COVID-19 Pandemic Ramifications on Residential Smart Homes Energy Use Load Profiles

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ABSTRACT

The COVID-19 pandemic has significantly affected people's behavioral patterns and schedules because of stay-at-home orders and a reduction of social interactions. Therefore, the shape of electrical loads associated with residential buildings has also changed. In this paper, we quantify the changes and perform a detailed analysis on how the load shapes have changed, and we make potential recommendations for utilities to handle peak load and demand response. Our analysis incorporates data from before and after the onset of the COVID-19 pandemic, from an Alabama Power Smart Neighborhood with energy-efficient/smart devices, using around 40 advanced

metering infrastructure data points. This paper highlights the energy usage pattern changes between weekdays and weekends pre– and post–COVID-19 pandemic times. The weekend usage patterns look similar pre– and post–COVID-19 pandemic, but weekday patterns show significant changes. We also compare energy use of the Smart Neighborhood with a traditional neighborhood to better understand how energy-efficient/smart devices can provide energy savings, especially because of increased work-from-home situations. HVAC and water heating remain the largest consumers of electricity in residential homes, and our findings indicate an even further increase in energy use by these systems.

1 INTRODUCTION

In March 2020, most US states officially ordered most residents to stay at home, with exceptions for essential workers or under specific circumstances, because of the COVID-19 pandemic. The stay-at-home mandates extended into May 2020 and later for some states. This sudden shift toward working from home and virtual schooling has led to significant changes in energy consumption patterns within both residential and commercial sectors. Researchers have studied how the COVID-19 pandemic has affected the energy use of residential homes [1, 2, 3, 4, 5]. These studies have shown that because of COVID-19 lockdowns and stay-at-home orders, energy use in residential homes has drastically increased, shifting energy peaks in the morning and evening and changing the shape of electrical loads.

The US Department of Energy heavily invests in research in connected communities, where a group of grid-interactive, efficient buildings [6] and other distributed energy resources work together to maximize building and grid efficiency. Alabama Power Smart Neighborhood homes, also known as Reynolds Landing, managed by Southern Company is a classic example of grid-interactive, efficient buildings. All 62 homes within Reynolds Landing signed a continuous datasharing agreement for 2 years, and 39 of these customers signed up to continue data collection and control for another year. During the pandemic, smart community homes with energy-efficient appliances and Internet of Things (IoT) infrastructure enable detailed analysis of device-level energy usage, which can provide more energy savings and capture human behavioral and lifestyle changes.

Because residential and commercial buildings account for nearly 73% of the nation's total electricity consumption, grid-interactive, efficient buildings can contribute to significant energy and peak demand savings. Grid-interactive, efficient buildings in Reynolds Landing consume less energy than standard homes and can reduce peak power usage, with almost a 34% reduction in peak winter heating electricity demand compared with standards homes [7].

In this paper, we analyzed how the COVID-19 pandemic has affected the energy load profiles in residential homes, using Reynolds Landing to make potential recommendations to utilities for handling peak load and demand response. We used neighborhood-level, home-level, and device-level data, including circuit-level power measurement, to provide more information about detailed behavior changes in life patterns than what is provided in existing literature.

Because of data availability, we performed device-level comparisons of energy use for major appliances, such as water heaters (WHs), HVAC systems, stoves, dryers, and washers, to understand how the behavior pattern changes of homeowners have affected electricity consumption. We also compared the Smart Neighborhood with a traditional neighborhood to better understand how energy-efficient/smart devices could provide energy savings that may be magnified by the increased amount of time that people are spending in their homes. Our findings indicate increased energy use by HVAC systems and WHs, specifically. This paper also highlights the energy usage pattern changes between weekdays and weekends before and after the onset of the COVID-19 pandemic (pre- and post-COVID-19). Weekend and weekday patterns were similar post-COVID-19, and weekend patterns were fairly different from pre-COVID-19 patterns.

The rest of this paper is organized as follows. Section 2 describes the related work in this area highlighting several studies that were conducted to analyze pandemic effects on residential energy consumption. Section 3 reports the data collection activity and specific data used. Section 4 analyzes total main power usage and device-level power consumption. Section 5 summarizes the findings and insights gathered.

2 RELATED WORK

Several studies have been conducted to understand how COVID-19 has affected energy consumption in households in different regions. Although details vary, the common finding is that COVID-19 has significantly affected the energy peaks and demand. A detailed report created by BC Hydro Power Smart indicates that the behavior of residents in British Columbia after COVID-19 generated significant shifts in energy peaks and drastic shifts in daily routines, including cooking, laundry, and sleeping patterns [1].

Although the overall New York electricity usage reported by the New York Independent System Operator was 2% to 18% less than the week ending April 3, 2020 as compared to the same week in previous two years, a substantial increase (nearly 23%) in consumption occurred for the residential sector, likely caused by the shift of workers from offices to homes [2]. A recent survey of several home residents in New York since the COVID-19 pandemic suggested that morning and evening peaks no longer occurred on weekdays, and a majority of the homes experienced higher electricity usage [3]. That study [3] analyzed the survey responses of 632 households in New York regarding the interactions among technology attributes, user behavior, and social influence factors. The study revealed a significant change in the shape of the load consumption profile, and the weekday energy usage post-COVID-19 closely aligned with the pre-COVID-19 weekend consumption patterns. An analysis performed on 113 homes in Austin, Texas [4] showed daily average residential demand in March 2020 increased by 20% compared with previous years because of stay-at-home orders. Daily demand from refrigerators post-COVID-19 has also been higher than pre-COVID-19. HVAC energy demand relative to cooling degree days has been higher than pre-COVID-19 and was the highest at the end of March 2020 because of stay-at-home orders.

A comprehensive and comparative analysis on hourly energy demand of the province of Ontario, Canada pre- and post-COVID-19 was performed recently to study the interconnectedness of the smart city concept to the resiliency of energy and health infrastructures in cities [5]. The data collected to analyze the impact of COVID-19 was from April of 2019 and 2020 using similar days. The monthly energy demand reduced greatly compared with pre-COVID-19. However, the daily energy demand is increasing post-COVID-19 compared with pre-COVID-19.

A study [8] was conducted to understand energy usage patterns of a 40-home neighborhood in Texas using energy measurements of four appliances: the refrigerator, dishwasher, washer, and dryer. This study showed that using device-level data is useful to better understand energy consumption patterns and residents' behavior in their homes in detail. The authors observed very little variation of energy usage for refrigerators among the households and use only increased during early morning (6 a.m. to 8 a.m.) and evening (6 p.m. to 8 p.m.). The washer and dryer showed a peak between 9 a.m. and 2 p.m., and all the households displayed a similar peak pattern. The time of use (TOU) and peak of dryer use shifted around an hour after washer usage. The load profiles of dishwasher showed two distinct peaks at 9 a.m. and 10 p.m. However, the

TOU of load profiles had a large variation among the homes. In terms of comparison with weekdays vs. weekends, the refrigerator showed the highest reduction of use, the dishwasher showed the highest variation of TOU, and the washer showed the least variation of TOU.

A recent work from Krarti et al [9] showed that the work from home situations caused as high as 30% increase in residential energy consumption during 2020 lockdown period due to HVAC, lightning etc. in various locations**.** Another South Korea study analyzed changes in building energy consumption, as well as highlighted the changes in building energy consumption based on building use type during COVID-19 [10]. In [11], the authors analyzed electricity use for HVAC, non-HVAC, and whole-home loads from 225 housing units located primarily Texas and other states across the U.S. in 2018 to 2020. The key findings are the highest percent changes for non-HVAC are 10 AM to 4PM with 11AM or 12PM having peak changes. For whole-home energy use, the highest percent changes are between 10AM to 1PM. HVAC usage is higher in 2020 compared to 2018, specifically between April and October. They also considered household income with energy loads; middle income households show minimum impacts when compared to high- and low-income households. A 40-home social housing building energy consumption data in Quebec City (Canada) was analyzed during four months of lockdown and it was found that overall consumption slightly increased, but consumption occurred throughout the day as opposed to having an evening peak before lockdown [12].

3 DATA COLLECTION

The Smart Neighborhood is a community of 62 homes (Figure 1) constructed by Alabama Power, equipped with IoT-enabled HVAC systems, WHs, refrigerators, and other devices. The neighborhood includes utility-owned, community-scale distributed energy resources (solar, battery storage and backup natural gas generator). This Smart Neighborhood development is the Southeast Unites States' first neighborhood to locally generate, store, and distribute power in conjunction with optimizing and controlling electrical loads within the neighborhood homes. Each home featured enhanced energy-efficient components and systems including 2x6 walls with blown-in insulation, triple pane low-e windows, attic radiant barrier, hybrid heat pump water heater, variable capacity heat pump, energy data monitoring center, induction cooking, smart outlets, and lighting. Each home is also sub-metered by circuit to identify general electrical consumption behaviors and evaluate other potential opportunities in energy savings and demand reductions.

Figure 1: : *Aerial view of the smart neighborhood TM. Image credit: Southern co.*

The traditional neighborhood homes were constructed to the minimum code requirements of the Alabama Energy code that follows IECC 2015 and included electric WHs and standard efficiency heat pumps for HVAC. The square footage of these homes is very similar to Smart Neighborhood homes and ranges from about 1500 to 2750 ft2.

To collect data, the Smart Neighborhood employs a multi-agent system (MAS), in which the historical data are not permanently stored. Therefore, an additional data collection module pulls data every 30 min and stores the data in a database. The original data is in JSON (JavaScript Object Notation) format, and it is stored in MongoDB [13]. Although MongoDB is ideal for storing semi-structured data such as JSON documents, many analytic tools such as Tableau and statistical methods still prefer tabular (i.e., relational) data. Therefore, the JSON format data is transformed into tabular data rows stored in relational tables in a PostgreSQL [14] database.

In this study, we used data collected from the Smart Neighborhood community from April and May of 2019 and 2020. Specifically, we retrieved energy usage data, including sensor data throughout a house, thermostat readings, whole house main power, HVAC and WH usage, and so on from April and May of 2019 and 2020. Because of connectivity and data collection issues, data from only 37 homes are included in the analysis; 33 of those homes are on the off-boarding list, and 4 homes only have data for one year, either 2019 or 2020.

Main power, WHs, and HVAC systems have 7 days of data available for April 2019, and 13 days of data available for May 2019. Other devices have 29 days of data available in April 2019, and 31 days of data available in May 2019. All days in April and May 2020 have data available.

Main power, WHs, and HVAC systems have less data available for 2019 because we excluded dates for control dispatch in which the optimization was dispatched to the neighborhood for HVAC control.

4 ANALYSIS

4.1 Total Energy Usage Analysis

In this section, we analyze how COVID-19 affected the energy usage in residential homes. First, we compared the total main power usage in 2019 and 2020. Figure 2 shows the hourly average neighborhood-level energy consumption per home comparison in a day using the data from April and May of 2019 and 2020. Although we observed a change in the energy load curve shape, the main power energy usage is similar between 2019 and 2020. The daily average usage in 2019 was 27.80 kWh, whereas it was 27.43 kWh in 2020. The post-COVID-19 data in 2020 shows increased electricity usage between 8 a.m. and 1 p.m., followed by reduced usage between 2 p.m. and 9 p.m.

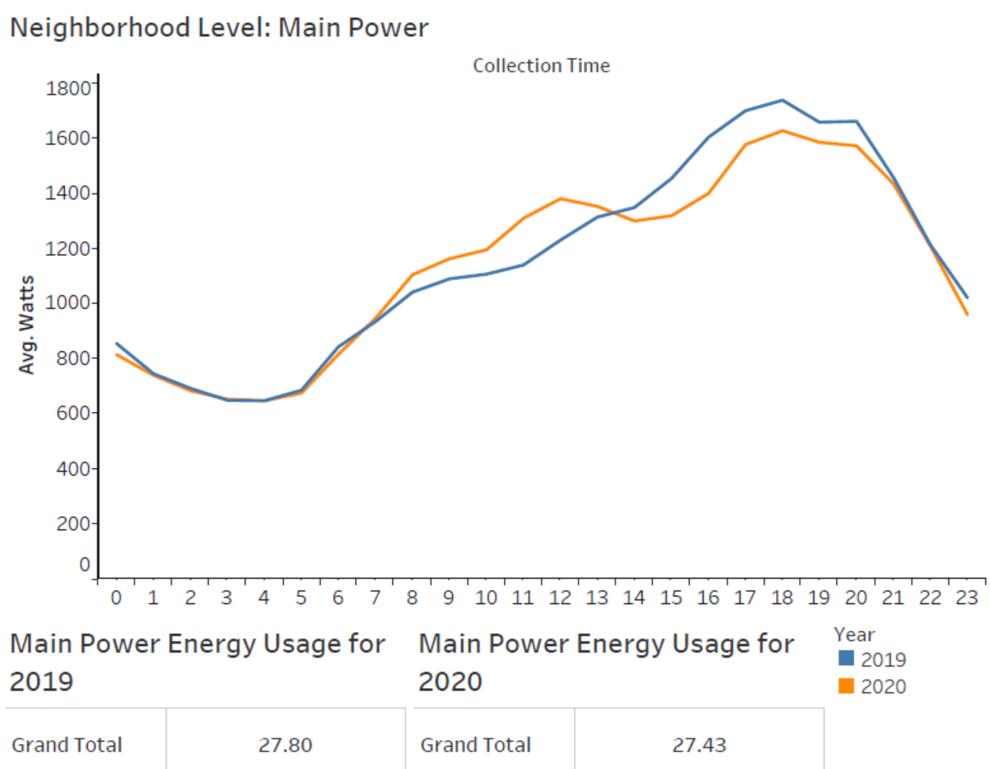


Figure 2 . Average hourly household electricity consumption using the data from April and May of 2019 and 2020 for the 37 homes.

HVAC is a large contributor to total energy use and is highly dependent on the weather, so drawing conclusions from the data without compensating for weather differences is difficult. To minimize the effect of weather differences, we developed a metric to calculate the *similarity of weather* between two days. By only comparing dates that have a high similarity of weather, we minimized the impact of weather differences. In previous work [15], we proposed a method to compute the weather similarity with weighted combination methods (correlations, Euclidean distance, etc.) using two arrays of weather parameters. In this paper, we calculated the similar weather scores for dates in April and May of 2019 and 2020.

Based on the data availability, we chose date pairs in which data were available with high similarity scores, which include two pairs: (1) May 10, 2019 and May 14, 2020, and (2) May 1, 2019 and May 29, 2020. Figure 3shows the average hourly household main power usage for two date pairs identified as having similar weather, and Figure 4shows the main power usage for each of the similar date pairs individually. Because main power includes the HVAC usage, which is heavily weather-dependent, these figures indicate that the energy usage is higher in 2020 given the similar weather patterns during those times. The increase in energy use is most significant between 8 a.m. and 5 p.m. This period aligns with the typical working hours of many people when they would usually be out of the house. With the increase in people working from home post-COVID-19, many homes would be occupied the entire day, resulting in increased energy use during working hours relative to pre-COVID-19.

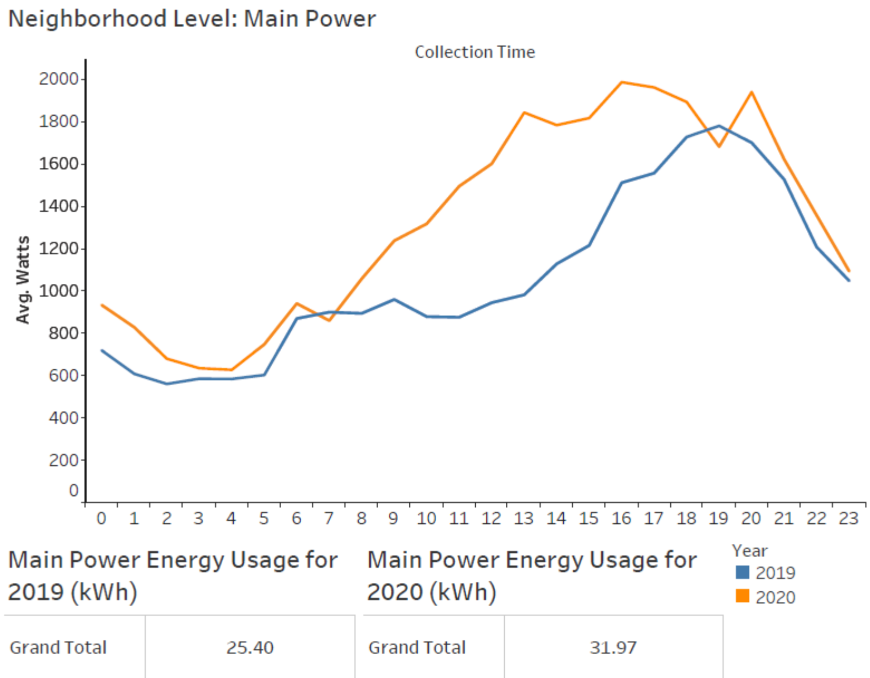
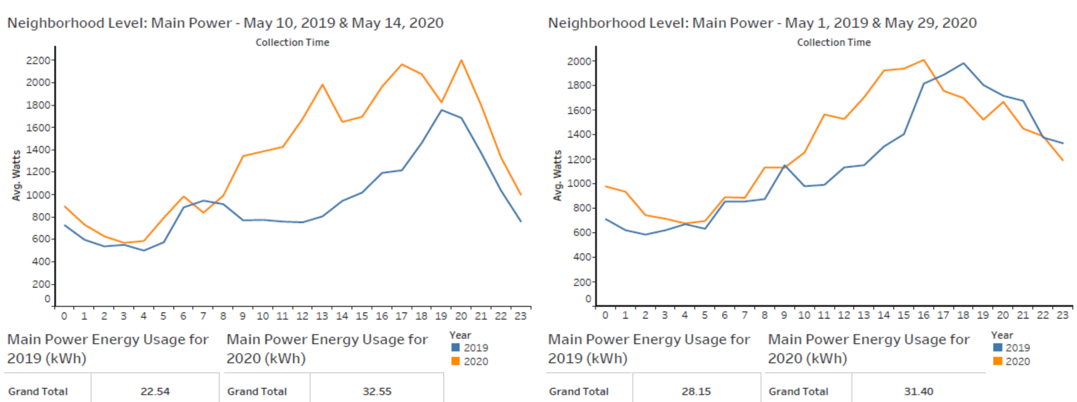


Figure 3.. Average hourly household electricity consumption using the data from two similar weather date pairs for the 37 homes.



(a) 5th rank pair (b) 8th rank pair

Figure 4. Average hourly household electricity consumption using data for similar weather date pairs for the 37 homes.

4.2 Device-Level Power Consumption Analysis

We closely examined the residents' energy usage pattern changes from 2019 to 2020 using device-level energy usage data collected from the neighborhood.

4.2.1 HVAC

The HVAC systems installed in the homes comprise a high-efficiency heat pump, a zoning system with zone control dampers in the supply air ducts, an internet-connected thermostat, and an energy recovery ventilator. The heat pump uses a variable-speed compressor and is paired with a fan-coil equipped with a variable speed blower; it has a seasonal energy efficiency ratio of 18 and a heating season performance factor of 12.

In addition to building construction and occupant behavior, weather can also significantly affect HVAC usage. As noted in Section 4.1, date pairs with similar weather were identified for comparing energy usage that includes the HVAC system because it is highly weather-dependent. Figure 5 shows hourly energy consumption of HVAC per home averaged over the neighborhood for two similar weather date pairs for 2019 and 2020. The average ambient temperature was slightly higher for 2020 dates than 2019 dates, especially during the daytime when the temperature went above 25°C, which led to a significant increase in the HVAC system usage.

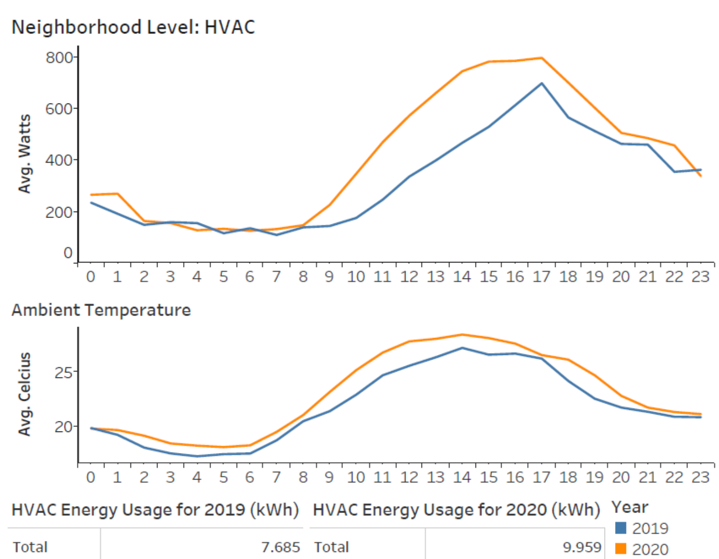
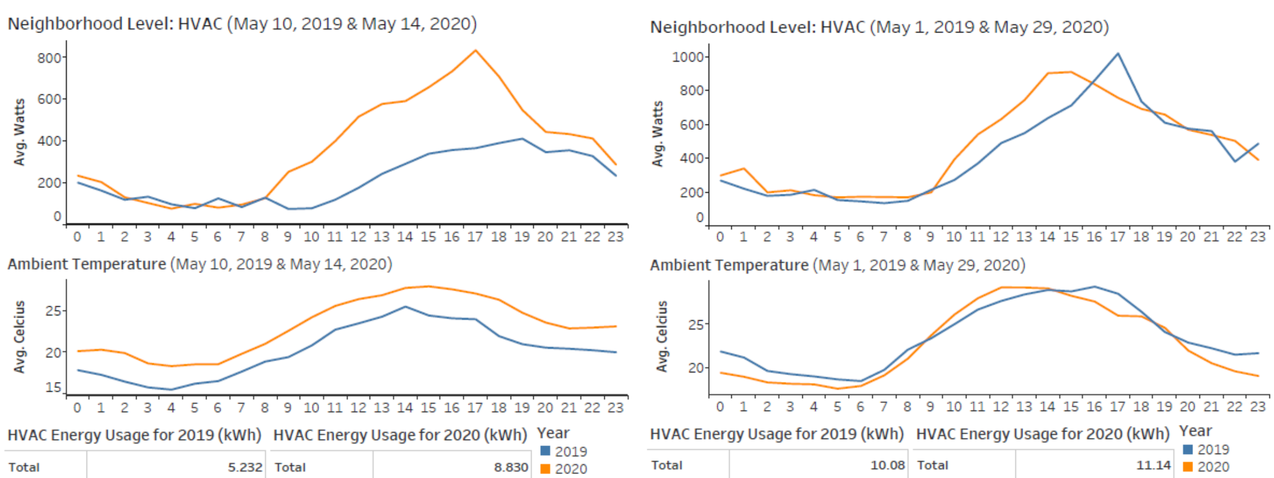


Figure 5. Average household HVAC electricity consumption using data for similar weather date pairs for the 37 homes.

Figure 6 shows the detailed HVAC usage from two date pairs. We observed a change and shift in HVAC usage, especially during normal business hours (8 a.m. to 5 p.m.) on weekdays. People often use a higher set point for their thermostat in the cooling season to reduce HVAC energy consumption when they are not at home, which likely accounts for the lower HVAC consumption during business hours in 2019 compared with 2020. The 2019 HVAC power consumption peak is also much sharper and later in the day than the 2020 peak. This can be attributed to HVAC systems running for longer periods to recover from unoccupied set points when occupants return from work. The 2020 HVAC peak is less sharp and earlier in the day than the 2019 peak, likely because of more constant thermostat set points.



(a) 5th rank pair (b) 8th rank pair

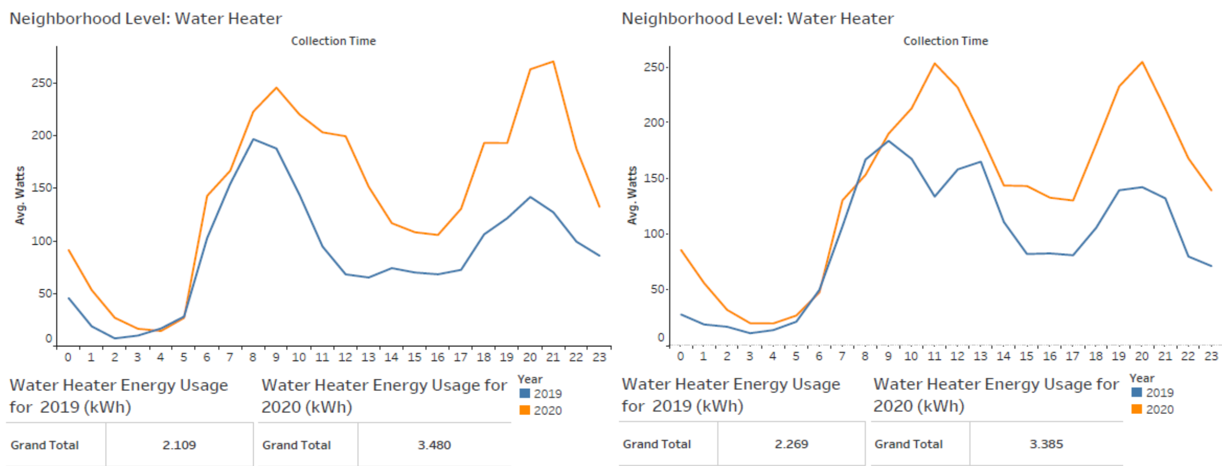
Figure 6. Average household HVAC electricity consumption for two similar weather date pairs for the 37 homes.

4.2.2 WHs

The WHs used in this neighborhood are 80 gallons (302.8 L) hybrid electric WHs with a uniform energy factor of 3.55. The WHs were oversized because they are HPWHs. This helps ensure ample hot water supply during high demand situations with less reliance on high capacity resistance heating. The hybrid WHs are installed in the homes' garages and contain a heat pump that extracts heat from the surroundings and electric heating elements. The WHs support multiple control modes, including heat pump, electric, high-demand, and energy-saver mode. Depending on the operating mode selected, the WH may use electric heating elements to recover more quickly to high–hot water use events. Mixing valves were installed at the output of each WH to limit the water temperature delivered to the fixtures and reduce the potential for scalding when the tank water temperature is heated above the desired temperature.

Figure 7 shows a comparison of the WH electricity consumption for weekdays and weekends for the 2019 and 2020 data sets. Overall, WH electricity consumption increased from 2019 by 65% for weekends and 50% for weekends in 2020. This change is reflected in increased energy consumption for nearly all hours of the day, which may be because of the increase in occupied hours and in more sanitization in 2020. WH usage has a clear peak in the morning on weekdays for all cases. The morning peak in 2019 was around 7 a.m. to 8 a.m., whereas in 2020, the peak was around 10 a.m. Because the ramp rates of the WH load between 5 a.m. and 8 a.m. are similar, we conclude that people likely generally took their morning showers at similar times in 2020 and 2019. However, the 2020 data shows significantly increased usage continuing after 8 a.m., whereas in 2019, the usage began ramping down. This larger peak could be caused by hot water use for dish washing or clothes washing during morning hours that typically did not occur in 2019 because of work conflicts. Another possible explanation is that in 2020, people took longer showers in the morning because of fewer scheduling pressures when working from home. Additionally, the pandemic has caused more people to eat at home than at restaurants, thus increasing hot water use for washing dishes in the evening and perhaps throughout the day.

Furthermore, use of hot water may have increased for hand washing as people were more aware of spreading germs.

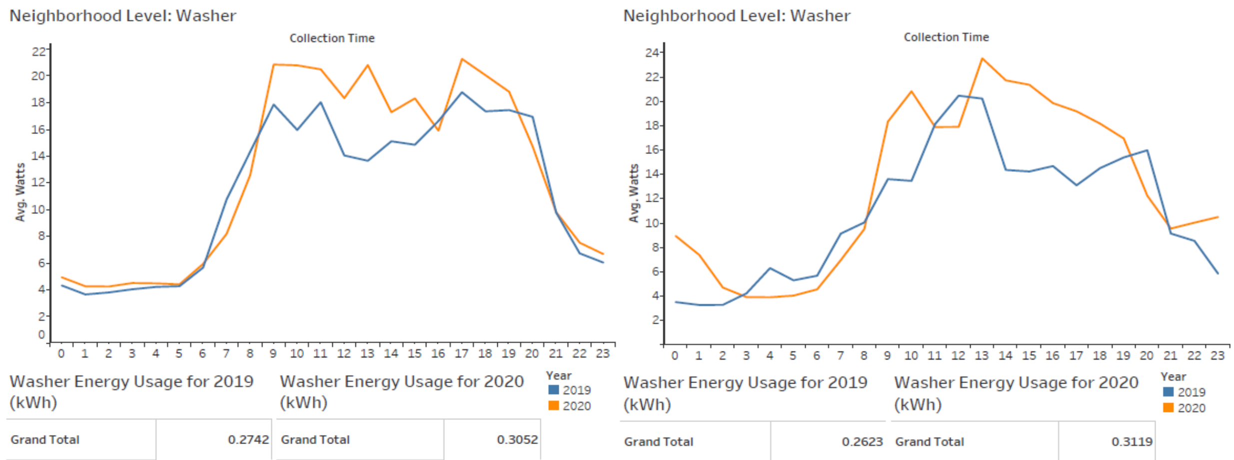


(a) Weekday (b) Weekend

Figure 7. Average household WH electricity consumption using data for 37 homes for (a) weekdays and (b) weekends.

4.2.3 Clothes washer

Figure 8 shows the comparison of hourly average household clothes washer energy consumption in the neighborhood during the weekdays and weekends in April and May of 2019 and 2020. Overall energy consumption increased from 2019 by 11% for weekdays and 19% for weekends in 2020. The increase in weekday clothes washer energy consumption occurred mainly during business hours and may be due to more use of the clothes washer by occupants working from home. Overall, the clothes washer energy consumption and usage pattern are only slightly different in 2020 and 2019.

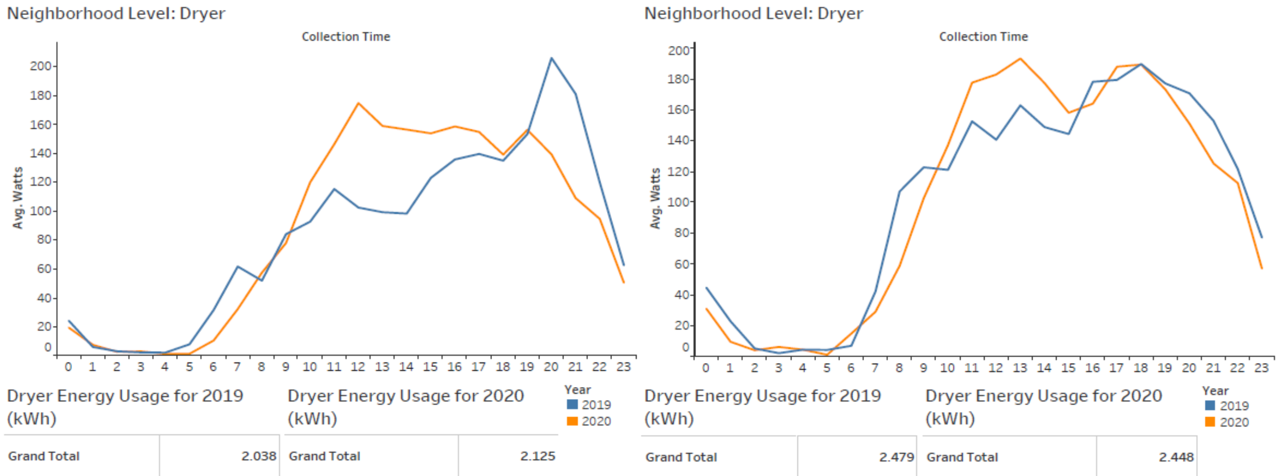


(a) Weekday (b) Weekend

Figure 8 Average household clothes washer electricity consumption using data for 37 homes for (a) weekdays and (b) weekends.

4.2.4 Clothes dryer

The clothes dryer energy consumption is shown in Figure 9. The overall energy consumption in 2020 for the clothes dryer was very similar to that of 2019, at less than a 5% difference. However, the usage pattern is significantly different during weekdays, when more energy was consumed during business hours and much less consumed during evening hours. This difference is likely caused by occupants working from home and being able to take breaks throughout the day to do laundry instead of only having time in the evenings when not working from home. This change also reduces the peak load of the clothes dryer because consumption is spread more evenly throughout the day.

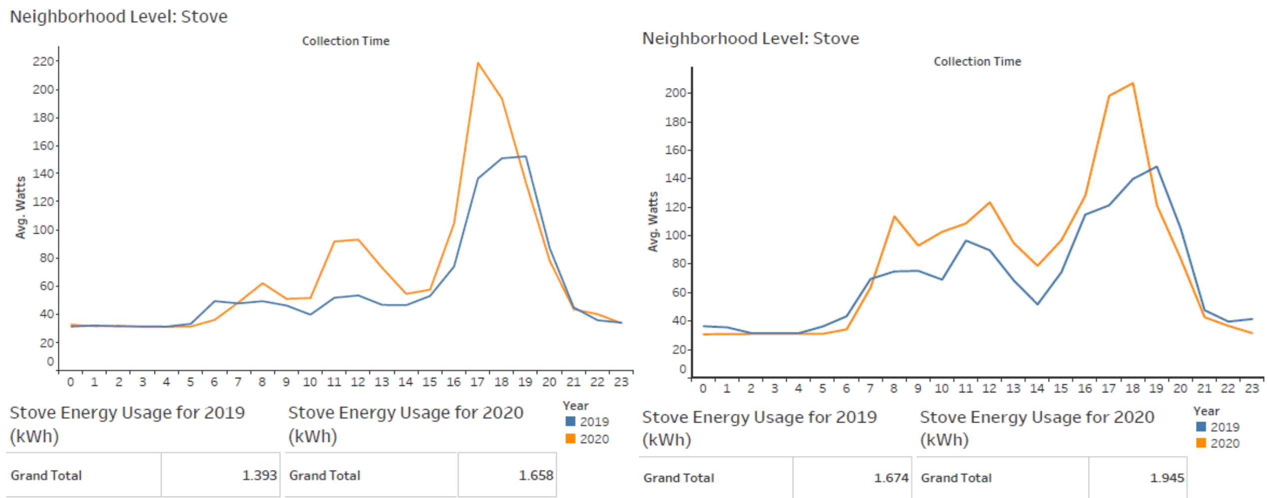


(a) Weekday (b) Weekend

Figure 9 Average household clothes dryer electricity consumption using data for 37 homes for (a) weekdays and (b) weekends.

4.2.5 Range

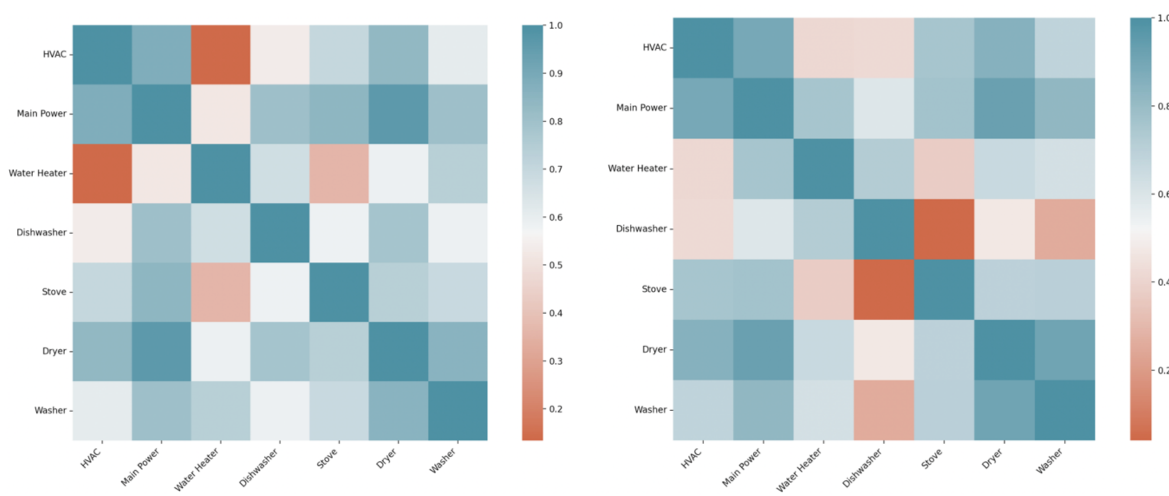
Figure 10 shows the average household range electricity consumption for the neighborhood on weekdays and weekends. Overall range energy usage increased from 2019 by 19% for weekdays and 16% for weekends in 2020. The 2020 weekdays data show increased range usage during lunch and dinner hours, likely because of fewer people going out to eat and instead cooking meals at home. Weekend range energy consumption increased significantly during dinner hours and slightly during other daytime hours, likely for the same reason.



(a) Weekday (b) Weekend

Figure 10 . Average household range electricity consumption using data for 37 homes for (a) weekdays and (b) weekends.

4.3 Smart Appliances Usage Correlation Analysis



(a) Correlation Analysis 2019 (April-May) (b) Correlation Analysis 2020 (April-May)

Figure 11 Average neighborhood-level correlation analysis based on the usage of smart appliances using data for 37 homes for (a) Pre-COVID period (2019) and (b) Post COVID period (2020).

We calculated the Pearson correlation among multiple smart appliances based on their average hourly energy usage (watts) for all 37 homes in the neighborhood. **Figure 11**shows the correlation among multiple smart appliances based on their energy usage during April-May 2019 (**Figure 11**(a)) and 2020 (**Figure 11**(b)). Brighter blue color indicates strong positive correlation between two appliances while the brighter red color indicates strong negative correlation .. We observed that every device is strongly correlated to HVAC and Main Power other than water heater and dishwasher. In comparison with the correlation between the early COVID period in 2019 and COVID period during 2020, we noticed that the dishwasher energy usage was highly correlated with energy usage of stove, dryer, and washer during 2019. While during 2020 energy usage of dishwasher shows negative correlation among with the appliances mentioned above.

4.4 Energy Saving Analysis

We compared the measured data from the Smart Neighborhood with the meter data from a baseline neighborhood of similarly sized homes constructed during the same time period. The baseline homes were constructed to the minimum code requirements of the Alabama Energy code and included electric WHs and standard-efficiency heat pumps for HVAC. The Alabama Energy code follows the Residential Provisions of the 2015 International Energy Conservation Code [12].

Figure 12shows the plots of energy usage comparison between the baseline neighborhood and Smart Neighborhood for May 10, 2019 and May 14, 2019, two similar weather days. The plots indicate that average energy usage in the baseline neighborhood was higher than in the Smart Neighborhood overall, which is mostly because of more energy-efficient HVAC systems, WHs, and building envelopes in the Smart Neighborhood. The increase in energy use from 2019 to 2020 is greater for the Smart Neighborhood at 44%, compared with the baseline neighborhood energy use increase of 31%. This difference could be attributed to several factors. The baseline neighborhood might not have many programmable thermostats in use that reduce HVAC energy consumption during unoccupied hours in the 2019 data. The baseline neighborhood might also have a smaller percentage of homeowners that could work from home in 2020. Additionally, much of the energy use attributed to more occupied hours, cooking, lighting, and miscellaneous electric loads in the Smart Neighborhood™ as compared to the baseline neighborhood energy use, resulting in a larger percentage increase in electricity consumption in the Smart Neighborhood™.

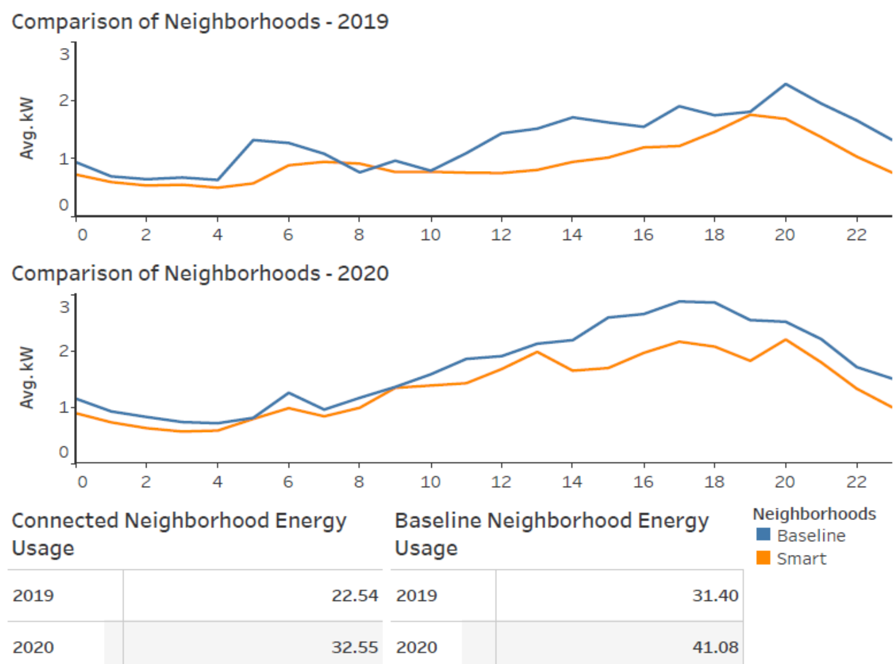


Figure 12 . Smart Neighborhood and baseline neighborhood comparison on May 10, 2019 and May 14, 2019.

5 CONCLUSIONS

Energy demand post-COVID-19 showed intriguing trends of an overall higher energy usage than in 2019 because of stay-at-home situation. However, the peak power usage was not as sharp as the 2019 peak, and the majority of increased energy usage occurred before the evening peak. Shifting load from the evening to earlier in the day should aid in the use of renewable energy generated from photovoltaic arrays and alleviate some of the challenges with rapidly increasing power production to respond to sharp evening peaks. Comparisons between a traditional neighborhood and the Smart Neighborhood clearly demonstrate how energy-efficient homes can reduce power consumption caused by the significant amount of time spent at home during the COVID-19 pandemic. Although daily demand increases for HVAC systems and WHs were much higher for individual homes, an overall energy increase for the neighborhood was also observed. This analysis of energy curve changes caused by the COVID-19 pandemic helps us understand changes in habits, lifestyle choices, and preferences in the near and long terms. This analysis can also help utilities toward better load forecasting, which enables cost savings for both utilities and customers by effectively managing the peak loads.

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