

© 2020 JOSEPH LOEND'A-NAMBA BONGUNGU

ESTIMATING RESIDENTIAL HOT WATER CONSUMPTION FROM SMART
ELECTRICITY METER DATA

BY

JOSEPH LOEND'A-NAMBA BONGUNGU

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Civil Engineering
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2020

Urbana, Illinois

Adviser:

Associate Professor Ashlynn S. Stillwell

ABSTRACT

Despite the fact that residential water heating is among the most energy-intensive aspects of the water sector, domestic hot water use is often poorly quantified. However, water-related energy savings in the residential sector are possible from the implementation of energy-efficient water heaters. Estimating hot water consumption from smart electricity meter data can help advance the body of knowledge regarding the urban energy-water nexus by employing data to validate and verify other published findings, and subsequently promote community resilience through energy and water resources efficiency. Using a non-intrusive load monitoring algorithm, this study disaggregated electricity for water heating from half-hourly ZIP code level smart electricity meter data for areas in the city of Chicago and estimated residential hot water consumption with quantified uncertainty. Results indicate that water heating accounted for 7-20% of total electricity consumption in the analyzed single-family residential homes, representing an average of 1-8 kWh of electricity consumption per day and 7-55 gallons of hot water per day. These results also demonstrated significant spatial variability, such that some areas of Chicago show higher per household hot water use.

Considering the challenges of building and deploying advanced metering infrastructure to monitor domestic water use and the fact that many residential customers have non-metered water accounts, using isolated water heating signals to develop a first-order estimate of domestic hot water use represents a valuable quantification of an energy-intense flow. The quantification of residential electricity used for water heating and domestic hot water use could help derive insights for effective policy making and energy efficiency programming to improve community resilience through enabling higher quality of life and highlighting areas with energy affordability issues. Understanding the urban energy-water nexus is vital to developing effective residential energy efficiency measures and promoting urban sustainability.

To my family, for their love and unconditional support.

ACKNOWLEDGMENTS

First and foremost, I would like to express the utmost gratitude to my advisor, Associate Professor Ashlynn Stillwell, for her continuous guidance, patience, and unfailing support throughout my M.S. degree. More than an advisor, she has been a counselor and comforter during the most challenging times of my academic journey at Illinois. I would like to thank Dr. Christopher Chini and Grace Wackerman for their permanent availability, support, and contributions that made this research possible. Many thanks to Anthony Bongungu, Nicolas Nkiere, and Johan Mufuta, my fellow Congolese brothers and Computer Science and engineering students at the University of Illinois at Urbana-Champaign, who helped me sharpen my code writing and debugging skills. I would also like to acknowledge Paul Francisco and Stacy Gloss from the University of Illinois' Indoor Climate Research and Training program, who contributed to the elaboration of this research by sharing their vast knowledge and expertise on the subject matter. Finally, I want to thank my fiancée, Ségolène Muderhwa, for her unconditional support and encouragement throughout this journey. This work has been supported by the Department of Civil and Environmental Engineering at the University of Illinois at Urbana-Champaign and the Illinois Water Resources Center (IWRC). Training data for the analysis were provided by Pecan Street Inc. Dataport. Commonwealth Edison electricity meter data were obtained from the Environmental Defense Fund, under a data sharing agreement with the University of Illinois.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS	vi
LIST OF SYMBOLS	vii
CHAPTER 1 INTRODUCTION	1
CHAPTER 2 BACKGROUND	3
CHAPTER 3 METHODS	17
CHAPTER 4 RESULTS	37
CHAPTER 5 POLICY AND SUSTAINABILITY IMPLICATIONS	51
CHAPTER 6 CONCLUSION	55
REFERENCES	58
APPENDIX A ESTIMATED ELECTRICITY FOR WATER HEATING AND DOMESTIC HOT WATER USE	70

LIST OF ABBREVIATIONS

AMI	Advanced Metering Infrastructure
DHW	Domestic Hot Water
DOE	United States Department of Energy
EDF	Environmental Defense Fund
EF	Energy Factor
EIA	Energy Information Administration
EPA	Environmental Protection Agency
ERWH	Electric Resistance Water Heater
GHG	Greenhouse Gas
HPWH	Heat Pump Water Heater
NILM	Non-Intrusive Load Monitoring
RECS	Residential Energy Consumption Survey
UN	United Nations

LIST OF SYMBOLS

C_p	Specific heat of water, Btu/lb using °F or kWh/kg using °C
CV(RMSE)	Coefficient of Variation of the Root Mean Square Error
ρ	Density of water
gal	Gallons
E_{WH}	Water Heater Energy Consumption
ft ³	Cubic Foot
m ³	Cubic Meter
kW	Kilowatt
kWh	Kilowatt-hour
BTU	British Thermal Unit
GW	Gigawatt
MBTU	Thousand British Thermal Units
V	Volume of Water Drawn

CHAPTER 1

INTRODUCTION

Electricity consumption in residential buildings in the United States has increased by 27% from 1990 to 2008, and is projected to increase by an additional 18% from 2009 to 2035 [1]. According to the Energy Information Administration (EIA), 223 GW of new electricity generating capacity will be needed by 2035 to meet the projected demand [1]. As Stankovic et al. observed, real-time smart meter data can provide better insights into households' activities and their implications for energy consumption [2]. The growing installation of advanced metering infrastructure (AMI) has facilitated the collection of real-time household electricity consumption data and presents an opportunity to better understand resource consumption in the residential environment [3, 4]. AMI offers multiple benefits for electricity service providers, who can now collect and analyze whole-house electricity consumption data, and also for customers whose energy use awareness could be increased by real-time consumption feedback [5].

As of 2015, water heating represented nearly 14% of total residential energy consumption [6]. According to EIA's Residential Energy Consumption Survey (RECS), water heating is the second most energy-intensive activity in the residential sector, following space heating and air conditioning [7]. Water heaters generate a considerable amount of residential greenhouse gas emissions. Most U.S. household water heating units use natural gas (51.7%), electricity (41.3%), and oil-derived fuel sources (6.7%) [7]. To effectively recommend a domestic water heating technology that could reduce energy consumption and greenhouse gas (GHG) emissions, a thorough analysis of the available water heating technology, residential water heater energy consumption, and domestic hot water use is crucial. To that end, this study used smart electricity meter data of single-family households in the city of Chicago to estimate residential electricity consumption for water heating and to predict domestic

hot water (DHW) use for different households in the city. A non-intrusive load monitoring technique was used to accomplish this objective and answer the following key research questions:

1. How can electricity for water heating be disaggregated from half-hourly total electricity consumption?
2. How can DHW volumes be estimated from electricity for water heating?
3. What temporal and spatial DHW use patterns can be detected from the estimated values?

It was anticipated that electricity consumption for water heating would vary spatially, as different households have different physical characteristics, occupancy levels, and appliance stock. Smart electricity meter data could also provide some insight on households' high-consumption appliances or activities, such as space heating, air conditioning, and electric water heaters, which are attractive targets for load shifting programs [8].

CHAPTER 2

BACKGROUND

2.1 Interdependence of Energy and Water Resources

Energy and water have been linked to the development of societies and cultures: these resources have helped build societies, enable economic growth, spur industrialization, and support quality of life for centuries [9, 10]. They are central to nearly every major challenge faced by the world today [11]. Universal access to affordable, reliable, and sustainable energy is at the heart of socioeconomic development; it is indispensable to basic human needs such as nutrition, transportation, warmth, and light [12]. Water is essential to life and the promotion of inclusive sustainable development; it maintains the functions of ecosystems and is a vital resource in the production of energy, food, and manufacturing services [9]. Unfortunately, accessible fresh surface water makes up a small fraction of the world’s water supply; thus, large energy supplies are needed for groundwater extraction, drinking water and wastewater treatment, and water conveyance [13]. Since some economic models do not value the importance of sustainable energy and water, they often lead to unsustainable use of water and energy resources, which in turn leads to environmental degradation.

Energy and water, the world’s most essential resources, are intricately interconnected. About 15 percent of the world’s water goes to energy production or transformation [14]. In the United States, nearly half of all water withdrawals are for the thermoelectric power sector [15]. Water is a critical input for hydroelectric power generation, an essential coolant of thermoelectric power facilities, and a critical resource in the extraction and production of fuels (e.g., coal, uranium, oil, and gas), as well as energy crops such as corn for ethanol [6, 13]. Energy is a critical resource to collect source water, to pump water to distribute in

pipes, to treat drinking water and wastewater, and for water reuse [16, 17]. Water heating is one of the most energy-intensive aspects of the water sector; Sanders and Webber estimated that the United States consumed approximately 12.3 quadrillion BTU of energy for water in 2010 [6]. Water is so energy intensive that “the United States spends more energy on water than for lighting” [13].

The interdependence of water and energy makes society vulnerable to cascading infrastructure failures. An increase in water use requires an increase in energy to supply the additional water needed and treat the subsequent wastewater [18]. Water shortages, floods, and drought often contribute to power outages [13]. Similarly, energy disruptions can cause water disruptions and public health concerns; most water treatment plants and wastewater facilities cannot operate during power outages. As an example, flooding resulting from the stormwater surge during Hurricane Sandy contributed to great disruptions of power service at wastewater treatment plants and caused untreated sewage spilling into waterways [19, 20]. This cause-effect relationship between the two resources is often overlooked despite the fact that a change in one often leads to a change in the other.

The energy-water nexus—the interdependence of energy and water resources—is especially pronounced in the residential environment [16]. Understanding the complex connections between water and energy in residential buildings is necessary to solve water and energy issues simultaneously and avoid moving problems from one resource dimension to another. It could help develop effective solutions to address the main drivers of consumption for both resources; thus, avoiding that a solution to a water supply-related issue creates an energy-use burden [18]. As the UN projects that approximately 66 percent of the world’s population will reside in cities by 2050 [21], the large ecological and economic footprint of cities will likely continue to increase. As of 2012, cities were estimated to be responsible for approximately 75% of total greenhouse gas emissions [22, 23]. Increased urban population, coupled with climate change, droughts, floods, and pollution, are putting additional stress on already-limited water and energy resources [24]. Water and energy co-involvement in nexus studies can help identify interdependencies as well as enable optimization of infrastructure for water and energy simultaneously to potentially create savings on peak loads for both resources [18]. Many studies on the influence of residential water use on energy consumption found that water heating and cooling use significantly more energy than drinking water supply and

wastewater services [25–27], motivating analysis of domestic hot water use and its energy implications.

2.2 Residential Water Heating

Residential water heating is among the most energy intensive aspects of the residential sector, following space heating and air conditioning [28]. Webber notes that “water heating is an important proxy for quality of life”; hot water serves multiple purposes, including human health and hygiene through showers or baths, disinfection and sterilization of medical equipment at hospitals, and dish and clothes washing in homes, among other uses [13]. In 2010, energy consumed for water heating represented between 13% and 17% of residential energy consumption in the United States [29]. In Australia, water heating accounted for 23% of total residential energy consumption in 2008 [30]. According to the U.S. Department of Energy, residential water heating required nearly 25% of the total energy consumed for water and steam supplied to the residential, commercial, industrial, and power sectors in 2010 [31]. Water heating is also a significant source of greenhouse gas emissions; therefore, reducing the energy consumed for water heating presents an opportunity for energy conservation and GHG emissions reductions in the residential sector [6]. Sanders and Webber quantified regional water heating trends in the United States and analyzed the trade-offs in primary energy consumption and GHG emissions from shifts in regional water heating technologies [6]. States with large fractions of coal-fired power generation have the largest potential for emissions reductions from a shift from electric to natural gas water heating [6].

Despite the energy implications of residential water heating, domestic hot water use is often poorly quantified. Proper domestic hot water energy quantification studies could support identification of household hot water demand, along with development of related policy measures [30]. Multiple studies [32–39] have monitored appliance-level hot water uses and developed models to estimate energy for water heating. Unfortunately, these studies are either limited in scope and number of participating households [32–35], or cannot easily be scaled [36–39]. Some studies have used low-resolution electricity data because they lacked access to submetering technologies [40–45].

2.3 Factors Affecting Residential Energy and Hot Water Consumption

Residential buildings account for approximately 39% of the total electricity use in the United States [46]. In the United Kingdom, the residential sector represented 45% of total electricity consumption in 2017 [47]. A thorough understanding of the determining factors that drive residential energy use is needed to effectively plan and execute energy efficiency programs that can reduce residential energy consumption and mitigate its impact on the environment [48, 49]. Social factors such as demographics, income levels, and household expenditure can influence energy and water resource consumption patterns [50]. According to Kavousian et al., weather, location, and physical characteristics of dwellings such as floor space, construction date, and construction materials are among the most important determinants of residential electricity consumption [49]. Household size is often correlated with affluence, socioeconomic status, number of occupants, and appliance stock [49]. Satre-Meloy et al. conducted a statistical analysis of household activities in 173 households in the United Kingdom, demonstrating that the number of occupants and high-consumption appliances such as space heaters, air conditioning, and water heaters were the most significant determinants of daily maximum electricity consumption, while daily minimum consumption was influenced most by weather, location, and physical characteristics of the building [51].

Many studies on the effect of ZIP code and cooling load on electricity consumption have reported that Cooling Degree Day (CDD) is the dominant factor in the summer, explaining a considerable portion of the variability in total electricity consumption [49, 52–54]. Locality and household size show considerable correlation with residential electricity consumption, most likely because they are correlated with several other variables that influence energy consumption, such as climate, building type, building materials, and socioeconomic status of the household [49].

2.3.1 Behavioral Determinants

A single focus on the promotion of more energy efficient technology might not be sufficient to slow the growth in total energy consumption and carbon dioxide emissions. “Higher

efficiency does not necessarily translate to lower consumption or emissions, and houses (and ‘lifestyles’) with less efficient goods may use less energy than those with more efficient goods” [55]. Multiple studies have demonstrated how lifestyle is relevant to energy consumption [8, 56–59]. Similarly structured households with the same physical characteristics could have widely varying energy and water usage, emphasizing behavioral differences among households’ occupants. For instance, in most houses, bathing uses the largest volume of hot water, followed by kitchen-related activities such as dishwashing, cleaning, and cooking [60]. Domestic hot water use in a household will reflect the differences in bathing and showering habits. Understanding the patterns of energy and water consumption associated with lifestyle factors can be beneficial to developing more effective and better tailored policies [59]. Age of occupants is another important factor that has a significant correlation with energy consumption. A study by Kempton showed that older household members tended to be more conscious about their electricity consumption and use less electric gadgets, while 19-35 year-old occupants’ consumption reflected their lifestyles, which often coincided with less time spent at home because of a full-time job [60].

2.3.2 Socioeconomic Factors

Besides lifestyle factors and climatic influences, residential electricity consumption is also affected by social, economic, and demographic conditions [61]. Rapid economic growth and improved living standards often induce an increase in energy consumption. While many studies claim that overall energy consumption increases with income level [8, 43, 54–56, 62], some studies suggest that there is no statistically significant correlation between income and electricity consumption [49, 63]. Household income affects the quantity and types of household appliances [4, 18, 60]; therefore, there could be a relationship between affluence and resources consumption. In many developing countries with low electrification rates, such as Burundi (9%), the Democratic Republic of Congo (19%), and Uganda (22%) [64], there is a clear correlation between affluence and resources consumption; people with higher purchasing power can afford to take multiple hot showers a day while the majority of the population restricts consumption, sometimes to the detriment of personal hygiene [65, 66]. In wealthier countries like the United States, “it is not clear if affluence causes energy and water

consumption, or if consumption causes affluence, but the relationship is salient” [13]. Based on the U.S. RECS, average annual water-heating energy consumption per household ranged from 11.8 MBTU for households earning less than \$10,000 USD in 2001, to 19.3 MBTU for those earning \$50,000 USD or more [67]. However, in 1993, low-income households across the United States were estimated to use 10.8 to 18.0 MBTU (3,165 to 5,275 kWh) to heat water [68]. Low-income families have exhibited above-average hot water energy consumption in other studies [69]. Evidence suggests that households that are not required to pay for their hot water expenditures consume above-average amounts of hot water [39].

2.3.3 Structural Determinants and Occupancy

Kavousian et al. demonstrated that house size had a considerable effect on daily minimum and daily maximum energy consumption during both winter and summer [49]. Larger houses have a greater heating and cooling energy demand because they have more volume to be conditioned and a higher heat loss or gain with the outside. The number of occupants, which is often correlated with the house size [49], is a non-negligible variable for electricity consumption. An increase in the number of occupants can increase the aggregate electricity consumption but decrease per capita consumption [49, 70, 71]. A Florida Power Corporation (FPC) study of monitored water heater energy use and demand in 200 residences in Central Florida using 15-minute electricity consumption data revealed that occupancy had the strongest influence on energy consumption variation [37]. Furthermore, the FPC observed that domestic hot water use was slightly higher on weekends, which could be justified by higher occupancy levels [37].

2.3.4 Water Heating Technology

Among the factors influencing domestic hot water and water heating energy consumption are the water heater type, its equivalent efficiency ratings or energy factor, the type of fuel used, the inflow water temperature, and the setpoint temperature. According to the DOE 2009 Water Heater Market Profile report, “about 27 million households have water heaters that are more than 10 years old and nearing the end of their functional lives”

[72]. Considering frequent updates in water heating technology, the residential water heating sector presents a great opportunity for substantial energy efficiency improvements and savings. Though water heating appliances sold in the U.S. market meet federal standards in place since 2004, there are other technology options such as ENERGY STAR-qualified water heaters, which consume 7 to 55 percent less energy, on average, than most models meeting federal standards. These ENERGY STAR water heaters could allow consumers to recover money invested in newer water heaters over the expected lifetime of the product [72].

In 1988, Congress enacted the National Appliance Energy Conservation Act (NAECA), which established national standards for home appliances such as fuel and capacity-based minimum efficiency standards for water heater performance; they were later updated in 2004 and 2013 [73]. Based on the current standard for a typical 50-gallon storage tank water heater, the minimum energy factor (EF) is 0.575 for gas water heaters and 0.904 for electric water heaters [72]. An EF is a measure of a water heater’s overall energy efficiency based on the amount of hot water produced per unit of fuel consumed over a typical day [72]; it accounts for recovery efficiency, standby losses, and cycling losses [29]. However, it does not include other efficiency losses external to the water heating system, such as improper insulation of tanks and pipes, which could cause higher-than-normal energy consumption. The federal government labels water heaters with different EF ratings based on the results of certain standardized tests to increase consumer awareness about the energy performance of end-use appliances [74].

2.3.4.1 Natural Gas and Electric Storage Tank Water Heaters

The majority of U.S. residential households use either natural gas or electric resistance storage water heaters; close to 95% of American households use storage tank-type water heating appliances for domestic activities such as cleaning, bathing, clothes washing, dish washing, and cooking [72, 75]. As the name implies, storage tank water heaters store heated water in a tank so that a quantity of hot water is readily available for domestic use. Though they are typically the lowest-priced water heaters in the market, the DOE estimates that they might be the most expensive to operate and maintain over their lifetime [76].

Though natural gas storage water heaters behave similarly to electric storage water heaters,

they have a lower efficiency factor because of high thermal losses caused partly by the central flue and the combustion efficiency of gas [75]. However, electric-resistance storage water heaters (ERWH) have higher operational costs than natural gas over their lifetime because electricity is typically more expensive per BTU than gas [29]. The most common 50-gallon ERWHs perform with EF ranging from 0.904 to 0.95, while tankless types have EF from 0.96 to 0.99 [29].

2.3.4.2 Tankless Water Heaters

Tankless or on-demand water heaters are usually wall-mounted and can save physical space since they do not use a tank. Though they show higher rated efficiencies than traditional tank-type water heaters and have the potential to significantly lower household energy expenditure and greenhouse gas emissions [77], they only account for 4 percent of the market share according to the most recent market data available [72]. Tankless or instant electric water heaters optimize the efficiency of the water heater since they are able to instantly heat a desired volume of water as it passes through the heater. They have shown higher energy efficiency by minimizing standby losses from the tank [29]. Tankless water heaters also have the potential to reduce energy consumption by 10-15% as they use less fuel than their storage tank counterparts [78]. The main limitation of tankless water heaters is their flow rate.

2.3.4.3 Heat Pump Water Heaters

Heat pump water heaters (HPWHs) have a storage tank, a compressor, and fan, all in one unit. There are two types of heat pump water heaters: ambient air and exhaust air. Exhaust air HPWH models, which use a heat pump to capture heat from indoor air and exhaust air to transfer to the water storage tank, cost almost twice as much as ambient air heat pumps [79].

HPWHs could potentially cut the cost of electric water heating by more than half compared to traditional tank-type water heaters [74]; typical HPWHs use less than half as much electricity per volume of water heated as typical ERWHs [79]. They also have the advan-

tage of allowing users to set operations according to preferences using a digital thermostat. The main downside is that heat pump water heaters require considerable maintenance and plumbing, with air filter replacement recommended every 1-2 years. They also present space constraints since most units are large and make considerable noise. Because the heat pump is on top of the water heating unit, a HPWH needs as much as 7 feet of clearance from floor to ceiling and about 1000 ft³ of uncooled space to capture sufficient heat from the surrounding air [80].

2.3.4.4 Domestic Solar Water Heater

Solar water heaters are typically composed of a roof-mounted collector, a circulating pump, one or two storage tanks, connecting pipes, and controls [81]. They are usually configured to preheat water and used as a backup to a conventional water heater. They typically have one tank to store thermal energy and one connected to a conventional storage-type water heater that uses either electricity or natural gas as fuel [82].

A domestic solar water heater installation typically reduces residential energy demands by 50-85% [83]. It is estimated that switching from a traditional storage tank water heater to solar and heat pump water heaters nationwide could significantly reduce total annual energy consumption by 1.85 quadrillion BTU per year, representing approximately 2 percent of U.S. total energy consumption [72]. Furthermore, domestic solar water heaters could potentially reduce U.S. CO₂ emissions from the residential and commercial building sectors by about 2-3% [82]. The major limitation of solar water heating deployment is rooftop availability, since energy supply is a function of the amount of solar radiation received [84].

2.4 Smart Metering Technology and Resources Management

As part of a smart city infrastructure initiative launched by the City of Chicago in 2016, a series of electric infrastructure modernization investments were made to contribute to Chicago's growing green economy, support environmental sustainability by reducing energy waste, and help Chicagoans save money on electricity [85]. Commonwealth Edison (ComEd),

the largest electric utility provider in Illinois and unique provider in Chicago, installed over 4 million smart electricity meters in homes and businesses across northern Illinois [86]. Smart metering technologies record resource consumption at fine temporal resolution and help eliminate estimated, unmetered usage by providing customers with accurate resource consumption information. Furthermore, smart meters can automatically generate timely and accurate bills, regardless of weather conditions or property access limitations and reveal information about customers' resource consumption patterns [87]. A study conducted by the Illinois Citizens Utility Board revealed that low-income electric customers in Illinois use less electricity and contribute less to the grid's peak load than their higher-income counterparts; since peak load drives overall system costs higher, "they may be paying more than their fair share for electricity" [88]. These findings reveal the capacity of advanced metering infrastructure to help researchers identify neighborhoods that use electricity less efficiently than others and guide utilities and policy makers in identifying where to focus efficiency efforts.

Utility providers advocate for the widespread implementation of advanced metering infrastructure (AMI), such as smart electricity meters or water meters, to allow customers to understand their energy use, make better informed energy decisions, and adjust their habits to decrease energy-related costs. In addition, smart meter data help energy companies manage power distribution more efficiently to avoid grid overload and potential blackouts, and reduce operational costs [89]. However, it should be noted that the success of smart metering technology strongly depends on perceptions, communications, and understanding between the users and the technology provider [90]. Many customers see AMI as a potential trade-off between data privacy and data accuracy [91]. Many people have expressed concerns over the potential of smart metering technology to reveal private information associated with their water or electricity consumption habits; thus, concerns persist regarding potential privacy issues such as illegal uses of their data by stalkers or burglars, commercial uses for targeted advertising, uses by law enforcement agencies, and uses by other parties for legal purposes [92].

2.5 Energy and Water Heating Policies

The most notable improvements in energy and water resources management were due, in part, to improvements in energy and water policies. Deason et al. stated, “policies are reflections of societal goals and aspirations” [93]. Policies can reach broader populations and accomplish impactful and sustainable results at a larger scope than individual-level interventions. In the United States, federal, state, and local entities play a key role in developing and implementing appropriate policies to address the production, distribution, and consumption of different resources. Increasing energy efficiency and reducing carbon emissions are among the main goals of American energy policies [56]. Unfortunately, as noted by Diamond et al., the majority of the implemented policies to regulate energy consumption address efficiency on a technology-by-technology scale rather than a societal basis.

Policymakers often implement a series of mandatory or voluntary measures—standards, rationing programs, restrictions, compliance measures, rebates, retrofits, and regulations—to improve energy and water resources efficiency. National efficiency standards for energy-using appliances aim to remove inefficient products from the marketplace and allow customers to access more energy-efficient products. Initial efficiency standards for water heating technology were first implemented in 1987, and took effect in 1990 [28]. The original standards required a minimum EF of 0.525 for natural gas water heaters and 0.864 for electric water heaters with a 50-gallon tank [28]. In January 2004, the DOE established updated national efficiency standards for water heaters: EF increased to 0.575 for natural gas water heaters and 0.904 for electric water heaters.

Starting April 2015, the DOE established its latest water heater energy efficiency standards. The new national efficiency standards state that the minimum EF for natural gas-fired water heaters with storage tanks of volume less than or equal to 55 gallons is 0.675, and for similar-size electric water heaters is 0.960 [28]. Though appliance retrofit to meet updated national efficiency standards may have considerable initial investment costs, these upgrades represent potential energy and cost savings in the long term.

2.6 Energy and Water Conservation in Urban Areas

Despite having less than 5 percent of the world’s population, primary energy consumption in the United States represents approximately one-fifth of global primary energy consumption [1]. Average American residents consume twice as much as average United Kingdom residents, and four times as much energy as residents of China or India [13]. Furthermore, the residential energy sector accounts for 37% of energy consumption in the United States [2], representing approximately 7% of the world’s energy consumption. Therefore, promoting energy efficiency and resource conservation in residential buildings could contribute to reducing greenhouse gas emissions, mitigating the consequences of climate change, and addressing societal problems like economic equality and racial injustice. To meet residential buildings’ energy demand and improve supply efficiency, it is important to analyze and understand the temporal flexibility of activities giving rise to energy demand [2].

Most water-related energy savings can be achieved by switching to energy-efficient water heaters, reducing domestic hot water use, and adoption of clean sources of energy for water heating [94]. These actions represent a combination of efficiency and resource conservation measures. Water resources efficiency has had a growing attention over the past two decades; in the United States, the federal government mandated improved efficiency of plumbing fixtures. Following the implementation of the Energy Policy Act of 1992, fixtures and appliances were redesigned to reduce water use by about half; for instance, new standards established that toilets be limited to 6 liters per flush and showerhead and faucet flow rates not exceed 9.5 liters per minute [95]. These new standards led to a 40-60% reduction of water used by these fixtures [96].

2.7 Data-driven Approaches for Resource Consumption Estimation

There are a variety of approaches used by researchers to estimate household electricity consumption at appliance end uses: non-intrusive load monitoring (NILM), sub-metering, load disaggregation, and modeling. The analysis of appliance end-use electricity consumption

could enable a better understanding of energy consumption and translate into meaningful energy feedback to households [2, 97]. NILM discerns individual loads from a single metering point by disaggregating to appliance end uses without appliance-level monitoring (see Figure 2.1) [5, 98, 99]. NILM techniques can effectively infer load profiles from smart meter data, but performance is highly dependent on data resolution [2]. Low-resolution smart electricity meters, on the order of minutes to hours, add complexity to the design of efficient NILM algorithms.

Electricity disaggregation was first proposed by Hart in 1970 [100], and subsequent research has created new data-driven approaches to estimate energy consumption. Liao et al., aiming to address the challenges of scalability and intrusiveness, proposed two algorithms for power load disaggregation at low-sampling rates (greater than 1 sec): supervised approaches based on Decision Trees and unsupervised methods based on Dynamic Time Warping [97]. These algorithms define an activity recognition approach for cooking, showering, and home entertainment, using NILM applied to smart meter active power readings and qualitative data such as appliance surveys. Wilson et al. combined qualitative data from household interviews and video ethnography with NILM and appliance-level power sensors to infer reliable time profiles for a range of domestic activities for two homes [101]. Kolter et al. used discriminative sparse coding to disaggregate hourly electricity data for unseen houses using appliance-level power consumption models built from weekly training datasets [102]. Birt et al. disaggregated base-load, heating, and cooling energy consumption from multiple houses using piece-wise functions of power consumption versus outdoor air temperature for each house [103]. Perez et al. developed a NILM algorithm using edge detection and k -means clustering to disaggregate air conditioning energy usage from 1-minute, 5-minute, and 15-minute whole-house power consumption data [104].

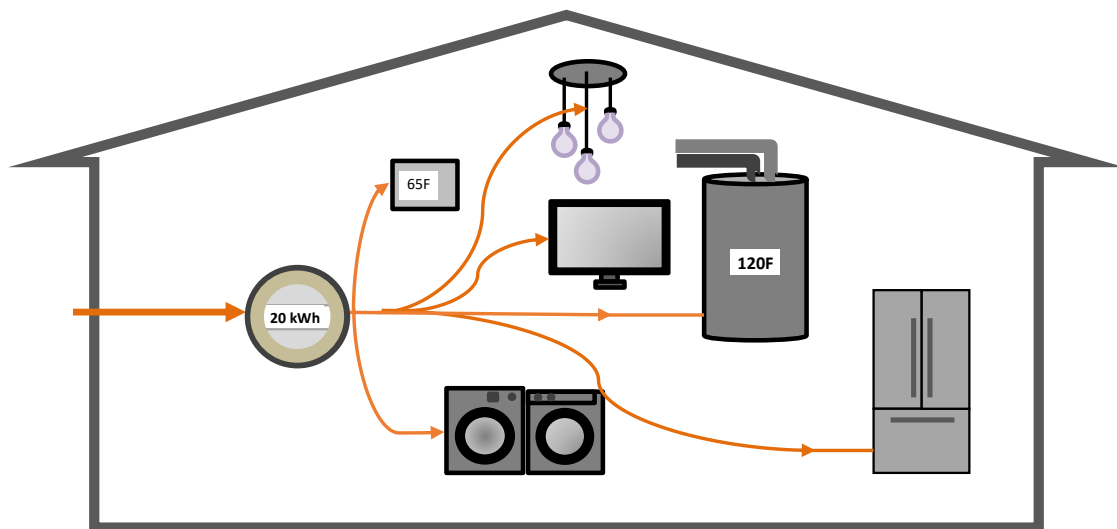


Figure 2.1: Electricity disaggregation aims to estimate appliance-level electricity consumption from smart electricity meter observations

CHAPTER 3

METHODS

3.1 Overview

The main objective of this study was to predict domestic hot water (DHW) use from smart electricity meter data for different areas of the city of Chicago. This chapter provides the details on the data sources used in this study, the data preparation process, and the assumptions, techniques, and non-intrusive load monitoring (NILM) methods used to design the model. The NILM algorithm developed in this study was inspired by Perez et al.’s non-intrusive disaggregation of residential air-conditioning loads from sub-hourly smart meter data [104].

3.2 Data

3.2.1 Data Sources

ComEd meter-level electricity consumption data used in this study were obtained through an existing data sharing agreement between the Environmental Defense Fund and the University of Illinois. ComEd is the largest electric utility company in Illinois and provides electricity to more than 4 million customers across Northern Illinois [86]. This energy data sharing program allows researchers, cities, energy efficiency providers, technology developers, and various clean energy innovators access to anonymous energy-use data from ComEd’s 4 million smart meters, which represents approximately 70% of the Illinois population [105].

This research, which aims to estimate electricity used for water heating and domestic hot water use in residential households in Chicago, leverages these data to help identify neighborhoods that are more vulnerable to energy affordability issues and those that could benefit the most from water heating appliance upgrades.

The data include 30-minute interval electricity usage for 2016, organized on a meter level for 366 ZIP codes across 24 counties in the ComEd service territory. Based on the anonymization protocol specified by the Illinois Commerce Commission (ICC), ComEd provides both five-digit and nine-digit ZIP code data, without identifying information such as customer names, addresses, or account numbers [94]. Furthermore, ZIP codes that contain less than 15 customers, or those with a single meter that accounts for more than 15% of the load within that data set, are omitted. The data are assembled by their delivery service classes: C23 for single-family residential households, C24 for multi-family residential households, C25 for single-family residential households with electric space heaters, C26 for multi-family residential households with electric space heaters, C27 for commercial buildings, C28 for small buildings, C29 for mid-size buildings, and C30 for large buildings.

In addition to the half-hourly electricity consumption data, minute-by-minute whole-house and appliance level electricity consumption data for six single-family homes were obtained from the Pecan Street Inc. Dataport, collected in Austin, TX. The Pecan Street Inc. dataset contains submetered 1-minute, appliance-level energy consumption data for 750 households, most of which are located in Texas with additional homes in Colorado, California, Maryland, New York, and Oklahoma [106]. Despite considerable climatological differences between Illinois and Texas and dissimilar monthly temperatures as seen in Figure 3.1, these households were selected to generate the disaggregation model’s parameters because they were among the few monitored single-family households with electric water heaters and a full year dataset. Austin has a humid subtropical climate with long, hot, and humid summers and short and mild winters, whereas Chicago has a humid continental climate with cold winters and hot and humid summers. Consequently, the Pecan Street Inc. dataset was filtered to only include the months where Austin’s water main temperatures were similar to Chicago’s June water main temperatures. The average water main temperature in Chicago in June 2016 was 65°F as shown in Figure 3.2. The average surface water temperature of Lake Austin, the city of Austin’s primary source of drinking water, averaged 50-70°F over March 2015

[107] (among the period of Pecan Street Inc. data records); therefore, the disaggregation parameters were extracted from the Pecan Street Inc. dataset for water heater electricity consumption during March as training data. Though water heating is not as correlated with weather as space heating and cooling, water heating loads are still sensitive to temperature conditions since the difference between the temperature of the water supplied to the water heater and the desired hot water delivery temperature affects the water heater’s daily energy consumption (see Equation 3.4). March was selected to minimize the error caused by the effect of cold inlet water temperature on water-heating loads.

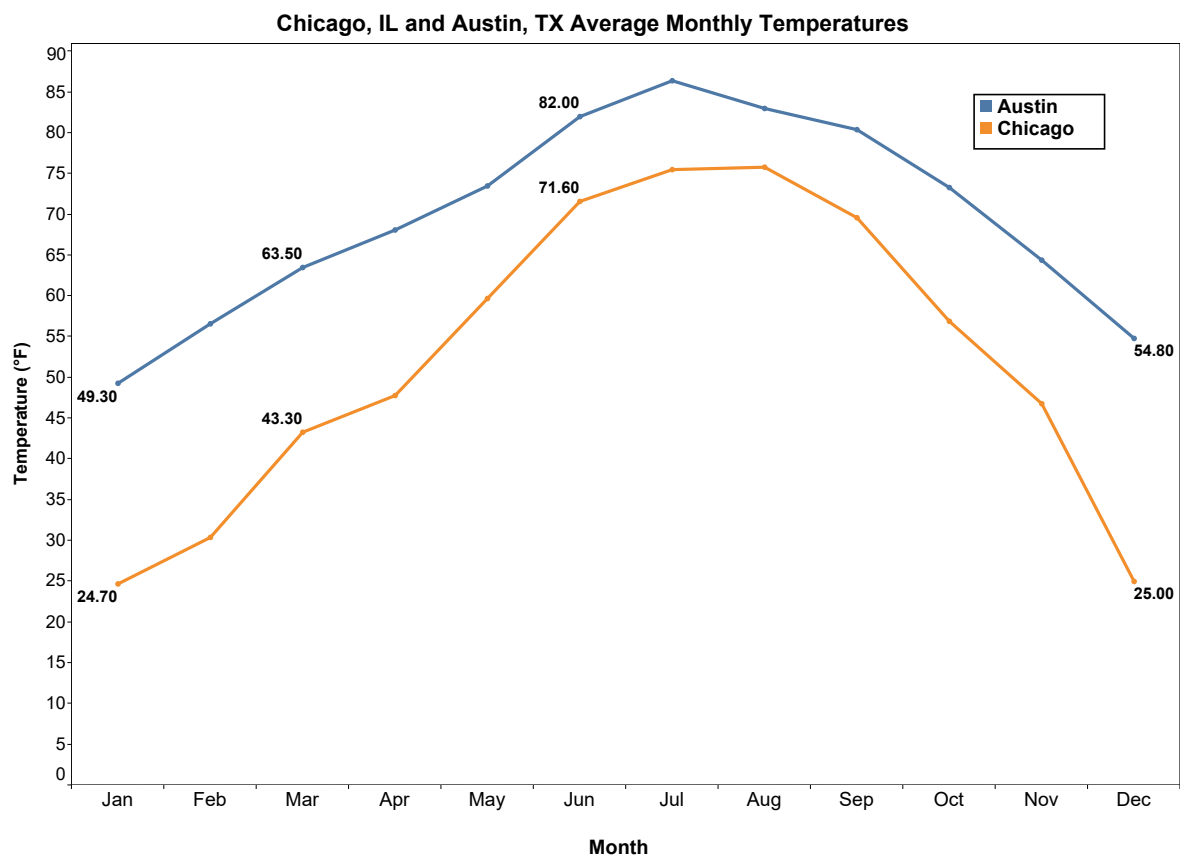


Figure 3.1: Comparison of Chicago 2016 average monthly outdoor air temperatures to Austin 2015 average monthly outdoor air temperatures [108]. Though the two cities have significant differences in terms of climate, their average monthly air temperatures were the closest in June, July, and August.

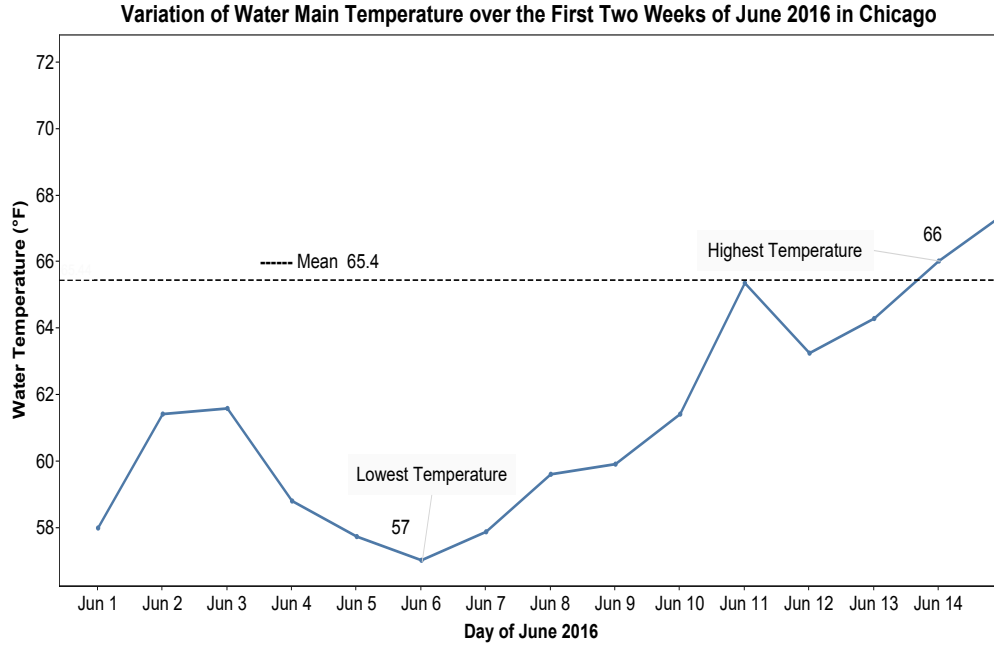


Figure 3.2: There are considerable variations in the average daily water main temperature recorded by the Chicago Park District along Lake Michigan’s lakefront [109]. Energy consumption for water heating is greater with lower water main temperatures.

Historical daily average outdoor air temperature data were obtained from the National Oceanic and Atmospheric Administration (NOAA) website to assess the potential impact of outdoor air temperature on daily domestic electricity use. An initial assumption that households are less likely to use space heating or cooling in the period starting from late-May to mid-June was made; therefore, households’ electricity consumption data could present a higher signal-to-noise ratio for water heating specifically during that period. Further analysis of historical climate data revealed that May 2016 in Chicago had an average daily temperature of 59.7°F, 255 Heating Degree Days (HDD) and 67 Cooling Degree Days (CDD), while June’s average monthly temperature was 71.6°F with 13 HDD and 216 Cooling Degree Days [108]. Considering the effect of outdoor air temperatures on domestic electricity consumption, it was important to select a sample from the ComEd data that would minimize the

potential error due to noise in the data. As seen in Figure 3.4, there is a strong correlation between outdoor air temperature and electricity consumption. Average outdoor air temperature explained 82% of the variability in household daily electricity use for a sample of 45 single-family homes in Chicago (See Figure 3.4). Since the model's accuracy used to disaggregate electricity for water heating from whole-house electricity consumption data strongly relies on the assumption that water heating loads are dominant, selecting a sample period with minimum cooling degree days and heating degree days was critical; therefore, the first two weeks of June were selected since space heating would not be the dominant load. As shown in Figure 3.3, the days with the highest electricity use for June correspond to the days with highest temperatures, namely June 11 and June 20, with daily average outdoor air temperatures of 81°F and 82°F, respectively.

Daily Average Outdoor Air Temperature vs Daily Average Residential Electricity Consumption in Chicago

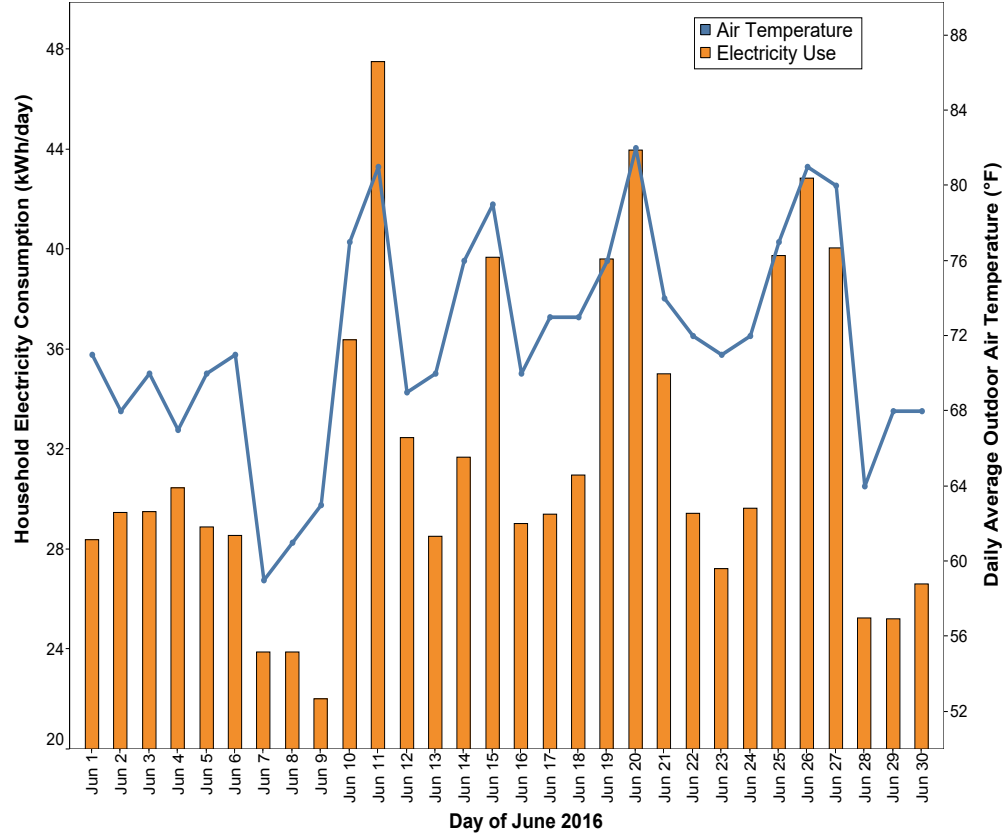


Figure 3.3: Daily average air temperatures varied in June 2016, as measured from the Chicago Midway weather station [108].

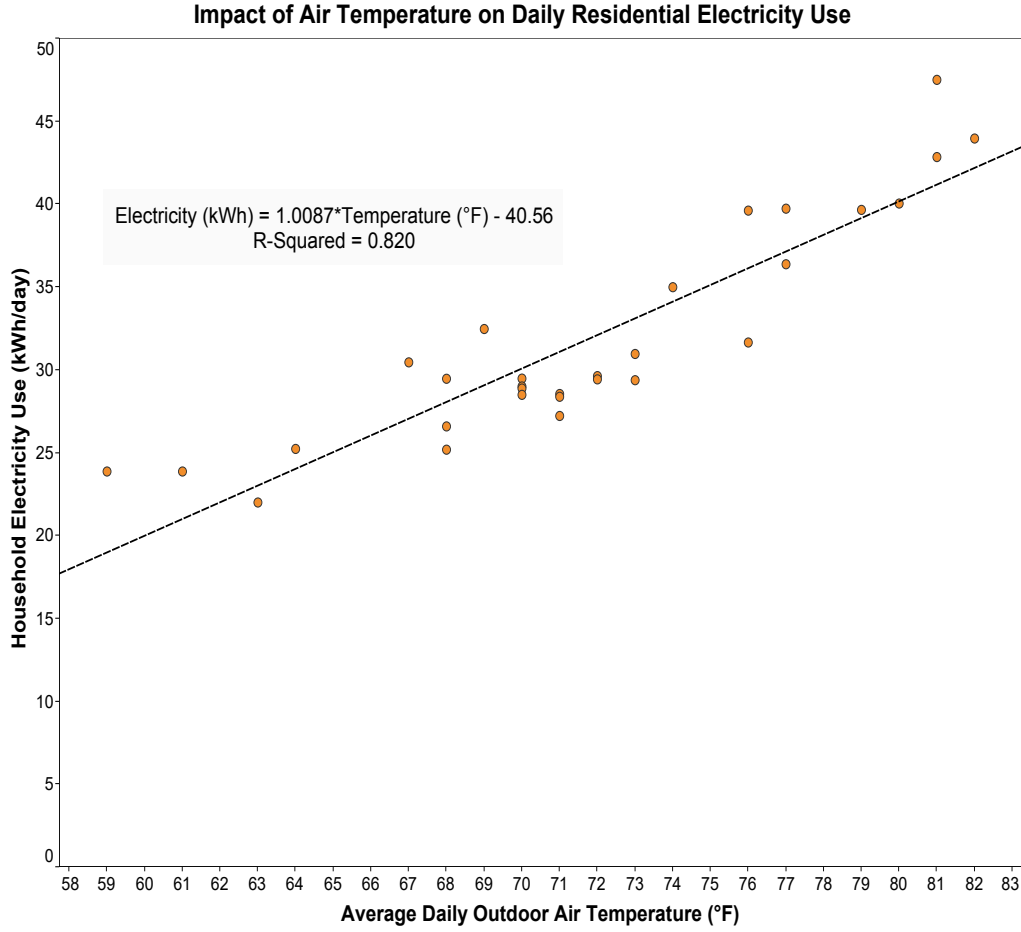


Figure 3.4: Electricity loads are sensitive to outdoor air temperatures. A simple linear regression model shows that 82% of the variation in household electricity use is explained by average daily outdoor air temperature, over the observed range [108].

3.2.2 Data Synthesis

This study considered single-family households with electric space heat. The main assumptions leading to this approach, aiming to minimize bias in the study are:

1. Single-family households with electric space heat are more likely to use an electric water heater.

2. Single-family households without electric space heating might use natural gas-fired water heaters, which will not allow isolating water heating signals from the data.

3. Multi-family households and other buildings might share a common water heater across several units, introducing bias in the estimating approach.

Figure 3.5 illustrates the spatial distribution of the data for single-family households with electric space heat considered in this study. There were a total of 1,042 single-family households with electric space heat in the city of Chicago located in 24 different ZIP codes. In this study, a sample of 120 households representing 8 different areas of the city was selected from the total. The city Central area (which covers the larger downtown area including the Loop, Near North Side, and Near South Side community areas) does not have single-family households with electric space heat. According to the Energy Information Administration, 16.7% of Illinois households use electricity for space heating [110]; therefore, this analysis of residential electricity for water heating could be a representative quantification approach for further research with natural gas data.

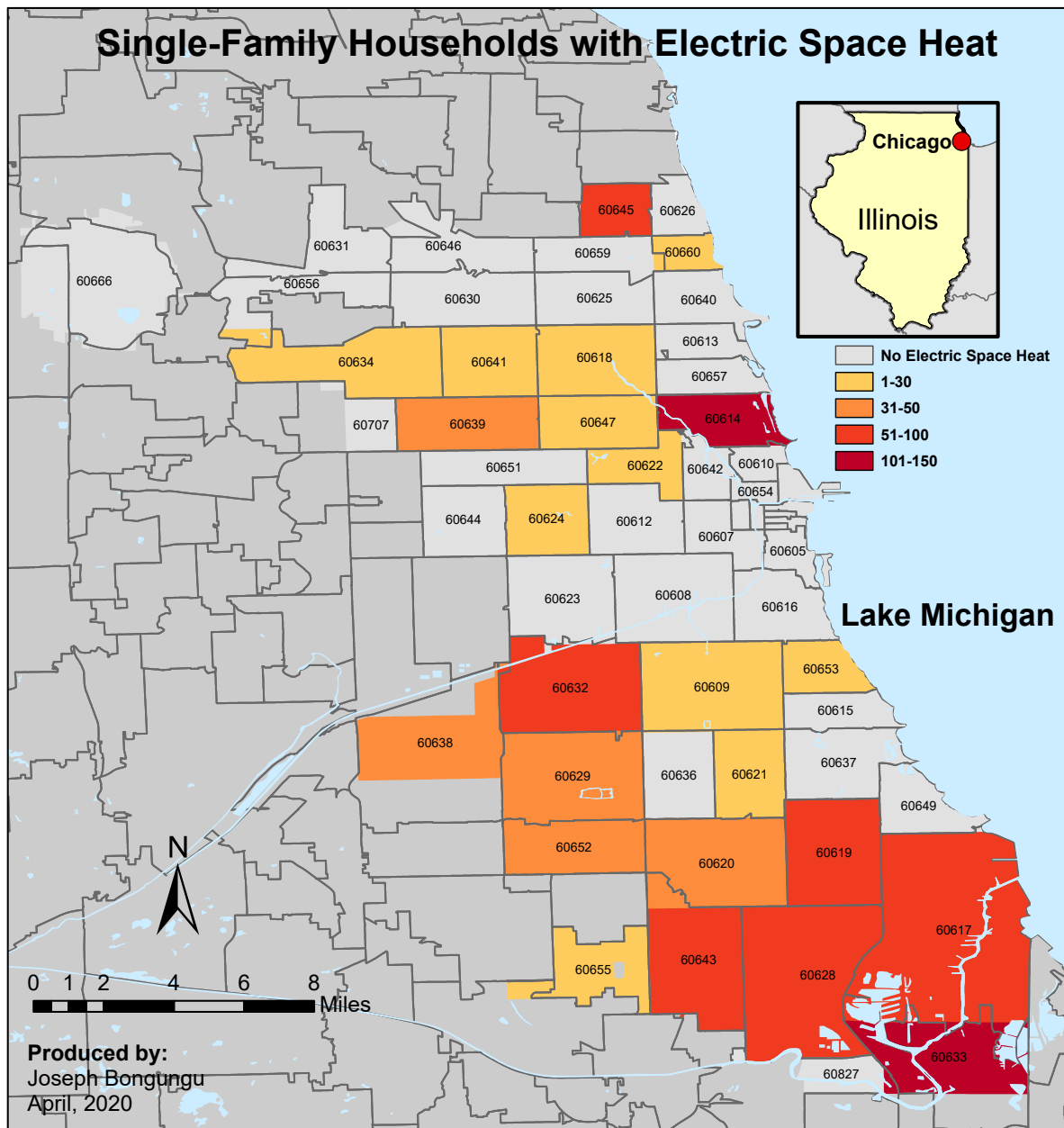


Figure 3.5: Single-family homes with electric space heat were selected as most likely to use electric water heaters. There were a total of 24 different ZIP codes containing single-family residential households with electric space heat. A sample 120 households from 1,042 single-family homes with electric space heat was used in this analysis.

3.2.3 Data Processing

Whole-house electricity consumption data for the first 14 days of June 2016 was taken from 120 single-family houses located in 8 different ‘sides’ representative of distinct parts of the city (see Figure 3.5 for ZIP code locations). Each side could be considered as a mini-city within Chicago since some parts of town are booming, certain parts are solidly prosperous, and others are in sharp decline [126].

June 2016 was selected because the model’s performance and accuracy depend on the key assumption that electric water heating is the dominant load for the time period considered in the energy disaggregation model. It was assumed that the first 14 days of June would provide better accuracy than other periods of time because the average daily outdoor air temperature, as shown in Figure 3.3, would minimize the number of heating or cooling degree days for that period of time, minimizing the presence of space heating or air conditioning in the electricity load profiles. However, it was anticipated that June 11, which had the highest average air temperature (81°F), would have considerable noise in electricity consumption data as air conditioning might have been in use.

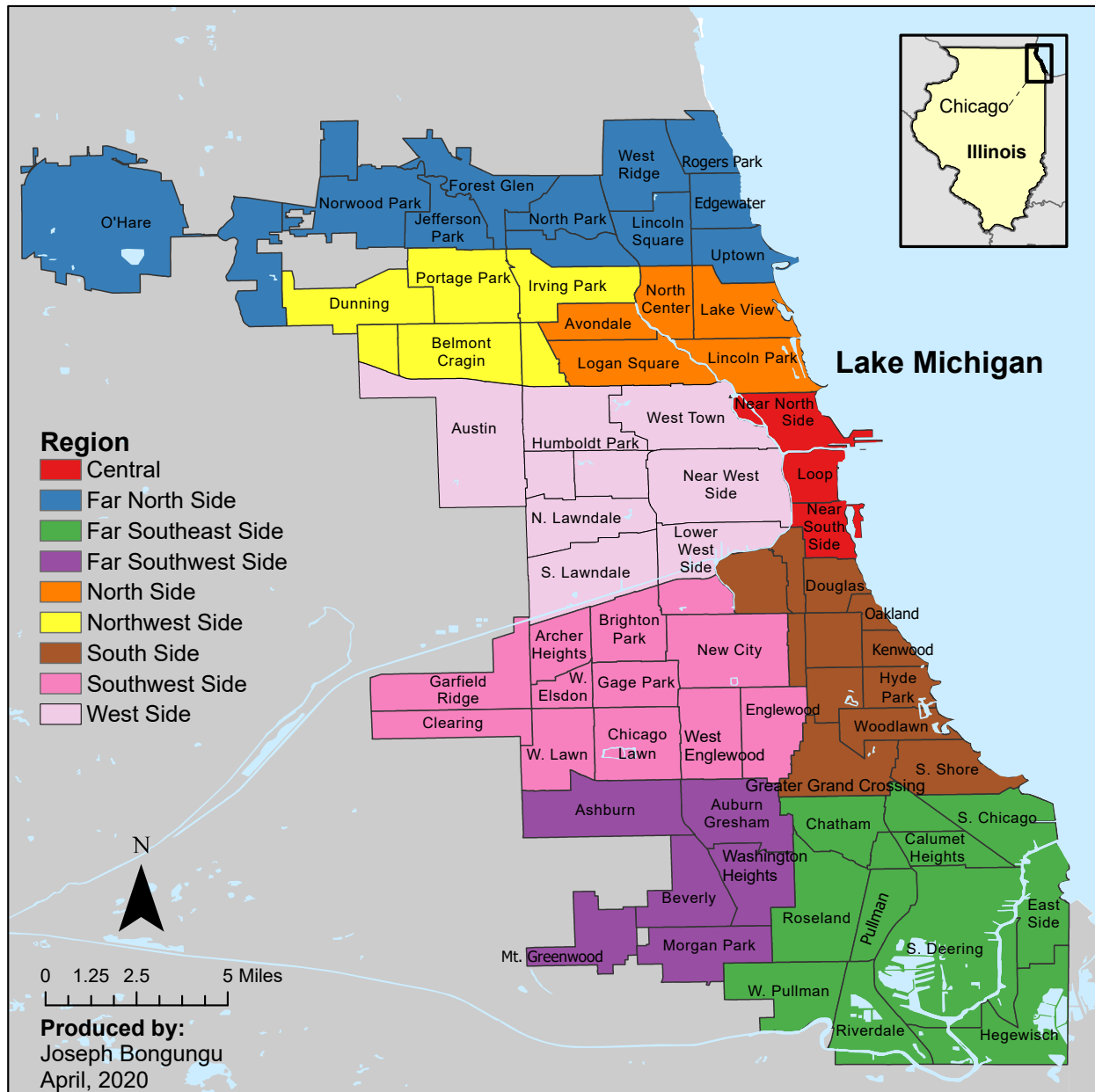


Figure 3.6: The study areas included different regions (“sides”) of Chicago. Central Chicago (The Loop, Near North, Near South) was the only region without single-family residential households with electric space heat.

3.3 NILM Disaggregation Algorithm

The model implements a non-intrusive load monitoring (NILM) technique to identify the electricity signal of water heating and disaggregate water heater energy use from half-hourly whole-house electricity consumption data. It follows a Decision-Tree (DT) approach as it measures, at each timestep, the magnitude of change in load that could indicate that the electric water heater is turning on or off, which is then used to identify single on and off events of electric water heater use for each day. The key assumptions of the model are:

1. All water heater appliances of the sampled households are assumed to be electric resistance water heaters with simple ON/OFF states.
2. The Pecan Street Inc. training data reflect water main temperatures that are similar enough to the Chicago households' inlet water temperatures to minimize differences in energy required for water heating.
3. The electric water heating load is assumed to be the dominant load during the first two weeks of June 2016 in Chicago since the daily average temperature during that period was about 65°F, likely not requiring significant heating or cooling [111].

Figure 3.7 illustrates the three essential steps followed by the NILM algorithm to disaggregate water heating energy use from half-hourly whole-house energy data.

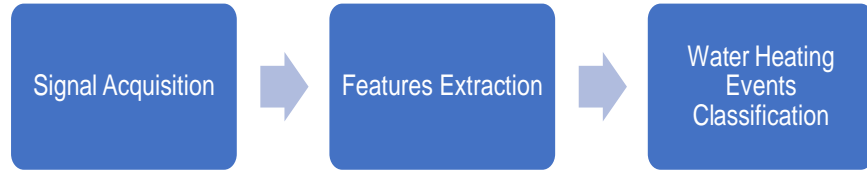


Figure 3.7: The NILM algorithm used in this study follows a three essential step process: signal acquisition, features extraction, and water heating events classification.

3.3.1 Signal Acquisition

Since the ComEd household smart electricity meter data do not include appliance-level ground truth data, the Pecan Street Inc. data were used as training data to extract the

main disaggregation parameters. These disaggregation parameters were then used to classify “on-off” events of water heaters used in Chicago households. A first set of disaggregation parameters was extracted using the 1-minute electricity consumption data, with a second training dataset downsampled to 30-minute resolution to match the sampling rate of ComEd whole-house load data. The electricity consumption data for each of the six Pecan Street Inc. households is separated by day and the energy difference between each time step, δE_i , is calculated as shown in Equation 3.1. The value of i in the study, the time interval between each electricity measurement, was 30 min.

$$\delta E_i = E_{i+1} - E_i \quad (3.1)$$

where:

δE_i is the change of energy between time t_i and the following time step t_{i+1} .

E_i is the total energy use measured at time t_i .

E_{i+1} is the total energy use measured at time t_{i+1} .

3.3.2 Feature Extraction

Following signal acquisition, the NILM algorithm proceeds to the extraction of appliance features or signatures. The algorithm assumes only one class of water heating power signature: steady-state. In other terms, electric resistance water heater signals were assumed to modulate from “on” to “off” states, though, in reality, the normal actions of electric water heaters include turn-on, turn-off, and electrical energy adjustment between upper and lower heating elements or mode changes that are termed as transients. Though analyzing transient states could provide better features — shape, duration, size, and harmonics of transient power fluctuations — to distinguish multiple appliances, extracting these types of signatures would require higher resolution data than the 1-minute or 30-minute data used in this study. High-resolution data are rich in informative transients and have the potential to broaden the research field and improve accuracy of load disaggregation, but there have not been enough studies devoted to this area [112]. The water heater features extracted from the training dataset constitute the NILM algorithm’s main disaggregation parameters: δE_{ON} ,

δE_{OFF} , WH_{ON} , and WH_{OFF} . The training dataset was filtered to only include March 1-31 data since the average water main temperature in Austin during that period, 67.8°F, was close to Chicago’s June average water main temperature (see Figure 3.2) [107]. Midnight to 6:00 AM was chosen as the training period to minimize interference of other appliance signals, which are more prevalent during later hours of the day, as load profiles approach peak energy consumption. It is critical that the water heater is the dominant load during the training period. The signal size parameters δE_{ON} and δE_{OFF} represent the changes in magnitude large enough to indicate that the water heater has either turned on or off.

The energy difference between each time step, δE_i , from March 1-31, was stored and used to generate δE_{ON} and δE_{OFF} . For instance, if the recorded water heater power went from 0 kW at time step t to a positive value at time t_{i+1} , it indicates an “on” event and the corresponding total grid energy value at time t_{i+1} , E_{i+1} , is recorded as $\delta E_{ON_{i+1}}$. Each household has an equivalent absolute δE_{ON} , which is the minimum of all the δE_i values corresponding to an “on” event. Similarly, if the recorded water heater power consumption went from a positive value at time step t to 0 kW at time t_{i+1} , it indicates an “off” event and the same procedure described for an “on” event is followed to extract δE_{OFF} . Table 4.1 shows the different disaggregation parameters extracted for each of the 6 households from the Pecan Street Inc. Dataport dataset. The averages of these parameters were used as the main parameters of the NILM algorithm to disaggregate energy for water heating from the ComEd dataset. In addition to signal size parameters, two constraints were derived to minimize false detection of “on” and “off” events: WH_{ON} and WH_{OFF} . These constraints prevent noise from other appliances from signaling a water heater “on” or “off” event. On days where multiple appliances were running simultaneously, non-water heater electrical loads could reach similar orders of magnitudes as water heating loads; therefore, the model could misinterpret the electricity loads and assimilate other appliance loads as water heating loads. WH_{ON} is the minimum total energy required to signal that the water heater did turn on, while WH_{OFF} is the upper limit signaling that it turned off. The system first had to be in an “off” state to signal an “on” switch; similarly, it needed to be “on” to signal an “off” switch. The WH_{ON} parameter was obtained from the total energy use data by taking the maximum energy value between midnight and 6:00 AM, during which the water heater unit dominates the energy profile. WH_{OFF} was calculated as half the value of WH_{ON} . The

disaggregation parameters derived from the training dataset were then used with the ComEd data to extract information about energy for water heating in single-family households in Chicago. Figure 3.8 shows the boundaries imposed on a typical day, WH_{ON} and WH_{OFF} , to prevent noise from other appliances such as the refrigerator from signaling a water heating “on” or “off” event.

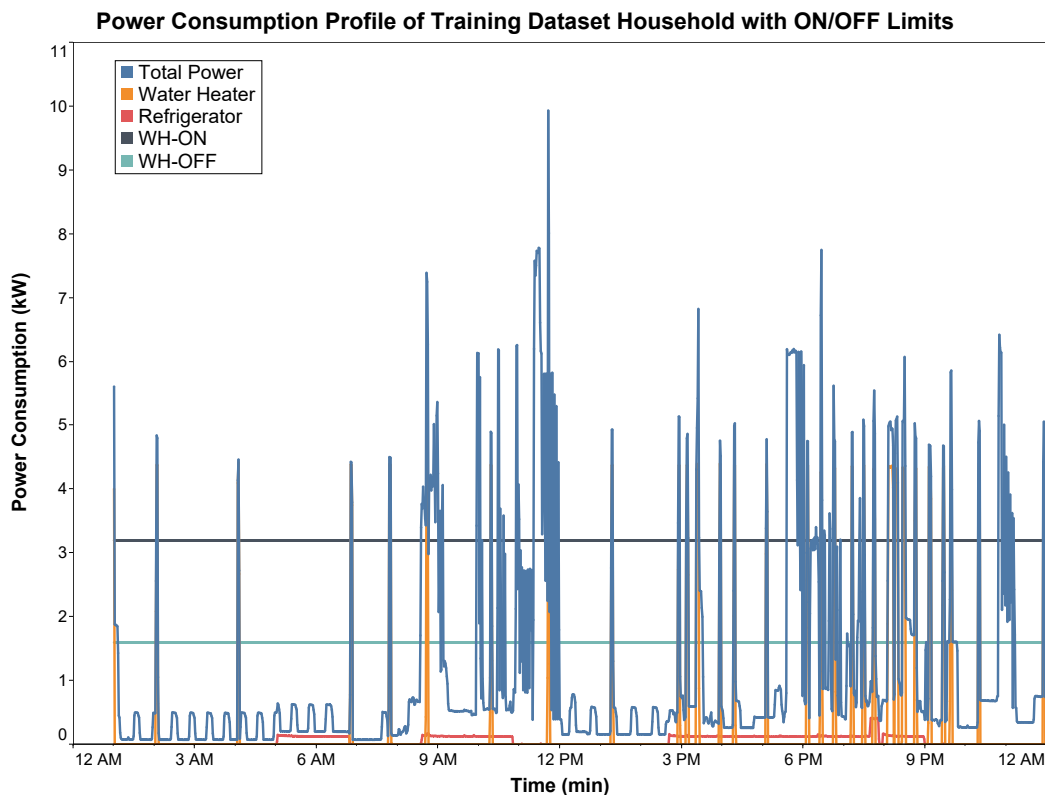


Figure 3.8: Electricity consumption profile of one household from the training dataset with disaggregation parameters WH_{ON} and WH_{OFF} plotted, representing respectively upper and lower boundaries for total electricity consumption indicating that the water heater was “on” during a time step.

3.3.3 Water Heater Events Classification

The final step in the load disaggregation process, appliance classification, refers to analyzing features extracted from whole-house electricity data to categorize specific water heater “on” / “off” events. There are two types of scenarios under which the water heater element turns on [113]:

1. When water temperature inside the storage tank drops below the minimum setpoint temperature as a result of conduction heat losses. The element will be on for approximately 18 minutes during a normal cycle, but it could last longer depending on the volume of water drawn.

2. When a large amount of water is drawn from the storage tank and replaced with incoming cold water, the water temperature can be far below the setpoint; therefore, the length of time that the element will be in use will vary.

As illustrated on the algorithm decision tree (see Figure 3.9), once the algorithm establishes that the water heater is either in an “on” or “off” state, it compares the stored difference in energy use between two consecutive data points to the signal size parameters δE_{ON} and δE_{OFF} . Following the first test, it then compares the total energy use at the following time step t_{i+1} to the constraints or boundary parameters, WH_{ON} and WH_{OFF} . If the difference in energy is large enough to signal that the water heater turned on ($\delta E_i \geq \delta E_{ON}$) and the electricity used at time t_{i+1} is greater than the lower limit ($E_{i+1} \geq WH_{ON}$), then the time step is stored as the system being turned on and in use.

The algorithm steps forward in time until the following two conditions are met:

1. $\delta E_i \leq \delta E_{OFF}$
2. $E_{i+1} \leq WH_{OFF}$, which means that the decrease in the electricity consumption was large enough to indicate that the water heater turned off and the total electricity used at time t_{i+1} was below the lower electricity use threshold.

Once the algorithm detects that the water heater is turned off, it steps forward in time until another signal indicating a water heater switch-on event is found. The decision process, illustrated in Figure 3.9, is repeated until the end of each day. The sum of the time step values stored during “on” events represents the total duration of the water heater operation. Electricity for water heating was estimated as shown in Equation 3.2 by multiplying the

accumulated water heater “on” events duration stored for each day with the average water heater power demand values obtained from the Pecan Street Inc. training data. Table 3.1 shows the average power demand of each of the 6 single-family households used as a training data set. Since the average water heater power demand is applied to the entire day, the estimated daily electricity for water heating values do not reflect differences due to appliance efficiency. As illustrated in Figure 4.1, the NILM algorithm either overestimates or slightly underestimates the electricity used for water heating.

$$E_{WH} = P_{AVG} \times t_{ON} \tag{3.2}$$

where:

E_{WH} is the estimated electricity used for water heating in kWh.

P_{AVG} is the average power demand of water heating element in kW.

t_{ON} is the estimated total duration of daily water heating “on” events in hours.

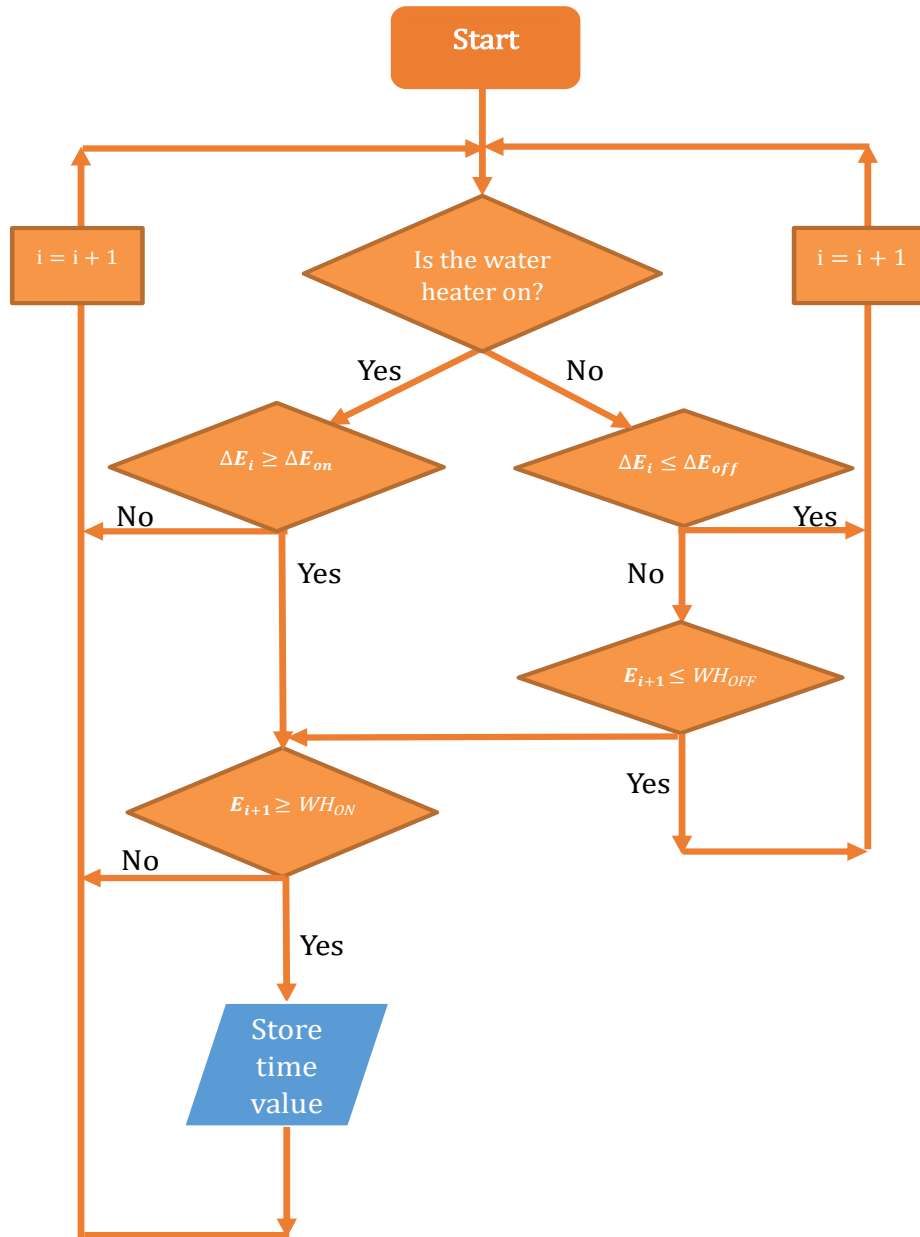


Figure 3.9: NILM algorithm decision tree to infer power signal of electric water heater and classify "on" and "off" events.

Table 3.1: NILM Algorithm Disaggregation Parameters

House	Power _{avg} (kW)	WH _{ON} (kW)	WH _{OFF} (kW)	$\delta E_{ON}(kW)$	$\delta E_{OFF}(kW)$
House 1	1.82	2.94	1.47	0.066	-0.102
House 2	1.53	1.73	0.87	0.141	-0.037
House 3	1.68	4.85	2.43	0.177	-0.029
House 4	1.78	4.87	2.53	0.058	-0.139
House 5	1.19	3.46	1.73	0.098	-0.027
House 6	1.74	3.20	1.60	0.061	-0.101

3.4 Domestic Hot Water Use Estimation from Extracted Water Heater Load

Domestic hot water (DHW) use was estimated using the isolated water heating signal for single-family households with electric space heat. Conventional storage tank water heaters are the most common type of water heater in the residential sector. Using the First and Second Laws of Thermodynamics, the volume of water heated from the inlet water temperature to the delivered DHW set temperature can be calculated.

Taking into account energy losses, inefficiencies, and waste heat, a measure rating the overall efficiency of a domestic water heater is necessary to calculate the actual volume of water heated as a function of energy consumption. The efficiency of electric storage water heaters is represented with an energy factor (EF) [29], defined by the following equation:

$$EF = \frac{E_{WH}}{E_{del}} \quad (3.3)$$

where:

E_{WH} is the useful water heater energy output.

E_{del} is the total amount of energy delivered to the water heater.

Water heater energy factors take into account standby losses estimated as the percentage of heat lost per hour from the stored water compared to the heat content of the water [114]. EF values for electric storage water heaters range from 0.90 for a standard model to 0.95 for a

high-efficiency model, based on insulating conditions and flue losses [29, 115]. The estimation of domestic hot water consumption is based on a number of simplifying assumptions:

1. The inlet water temperature ranged from 57°F to 66°F during the first two weeks of June 2016 in Chicago (see Figure 3.2).
2. Water density ranges from 988.5 kg/ m^3 at 66°F (or 18.9°C) to 999.1 kg/ m^3 at 57°F (or 13.9°C) [116].
3. Specific heat of water ranges from 4.182 kJ/kg°C for 57°F (or 13.9°C) to 4.187 kJ/kg°C for 66°F (or 18.9°C).
4. The constancy of the thermostat setpoint temperature at 120°F (or 48.9°C), based on recommendations [117].
5. The effect of the ambient temperatures on DHW use is negligible.
6. Water heater units are small electric storage systems operating on continuous tariffs; which implies that energy consumption roughly tracks hot water use with a small delay.

For a given water heater electricity consumption rate, E_{WH} , the daily volumetric flow rate of hot water drawn, V , is estimated using the following equation:

$$V = \frac{E_{WH} \times EF}{\rho C_p (T_{tank} - T_{in})} \quad (3.4)$$

where:

V is the daily hot water volume draw in m^3 /day

E_{WH} is the disaggregated daily electricity for water heating in kWh/day.

EF is the storage tank electric water heater energy factor.

ρ is the density of water in kg/ m^3

C_p is specific heat of water in kWh/kg °C

T_{tank} is the thermostat setpoint or desired hot water delivery temperature in °C

T_{in} is the temperature of the water supplied to the electric water heater in °C

Uncertainty exists in each of these input parameters and is quantified through high-low methods.

CHAPTER 4

RESULTS

4.1 Overview

This analysis demonstrates the potential of smart electricity meter data to reveal domestic hot water use information. First, 6 single-family homes from a 1-minute resolution training dataset, located in Austin, TX, were used to extract the NILM disaggregation parameters, and then to validate the disaggregation technique used in this study by comparing ground truth data to the estimated values. Since these 6 households had sub-metered electric water heaters, they were used as a benchmark to evaluate the performance of the algorithm with meter readings at both 1-minute intervals and 30-minute intervals. The algorithm showed satisfactory performance with 1-minute data and minimal error during early hours of the day (midnight to 8:00 AM), which corresponds to the period of time when the water heater is the dominant load. During later hours, closer to peak consumption hours, the algorithm showed increasing error and greater tendency to overestimate water heating loads due to lower signal-to-noise ratio; the algorithm could not always distinguish loads of the same magnitude as water heating loads.

Secondly, the algorithm’s performance was evaluated using the training dataset down-sampled to 30-minute. Due to the coarser temporal resolution of the data, the algorithm’s performance significantly decreased; by aggregating loads to 30 minute intervals, the probability that water heating “on” and “off” events are correctly detected decreased given that the average duration of consecutive “on” times was less than 15 minutes. Following the algorithm’s performance evaluation, the 120 Chicago single-family households from the ComEd dataset were used as input to the NILM disaggregation algorithm to generate outputs of daily

electricity for water heating as a measure of hot water consumption. The 120 households, spanning over 20 different ZIP codes, were grouped according to their respective region, as defined by the City of Chicago [118] and shown in Figure 3.6, to evaluate spatial variability in water heating energy loads and corresponding DHW use volumes. Average estimated electricity for water heating and DHW use categorized by regions are included in Tables A.1 and A.2 in the Appendix.

4.2 Disaggregation Model Validation

Figure 4.1 shows values of the daily water heating energy consumption estimated from the NILM algorithm compared with the measured values reported by the submeter over each day for a single-family home in Austin, TX. The estimated energy aligns closely with actual energy for water heating throughout the evaluated time period of March 1-31. Estimated values were consistently closer to measured values from midnight to 8:00 AM compared to other times of the day. During the rest of the day, the algorithm was less accurate because there were other loads in the profile, equivalent to other appliances used throughout the day, that had similar magnitudes; thus, the algorithm detected false events and overestimated water heating energy for those hours. A parity plot of data ranging from midnight to 8:00 AM on March 1-4 of estimated electricity for water heating vs. measured water heating energy consumption exhibited a higher coefficient of determination, R-squared, value and substantially lower coefficient of variation of the root mean square error, CV(RMSE), than full day data (midnight to midnight). This result confirms that the model performs better when the water heater is the dominant load.

The training data set used in this analysis was collected at a 1-minute sampling rate by Pecan Street Inc. Since smart meters installed in Chicago’s households report energy usage in 30-minute intervals, the training data set had to be downsampled to 30-minute to extract proper disaggregation parameters. However, from the disaggregation results plotted in Figure 4.1, the accuracy of the model’s predicted values decreases as the data become coarser. Typical hot water draw events have a duration of less than 10 minutes with the majority of volume drawn often less than 2 gallons [39]. Consequently, downsampling to 30-

minute resolution adds considerable noise to the data, making it more difficult for the NILM algorithm to accurately distinguish water heater-related events from the base load. Figures 4.1 and 4.2 show a comparison of the electricity load profile and disaggregation for 1-minute and 30-minute data. It is substantially more challenging to accurately measure water heater cycle numbers with the 30-minute data. By taking the sum across 30 minutes, anomalies and spikes of water heating-related events cannot be detected by the algorithm. Table 4.1 shows differences between the model’s predictability for different data resolutions, quantified as CV (RMSE). CV (RMSE) was adopted in the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guideline 14 as a measure to evaluate prediction uncertainty of energy inverse models [119]; the minimum acceptable level of performance of an energy prediction model corresponds to a CV(RMSE) within $\pm 30\%$ when using hourly data. The average CV(RMSE) for the 6 houses in the training data set at 1-minute intervals is 1.2%, while the corresponding data downsampled to 30-minute intervals yielded a value of 33%. When aggregated by day, the algorithm appears to considerably overestimate the corresponding daily energy for water heating disaggregated from downsampled data versus the estimates obtained from the 1-minute resolution data (see Figure 4.1).

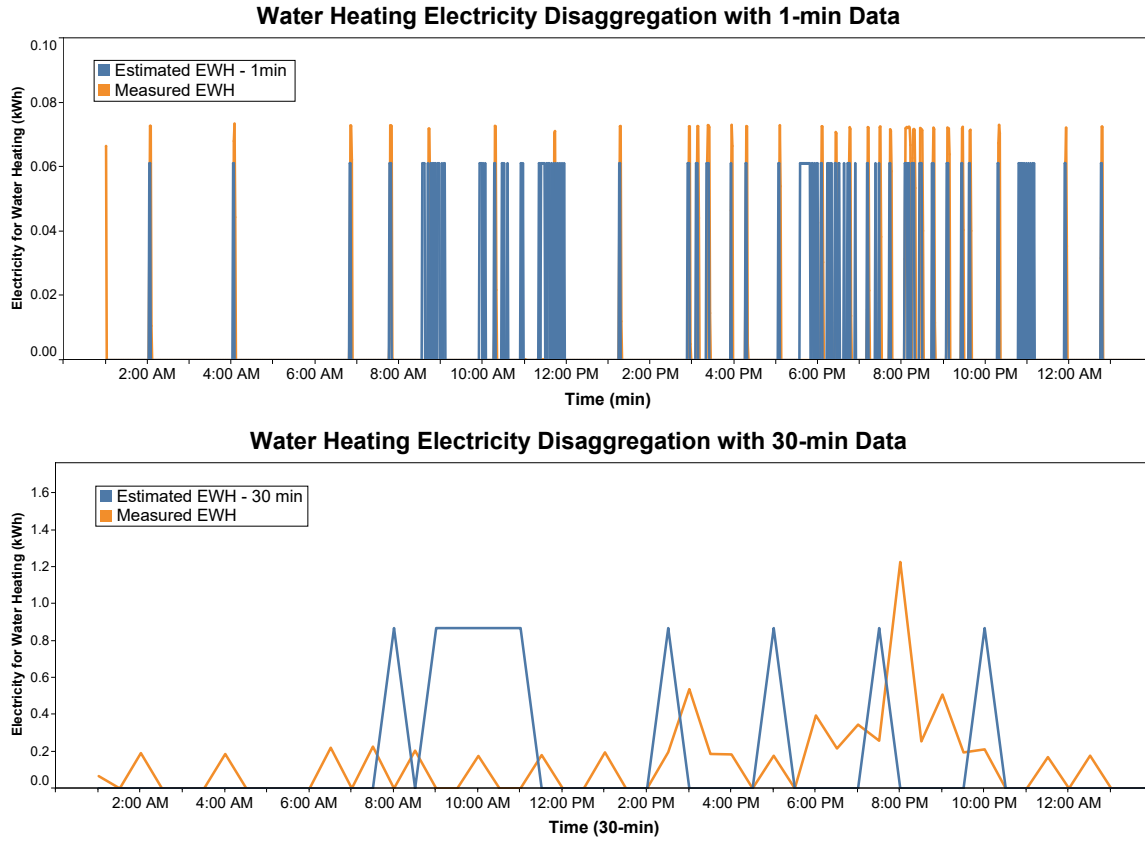


Figure 4.1: Comparison of the ability of the algorithm to estimate electricity for water heating (EWH) for a single day at different sampling resolutions. The top plot uses 1-minute data and the bottom plot uses data downsampled to 30-minute intervals. As data resolution decreases, the model disaggregates the water heating load less accurately. Measured electricity for water heating (EWH) denotes the actual values obtained from the sub-metered electric water heating system. Estimated EWH-1min is the disaggregated energy for water heating from 1-minute electricity consumption data.

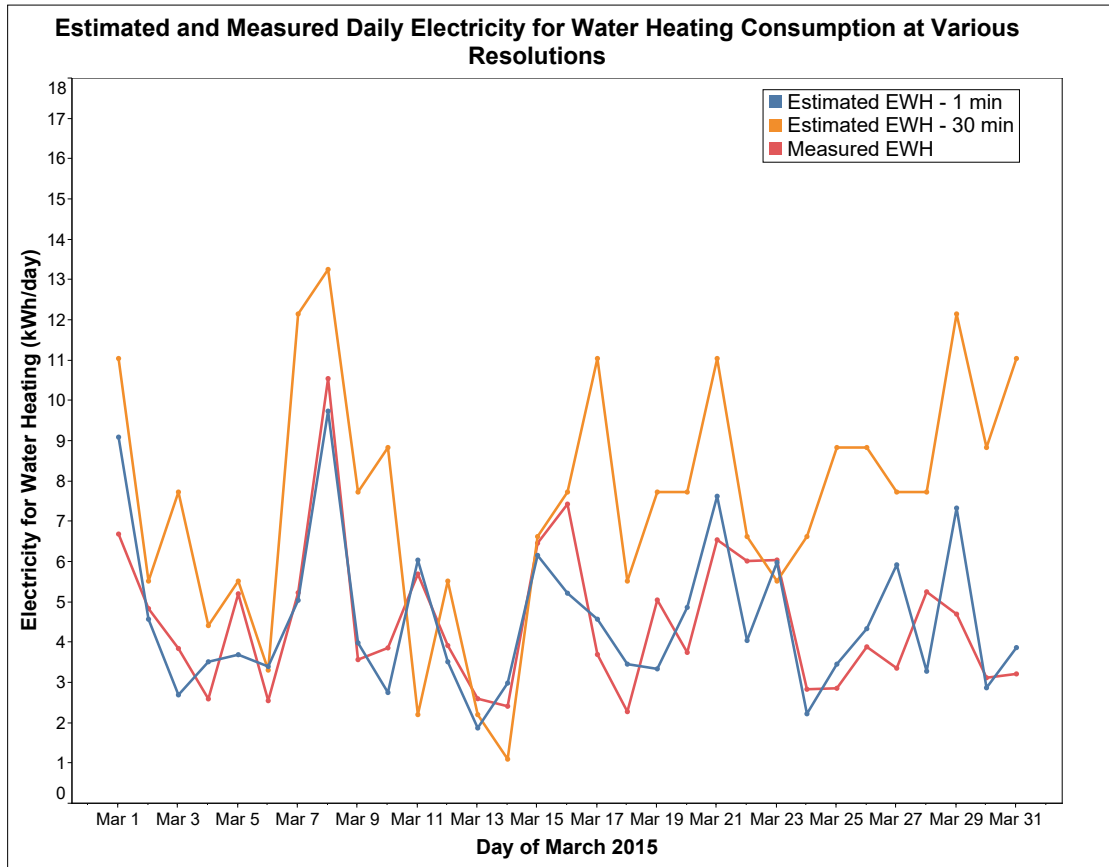


Figure 4.2: Comparison of the aggregated daily electricity for water heating estimated at 1-minute and 30-minute sampling rates with the actual values from sub-metered water heating appliance for the period of March 1-31. As energy use data becomes coarser, the model tends to overestimate the energy use for water heating.

Table 4.1: CV(RMSE) values for energy disaggregation model’s performance evaluation.

House ID	CV(RMSE) at 1-min	CV(RMSE) at 30-min
871	2.0%	38.0%
1632	0.8%	22.9%
1700	1.1%	35.3%
2710	0.9%	41.6%
7951	1.4%	23.4%
8188	1.4%	33.9%

4.3 Electricity for Residential Water Heating Estimate

Disaggregating water heater electricity loads from aggregate household load data was the first step to developing the domestic hot water usage profile. The average household daily water heating electricity consumption for the sample of 120 single-family residential homes analyzed in this study was estimated to be 1-8 kWh/day, which represented approximately 7-20% of the daily total household electricity consumption (see Figure 4.3). As validation, the EIA estimates that electric water heating consumes 12 kWh/day per household, on average. Though the disaggregation model tends to overestimate the duration of water heater “on” events, the overall average estimated electricity for water heating is lower than EIA’s estimated average because the average power demand of the water heater used in the calculations was 2 kW, which was obtained from the 6 training households, though most water heater element sizes are 3-4 kW. The 15 households located in the Far North Side, which averaged a daily total electricity consumption of 42 kWh, had the highest estimated daily energy for water heating at 8 kWh (see Tables A.1 and Table A.3). The 15 households representing the South Side, which had the lowest total daily average electricity use of 13 kWh (see Table A.3), showed the lowest average daily electricity for water heating (1 kWh). Figure 4.4 shows a comparison of these two extremes, highlighting high spatial

variability of estimated values of electricity for water heating. Electricity for water heating represented approximately 20% of the daily total electricity consumption for the Far North Side households, while accounting for 8% in South Side households. The results demonstrate that high daily electricity for water heating values were located in the Far North Side, Far Southwest Side, West Side, North Side, and Southwest Side, while the South Side, Northwest Side, and Far Southeast show lower average values. Most neighborhoods located in the North Side and Far North Side of Chicago have median household income and median home values that are higher than the average.

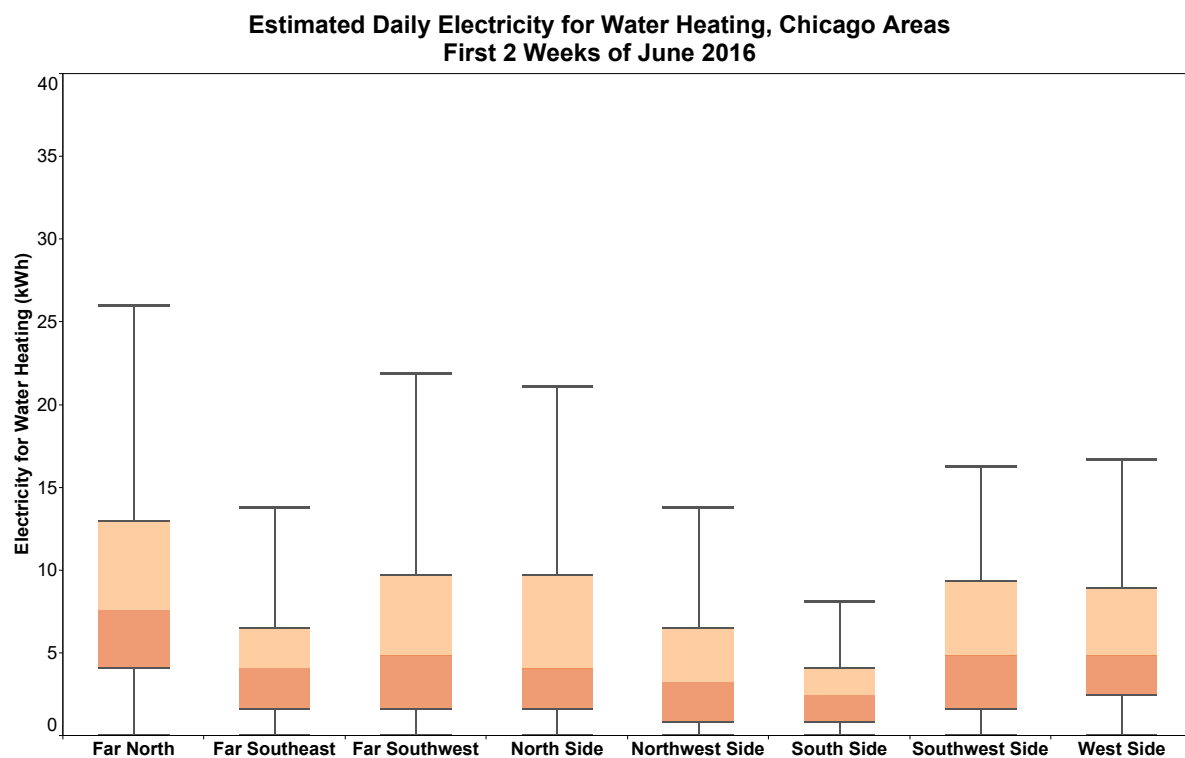


Figure 4.3: A box and whisker plot showing the daily energy for water heating distribution for the first two weeks of June 2016 from a sample of 120 single-family households located in 8 different areas of Chicago. These single-family residential homes used an average of 1-8 kWh per day for water heating, which accounted for 7-20% of total electricity consumption.

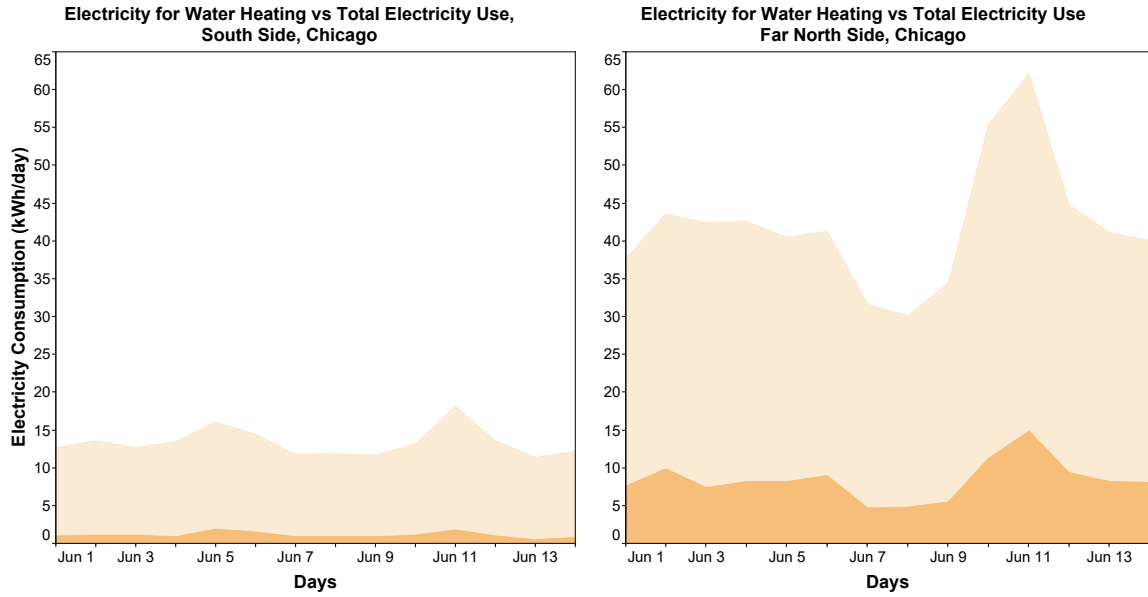


Figure 4.4: Comparison of estimated daily electricity for water heating as a portion of total daily electricity use for single-family residential households in the South Side (left) and Far North Side (right) of Chicago.

In addition to spatial variations, the estimated daily water heating electrical loads for the first two weeks of June 2016 show considerable temporal variations (see Figure 4.5). Daily electricity use for water heating varies from June 1-14. Fridays and Saturdays (June 3-4 and 10-11) almost consistently exhibit higher consumption than other days, while Wednesdays and Thursdays (June 1-2 and 8-9) are slightly lower. As shown in Figure 4.5, on Saturday, June 11, 2016, almost all households, representing 8 different Chicago areas, experienced a higher electricity for water heating load than the rest of the days analyzed in this study. The households representing the Far North Side required an average of 14.9 kWh for water heating purposes.

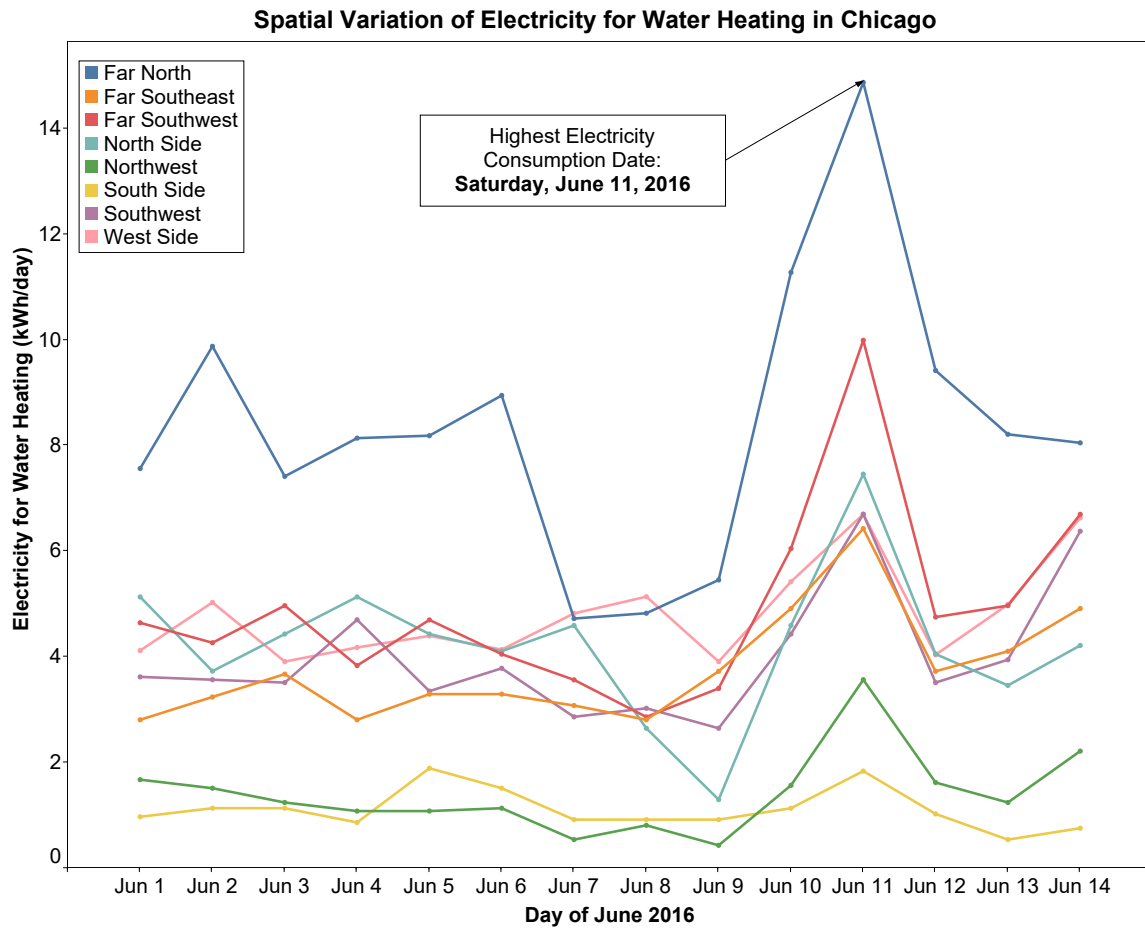


Figure 4.5: Considerable temporal and spatial variations of daily water heating loads for the first two weeks of June 2016 in Chicago are observed. The Far North is estimated to consistently use more electricity for water heating than the other areas. June 11 shows higher consumption levels than any other day.

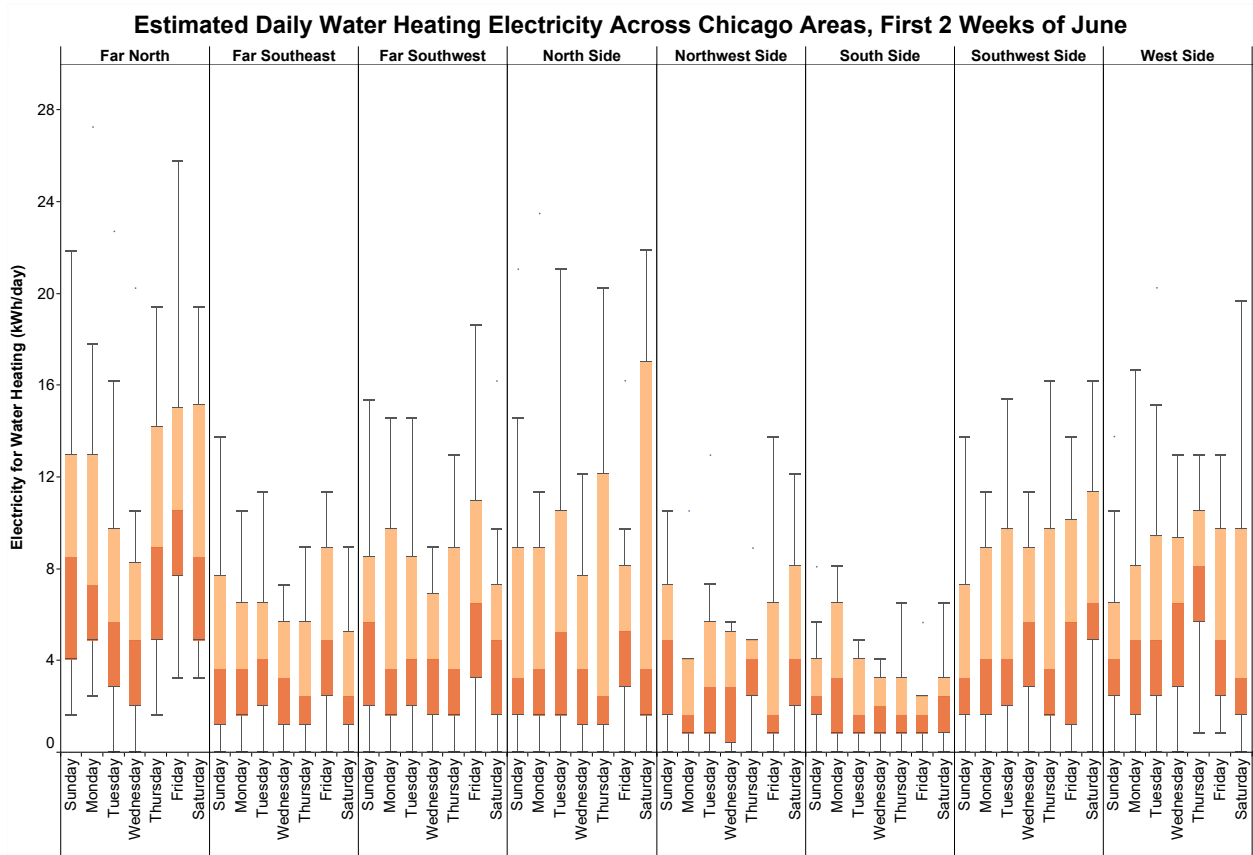


Figure 4.6: Impact of the day of the week on average estimated daily water heating electrical loads over the first two weeks of June 2016 in Chicago.

4.4 Domestic Hot Water Use Estimate

Estimating hot water consumption from smart electricity meter data alone presents some considerable uncertainty as described previously in Chapter 3. Average hot water consumption varies substantially across homes based on user behavior and preferences regarding the duration of hot water draw events (e.g., showers, clothes washing, or dishwashing). From the estimated daily DHW values, daily volumes of hot water drawn during the first two weeks of June ranged from as low as 3 gallons per day to as high as 98 gallons per day. Figure 4.7 shows the average daily distribution of estimated hot water use at the 120 single-family

residential households sampled for the 8 Chicago areas. Similarly to estimated electricity for water heating, Far North Side, North Side, Far Southwest Side, and West Side have higher average daily hot water use than other areas.

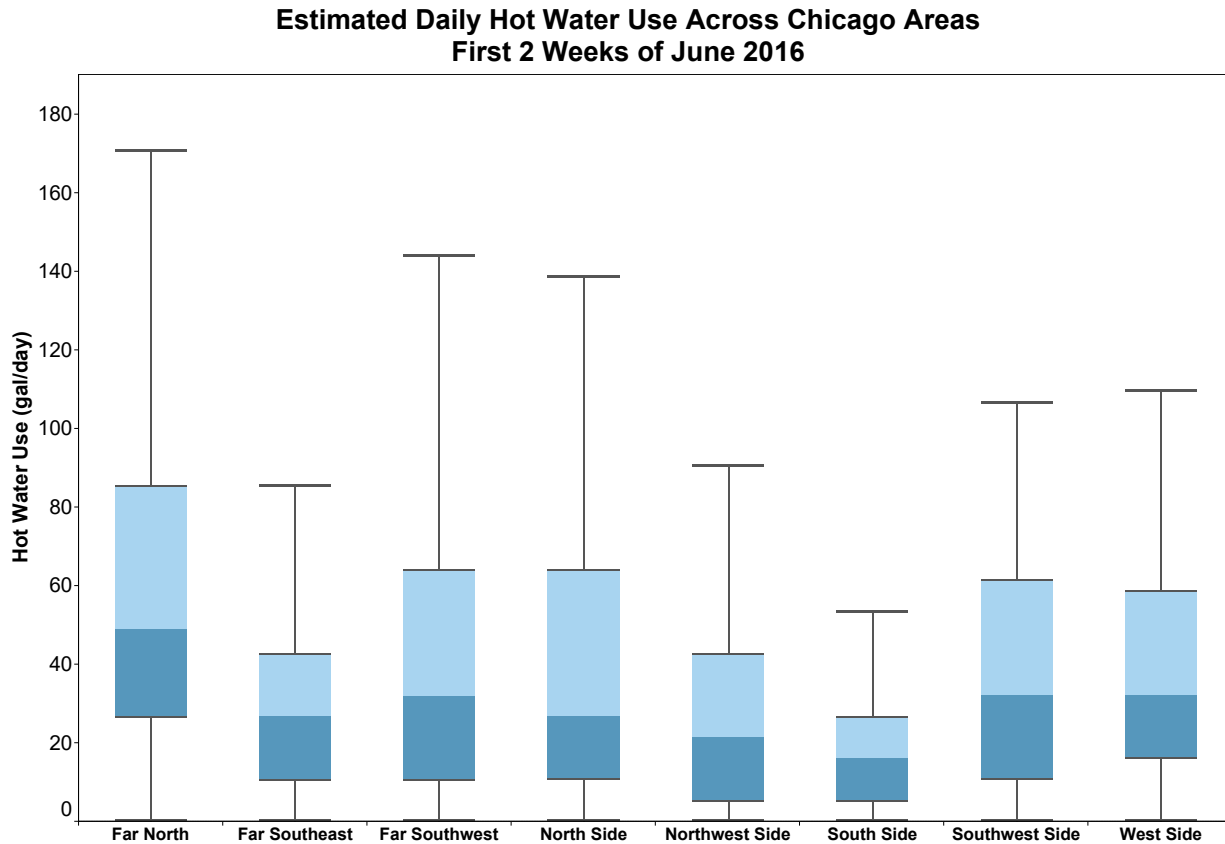


Figure 4.7: A box and whisker plot showing the daily hot water use distribution for the first two weeks of June 2016 for a sample of 120 single-family households located in 8 different areas of Chicago. These single-family residential homes used an average of 7-55 gallons per day.

Domestic hot water use within each single-family residential household is highly variable from day to day as seen in Figure 4.8 and Figure 4.9. The highest estimated daily hot water use was observed on Saturday, June 11, 2016. This observation does not imply that all households analyzed in this study used more hot water on that specific day, because the load disaggregation algorithm cannot easily distinguish other appliances with similar electricity

load magnitudes to the water heater. June 11 also had the highest average outdoor air temperature over the study period (see Figure 3.3), the electricity disaggregation algorithm could have misinterpreted space cooling load for water heating loads. As seen in Figure 4.8, Friday and Saturday appear to have higher average domestic hot water volumes used than the rest of the days.

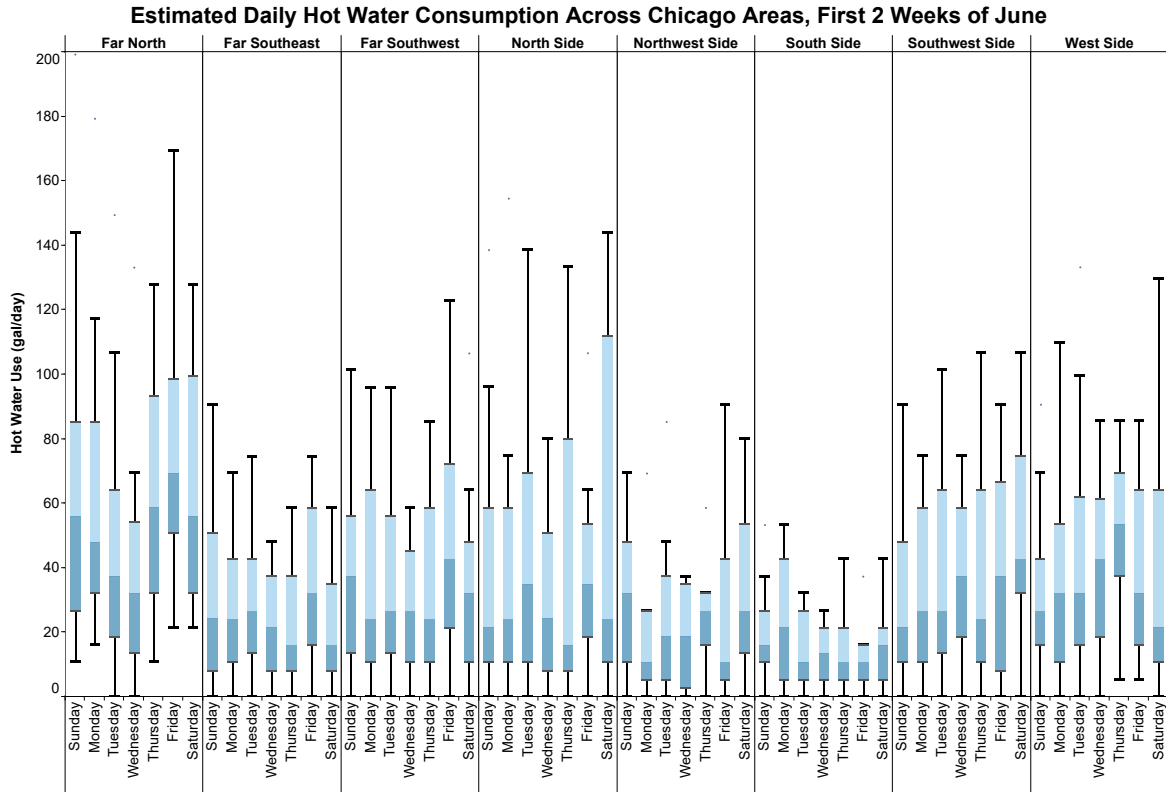


Figure 4.8: Impact of the day of the week on average estimated domestic hot water use over the first two weeks of June 2016 in Chicago.

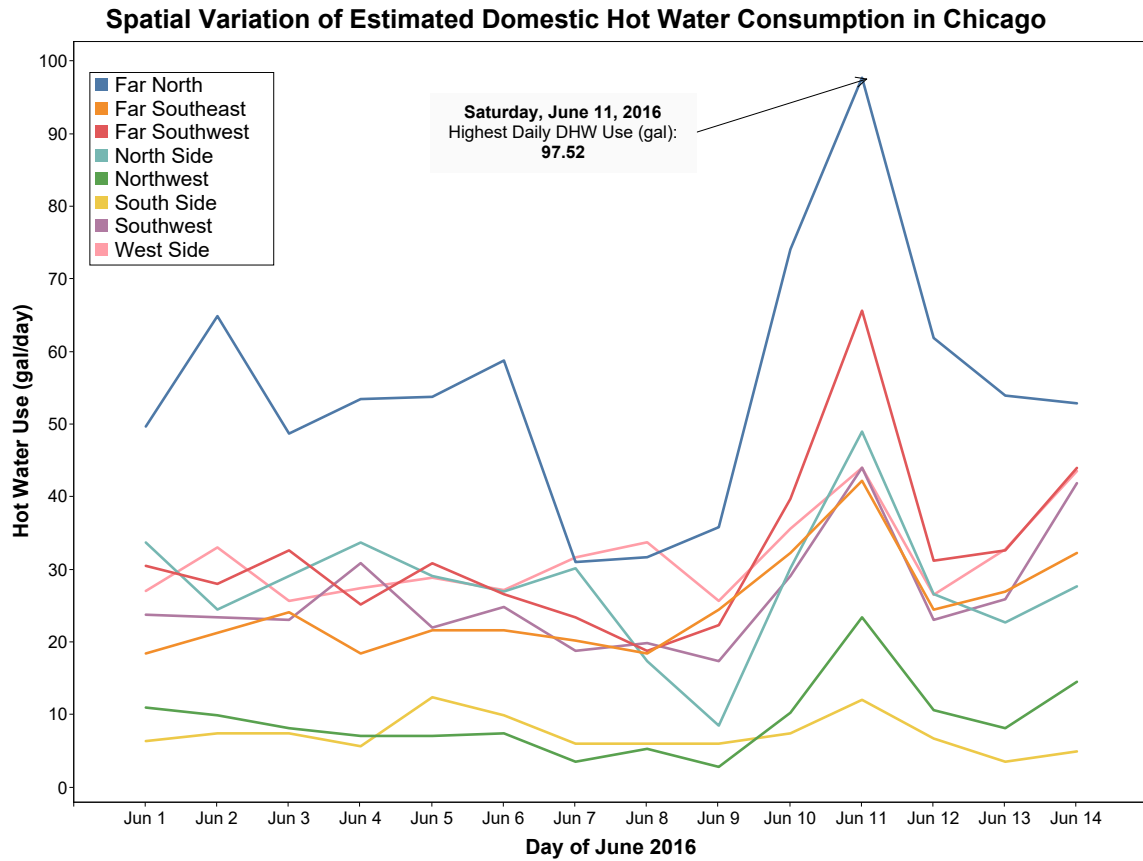


Figure 4.9: Considerable temporal and spatial variations of daily hot water use for the first two weeks of June 2016 in Chicago are observed. The Far North is estimated to consistently use more hot water than the other areas. June 11 shows the highest hot water consumption levels.

4.5 Model's Limitations

The estimated domestic hot water use profile relies on the assumption that the majority of the water heating appliances of residential households in Chicago are small electric storage systems and the water heater is the dominant load. Small electric storage systems usually operate on continuous tariffs, which implies that energy consumption roughly tracks hot

water use with a small delay; these small systems are usually installed in smaller homes and rental houses, while large electric storage systems are more prevalent in larger homes [30]. These assumptions regarding water heating systems are not always valid and could introduce a bias in the estimated results. Furthermore, the degree to which the estimated electricity for water heating is close to the actual electricity used by the water heater is dependent on how many loads mimic the electric water heater. In fact, the algorithm does not always successfully discriminate between changes in electricity use induced by the water heater and other appliances if they are the same magnitude. When the electric water heater is not the dominant load, the load can still be perceived as the water heater.

In summary, the main limitations of the NILM technique employed in this study are:

1. It does not perform well during peak load hours where multiple appliances are in use and the water heater is not the dominant load; therefore, it would not yield accurate results for cold winter days and hot summer days.
2. It lacks ground truth data that can be used as a benchmark to evaluate its performance.
3. It assumes a constant power demand, when in reality, electric storage water heating units' power demands vary depending on the appliance state and quantity of water heated; therefore, it cannot capture actual appliance power variations.
4. It cannot be used for households with large electric storage systems since these systems generally operate on off-peak tariffs with overnight boosting; therefore, energy consumption and hot water use with these large systems are disconnected.

CHAPTER 5

POLICY AND SUSTAINABILITY IMPLICATIONS

This study has shown that a NILM algorithm could disaggregate smart electricity meter data and generate a first-order estimate for household electricity for water heating and hot water use. This technique requires a training period in which the water heater is the dominant load to extract proper disaggregation parameters. Additionally, NILM algorithm performance depends on the resolution of the input data; a comparison between two different sampling periods (1 minute and 30 minutes) reveals that a 30-minute sampling period yields increased error in the algorithm to distinguish between water heating electricity loads and other appliance loads. However, from midnight to 6:00 AM, during days when space heating or cooling are not needed and water heating is the dominant load, a 30-minute sampling period could yield reasonable results assuming that water heater, refrigerator, and minor plug loads constitute the base load profile.

Lower hardware storage requirements of lower frequency smart meter data come at the cost of granularity [104]. For a more effective analysis and understanding of the temporal and spatial variation of residential activities that give rise to energy demand, better energy data are needed. Reliable and adequate energy consumption data are needed to progress economically, socially, and technologically [120]. Comprehensive energy data are critical for empowering consumers to improve their behavior, for designing effective policies, and for driving energy innovation [120]. Accessible and high quality energy data could help evaluate current energy policies, but also proactively design more efficient and customer-centric energy policies [120]. Residential customers who have access to their own electricity consumption data, and can infer appliance-level end uses through these data, can realize considerable energy savings by adapting their energy consumption behavior and opting for energy-saving products. Furthermore, customers who are aware of the different types of time-

variant electricity pricing can adjust their energy use to save money and reduce pollution [121]. Advances in data analytics could help utilities, researchers, and policy makers extract additional benefits from large volumes of energy consumption data generated by smart meters. Additionally, consistent data formats could help achieve optimal interoperability for smart meters, customer devices, and communications systems [87]. However, strengthening cybersecurity and customer privacy protections must be a key focus for utilities as smart meters deployment expands.

Ignoring the significance of the residential energy-water nexus has led many water-related policies and strategies to ignore energy, as well as energy-related policies to ignore water. Effective residential water heating policies could lead to energy-water-carbon reductions. Since many Chicago customers have non-metered water accounts [122], a first-order estimate of domestic hot water use from ZIP code level electricity data offers a valuable quantification of population-scale hot water consumption for different regions, which could further inform the residential energy-water nexus. In 2013, in an effort to reduce energy waste throughout the city, cut environmental pollution, and make the city more efficient and sustainable, the City of Chicago passed the Chicago Energy Benchmarking Ordinance [123]. This policy aimed to increase visibility and awareness of energy use information to improve the city's overall energy resources management. The Energy Benchmarking focuses primarily on large buildings and properties of 50,000 square feet or greater, requiring measurement and reporting of whole-building energy use on an annual basis, and with data verification once every three years to track energy consumption and basic building characteristics using ENERGY STAR Portfolio Manager [123]. This new program also requires the city to collect and report buildings' water usage data from its Department of Water Management and Department of Finance. Unfortunately, there is no such program for smaller residential buildings; implementing a similar benchmarking program for other types of buildings, and residential households in particular, could provide beneficial insight into residential household energy and water usage, as well as appliance performance.

Water heating technological transitions have been slow and unresponsive to short-term price fluctuations mainly because the lifespan of water heaters typically range between 10 and 30 years [31]. Tank types water heaters are the lowest-priced water heating technology in the market, but also more expensive to operate and maintain over the appliance life-

time, compared to other technologies such as on-demand water heaters, heat pump water heaters, and solar water heaters [1]. Furthermore, natural-gas fired water heaters account for 64% of water heaters market share in the East North Central census region, including Chicago, according to the 2015 RECS data [7]. Combusting one therm of natural gas emits approximately 11 pounds of carbon dioxide [124]; therefore, there is a significant potential to reduce overall greenhouse gas emissions by promoting alternative residential water heating technologies that use renewable and clean energy sources.

Global energy production, which is dominated by fossil-based energy fuels such as coal, oil, and natural gas, is the dominant contributor to climate change; it accounts for around 60 percent of total greenhouse gas emissions [11]. Environmental degradation and climate change, stemming from unsustainable energy systems, are posing a serious threat to the planet’s ecological balance, biodiversity, and climate [10]. Many states and private entities have sacrificed long-term environmental sustainability for short-term economic benefits; dismissing the fact that, as former UN Secretary General Ban Ki-moon said, “...sustainable development is not possible without sustainable energy” [10]. Climate change is also anticipated to affect water resources availability and accessibility: it increases sea levels, ocean acidity, and water temperatures; it reduces precipitation and streamflows and increases frequency and intensity of extreme events in many regions of the world [125]. These conditions affect not only global water, but also food and electricity production and demand [126–129]. Climate change and environmental degradation exacerbate societies’ vulnerabilities due to the interdependence of energy and water.

Different policies are in place to address challenges caused by environmental degradation, to mitigate and reverse the effects of climate change and to prevent cascading failures due to the intricate relationship of energy and water. Through the 2015 Paris Agreement, United Nations Member States reached historic agreement and set global agendas that would guide development priorities to limit global temperature rise to below 2°C and ensure continuous and progressive global efforts towards a de-carbonization of the world’s energy system [10, 130]. According to the UN, the world’s energy systems will need to serve 9 billion people by 2014; two-thirds of these people are expected to be from urban areas, whose population is projected to increase to a total of 6.3 billion people by 2050 [21, 131]. Meeting these needs will be challenging without increasing the share of renewable energy in the global energy

mix, increasing access to affordable and sustainable energy, and increasing the global rate of improvements in energy efficiency and resources management in the urban sector [10]. In the United States, multiple plans have been elaborated to tackle climate change; one of them, the Green New Deal, supports “meeting 100 percent of the power demand in the US through clean, renewable, and zero-emission energy sources” and “building or upgrading to energy-efficient, distributed, and ‘smart’ power grids, and working to ensure affordable access to electricity” [132].

Energy affordability is a serious concern for many communities in the United States, and has significant implications on quality of life. Based on the 2015 RECS, one in three American households faced a challenge in paying energy bills or sustaining adequate heating and cooling in their homes in 2015; one in five households reduced necessities such as food and medicine to pay an energy bill; and 14% reported receiving a disconnection notice for energy service [7]. The same survey also revealed that households that included children and whose residents identified with a minority racial group experienced more energy insecurity [7]. Energy insecurity is associated with diverse issues such as low income, substandard housing conditions, improper thermal insulation of dwellings, and restrictive behaviors induced by the inability to afford high energy bills [133]. The analysis of household electricity consumption data at the appliance-level could help detect appliances or behavioral patterns that contribute the most to household energy loads and help tailor proper time-variant electricity pricing that can help households that are more prone to energy insecurity save money and reduce emissions.

CHAPTER 6

CONCLUSION

Understanding the urban energy-water nexus is critical to improving energy and water resources supply and management efforts, given increasing urbanization and the interdependency of water and energy. Limited energy supply could not only result in challenges for water supply, conveyance, and treatment, but also in water heating. Water heating being one of the most energy-intensive activities of the urban water sector [6], estimating energy for water heating can help advance the body of knowledge regarding the urban energy-water nexus and promote community resilience through energy efficiency. This study used 30-minute resolution, anonymized ZIP code level smart electricity meter data to disaggregate electricity for water heating values and develop domestic hot water use profiles for different areas in Chicago. This data-driven approach to quantifying electricity for residential water heating and domestic hot water use could pave the way for improved resource consumption estimation to assist policymakers and utility managers in promoting residential energy and water efficiency measures, in the absence of metered hot water data. Quantifying electricity for residential water heating can support sustainable development goals in meeting future demands of water and energy under population growth, urbanization, changing socio-economic conditions, and climate change.

By quantifying electricity used for water heating and hot water consumption at the household scale, this study answered the following research questions to contribute to the body of knowledge regarding the residential energy-water nexus:

1. *How can electricity for water heating be disaggregated from half-hourly total electricity consumption?* A non-intrusive load monitoring algorithm was used to identify electricity signals for water heating and disaggregate water heating electricity from whole-house electricity consumption data. The NILM algorithm followed a Decision Tree-

based approach, which is a low-complexity supervised approach that can be trained using a very small aggregate dataset, to quickly identify “on” and “off” states of the water heating appliance while ignoring power fluctuations within each state. Results indicate that water heating in the analyzed single-family residential homes accounted for 7-20% of total electricity consumption, representing an average of 1-8 kWh of electricity consumption per day.

2. *How can domestic hot water volumes be estimated from electricity for water heating?* Domestic hot water usage profiles were developed for a sample of 120 single-family households, representing 8 different areas of the city of Chicago, from estimated electricity for water heating values, assuming a range of efficiency factors for water heating appliances. Results indicate that single-family residential homes analyzed in this study used an average of 7-55 gallons per day.
3. *What temporal and spatial domestic hot water use patterns can be detected from the estimated values?* The results showed that residential electricity for water heating and domestic hot water volumes are highly variable. Water heating in the analyzed single-family households accounted for 8-20% of total electricity consumption, representing a wide range of estimated daily average hot water use: as low as 7 gallons for households sampled from the South Side to 95 gallons for certain households in the Far North Side. Regarding temporal patterns, households across all the 8 regional areas of Chicago considered in this study consistently showed higher water heating electricity consumption on Saturday, June 11, 2016, compared to other days analyzed in this study. The spread of electricity consumption appears to be greater in the Far North sample than any other region.

Although domestic hot water use can be directly tied to household occupancy, there is a substantial variation based on occupant behavior. Similarly structured households with the same physical characteristics could have widely varying energy and water usage, emphasizing behavioral differences among households’ occupants. The majority of homes considered in this study showed great variability in electricity consumption. Understanding of variability in residential energy consumption could explain variability in rates of energy efficiency program

participation, as well as factors that affect these differences, to more-efficiently achieve energy savings in a greater number of homes [134].

It is not recommended to rely exclusively on NILM since it introduces inference uncertainty depending on the accuracy of the NILM algorithm and appliance type [2]. This work relies on multiple assumptions that can be improved using physical sensors to obtain ground truthed data from a sample of households representative of the dataset for disaggregation. It is important to establish a benchmark from observed data to evaluate the performance of NILM algorithms. Useful training data could be generated by appliance time diaries that could be completed by households [2]. The results of this comprehensive study further support the need for higher-resolution smart electricity meter data to develop more accurate energy disaggregation models.

REFERENCES

- [1] Ltd DR International. 2011 Buildings Energy Data Book. Technical report, U.S. Department of Energy, 2012.
- [2] Lina Stankovic, Vladimir Stankovic, Jing Liao, and Clevo Wilson. Measuring the Energy Intensity of Domestic Activities from Smart Meter Data. *Applied Energy*, 183(1):1565–1580, 2016.
- [3] Robert Bartels and Denzil G. Fiebig. Metering and Modelling Residential End Use Electricity Load Curves. *Journal of Forecasting*, 15(6):415–426, 1996.
- [4] John A. Masiello and Danny S. Parker. Factors Influencing Water Heating Energy Use and Peak Demand in a Large Scale Residential Monitoring Study. *Residential Buildings: Technologies, Design, Performance Analysis, and Building Industry Trends*, 15:157–170, 1992.
- [5] Ebony T. Mayhorn, Ryan S. Butner, Michael C. Baechler, Greg P. Sullivan, and He Hao. Characteristics and Performance of Existing Load Disaggregation Technologies. Technical report, U.S. Department of Energy, 2015.
- [6] Kelly T. Sanders and Michael E. Webber. Evaluating the Energy Consumed for Water Use in the United States. *Environmental Research Letters*, 7(3):034034, 2012.
- [7] U.S. EIA. Residential Energy Consumption Survey 2015, 2015. URL <https://www.eia.gov/consumption/residential/>.
- [8] Robert Kohlenberg, Thomas Phillips, and William Proctor. A Behavioral Analysis of Peaking in Residential Electrical-Energy Consumers. *Journal of Applied Behavior Analysis*, 9(1):13–18, 1976.
- [9] WWAP (United Nations World Water Assessment Programme). The United Nations World Water Development Report 2015: Water for a Sustainable World. Technical report, UNESCO, 2015.

- [10] United Nations Development Programme. Delivering Sustainable Energy in a Changing Climate: Strategy Note on Sustainable Energy 2017-2021. Technical report, UNDP, 2016.
- [11] United Nations. The Sustainable Development Goals Report 2019. Technical report, UN, 2019.
- [12] World Bank. Access to Energy is at the Heart of Development, 2018. URL <https://www.worldbank.org/en/news/feature/2018/04/18/access-energy-sustainable-development-goal-7>.
- [13] Michael E. Webber. *Thirst for Power: Energy, Water, and Human Survival*. Yale University Press, New Haven, CT, 2016.
- [14] IEA. World Energy Outlook 2012, 2012. URL <https://doi.org/10.1787/weo-2012-en>.
- [15] M.A. Maupin, J.F. Kenny, S.S. Hutson, J.K. Lovelace, N.L. Barber, and K.S. Linsey. Estimated Use of Water in the United States in 2010: USGS Circular 1405. Technical report, U.S. Geological Survey, 2014.
- [16] Ashlynn S. Stillwell, Cary W. King, Michael E. Webber, Ian J. Duncan, and Amy Hardberger. The Energy-Water Nexus in Texas. *Ecology and Society*, 16(1):2, 2011.
- [17] R. Goldstein and W. Smith. Water Sustainability (Volume 4): U.S. Electricity Consumption for Water Supply Treatment – The Next Half Century. Technical report, Electric Power Research Institute, 2002.
- [18] S.J. Kenway, P.A. Lant, A. Priestley, and P. Daniels. The Connection Between Water and Energy in Cities: a Review. *Water Science Technology*, 63(9):1983–1990, 2011.
- [19] Michael Schwartz. Sewage Flows After Storm Expose Flaws in System, November 2012. URL <https://www.nytimes.com/2012/11/30/nyregion/sewage-flows-after-hurricane-sandy-exposing-flaws-in-system.html>.
- [20] Raw Sewage Still Plagues Long Island Homes Five Weeks After Sandy, December 2012. URL <https://newyork.cbslocal.com/2012/12/04/raw-sewage-still-plagues-long-island-homes-5-weeks-after-sandy/>.
- [21] UN Department of Economic and Social Affairs. World Urbanization Prospects: The 2014 Revision. Technical report, United Nations, 2014.

- [22] Konrad Otto-Zimmermann. From Rio to Rio+20: the Changing Role of Local Governments in the Context of Current Global Governance. *Local Environment*, 17(5):511–516, 2012.
- [23] Richard Dobbs, Sven Smit, Jaana Remes, James Manyika, Charles Roxburgh, and Alejandra Restrepo. Urban World: Mapping the Economic Power of Cities. Technical report, McKinsey Global Institute, 2011.
- [24] Christopher M. Chini, Megan Konar, and Ashlynn S. Stillwell. Direct and Indirect Urban Water Footprints of the United States. *Water Resources Research*, 53:316–327, 2017.
- [25] Gary Klein, Martha Krebs, Valerie Hall, Terry O’Brien, and B.B. Blevins. California’s Water-Energy Relationship. Technical report, California Energy Commission, 2008.
- [26] Ronnie Cohen, Barry Nelson, and Gary Wolff. Energy down the drain: The hidden costs of california’s water supply. Technical report, Natural Resources Defense Council, 2004.
- [27] Angela Arpke and Neil Hutzler. Domestic Water Use in the United States: A Life-Cycle Approach. *Journal of Industrial Ecology*, 10(1-2):169–184, 2008.
- [28] U.S. DOE. 2010 Buildings Energy Data Book. Technical report, U.S. Department of Energy, 2011.
- [29] U.S. DOE. Energy Star Residential Water Heaters: Final Criteria Analysis. Technical report, U.S. Department of Energy, 2008.
- [30] E3 Equipment Energy Efficiency. Water Heating Data Collection and Analysis: Residential End Use Monitoring Program. Technical report, Commonwealth of Australia, 2012.
- [31] Kelly T. Sanders and Michael E. Webber. Evaluating the Energy and CO₂ Emissions Impacts of Shifts in Residential Water Heating in the United States. *Energy*, 81(1):317–327, 2015.
- [32] William B. DeOreo, Peter Mayer, Benedykt Dziegielewski, and Jack Kiefer. Residential End Uses of Water, Version 2: Executive Report. Technical report, Water Research Foundation, 2012.
- [33] NAHB Research Center, Inc. Domestic Hot Water System Modeling for the Design of Energy Efficient Systems. Technical report, National Renewable Energy Laboratory, 2002.

- [34] C. C. Hiller. New Hot Water Consumption Analysis and Water-Heating system sizing methodology. In *ASHRAE Transactions: Symposia99*, volume SF-98-31-3, pages 1864–1877, 1998.
- [35] D.W. Abrams and A. C. Shedd. Effect of Seasonal Changes in Use Patterns and Cold Inlet Water Temperature on Water-Heating Loads. *ASHRAE Transactions*, 11 1996.
- [36] Hugh Henderson and Jeremy Wade. Disaggregating Hot Water Use and Predicting Hot Water Waste in Five test homes. Technical report, U.S. Department of Energy, 2014.
- [37] Matthew P. Bouchelle and Danny S. Parker. Factors influencing water heating energy use and peak demand in a large scale residential monitoring study. *Twelfth Symposium on Improving Building Systems in Hot and Humid Climates*, 5 2000.
- [38] M Perlman and B.E. Mills. Development of Residential Hot Water Use Patterns. *ASHRAE Transactions*, 91(2), 1985.
- [39] Jim Lutz and Moya Melody. Typical Hot Water Draw Patterns Based on Field Data. Technical report, Lawrence Berkeley National Laboratory, 11 2012.
- [40] M Aydinalp, V. Ugursal, and A. Fung. Conditional Demand Analysis for Estimating Residential End-Use Load Profiles. *The Energy Journal*, 5(3):81–97, 1984.
- [41] M Aydinalp, V. Ugursal, and A. Fung. Modelling of Residential Energy Consumption at the National Level. *Journal of Industrial Ecology*, 27(4):441–453, 2003.
- [42] Gaetan Lafrance and Doris Perron. Evolution of Residential Electricity Demand by End-Use in Quebec 1979-1989: A Conditional Demand Analysis. *Energy Studies Review*, 6(2):164–173, 1994.
- [43] Marcos P.E. Lins, Angela C. Moreira da Silva, and Luiz P. Rosa. Regional Variations in Energy Consumption of Appliances: Conditional Demand Analysis Applied to Brazilian Households. *Annals of Operations Research*, 117:235–246, 2002.
- [44] Michael Parti and Cynthia Parti. The Total and Appliance-Specific Conditional Demand for Electricity in the Household Sector. *The Bell Journal of Economics*, 11(1):309–321, 1980.
- [45] Lukas G. Swan and Ismet V. Ugursal. Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques. *Renewable and Sustainable Energy Reviews*, 13(8):1819–1835, 2009.

- [46] Candance Roulo. New Efficiency Standards for Residential Water Heaters Are on the Horizon, June 2015. URL <https://www.contractormag.com/residential-plumbing/new-efficiency-standards-residential-water-heaters-are-horizon>.
- [47] HM Government (Government of the UK). The Clean Growth Strategy: Leading the Way to a Low Carbon Future. Technical report, United Kingdom Department for Business, Energy and Industrial Strategy, 2017.
- [48] Reinhard Haas. Energy Efficiency Indicators in the Residential Sector: What Do We Know and What Has to Be Ensured? *Energy Policy*, 25(7–9):789–802, 1997.
- [49] Amir Kavousian, Ram Rajagopal, and Martin Fischer. Determinants of Residential Electricity Consumption: Using Smart Meter Data to Examine the Effect of Climate, Building Characteristics, Appliance Stock, and Occupant’s Behavior. *Energy*, 55(15):184–194, 2013.
- [50] Manfred Lenzen, Christopher Dey, and Barney Foran. Energy Requirements of Sydney Households. *Ecological Economics*, 49(3):375–399, 2004.
- [51] Aven Satre-Meloy, Marina Diakonova, and Philipp Grunewald. Daily life and demand: an analysis of intra-day variations in residential electricity consumption with time-use data. *Energy Efficiency*, 49(3):375–399, 2019.
- [52] James C. Cramer, Bruce Hackett, Paul P. Craig, Edward Vine, Mark Levine, Thomas M. Dietz, and Dan Kowalczyk. Structural Behavioral Determinants of Residential Energy Use: Summer Electricity Use in Davis. *Energy*, 9(3):207–216, 1984.
- [53] Joao P. Gouveia, Patricia Fortes, and Julia Seixas. Projections of energy services demand for residential buildings: Insights from a bottom-up methodology. *Energy*, 47(1):430–442, 2012.
- [54] Marcos J. Pelenur and Heather J. Cruickshank. Closing the Energy Efficiency Gap: a Study Linking Demographics with Barriers to Adopting Energy Efficiency Measures in the Home. *Energy*, 47(1):348–357, 2012.
- [55] Mithra Moezzi and Loren Lutzenhiser. What’s Missing in Theories of the Residential Energy User. Technical report, Center for Urban Studies Publications and Reports, 2010.

- [56] Rick Diamond and Mithra Moezzi. Changing Trends: A Brief History of the US consumption of Energy, Water, Beverage and Tobacco. Report LBNL-55011, American Council for an Energy Efficient Economy, Washington, DC, August 2004.
- [57] Elham Delzendeh, Song Wu, Angela Lee, and Ying Zhou. The Impact of Occupants' Behaviours on Building Energy Analysis: A Research Review. *Renewable and Sustainable Energy Reviews*, 80:1061–1071, 2017.
- [58] Shan Hu, Da Yan, Elie Azar, and Fei Guo. A Systematic Review of Occupant Behavior in Building Energy Policy. *Building and Environment*, 175:106807, 2020.
- [59] Thomas F. Sanquist, Heather Orr, Bin Shui, and Alvah C. Bittner. Lifestyle Factors in U.S. Residential Electricity Consumption. *Energy Policy*, 42(C):354–364, 2020.
- [60] Willett Kempton. Residential Hot Water: A Behaviorally-Driven System. *Energy*, 13(1):107–114, 1988.
- [61] Joseph C. Lam. Climatic and Economic Influences on Residential Electricity Consumption. *Energy Conversion and Management*, 39(7):623–629, 1998.
- [62] Jeffrey Harris, Rick Diamond, Maithili Iyer, Christopher Payne, Carl Blumstein, and Hans-Paul Siderius. Towards a Sustainable Energy Balance: Progressive Efficiency and the Return of Energy Conservation. *Energy Efficiency*, 1:175–188, 2008.
- [63] Stewart Barr, Andrew W. Gilg, and Nicholas Ford. The Household Energy Gap: Examining the Divide Between Habitual- and Purchase-Related Conservation Behaviours. *Energy Policy*, 33(11):1425–1444, 2005.
- [64] The World Bank. Access to Electricity (% of population), N.d.
- [65] United Nations Environment Programme. Water Issues in the Democratic Republic of Congo: Challenges and Opportunities. Technical report, UN, 2011.
- [66] Water and Sanitation Program. An AMCOW Country Status Overview: Water Supply and Sanitation in the Democratic Republic of Congo. Technical report, World Bank, 2011.
- [67] C. Aguilar, D.J. White, and David L. Ryan. Domestic Water Heating and Water Heater Energy Consumption in Canada. Technical report, CBEEDAC, 2005.
- [68] M. A. Martin and M.B. Gettings. Review of Water, Lighting, and Cooling Energy Efficiency Measures for Low-Income Homes Located in Warm Climates. Technical report, Oak Ridge National Laboratory (ORNL), 1998.

- [69] Frederic S. Goldner. Energy use and domestic hot water consumption - phase 1. final report. Technical Report NYSERDA-94-19, New York State Energy Research and Development Authority, Albany, NY, 1994.
- [70] Douglas F. Barnes, Kerry Krutilla, and William Hyde. The Urban Household Energy Transition: Energy, Poverty, and the Environment in the Developing World. Technical report, ESMAP World Bank, 2004.
- [71] Wang Xiaohua and Feng Zhenmin. Common Factors and Major Characteristics of Household Energy Consumption in Comparatively Well-Off Rural China. *Renewable and Sustainable Energy Reviews*, 7(6):545–552, December 2003.
- [72] David Ryan, Ray Long, Daniel Lauf, Meredith Ledbetter, and Ari Reeves. Energy Star Water Heater Market Profile. Technical report, U.S. Department of Energy, 2010.
- [73] Elizabeth Doris, Jaquelin Cochran, and Martin Vorum. Energy Star Water Heater Market Profile. Technical Report NREL/TP-6A2-46532, NREL, 2009.
- [74] American Council for an Energy Efficient Economy (ACEEE). Watts in a Drop of Water: Savings at the Water-Energy Nexus, 2014. URL <https://www.aceee.org/sites/default/files/watts-in-drops.pdf>.
- [75] Jeff Maguire, Xia Fang, and Eric Wilson. Comparison of Advanced Residential Water Heating Technologies in the United States. Technical Report NREL/TP-5500-55475, NREL, 2013.
- [76] U.S. Department of Energy. Storage Water Heaters, 2018. URL <https://www.energy.gov/energysaver/water-heating/storage-water-heaters>.
- [77] R. Ries, R. Walters, and D. Dwianoro. Assessing the Energy Savings of Tankless Water Heater Retrofits in Public Housing. Technical report, U.S. Department of Energy, 2013.
- [78] U.S. Department of Energy. Tankless or Demand-Type Water Heaters, N.d. URL <https://www.energy.gov/energysaver/heat-and-cool/water-heating/tankless-or-demand-type-water-heaters>.
- [79] Barbara G. Ashdown, David J. Bjornstad, Gabrielle Boudreau, Melissa V. Lapsa, Susan Schexnayder, Barry Shumpert, and Frank Southworth. Heat Pump Water Heater Technology: Experiences of Residential Consumers and Utilities. Technical Report ORNL/TM-2004/81, U.S. Department of Energy, 2004.

- [80] Carl Shapiro, Srikanth Puttagunta, and Douglas Owens. Measure Guideline: Heat Pump Water Heaters in New and Existing Homes. Technical report, U.S. Department of Energy, 2012.
- [81] State of Illinois. Domestic Hot Water Use, N.d. URL <https://www2.illinois.gov/sites/KeepWarm/Documents/hotwaterheating.pdf>.
- [82] Paul Denholm. Technical Potential of Solar Water Heating to Reduce Fossil Fuel Use and Greenhouse Gas Emissions in the United States. Technical Report NREL/TP-640-41157, U.S. Department of Energy, 2007.
- [83] Hannah Cassard, Paul Denholm, and Sean Ong. Technical and Economic Performance of Residential Solar Water Heating in the United States. *Renewable and Sustainable Energy Reviews*, 15(8):3789–3800, 2011.
- [84] Lisa Frantzis, David Friedman, Sarah Hill, Peter Teagan, Steven Strong, and Marilyn Strong. Building-Integrated Photovoltaics (BI-PV)—Analysis and U.S. Market Potential. Technical Report NREL/TP-472-7850, U.S. Department of Energy Office of Building Technologies, 1995.
- [85] City of Chicago. Smart Grid for a Smart Chicago, 2010. URL <https://www.chicago.gov/city/en/progs/env/smart-grid-for-a-smart-chicago.html>.
- [86] ComEd. Data Services Handbook for Third Parties, N.d. URL <https://www.comed.com/SiteCollectionDocuments/SmartEnergy/ADSHandbook.pdf>.
- [87] US DOE Office of Electricity Delivery and Energy Reliability. Advanced metering infrastructure and customer systems - Results from the SGIG program. Technical report, U.S. Department of Energy, 2016.
- [88] David Thill. Illinois Smart Meter Data Illustrates Demographic Divides in Electricity Use, June 2019. URL <https://energynews.us/2019/06/27/midwest/>.
- [89] What You Need to Know About ComEd Smart Meters, November 2017. URL <https://chicago.cbslocal.com/2017/11/06/know-comed-smart-meters/>.
- [90] Alexa Spence, Christina Demski, Catherine Bulter, Karen Parkhill, and Nick Pidgeon. Public Perceptions of Demand-Side Management and a Smarter Energy Future. *Nature Climate Change*, 5(6):550–554, 2015.
- [91] Aleksandra Michalec, Enda Hayes, James Longhurst, and David Tudgey. Technical and Economic Performance of Residential Solar Water Heating in the United States. *Utilities Policy*, 56:33–40, 2019.

- [92] Eoghan McKenna, Ian Richardson, and Murray Thomson. Smart meter data: Balancing consumer privacy concerns with legitimate applications. *Energy Policy*, 41(C):807–814, 2012.
- [93] Jonathan P. Deason, Theodore M. Schad, and George W. Sherk. Water Policy in the United States: A Perspective. *Water Policy*, 3(3):175–192, 2001.
- [94] Gyan Chhipi-Shrestha, Kasun Hewage, and Rehan Sadiq. Water-Energy-Carbon Nexus Modeling for Urban Water Systems: System Dynamics Approach. *Journal of Water Resources Planning and Management*, 143(6):04017016, 2017.
- [95] Amy Vickers. The Energy Policy Act: Assessing Its Impact on Utilities. *Journal of the American Water Works Association*, 85(8):56–62, 1993.
- [96] Thomas D. Rockaway, Paul A. Coomes, Joshua Rivard, and Barry Kornstein. Residential Water Use Trends in North America. *Journal of the American Water Works Association*, 103(2):76–89, 2011.
- [97] Jing Liao, Georgia Elafoudi, Lin Stankovic, and Vladimir Stankovic. Non-intrusive Appliance Load Monitoring Using Low-Resolution Smart Meter Data. In *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 535–540, 2014.
- [98] Michael Zeifman and Kurt Roth. Nonintrusive Appliance Load Monitoring: Review and Outlook. *IEEE Transactions on Consumer Electronics*, 57(1):76–84, 2011.
- [99] Tom Hargreaves, Michael Nye, and Jacquelin Burgess. Keeping Energy Visible? How Householders Interact with Feedback from Smart Energy Monitors in the Longer Term. *Energy Policy*, 56:1870–1891, 2013.
- [100] Georges W. Hart. Nonintrusive Appliance Load Monitoring. *Proceedings of the IEEE*, 80:1870–1891, 1992.
- [101] Charlie Wilson, Tom Hargreaves, and Richard Hauxwell-Baldwin. Smart Homes and Their Users: A Systematic Analysis and Key Challenges. *Personal Ubiquitous Comput.*, 19(2):463–476, February 2015.
- [102] J. Zico Kolter, Siddarth Batra, and Andrew Y. Ng. Energy Disaggregation via Discriminative Sparse Coding. *Proceedings of the 23rd International Conference on Neural Information Processing Systems*, 1:1153–1161, 2010.

- [103] Benjamin J. Birt, Guy R. Newsham, Ian Beausoleil-Morrison, Marianne M. Armstrong, Neil Saldanha, and Ian H. Rowlands. Disaggregating Categories of Electrical Energy End-Use from Whole-House Hourly Data. *Energy and Buildings*, 50:93–102, 2012.
- [104] Krystian X. Perez, Wesley J. Cole, Joshua D. Rhodes, Abigail Ondeck, Michael E. Webber, Michael Baldea, and Thomas F. Edgar. Nonintrusive Disaggregation of Residential Air-Conditioning Loads from Sub-Hourly Smart Meter Data. *Energy and Buildings*, 81:316–325, 2014.
- [105] New Illinois Data-Sharing Program to Spur Clean Energy Solutions, Cost Savings, 2017.
- [106] Data-Driven Insights from the Nation’s Deepest Ever Research on Customer Energy Use, Pecan Street Research I, author=McCracken, B. and Crosby, M. and Holcomb, C. and Russo, S. and Smithson, C., year=2013, institution=Pecan Street Research Institute.
- [107] Lower Colorado River Authority (LCRA). Average Surface Water Temperatures of the Highland Lake 1982-2009, 2019. URL <https://hydromet.lcra.org/reports/Temperature/4-30-2015>.
- [108] National Weather Service. Preliminary Monthly Climate Data (CF6), 2013. URL <http://www.weather.gov/climate/>.
- [109] National Weather Service. Data Portal-Average Water Temperature, N.d. URL <https://data.cityofchicago.org/Parks-Recreation/Average-Water-Temperature/i6wj-zt53>.
- [110] EIA. Illinois State Energy Profile, N.d. URL <https://www.eia.gov/state/print.php?sid=IL>.
- [111] Anthony D. Amato, Matthias Ruth, Paul Kirshen, and James. Horwitz. Regional Energy Demand Responses to Climate Change: Methodology And Application to the Commonwealth of Massachusetts. *Climatic Change*, 71:175–201, 2005.
- [112] Lei Yan, Jiayu Han, and Runnan Xu. Lifted: Household appliance-level load dataset and data compression with lossless coding considering precision, 2019. URL <https://arxiv.org/ftp/arxiv/papers/1911/1911.01581.pdf>.
- [113] Liam Paull, Howard Li, and Liuchen Chang. A Novel Domestic Electric Water Heater Model for a Multi-Objective Demand Side Management Program. *Electric Power Systems Research*, 80(12):1446–1451, 2010.

- [114] U.S. DOE Energy Efficiency and Renewable Energy. Selecting a New Water Heater. Technical Report DOE/GO-10095-064, U.S. Department of Energy, 1995.
- [115] Steven Ryan. Making ENERGY STAR Water Heaters a National Early Replacement Priority. Technical report, U.S. EPA, ENERGY STAR, 2016.
- [116] Pedro J. Fierro and Evan K. Nyler. Ground Water Manual, from The Water Encyclopedia, Third Edition, Hydrologic Data and Internet Resources. Technical report, U.S. Department of the Interior, Bureau of Reclamation, 1977.
- [117] U.S. Department of Energy. Savings Project: Lower Water Heating Temperature, N.d. URL <https://www.energy.gov/energysaver/services/do-it-yourself-energy-savings-projects/savings-project-lower-water-heating>.
- [118] City of Chicago. City of Chicago Community Areas and Sides, N.d. URL <https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Community-Areas-current-/cauq-8yn6>.
- [119] ASHRAE. ASHRAE Guideline 14-2002 Measurement of Energy and Demand Savings, 2002.
- [120] Andy Bilich. Why Better Energy Data Equals Better Lives – Now More than Ever, 2017. URL <http://blogs.edf.org/energyexchange/2017/10/19/why-better-energy-data-equals-better-lives-now-more-than-ever/>.
- [121] EDF Clean Energy. Time-Variant Electricity Pricing Can Save Money and Cut Pollution, 2015. URL https://www.edf.org/sites/default/files/time-variant_pricing_fact_sheet_-_april_2015.pdf.
- [122] City of Chicago. Understanding Your Utility Bill, 2018. URL https://www.cityofchicago.org/city/en/depts/fin/supp_info/utility-billing/understanding-yourutility-bill.html.
- [123] Pedro J. Fierro and Evan K. Nyler. 2017 Chicago Energy Benchmarking Report. Technical report, City of Chicago, 2017.
- [124] U.S. Energy Information Administration. Carbon Dioxide Emissions Coefficients, 2016. URL eia.gov/environment/emissions/co2_vol_mass.php.
- [125] UN Water. Water and Climate Change, n.d. URL <https://www.unwater.org/water-facts/climate-change/>.

- [126] Jeannette Sieber. Impacts of, and Adaptation Options to, Extreme Weather Events and Climate Change Concerning Thermal Power Plants. *Climatic Change*, 121:55–66, 2013.
- [127] Wendy S. Jaglom, James R. McFarland, Michelle F. Colley, Charlotte B. Mack, Boddu Venkatesh, Rawlings L. Miller, Juanita Haydel, Peter A. Schultz, Bill Perkins, Joseph H. Casola, Jeremy A. Martinich, Paul Cross, Michael J. Kolian, and Serpil Kayin. Assessment of Projected Temperature Impacts from Climate Change on the U.S. Electric Power Sector using the Integrated Planning Model. *Energy Policy*, 73:524–539, 2014.
- [128] Jayant A. Sathaye, Larry L. Dale, Peter H. Larsen, and Gary A. Fitts. Estimating Impacts of Warming Temperatures on California’s Electricity System. *Global Environmental Change*, 23:499–511, 2013.
- [129] Kelly T. Sanders. Critical Review: Uncharted Waters? The Future of the Electricity-Water Nexus. *Environmental Science & Technology*, 49(1):51–66, 2015.
- [130] UN Climate Change. Historic Paris Agreement on Climate Change: 195 Nations Set Path to Keep Temperature Rise Well Below 2 Degrees Celsius, 2015. URL <http://newsroom.unfccc.int/unfccc-newsroom/finale-cop21/>.
- [131] WWAP (United Nations World Water Assessment Programme). The United Nations World Water Development Report 2012: Managing Water under Uncertainty and Risk. Technical report, UNESCO, 2012.
- [132] Alexandria Ocasio-Cortez et al. H.res.109 - Recognizing the Duty of the Federal Government to Create a Green New Deal, February 2019.
- [133] Francisco Estrada, Botzen Wouter W.J., and Richard S.J. Tol. A Global Economic Assessment of City Policies to Reduce Climate Change Impacts. *Nature Climate Change*, 7:403–406, 2017.
- [134] Philip Kelsven. One of These Homes is Not Like the Other: Residential Consumption Variability. *UC Berkeley 2013 Conference Proceedings*, pages 1446–1451, 2013.

APPENDIX A

ESTIMATED ELECTRICITY FOR WATER HEATING AND DOMESTIC HOT WATER USE

In this section, the various results discussed in Chapter 4 are provided. These include estimated electricity for water heating and estimated residential hot water use (Tables A.1-A.2), and total average daily electricity use per region (Table A.3).

Table A.1: Estimated Daily Electricity for Water Heating

Date	Electricity for Water Heating (kWh/day)							
	Far North	North	Northwest	West	Southwest	Far Southwest	South	Far Southeast
6/1/2016	7.56	5.13	1.68	4.12	3.51	4.75	0.97	2.81
6/2/2016	9.88	3.73	1.51	5.03	3.51	4.97	1.13	3.24
6/3/2016	7.42	4.43	1.24	3.91	3.57	4.27	1.12	3.67
6/4/2016	8.14	5.13	1.08	4.18	2.65	3.4	0.86	2.81
6/5/2016	8.19	4.43	1.08	4.4	3.03	2.86	1.89	3.29
6/6/2016	8.95	4.11	1.13	4.14	3.35	4.7	1.51	3.29
6/7/2016	4.72	4.59	0.54	4.82	4.7	3.83	0.92	3.08
6/8/2016	4.83	2.65	0.81	5.14	2.86	3.56	0.92	2.81
6/9/2016	5.45	1.30	0.43	3.91	3.78	4.05	0.92	3.73
6/10/2016	11.23	4.59	1.57	5.42	3.62	4.64	1.13	4.91
6/11/2016	14.87	7.46	3.57	6.70	3.94	4.97	1.84	6.43
6/12/2016	9.42	4.05	1.62	4.04	4.43	6.05	1.03	3.73
6/13/2016	8.21	3.46	1.24	4.99	6.7	9.99	0.54	4.10
6/14/2016	8.05	4.21	2.22	6.63	6.38	6.70	0.76	4.91
AVERAGE	8.35	4.23	1.41	4.82	4.00	4.91	1.11	3.77

Table A.2: Estimated Domestic Hot Water Use (gal/day)

Date	Hot Water Use (gal/day)								
	Far North	North	Northwest	West	Southwest	Far Southwest	South	Far Southeast	
6/1/2016	50 ± 5	34 ± 4	11 ± 1	27 ± 3	23 ± 2	31 ± 3	6 ± 1	18 ± 2	
6/2/2016	65 ± 7	25 ± 3	10 ± 1	33 ± 4	23 ± 2	33 ± 3	7 ± 1	21 ± 2	
6/3/2016	49 ± 5	29 ± 3	8 ± 1	26 ± 3	23 ± 3	28 ± 3	7 ± 1	24 ± 3	
6/4/2016	54 ± 6	34 ± 4	7 ± 1	27 ± 3	17 ± 2	22 ± 2	6 ± 1	18 ± 2	
6/5/2016	54 ± 6	29 ± 3	7 ± 1	29 ± 3	20 ± 2	19 ± 2	12 ± 1	22 ± 2	
6/6/2016	59 ± 6	27 ± 3	8 ± 1	27 ± 3	22 ± 2	31 ± 3	10 ± 1	22 ± 2	
6/7/2016	31 ± 3	30 ± 3	4 ± 1	32 ± 3	31 ± 3	25 ± 3	6 ± 1	20 ± 2	
6/8/2016	32 ± 3	17 ± 2	5 ± 1	34 ± 4	19 ± 2	23 ± 3	6 ± 1	18 ± 2	
6/9/2016	36 ± 4	9 ± 1	3 ± 1	26 ± 3	25 ± 3	27 ± 3	6 ± 1	25 ± 3	
6/10/2016	74 ± 8	30 ± 3	10 ± 1	36 ± 4	24 ± 3	31 ± 3	7 ± 1	32 ± 3	
6/11/2016	98 ± 10	49 ± 5	23 ± 3	44 ± 5	26 ± 3	33 ± 3	12 ± 1	42 ± 5	
6/12/2016	62 ± 7	27 ± 3	11 ± 1	27 ± 3	29 ± 3	40 ± 4	7 ± 1	25 ± 3	
6/13/2016	54 ± 6	23 ± 2	8 ± 1	33 ± 4	44 ± 5	66 ± 7	4 ± 1	27 ± 3	
6/14/2016	53 ± 6	28 ± 3	15 ± 2	44 ± 5	42 ± 4	44 ± 5	5 ± 1	32 ± 3	

Table A.3: Average Daily Electricity Use (kWh)

Date	Total Electricity Use (kWh/day)									
	Far North	North	Northwest	West	Southwest	Far Southwest	South	Far Southeast		
6/1/2016	37.71	27.02	20.42	26.44	29.25	35.76	12.69	25.55		
6/2/2016	43.53	25.18	19.70	27.09	29.57	30.30	13.54	24.07		
6/3/2016	42.34	26.81	19.28	26.67	29.25	30.86	12.69	25.70		
6/4/2016	42.58	30.38	18.42	25.11	23.29	24.85	13.48	22.98		
6/5/2016	40.48	28.42	17.74	26.11	25.04	24.28	16.02	26.09		
6/6/2016	41.27	25.31	19.08	23.72	27.41	31.78	14.45	23.49		
6/7/2016	31.61	24.70	15.32	29.39	34.59	33.38	11.77	25.00		
6/8/2016	30.06	20.42	15.57	27.64	24.75	25.49	11.86	20.70		
6/9/2016	34.48	16.70	14.83	26.84	28.64	28.12	11.66	24.81		
6/10/2016	55.39	32.18	21.57	30.86	28.65	30.22	13.17	29.76		
6/11/2016	62.14	49.35	31.03	34.31	30.43	31.40	18.10	41.89		
6/12/2016	44.75	29.21	23.46	25.95	32.09	35.74	13.58	29.46		
6/13/2016	41.04	24.49	19.97	28.88	44.86	50.01	11.37	27.41		
6/14/2016	40.09	29.45	25.44	33.62	37.27	35.83	12.18	30.42		
AVERAGE	41.96	27.83	20.13	28.05	30.36	32.00	13.33	26.95		