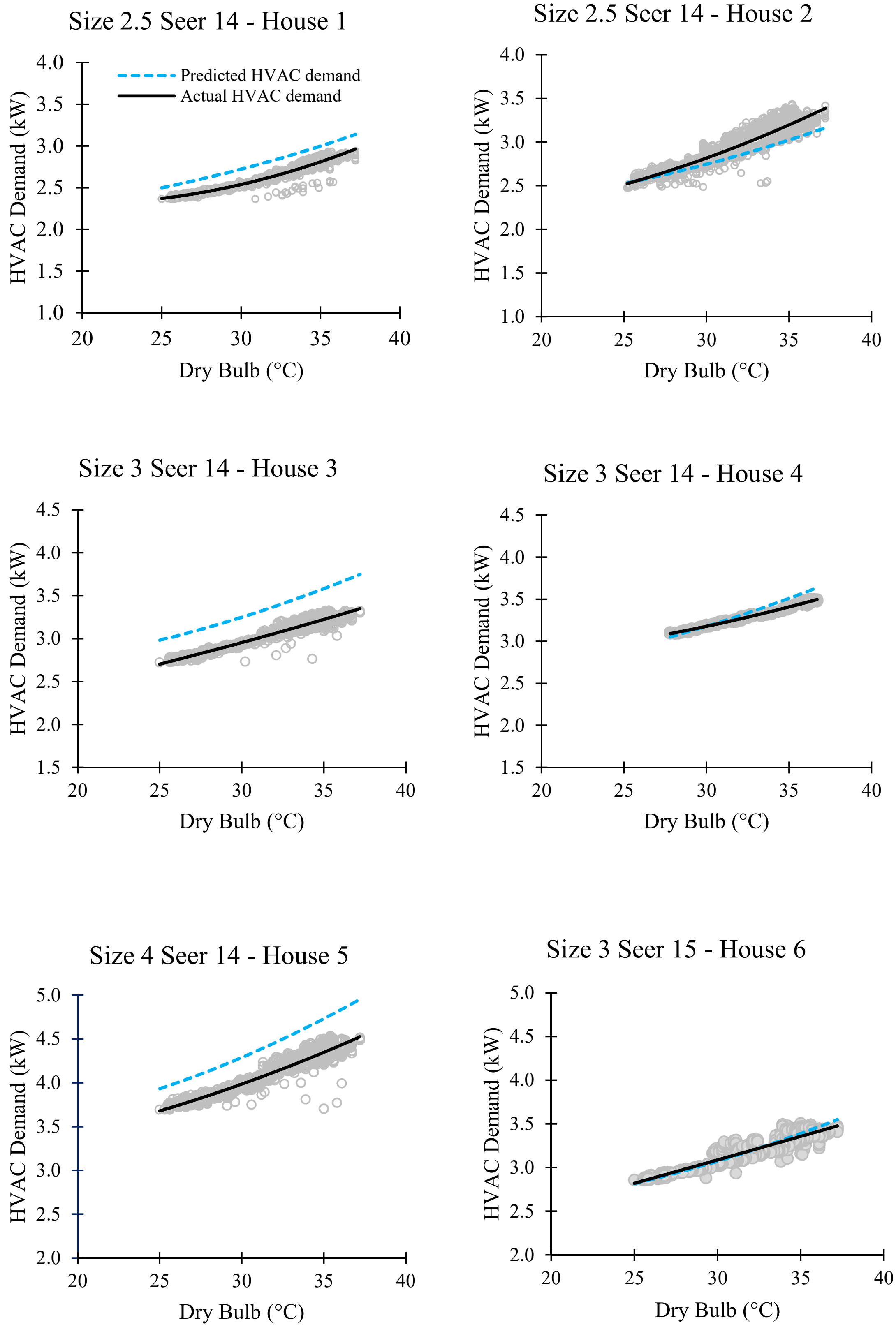

Figure 5.7 *Examples of predicted and measured demands of residential HVAC systems*

The following steps (Figure 5.2) develop the HVAC system rating applied to evaluate energy efficiency of HVAC system in each residential building. The range of outdoor dry-bulb temperatures in the cooling season as the predictor are used to determine values of predicted and actual HVAC demands (as the dependent variables). Using the values of predicted and actual HVAC demands in the HVAC system rating equation (Equation 5.7), the resulting distribution of HVAC system ratings shown in Figure 5.8. Most of the houses (78%) have the HVAC system rating ranging from 0.9 to 1. This range is chosen to be the average efficiency evaluation of HVAC system. If the rating is lower than 0.9 or higher than 1, the HVAC system is evaluated as inefficient (22% of total houses), meaning that there may be an issue associated with the HVAC system that requires servicing, and this issue is detectable from the energy use data method developed.

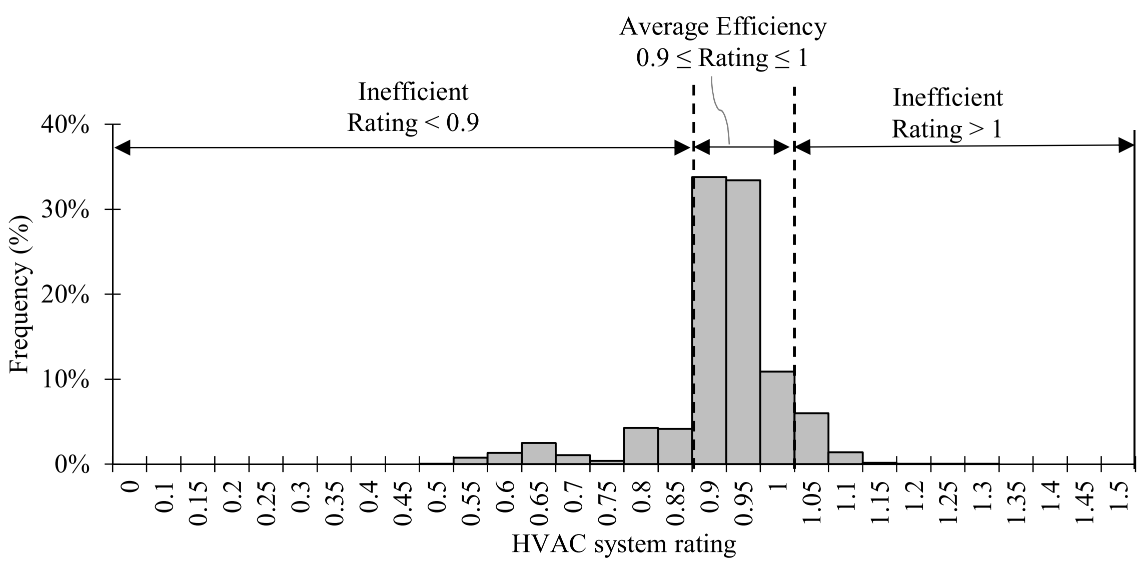

Figure 5.8 *HVAC efficiency evaluation based on the distribution of HVAC system rating.*

5.4. Conclusion

Compared to traditional methods such as a home energy audit or HVAC system tune up that require information or engagement from the homeowner, and can be more costly, time intensive, and intrusive, the method proposed in this research overcomes these barriers, only using limited energy data from HVAC system to assess energy efficiency. From the modeled HVAC system data, and from the studied real world residential buildings in Austin, Texas, this paper develop the HVAC system rating to evaluate the efficiency of an HVAC system. A case studied house with different condenser airflow faults show the reduction of HVAC system efficiency is detectable using this method. The results of this work will help homeowners and service technicians to determine whether there is a need to upgrade or service an HVAC system.

5.5. Acknowledgements

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CHAPTER 6. CONCLUSIONS, LIMITATIONS AND FUTURE WORKS, RESEARCH CONTRIBUTION

6.1. Conclusions

This dissertation focuses on data-driven modeling methods for improved residential building electricity consumption prediction and HVAC efficiency evaluation. First, when developing the inverse models to predict the energy use in residential buildings (Objective 1), change-point models using monthly energy consumption is found as an appropriate model. In addition, by using the proposed methodology for outlier detection, outliers in the data are found to occur especially in holiday months in heating season (e.g. December or January) or middle of cooling season (e.g. June or July). Characteristics of these outliers and the reasons for their occurrence are investigated through the one-minute interval circuit-level disaggregated energy use data, the results of which are used to determine whether or not to keep or remove the identified outliers for better prediction of energy use.

Second, for Objective 2, for three different climate zones, inverse change-point model is used to make the prediction of electricity use in residential buildings in four locations throughout the U.S, including Louisiana, Texas, Pennsylvania, and Indiana. For homes with pattern outliers identified, the evaluation of these outliers are based on the examination of four requisite tests. A methodology is developed, including the use of a “segmented” change-point models or using relaxed regression prerequisite criteria in cooling or heating seasons, to enable additional homes to have models that can predict consumption, and to improve the ability of change point models to predict consumption. This method improves the overall model performance by 13% of RMSE and 8% of CV-RMSE across studied datasets. The improved sequence of inverse change-point model development also reduce the number of houses that do not have a model developed from 40.0% to 29.2%.

Finally, for Objective 3a and 3b, to evaluate the energy efficiency in HVAC systems, a methodology is developed to use limited data about buildings, similar to the data that would be available to a utility company on the building stock from assessors data, to predict HVAC electricity demand curve. When compared to the demand prediction from a detailed HVAC system model ACHP, the proposed prediction method is found to have strong agreement. This methodology is then used to compare to the actual measured energy demand of HVAC systems to assess the efficiency of operation of the HVAC system. Based on analysis of 32 homes in the Austin area, it is found that 67.2% of total houses are evaluated as having average HVAC energy efficiency. If the value of HVAC rating is under 0.9 or higher than 1, the HVAC system in this house is evaluated as inefficient and requires the attention of HVAC maintenance services to increase the efficiency of the HVAC system.

6.2. Limitations and future works

This study focuses on residential buildings and their HVAC systems. When developing the inverse change-point model, a small number of houses in the studied dataset have a large variation in energy use, limiting the fitness and accuracy of the electricity use prediction of the model. Therefore, further work is needed to improve the current data-driven methods for better model performance in such houses, and to further explain why such patterns occur. In addition, the impacts of climate and variations in occupant characteristics on change-point model development using other independent variables beyond weather data would be desirable for further study to enhance the investigation of the occurrence, causes and treatment of energy use outliers as well as the prediction of energy use data in residential buildings.

For the improvements of inverse models of houses that have pattern outliers in various climate zones, further study can better characterize these outliers and behaviors across a broad range of homes at a highly detailed level, and is the subject of future work. This will help to determine and characterize specific signature evident in inverse models, and associate them with specific occupant behaviors.

For the evaluation of HVAC energy efficiency and the prediction of HVAC demand, this research focuses on a smaller subset of residential buildings in Texas. These houses represent only one zone in the ASHARE climate zone ranges. Further study should be conducted for diverse types of residential buildings in multiple climate zones. This will help to determine how the method for the evaluation of HVAC energy efficiency and the prediction of HVAC demand works, and what the levels of HVAC energy efficiency are in each of the ASHRAE climate zones. In addition, other fault types should be investigated to understand the impact on HVAC energy demand, and what level of detection of such faults can be achieved through the proposed methods.

6.3. Research contribution

The findings of this study have significance, in particularly for the residential building systems, energy efficiency, and HVAC community. Modeling methods for energy consumption and energy demand are highly important for identifying both inefficiencies in HVAC systems and opportunities for behavioral energy efficiency improvements. For behavioral energy efficiency, the developed improved inverse modeling methods can provide a more reliable prediction of energy consumption in residential buildings, to help improve homeowner confidence in the predictions. With improved confidence in such predictions, the results of such models can provide more actionable information from an energy efficiency and savings perspective. In addition, a better understanding of why outliers in energy data occur and how these outliers should be treated, the results of this, will further help improve energy prediction methods.

The developed methodology for the evaluation of HVAC system energy efficiency in residential buildings is important in the case where the efficiency of a system is desired, yet there is limited availability of energy and weather data. Such would be the case, for example, if a utility company is seeking to determine which homes in their service area to target for HVAC energy efficiency upgrades. Traditionally such evaluation would require more costly and intrusive energy audits, and require the collaboration with homeowners. The proposed methods developed as part of this investigation can overcome such barriers to identify potential opportunities for efficiency improvements. The proposed methods of continuous monitoring of the HVAC system demand would also enable ongoing evaluation of performance, thus also enabling the identification of issues with HVAC systems earlier on, before failure occurs.

The application of this research has benefits for homeowners and/or occupants of residential buildings and the utility companies that supply energy to these homes. The feedback provided to homeowners using the improved data-driven modeling and HVAC efficiency evaluation can raise the general awareness of the homeowners and/or occupants in energy savings in their residential buildings, and in particular, know the efficiency status of HVAC system and be notified of abnormal energy consumption of other end-uses. For utilities, the information resulting from the proposed models can be used to target those customers that would most benefit from efficiency upgrades and other commonly implemented rebate programs.

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