Monitoring Home Electrical Power Consumption Patterns Using Secondary Wireless Meters

Prateek Shrestha and Kim Trenbath

National Renewable Energy Laboratory

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Preface

This report presents findings from the field deployment of whole-home electrical metering equipment in 17 residential buildings across the Denver metro and Aspen areas of Colorado. This project used data acquired from March to November 2024 as part of the *Powerblade* project, which was a BENEFIT FOA project led by the University of California, Berkeley, in partnership with the National Renewable Energy Laboratory, awarded in 2017 (DE-FOA-0001632, FY 17 BENEFIT FOA). This study utilized wireless *Ingot-2* meters from Copper Labs Inc. to capture minute-resolution whole-home electrical consumption data. The data, analyzed using non-personally identifiable information available to the research team, provide high-temporal-resolution insights into usage patterns and drivers of peak electrical load in participating households, offering valuable perspectives on residential energy consumption.

It is important to note that this report does not analyze consumption patterns based on geographic categorization or seasonal variations over a full calendar year. Recruitment of study participants was limited by both time and budget constraints. Despite these limitations, the findings provide quantitative insights into load profiles and temporal usage patterns in residential settings, contributing valuable data to the broader understanding of household energy consumption.

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List of Acronyms

AMI	advanced metering infrastructure
AMR	automated meter reading
DAV	Data Access Viewer
DOE	U.S. Department of Energy
EV	electric vehicle
GEE	Generalized Estimating Equations
HPWH	heat pump water heater
ID	identifier
MF	multifamily
NASA	National Aeronautics and Space Administration
NREL	National Renewable Energy Laboratory
POWER	Prediction of Worldwide Energy Resources project
PV	photovoltaics
RF	radio frequency
SFD	single-family detached

Executive Summary

This report presents analysis of high-temporal-resolution whole-home electrical consumption data obtained from 17 residential buildings located in the Denver metro and Aspen regions of Colorado as well as survey data collected from the participants related to building characteristics and equipment types. The electrical consumption (load) data was obtained using wireless devices manufactured by Copper Labs Inc.[1] that collected data being broadcast from advanced metering infrastructure (AMI) or automated meter reading (AMR) whole-home electrical meters and relayed the data to a central server.

Traditional metering systems, which typically collect data at hourly or daily intervals, lack the granularity required to capture nuanced energy behaviors, such as the power cycles of individual appliances or brief but intense usage spikes. By using minute-resolution data collection, this study uncovers valuable insights into household electricity use, identifying peak load times and patterns that contribute to unnecessary energy use.

The National Renewable Energy Laboratory worked with Copper Labs and local nonprofits and utilities in Colorado to identify homes with suitable AMI/AMR meters. The participants from the identified homes were recruited through a systematic recruitment plan.

In this study, we first evaluate the general characteristics of raw time series data and 24-hour average load profiles for specific homes that participated in the study. We also present aggregate data analysis for homes with overlapping data collection periods. We then perform categorical comparisons of aggregated data that highlight features of the electrical load being influenced by factors such as the presence of rooftop solar photovoltaics (PV), electric versus gas appliances for space and water heating, number of occupants, and occupants working from home. Although this analysis is performed on a small sample size (n = 17), we present the data collected from all the homes that participated in the study in the appendices of this report.

From our data analysis, we find that homes with rooftop solar PV systems have drastically different load profiles compared to homes without rooftop PV systems. Instead of the morning and evening peaks expected in a load profile, homes with rooftop solar PV tend to have a dip toward the middle of the day and have no notable peak during the morning and evening hours. Most of the time, homes experience an average load of roughly 0.5 kW and peak loads of roughly 12 kW. Single-family detached homes have slightly greater (roughly 200 W more) average load, but a much wider load range (the difference between maximum and minimum) of loads compared to multifamily units. Load ranges also increase with increasing square footage; homes less than 1,000 ft^2 can be expected to have significantly less load than larger homes. Homes with electric vehicles have roughly the same median load, but a much wider range of loads. Rooftop solar PV systems significantly reduce the median load—up to 0.5 kW. Since our data mostly span the cooling season, we also analyzed the load patterns for cooling system types categorized as heat pumps and traditional central air conditioners. During a heat wave event, homes with heat pumps can experience lower median and peak loads compared to homes with traditional central air-conditioning systems. Homes with electric water heaters have a lower

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[1] https://www.copperlabs.com/tech/

median load than those with electric heat pump water heater systems but almost double the load range. Homes with electric resistance stoves have a much wider range of loads. In terms of the number of occupants, the median load is only slightly different between homes with two, three, or four occupants. Homes with maximum work-from-home fraction also have the highest variability in the load. Finally, newer homes do not necessarily have lower loads but a much wider range of loads.

This report emphasizes the importance of high temporal resolution in residential building electricity use analysis. This information can be used to better understand the impact of energy efficiency measures.

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1 Introduction

Whole-home electrical metering data with high time resolution are essential for understanding and optimizing energy usage in residential settings. By capturing electricity consumption at intervals of seconds or minutes, these data provide a detailed view of how power is used across different times of day and helps identify peak usage patterns, appliance-level consumption, and potential inefficiencies. This granularity enables homeowners and utility companies to make informed decisions for energy conservation, cost savings, and demand-side management. Additionally, it supports the development of smart home technologies and grid integration strategies, such as demand response programs, which are critical for balancing energy supply and demand in increasingly renewable-powered grids. Ultimately, high-resolution data are a key tool for increasing energy efficiency and reducing costs.

The rising demand for energy efficiency in residential settings has driven interest in high-resolution whole-home electrical metering. Traditional household electricity data collection methods, typically recorded at hourly or daily intervals, offer limited insight into the dynamics of energy consumption. High-temporal-resolution metering, however, captures electricity usage in real time or at intervals of a few seconds, revealing more detailed consumption patterns that are often missed at lower frequencies of data reporting. These high-resolution data can be used to identify the usage cycles of specific appliances, peak load times, and standby power consumption, all of which are crucial for targeted energy-saving interventions. Additionally, high-resolution data support demand response strategies, helping utilities balance grid loads more effectively, especially as renewable energy sources, which are inherently variable, become more prevalent. This study leverages high-temporal-resolution metering to gain a comprehensive understanding of household electricity use, which is essential for both individual energy management and broader grid resilience initiatives.

The National Renewable Energy Laboratory (NREL) conducted this research study by deploying wireless whole-home electrical meters manufactured by Copper Labs Inc. in homes situated in the Denver metro and Aspen areas of Colorado. This report presents analysis of 17 of the homes whose participants responded to additional survey questions needed for the analysis.

1.1 Research Questions

The following research questions were analyzed from the dataset collected for this study:

- What are the average electrical loads for each home at different times of the day?
- What percentage of time do the homes operate at or near peak load?
- What major patterns can be observed from high-temporal-resolution whole-home electrical load data?

2 Methods

A combination of wireless electrical metering equipment and a survey of home characteristics were employed for data collection.

2.1 Data Collection Equipment

The wireless “Ingot 2” devices from Copper Labs Inc. (referred to as “Copper meter(s)” from here on) were used for the whole-home electricity consumption monitoring effort.

Figure 1 shows a wireless Copper home meter, which plugs into a regular 120-V, 15-A interior or exterior wall outlet (receptacle). The antennae built into the Copper meter receive signals from smart meters such as automated meter reading (AMR) meters that continuously broadcast meter readings through 900-MHz radio frequency (RF) band or from advanced metering infrastructure (AMI) meter through a Zigbee network connection. The Copper meter then relays the received data securely to a Copper Labs server via a 2.4-GHz Wi-Fi connection using the home Wi-Fi router as the gateway device.

Figure 1. Copper Ingot-2 whole-home electrical meter

2.2 Recruitment of Participants

Study participants were recruited from the Denver metro and Aspen areas in Colorado through seminars, mass emails, and symposium events at NREL. NREL also engaged in discussions with several agencies and utilities and secured the support of local energy utilities in Colorado, which helped in getting participants from the Aspen region. NREL procured the Copper meters in September 2023 and deployed the pilot batch in November 2023. We secured a total of 31 participants by May 2024. We recruited only homes with Copper-meter-compatible AMR or AMI meters into the study whose data we were able to access via the Copper Labs application programming interface.

Section 3.2 discusses the down-selection process from these 31 participants for the full data analysis based on the data collection period length and responses received from the survey questions listed in Section 2.3.

2.3 Participant Survey

The study participants were asked the following questions either during recruitment through an online questionnaire or via email follow-up:

- What is the name of the electric utility serving the household?

- Does the home have a reliable Wi-Fi connection?
- What type of residential building is your home? (Options: mobile home/single-family detached/single-family attached/multifamily/townhome/apartment/condo/other)
- What is the total square footage of your home? (Metered space—electrical)
- How many occupants live in your home? (Do not count pets, metered space—electrical)
- Year built?
- Presence of electric vehicle (EV)? (Yes/no)
- Primary space heating fuel type? (Gas/electric/other)
- Water heater fuel type? (Gas/electric/other)
- Clothes dryer fuel type? (Gas/electric)
- Stove fuel type? (Gas/electric/other)
- Presence of rooftop solar photovoltaic (PV) generation system? (Yes/no)
- What fraction of the time do you think you worked from home between Jan. 1, 2024, and Nov. 1, 2024? (0%–25% / 25%–50% / 50%–75% / 75%–100%)

Emphasis was given to the primary heating fuel type, water heater type, and stove and clothes dryer type since these appliances and equipment often correspond to the highest electricity consumption in a residential building (U.S. Energy Information Administration 2020; U.S. Department of Energy [DOE] n.d.; Chariot Energy n.d.).

Vintage data, square footage, and primary space heating fuel data that were not self-reported by some participants were obtained through a website search on Zillow.[2]

Supplementary weather data were obtained from the National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resources (POWER) project's Data Access Viewer (DAV) tool.[3]

In addition, we also collected the physical address of homes directly from participants via secure email. Any personally identifiable information such as participant name and address were de-identified by associating a unique home identifier (Home ID numbers) to each home, and personally identifiable information was kept secure on a password-protected NREL computer.

2.4 Data Analysis

The raw data of electrical loads were initially inspected as part of the exploratory data analysis. Any dataset that showed unusual spikes was filtered for outliers above and below 1.5 times the interquartile range before performing further descriptive statistical analyses. The data distribution was investigated for normality using quantile-quantile plots and the Anderson-Darling test where applicable. The quantile-quantile plots and Anderson-Darling test indicated that the data were non-normally distributed; hence, the nonparametric Kruskal-Wallis test was performed for categorical comparisons of pooled datasets.

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[2] Available through https://www.zillow.com/z/corp/about/

[3] https://power.larc.nasa.gov/data-access-viewer/

Generalized Estimating Equations (GEE) analysis was performed to model the relationship between various predictors and power consumption (load) while accounting for the correlation within clusters of data. One-hot encoding was used for categorical data. All continuous data were preprocessed to remove the outliers and invalid values. Outliers were defined as the data points located outside 1.5 times the interquartile range below and above the first and third quartiles.

3 Results

Figure 2 shows the spatial distribution of the participating households in the Denver metro area and Aspen regions of Colorado; the size of the blue circles denotes the number of homes in the area (smallest blue circle corresponds to one home).

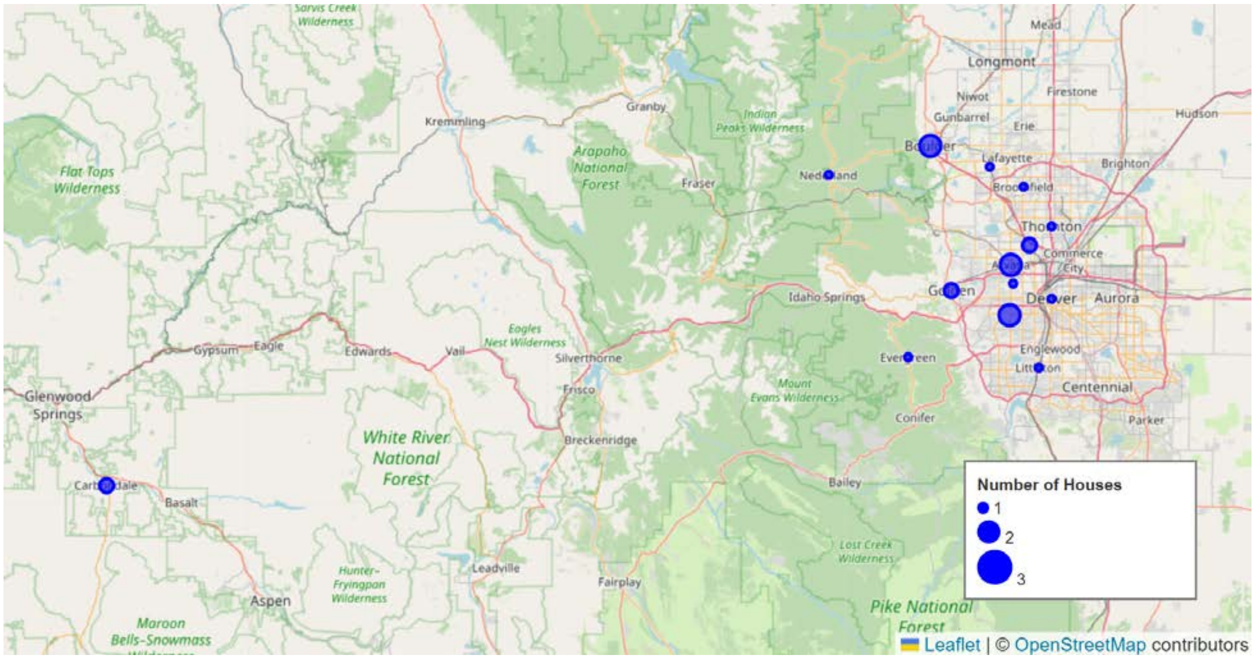


Figure 2. Spatial distribution of study homes in Colorado.

Basemap credit: OpenStreetMap. Total number of homes represented in this figure: n = 17.

3.1 Sample Size

This report presents data analysis from 17 homes. All homes from the set of 17 homes have Xcel Energy as the utility, and the meters are AMI meters. The homes with rooftop solar PV installations have net metering capability. Tables 1–3 provide the summary of the self-reported survey responses by the study participants. Table 1 shows that the average livable area of the study homes is roughly 2,200 ft^2. Table 2 shows that majority of homes have two occupants, followed by homes with four occupants. The filtered set of 17 final homes includes 16 single-family detached homes and one multifamily building.

Table 1. Summary Statistics of the Livable Area Square Footage of the 17 Study Homes

Note: Kurtosis and skewness values were both 1.0 for the data presented in this table.

Statistic	Livable Area (ft^2)
Mean	2,242
Median	2,079
Standard Deviation	850
Minimum	989
Maximum	4,400

Table 2. Number of homes by number of occupants

Number of Occupants	Number of Homes (% of total)
1	1 (6%)
2	8 (47%)
3	3 (18%)
4	4 (23%)
5	1 (6%)

Table 3 provides the results from the participant survey representing the final set of 17 homes for full data analysis, which is presented in subsequent sections.

Table 3 provides the results from the participant survey representing the final set of 17 homes for full data analysis.

Table 3. Participant Survey Results

Home ID*	City	Utility	Housing Type**	Year Built	EV***	Primary Space Heating Fuel	Water Heater	Dryer	Stove	Rooftop Solar	WFH ˡ Fraction (%)
1	Boulder	Xcel Energy	SFD	1957	Yes	Heat pump	Electric	Electric	Electric Induction	No	75–100
4	Carbondale	Holy Cross	SFD	1980	Yes	Heat pump	Electric	Electric	Electric	Yes	0–25
5	Lakewood	Xcel Energy	SFD	1994	Yes	Gas	Gas	Electric	Electric	No	50–75
7	Denver	Xcel Energy	SFD	1991	Yes	Gas	Gas	Electric	Electric	No	50–75
9	Littleton	Xcel Energy	SFD	1975	No	Heat pump	Electric	Electric	Electric	Yes	50–75
10	Lakewood	Xcel Energy	SFD	1972	Yes	Heat pump	HPWH ǂ	Electric	Electric	No	75–100
11	Thornton	Xcel Energy	SFD	1998	No	Gas	Gas tankless	Electric	Electric	No	0–25
12	Nederland	Xcel Energy	SFD	1998	Yes	Propane	Propane	Electric	Electric	Yes	75–100
13	Louisville	Xcel Energy	SFD	1978	Yes	Gas	Gas	Electric	Electric	Yes	25–50
14	Arvada	Xcel Energy	SFD	1970	No	Heat pump	Gas	Electric	Electric	No	75–100
15	Wheat Ridge	Xcel Energy	SFD	1950	Yes	Heat pump	HPWH	Electric	Electric	Yes	50–75
16	Evergreen	Xcel Energy	SFD	2011	Yes	Gas	Gas	Electric	Electric	Yes	25–50
17	Broomfield	Xcel Energy	SFD	1971	No	Heat pump	Gas	Electric	Electric	No	50–75
18	Westminster	Xcel Energy	SFD	2013	No	Gas	Gas	Electric	Gas	Yes	75–100
20	Lakewood	Xcel Energy	MF	1978	No	Gas	Gas boiler	Electric	Electric	No	25–50
22	Boulder	Xcel Energy	SFD	1973	No	Heat pump	Gas	Electric	Gas	Yes	75–100
23	Golden	Xcel Energy	SFD	1961	Yes	Gas	HPWH	Electric	Electric Induction	No	50–75

Notes:
* Only showing homes with usable data
** SFD = Single-family detached; MF = Multifamily
***EV = Electric vehicle
ˡ WFH = Working from home
ǂ HPWH = Heat pump water heater

3.2 Data Filtering

We had originally recruited 31 homes for the study. Some of those homes were removed from the study due to data quality issues. Some meters were disconnected, and a few had issues such as long wireless communication path, RF interference, or other technical difficulties. The useful electrical power (load) data consisted of 27 homes out of 31 that were initially recruited in the study. From there, 23 out of the 27 research participants with useful electrical load data responded to some but not all the survey questions listed in Section 2.3. A total of 21 participants answered all the survey questions. Among these 21 homes, we filtered out four homes for load profile and aggregate categorical analysis because of their shorter electrical data collection span. In order to maintain consistency in the load profile analysis, we omitted the electrical data from Home IDs 2, 3, 6, 8, and 21, which had relatively short durations of available electrical data. Home IDs 19 and 21 did not have full survey responses, so they had to be filtered out from the full detailed analysis. This resulted in a much greater overlap across the 17 remaining homes in terms of available electrical data spanning May 8 to Oct. 13, 2024, and available survey responses. Hence, the results presented below add up to a sample size of 17 homes.

Figure 3 shows the start and end dates of all the connected Copper meters as unique timelines of electrical data collection corresponding to each home.

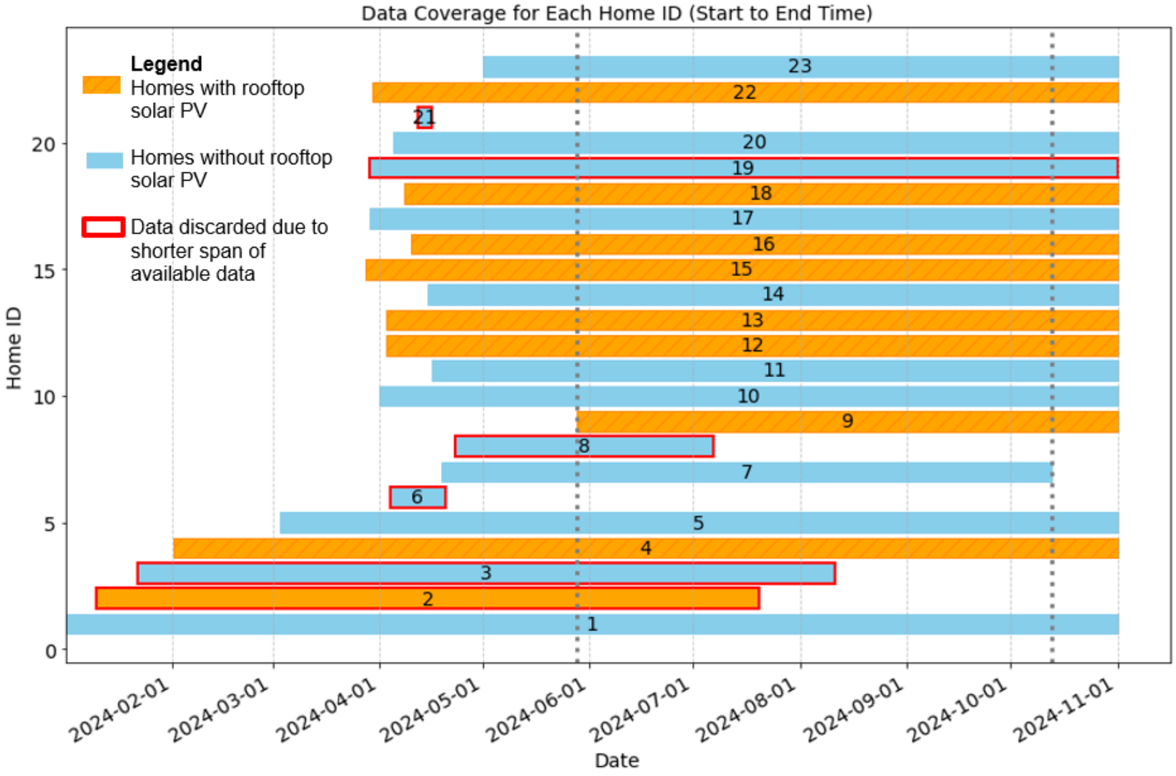
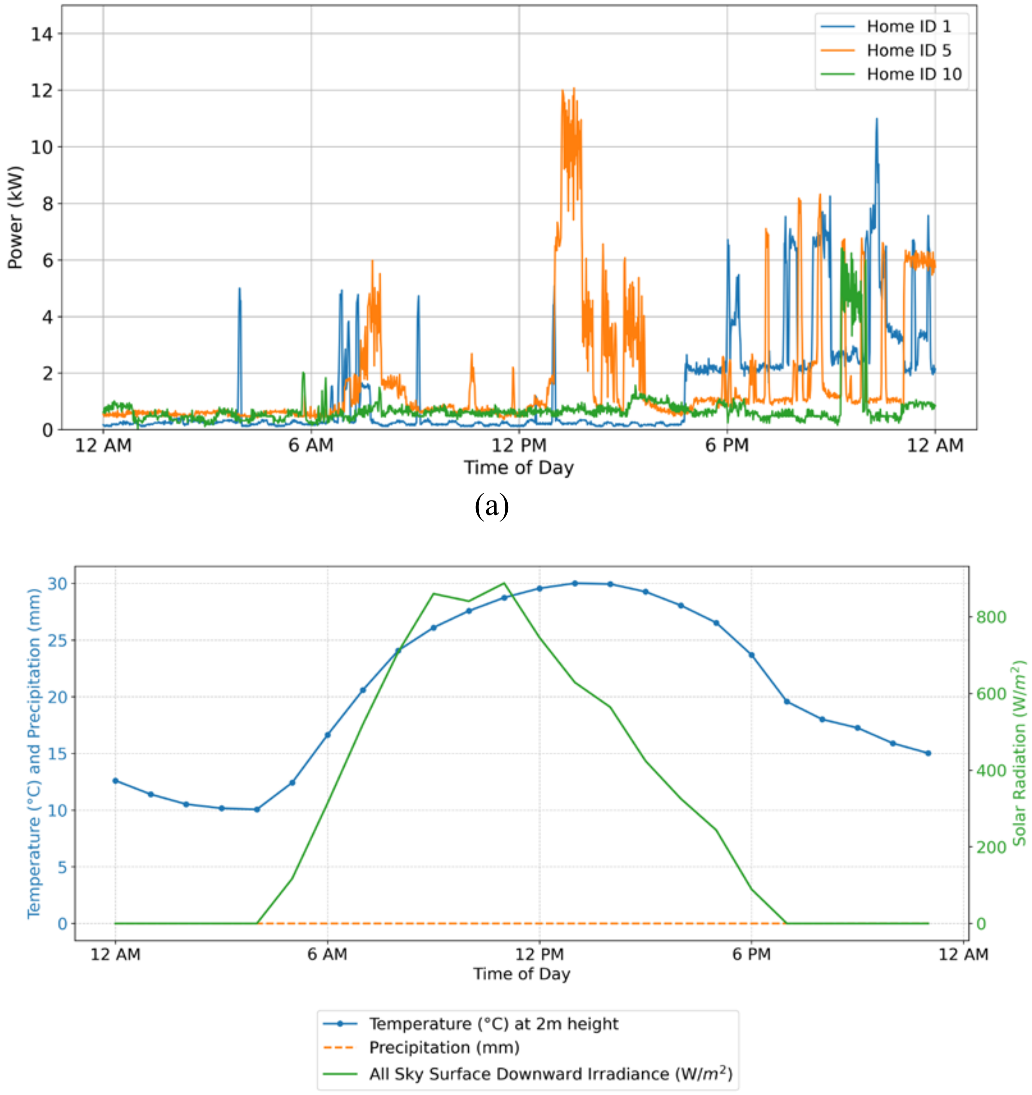


Figure 3. Electrical power data collection periods for all the study homes with some survey responses.

The dotted vertical lines indicate the time frame considered for comparing average load profiles—May 28 to Oct. 13, 2024—encompassing much of the collected data.

3.3 Raw Time Series Data

First, we investigated the major differences in load profiles of homes with and without rooftop solar PV. Figure 4 shows the 1-minute-resolution time series plot of power consumption in Home IDs 1, 5, and 10 (all three have EVs and no rooftop solar PV) for a period of 24 hours on a clear summer day (June 1, 2024), as evaluated through free online weather data based on satellite observations provided by the NASA POWER DAV tool (weather data shown in Figure 4(b)).



(a)

(b)

Figure 4. (a) Time series plot of minute-resolution electrical power consumption data from Home IDs 1, 5, and 10 for a 24-hour period on June 1, 2024. (b) 24-hour weather data near the location of Home IDs 1, 5, and 10 on June 1, 2024, showing dry-bulb temperature at 2 m height above ground surface (°C), precipitation (mm), and the all-sky surface downward irradiance (W/m^2) as a surrogate for cloud cover estimation. High values of the downward irradiance indicated lack of cloud cover.

(Data Source: NASA POWER DAV tool)

Note: Time axis shows both date and hour of the day.

Figure 4(a) shows the morning and evening spikes of the peak load in Home IDs 1 and 10. From Table 3, Home ID 5 uses natural gas for primary space heating, whereas Home IDs 1 and 10 use electric heat pump for primary space heating. Home ID 1 uses an electric resistance water heater and an induction stove, whereas Home ID 10 uses an electric heat pump water heater and an electric resistance stove. Since the data corresponds to a clear summer day, the midday peak of Home ID 5 may be attributed to the central air conditioning trying to meet the high cooling demand of this larger-than-average home (4,400 ft^2), or a load event such as EV charging or running electrical appliances. Figure 4(b) shows the weather data at a location equidistant to Home IDs 1, 5, and 10, which were within 30 miles of each other in similar terrain east of the Rocky Mountain Front Range (Home ID 1 is in Boulder, Colorado, and Home IDs 5 and 10 are in Lakewood, Colorado).

Figure 5 shows the 1-minute electrical load data for the same day as Figure 4 but for Home IDs 4, 13, and 15. Each of these homes has an EV in addition to rooftop solar PV. Home IDs 4 and 15 have electric heat pumps for space heating and cooling, whereas Home ID 13 has a natural-gas-fueled primary heating system and a central air conditioner. All three homes have electric resistance stoves.

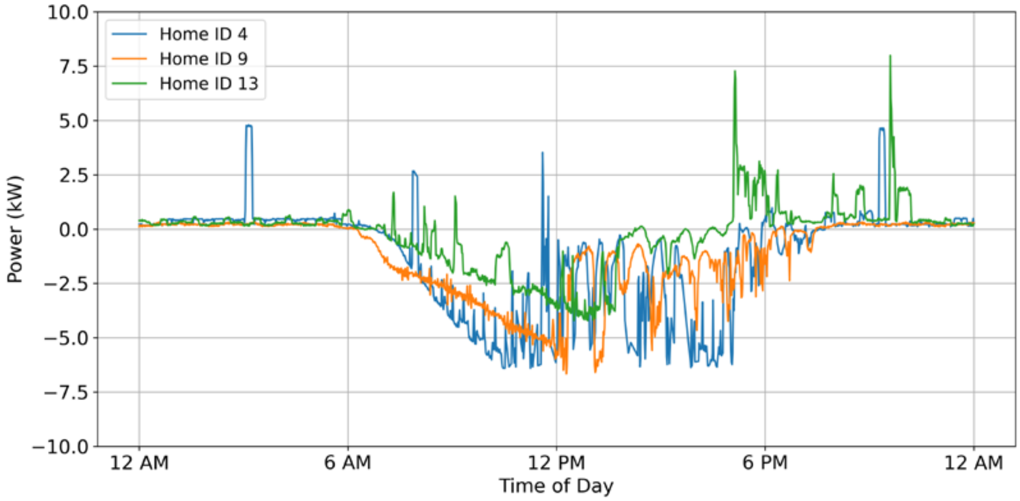


Figure 5. Time series plot of minute-resolution electrical power consumption data from Home IDs 4, 9, and 13 for a 24-hour period between June 1 and 2, 2024.

Note: Time axis shows both date and hour of the day.

Figure 5 shows 24-hour load patterns that dip to negative values for the daytime due to the power generation from the rooftop solar PV. Depending on occupant behavior (e.g., cooking, dishwashing, vacuuming) and/or equipment schedules, there can be significant evening spikes in instantaneous loads that often correspond to peak loads throughout the 24-hour period. The time series plots from the raw 1-minute-resolution data for all homes with available survey responses shown in Appendix B illustrate that some homes like Home ID 12 do not show this daily dip in the 24-hour data from June 1, possibly because these homes also have battery storage. Although we did not explicitly collect survey data on battery storage, one respondent mentioned having battery storage in addition to rooftop solar as extra information in their survey response.

3.4 24-Hour Average Load Profile Analysis

Appendix A provides the average 24-hour load profiles for all 17 homes that were included in the load profile analysis, which indicates that some of the homes have significantly different load profiles compared to the typically expected shape of the load profile. This may be due to factors such as the presence of heat pump equipment for space and water heating, rooftop solar PV, and EVs. We will discuss these factors in greater detail in the subsequent sections. Note that the homes with rooftop solar PV installation show negative power readings on the 24-hour load profiles. We will focus our discussion on the nature of the average load profile and note the times of the day when we can expect to see peak loads in those homes. We have selected a few examples from Appendix A for discussion.

Figure 6 illustrates the average 24-hour load profile for Home ID 5 along with a shaded region indicating the range of data (difference between the maximum and minimum values) around the load profile line that was observed for the full data collection period considered for the load profile analysis (May 28–Oct. 18, 2024). It is typical for residential buildings to experience relatively high electrical loads during the evening hours due to typical occupant lifestyles (U.S. Energy Information Administration 2024). Table 3 shows this home has large square footage (4,400 ft^2), has an EV, uses gas for space and water heating, uses electricity for the clothes dryer and stove, and has no rooftop solar PV.

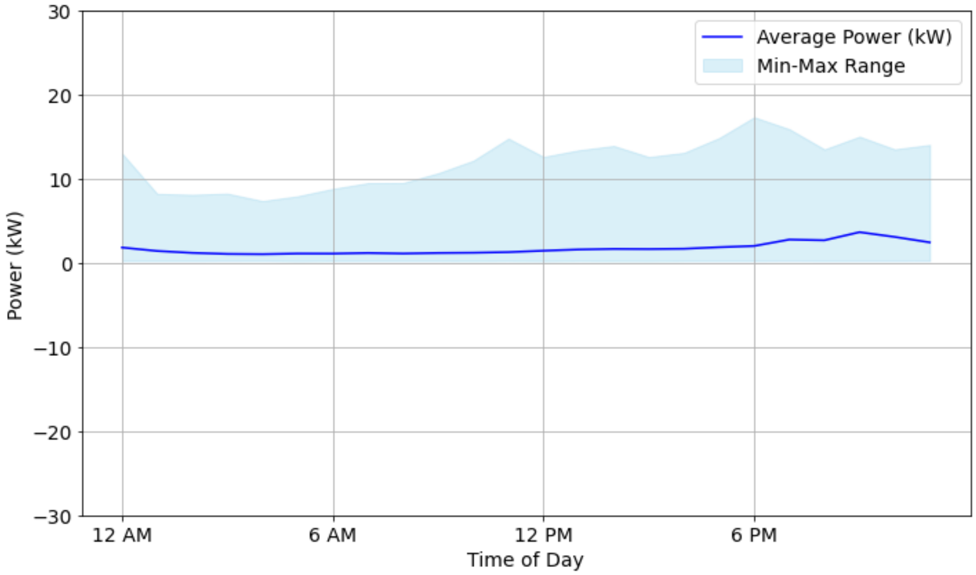


Figure 6. 24-hour average load profile of one study home (Home ID 5).

Note: Time axis shows hour of the day. The dark blue line is the average-value line, and the blue shaded area shows the region between the maximum and minimum values (range of data) at the corresponding time of the day for the entire data collection period.

By contrast, Figure 7 shows the 24-hour profile of a home (Home ID 22) with rooftop solar PV installed. The average load profile of this home is representative of all homes in the dataset that have rooftop solar PV installations; the profile shows a dip during the midday hours corresponding to solar power generation and little to no positive power consumption peaks.

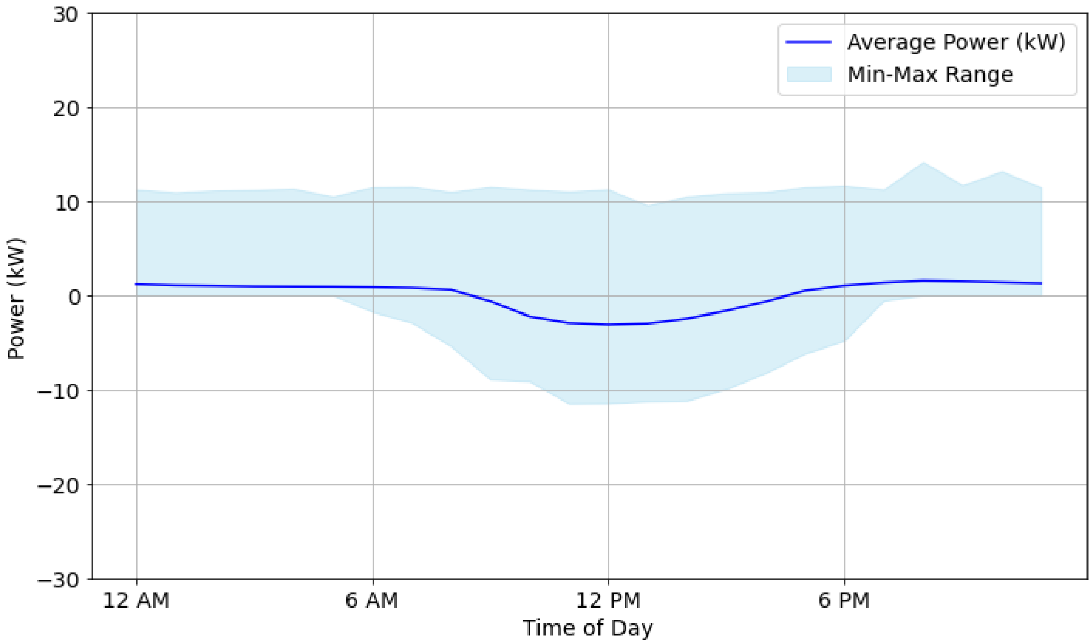


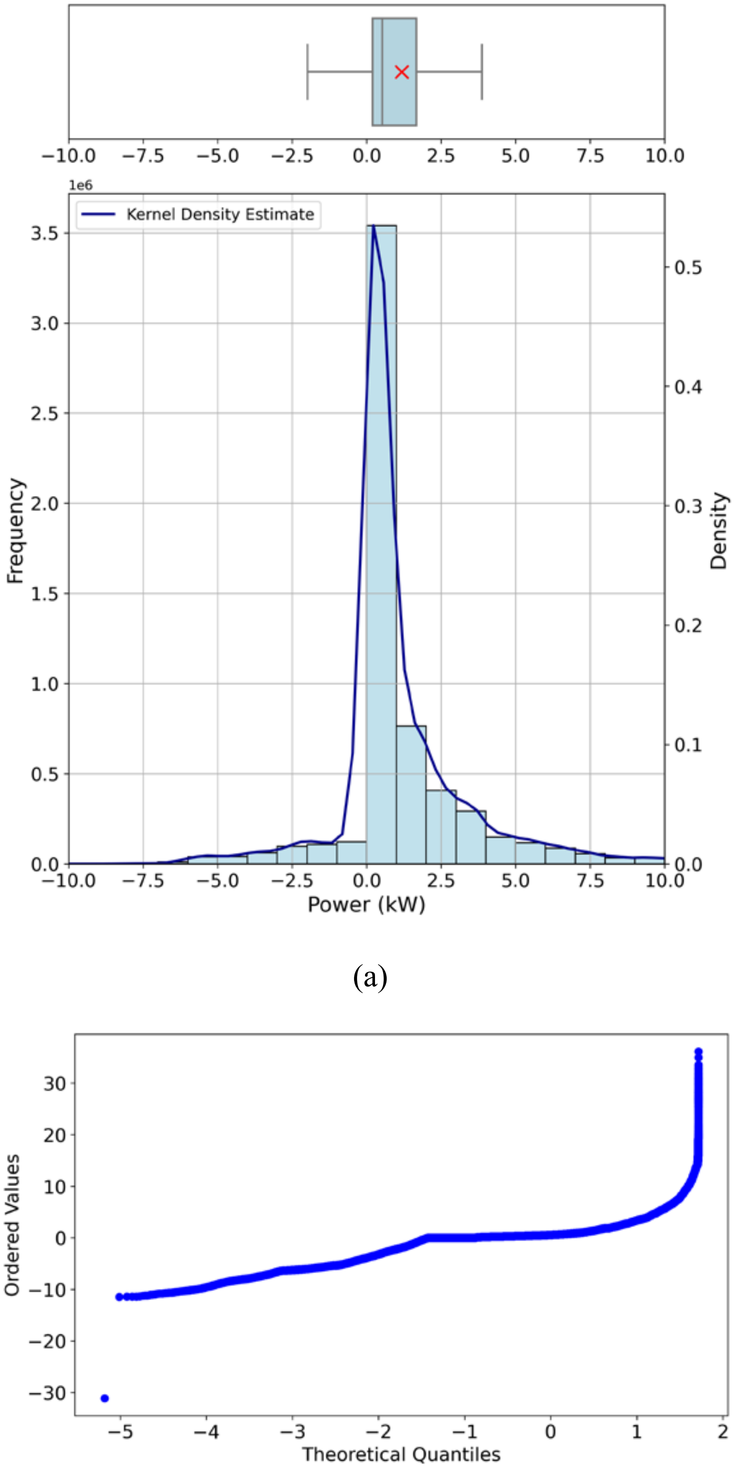
Figure 7. 24-hour average load profile of Home ID 22.

Note: Time axis shows hour of the day. The dark blue line is the average-value line, and the blue shaded area shows the region between the maximum and minimum values (range of data) at the corresponding time of the day for the entire data collection period.

3.5 Aggregate Power Consumption Patterns

When we pooled together electrical consumption data from all homes and categorized the "near-peak load" period as the fourth quartile in the overall set of values, we found that power consumption exceeds the near-peak load mark for a quarter of the time.

Figure 8 provides a summary of the aggregated electrical consumption data from all study homes and indicates that the underlying distribution of instantaneous loads is non-normal. Further investigation using the Anderson-Darling test confirmed that the pooled data were not normally distributed (critical p-value > 0.5 for 15% level of significance). This observation justified the use of the nonparametric Kruskal-Wallis test for subsequent categorical comparisons of electrical load.



(a)

(b)

Figure 8. Frequency distributions of all 1-minute load data pooled together from the filtered study homes shown as (a) discretized with Kernel Density Estimate overlay and (b) quantile-quantile (Q-Q) plot indicating non-normal distribution of the pooled data.

Peak Load Distribution

Figure 9 shows the distribution of maximum load recorded in each home of the filtered dataset. Among all homes in the filtered dataset, we found the mean value of the peak load to be 12.84 kW, and the maximum recorded power was 22.66 kW.

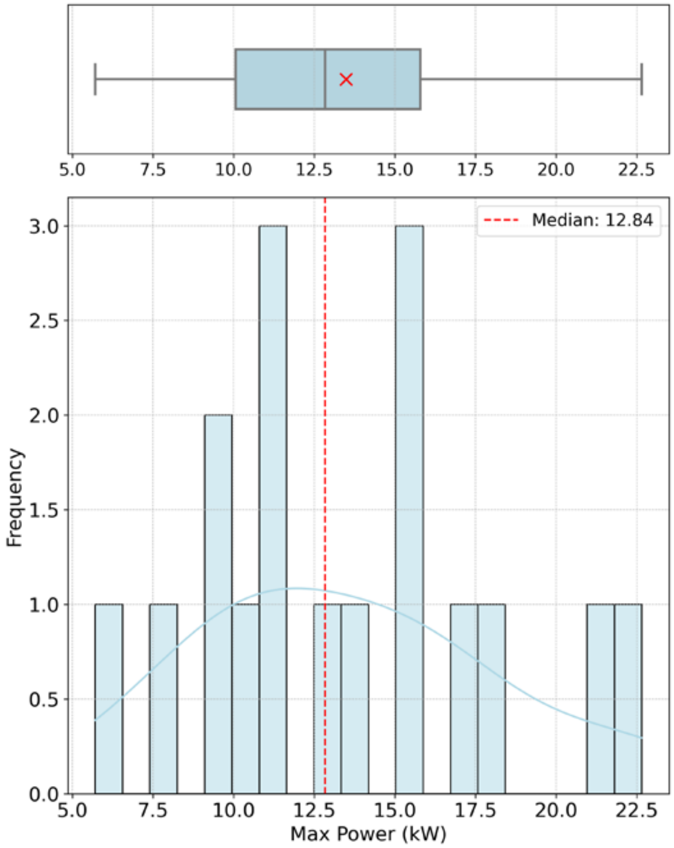


Figure 9. Distribution of peak loads across all homes in the filtered dataset (n = 17).

Note: The red cross mark in the top horizontal box-and-whisker plot indicates the mean value, and the vertical red dashed line indicates the median value. Outliers (data lying outside the whisker limits) are not shown in the box plot.

Due to the fundamentally different characteristics of the load profiles for homes with and without rooftop solar PV, we consider their average load profiles separately.

Figure 10 shows that the peak loads tend to occur in the late evenings irrespective of the presence of rooftop solar PV. However, homes with rooftop solar PV exhibit a characteristic dip during midday, representative of solar power generation.

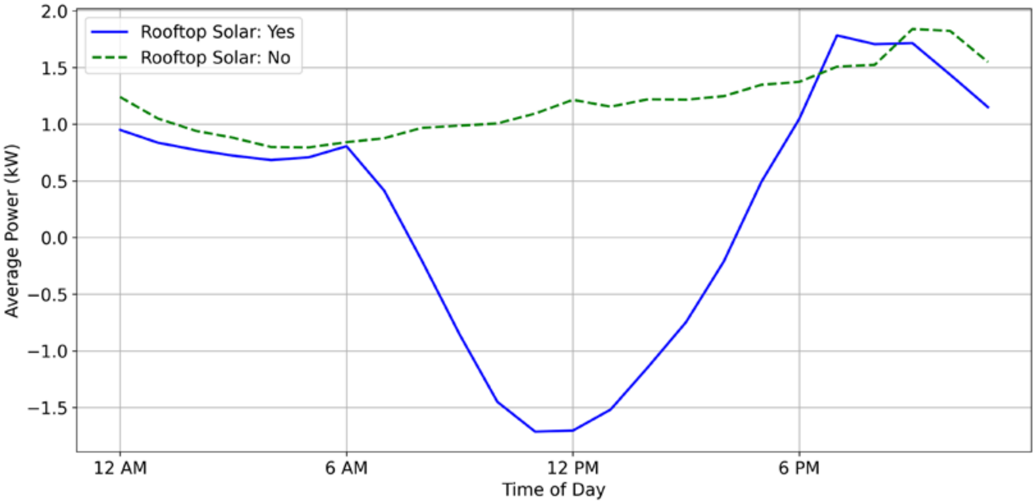


Figure 10. Average loads for homes with and without rooftop solar PV installations for a typical 24-hour period (averaged over the total data collection duration for the filtered dataset)

Categorical Analysis Based on Survey Data

We categorized and compared the load data of the dataset for the answers provided by the participants for the various survey questions. Despite noting a limitation that the effect of categories can interact with each other, and the effect of each category on the load cannot be isolated, we proceeded with the categorical analysis to identify general trends. All homes had electric clothes dryers. The following figures present graphical comparisons between power consumption across homes in various categories with the help of violin plots. Violin plots are chosen for data representation because they can represent modes in addition to the information provided by box-and-whisker plots. The top green and bottom blue dashed lines for each violin plot indicate the third and first quartiles (Q3 and Q1), respectively. The middle line in each violin plot indicates the median value (Q2). The top and bottom dotted lines indicate 1.5 times the interquartile range (Q3–Q1) above Q3, and below Q1, respectively. Figures 11–20 do not show the outliers above and below the top and bottom whisker edges. Also, erroneous power readings as indicated by "nan" (not a number) designation in the collected data were omitted from all analyses. The numbers shown above each violin plot indicate the sample size in each category, and the central red cross mark indicates the mean value.

It should be noted that the results presented here are instantaneous electrical power in units of kilowatts for each minute of data collection; they are not to be confused with the total electrical energy consumption (kilowatt-hours) during a certain time interval. It should also be noted that we present the impact of each categorization one at a time initially to demonstrate the basic nature of distribution across different categories. Later in this report we investigate the combined impact of all categories on the load using statistical techniques.

Figure 11 shows that the load variation was much higher for single-family detached homes compared to the multifamily home unit. The mean load for single-family detached homes was 0.74 kW and that of multifamily homes was 1.04 kW. The difference between the means is statistically significant, verified through the nonparametric Kruskal-Wallis test (H = 61,216, p = 0.00). The average square footage was 2,343 ft^2 for the single-family detached category and

1,111 ft^2 for the multifamily category. However, it is important to note that there was just one multifamily unit in this comparison.

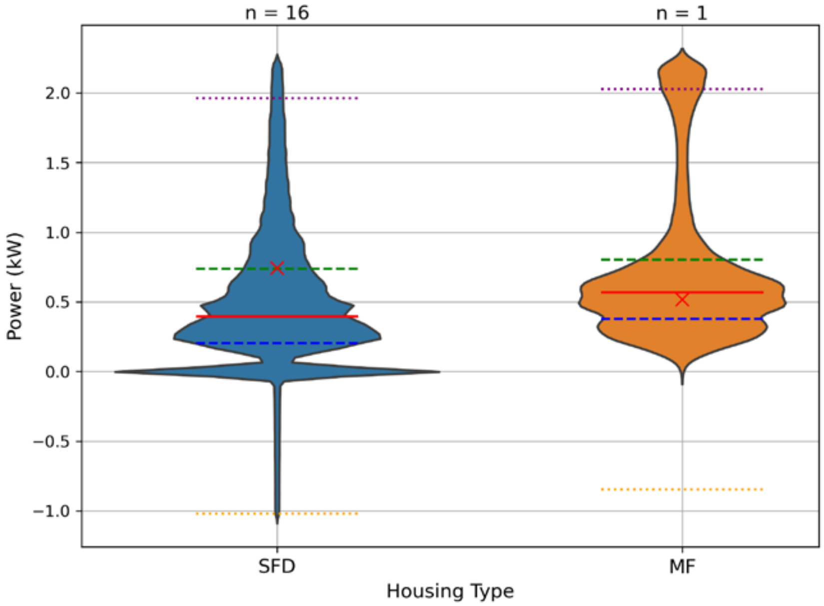


Figure 11. Load comparison by housing type.

SFD = single-family detached, MF = multifamily

Figure 12 shows that electrical load has a positive covariance trend with square footage of the homes having rooftop solar PV as well as those having no rooftop solar PV, suggesting that square footage has a strong influence on the peak load.

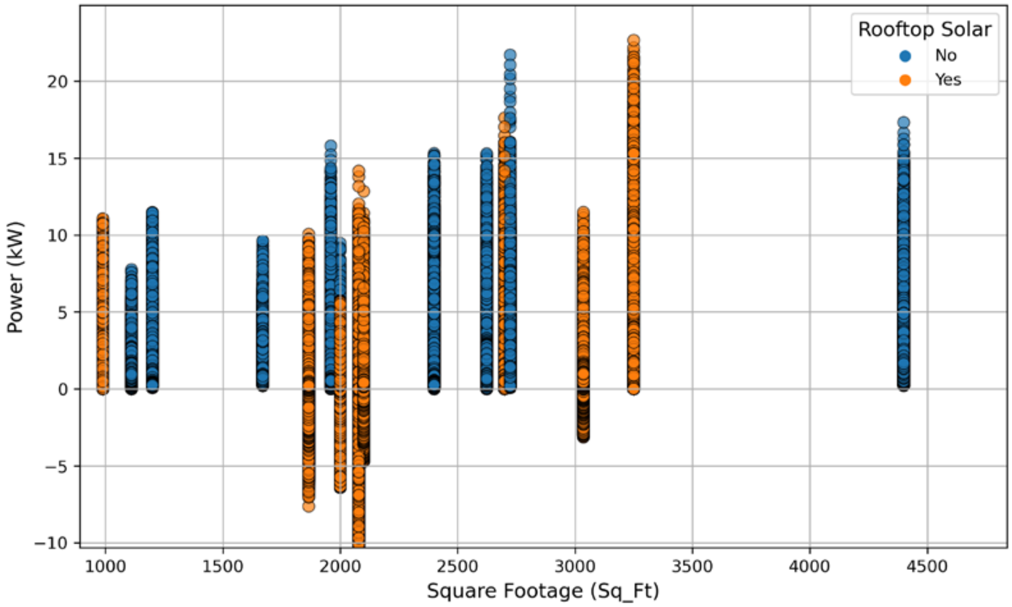


Figure 12. Load covariance with home square footage for all pooled load data segregated as belonging or not belonging to homes with rooftop solar PV

Figure 13 shows that homes with EVs have almost identical load distribution compared to homes without EVs, although the extremely large number of data points from the 1-minute-resolution filtered dataset results in a statistically significant difference of means (H = 7,286 p = 0.00). The mean load of homes with EV was 0.93 kW, whereas the mean load of homes without EVs was 0.52 kW.

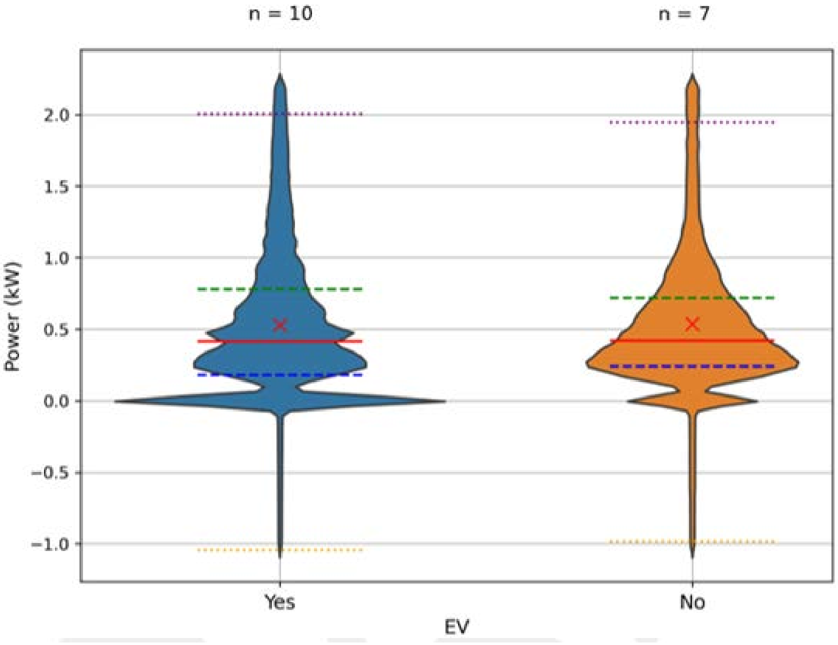


Figure 13. Load comparison by EV ownership

Homes with rooftop solar PV installation have significantly lower power consumption, as expected, as shown in Figure 14. Homes without rooftop solar PV have a median power consumption of 0.58 kW, while homes with rooftop solar have a median power consumption of 0.20 kW ($H = 6.26 \times 10^5$, $p = 0.00$).

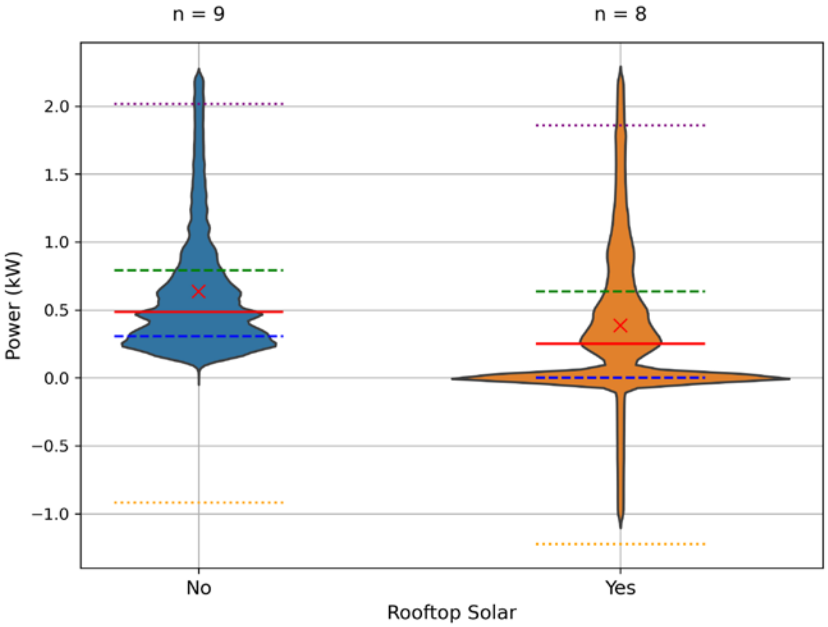


Figure 14. Load comparison by rooftop solar PV installation category

Figure 15 shows that the load distributions of homes using natural gas, propane, and electric heat pumps as the primary space heating fuel were almost identical, although the means were statistically different ($H = 5 \times 10^4$, $p = 0.00$). It must be noted that the data presented here come from a cooling season, meaning that the load categorizations in the first violin plot in Figure 15 reflect the use of air conditioning for meeting the cooling demands. The location of the home using propane as heating fuel was at a higher elevation close to mountainous terrain, which could have led to lower cooling demands for the data collection duration.

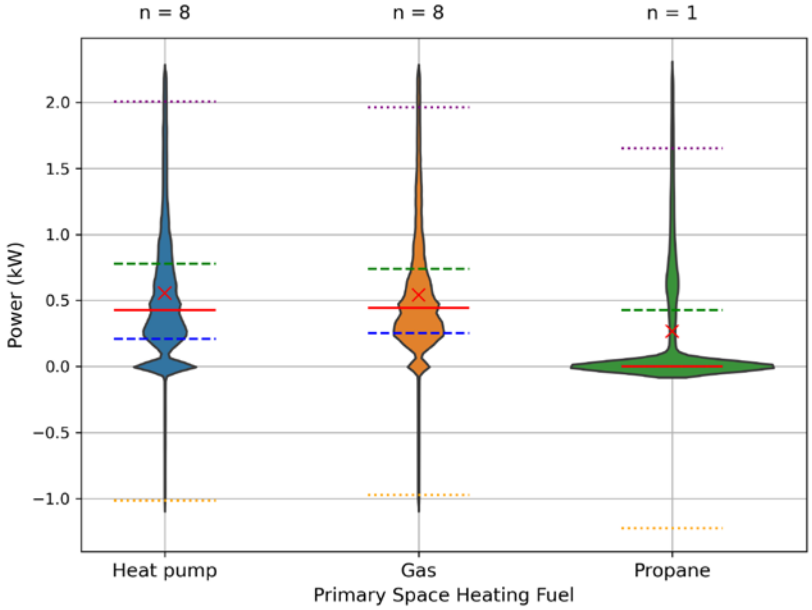


Figure 15. Load comparison by primary space heating fuel type

Figure 16 shows the distributions of collected data for home categorizations by water heater type (H = 99,904 p = 0.00).

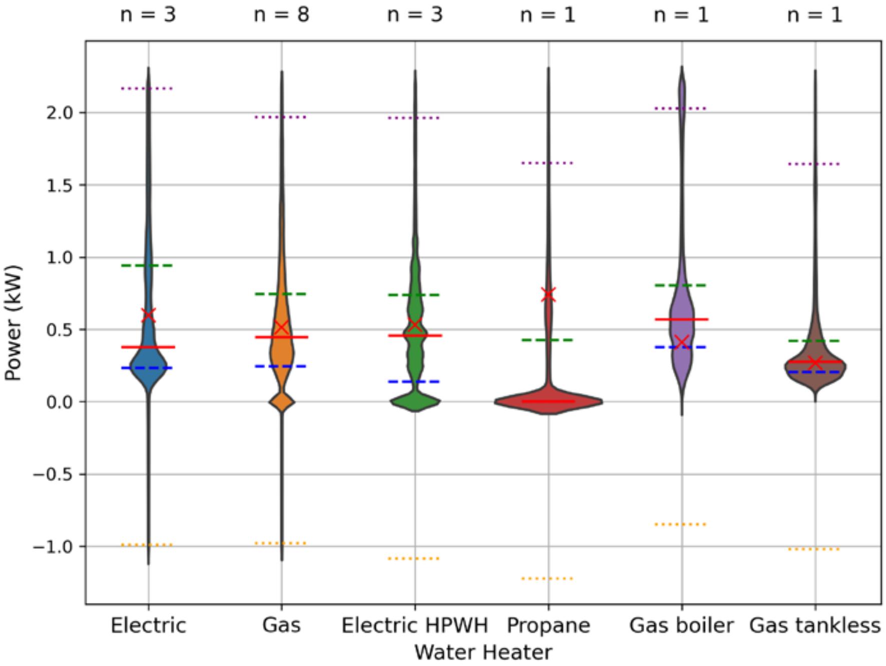


Figure 16. Load comparison by water heater type

Figure 17 shows that homes with electric resistance stoves did not necessarily have the highest electrical loads at all times compared to other stove types. Instead, homes with electric induction stoves had the highest near-peak loads, although electric induction stoves consume less overall energy compared to electric resistance stoves. Electric resistance stoves had the highest mean loads among all three stove types ($H = 8.9 \times 10^4$, $p = 0.00$). Electric induction stoves, while having higher peak load compared to traditional resistance stoves, are more energy efficient overall (DOE 2023). This is because induction cooking directly heats the cookware using electromagnetic fields, leading to faster cooking times and less wasted heat. In contrast, resistance stoves heat coils that emit heat into the air, which is less efficient. Higher peak load occurs because induction stoves rapidly bring heat to high levels, especially during the initial phase of cooking. However, because the cooking process is faster and more controlled, induction stoves use less overall energy to complete the cooking tasks (DOE 2023). Given the very small sample size in this study, we cannot rule out the effect of confounding factors such as home square footage.

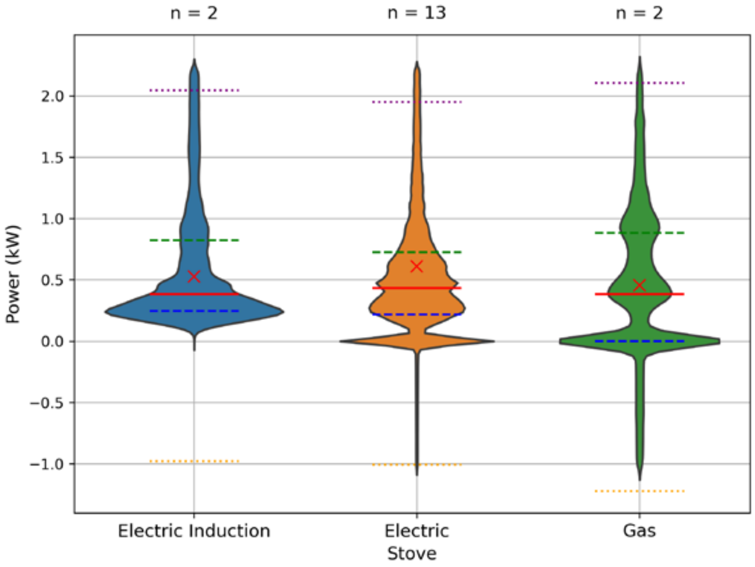


Figure 17. Load comparison by stove type

Figure 18 shows the power consumption by the number of occupants in the home. Homes with three occupants are found to have the minimum average load, while homes with the maximum number of occupants are found to have the highest fraction of loads near the peak load of the entire data pool ($H = 3.3 \times 10^5$, $p = 0.00$).

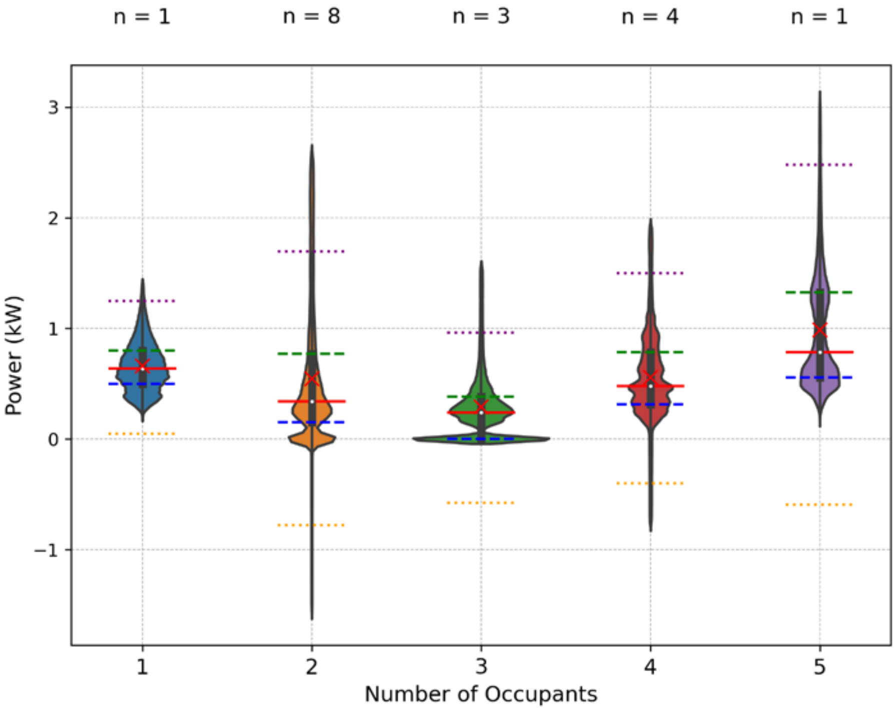


Figure 18. Load comparison by number of occupants

Figure 19 shows that homes in which people mostly worked from home showed the maximum range of loads. Homes where people rarely worked from home also showed slightly higher power consumption. There is an overall slight but statistically significant increase in the median values when the fraction of time that occupants worked from home increases ($H = 4.2 \times 10^4$, $p = 0.00$).

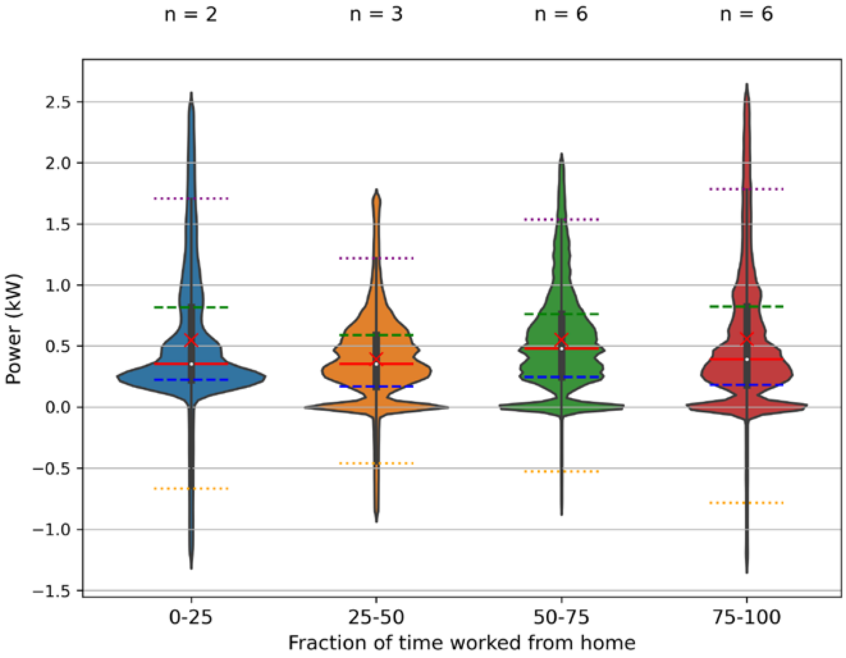


Figure 19. Load comparison by fraction of the time worked from home

Figure 20 shows the categorization of load by home vintage, noting that home size can play a confounding effect. Older homes did not have higher loads, possibly due to renovations and remodeling over time. The homes with relatively higher average loads were built between 1991 and 2010 ($H = 5.9 \times 10^4$, $p = 0.00$).

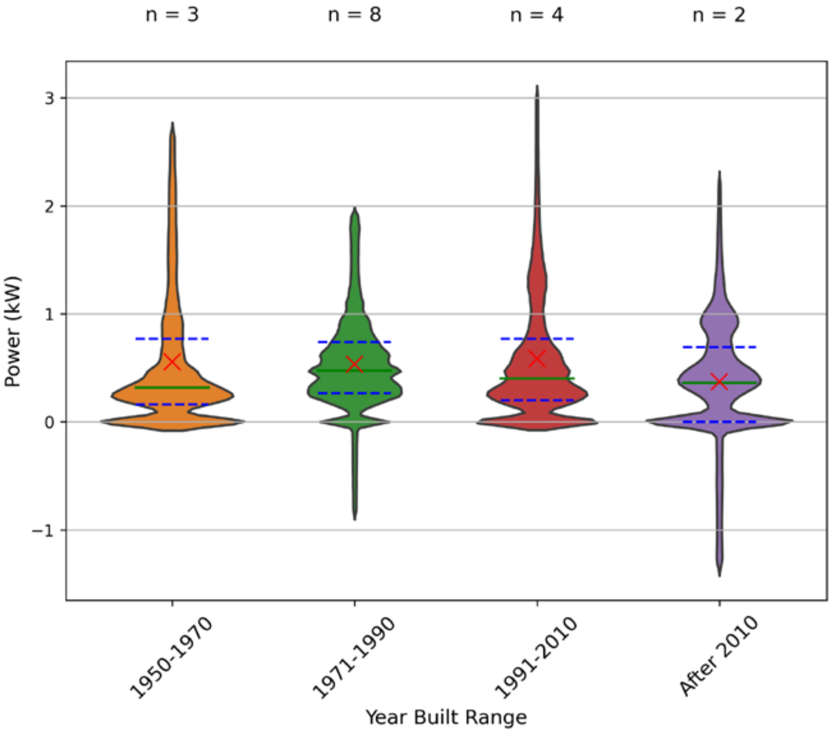


Figure 20. Load comparison by home vintage

Multivariate Analysis With Generalized Estimating Equations

GEE analysis was performed to model the relationship between various predictors and power consumption (load) while accounting for the correlation within clusters of data. In this case, the data represent multiple observations from different homes, which are grouped into clusters, and GEE is particularly useful for handling correlated data within these clusters. The method allows for robust estimation of the regression coefficients despite the correlation of observations within the same cluster. To perform the analysis, a GEE model with a Gaussian family and an exchangeable dependence structure was specified, which assumes that the correlation between observations within a cluster is constant. This approach was chosen because it provides robust standard errors that are less sensitive to misspecification of the correlation structure, making it suitable for large datasets like this one, with more than 1.5 million observations across five clusters. The regression analysis was conducted iteratively, and the model was fit to the data using robust covariance estimates to ensure accurate parameter estimation and statistical significance. Table 4 and Table 5 present the GEE analysis results with variable names shown in Table 5 as categorized after the one-hot encoding process.

Table 4. GEE Regression Results (Summary)

Dependent variable:	Power (kW)	No. observations:	1535291
Model:	GEE	No. clusters:	5
Method:	GEE	Min. cluster size:	224017
Family:	Gaussian	Max. cluster size:	438736
Dependence structure:	Exchangeable	Mean cluster size:	307058.2
Covariance type:	Robust	No. iterations:	60
		Scale:	3.804

Table 5. GEE Regression Results (Details)

Variable	Coefficient	Standard Error	z	P > |z|	[0.025	0.975]
Sq_Ft	0.0002	9.93E-18	1.9E+13	0	0	0
Num_Occupants	0.2724	1.85E-14	1.5E+13	0	0.272	0.272
Year Built	-0.0004	3.73E-17	-1.1E+13	0	0	0
Housing Type_SFD	0.0074	4.44E-16	1.7E+13	0	0.007	0.007
EV_Yes	0.7173	3.74E-14	1.9E+13	0	0.717	0.717
Primary Space Heating Fuel_Heat pump	-0.0057	1.45E-14	-4.0E+11	0	-0.006	-0.006
Primary Space Heating Fuel_Propane	0.0429	1.31E-14	3.3E+12	0	0.043	0.043
Water Heater_Electric Heat Pump	0.3469	1.95E-14	1.8E+13	0	0.347	0.347
Water Heater_Gas	-0.0298	2.08E-15	-1.4E+13	0	-0.03	-0.03
Water Heater_Gas boiler	0	0	nan*	nan	nan	0
Water Heater_Gas Tankless	0	0	nan	nan	0	0
Water Heater_Propane	0.0429	1.31E-14	3.3E+12	0	0.043	0.043
Rooftop Solar_Yes	-0.32	2.24E-14	-1.4E+13	0	-0.32	-0.32
WFH Fraction (%)	0	0	nan	nan	0	0
Skew:	2.2950	Kurtosis:	8.0757			
Centered Skew:	2.2950	Centered kurtosis:	8.0757			

* nan = not a number

The GEE results can be interpreted as follows:

Model Diagnostics:

- Skew (2.2950) and Kurtosis (8.0757): These values suggest that the residuals from the model are somewhat skewed and have heavy tails (leptokurtic). While this may not be unusual for large datasets, it may be worth investigating whether transformations (e.g., log transformation) could help normalize the distribution and improve model fit.
- P-values (P > |z|): All p-values are significant ($p < 0.05$), which indicates that the coefficients are statistically significant. However, given the large number of data points collected with 1-minute resolution spanning several months, even trivial effects are likely to be significant, so it is essential to focus on the practical significance of these coefficients.

Coefficients:

- Sq_Ft (Square Footage): The coefficient is very small (0.0002), suggesting that for every additional square foot of space in a home, power consumption increases by a minuscule proportion of a kilowatt. While this value seems reasonable for large datasets, its small size might indicate that square footage alone is not a strong driver of power consumption compared to other variables, or the scaling of this variable needs to be adjusted.
- Num_Occupants (Number of Occupants): The coefficient of 0.2724 suggests that each additional occupant increases power consumption by about 0.2724 kW. This is a reasonable result, as more people typically use more energy, but we should consider whether there is a threshold or diminishing returns (e.g., families with more occupants may not use proportionally more energy).
- Year Built: The negative coefficient (-0.0004) suggests that newer homes (with a higher year built) have slightly lower power consumption, which could make sense if newer homes are more energy efficient. However, this effect is quite small, and it might be influenced by other confounding factors, e.g., newer homes tend to be more energy efficient, but they also may have larger square footage.
- Housing Type (Single-Family Detached): The positive coefficient (0.0074) indicates that single-family detached homes consume more power than other housing types. This aligns with expectations, as larger, detached homes generally require more energy for heating, cooling, and appliances. There was only one home that was not single-family detached in the filtered study data.
- EV_Yes (Electric Vehicle Ownership): A coefficient of 0.7173 suggests that homes with EVs consume an additional 0.7173 kW, which is consistent with home EV charging increasing a home’s electricity usage.
- Primary Space Heating Fuel: For homes using heat pumps or propane for heating, the results show very small effects (-0.0057 for heat pumps, 0.0429 for propane). The small effect for heat pumps makes sense, as they are typically more energy efficient compared to traditional electric resistance heating. A study limitation to highlight here is that the data collection period was over the summer months. A more comprehensive and longer study period (at least a full calendar year) encompassing a larger sample size will impact this result since data from both heating and cooling seasons will be included in a longer study period.

- Water Heater Types: The coefficients for electric heat pump water heaters (0.3469), gas (-0.0298), and propane (0.0429) indicate that water heaters significantly affect power consumption, with electric water heaters being the biggest contributor to consumption. These results seem realistic, as water heating is typically one of the highest power consumers in a home.
- Rooftop Solar PV: The negative coefficient (-0.3200) suggests that homes with solar panels consume less power, which is consistent with expectations, as solar panels offset grid power consumption.
- WFH (Work from Home) Fractions: The coefficients for 50%–75% and 75%–100% work-from-home fractions (-0.3927 and 0.4001, respectively) indicate that power consumption increases for homes with a higher percentage of individuals working from home.

Other Considerations:

- Nonzero Coefficients for Water Heater Types: The presence of nonzero coefficients for some water heater types is expected, but the two categories "Water Heater_Gas boiler" and "Water Heater_Gas tankless" have coefficients of 0, which might be due to multicollinearity, lack of data, or insufficient variation in these categories.
- Multicollinearity: Multicollinearity is a situation in which two or more independent variables in a regression model are highly correlated, meaning they contain overlapping or redundant information. This can make it difficult to determine the individual effect of each predictor on the dependent variable, leading to unreliable coefficient estimates. There could be some degree of multicollinearity among variables like housing type, year built, and square footage. This could cause some coefficients to become insignificant or difficult to interpret. Extremely small standard errors and extremely large z-values in the GEE results indicate that there is existing multicollinearity in the model. Isolating the individual impact needs more complexity with interactions between the predictor variables.

Overall, the GEE results are reasonable in the context of modeling residential electrical loads. Several predictors (square footage, number of occupants, water heater type, EV ownership, etc.) make intuitive sense. However, given the large number of data points due to the 1-minute-resolution data spanning several months, some coefficients are very small or slightly counterintuitive (e.g., small negative effect for heat pumps or propane heating). Additionally, the skew and kurtosis suggest the residuals may not be perfectly normal, and further model refinement (e.g., log transformations or addressing multicollinearity) might be warranted to improve the model's robustness.

The nan (not a number) values in the GEE regression results indicate that the corresponding coefficients for those variables could not be estimated. This typically happens when the following situations occur:

- Perfect collinearity: Some variables may be perfectly correlated with others or the outcome (e.g., Gas boiler, WFH Fraction), making their effects unidentifiable.
- Sparse categories: Rare categories cannot be reliably estimated.
- Dummy variable trap: Including all category levels can cause redundancy.
- Overfitting: Too many predictors with limited data lead to instability.

4 Discussion

It is important to highlight that the analysis presented in this report has several limitations, such as:

- Small sample size
- Some meters being disconnected by the participants for various reasons
- Data interruptions (some meters stopped transmitting data to the central server due to reasons like RF interference).

Hence, direct comparisons of total energy use were not possible for the entire study period. Future studies can target specific dates and perform comparisons for specific periods of interest with no data gaps across all the study homes, depending on the research needs.

We also did not have a long enough study period to collect enough data from all homes to compare seasonality effects with statistical confidence. Although the full study period was intended from Jan. 1 to Nov. 1, 2024, the ongoing nature of enrollment of the participants into the study meant that there was a limited period of overlap between all study homes where there were continuous data streaming from all connected meters at the same time. The meters of some homes got disconnected and did not get reconnected for various reasons such as travel, remodeling, or forgetting to reconnect. Hence, we had to shorten the data evaluation period to only May 28 to Oct. 13, 2024.

The homes in this study varied widely in square footage, and because the data were not normalized for floor area, square footage may act as a confounding factor in interpreting energy use patterns. Additionally, some households made equipment upgrades or acquired electric vehicles during the study period, which could further obscure trends and introduce variability unrelated to the primary factors under investigation.

Future studies can explore seasonality effects and dependencies on weather variables to fully leverage the high-temporal-resolution capabilities of the Copper Ingot device, which were not fully examined in this report. High-temporal-resolution data such as those measured by the Copper meter can be a great tool in communicating real-time situations to home occupants regarding power consumption, equipment malfunctions, or even risk of electrical short-circuiting. Future studies can explore not just the power consumption aspect from an energy efficiency standpoint but also prompt fault detection and equipment longevity aspects such as automated equipment schedule optimization for short cycling prevention, where applicable. These insights may eventually guide residential building retrofits to (1) perform informed equipment upgrades, and (2) provide greater safety and lower the cost of equipment replacement over the lifetime of the home.

Many lessons were also learned via the implementation of this study, such as the importance of constantly monitoring the incoming data and notifying the participant to reconnect the meter if a disconnection was noticed or suspected. It is also important to fully collect the survey data and fill any data gaps with follow-up outreach when needed.

5 Conclusions

Through the analysis of results from the data collected from 17 homes, spanning a diverse set of heating fuels, appliances, occupancies, and vintage periods, we investigated the basic characteristics of electric load profiles and load distributions. This deployment effort successfully generated a pilot dataset that can potentially provide insights into future research related to whole-home electrical load profiles in residential buildings. Besides lessons learned for the deployment of wireless technology like the Copper Ingot 2 device, this work also identified some interesting characteristics of electric power consumption patterns in residential buildings.

We found that homes with rooftop solar PV systems have drastically different load profiles compared to homes without rooftop PV systems. Instead of the morning and evening peaks expected in a load profile, homes with rooftop solar PV tend to have a dip toward the middle of the day and have little or no significant peak during the morning and evening hours. We noted that most of the time, we can expect homes to experience roughly 0.5 kW of average load and roughly 12 kW of peak load. Single-family detached homes have a slightly greater (roughly 200 W more) average load, but a much wider range of loads compared to a multifamily apartment building unit.

There is also an increasing trend in load ranges with increasing square footage. Homes with less than 1,000 ft^2 area can be expected to have significantly less load than larger homes. Homes with EVs have roughly the same median load, but a much wider range of loads. Rooftop solar PV systems reduce the median load by up to 0.5 kW.

In terms of space heating type, the difference in overall load is very small, but during a heat wave, homes with heat pumps can experience lower median and peak loads compared to homes without heat pumps. Homes with electric resistance water heaters have a lower median load than those with electric heat pump water heater systems but almost double the range. Homes with electric induction stoves have higher load than those with electric resistance stoves, but homes with electric resistance stoves have a much wider range of load.

In terms of the number of occupants, the median load is only slightly different between homes with two, three, or four occupants. Homes with maximum work-from-home fraction also have the highest variability in the load. Finally, newer homes do not necessarily have lower load but do have a much wider range of loads.

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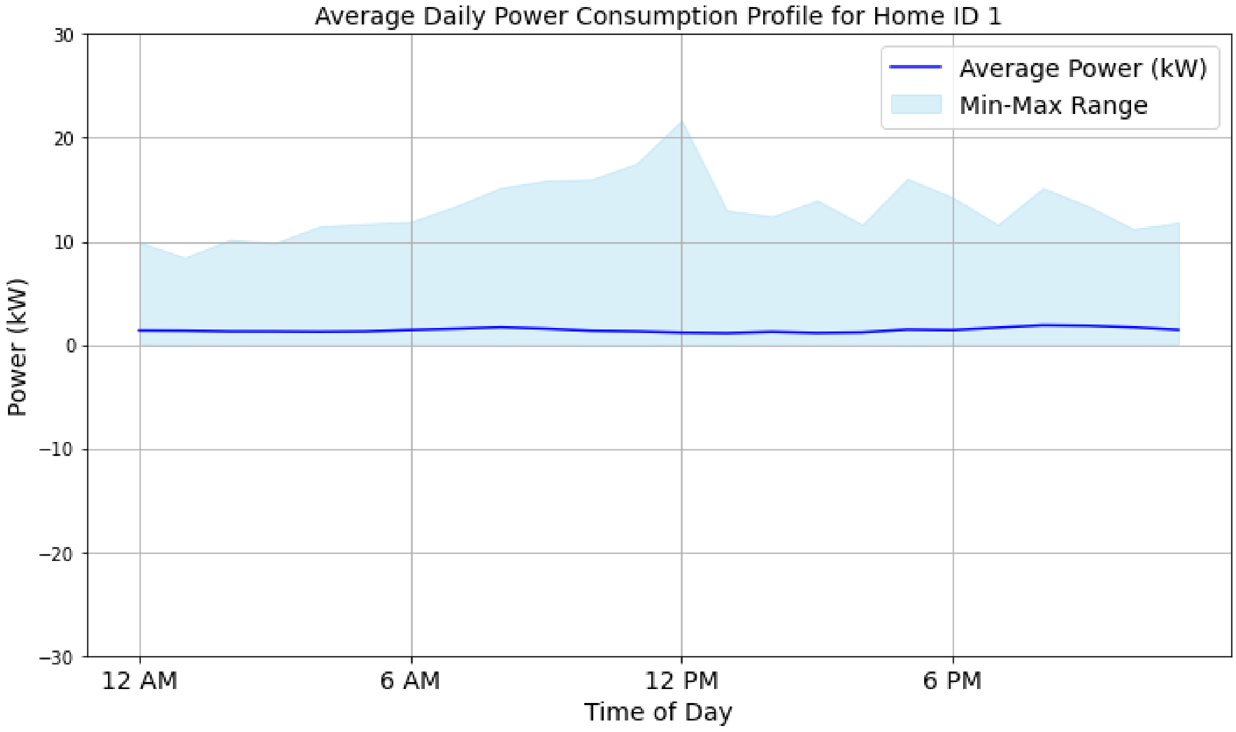
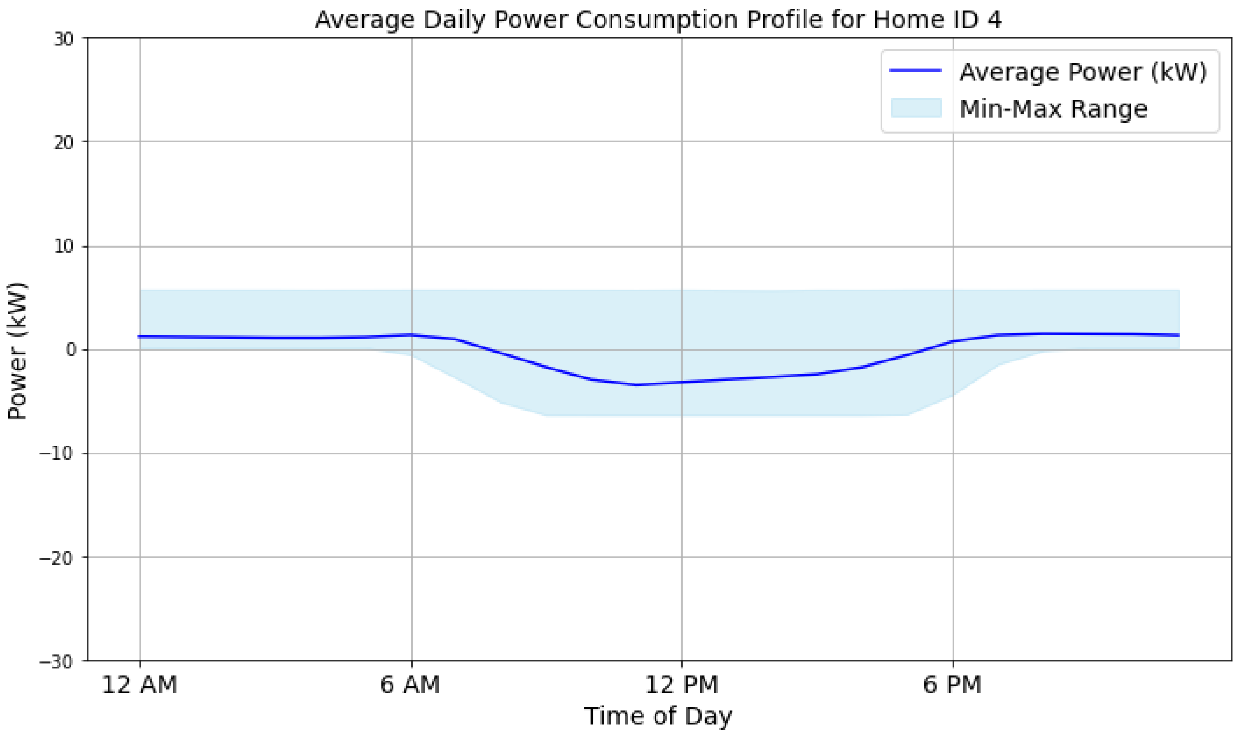
Appendix A: Individual 24-Hour Load Profiles of All Study Homes

Note: The solid line represents the average power consumption (averaged over data collection period specific to the Home ID), and the shaded region shows the range of data.

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Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
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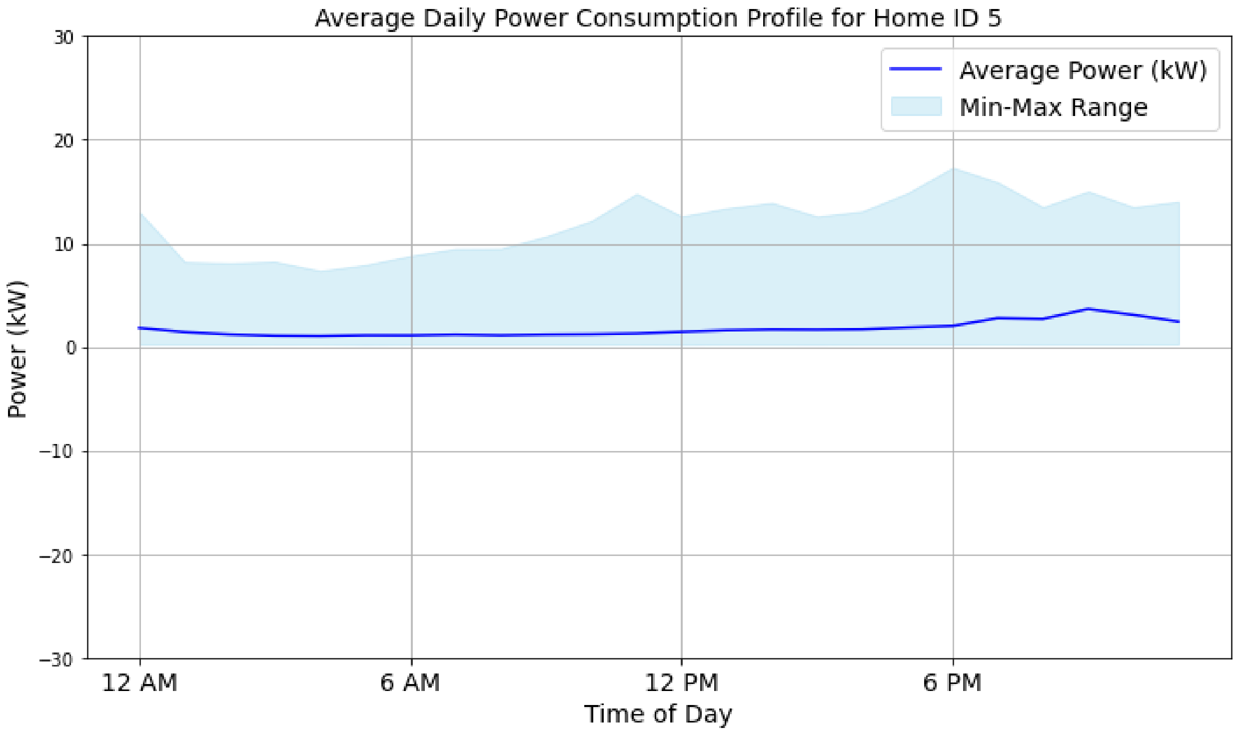
6 AM
12 PM
6 PM
Time of Day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Average Power (kW)
Min-Max Range
Power (kW)
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10
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−10
−20
−30
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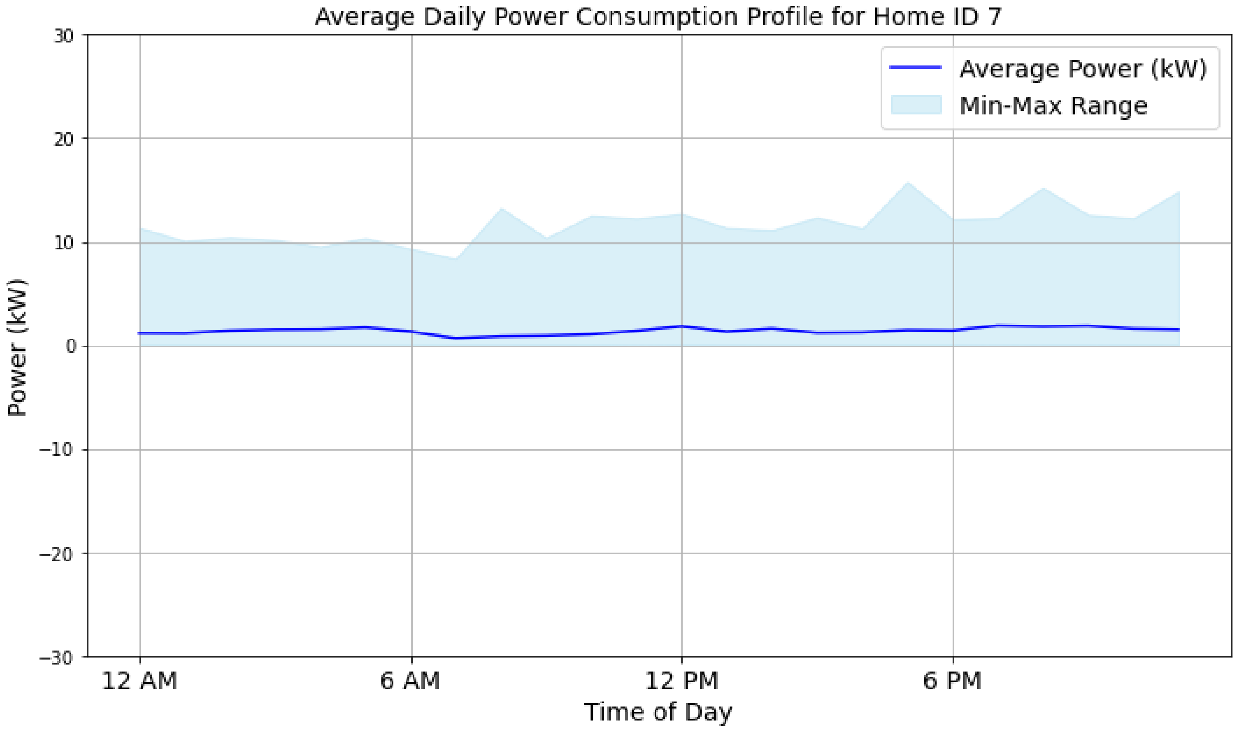
6 AM
12 PM
6 PM
Time of Day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Average Power (kW)
Min-Max Range
Power (kW)
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20
10
0
−10
−20
−30
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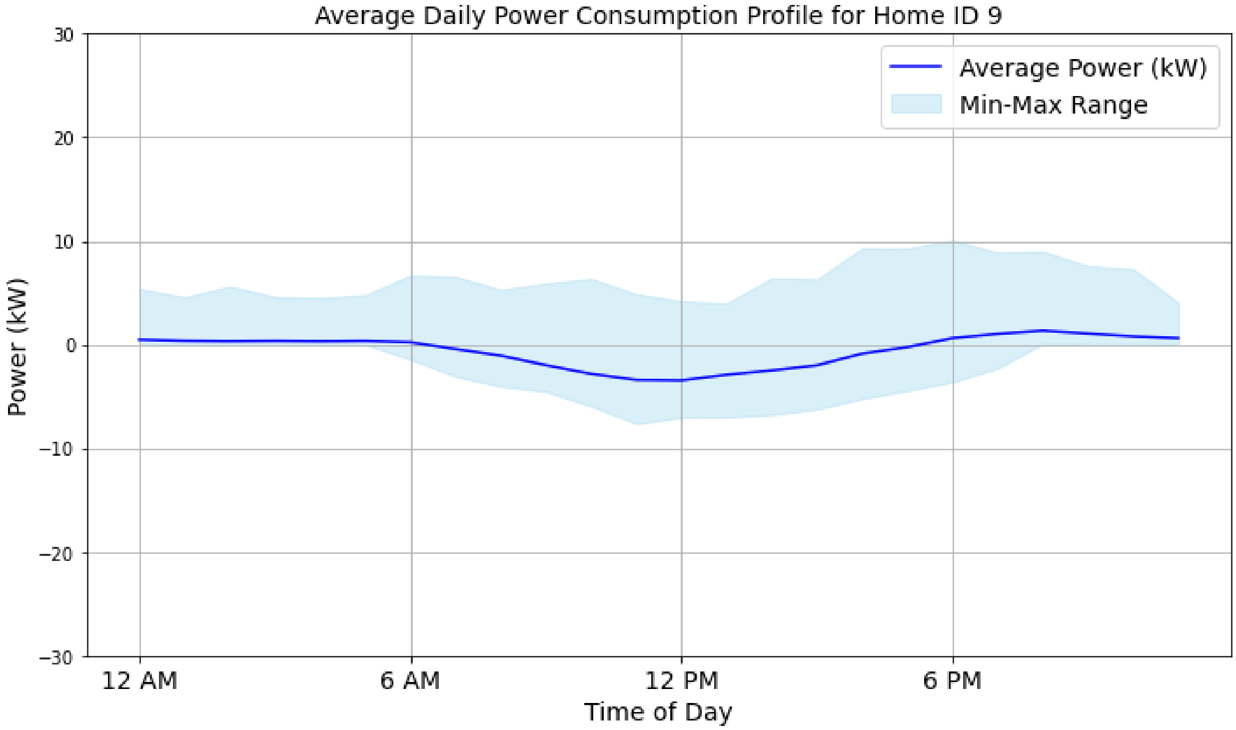
6 AM
12 PM
6 PM
Time of Day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Average Power (kW)
Min-Max Range
Power (kW)
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−10
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−30
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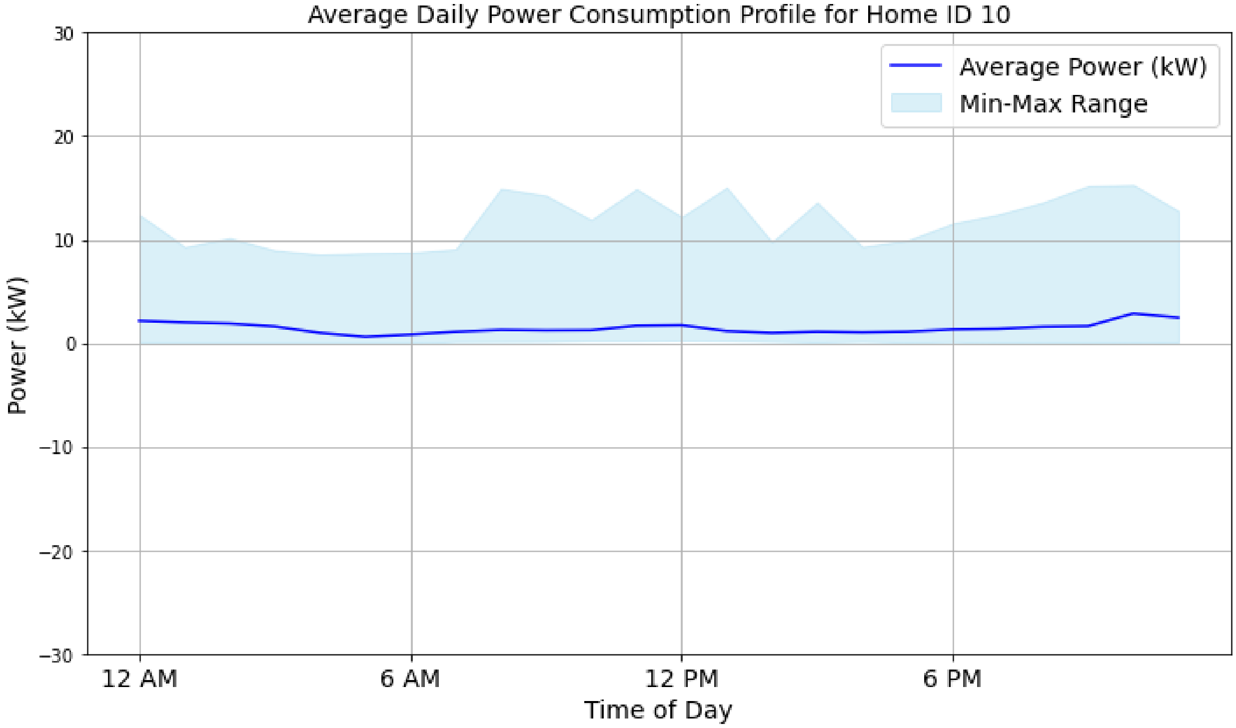
6 AM
12 PM
6 PM
Time of Day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Average Power (kW)
Min-Max Range
Power (kW)
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20
10
0
−10
−20
−30
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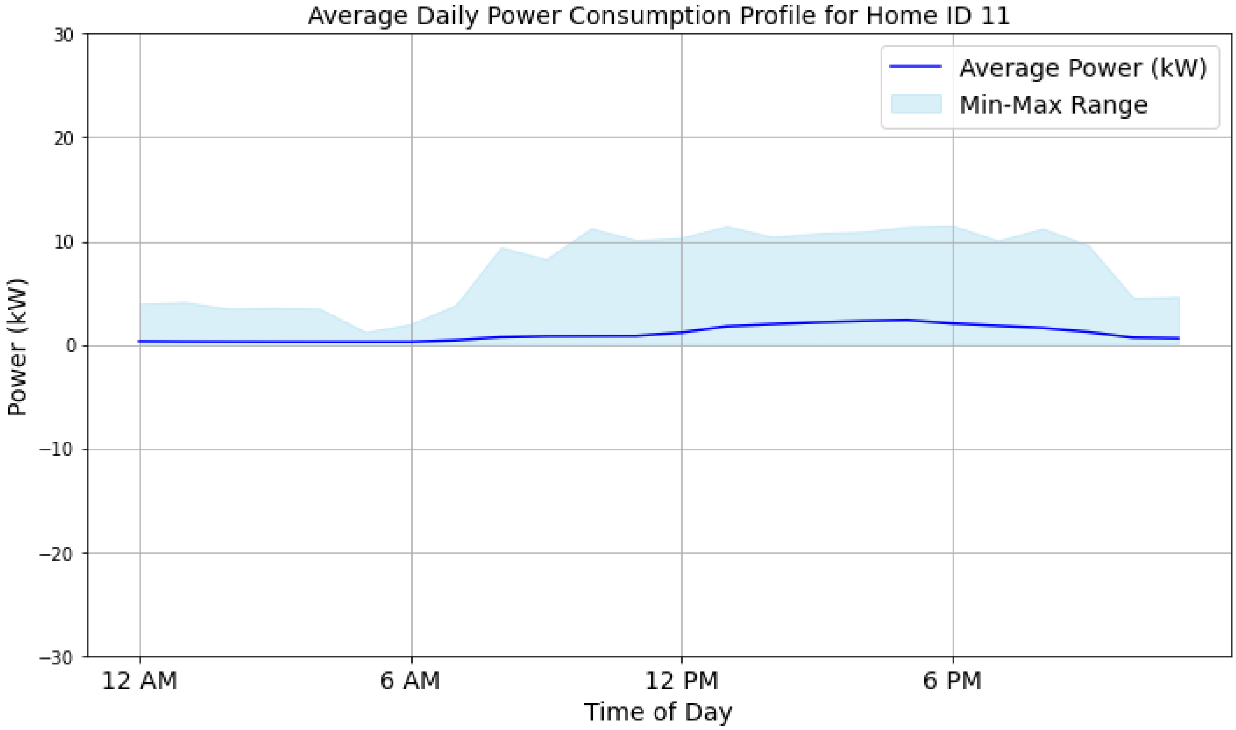
6 AM
12 PM
6 PM
Time of Day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Average Power (kW)
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Power (kW)
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6 AM
12 PM
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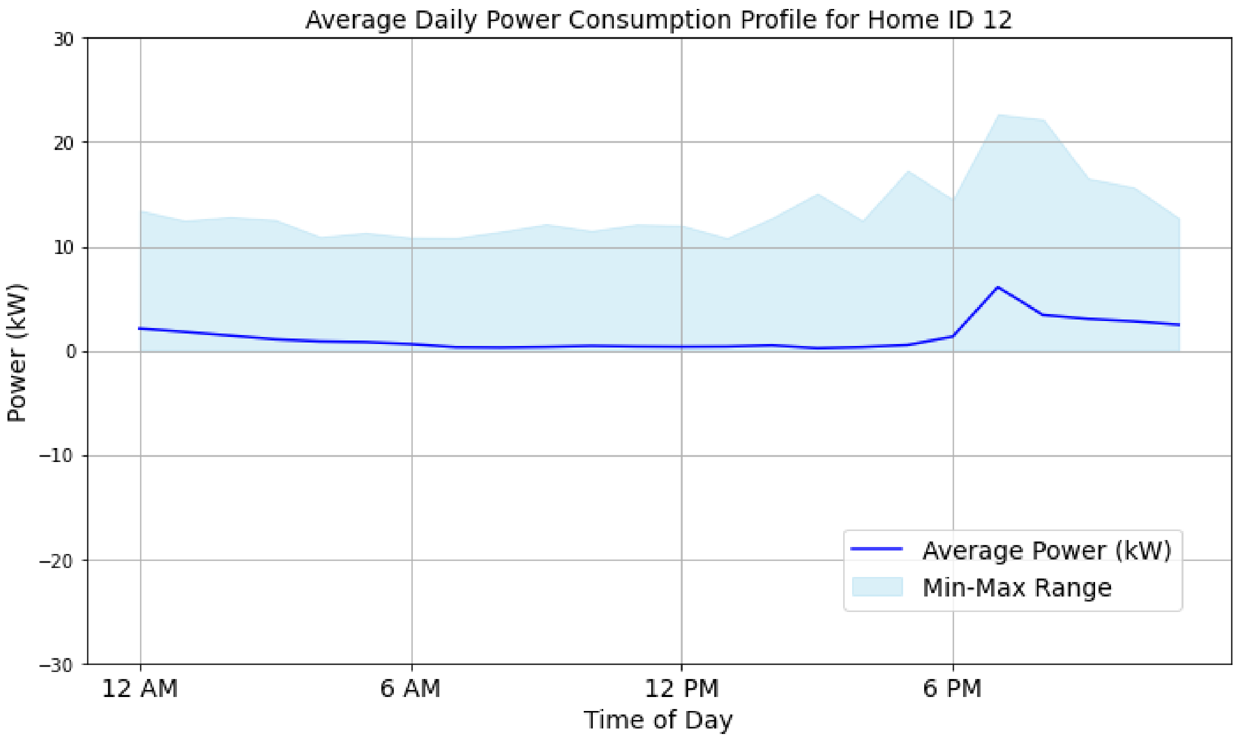
Time of Day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−10
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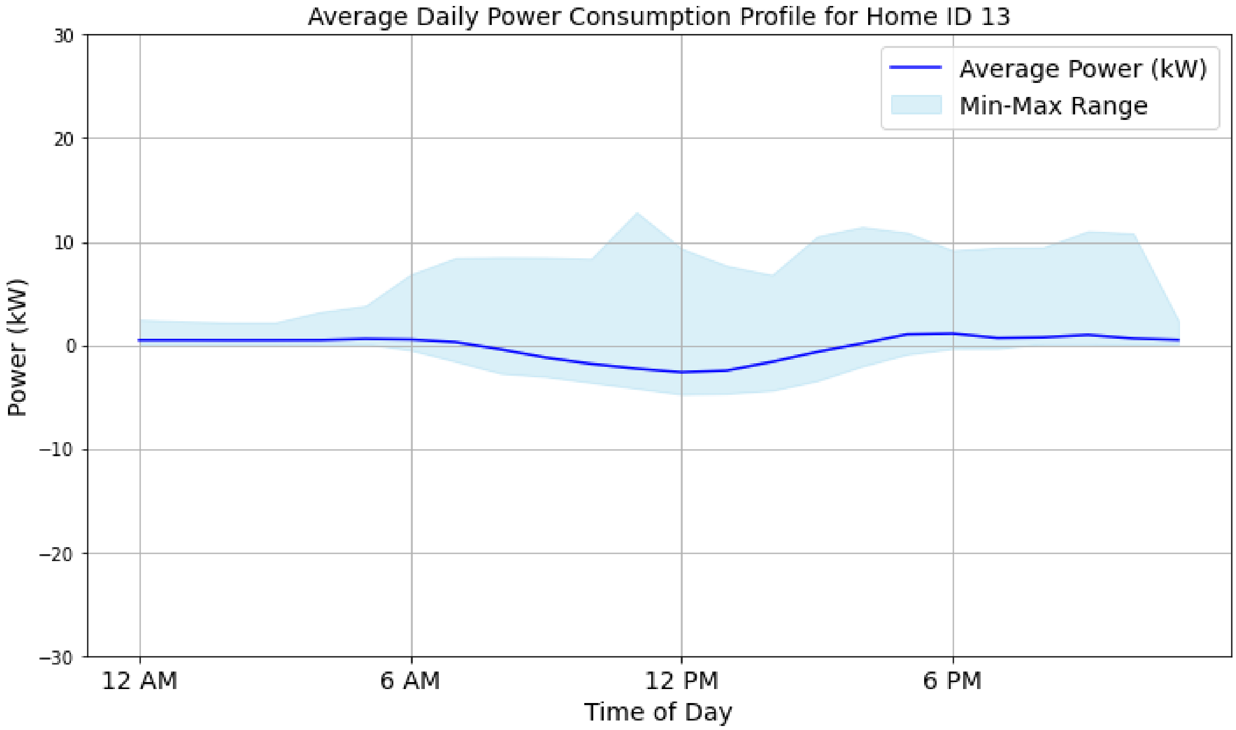
12 AM
6 AM
12 PM
6 PM
Time of Day
Average Power (kW)
Min-Max Range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Power (kW)
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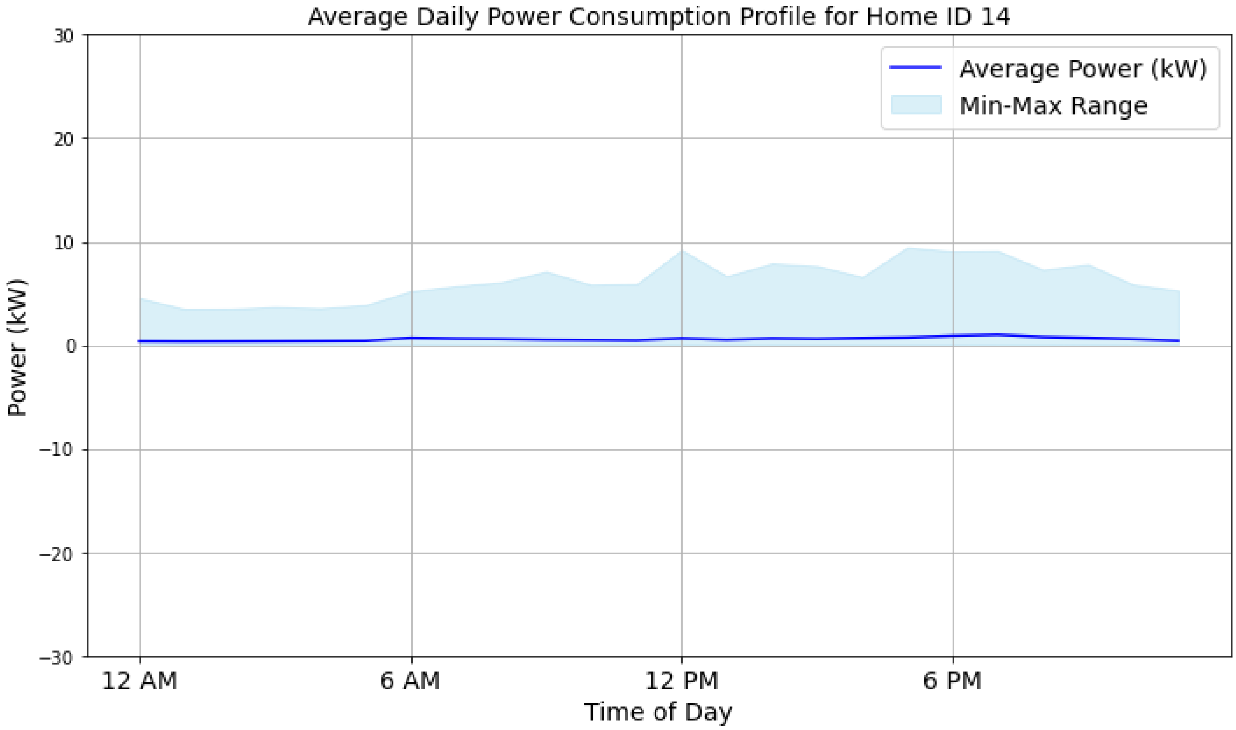
6 AM
12 PM
6 PM
Time of Day
Average Power (kW)
Min-Max Range



Average Daily Power Consumption Profile for Home ID 14
Average Power (kW)
Min-Max Range
Power (kW)
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10
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−10
−20
−30
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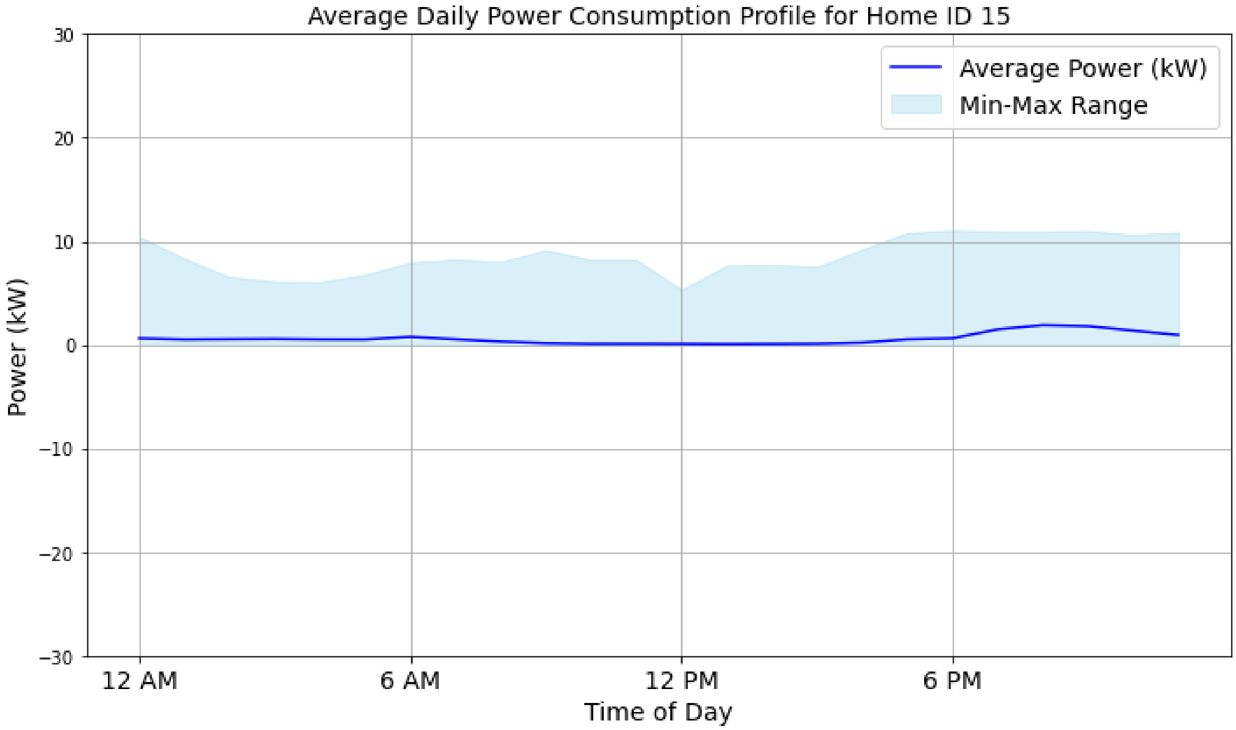
6 AM
12 PM
6 PM
Time of Day



Average Daily Power Consumption Profile for Home ID 15
Average Power (kW)
Min-Max Range
Power (kW)
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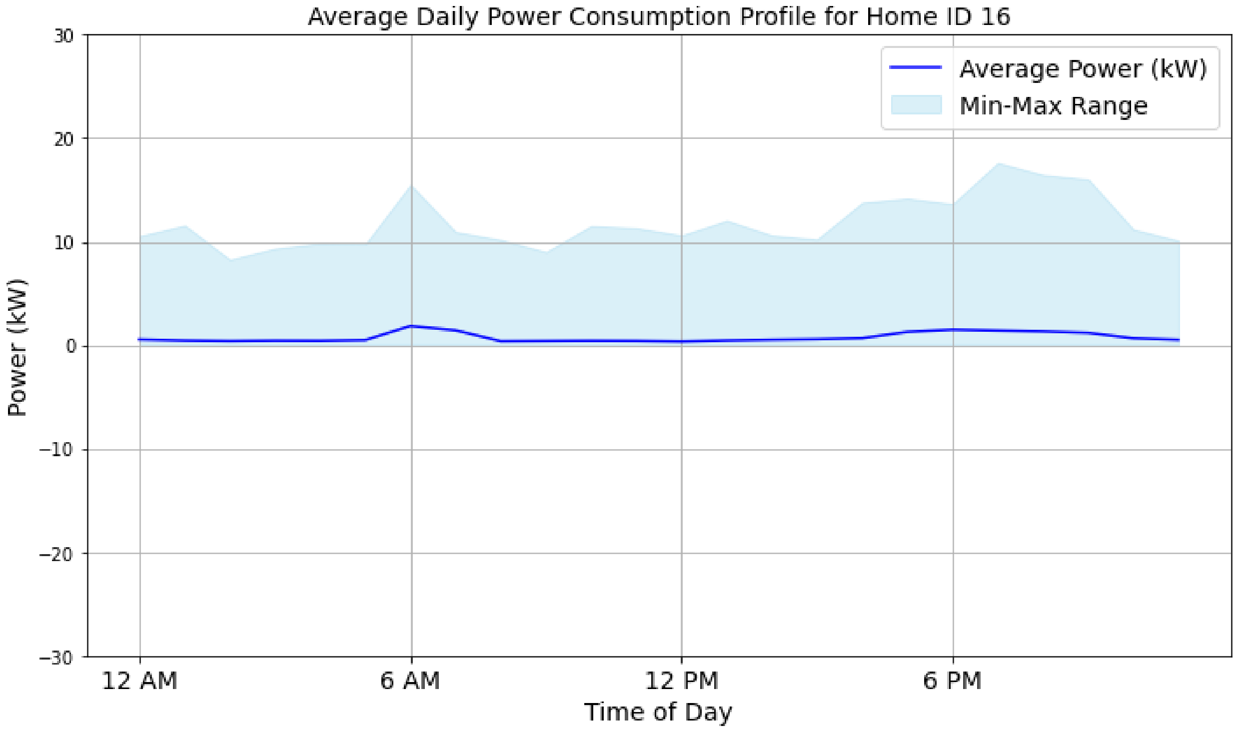
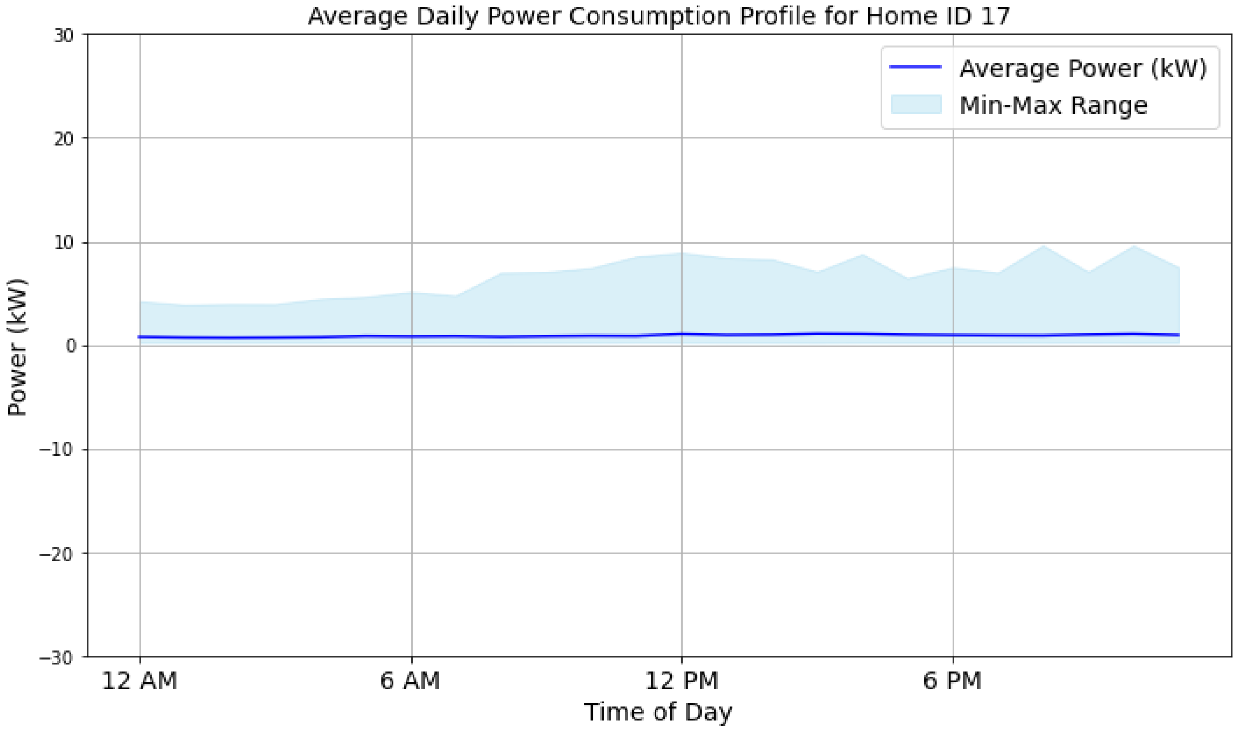
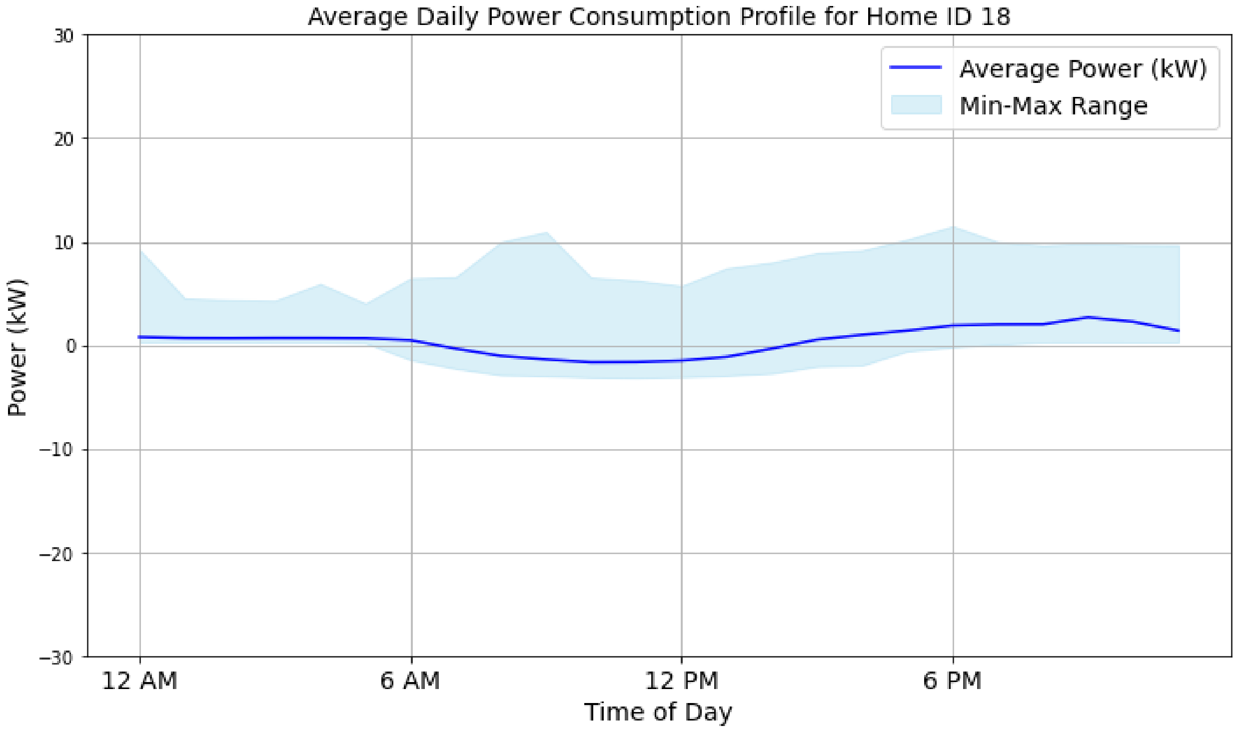
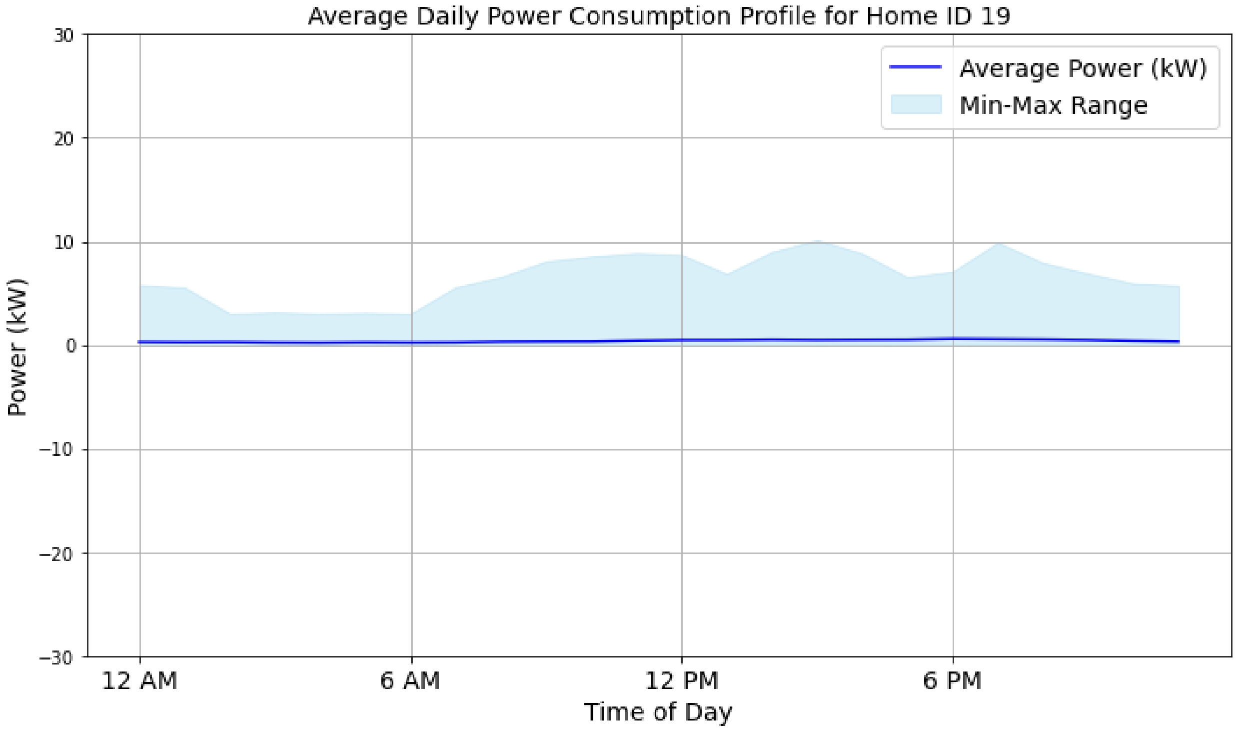
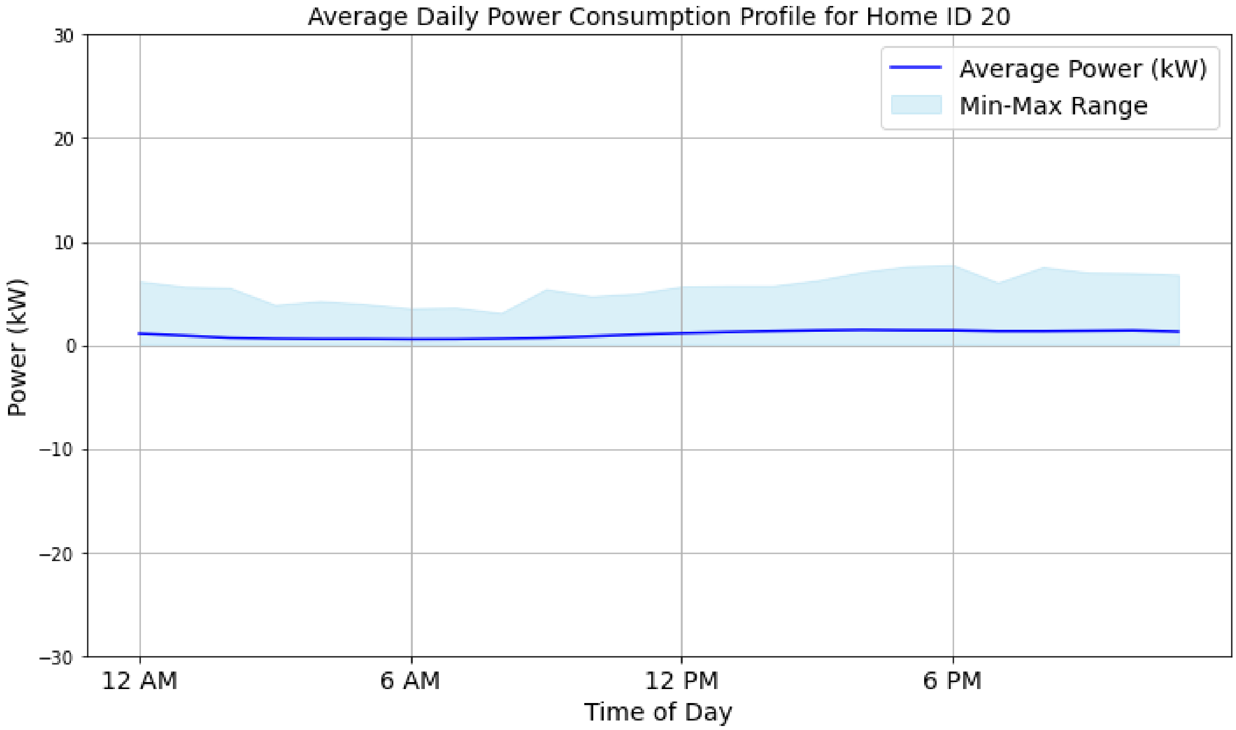
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day

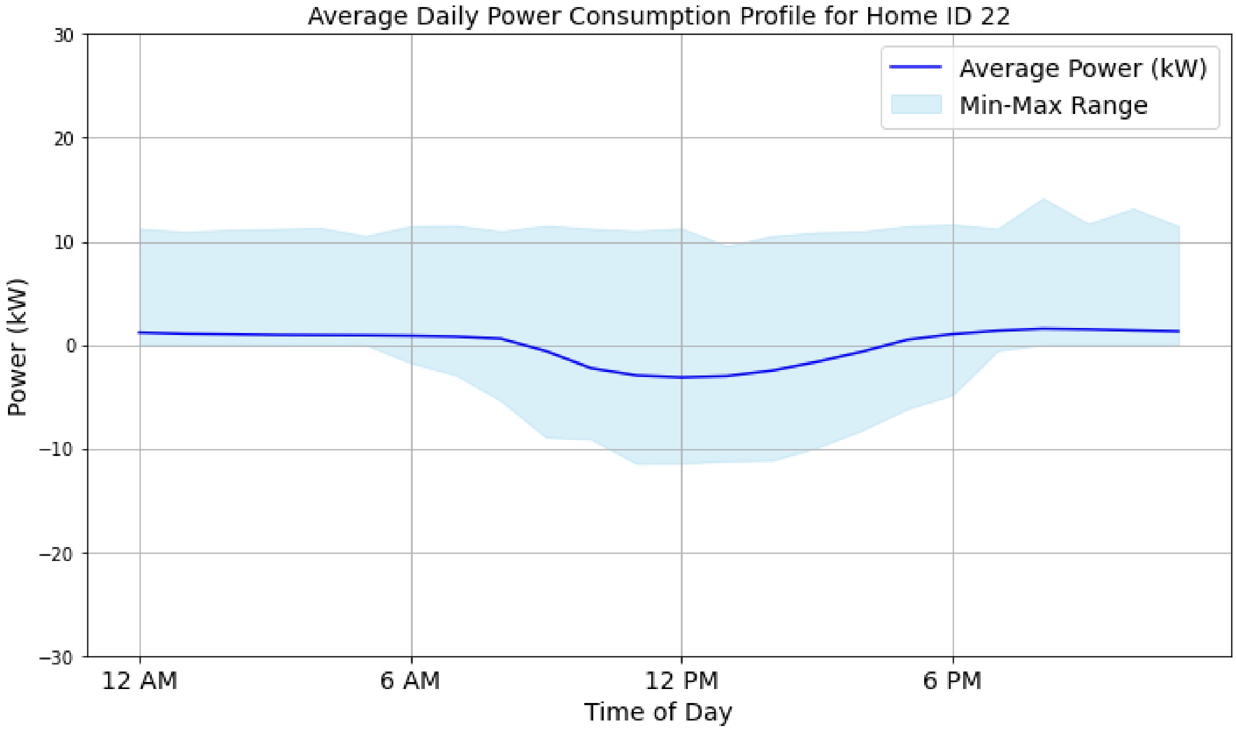

Average Daily Power Consumption Profile for Home ID 16
Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day

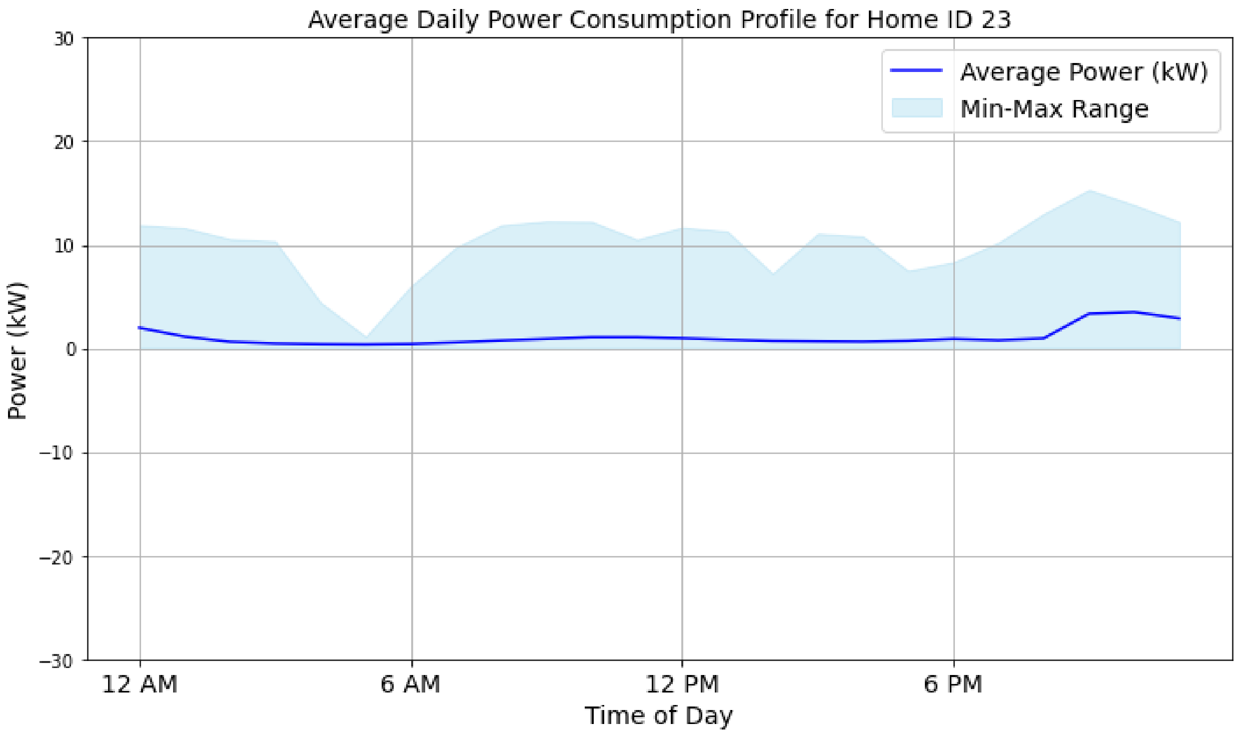

Average Daily Power Consumption Profile for Home ID 17
Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day


Average Daily Power Consumption Profile for Home ID 18
Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day


Average Daily Power Consumption Profile for Home ID 19
Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day

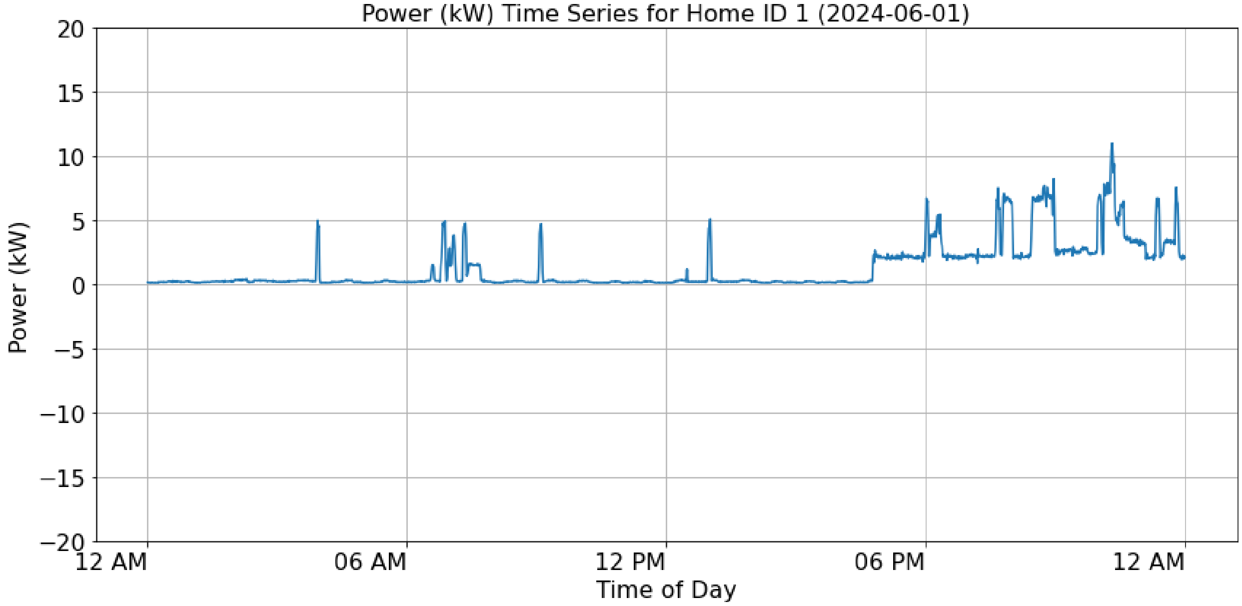

Average Daily Power Consumption Profile for Home ID 20
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day
Average Power (kW)
Min-Max Range

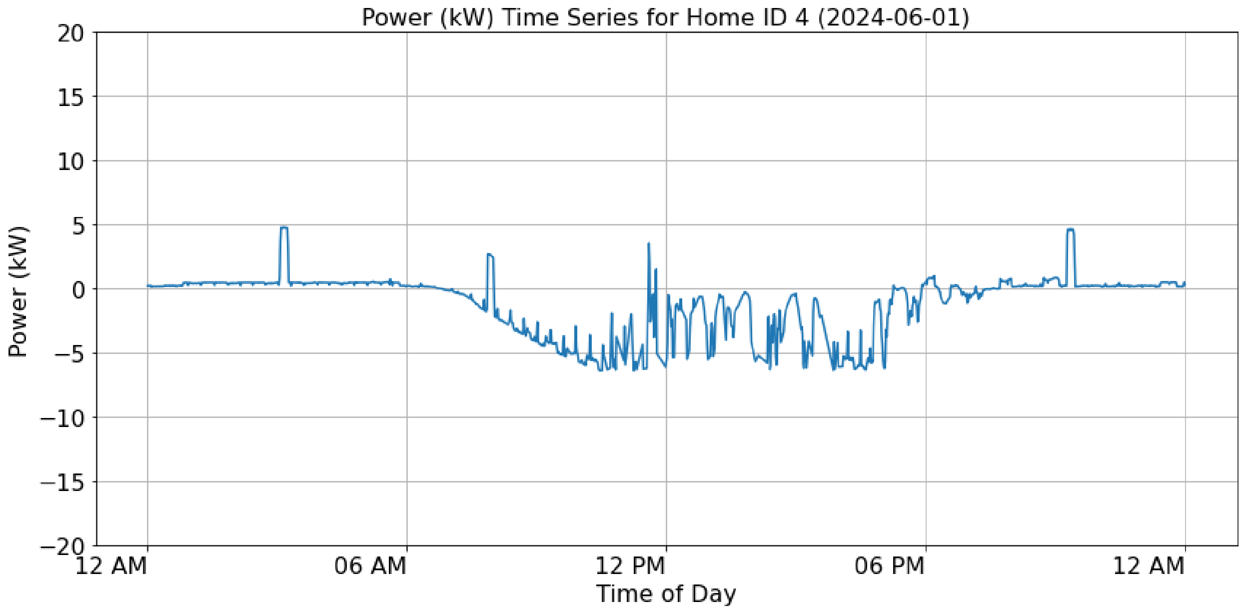

Average Daily Power Consumption Profile for Home ID 22
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day
Average Power (kW)
Min-Max Range

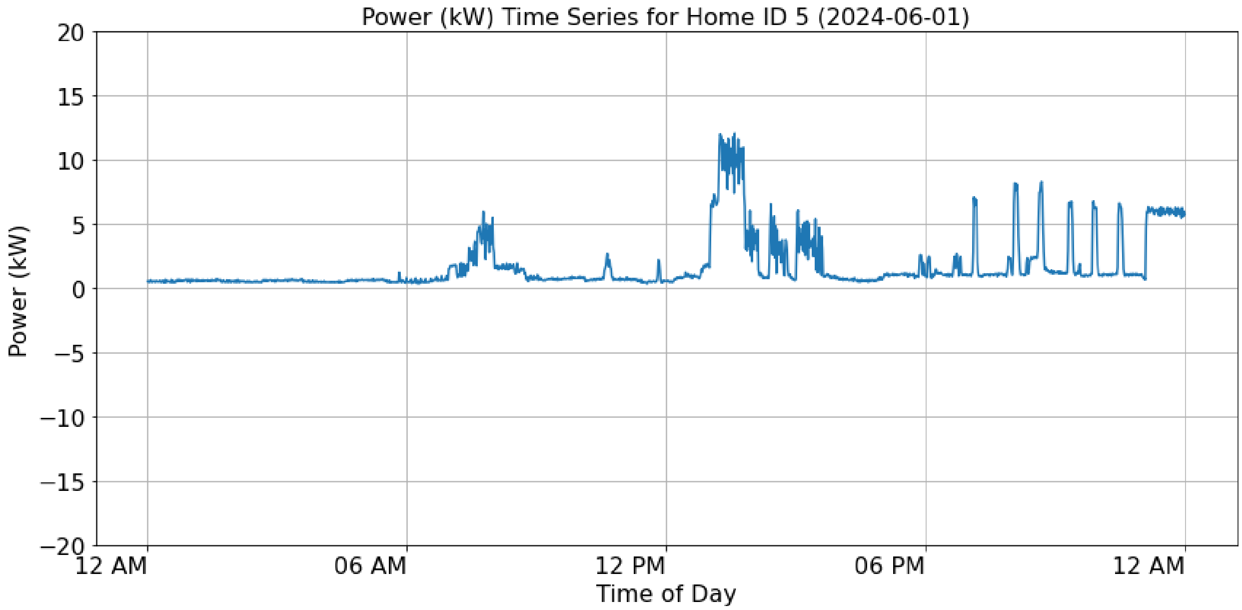

Average Daily Power Consumption Profile for Home ID 23
Average Power (kW)
Min-Max Range
Power (kW)
30
20
10
0
−10
−20
−30
12 AM
6 AM
12 PM
6 PM
Time of Day

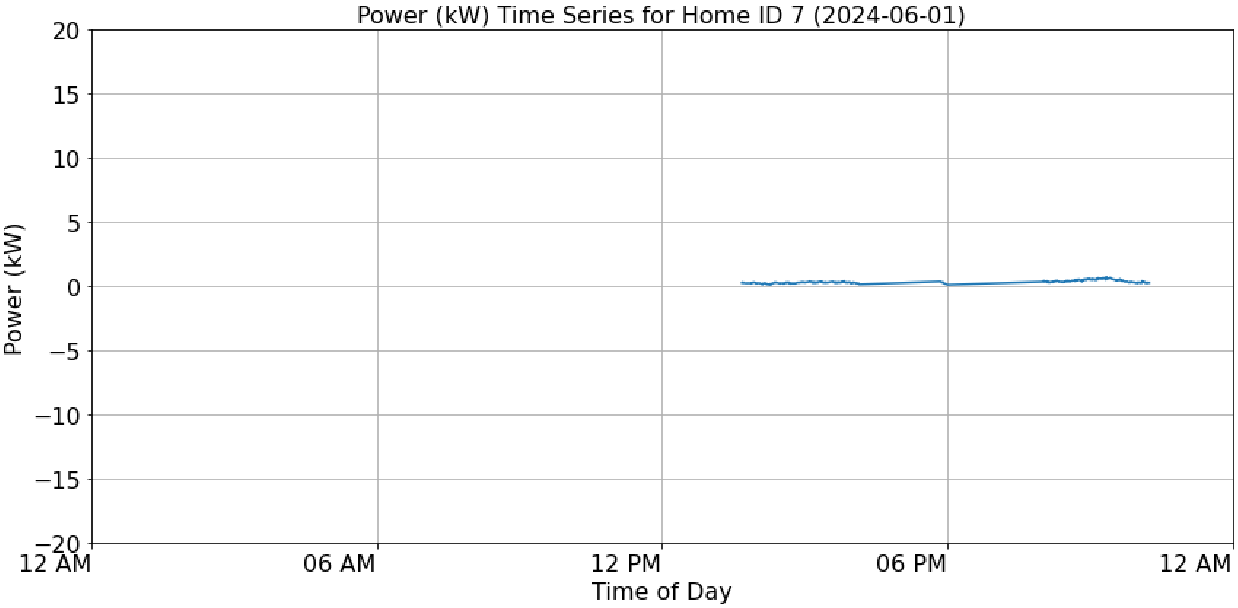
Appendix B: Raw Time Series Plot of Electrical Loads From All Study Homes for a Single 24-Hour Period (June 1, 2024)

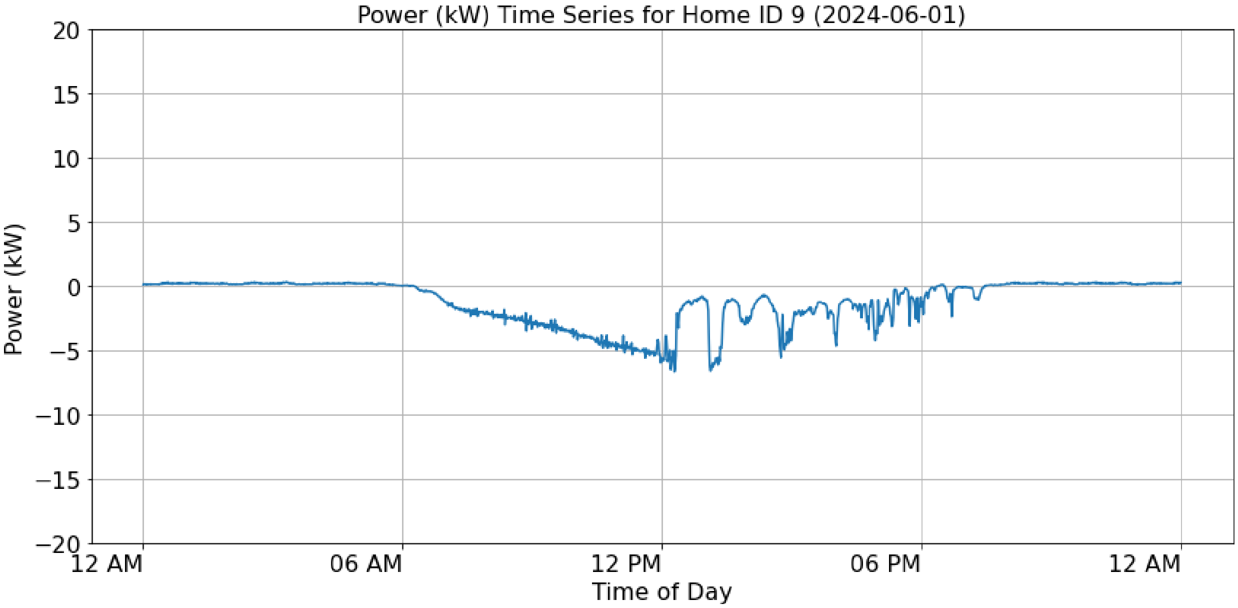
The figures shown in this appendix are for a single clear summer day (June 1, 2024). These plots help to show how electrical loads fluctuate for each of the study homes. Corresponding home characteristics are provided in Table 3 and the weather data associated with this day are shown in Figure 4. The dataset presented here is for all the homes that initially participated and generated electrical power data and answered all the survey questions. Homes showing negative power consumption have rooftop solar PV installed.

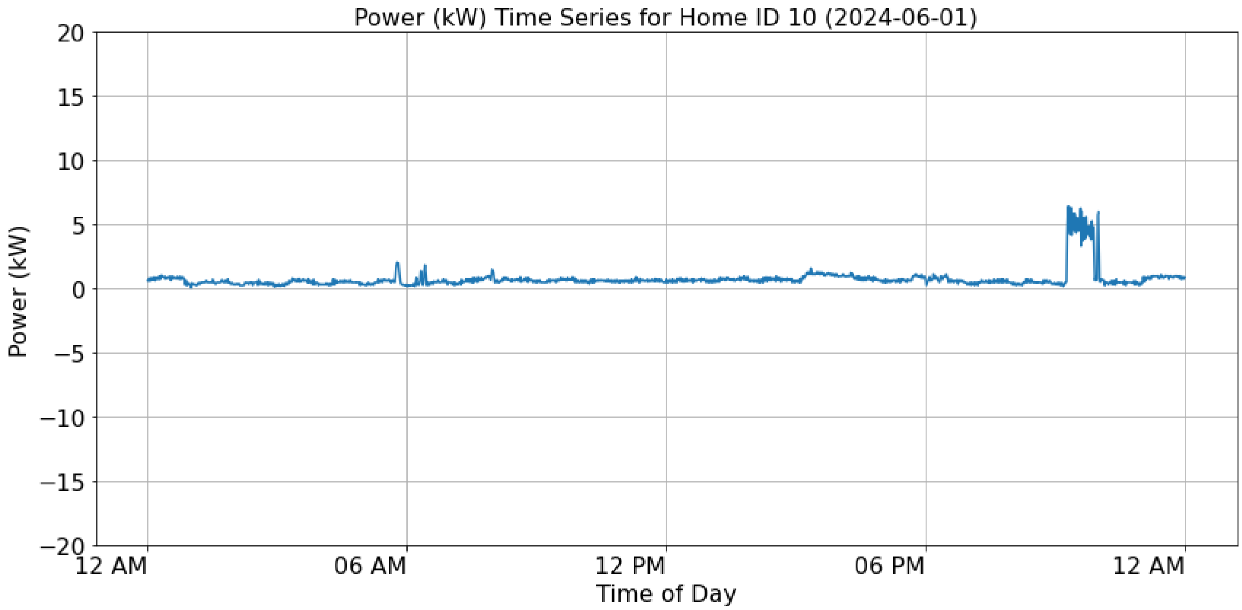


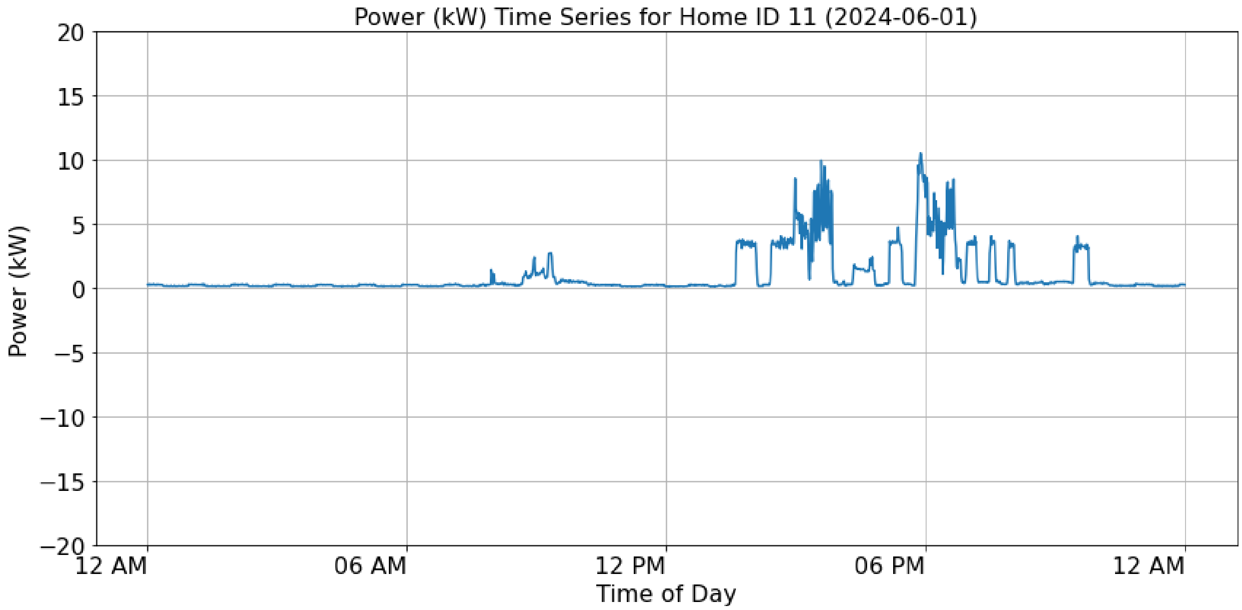

Power (kW) Time Series for Home ID 4 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

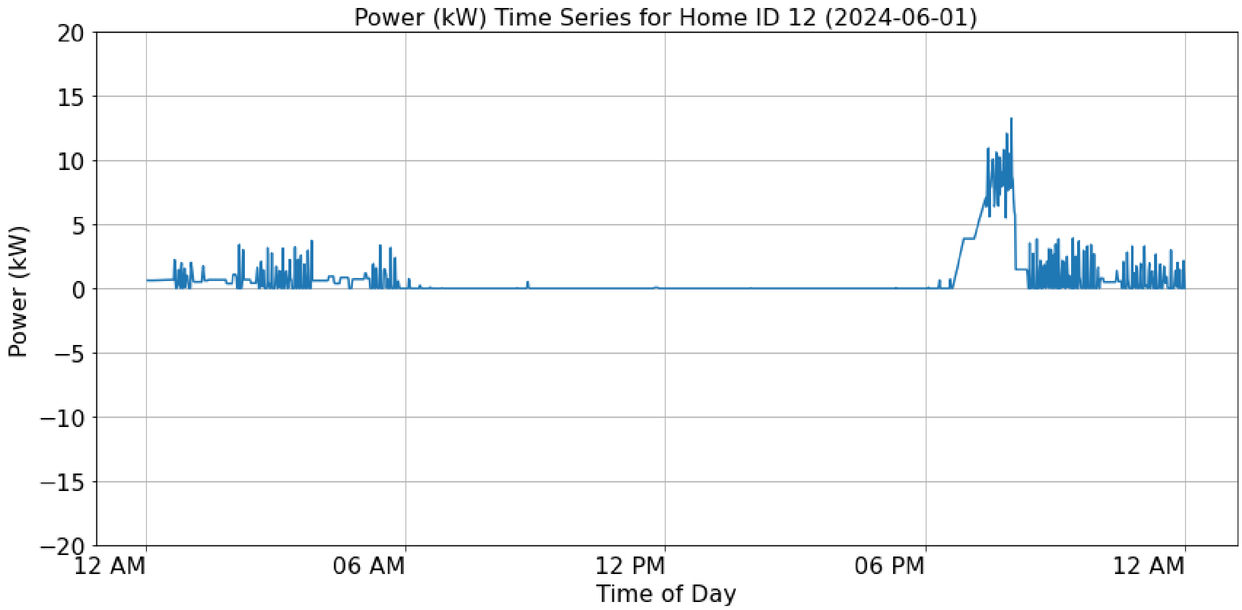

Power (kW) Time Series for Home ID 5 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

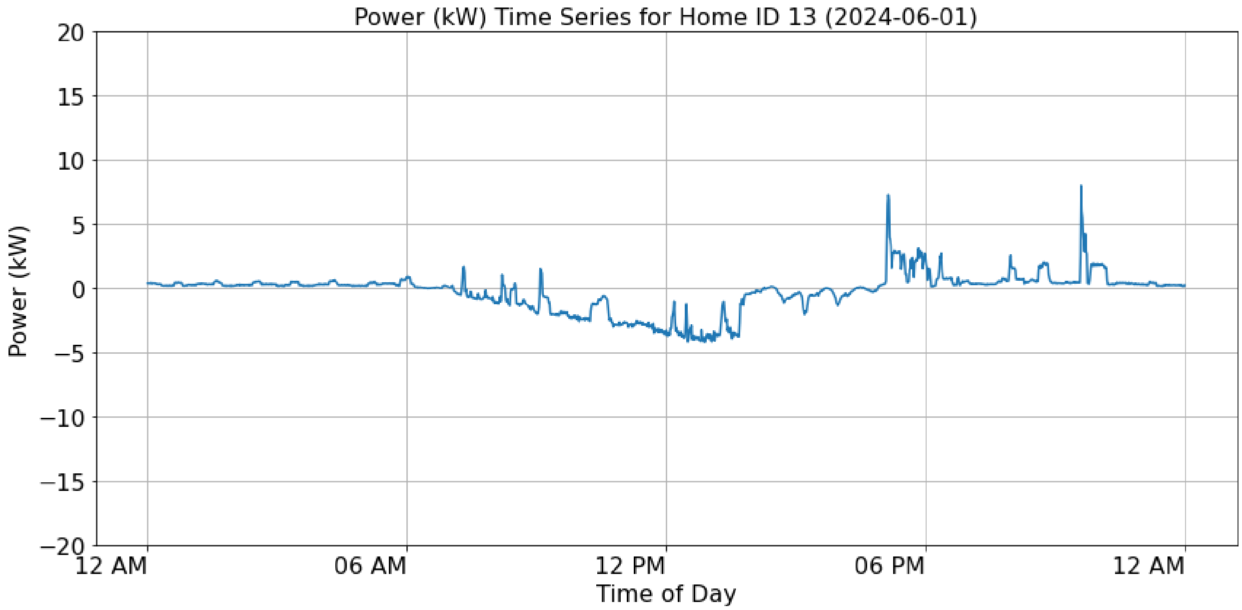

Power (kW) Time Series for Home ID 7 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

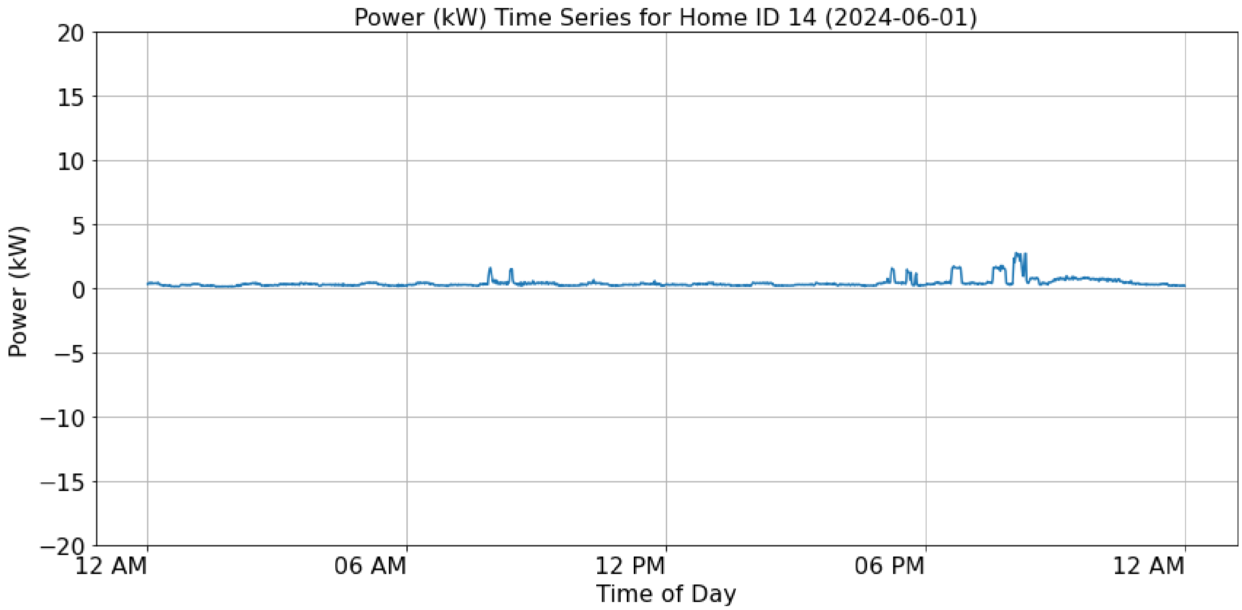

Power (kW) Time Series for Home ID 9 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

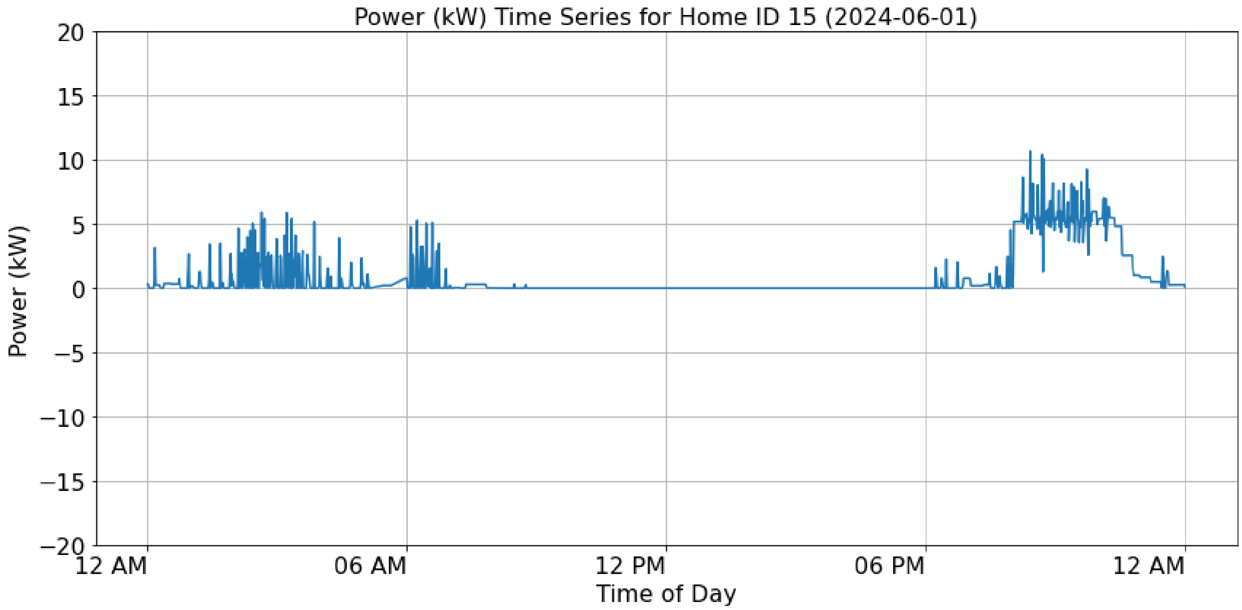

Power (kW) Time Series for Home ID 10 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

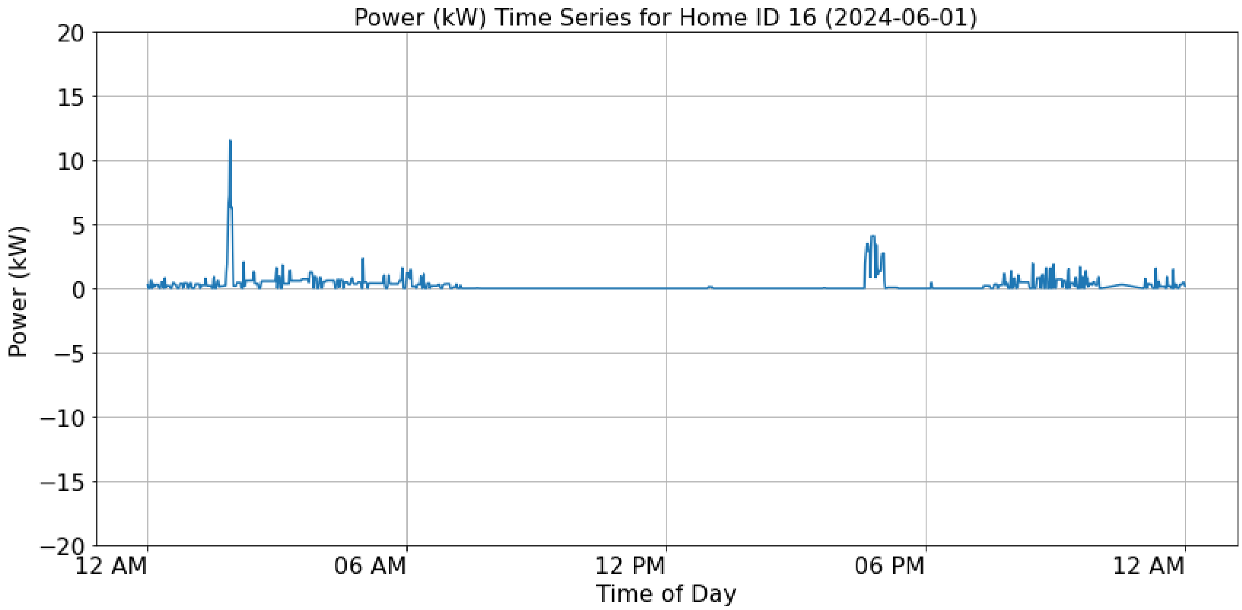

Power (kW) Time Series for Home ID 11 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

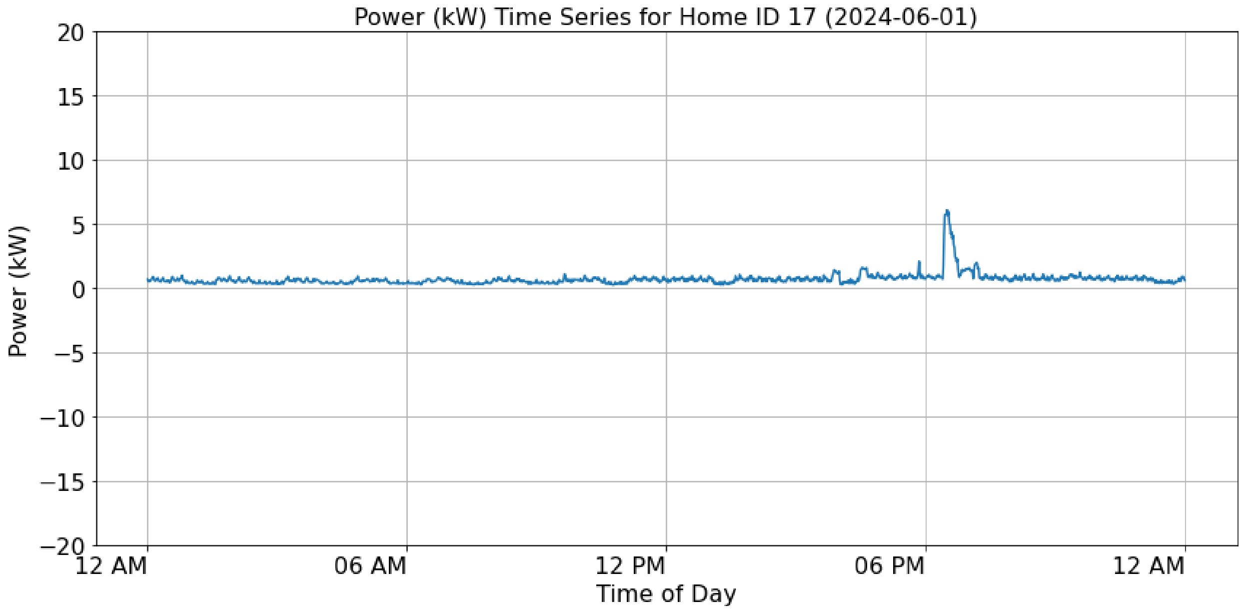

Power (kW) Time Series for Home ID 12 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

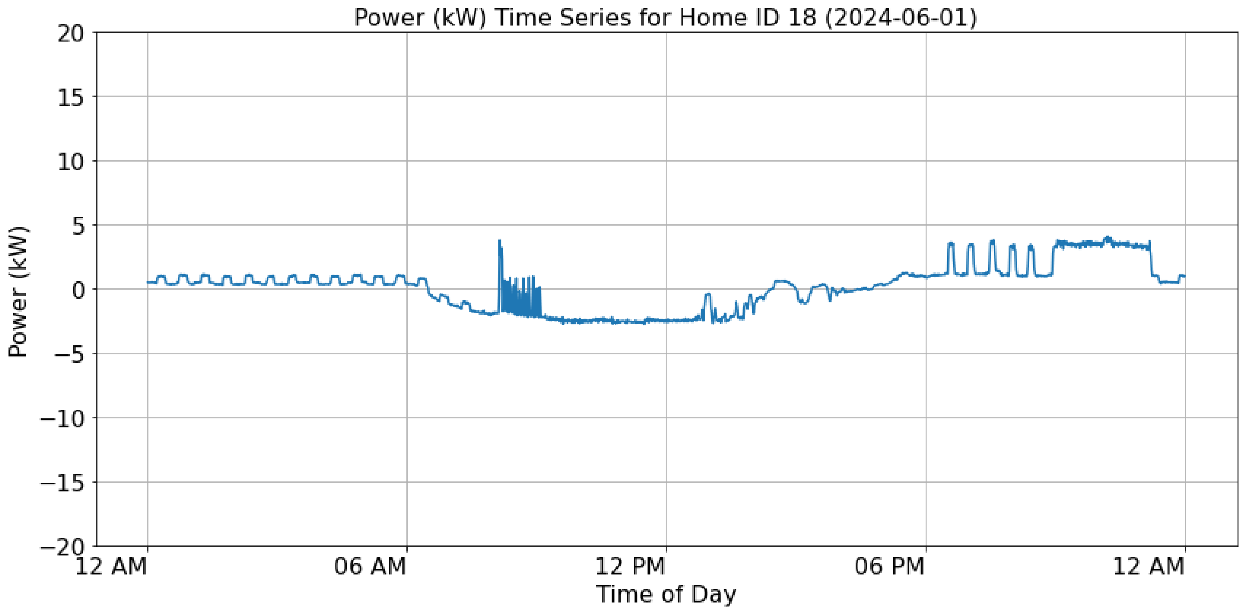

Power (kW) Time Series for Home ID 13 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

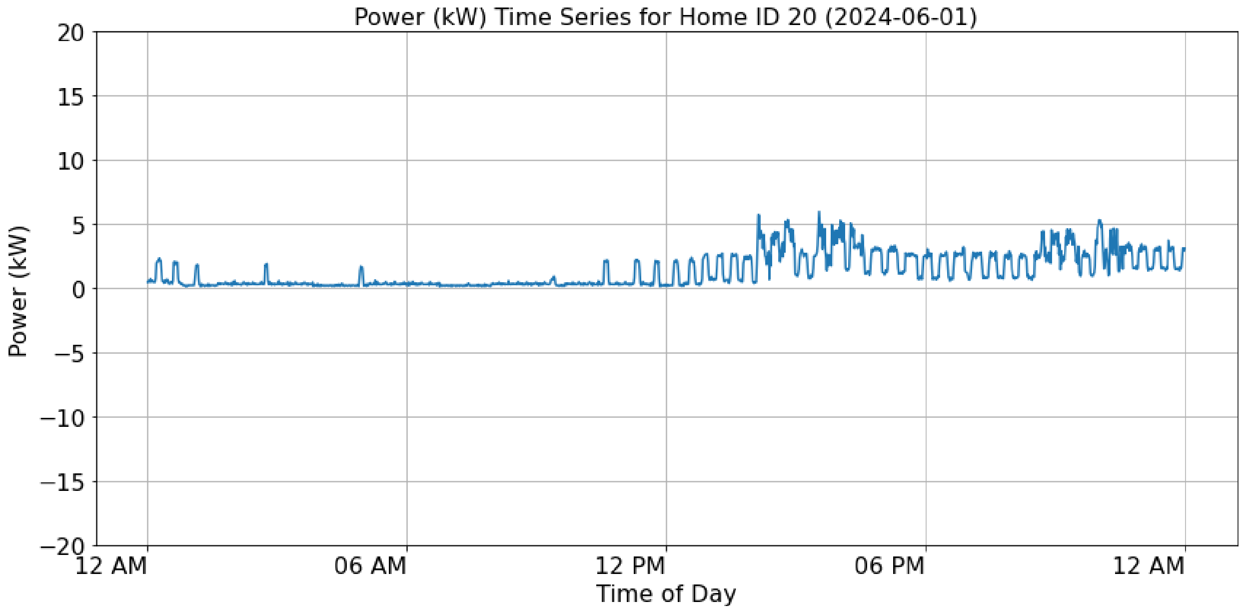

Power (kW) Time Series for Home ID 14 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

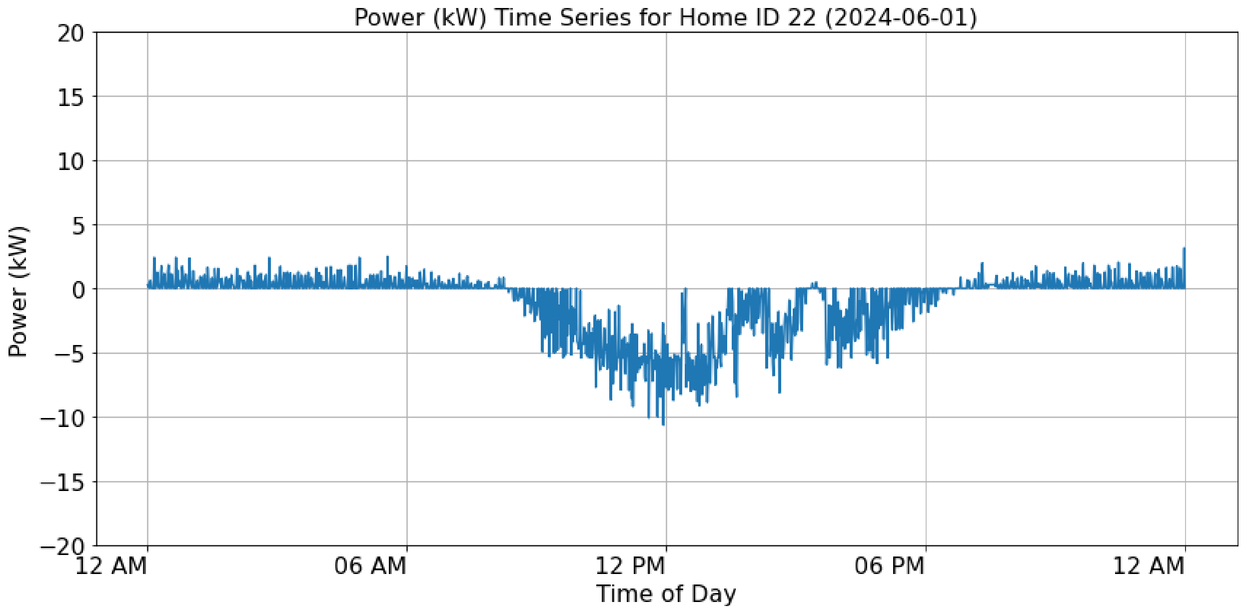

Power (kW) Time Series for Home ID 15 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day

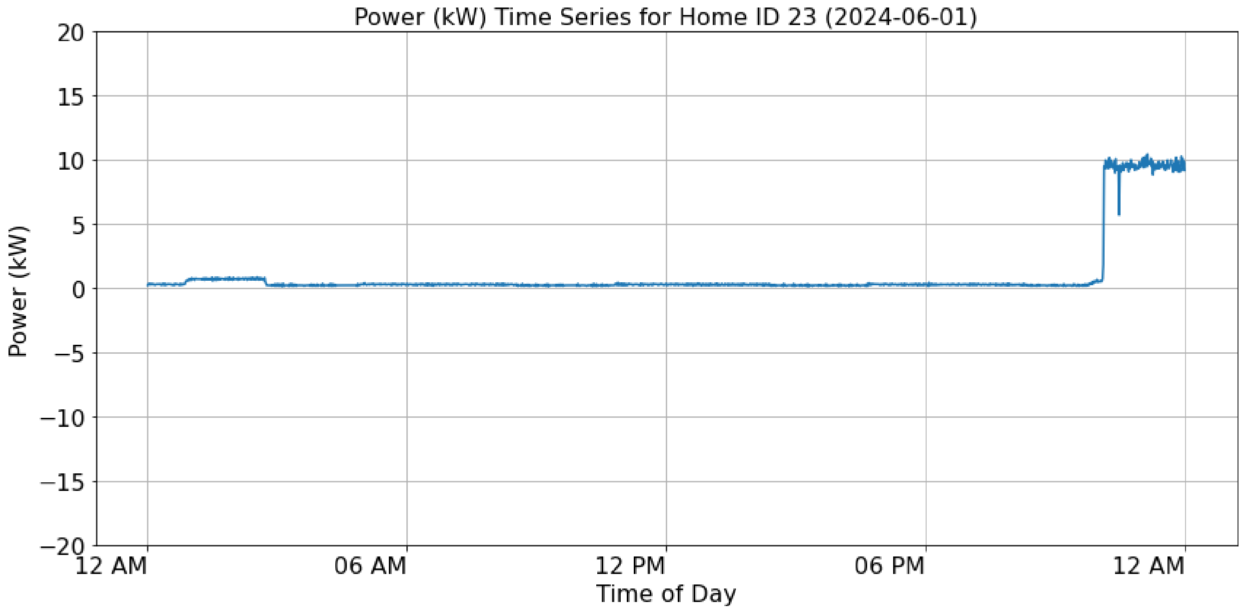

Power (kW) Time Series for Home ID 16 (2024-06-01)
20
15
10
5
0
−5
−10
−15
−20
Power (kW)
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day


Power (kW) Time Series for Home ID 17 (2024-06-01)
20
15
10
5
0
−5
−10
−15
−20
Power (kW)
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day


Power (kW) Time Series for Home ID 18 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day


Power (kW) Time Series for Home ID 20 (2024-06-01)
Power (kW)
20
15
10
5
0
−5
−10
−15
−20
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day


Power (kW) Time Series for Home ID 22 (2024-06-01)
20
15
10
5
0
−5
−10
−15
−20
Power (kW)
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day


Power (kW) Time Series for Home ID 23 (2024-06-01)
20
15
10
5
0
−5
−10
−15
−20
Power (kW)
12 AM
06 AM
12 PM
06 PM
12 AM
Time of Day