DATA-DRIVEN MODELING AND ANALYSIS OF RESIDENTIAL BUILDING ENERGY CONSUMPTION AND DEMAND FLEXIBILITY

By

Emily Kawka

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ABSTRACT

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Buildings are responsible for approximately 74% of total electricity consumption, the leading contributor of carbon dioxide emissions in the United States. As initiatives aim toward net zero emissions through electrification and clean energy, building energy efficiency measures are crucial to achieve this clean energy transition. Through measuring energy use, this increases the accuracy of building use assumptions, which drive how energy use reduction is investigated and targeted. As disruptive events and technology shift how occupants use residential buildings, this has the potential to shift how they consume their energy. In this thesis, high resolution, disaggregated energy use data is used to model and analyze energy use for two specific disruptions: the COVID-19 pandemic and electric vehicles (EVs). The first study measures how COVID-19 impacted residential building energy use. The findings of this research indicate an increase in energy use for both weather-dependent loads and weather-independent loads during the COVID-19 pandemic. Additional analyses give insight to the pandemic's impact by household income, demonstrating the lowest and highest income groups experiencing larger increases in consumption while remaining populations experienced smaller shifts. The second study analyzes residential EV charging behavior and models the maximum load reduction potential for demand response in the Midcontinent Independent System Operator (MISO) region. The results of this study indicate relatively consistent charging use patterns across a full year, weekend charging is more distributed throughout the daytime compared to weekday charging, and there are significant opportunities to reduce or shift EV loads during typical peak load periods.

This thesis is dedicated to my parents whose love and support enabled me to reach this opportunity and to all those who mentored me during my journey to pursue my passions.

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INTRODUCTION

In the United States, the largest contributor of carbon dioxide (CO_2) emissions is from the electric power sector [1]. With 60% of total electricity generation sourced from fossil fuels—mainly coal, natural gas, and petroleum, the electric power sector is responsible for 28% of total CO_2 emissions in the U.S. Buildings are a leading consumer of electricity, with total electricity use of 2.74 trillion kWh in 2020. This is 73.7% of the total consumption, with 38.9% from the residential sector and 34.8% from the commercial sector [2]. Buildings continue to have the largest impact on grid loads during peak hours, where buildings are responsible for 76% of the total electricity load [3]. Peak load periods typically use more carbon intensive energy generation sources to compensate for the additional demand, and therefore worsen the environmental impact of grid operations. This comes on top of other consequences, such as creating stress on the grid to ramp up quickly to meet peak demand and increasing energy. These issues exist with the current grid operations and electricity demand, but with initiatives aiming for net zero emissions through electrification [4,5], demand is expected to increase [6].

These electrification efforts introduce new and larger loads. For example, heating loads are expected to increase substantially in the coming years due to changes toward electrified heating, such as the more widespread use of heat pumps [7]. Another example where substantial increases to electric loads is the adoption and therefore the charging of electric vehicles [8]. While it is assumed that net zero emissions through electrification will be accomplished through a cleaner, more renewable energy-sourced grid, it is important to reduce electricity loads where possible and to optimize grid operations. These actions will help to minimize the environmental impact of the current grid while it remains dependent on fossil fuels, but it will also help to ease the transition into using renewable energy sources.

To reduce electricity loads specifically for buildings, one approach is to implement energy efficiency techniques to the building envelope to reduce heating and cooling loads [9], which are the largest electricity consumption end uses in the residential sector [2]; other energy efficiency approaches can also help. Another way to reduce grid loads is to reduce electricity demand; this is most typically accomplished through demand response (DR) programs. DR allows for buildings to participating in reducing or shifting their electricity loads during peak demand periods, which help to stabilize grid operations, optimize energy generation, and reduce electricity costs [10]. DR can also assist with the transition to renewable energy sources. The current primary sources of renewable energy are solar and wind power. Due to their reliance on weather conditions, such as solar irradiation or wind speed, the power generation from these sources are highly variable. DR is one strategy that can help to optimize wind and solar power generation by matching electricity demand to generation, as opposed to the current structure of matching generation to meet demand.

In understanding how to reduce building energy use, it is important to understand how, when, and to what magnitude buildings are used. Tools such as building energy modeling can help to investigate ways to reduce energy use. These tools require building use assumptions include occupancy schedules—when people are typically occupying a space, internal load use—what devices, appliances, and/or systems are people using, and HVAC system operations—what setpoints and/or schedules do they input. As these assumptions are established based on typical building use behavior collected in research studies, it is important to verify these assumptions as buildings and occupant behavior evolves.

In recent years, disruptive events and technology have emerged and changed the way occupants use their buildings. Major events such as the COVID-19 pandemic have influenced people to spend less time in the office, at school, in restaurants, and at hotels and more time at home working, learning, and cooking. Disruptive technologies such as electric vehicles (EVs) are also introducing new and relatively large electricity loads for buildings, in particular residential buildings where most EVs are charged. This adoption is expected to grow as EVs increase its share in the vehicle market [8]. As these changes can affect how occupants use their energy, it is important to review the way in which their use has shifted, increased, or decreased to provide more accurate energy use assumptions. In the research that follows, these disruptions are investigated for residential buildings using high resolution, disaggregated energy use data. There are two main objectives: *Objective 1* is to quantify how the COVID-19 pandemic has impacted residential building energy use and *Objective 2* is to model the maximum load reduction potential for EVs charged in residential buildings.

Objective 1 aims to quantify how much shifts in residential energy use have occurred due to COVID-19, as there are limited research efforts to quantify this at the household level. With hourly energy use data from 225 housing units across the years 2018-2020, analyses are conducted on weather-dependent loads, non-weather-dependent loads, and whole-home loads. Additionally, the data is divided based on household income to compare how COVID-19 impacted different income levels. The results of the study show how the loads shifted during pandemic-impacted months compared to non-pandemic-impacted months through electricity load profiles.

The purpose of *Objective 2* is to provide the maximum load reduction potential for residential EV charging for DR in the Midcontinent Independent System Operator (MISO) region. In conducting this research, the model development process is divided into three parts: probability of charging, level of charge, and EV population. The probability of charging is produced using the disaggregated electricity use data to understand when occupants are charging their EVs. The level of charge is evaluated by combining the anticipated charging levels based on available EV technology, i.e., plug-in electric versus plug-in hybrid electric, and charging infrastructure (Level 1 versus Level 2 charging). The EV population for the MISO region was then estimated using existing vehicle registration data and population data down to the county level. The results provide an analysis of the charging behavior and the load percentage of the EV charging across the MISO region compared to the total maximum peak load.

This thesis is organized into two chapters, followed by a conclusion section. Chapter 1 is a published journal article on the impacts of the pandemic on residential building energy use. Chapter 2 focuses on the analysis and modeling techniques used to evaluate the maximum load reduction potential for EV charging at residential buildings as a function of time. The conclusion section summarizes the findings of each study, along with research limitations and future work, and closes with research contributions resulting from these research efforts.

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CHAPTER 1. IMPACTS OF COVID-19 ON RESIDENTIAL BUILDING ENERGY USE AND PERFORMANCE

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1.1. Abstract

Following the declaration of the COVID-19 pandemic and the rise in cases across the United States, the typical daily routines of millions were disrupted as the country attempted to control the spread of the virus. As a result, homes became makeshift offices, classrooms, restaurants, and entertainment centers. With these changes in how residential buildings are used, surveys and grid-level studies have been conducted to understand how energy use has shifted due to the pandemic. However, there are limited efforts that review the impact of energy use at the household level. In this study, high-resolution, disaggregated data is analyzed to measure the shifts in electricity use related to HVAC loads, non-HVAC loads, and whole-home loads in a comparison of 225 housing units over the years of 2018 to 2020. Key findings from the analyses indicated increased electricity use during periods that occupants would usually be away from home. The most percent increases in non-HVAC residential loads occurred between 10 AM to 5 PM; HVAC loads increasing in total daily consumption compared to the same average daily temperatures of previous years. Additionally, dividing the data by household income, the lowest income and higher income households experienced the larger increases in consumption, while the middle income groups experience smaller shifts.

Keywords

COVID-19 pandemic, residential buildings, energy use, load profiles

1.2. Introduction

Beginning in mid-March of 2020, the COVID-19 pandemic caused significant disruption across the United States. With 45 states announcing state, county, or city-wide stay-at-home orders, at least 316 million people were asked to remain at home in an effort to control the spread of the virus [1]. Across all 50 states, public and private primary, secondary, and post-secondary school closures affected nearly 100 million children and students, displacing them from childcare centers, classrooms, and lecture halls [2]. In-person classroom environments were replaced with remote learning, where most students completed their schooling at home on a computer or tablet. In addition, business operations were also temporarily restricted, generally resulting in non-essential employees either working from home, being furloughed, or laid off. The U.S. Bureau of Labor Statistics (BLS) reported over 35% of the workforce worked from home in May 2020, totaling at 48.7 million workers [3]. At the same time, 49.6 million people were reportedly unemployed, resulting in a 13.3% unemployment rate, a slight improvement from 14.7% recorded in April 2020 [3-5]. These numbers are significantly higher than the 3.5% and 4.4% unemployment rates recorded in February and March 2020, respectively [6, 7]. These statistics show some of the initial impacts of the pandemic; moving forward throughout 2020 and into 2021, COVID-19 has continued to influence the daily lives of millions.

The U.S. Bureau of Transportation Statistics illustrated the sustained impact of COVID-19 through its *Mobility Over Time: National, State, and County level*, in which the population of people staying home per day is provided in 2019, pre-pandemic, and in 2020, during the pandemic [8]. Within the period of March-December 2020, the monthly average population (in millions) ranged from 75.2 to 94.9 and averaged 85.0, while the pre-pandemic population ranged from 60.1 to 66.5 and averaged 63.6. Overall, these populations are both higher and more variable during the pandemic. The U.S. BLS also illustrated this continued impact in a review of unemployment over the course of the pandemic, including a 54.4% decrease in the unemployment rate since April 2020 with a 6.7% unemployment rate reported in December 2020. This unemployment rate, however, is still nearly double the rate prior to the pandemic [9]. In analyzing the employment recovery, compared to past recessions, 2020 had the sharpest decrease in the unemployment rate, but appeared to slow in its recovery by September, resulting in 10.7 million people unemployed in December 2020. [9, 10]. In summary, the majority of unemployed workers returned to work, though remaining unemployed persons will likely endure the slow process of being matched to new jobs.

In addition to this reduction in travel and employment, the Pew Research Center conducted a survey in October 2020 on those who teleworked, indicating that 20% of employed adults worked from home prior to the pandemic, 71% are currently working from home, and 54% would want to work from home all or most of the time after the pandemic [11]. PwC also conducted a survey related to remote working capturing responses from both employees and employers [12], finding that four in five executives are looking to extend remote work options compared to pre-pandemic periods, the majority of employees would prefer to be remote for at least three days per week while the majority of executives preferred employees be in person at least three days per week, and 87% of executives are expecting to transition their offices with mixed plans of reducing central office spaces and/or opening more locations. With these current and projected disruptions in daily human activity, much of the U.S. population is shifting away, at least in part, from the office and other commercial buildings and spending more time in their homes.

As a result of these substantial changes in lifestyle, the COVID-19 pandemic has significantly impacted when and how electricity is consumed. For example, during the first several months of the pandemic, in ERCOT, encompassing much of Texas, peak electricity demands were found to be 2% to 4% lower, and loads from 6:00 am -10:00 am were consistently reduced by 6% to 10% [13]. For PJM, servicing the northeast region of the U.S., peak electricity demands were estimated to be 6.5% to 15.2% lower, and total electricity demand averaged 7.9% reduction [14]. For MISO, servicing much of the Midwest region, the total load was estimated to be 5% lower, with morning electricity use peaks shifting to later in the day [15]. Such changes in load patterns continued to evolve throughout 2020 as people adjusted to a different lifestyle during the pandemic and reflect the substantial and unprecedented changes in people's daily routines.

Further evidence for such lifestyle adjustments and corresponding change in energy consumption behavior is supported by reports on broadband data usage, as there was a 47% increase in average data usage from 273.5 GB to 402.5 GB during the first quarters of 2019 and 2020, respectively [16]. Much of this data usage was attributed to streaming services, though there were also increases in social media use, remote work applications, and gaming. In Zoom's reflection of 2020, the company reported a 30x growth in daily meeting participants in just three months, resulting in 300 million participants that has continued to grow even one year following the start of the pandemic [17]. Based on a survey conducted in January-February 2021, the Pew Research Center reported that most social media platforms such as Facebook and Instagram showed no statistically significant change from 2019 to 2021, while YouTube and Reddit experienced statistically significant changes from 2019 to 2021 with an increase from 73% to 81% and 11% to 18%, respectively [18]. Such data support increased use of electronics (i.e. plug loads) and internet services in residential buildings.

Beyond personal electronic usage, the use of household appliances is also likely to have increased. Following restaurant restrictions and stay-at-home orders, search data containing the words food, restaurant, recipe, or delivery was analyzed in both English and Spanish revealing searches for restaurant decreased by three times, recipe and delivery increased by three-four times, and food remained relatively constant, all in comparison to their respective trends at the beginning of 2020 [19]. With respect to post-pandemic behavior, survey data indicates that more than half of participants would cook at home more, 1 in 3 stated they would eat out less, and 40% indicated that they will participate in more takeout and delivery compared to pre-pandemic periods [20]. With these existing and anticipated changes, for both electronics and appliance loads there is little quantification in the existing literature of the level of impact of the pandemic on the electricity use from these and other end uses in residential buildings in the U.S.

Beyond increased appliance and electronics electricity use, heating, cooling, and lighting loads in residential buildings are also likely to be impacted. For lighting, unlike some appliances such as refrigerators which operate regardless of the presence or non-presence of people in their homes, lighting is only typically used when a space is occupied. Various recent studies have suggested that occupancy and lighting energy use are linked [21]. For heating and cooling (HVAC) energy use, for the estimated 58% to 64% of households that have programable thermostats [22, 23] that can be used to automatically set back setpoints during unoccupied periods, such level energy savings is not possible if the home is occupied more often. As such, those households using the setback features would be limited in their ability to substantially benefit from reduced heating and/or cooling energy use during unoccupied periods in their homes. In addition, given the substantial increase in time that people have spent in their homes during the pandemic, this may also have led to differences in temperature tolerances which would influence HVAC use. Similar to electronics and appliance loads, there has been very little quantitative data reported demonstrating the impacts of COVID-19 on energy use of lighting and HVAC loads in individual buildings.

Such an understanding of time-dependent energy consumption behavior is important for several reasons, the first of which is for supporting the reliable operations of the electric grid. Under pre-COVID scenarios, residential buildings were responsible for approximately 38% of electricity use [24], and in some locations 50% or more of peak demands [26]. During the pandemic, high-level analysis, such as in California, suggest an 8.9 to 12.4% increase in residential electricity use during this period [26, 27]. However, there has generally been limited information quantifying consumption variations by sector, and at the individual household level. As such, as a substantial consumer of electricity, this points to a need for measured data and analysis to quantify such changes. The second reason energy consumption patterns are important to assess is that the increased use of electricity in the residential sector also shifts additional energy costs to households. For low-income households that operate under budget-constrained conditions, such an increase could be a substantial financial burden, relative to middle- and higher-income households that would be less financially impacted by higher energy bills. Therefore, while additional studies offer details such as regional energy demand or energy use survey data to assess COVID-19's impact on energy consumption [28], it is beneficial to study measured data from individual households to understand the direct impact on energy use behavior [29].

In this study, several years of measured, high-frequency, disaggregated residential electricity consumption data from households located primarily in Austin, Texas, in ASHRAE Climate Zone 2A [30], is used to study the comparative energy consumption behavior of households, including pre-pandemic and during the COVID-19 pandemic, in 2020. First the data is quality controlled, eliminating substantial missing or erroneous data. The electricity use data is then separated into thermostatic loads, specifically from the HVAC system, and activity-driven loads (ADLs), also called non-HVAC loads, for the analysis. ADLs include loads that are present due to occupants' behavior. Such a division in the data is made since HVAC loads are dependent on weather conditions, while non-HVAC loads generally are considered to not be substantially influenced by weather. By isolating the weather-dependent loads, these loads are weather normalized, supporting a better comparison of HVAC energy use. Using data analysis techniques, energy consumption patterns are compared across the measured data for the overall assessment of energy use impacts, as well as subdivided by household income to compare variations across income groups.

The results of this research have significant implications and applications. Of substantial importance is its implications for building energy modeling applications. Current building energy modeling methods for residential buildings rely on historical data and assumptions regarding internal loads and occupant behavior for HVAC and non-HVAC loads. COVID-19 has introduced unprecedented changes in how residential buildings are used, and as a result, how HVAC and non-HVAC loads are consumed. With both loads impacted by occupant presence, people may be adjusting their setpoints and/or schedules for their HVAC systems or using their ADLs throughout the day. In addition to these changes in usage, there are the added loads of using their homes as substitutes for the office, classrooms, restaurants, and entertainment. These changes in daily usage demonstrate a likely difference in how energy is being consumed.

This research is organized into four sections. In Section 2 and 3, the analyzed data is explained with respect to how the data was collected from the housing units, how the data was organized for the paper, and the methodology used to evaluate the data. In Section 4, comparisons across pre-pandemic and post-pandemic electricity use are made, with discussion of the results as it relates to the magnitude and time. Following this in Section 5, conclusions are drawn to highlight the primary changes in the energy use behavior as a result of the pandemic, and its implications for the re-evaluation of previous assumptions about residential energy use and consideration of future assumptions for use moving forward.

1.3. Data

The data analyzed in this study was gathered from individual circuit-level energy use data in 225 housing units in locations primarily in Texas, but also in several other states across the U.S. [31]. The data was selected based on quality and availability, as discussed in the Data Quality Control section below, for housing units providing a full year (January 1-December 31) of data during the years of 2018, 2019, and 2020. The data was divided into three datasets to accommodate different data comparisons and are referenced throughout the paper as *2020 Only*, *2018 vs. 2020*, and *2018-2020.* The *2020 Only* dataset contains 225 housing units with locations in Texas (n=156); New York (n=60); California (n=5); and Colorado (n=4). The *2018 vs. 2020* dataset contains 76 housing units located in Texas (n=71); Colorado (n=3); and California (n=2). The *2018-2020* dataset contains 26 housing units located in Texas (n=22); Colorado (n=2); and California (n=2).

To collect the energy use data, a home energy monitoring system [32] was used to regularly measure and record electricity use for each home. CT (current transformer) coils were placed on each circuit, enabling data collection for the whole home as well as from individual circuits. This submetering of building energy usage provides disaggregated data on the duration, magnitude, and frequency of household usage of appliances and other energy consuming systems. Within the analysis, the circuit-level data was separated into three groups to review the electricity consumption: the whole home electricity usage, the total electricity usage of all heating, ventilation, and air conditioning (HVAC) system components, and the total electricity usage of all non-HVAC related electricity-consuming devices, such as lights, appliances, and plug loads. The whole home electricity usage represents all electricity consumed by the home, only excluding electric vehicle charging consumption. If the home had solar generation, this was also excluded from this analysis. In aggregating the energy use data for the HVAC systems, all heating unit components and all air conditioner components, including the interior air handler, fan and furnace and exterior air compressor/condenser unit, were accounted for to represent the HVAC loads. It is noted that since electricity consumption was the focus of this effort, if the heating system used gas for heating, only the fan electricity consumption was included in the analysis during the heating season. The use of electricity or gas for heating provides distinct energy consumption signatures for HVAC loads, as discussed further below. In characterizing the non-HVAC loads, the whole home (total) electricity use minus the HVAC energy use was used to calculate these loads. This method was followed instead of summing the non-HVAC circuits, since for some homes, particularly larger homes with more circuits, not all circuits were monitored due to limitations of the number of inputs to the home energy monitoring system utilized.

Supplemental data containing information specific to the studied housing units was used characterize the occupants, their homes, and the outdoor environmental conditions. This data was obtained from metadata, energy audit data and household survey data collected in 2017 and 2019, and weather data from weather stations closest to the locations of monitored homes. The metadata provided the residential building type, city, state, building construction year, and total area. The energy audit and household survey data provided the number of occupants in each household and total annual household income. In the case that the metadata did not provide the building construction year and total area, the survey data was used instead. The weather data was used for Austin, Texas, from the local weather station, where the majority of the housing units are located.

Within the weather data, the temperature data was used to analyze HVAC use of the 71 housing units located in Austin for the *2018 vs. 2020* dataset.

Table 1 includes the housing characteristics with respect to housing units in the U.S. and in Texas. As shown, the analyzed data, in aggregate, has a higher percentage of single-family homes, newer and larger buildings, and smaller household sizes. The corresponding response percentages of housing units providing the supplemental data on the building type, building age, building area, and household size were 100%, 96-97%, 98-100%, and 40-42%, respectively.

***Table 1.1**. Characteristics of housing units in the study relative to summary statistics at the state and country level.*

Category	**U.S. homes[a,b] (in thousands)**	**Texas[a,b] (in thousands)**	**2020 Only**		**2018 vs. 2020**		**2018-2020**
			All	*Income*	*All*	*Income*	*All*
Housing Units	139,684	11,283	225	108	76	40	26
Single-Family Homes	63%	66%	94.2%	95.4%	90.8%	95.0%	88.5%
Median Building Age	44	35	23	22	14	13	13
Avg. Area, m^2	160	167	209	187	200	189	202
Avg. Household Size	2.62	2.85	2.18	2.19	1.84	1.80	2.09

[a] American Housing Survey (AHS), 2019 [33]
[b] United States Census Bureau, 2014-2019 [34]

1.2.1 Income Level Data

The total annual household incomes for the studied housing units were taken from energy audit and household survey data collected in 2017 and 2019. Within this process of combining the audit and survey data, the 2019 data was prioritized over the 2017 data, such that the 2017 data was used only if no income data was provided from 2019. As a result, the *2020 Only* dataset and *2018 vs. 2020* dataset contained 108 housing units and 40 housing units, respectively, with household income data. The selected income ranges were chosen based on the granularity of the available energy audit and household survey data, resulting in six ranges: Less than $50,000, $50-74,999,

$75-99,999, $100-149,999, $150-299,999, and $300-1,000,000, each with 9 to 33 housing units for the *2020 Only* dataset, and 4 to 10 housing units for the *2018 vs. 2020* data.

1.2.2 Data Quality Control

To account for potential outliers within the data, the top and bottom 0.5% of data was removed for all circuit data in all homes. These outliers can be caused by events, such as system updates or reconnections between the usage measurements and data collection. The data was also inspected for completeness by grouping the data by month, year, and unit. If a housing unit contained 90% or more of available data points per month and year, for all months and years in the analysis, the housing unit was included in the study. These data quality control methods are consistent with other related research [35, 36].

1.4. Methodology

To conduct the analysis, the data was grouped into three categories of energy consumption: HVAC loads, non-HVAC loads, and the total overall loads. These categories were chosen to provide an overview of the total energy usage of the housing units, while also providing separate analyses for the weather dependent loads and non-weather dependent loads. For the HVAC loads, these loads are largely dependent on outdoor weather conditions, given the efficiency of both the HVAC system and the building’s need for heating or cooling are both impacted by the variation in outdoor temperature conditions. With weather being variable across years, weather normalization for this data enables a fairer comparison across years. To normalizing the data, the total daily HVAC loads were plotted against the average daily temperature. This is a common approach used in similar analyses to normalize data influenced by outdoor temperatures [37]. In addition, linear regression models were fit to each year’s data as an added metric to compare the HVAC use. This method of comparison is frequently used in related studies to represent HVAC consumption during heating or cooling periods [38-40].

In analyzing the non-HVAC loads, previous studies suggest these loads are not generally impacted by weather conditions [36, 41]. For this reason, these loads were separated from the HVAC loads and were not weather normalized. For this analysis, the median hourly loads were determined from across all housing units in each dataset, for each month and year. The data was then represented through load profiles, in which the median hourly loads were plotted against the time of day on an hourly basis. Such load profiles are often used to characterize building energy use.

For the total overall loads, similar methods to the non-HVAC loads analysis were used. Although this data includes weather-dependent loads, these loads were not weather normalized to allow for a complete picture of the load behavior across a day-long period. The study further evaluates the energy consumption with respect to various income levels. In conducting this analysis, the non-HVAC loads were used for the analysis also in the form of load profiles, as explained previously.

1.5. Results and Discussion

This section is organized in the following order: non-HVAC loads based on *2018-2020* dataset; non-HVAC loads based on *2018 vs. 2020* dataset, along with hourly percent changes, variances, and rate of change; whole-home loads based on *2018 vs. 2020* dataset; HVAC loads based on *2018 vs. 2020* dataset; and non-HVAC loads by income group based on *2018 vs. 2020* dataset.

The non-HVAC load profiles comparing each year between 2018-2020 by month and time of day is shown in Figure 1. The plot uses the *2018-2020* dataset to compare the three years, along with the *2020 Only* dataset to reference the trends within a larger sample size of homes. The vertical axis represents the median hourly non-HVAC load (kWh) across all days of each month, per hour of the day and year. The horizontal axis represents the time of day for the 24-hour period, in which data is provided at an hourly frequency. For complete months of data during the COVID-19 pandemic (April-December), the average total daily non-HVAC load for 2020 was 11.8 kWh, increasing from an average of 10.9 kWh and 11.0 kWh from 2018 and 2019, respectively. The average percent change in total daily non-HVAC load was +21.2% for 2018 to 2020 and +20.1% for 2019 to 2020, with median percent changes of +20.5% and +19.6% for 2018 and 2019, respectively. These increases in the total daily non-HVAC loads provide evidence that occupants increased their use of their appliances and other plug-loads, likely caused by an increase in the time people are spending at home.

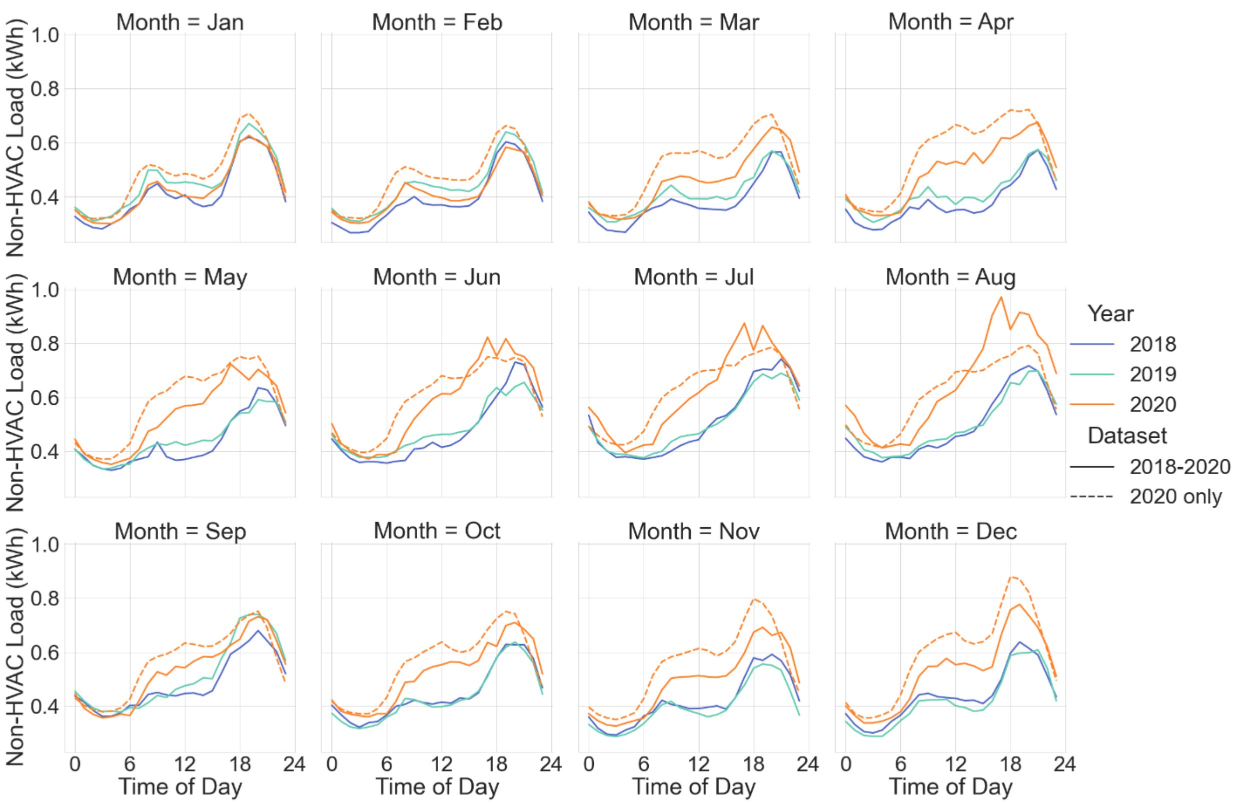

Figure 1. Median hourly non-HVAC loads for each month during the years 2018, 2019, and 2020. Datasets 2018-2020 and 2020 Only are both represented.

Comparing the same months across pre-pandemic (2018, 2019) and pandemic (2020) years, the maximum and minimum percent change occurred during August and September, respectively, including an increase of 31.2% and 29.5% in August, and an increase of 9.9% and 3.1% in

September. For daily loads, August 2020 had a median daily non-HVAC load of 15.6 kWh, compared to 11.9 kWh and 12.0 kWh in 2018 and 2019, respectively. This increase in non-HVAC energy use could be a result of the surge in COVID-19 cases reported during mid-to-late July and early August [42, 43], and the peak in COVID-19 deaths during this time, influencing people to reside in their home more to reduce chances of contracting the virus. For September, the 2020 non-HVAC median daily load was 12.7 kWh compared to 11.5 kWh and 12.3 kWh in 2018 and 2019, respectively. As this is generally when public K-12 schools are back in session, it would be expected that energy use would increase if remote learning were in use and minimal change would occur if schools continued in-person learning. In reviewing the implemented policy during this time in Austin where majority of the housing units are located, public schools offered both in-person and remote options in Fall 2020 [43-45]. This may partially explain the slightly lower increase in consumption compared to pre-pandemic periods. In analyzing the percent changes with respect to the time of day, the largest percent changes occurred between 11 AM and 4 PM compared to 2018, and 11 AM to 5 PM compared to 2019, further suggesting that people are spending more time in their homes when they would typically be at work or school outside of the home. While the *2018-2020* dataset offers additional comparison for energy use behavior across past years, the remaining analyses use the *2018 vs. 2020* dataset to compromise between a larger sample size and comparison of past usage behavior. This is also accompanied by *2020 Only* data for reference, as this dataset is even larger. Similar to Figure 1, the median hourly non-HVAC load profiles comparing *2018 to 2020* is shown in Figure 2.

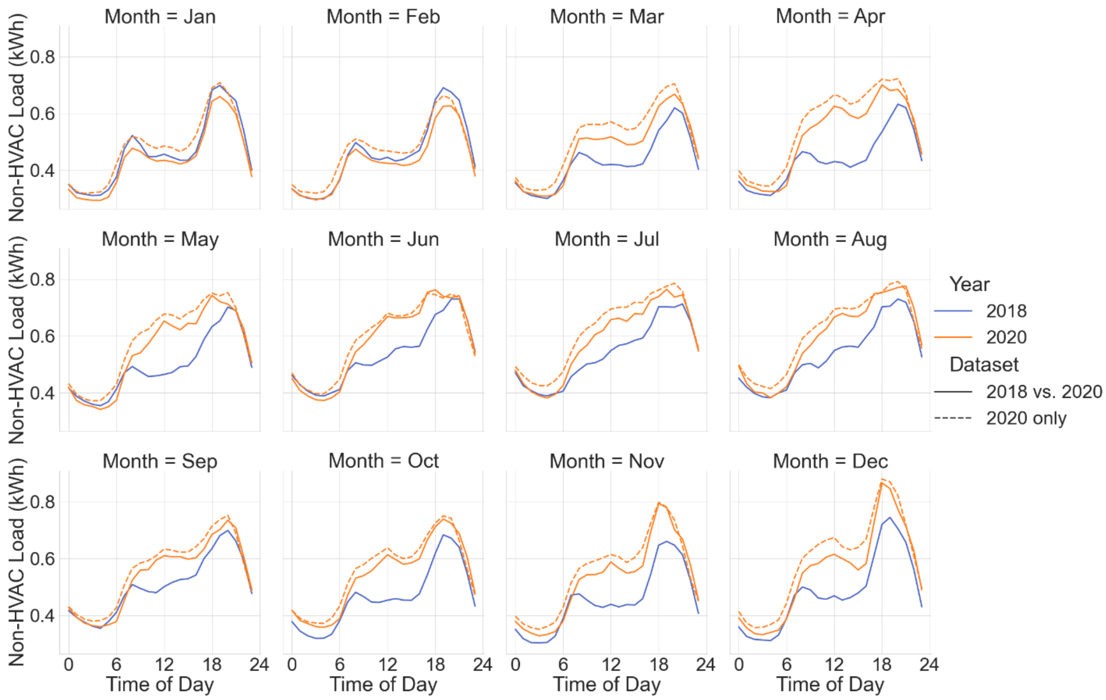

Figure 2. Median hourly non-HVAC loads per month during years 2018 and 2020, represented through datasets 2018 vs. 2020 and 2020 Only.

In examining the pandemic-impacted months (April-December), the average and median percent increases in total daily non-HVAC loads were +12.5% and +11.3%, respectively, with an average load change from 11.8 kWh in 2018 to 13.3 kWh in 2020. This is a smaller percent change compared to the *2018-2020* data, possibly explained by the *2018 vs. 2020* dataset being less sensitive to large fluctuations in the data, such as in the evening hours in Figure 1, as the dataset contains are larger sample size. The largest total daily percent change occurred in April with a +18.6% increase, while the smallest percent change occurred in September with a +7.0% increase. With April being the first full month in the pandemic, this was likely the result of the stay-at-home orders imposed during this time. This contrasts with the prior analysis, likely due to the higher sensitivity to variation in the data, i.e. during the evening hours of August, as the *2018-2020* dataset has a smaller sample of housing units. For September, this was possibly influenced by school being back in session as previously discussed.

In reviewing the percent changes with respect to time of day, Figure 3 provides the hourly percent changes from 2018 to 2020 with the vertical axis representing the percent change in non-HVAC loads per hour and the horizontal axis representing the time of day. This analysis shows that the largest percent changes occurred between 10 AM and 4 PM. Within this timeframe, the peak percent changes occurred at either 11 AM or 12 PM. The maximum hourly percent change across all months occurred in April at 12 PM with a +45.2% increase from 0.43 kWh to 0.63 kWh. These results are similar to the *2018-2020* data, as it indicates people are spending more time at home when they would usually be away at places, such as at work or school. With the peak percent changes occurring around 11 AM and 12 PM, this shift could be associated with people using their kitchen appliances during this time to make lunch, increasing their energy consumption during a time when they would typically have lunch at work, school, or restaurants.

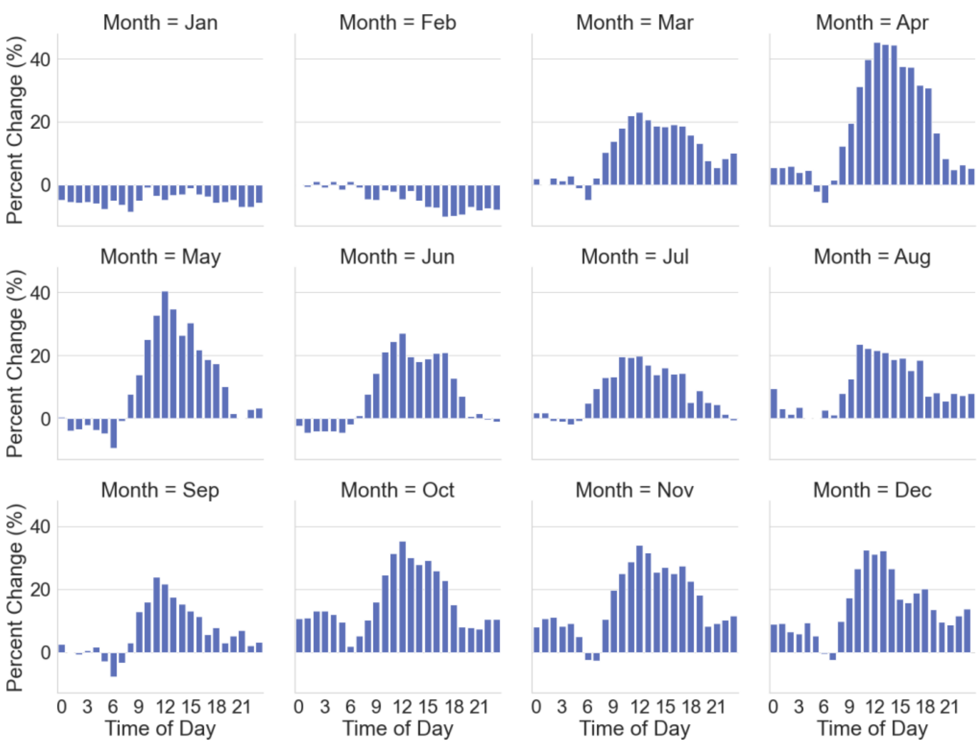

Figure 3. Percent change in median hourly non-HVAC loads per hour of the day and month from year 2018 to 2020.

The analysis of the *2018 vs. 2020* non-HVAC load profiles was evaluated further with respect to variance and rate of change. In Figure 4, the variance between the median hourly non-HVAC loads is given, with the vertical axis representing the variance in kWh^2 and the horizontal axis representing the time of day with an hourly frequency. The results show the largest variance during the pandemic-effected months occurred between 11 AM and 5 PM, with the majority of peak variance occurring at either 11 AM or 12 PM. The overall maximum variance occurred at 12 PM in April. These trends are consistent with the previously discussed trends for people occupying their homes during these times.

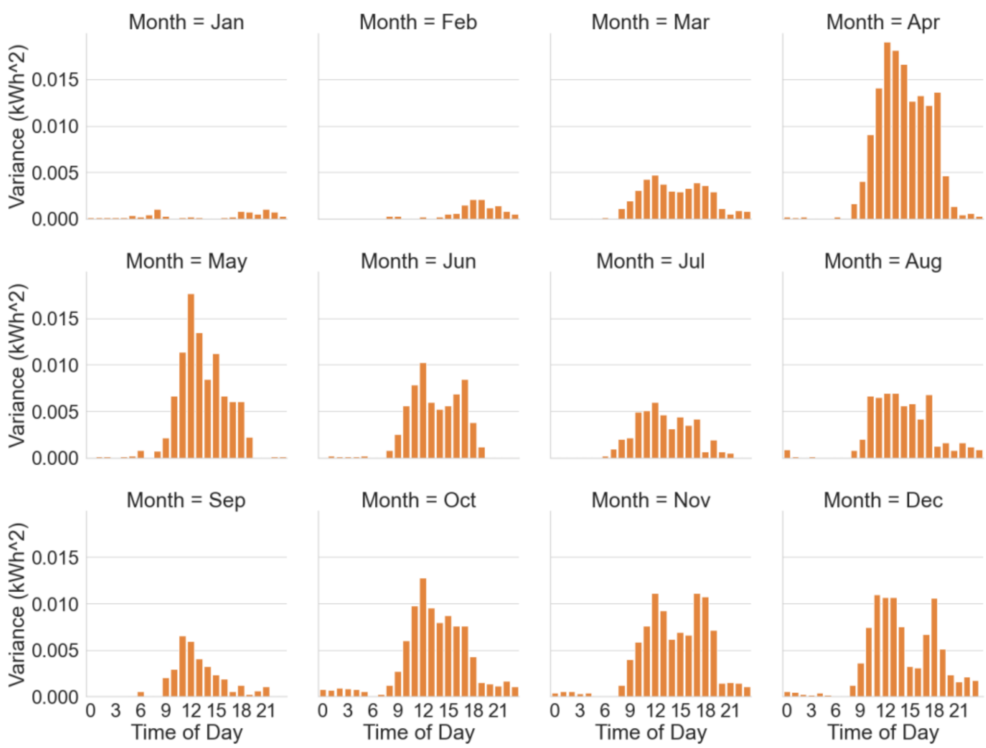

Figure 4. Variance of median hourly non-HVAC loads from the 2018 vs. 2020 dataset, per hour and month.

In Figure 5, the rate of change across each hour of the day per month and year is given for the median hourly non-HVAC loads from 2018 vs. 2020. The vertical axis represents the change in non-HVAC load across each hour in kWh/h. The horizontal axis represents the time of day with an hourly frequency. In reviewing the rate of change during pandemic-effected months, the majority of the largest increases occurred between 8:00 AM and 11:00 AM, while the majority of largest decreases occurred between 7:00 PM – 8:00 PM. The ramping up in energy use occurs after people would typically leave their homes, so during this period people may be logging onto their computers/tablets to begin work or school. This result may also indicate that people are waking up later in the day as they do not need to consider added time to commute to their usual daytime location.

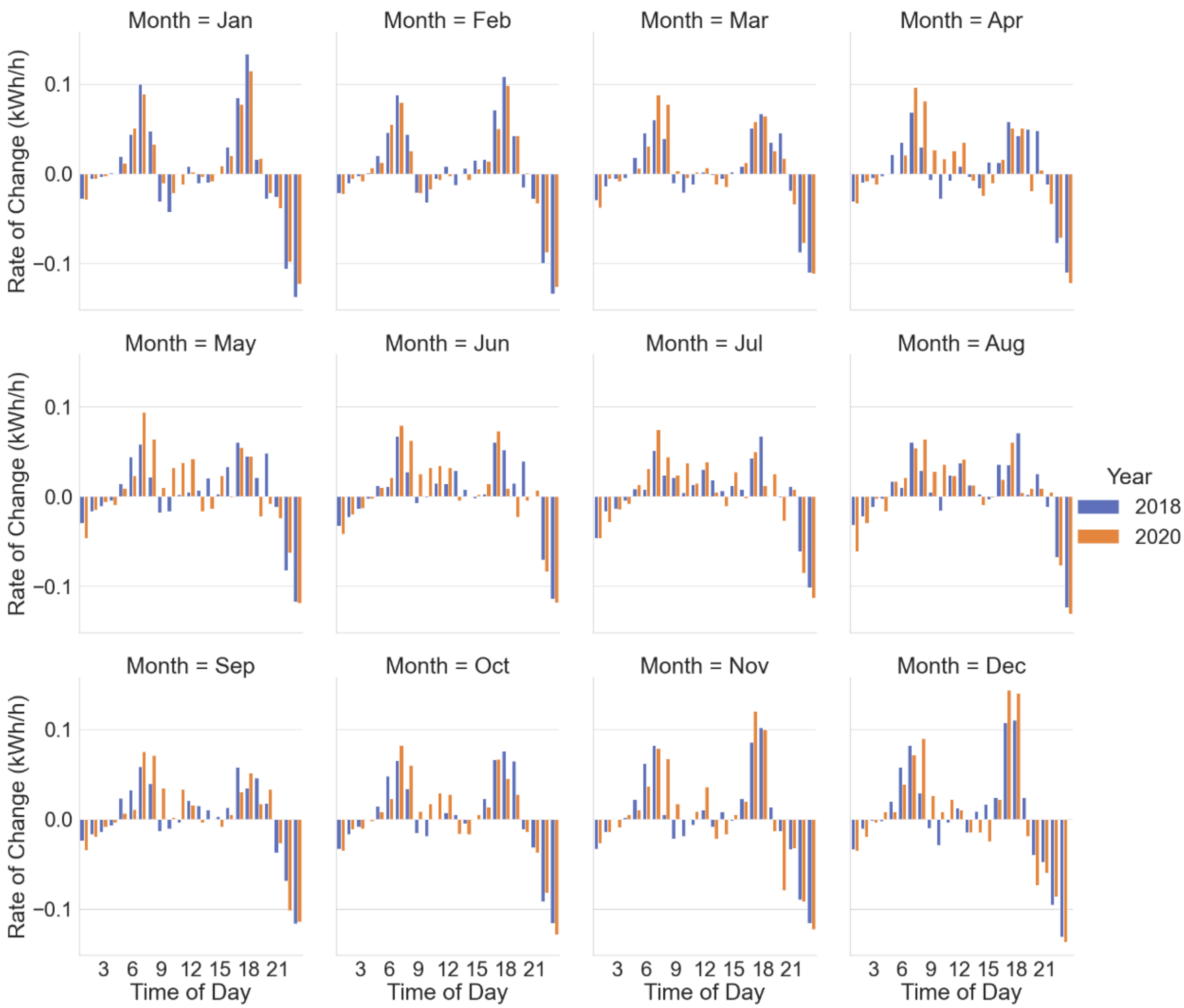

Figure 5. Rate of change for median hourly non-HVAC loads across each hour of the day, per month and year.

To study the *2018 vs. 2020* data further, the total, whole-home loads (non-HVAC and HVAC loads) and HVAC loads were analyzed. The whole-home load profiles are shown in Figure 6 with a similar format as Figure 1 and Figure 2, with the vertical axis representing the total combined loads in kWh, the horizontal axis representing the time of the day with an hourly frequency, and the *2020 Only* dataset plotted for reference. The results show an average and median percent increase of 8.7% and 8.1% in the total daily load, respectively. The average load was 22.9 kWh in 2018 and 24.3 kWh in 2020. The months of April and October had the largest percent increase in total daily load with a 26.4% increase to 15.1 kWh and 25.3% increase to 18.9 kWh, respectively. In May, June, and September, there was a lower total daily combined load with percent decreases of 3.8%, 5.3%, and 4.5% to 22.5 kWh, 31.3 kWh, and 22.6 kWh respectively. In reviewing the data on an hourly basis, majority of the largest increases occurred between 10 AM and 1 PM.

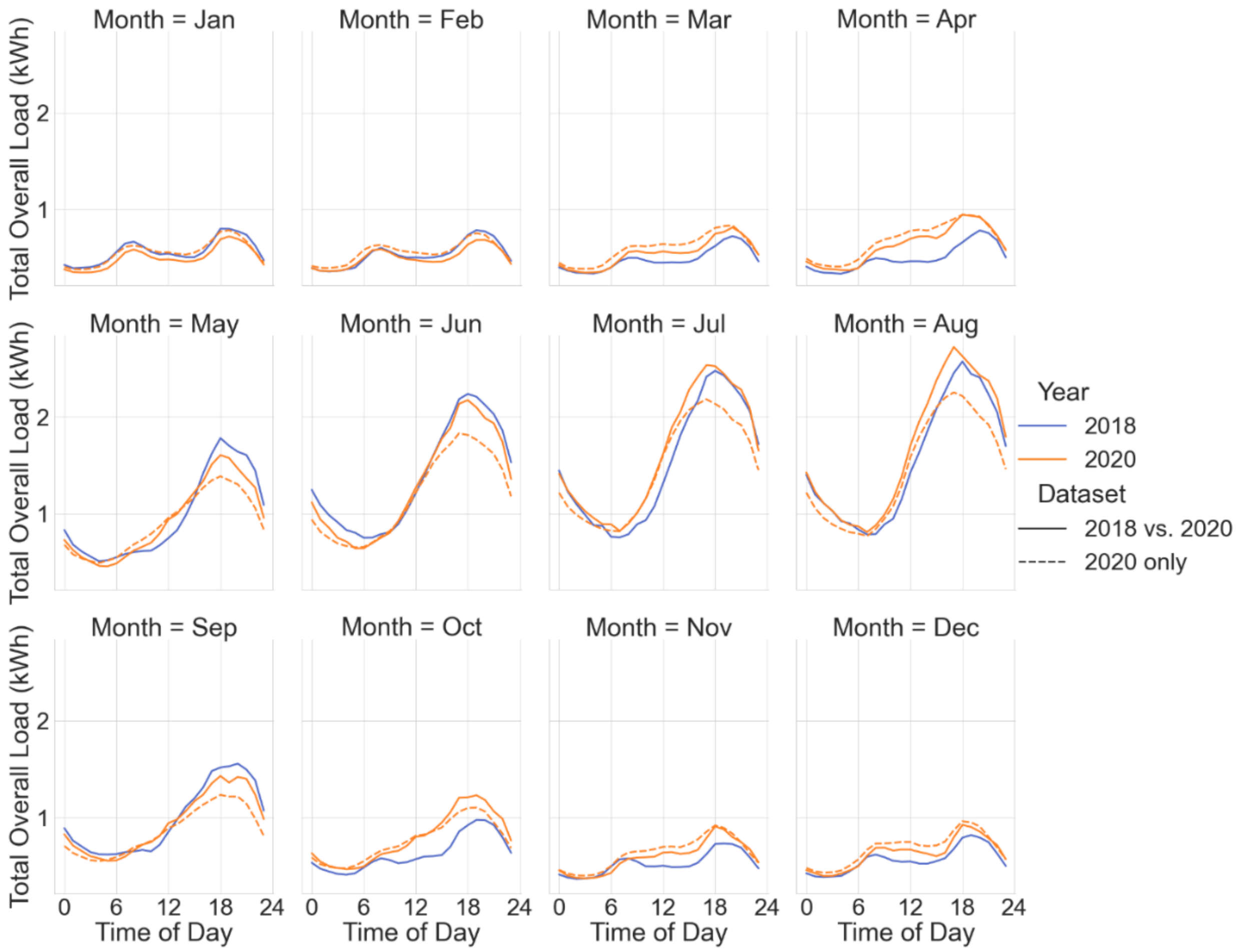

Figure 6. Median hourly whole home load (combined HVAC and non-HVAC loads), across each month for years 2018 and 2020, represented by datasets 2018 vs. 2020 and 2020 Only.

In understanding these results, it appears the months with the largest impact were during periods that typically experience relatively mild temperatures, while the other months may experience warmer temperatures and could, therefore, be influenced by the use of the HVAC systems of these housing units. Given that HVAC loads dominate summer electricity use patterns, variations in the weather conditions across 2018, 2019, and 2020, likely impacted these results. For this reason, the following analysis normalizes for the temperature differences across these months and years.

The weather-normalized HVAC loads for the *2018 vs. 2020* dataset are represented in Figure 7. The vertical axis represents the total daily HVAC load calculated from the median hourly HVAC loads for each month. The horizontal axis represents the average daily temperature calculated from the weather data for Austin, TX. The months chosen for the analysis are months with a higher number of cooling degree days. It is also noted that housing units analyzed are only those located in Austin, Texas, which was chosen to minimize differences in HVAC system usage and preferences across climate zones and locations [30]. Linear regression models were fit to the data for each month and year, accompanied by their respective equations and coefficients of determination.

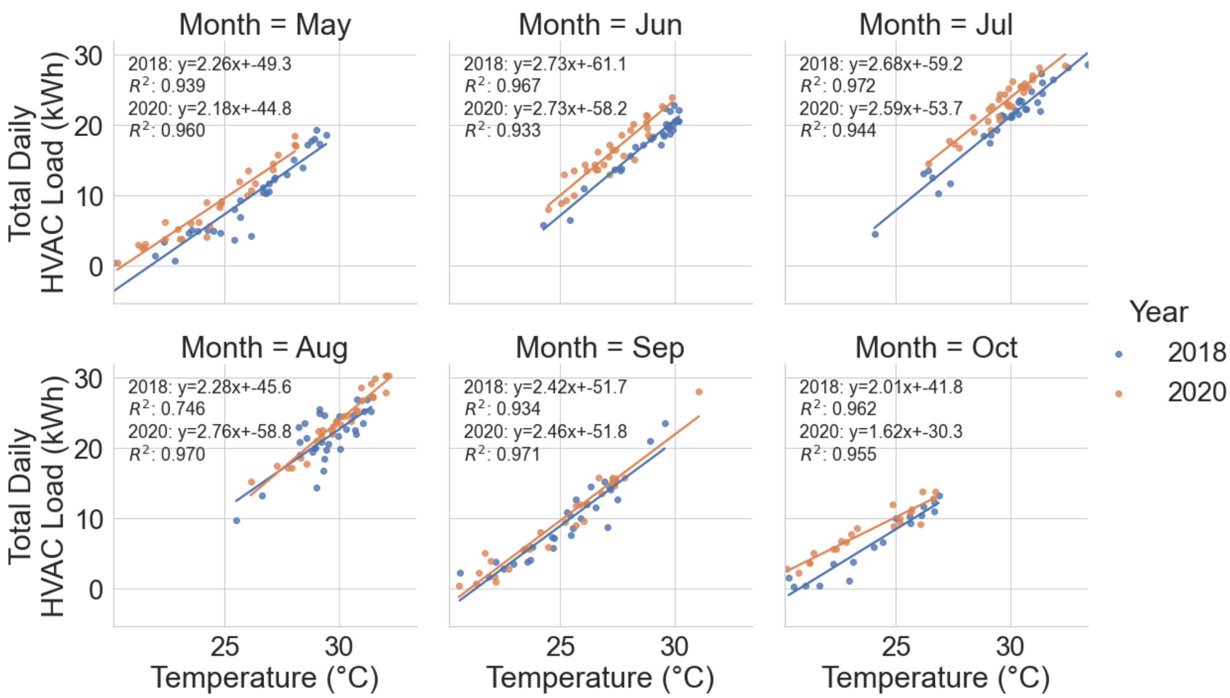

Figure 7. Total daily HVAC loads based on the median hourly HVAC loads as a function of the average daily temperature. The data is represented by month and year and fitted with a linear regression model.

There is an overall increase in the HVAC loads under equivalent weather conditions for 2020 compared to 2018, with May, June, July, and October having the greatest separation between years. September appears to have smaller differences between the two years, while August has some overlap for lower temperatures. These trends are consistent with the previous analyses, as they show that people are using their HVAC systems more under equivalent outdoor temperature conditions during 2018, likely due to longer periods of occupancy and thus limited to no setbacks in HVAC use during these times that were previously unoccupied. Some of this variation may also be due to variation in setpoints adjusted by the homeowners. September also appears consistent with the previous trends in non-HVAC use, as there was minimal change during this month. August does not seem to follow the same trends as the other months, however, which is somewhat unexpected as it is typically one of the warmest months of the year.

Next the load profiles across income ranges were analyzed, as seen in Figure 8. The vertical axis represents the median hourly non-HVAC loads, and the horizontal axis represents the time of day at an hourly frequency. To compare different income ranges, each row represents a different household annual income group and is represented by numerical values (Group 1 – Less than $50,000, Group 2 – $50-74,999, Group 3 – $75-99,999, Group 4 – $100-149,999, Group 5 – $150-299,999, and Group 6 – $300-1,000,000), and each column represents each month during the pandemic-affected period. Similar to Figures 1, 2 and 6, both the *2018 vs. 2020* dataset and *2020 Only* dataset are represented with the solid line representing the *2018 vs. 2020* comparison and the dashed line representing the *2020 Only* dataset with the larger sample size of housing units.

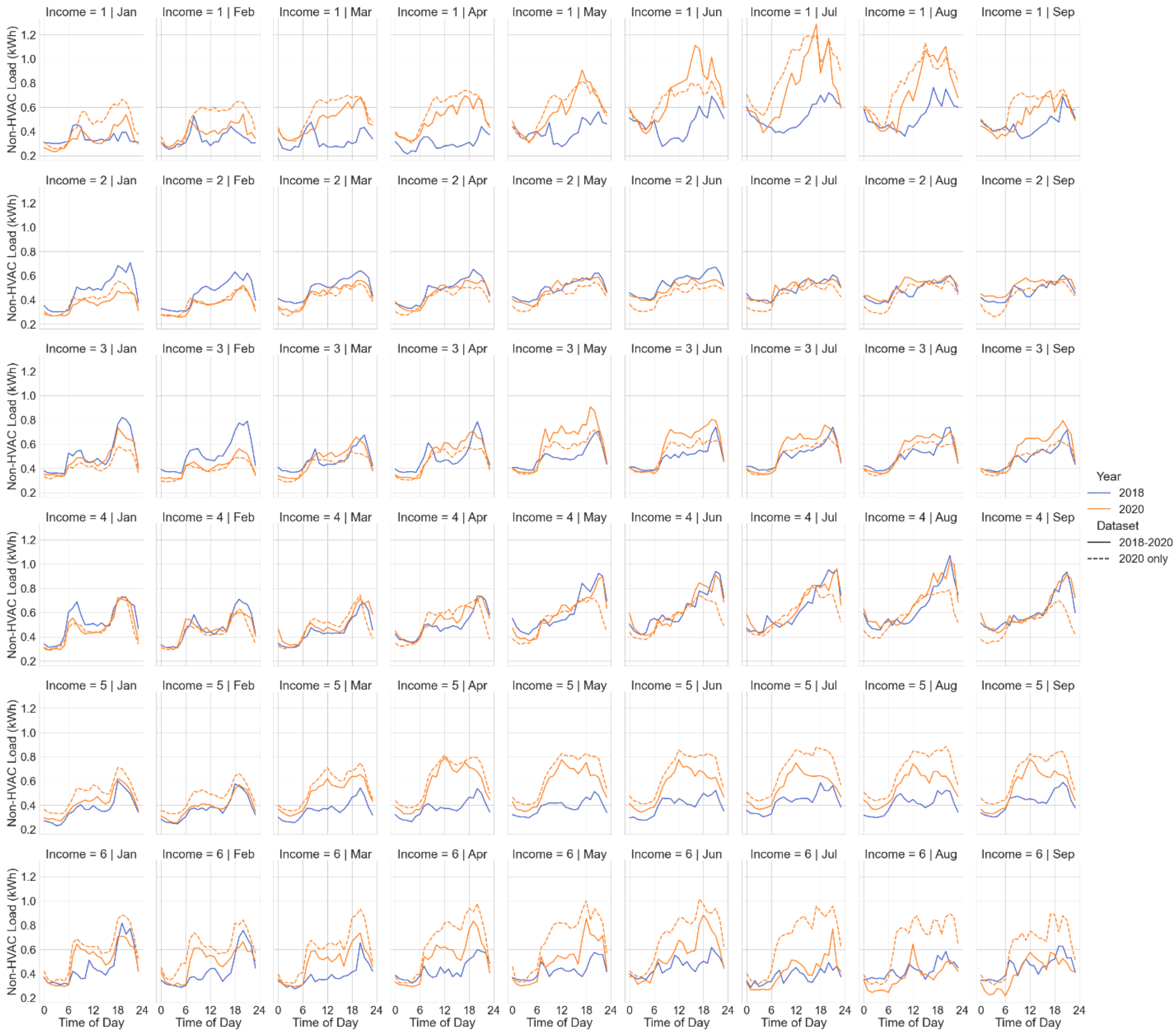

Figure 8. The median hourly non-HVAC loads for each month across different income ranges. Each row represents the different income range groups and each column represents a different month. The key for the income range groupings is as follows: 1 – Less than \$50,000, 2 – \$50-74,999, 3 – \$75-99,999, 4 – \$100-149,999, 5 – \$150-299,999, and 6 – \$300-1,000,000.

In understanding the load profiles by income group by first observing the pre-pandemic months, January ranged from -23.3% to 12.5% change in total daily non-HVAC loads across 2018 to 2020, depending on the household income, averaging at -2.9%, and February ranged from -21.1% to 15.4% change, averaging at -1.4%. Both of these variations are to be expected from year-to-year and are fairly small on average. After transitioning to stay-at-home precautions during March, April ranged from -5.8% to 66.9% change in total daily non-HVAC loads, averaging at 23.4%, which are much higher increasing compared to the pre-pandemic months.

For individual impacts on the household income groups during April, the largest increase of 66.9% was for the less than $50,000 group (1) with an increase from 7.2 kWh to 12.1 kWh. This trend could be a function of the decline in the service industry during the pandemic affecting those with lower incomes. The second largest percent change was in the $150,000-$299,999 household income group (5) with a 50.5% increase from 9.0 kWh to 13.5 kWh. One possible explanation for this change could be that this group contains individuals that could be taking more precaution during the pandemic and, therefore, spending more time inside their homes. These individuals in higher income households may have also held jobs that previously required in-person office work thus they were away from their homes during the day, however during the pandemic their jobs allowed them to work 100% or nearly 100% remotely. Though the $300,000-1,000,000 household income group (6) does not experience as large of shifts in its loads for *2018 vs. 2020*, there does appear to be similarities in the load profiles for Group (5) and (6) based on the *2020 Only* dataset. This discrepancy could be a product of the variability in the smaller sample of housing units and benefit from further investigation. In the following months, similar trends continued to occur with the low-income group (1) and higher income groups (5) and (6).

The income groups that experienced the smallest changes in April were the middle income ranges at $50,000-74,999 (2), $75,000-99,999 (3), and $100,000-149,999 (4), with changes of -5.8%, 2.8%, and 5.2%, respectively. In contrast to the higher income group (5), these could be individuals at a lesser risk for serious effects from the virus and, thus, took less precaution for staying at home. Another reason could be they held jobs that require in-person work, i.e. essential workers, such as in the healthcare industry. Group (2) and (4) continued to experience occurrences of negative change during the pandemic-affected months, with the highest income group (6) also experiencing negative change during August and September based on its *2018 vs. 2020* representation. While this trend appears with Group (6), it is important to note again its similarity to Group (5) for the *2020 Only* dataset which still held a large increase in the non-HVAC loads. Group (3) appears not to have been significantly affected until May, in which the total daily load increased from 11.8 kWh to 14.6 kWh, possibly indicating that this group required an adjustment period before occupying their home or these people may be essential workers that are subject to the fluctuation in the number of cases/hospitalizations.

1.6. Conclusions

As residential buildings became makeshift offices, classrooms, restaurants, and entertainment centers, the impacts of the COVID-19 pandemic on the energy use in these buildings can be represented through the analyses of non-HVAC loads, HVAC loads, and whole-home loads. Key findings include the following:

- The largest percent changes in non-HVAC loads occurred between 10 AM - 4 PM; peak changes occurring at 11 AM or 12 PM. This increase during this timeframe provides evidence of residential buildings being occupied and consuming electricity during periods people would normally be at the office or school. The peak increase during typical lunch hours may indicate an increased use of kitchen appliances, suggesting further investigation into the individual appliances that are causing these shifts.
- The hourly rate of change in non-HVAC loads showed the largest increases between 8 AM - 11 AM; the largest decreases was between 7 PM - 8 PM. Without the need to commute to work, it is possible that people are waking up later in the day before logging in for work

or school. Similarly, without the commute home, the evening peak may have shifted earlier as occupants can assume their evening routines sooner compared to pre-pandemic periods.

- Whole-home energy use increased when people would usually be away from home for work, with majority of percent increases occurring between 10 AM - 1 PM.
- HVAC load analysis demonstrate occupants used more energy for similar average daily temperatures when comparing 2020 to 2018; the largest increases commonly occurred during April and October, and the smallest during September.

  The lowest household income group and highest household income groups experienced the largest percent increases in total daily loads, while the middle income groups experienced a lowest impact during the pandemic. These trends may be a product of the job occupations these income groups held during this period either leading to job loss, essential work, or remote work.

The COVID-19 pandemic has transformed how residential buildings are used, and as survey data suggests greater adoption of remote working and home cooking, among other activities, for post-pandemic behavior compared to pre-pandemic behavior, these shifts in energy use should be considered for future assumptions of residential energy use, now and moving forward. In addition to studying individual appliance load profiles, projections for residential energy use would benefit from investigation to gain insight on how assumptions may need to be adjusted based on the projected adoption of the behaviors formed as a result of the pandemic.

1.7. Acknowledgements

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APPENDIX

APPENDIX

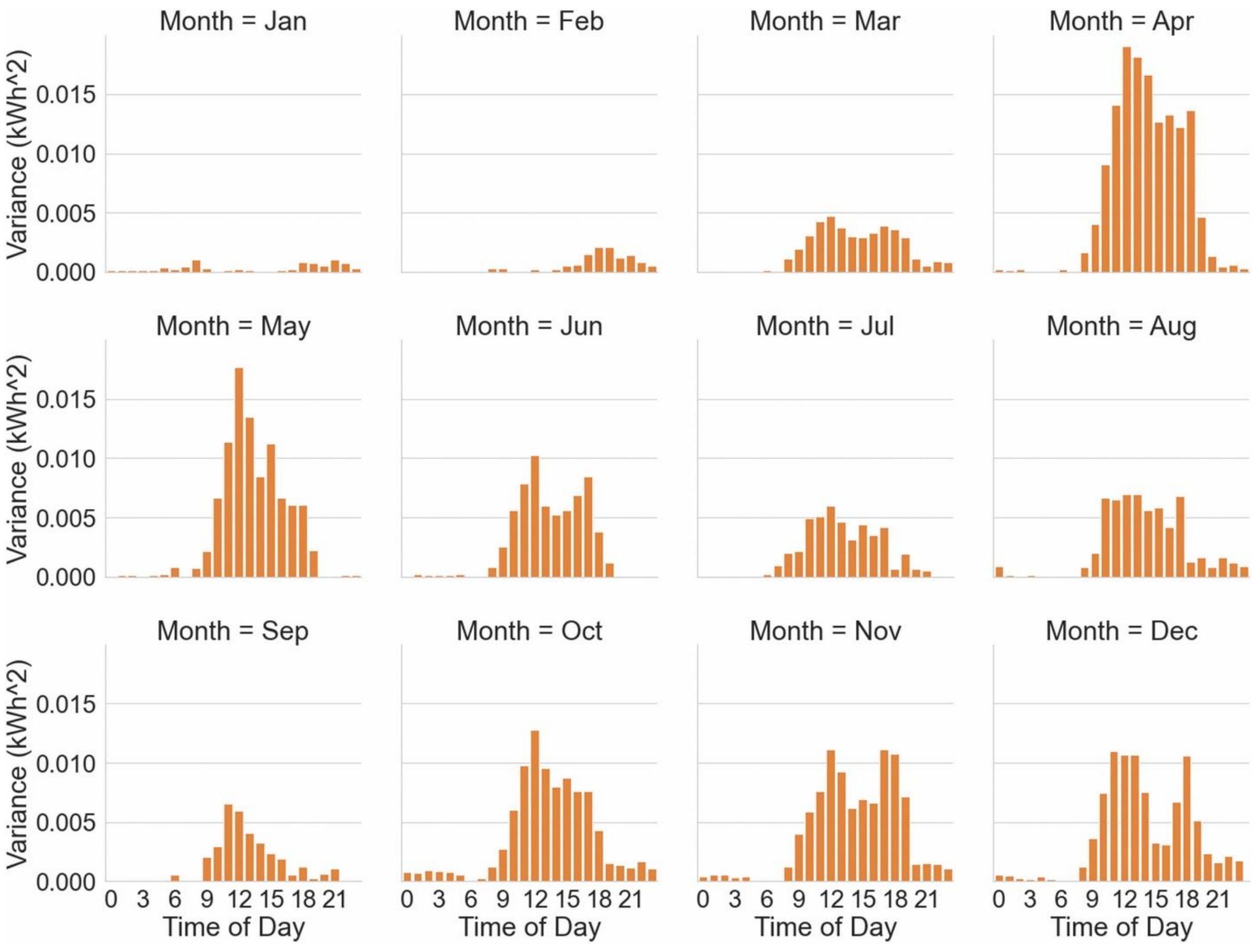

Figure 1.A1. Variance of median hourly non-HVAC loads from the 2018 vs. 2020 dataset, per hour and month. The vertical axis representing the variance in kWh2 and the horizontal axis representing the time of day with an hourly frequency.

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CHAPTER 2. DATA-DRIVEN RESIDENTIAL ELECTRIC VEHICLE CHARGING BEHAVIOR AND LOAD PROFILE MODELING FOR DEMAND RESPONSE IN THE MISO REGION

Emily Kawka, Kristen Cetin, Srishti Banerji, "Data-Driven Residential Electric Vehicle Charging Behavior and Load Profile Modeling for Demand Response in the MISO Region", Energy and Buildings, (in preparation)

2.1. Introduction

In the U.S., residential buildings utilize 39% of total generated electricity, making it one of the most energy-intensive sectors [1]. Nearly half of this electric load is associated with heating, cooling and ventilation systems; large appliances, plug loads and lighting are also important contributors. A load that has been increasing in recent years associated with residential energy consumption is the charging of electric vehicles (EVs).

Historically vehicles used by homeowners have not been EVs, rather they have been those that use combustion of petroleum products with internal combustion engines (ICEs). As technology has developed in recent years, there has been a rising adoption of EVs. According to the U.S. Department of Energy, sales of EVs, including Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs), has increased rapidly from 17,763 in 2011 to 326,644 in 2019 [2]. This rapid growth in EV sales is due, in part, to declining battery costs, improvements in charging infrastructure, increase in customer awareness, and government support. Currently, the U.S. is the third-largest EV market, with sales of all-electric vehicles projected to reach 50% of new vehicle sales by 2030 [3,4].

EVs do not release exhaust emissions since they run on electricity, however, emissions from the source of electricity, such as a power plant, may be produced. Therefore, greenhouse gas emissions can be effectively reduced when EVs are dominantly powered by renewable energy sources such as wind, hydro, and solar, rather than fossil fuels such as coal, oil, and natural gas. Despite renewable sources being better for the environment than fossil fuel generators, power output from renewable energy sources is intermittent due to the fluctuating conditions associated with the natural resources harvested. Therefore, currently the large-scale integration of renewables with the power grid poses challenges for maintaining electric grid stability and power balance, particularly during peak demand hours. In particular, EVs must be charged on a regular basis, and are projected to represent a substantial electric grid load as their adoption grows, rivaling that of residential HVAC systems.

The benefit of EVs is that they offer substantial flexibility for charging times and can serve as a significant source of grid flexibility by reducing (or increasing) electric loads [5]. Demand response (DR) is one form of grid flexibility services can be implemented to strategically lower demand and optimize the utilization of renewable energy by modifying the end user's charging schedules for EVs. By managing the energy demand for EV charging, grid stability can be improved through peak shaving, valley filling, and load shifting [6]. In addition, electric vehicles can supply power back to the grid by discharging their batteries, i.e., Vehicle-to-Grid (V2G) technology [7]. This can help alleviate the variabilities in renewable energy generation and provide support to the grid during peak demand periods.

The capability of EVs to contribute to DR is heavily influenced by EV charging characteristics. There are three types of EV charging based on charging power: Level 1, Level 2, and DC Fast Charging [8-10]. Level 1 charging operates at 120-volt AC providing power output in the range of 1.2-1.9 kW and adding 2-5 miles of range per hour. This level of EV charging has the slowest charging speed and is primarily accessible at residential locations. Level 2 charging utilizes 208- or 240-volt AC supplying power in the range of 3–20 kW and adding 10-50 miles of range per hour. The EV charging power is also governed by the onboard charger in the vehicle and the size of the EV battery [11]. PHEVs have a smaller onboard battery than BEVs since PHEVs accommodate battery and combustion engines. At present, the charging capacity for the majority of PHEVs on the market is in the range of 3.3-3.7 kW, while that of BEVs is in the range of 3.3-11 kW. Level 2 EV charging stations can be installed at residential locations, workplaces, and other public parking spaces. DC Fast Charging can utilize up to 480-volt providing an output power of 55 kW and is significantly faster than Level 1 and Level 2 charging. DC Fast charging is available at public charging stations and can add around 210 miles of range in one hour [9,12]. It is not currently used in residential applications.

Most EV drivers charge their vehicles at home, approximately 80% of the time since it is considered convenient and relatively inexpensive [13]. With the substantial increases in the number of EVs, an unprecedented increase in residential power demand is expected. Nonetheless, EVs offer a large potential for charging flexibility. For instance, EVs can be charged overnight when the electric load on the grid is lower. Residential EV load profiles are dependent on multiple factors which impact the charging power and the charged energy, such as the make and model of EV, user charging habits (frequency, time, and duration of charging), and level of charging. By characterizing the EV charging behavior, the flexibility in demand response can be quantified. This information will help the transmission and distribution system operators to plan for the integration of renewable energy into the grid and future expansion of charging infrastructure to meet the growing power demands.

Several previous studies have worked on modeling and estimating electric vehicle charging loads under various scenarios. However, the majority of these studies synthesized the charging scenarios, mainly using survey travel data rather than measured EV charging data. Axsen et al. [14] employed a sample of survey responses from new PHEV buyers in California to determine EV charging behavior and driving patterns. The results were used to predict future reductions in GHG emissions through the estimated future purchase of PHEVs. Kim and Rahimi [15] created different EV charging scenarios based on survey data on travel patterns in Los Angeles, California. This study estimated the future energy load at the city level, which indicated a possibility of energy shortage in 2030 due to EV charging loads. Wang et al. [16] simulated trips and charging load profiles using the National Household Travel Survey (NHTS) data to assess multi-location charging loads. The study found that home charging can fulfill the energy demand of the majority of PHEVs under average conditions.

Fewer studies in the literature analyzed EV charging and its impact on the grid using energy measurements. Xydas et al. [17] utilized data analysis methods based on clustering and fuzzy logic to analyze EV charging data from 255 public charging stations in the UK. The study investigated the characteristics of EV charging load in different geographical areas for demand-side management. Kara et al. [18] assessed the benefits of smart charging using data from 2000 non-residential electric vehicle supply equipment (EVSE) in Northern California. However, neither of these studies focused on charging behavior in homes. Neaimeh et al. [19] studied the impact of the increase in EVs on electricity distribution networks by combining EV charging profiles from onboard monitoring and residential smart meter load demand in the UK. The findings of the study revealed that spatial and temporal diversity in EV charging can reduce the impact on electricity distribution networks.

A review of the literature shows that studies on the analysis of residential EV charging patterns in the U.S are limited in number. Zhao et al. [13] utilized aggregated residential load data from Texas, Colorado, and California. Residential EV charging patterns were extracted from the aggregated data using a non-intrusive load extracting (NILE) algorithm developed by the authors. The disaggregated data was used to quantify the flexibility of EV cluster charging in demand response. It was found that residential EV charging has more flexibility on the weekends than on weekdays. Another research study carried out by Kim [20] comprised of analyzing energy meter data for residential customers in San Diego with and without EV charging loads under time-of-use (TOU) rates. The analysis revealed that EV charging load profiles have a direct correlation between TOU rate structure and EV charging demand peaks.

Some studies regarding residential EV charging behavior have been carried out in other countries. For instance, Quirós-Tortós et al. [21] monitored the residential charging behavior of 221 EVs (Nissan LEAFs) in the UK and Europe. Probability density functions were employed to create EV profiles capturing charging times, the number of charging events, initial and final state of charge (SOC) for weekdays and weekends. Khoo et al. [22] utilized charging reports from 121 households and 57 fleets in a participation-based study in Australia to develop statistical models of charging behavior. The EV charging events data comprised of information on charging frequency, charge duration, and energy consumed. The study found that each fleet charging session lasted 2.8 hours and used 6.8 kWh on average, whereas each household charging session took 2.5 hours and used 6 kWh.

Even though several research studies consider the flexibility potential of residential EV charging and its role in maintaining grid stability, only a handful of studies in the literature have analyzed the flexibility of metered disaggregated data from residential EV charging. This paper aims to address this gap with disaggregated energy use data for EVs, for use in evaluating the maximum load reduction potential for flexibility services through demand response, both at the building level, then aggregated to the grid level. The use of this data limits errors that may occur, for example, from the use of NILM algorithms required for use of aggregated data. Using circuit-level

EV end use charging data, the probability of charging events was calculated. These charging events were then used to develop a load profile by combining anticipated charging levels based on available EV technology (BEV vs PHEV) and charging infrastructure (Level 1 vs Level 2). The load profile was then scaled in accordance with the estimated populations of vehicles in the region down to the county level, to the grid bus level, then aggregated for the MISO region.

This research is organized into four sections. Section 2 details how the circuit-level data was collected from the housing units and prepared through various quality control strategies for the EV charging model. Section 3, methodology, is subdivided into three key components used to develop the final load profile: Probability of Charging, Level of Charge, and EV Population in the MISO Region. Section 3, results and discussion, reviews the probability of charge from a yearly and daily perspective, along with the maximum load reduction potential for the MISO region. Section 5, conclusions, highlights the observed energy use behavior and the implications of this work, in addition to limitations and suggested future work.

2.2. Data

The circuit-level energy use data [23] was gathered from a total of 46 housing units, with the large majority (96%) located in Texas, and being single-family homes (91%). The data was extracted on a minute frequency across the full year of 2018. This frequency was selected to deliver a full profile of a typical day for EV charging. The duration of one year was selected to capture a range of occupant behaviors, particularly as previous studies have suggested that energy use and occupancy patterns are relatively consistent from year-to-year [24-25]. While there appeared to be minimal changes in charging behavior from a quarterly, monthly, and weekly perspective during data exploration, the entire year to increase the amount of data used, and to best represent a typical day to minimize potential bias should slight differences in behavior exist across the year.

Regarding the year selected, while more recent time periods were preferred due to the increased use of electric vehicles thus increasing the datasets size, and the more limited available data prior to this time.

The energy use data was collected using a home energy monitoring system [26] using CTs (current transformers) to measure and record the electricity data for individual circuits throughout each housing unit. The energy use data is represented in a disaggregated structure providing the electricity use of individual appliances and other electricity consuming systems with its respective timestamp and magnitude. For the EV charging model, the data for a single EV charging circuit for each housing unit was incorporated into developing the model.

For data quality control, the selected housing units were based on the availability and quality of the data. The housing units selected had 90% or greater data available for each month studied. To account for potential outliers within the dataset, the top and bottom 0.5% of data were removed based on the whole home electricity use, excluding solar generation and EV charging. These potential outliers could be the result of system updates or reconnections to the central database. These quality control measures were taken based on similar methods in related research [27-28].

To characterize the dataset, the associated metadata for the housing units showed the median and mean housing unit ages were approximately 14 and 23 years, respectively. These are newer than the national and state medians of 46 and 37 years, respectively, for single-family detached units [29]. For the total areas of the housing units, the median and mean areas at approximately 218 and 228 m^2. These are slightly larger than the national and state medians of 167 and 174 m^2, respectively, for single-family detached units. In reviewing the vehicle characteristics, available audit and survey data for years 2017 and 2019 showed 45.0-52.4% of vehicles were PHEVs, all of which were Chevrolet Volts. For the BEVs, 28.6-35% were Tesla models and the remaining were

Mitsubishi and Nissan. The car years ranged from 2012 to 2018.

2.3. Methodology

The model for the EV charging behavior was formed by combining three parts: the probability of EV charging, the level of electricity demand as a function of time, and the distribution of types of EVs in the region of study. The following sections address how each of these components of this method were conducted.

2.3.1 Probability of EV Charging

For modeling when EV charging events occurred, the circuit-level energy use data was analyzed to identify all housing units that had at least one electric vehicle and contained data through the full year of 2018. The data quality control methods outlined in the Data section were then followed, resulting in a total of 46 qualifying housing units.

For each housing unit, the EV charging circuit was queried at a minute frequency. To characterize when an EV charging event was occurring, it was assumed that whenever the power value for each circuit reached 1 kW or greater the EV was charging. This cutoff value was selected because the minimum Level 1 charging power is 1.2 kW and to avoid any potential measurement errors due to events such as system updates, reconnections to the data collection database, or EV discharging. To calculate the probability of charging, the total number of vehicles charging was divided by the total number of cars in the dataset, for each timestamp throughout 2018.

The probability values were analyzed with respect to several timeframes, including day of the week, weekday to weekend, month, and quarter, as well as across the full year. With relatively minimal variation in the different timeframes and consideration for providing a non-complex input for the demand response flexibility analysis, the probability model was assumed to be similar daily across the year. Based on this assumption, the average probability for each minute of the day was calculated.

2.3.2 Level of Charge

To develop a representative demand profile of the type of EVs being charged, ratios for residential use of Level 1 and Level 2 charging for BEVs and PHEVs from XXXX [9] were used to estimate the distribution of each charging type in the MISO region. For each charging type and EV technology, typical charging levels include: Level 1 charging at 1.92 kW for both BEVs and PHEVs, Level 2 charging at 3.3 kW for PHEVs, and Level 2 charging for BEVs at 6.6 kW. These charging levels were selected based on previous studies [8-11].

2.3.3 EV Population in the MISO Region

To scale EV charging to the MISO region, various methods were used to estimate the EV population (# of vehicles and type of vehicle) down to the county level. These methods were selected based on data availability in each county of study. Available data included county and/or state EV registration data [30-32] for the eight MISO region states: Illinois, Iowa, Montana, Michigan, Minnesota, Tennessee, Texas, and Wisconsin. The highest priority method for assigning EV populations to counties was directly extracting EV registration data. Where available, this data included the number of registered EV per county, zip code, or GeoID and distinguished between BEV and PHEV technology. For states, such as Iowa and Illinois, whose data provided total EVs per county or total BEVs per county, the number of BEVs and PHEVs were estimated based on given total ratios or the average ratio of the known counties from the other states. Following this step, the summation of the BEVs and PHEVs per county were evaluated.

For the remaining states without county-level EV registration data, the state total BEV registration data [33] was used along with the county census population data [34]. For determining each county's total number of BEVs, the county population was multiplied by the state's total BEVs divided by the state's total population. As the state total registration data was limited to BEVs only, the PHEVs were assumed to be similar to the BEV to PHEV ratios for the known county-level registration data. The median ratio for the BEV to PHEV was 1.0. To verify this ratio, the cumulative U.S. EV sales, reported by Argonne National Lab [35], was roughly double the total BEV's registered in the US [34], supporting that there is nearly a 1:1 ratio. After calculating the total BEVs and PHEVs per county, the counties were then mapped to their assigned grid bus within the MISO region, and the total BEVs and PHEVs were summed together for each bus.

To combine these three steps to create the load profile for each bus, Equations 1 and 2 were used and summed together for each bus and timeframe:

$$\#\, BEV \times f \times \left(Level\,1 \left(\frac{0.15}{0.15 + 0.37}\right) + Level\,2 \left(\frac{0.37}{0.15 + 0.37}\right)\right) \tag{1}$$

$$\#\, PHEV \times f \times \left(Level\,1 \left(\frac{0.50}{0.50 + 0.25}\right) + Level\,2 \left(\frac{0.25}{0.50 + 0.25}\right)\right) \tag{2}$$

The number of BEVs and PHEVs represent the number of EVs per bus. f represents the probability of an EV charging event at the respective time during the day. Level 1 and Level 2 represent the typical levels of charge at each charging type per EV technology. The remaining ratios represent the share of residential Level 1 and Level 2 charging per EV technology.

2.4. Results and Discussion

The results of the analysis include the charging probability each day across 2018, the average probability across a typical day, the average probability grouped by weekdays versus weekends, and the maximum load reduction potential compared to the maximum peak load for the MISO region as a whole.

The probability of charge across 2018 by time of day is represented as a heatmap in Figure 9. The vertical axis represents the day of the year; the horizontal axis represents the time of day at a minute frequency, and the color gradient represents the probability of an EV charging event with the probability of charge increasing as the color darkens. In examining the figure with respect to the day of the year, the pattern of EV charging events appears to be relatively consistent across the full time period. There is a decrease in EV charging events between 6 AM to 10 AM, then a gradual increase in events until 7 PM. Charging events slightly decrease between 7 PM to 10 PM. Then at 10 PM, there is a distinct increase in charging events, likely due to a scheduled charge time set using smart charging devices to start EV charging during off-peak hours. During the early morning, there is a slight decrease in EV charging events earlier in the year compared to the remainder of the year. This could be due to changes in driver behavior with a slight decrease in travel resulting in a decreased need for charging. Overall, there are some slight variations across the full year. For the scope of this project, these variations were considered random and incorporated into the probability model as shown in Figure 10.

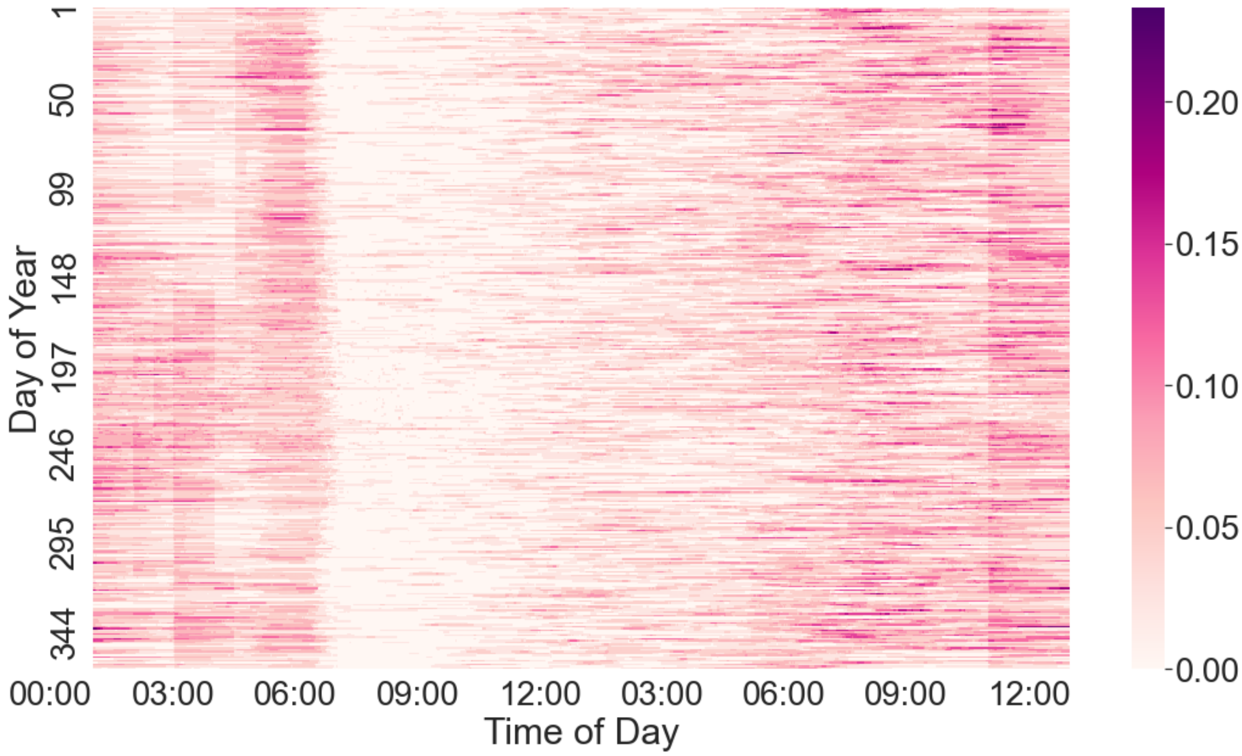

Figure 9. Heatmap for the probability of EV charging occurring by day of the year and time of day. The darker shades indict a higher chance (0.15 = 15% chance of charging) of EV charging while the lighter shades indicate a smaller chance of charging.

For Figure 10, the probability of the EV charging events represented in Figure 9 were averaged across the full year by each minute in a day. The vertical axis represents the probability of an EV charging event, and the horizontal axis represents the time of day at a minute frequency. In reviewing Figure 10 and as noted in Figure 9, the majority of charging occur during the evening and night hours, as might be expected, with a gradual increase in events between 6 AM to 7 PM. Between 7 PM to 10 PM, there is a slight decrease. This could be due to some vehicles reaching their charging capacity or due to EV use for evening activities. At 10 PM, this is a more defined increase in charging events, likely due to smart charging capabilities to start the EV charging during off-peak hours. There are other increases in EV charging between 2 AM and 4 AM, likely also due to smart charger use. In reviewing non-charging occurrences, it appears that are minimal charging events between 6 AM to 10 AM as this would likely be when EV users are using their vehicles to commute to the office, school, etc.

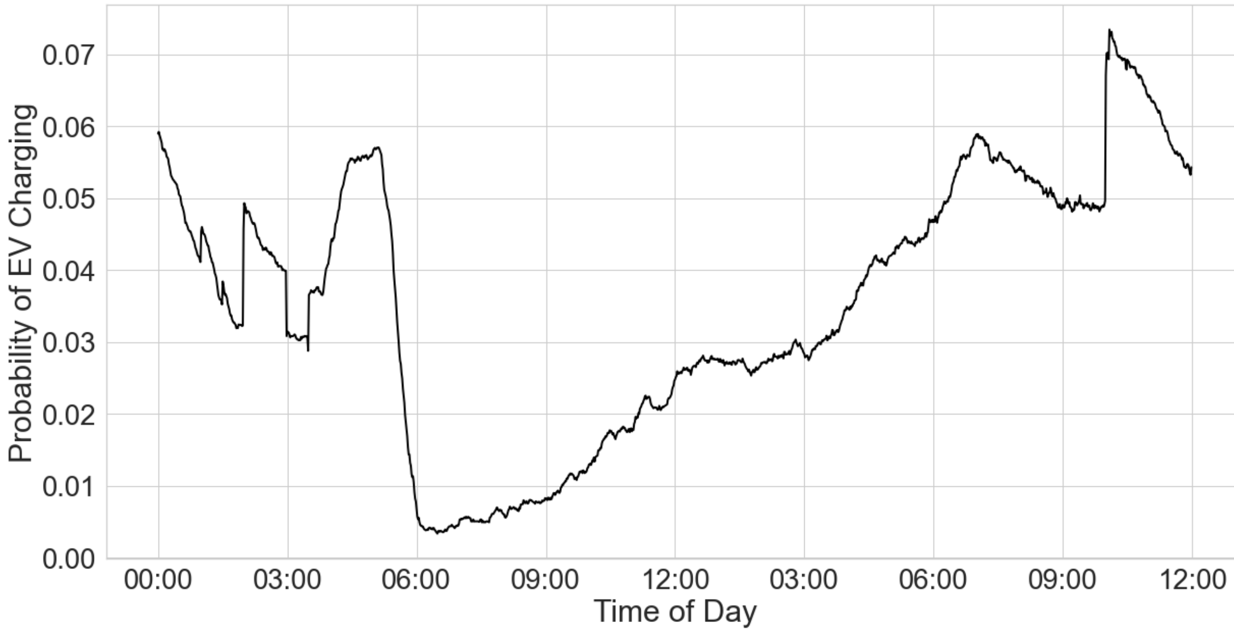

Figure 10. The average probability of an EV charging per the time of day.

While not included in the final load profile for the demand response flexibility analysis, there were some differences observed in the probability of EV charging on weekdays and weekends. Figure 11 characterizes these differences with the vertical axis representing the probability of EV charging and the horizontal line representing the time of day at a minute frequency. The black line represents the weekday charging probability and the orange line represents the weekend charging probability.

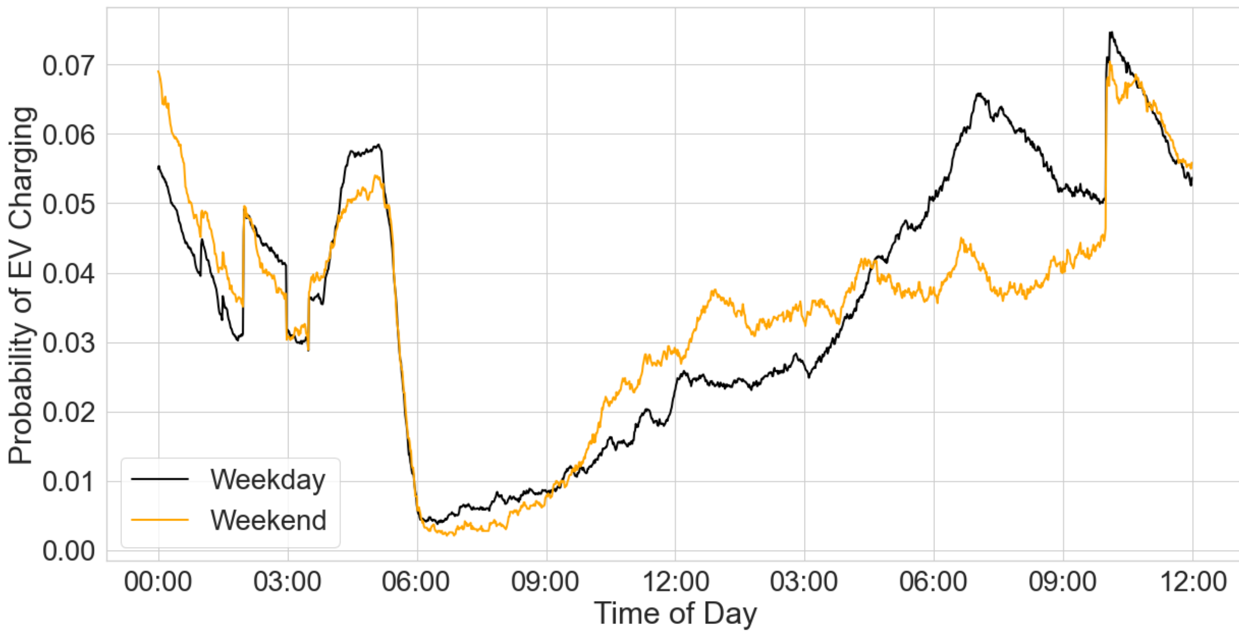

Figure 11. The average probability of an EV charging per the time of day, grouped by weekday and weekend.

The trends identified in Figure 11 show an increase in charging on the weekend between 12 AM to 2 AM. This trend paired with a slight decrease in events at 10 PM may indicate drivers using their vehicles later in the evening and, therefore, shifting their demand to later hours. There is, however, a decrease in charging events between 2 AM and 5 AM. It might be possible that the users that typically charge during this time have a decreased demand for charging over the weekend or they are charging during other times of the day. Between 6 AM and 10 PM, there is a similar gradual increase in EV charging events for the weekend compared to the weekday, although it does not reach the same magnitude of EV charging events as the weekday presents. Instead, there appears to be even fewer charging events between 6 AM to 10 AM, a larger number of events for 10 AM to 4:30 PM, and fewer charging events between 4:30 to 10 PM. The first observation could be a result of morning travelers who typically return home in the morning and charge are not commuting on the weekends, and therefore, their EVs do not need to charge. The next observation is likely due to more users being able to charge during the day, when they would typically be away from home during the weekday. The evening observation is likely the result of users being able to charge during the day and the lack of users returning from their weekday activities and having their EV batteries depleted from their commute.

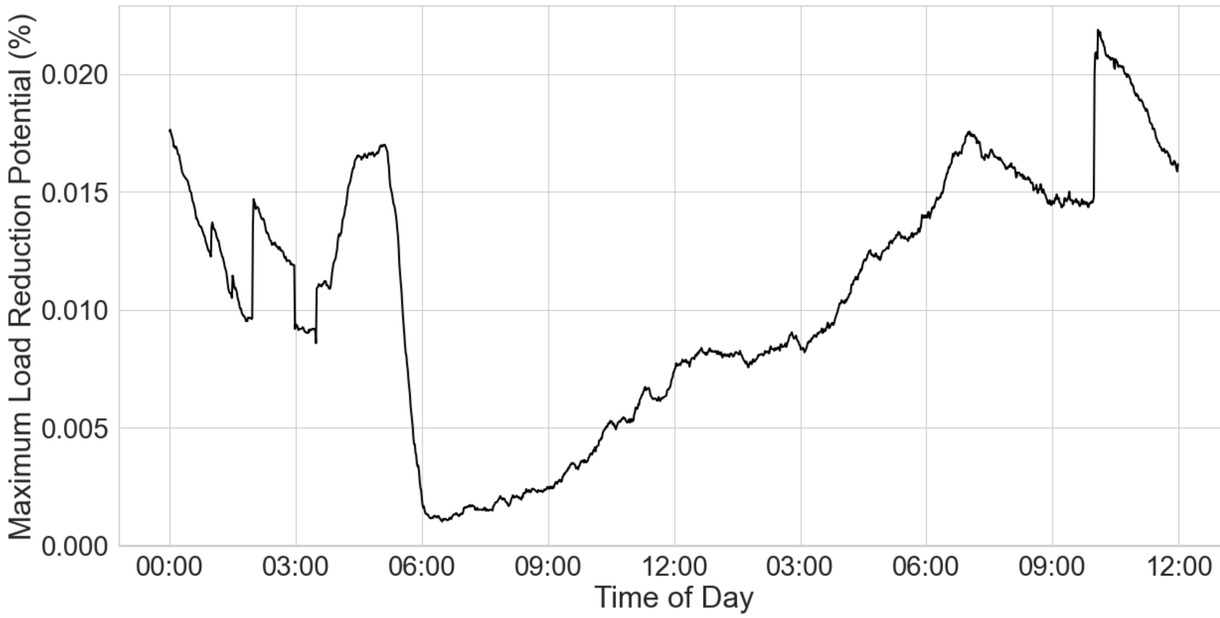

Figure 12. Maximum load reduction potential across the MISO region per the time of day, relative to the peak demand value for the MISO region.

Figure 12 shows the maximum load reduction potential of EVs relative to the peak demand value for the MISO region. The vertical axis represents the maximum load reduction potential in percent and the horizontal axis represents the time of day at a minute frequency. The trends follow those in Figure 2, as expected. With respect to the percentage range found, this number is relatively minimal compared to the load percentages of other household appliances. However, this load is expected to increase significantly in the next few decades as the EVs use grows.

2.5. Conclusions

With rapid EV adoption in the U.S., this represents both a significant increase in electrical energy needs from the grid, as well as an opportunity for EV charging to support demand respond (DR) and load flexibility. EVs participating in demand response would help to shift loads to minimize stress on the grid and support the use of renewable energy resources. This research helps to quantify the maximum load reduction potential that can be achieved with EV charging for DR with current EV adoption. This load availability is likely to substantially increase moving forward as the adoption of EVs is expected to significantly increase. The following highlights the findings of the study:

- EV charging behavior is relatively consistent throughout the year, though there are smaller intervals of variation. This may be due to changes in driver behavior during certain days or months of the year, i.e., more trips during warmer months or the holidays.
- Most charging events occur during the evening and night hours. This pattern is likely due to smart chargers scheduling charging to occur during non-peak hours.
- There is a gradual increase in the charging event likelihood between 6 AM to 7 PM. This pattern is likely a result of occupants immediately charging their vehicles after their daytime activities. Then, between 7 PM to 10 PM, there is a decrease in likelihood which may be a result of vehicles reaching their charging capacity or EVs are being used for evening activities.
- Weekend charging in general has smaller peaks than weekday charging events but has a higher likelihood of charging events during the day when users would typically be away on weekdays. There also appears to be a shift in charging with fewer vehicles charging at 10 PM and an increase in events from 11 PM to 2 AM, likely a result of drivers using their vehicles later in the evenings compared to the weekday.
- For the maximum load reduction potential, the majority of EV charging loads are during the evening and night hours. The daytime load follows a similar pattern to whole-home residential energy use, which indicates opportunities to shift these loads to occur during

off-peak hours or to help stabilize grid operations during peak hours.

With opportunities to lessen the impact of EV charging loads on the grid, this research can help to predict the maximum load reduction potential as EV vehicle technology, charging technology, and population evolves. Limitations to this study include a limited number of housing units with consistent EV data, similar to other studied conducted on EV charging in this area. Similarly, limited numbers in vehicle types and charging technologies in the dataset resulted in limited differentiation in charging behavior between BEV and PHEV and/or Level 1 and Level 2 chargers. Considering future research efforts, identifying differences in charging use for the different vehicle and charging technologies can provide greater accuracy to the model. For optimal grid operation planning, it would also be valuable to collect data that identify when EVs are plugged in (but not being charged) and how much battery capacity/depletion is available.

2.6. Acknowledgements

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CONCLUSIONS, LIMITATIONS, AND FUTURE WORK, RESEARCH CONTRIBUTION

3.1. Conclusions

This thesis provides research on the modeling and analysis of high-resolution, disaggregated energy use data from residential buildings to quantify shifts in electricity use and evaluate the available load flexibility for DR. The first study (*Objective 1*) investigates the impact of the COVID-19 pandemic on residential building energy use using hourly, circuit-level data from 225 housing units. The data is reviewed based on weather-dependent loads, non-weather-dependent loads, and whole-home loads and provides measured shifts in energy use across the years 2018-2020. Additionally, an analysis is conducted to compare the shifts in energy use across different income-levels. In the second study (*Objective 2*), an electricity load profile is modeled based on circuit-level EV charging energy use data, availability of current EV vehicle and charging technology, and registration and population data. This load profile is scaled to the MISO region to produce the maximum load reduction potential based on the total maximum peak load for the region.

The results of *Objective 1* demonstrate that electricity use during the pandemic compared to pre-pandemic periods increased during times when occupants would typically be away from home. For non-weather dependent loads, the largest percent increases occur during 10 AM to 5 PM, and for weather-dependent loads, there is an increase in total daily consumptions for the same average daily temperatures of previous years. In the analysis grouped by household income, the lowest and highest income groups have the larger increases in electricity consumption, while the middle income groups have smaller shifts.

The results of *Objective 2* indicate that EV charging behavior is relatively consistent across the year. Charging events are most likely to occur during evening hours, likely a result of smart charging technologies. Daytime charging appears to have a similar profile to typical electricity demand profiles, with a peak use at approximately 7 PM. This presents some opportunities for these loads to be shifted to optimize grid performance using DR flexibility services. The analysis reviewing weekday versus weekend charging shows a higher likelihood of vehicles charging during the day on the weekend, but a delay in charging compared to the weekday during evening periods.

3.2. Limitations and future work

The research conducted in both studies relies on residential building energy use data with consistency across full years at a minute to an hourly frequency. With relatively limited housing units available that meet the data quality standards for these studies, this limits the representation of typical energy use behavior. (It is noted, however, that the dataset used is considered to be the largest disaggregated dataset collected in the U.S.) As energy efficiency efforts progress, it is highly suggested to widen the availability of disaggregated energy use to aid in the accuracy and representativeness of energy use studies.

For each study, there are several considerations for future work. For <u>*Objective 1*</u>, as occupants rethink their post-pandemic habits, such as remote work or home cooking, investigating different levels of adopting these shifts in behavior should be considered for future residential energy use assumptions. Other recommendations are to review individual appliances load profiles before and during the pandemic to gain a deeper perspective on how energy use has shifted. For <u>*Objective 2*</u>, the EV charging energy use model could benefit from improvements in the differentiation and representation of different EV and charging technologies to provide verification for any differences in energy use behavior, i.e., BEV versus PHEV, smart charging capabilities, and Level 1 versus Level 2 charging. With limitations in the scope of the project, further work could be conducted to predict when charging events occur on a more granular scale. This concept can also be applied to predicting the populations of EV vehicle and charging technology in different locations. Regarding demand flexibility, insights into when EVs are plugged in along with battery capacity/depletion would be valuable for planning optimal grid operation.

3.3. Research contribution

The results of these studies are important for building energy efficiency efforts and smart building-to-grid operations. By modeling and analyzing the residential electricity use, assumptions on building energy use are improved and help to produce more reliable models for energy consumption. This increase in accuracy helps to inform the appropriate measures to take in addressing both energy efficiency at the building and grid level. By providing a measured impact of the COVID-19 pandemic on residential energy use, this enables better predictions of energy use should pandemic-related behavior reoccur or continue in regular energy use behavior. In estimating the maximum load reduction potential for the MISO region, this provides how much load reductions and/or shifting is available for DR programs to manage and how it may impact transmission and distribution. Additionally, the EV charging load profile model is developed in a manner that allows for it to be adaptable to updates in EV technology and availability. This is important considering that EVs are a relatively new technology with opportunity for variability in both the vehicle technology and its charging capabilities.