Disaggregated Electricity Consumption Patterns in Households Using Appliance Load Profiles

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By

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CERTIFICATE

It is certified that the work contained in this thesis, titled "Disaggregated Electricity Consumption Patterns in Households Using Appliance Load Profiles" by Shishir Maurya (2021713001), has been carried out under my supervision and is not submitted elsewhere for a degree.

______16 May 2024___
Date

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Advisor: Prof. Vishal Garg

For MOTHER
EARTH

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ABSTRACT

This thesis focuses on the residential electricity demand in India, where the residential sector makes up 27% of the overall electricity usage. The study aims to provide a detailed understanding of the consumption patterns of household appliances. To achieve this, the electricity consumption of individual household appliances in 21 homes across different locations in Hyderabad was monitored. Device-level monitoring equipment, such as smart meters and sockets, was used to collect data for 61 days in summer (1 May 2023 to 30 June 2023) and 30 days in winter (1 Nov 2023 to 30 Nov 2023). The dwellers were chosen on a voluntary basis and had the option to opt out of the study at any point. The study focuses on two aspects of residential electricity consumption patterns: household and appliance levels. For the household-level study, five homes with a greater number of monitored appliances were selected and analyzed for load profiles of regularly used major appliances and daily electricity breakdown during the peak summer (15 May 2023 to 14 June 2023). Moreover, consumption patterns of ACs and geysers were studied individually in detail for the summer and winter. On the other hand, appliance-level analysis was conducted on the appliances, namely washing machine, refrigerator, television and water purifier for summer and winter. Load profiles of these appliances were created to understand seasonality in their usage patterns.

The household-level analysis of five homes during peak summer found that six major appliances, namely AC, geyser (domestic water heater), refrigerator, washing machine, television and water purifier, consumed approximately 71% of the total daily electricity. Based on the analysis, it was found that the primary energy consumers in a typical home are the ACs and geysers. During periods of low solar availability, air conditioners accounted for the majority of electricity consumption, while geysers and washing machines were used more frequently during peak solar hours. By implementing a range of strategies, such as adjusting thermostat settings, utilizing fans alongside air conditioners, and opting for high-efficiency models of air conditioners, there is a potential to reduce daily electricity consumption by approximately 10% (437 Wh per home). Another potential measure to consider is the introduction of a district cooling system that incorporates thermal storage, which would shift the energy usage of air conditioners to daytime hours, thus further decreasing nighttime demand. Shifting the geyser usage can redirect 1.05 kWh

of daily electrical energy consumption per household during peak solar hours. Additionally, replacing geysers with heat pumps can significantly reduce domestic hot water energy consumption to one-third of the current daily usage. By analyzing these consumption patterns, the study identifies peak consumption periods and explores potential strategies to shift electricity consumption to peak solar hours so that energy from solar PV can be utilized. Moreover, the study also focuses on appliance-level consumption patterns, highlighting the AC and geyser usage trends. It was observed that when the daily average temperatures are greater than 29°C, the energy consumption of ACs tends to be high. Conversely, geysers are utilized in both summer and winter seasons, with a higher energy consumption pattern evident during the winter months. The average load the ACs and geysers imparted during usage was 0.6 kW and 1.87 kW per appliance, respectively.

The thesis concludes by providing recommendations on how households can reduce their energy usage and shift their usage patterns to peak solar hours. These include adjusting the setpoints of air conditioners to higher temperatures, using ceiling fans with air conditioners, and utilizing appliances with higher energy efficiency ratios. Ongoing research and adaptation will be crucial to maximize the benefits of these innovations for both consumers and the broader energy ecosystem. The findings of this study provide insights for policymakers, utility providers, and residents looking to reduce energy consumption and achieve a more sustainable energy system. Overall, this thesis report provides a detailed analysis of the electricity consumption patterns of households in Hyderabad and offers practical recommendations for shifting usage patterns to peak solar hours.

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Chapter 1

1. INTRODUCTION

1.1. Background

As the demand for residential electricity surges, utilities encounter challenges in allocating the required resources to effectively meet this growing demand. In this case, it is necessary to understand how a typical household's energy use is divided throughout the day. In the Indian context, the residential sector represents a substantial portion, amounting to 27% of the overall electricity usage, second only to the industrial sector's consumption [1]. Projections indicate that this sector is experiencing a CAGR of 6.2% and will consequently witness an increase in the power demand for household appliances [2]. Given India's commitment to achieving net zero emissions by 2070, the residential sector is significant in this endeavour. To reduce residential electricity consumption, it becomes crucial to closely monitor and account for the electricity usage at the appliance level within households, in addition to the overall consumption. This study captures these consumption patterns using appliance load profiles, which are the average distribution of the load imparted by each appliance throughout the day in an ordinary residential unit. Appliance load profiles can be generated by monitoring the electricity consumption of individual household appliances, enabling us to get a basic notion of where a household's energy use might be attributed. Understanding when and how appliances are used allows us to examine peak consumption periods in a household and, subsequently, overall energy demand. Additionally, it will assist in exploring the potential for redistributing the energy consumption of high-demand appliances to achieve a more consistent demand curve.

The increasing global demand for electricity and growing concerns about environmental sustainability have intensified the need for a thorough understanding of residential electricity consumption patterns. As populations continue to urbanise and technological advancements infiltrate households, the dynamics of electricity usage within residential settings have become increasingly complex. This thesis explores residential electricity consumption patterns, aiming to provide valuable insights for policymakers, utility providers, and residents alike.

1.2. Technological Influences

Technological influences on residential electricity consumption patterns have significantly evolved, shaping how households use and manage energy. Several vital technological factors contribute to these consumption patterns:

1. Smart Home Technologies: The introduction of smart home devices has significantly changed how residents interact with and control their appliances and systems. Smart thermostats, lighting controls, and home automation systems allow for more precise management of energy usage. Residents can schedule and optimise their devices, increasing energy efficiency and reducing overall consumption.
2. Energy-Efficient Appliances: The development and widespread adoption of energy-efficient appliances have substantially impacted residential electricity consumption. Household appliances such as ENERGY STAR-rated refrigerators, washing machines, and HVAC systems consume less energy while delivering the same level of service, thus leading to overall energy savings.
3. Renewable Energy Integration: Residential solar panels and other distributed energy resources enable homeowners to generate their own electricity. Sources of renewable energy (solar panels, wind turbines, etc.) in homes can decrease our reliance on conventional power sources like coal and oil. This means we can generate our own energy and even contribute to the power grid when we have extra energy. By doing this, we can help create a more sustainable and decentralised energy system.
4. Smart Meters and Advanced Metering Infrastructure (AMI): The deployment of smart meters and AMI enables real-time monitoring of electricity consumption. This provides consumers with more detailed insights into their usage patterns and allows utility providers to implement demand response programs, encouraging load-shifting and energy conservation during peak periods.
5. Internet of Things (IoT): The introduction of IoT devices in homes contributes to energy efficiency and increased electricity consumption. While smart devices optimise energy use through automation and data-driven decision-making, the increasing number of connected devices also adds to the overall demand for electricity.
6. Home Energy Management Systems (HEMS): HEMS provide residents with centralised control and monitoring of their energy consumption. These systems often integrate with

various smart devices and appliances, offering real-time data analytics and recommendations to optimise energy use and reduce overall consumption.

Understanding the interplay of these technological influences is essential for effectively predicting and managing residential electricity consumption patterns. Ongoing research and adaptation will be crucial to maximising the benefits of these innovations for both consumers and the broader energy ecosystem as technology advances.

1.3. Problem Statement

Monitoring electricity at the household level can be achieved by employing an energy meter to measure the overall electricity consumption. Appliance-level electricity monitoring can be conducted using various methods, depending upon the resolution of data, availability of hardware, and the level of intrusiveness desired. There are two approaches to appliance-level electricity monitoring:

1. *Intrusive approach*: involves physical measurement of electricity consumption at the appliance level. In this approach, appliance-level monitoring is done using smart plugs, while household-level monitoring is done using energy meters. It is more reliable and accurate.
2. *Non-intrusive approach*: generating appliance-level electricity data using smart meter data by applying various disaggregation algorithms. This approach estimates the appliance-level consumption data and is generally less accurate.

Our study has four components based on the intrusive approach of electricity monitoring:

1. Household level study: electricity consumption patterns during peak summer in five homes are analysed at the household level.
2. AC usage patterns
3. Geyser (domestic water heater) usage patterns
4. Appliance level study: Seasonal load profiles of regularly used household appliances

A detailed explanation of the equipment and methodology used in this study is provided in Chapter 3.

1.4. Thesis Contributions

This thesis has the following key contributions:

1. Load profiles of ACs and geysers during the summer and winter months, providing seasonal insights into these appliances' power usage patterns and their usage probability.
2. Analysis of disaggregated energy usage of a typical household. The research sheds light on the usage and electricity consumption of regularly used common household appliances.
3. Strategies to potentially shift the appliance usage to solar peak hours so that the demand can be met by the solar PV power generation.
4. Measures to reduce the daily electricity consumption in households.

1.5. Thesis Organization

This thesis is organized into chapters as follows for the remaining part:

- Chapter 2 provides the literature survey concerning the residential electricity consumption patterns, load profiles and different residential energy datasets available.
- Chapter 3 describes the intrusive load monitoring methodology used in the different phases of the study to collect the residential electricity consumption data during summer and winter.
- Chapter 4 discusses the household-level electricity consumption for five homes in Hyderabad using conditional demand analysis and appliance load profiles.
- Chapter 5 investigates the AC usage patterns and trends during summer and winter.
- Chapter 6 shows the geyser (domestic water heater) usage patterns and trends during summer and winter.
- Chapter 7 discusses the seasonal load profiles of home appliances such as refrigerators, washing machines, televisions, and water purifiers.
- Chapter 8 consists of discussions on the observations from this work, its limitations and future scope of research.

Chapter 2

2. LITERATURE REVIEW

2.1. Electricity Consumption Patterns

Electricity consumption patterns and load profiles are critical aspects of energy management and forecasting. Several key studies have explored various methods and techniques to analyse and predict electricity consumption patterns using load profiles. Barkhordar et al. [3] introduced a decomposition method to extract detailed load curves from aggregate data. Tajeuna et al. [4] proposed a network-based method to track evolving consumption patterns, aiding load forecasting. Yu et al. [5] employed deep neural networks for residential load prediction. Chew et al. [6] developed a two-stage clustering approach for load shape analysis, supporting demand response strategies. Another approach distinguished appliance, lighting and plug load profiles from the smart meter dataset [7]. Research in Dubai explored factors affecting residential load profiles and used classification algorithms for prediction [8]. Moreover, Bayesian Network techniques were employed to monitor building energy consumption patterns [9], and machine learning was used to analyse residential electricity consumption in Ireland, considering temperature and temporal factors [10]. One study explores electricity consumption in Austrian and German homes, revealing limitations in standard load profiles and proposing a stochastic model [11]. Another introduces a smart meter-based framework, achieving 82% precision and 81% recall in predicting household characteristics for improved energy management and reduction of emissions [12].

2.2. Residential Load Profiles

A method for non-intrusive load monitoring (NILM) in the residential buildings sector was proposed by H. Park [13]. The method utilizes the measured total active power consumption and classifies appliances based on their observed operational characteristics in experiments. The classification is done using ON/OFF state models, multi-state models, and composite models. Lan et al. [14] proposed an approach that enables the generation of numerous load profiles solely based on the average load profiles of distinct appliances sampled at 1 hour. These load profiles possess a higher temporal resolution compared to the average data of various households or appliances. Buddhahai et al. [15] present a methodology for analyzing data that enables the identification of load profiles and power consumption of household devices through the utilization of a multitarget classification algorithm. Teng et al. [16] suggested using a profile-matched time-shift method to ascertain the load profiles and power usage of household appliances in a smart home system. Marcu et al. [17] determined the energy usage and power patterns of household devices through the implementation of non-invasive load monitoring and power signatures. Moussa et al. [18] presented a technique for creating a daily load profile for residential areas while also taking into account the design of a microgrid energy management system (EMS). However, the proposed EMS takes into consideration both power flow exchange and power quality concerns. Jabian et al. [19] examined the present condition of modelling the load profiles of residential electricity and suggested areas for future research and applications. They also classified and grouped 32 models for residential electricity load profiles. Islam et al. [20] explored the distribution of load profiles in residential energy usage through the implementation of adaptive k-means clustering. It discovers primary patterns in energy consumption and offers utilities valuable information to enhance demand response and pricing tactics.

2.3. Intrusive Studies

Several studies using an intrusive approach have been conducted on usage patterns of household devices. Y. Jin et al. [21] did a case study of the energy use of one television in a household in Beijing for a year. Another study was conducted by K. S. Cetin et al. [22] in Austin, Texas, which monitored four major appliances (refrigerator, clothes washer, clothes dryer, and dishwasher) for one year in more than 40 residences. Issi et al. [23] did an electricity analysis of twelve appliances in a typical two-family household for three months in Türkiye. Furthermore, the energy consumption patterns of 150 houses in France and Spain were examined, with a detailed analysis of heating, domestic hot water and electricity consumption of 50 homes for one and half years by T. Csoknyai et al. [24]. Additionally, an assessment was made on the effectiveness of a persuasive game in promoting energy conservation within the community.

2.4. Non-Intrusive Studies

Non-intrusive studies, such as air conditioner usage patterns in 11 homes in Hyderabad, India, were conducted by P. Ramapragada et al. [25] for 19 days during summer. Huber et al. [26] did an extensive review of numerous Deep Learning approaches to apply to low-frequency NILM methods. Czétány et al. [27] used clustering on one-year energy meter data of 1186 houses in Hungary to study the effect of seasonality, day of the week, geographical location, and type of residential unit on daily electricity consumption. A. Muroni et al. [28] used Knowledge Discovery in Database (KDD) to extract occupancy, equipment, and light usage patterns from 12 Dutch residences and integrate them with building performance simulation to reduce energy consumption.

2.5. Residential Electricity Consumption Datasets

There are several publicly accessible energy datasets from across the globe, such as REDD [29], containing energy consumption data of 10 homes for a total of 119 days for 268 appliances; UKDALE [30], containing aggregate and appliance level data from five homes with one home monitored for 655 days comprising of 54 appliances in the UK, and REFIT [31] collected raw electrical consumption data from 20 homes in the UK for a span of two years. Iqbal et al. [32] summarized various open-source energy datasets. Indian datasets such as IAWE [33] contain data on 11 appliances, water and ambient parameters using 33 sensors in one home over 73 days. Another dataset, IEDL [34], monitored five appliances (refrigerator, mixer, television, water pump and washing machine) in one home for a period of one year. Moreover, I-BLEND is a 52-month energy dataset collected from seven commercial and residential buildings of Indraprastha Institute of Information Technology Delhi in Delhi, India [35].

2.6. Gaps Identified

The studies mentioned above collectively add to our understanding of electricity consumption patterns using diverse methodologies, including decomposition, clustering, and machine learning techniques. They emphasise the significance of load profiles in enhancing energy management, forecasting, and optimising electricity consumption in various contexts. However, more studies are required to explore the demand driven by individual appliances in a household, which contributes to understanding the load-shifting potential in the residential sector. Although the studies illustrated the forecasting and energy management potential of the load profiles, it is necessary to understand the power requirements of individual devices in the daily cycle to effectively comprehend household electricity consumption patterns and the potential to shift the devices that generate high loads to solar hours from off-solar hours. Moreover, most of the above studies were conducted in Europe and the US, and there are very few studies available in the Indian context. The electricity data in the above studies has been collected either by intrusive or non-intrusive approaches.

In this study, we addressed this gap by examining the appliance-specific usage profiles of five households in Hyderabad, India. To conduct our analysis, we collected and compiled empirical data on the primary electricity consumption of 5 Indian middle-class homes for 61 days (1 May 2023 to 30 Jun 2023). The gathered data provides valuable insights for a more comprehensive and in-depth study that can be conducted for a longer duration. Our study's primary objective is to ascertain household appliance usage patterns in peak summer. The usage patterns are presented based on the daily average power consumption distribution of the appliance in question in 30-minute time increments throughout the day. Additionally, the probability of appliance usage is also linked with each time step. In this study, we have also conducted a pilot using an intrusive load monitoring method to capture disaggregated data in homes, as this method provides more accurate and reliable data than the non-intrusive method.

3. METHODOLOGY

The following subsections provide detailed descriptions of the experimental setup and the computational and data acquisition methodologies utilised to understand the disaggregated electricity consumption patterns at both household and appliance levels.

3.1. Data Acquisition Equipment and Methods

In this study, IoT-based devices were used to collect electricity data at the appliance and household levels. The data was collected at the appliance level using a smart plug, as shown in Figure 1. The smart plugs measured instantaneous RMS power consumption every second of the connected appliance.

Figure 1: Smart plug used to collect appliance load time-series data.

Current-Transformer based smart energy meter, as shown in Figure 2, was used to measure electricity consumption at the household level. These smart meters measure instantaneous RMS power, voltage, current and cumulative household energy consumption every minute.

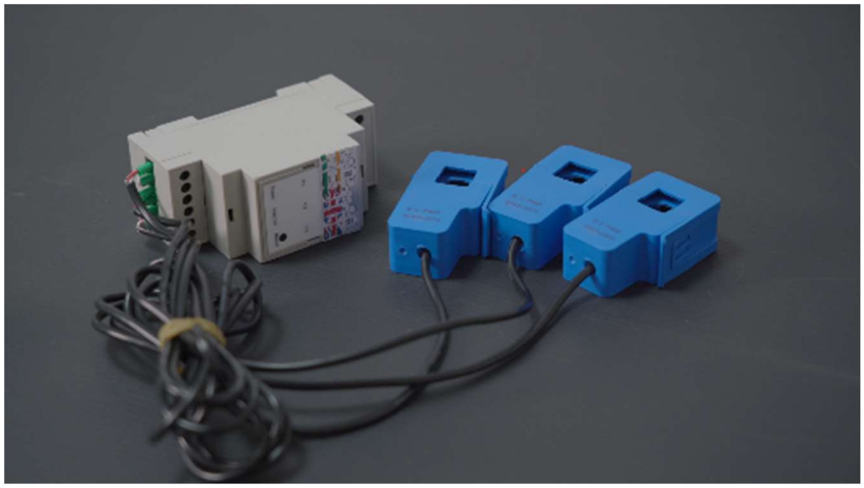

Figure 2: Smart energy meter used to collect household electricity time-series data.

These smart energy meters were installed into the household's electricity supply distribution board, as per the circuit diagram shown in Figure 3. It is to be noted that the smart meter can be configured in a single-phase arrangement as well, in which only one CT is attached to measure the phase current.

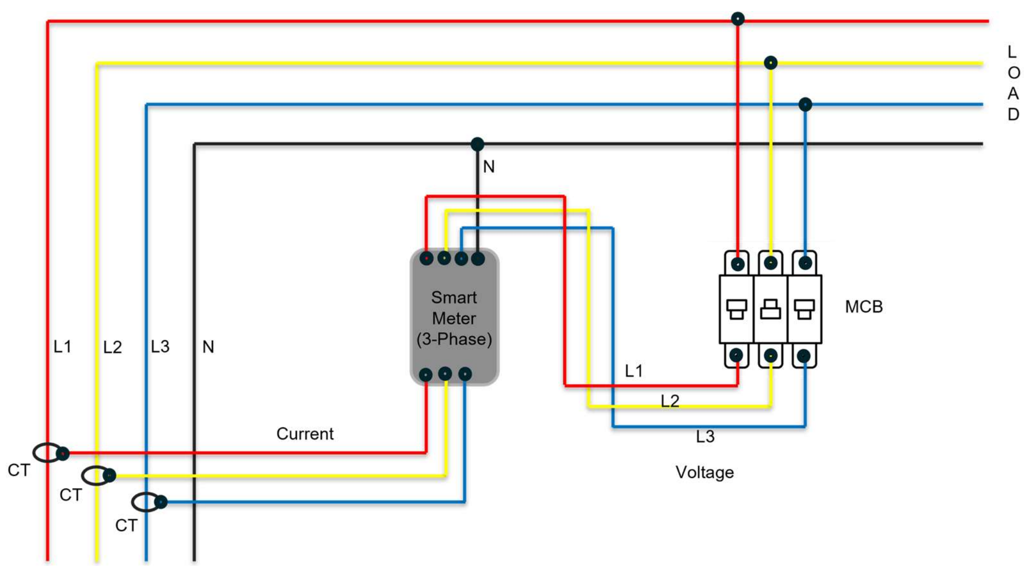

Figure 3: Circuit diagram of the smart meter installation.

The data collection devices used in this study have no built-in data storage capabilities. These devices remain connected to the internet and log data into a cloud-based AWS application server via the MQTT protocol. The block diagram of the data acquisition approach employed in this research is illustrated in Figure 4. A depiction of the smart energy meter and smart plug installation within a household is provided in Figure 5.

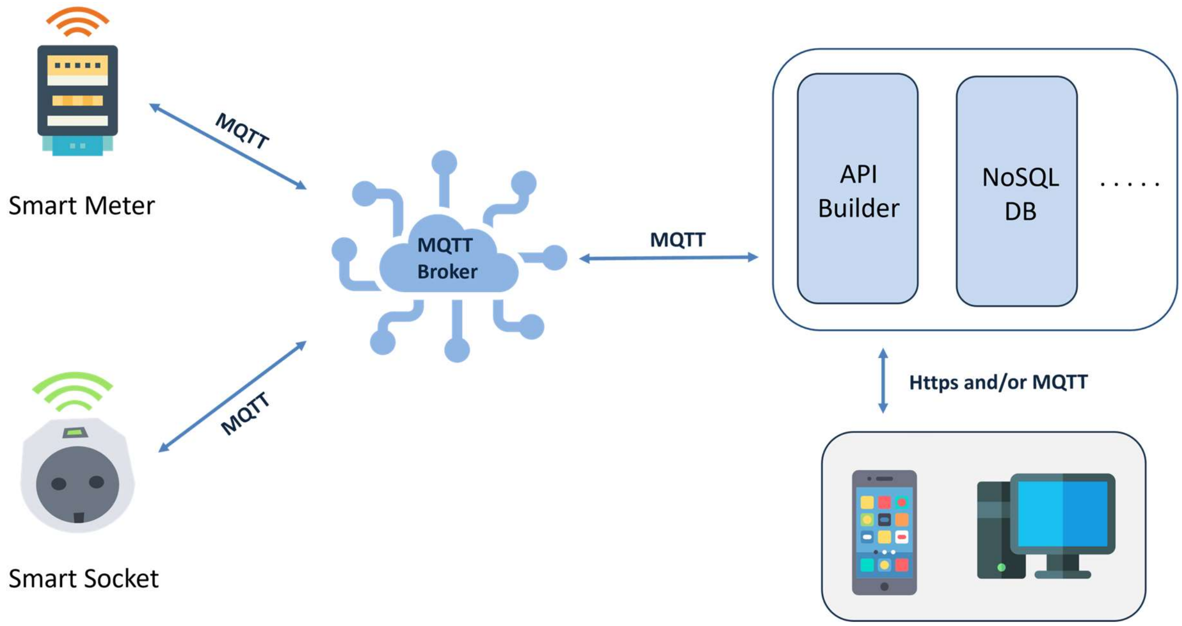

Figure 4: Block diagram of data collection mechanism.

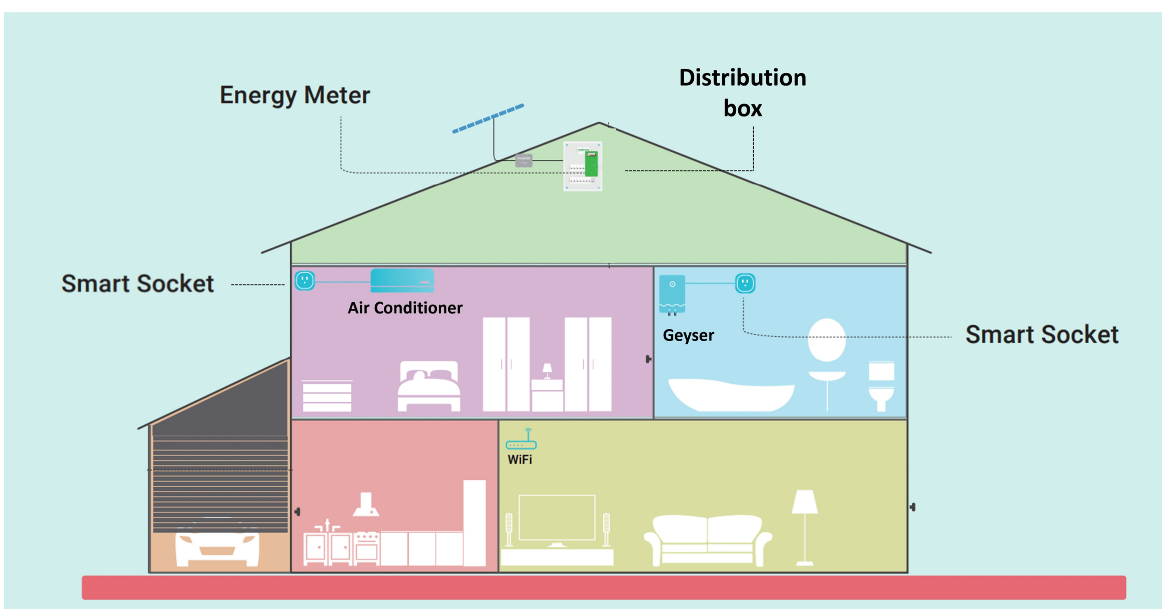

Figure 5: Demonstration of device installation in a typical home.

Table 1 gives the devices' accuracy and describes the data types collected using these devices.

Table 1 Device and Data-type summary.

S. No	Device	Data type	Error	Data Intervals	Measured value	Unit
1	Smart Plug	Instantaneous RMS Power	± 2 %	1 sec	Load	Watt
2		Energy		1 sec	Energy	Watt-hour
3	Smart Meter (each phase)	Cumulative energy	± 2 %	1 sec	Energy	Watt-hour
4		Instantaneous RMS power		1 sec	Load	Watt
5		Instantaneous RMS voltage		1 sec	Voltage	Volt
6		Instantaneous RMS current		1 sec	Current	Ampere

Figure 6 shows a washing machine connected to a smart plug, and Figure 7 shows a smart energy meter connected to the electrical distribution board at the household's electricity supply.

Figure 6: A washing machine plugged into a smart plug for appliance-level electricity consumption monitoring.

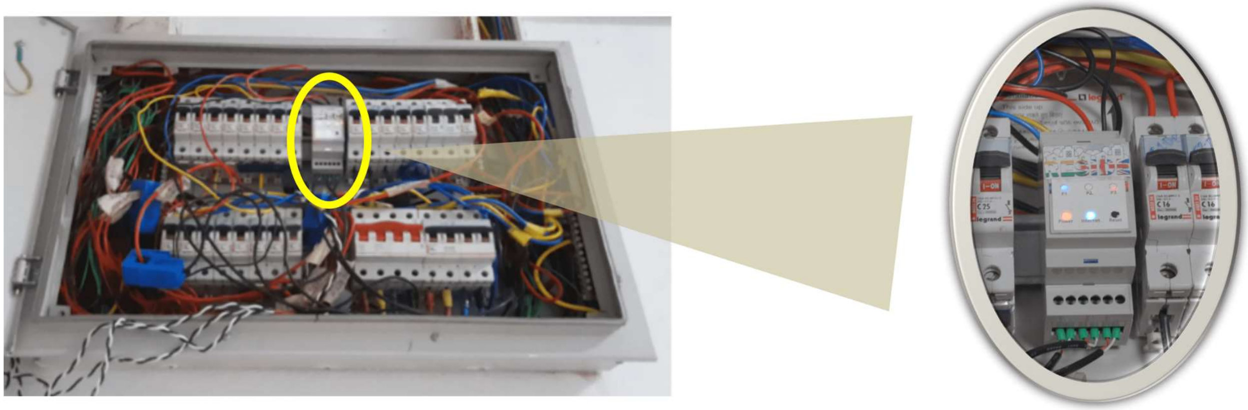

Figure 7: A 3-phase energy meter installed in the distribution box to measure total household electricity consumption.

3.2. Data Processing

The data was stored in NoSQL database format on a cloud-based application server. It was downloaded from the application server and imported to a local MongoDB server into two different collections: namely, 'energy_meter_sec' for the per-second total electricity data from the smart energy meter and 'socket_power' for the per-second appliance power data. The concerned data is then extracted into a raw '.csv' file, which is processed into a suitable format for the analyses performed in the study. Figure 8 shows the workflow of the data export process.

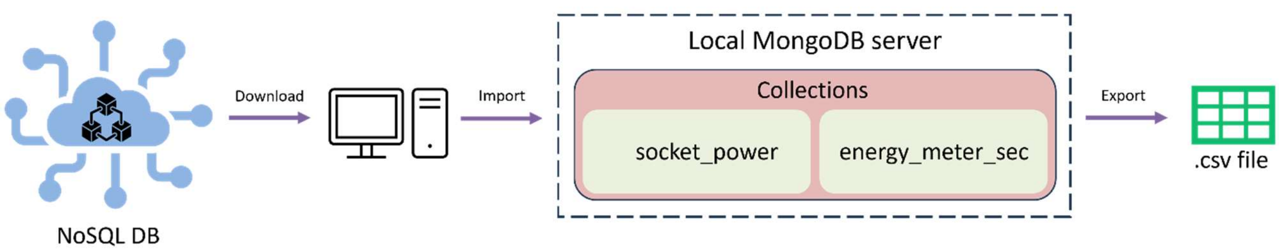

Figure 8: Data export process.

There were four instances identified where data loss was possible, and are as follows:

1. *Power cut:*

   During power cuts, no data was sent and stored on the server. This is equivalent to the appliance being turned off, as there is no power input. Hence, this gap is considered a period when the appliances remain non-operational. Thus, the power consumption during this period is filled with zero.

2. *Server downtime:*

   A server downtime was observed between 15 Jun 2023 to 18 Jun 2023. Hence, these days were eliminated from the data and were not considered for analysis.

3. *Internet loss:*

   During internet loss, no data is captured from the appliances as there is no built-in storage in the smart sockets. Hence, to maintain uniformity, the days when there was internet loss were not considered in this study.

4. *Randomly Missing data at the device level:*

   The system achieved approximately 97 % data collection, and the remaining 3 % loss was sparsely spread over the period of study. Hence, the randomly missing data was forward filled in case of power values in the smart energy meter and smart plug data. The total energy consumption was cumulatively logged, and only the daily energy consumption at the end of the day was utilised in this study. Hence, it was not required to fill in the missing energy values.

Appropriate mechanisms were in place to identify and mitigate the above faults.

The methodology of data collection mentioned in this thesis is part of a published work entitled "Understanding Seasonal Variations in Residential Electricity Consumption: A Pilot Study Using Electric Load Profiles" in the Air Conditioning and Refrigeration Journal [36].

3.3. Data Collection and Target Description

This section discusses the selection of households, the duration and type of analysis, which was conducted as a part of this study. In this study, a total of 21 households in Hyderabad were equipped with monitoring devices to monitor the household and appliance-level electricity consumption data. We monitored several different kinds of appliances in these homes during May, June, and November of 2023. Among these homes, five homes were identified with a greater number of home appliances belonging to 12 unique categories given in Table 4. Out of these 12 categories, seven appliances were common in the five homes. Six of these common appliances, namely AC, geyser, refrigerator, washing machine, television and water purifier, are the regularly used appliances, and the seventh, namely the mixer-grinder, is a sparingly used appliance. The users of these homes agreed to participate in a detailed study where daily household and appliance-level electricity consumption was monitored through data analysis and telephone surveys. These users were willing to share their total electricity data for the summer month. Hence, we selected these homes to understand a typical household's daily electricity consumption breakdown and appliance profiles of regularly used appliances during the peak summer. The electricity data from these five homes was collected from 1 May 2023 to 30 Jun 2023, and the analysis was performed for the peak summer period from 15 May 2023 to 14 Jun 2023.

Furthermore, usage profiles of air conditioners and geysers monitored in all 21 homes were created for both the winter (1 Nov to 30 Nov 2023) and summer 1 May to 30 Jun 2023) months. The household summary of the AC and geyser ownership is given in Table 2. The homes used in the summer and winter studies differ as the data collection was conducted per the user's consent. The users had the liberty to opt-out at any point in the study, and hence, some of the homes used in summer and winter are different but have similar archetypes and appliance ownerships. Moreover, the load profiles of the remaining major appliances, namely washing machines, refrigerators, televisions, and water purifiers, were created for the summer and winter months. Appliances in the overall monitored homes, including the five homes used in the detailed study, were considered in creating appliance-wise load profiles.

Table 2: Summary of AC and geyser usage analysis

Appliance	Summer (1 May to 30 Jun)			Winter (1 Nov to 30 Nov)		
	No of homes	Appliances monitored	occupants	No of homes	Appliances monitored	occupants
ACs	13	15	48	9	10	31
geysers	19	27	74	12	16	46

This thesis describes the four parts of this study as follows:

1. Household-level electricity consumption
2. Air conditioner usage
3. Geyser usage

4. Appliance load profiles

3.4. Household-Level Electricity Consumption Analysis

This investigation delves into the overall and disaggregated electricity consumption patterns at the household level. The data collection spanned 61 days, commencing on 1 May 2023, and concluding on 30 Jun 2023. A total of 5 homes had the measuring equipment installed, and the acquired data was examined for inconsistencies using data analysis and daily telephonic polls. The housing units included in this study were selected voluntarily at several sites throughout Hyderabad, India. Residents of various homes and apartment complexes were approached by researchers and given invitations to take part in the study. The household information is shown in Table 3.

Table 3: Household information of the houses used in the study.

House ID	Dwelling type	Floor area (sq. ft.)	Number of adults	Number of children	No. of appliances monitored
H1	2-BHK	1112	5	0	10
H2	2-BHK	1025	2	0	9
H3	2-BHK	1025	3	1	8
H4	3-BHK	1575	5	1	13
H5	2-BHK	700	2	2	8

We chose homes with various appliances to track most of the total electricity consumption. We observed a combined count of 48 appliances in the chosen settings, representing 12 unique categories. The appliance categories monitored in the investigation are listed in Table 4.

Table 4: Appliance categories monitored across the five selected homes.

Air Conditioner	Mixer-Grinder	Geyser

Washing Machine	Electric Kettle	Water Purifier
Television	Refrigerator	Dishwasher
Microwave Oven	Chimney	Rice Cooker

Out of these appliances, eight appliances, namely air conditioner, geyser, refrigerator, washing machine, water purifier, television, chimney, and dishwasher, are regularly used appliances. While mixer-grinder, electric kettle, rice-cooker and microwave oven are sparingly used appliances. Among the five homes, there were seven common appliances, namely AC, geyser, washing machine, refrigerator, television, water purifier and mixer-grinder. Hence, load profiles of the six regularly used common appliances were created for the peak summer period. These crucial appliances are widely used in households and contribute considerably to overall electricity usage. In order to understand the daily electricity consumption patterns of households during the summer peak season, energy consumption breakup and daily load profiles were produced, averaging over 30 days from 15 May 2023 to 14 Jun 2023. One particular household comprised multiple air conditioners and geysers. Therefore, in the time series data, the loads of similar devices were summed up in the time series and presented as one household appliance. The energy consumption breakdown of households was determined by the daily energy consumption of the four significant appliances (air conditioner, geyser, refrigerator and washing machine), and the household's daily total energy consumption averaged over the peak summer period. The appliance-wise total daily energy consumption was then disaggregated based on solar peak and off-peak hours consumption.

3.5. Load Profile Generation

The techniques previously discussed enabled the development of a precise dataset comprising authentic load profiles classified at the individual appliance level in Indian households situated in a sub-tropical region.

This section describes the load profile generation methodology applied in the study. The methodology used here is published as a part of the work "Summer Electricity Consumption Patterns in Households Using Appliance Load Profiles" in the proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities and Transportation, Buildsys23, 15 Nov 2023, Istanbul, Turkey [37]. In order to create appliance load profiles, the appliances' load data were sampled at 30-minute intervals by averaging the load during the intervals according to Equation (1). Here, L_t is the average load (Watts) in 30 minutes for each time-interval 't' where t ∈ {(23:30, 00:00], (00:00, 00:30], ………., (23:00, 23:30]}. N is the number of seconds in 30 minutes, i.e., 1800 seconds and x_i is the load (Watt) at i^{th} second in the corresponding time interval 't'.

$$L_t = \left[\frac{1}{N}\sum_{i=1}^{N} x_i\right]_t \qquad \ldots(1)$$

The individual appliance loads were then averaged for the selected 30-day period according to the corresponding time from 00:00 hours to 23:30 hours to represent the daily average usage of the appliance resulting in their load profiles based on Equation (2) where N = 30 total number of days, L_i = load (Watt) on i^{th} day at a given timestep t ∈ {00:00, 00:30,………., 23:30}, and A_t = average load (Watts) in 30 days of a given appliance at timestep 't'.

$$A_t = \left[\frac{1}{N}\sum_{i=1}^{N} L_i\right]_t \qquad \ldots(2)$$

Subsequently, each household's appliance load profiles were averaged to create the daily average load profiles of each of the four selected appliance categories for the five households with the help of Equation (3). Here, N = number of homes, A_i = average load (Watt) of the given appliance in i^{th} home at a given timestep t ∈ {00:00, 00:30, ………., 23:30}, and LP_t = average load (Watts) per home at a given timestep 't'.

$$LP_t = \left[\frac{1}{N}\sum_{i=1}^{N} A_i\right]_t \qquad \ldots(3)$$

Similarly, to find the appliance usage probability, each data cell in the resampled individual appliance data file is first replaced with a '1' if the cell has a load > threshold load (W) and with a '0' if not. The threshold depends on the minimum power observed of the concerned appliance, such as 20 W for the AC., etc. This was done to exclude any standby power values when the appliance was left turned ON while not in use. The usage probability of a given appliance in a household was then calculated according to Equation (4). Here, N = number of days, $v_i \in \{0,1\}$ is the value in the data cell on i^{th} day at a given timestep t ∈ {00:00, 00:30, ………, 23:30}, and ρ_t = usage probability of the appliance in 30 days at a given timestep 't'.

$$\rho_t = \left[\frac{1}{N}\sum_{i=1}^{N} v_i\right]_t \qquad \ldots(4)$$

Ultimately, the individual usage probabilities of the given appliance type were averaged over five homes corresponding to the timestep 't' to get the overall usage probability of the appliance.

3.6. Appliance Level Electricity Consumption

In this study, electricity consumption patterns at the appliance level were studied instead of at the home level. The study was conducted for the summer (1 May 2023 to 30 June 2023) and winter (1 Nov 2023 to 30 Nov 2023) seasons in Hyderabad in the year 2023. For summer, the months of May and June are considered. On the other hand, winter month was taken as November. During this period, regularly used major appliances like ACs, geysers (domestic water heaters), washing machines, refrigerators, televisions, and water purifiers were monitored in different homes, and their average load profiles were created. The load profiles give an idea of the probability of usage of these appliances in each timestep. It shows the average load imparted by an appliance among the given group in each appliance category.

3.7. Climate of Hyderabad

The design conditions for heating and cooling are 13.9 ºC and 40.2 ºC, respectively, in Hyderabad [38]. The average low and average high temperatures during January month are 29.7 ºC and 15.9 ºC, respectively, and during May month, the average high and average low temperatures are 39.7 ºC and 29.6 ºC, respectively, in Hyderabad [39]. Overall, Hyderabad experiences a semi-arid climate, with its summer season spanning from April to June. The peak summer typically occurs from mid-May to mid-June, with average daily high temperatures surpassing 35 ºC, while the winters occur between November and January, with average low temperatures dropping around 15 ºC [39]. The households in this study were chosen by approaching various inhabitants residing in houses and apartment buildings and extending invitations to participate in the investigation. The inhabitants signed a consent form to permit the installation of the metering devices to capture their electricity consumption anonymously during the study period.

Chapter 4

4. HOUSEHOLD ELECTRICITY CONSUMPTION PATTERNS

4.1. Introduction

In this section, the observations from the household-level study are discussed. The methodology is discussed in Chapter 3. In this study, five households in Hyderabad were monitored during the summer from 1 May 2023 to 30 Jun 2023. A total of four household appliances, namely air conditioner, geyser, refrigerator, and water purifier, were monitored in all five homes, and their electricity consumption pattern is analyzed at the household level based on the methodology stated in Chapter 3. This chapter discusses the daily electrical energy consumption breakup of the chosen households through conditional demand analysis. Conditional demand analysis (CDA) is a statistical technique for estimating household energy use, in this case, at a disaggregated level.

4.2. Energy Consumption Breakup

Figure 9 depicts the daily average energy consumption of the major household appliances comprising an air conditioner, geyser, refrigerator, television, water purifier, and washing machine out of the total household energy for the duration of the 30-day peak summer period (15 May 2023 to 14 Jun 2023). It indicates that these four appliances contribute to approximately 71% of the total energy consumption in a typical household. Hence, it is crucial to evaluate their load profiles to comprehend a household's energy consumption patterns.

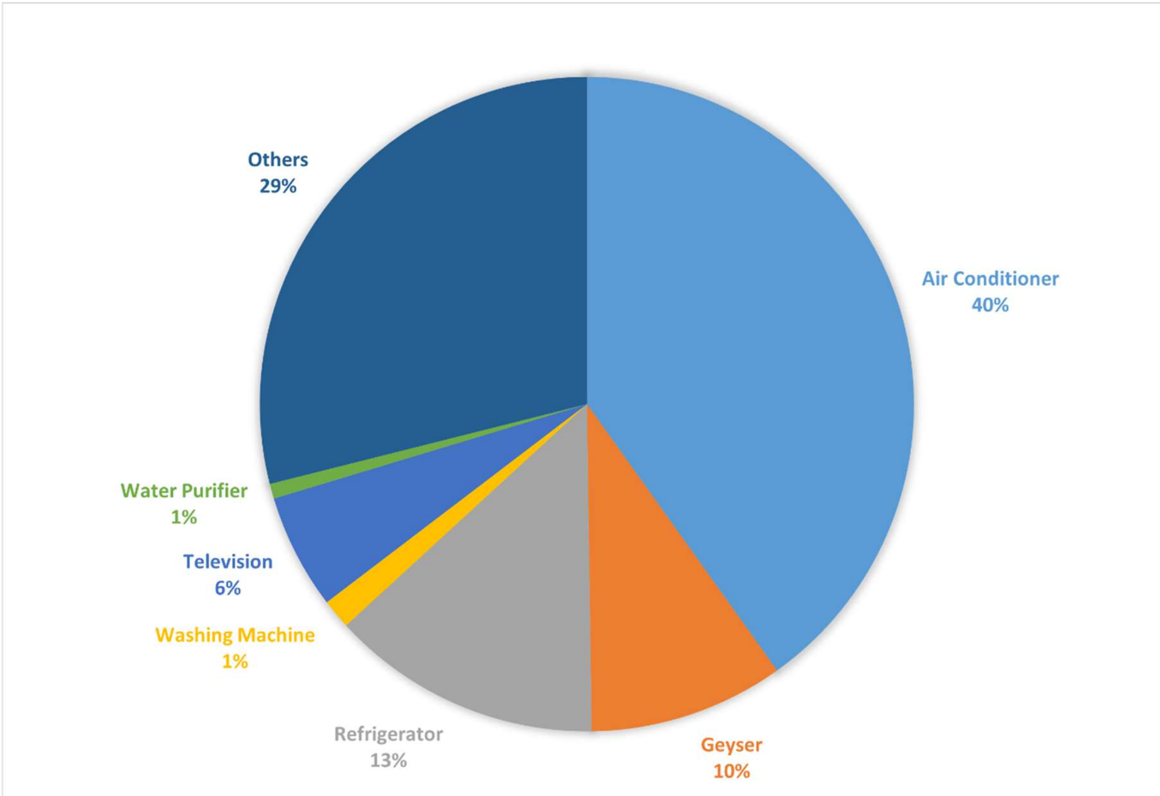

Figure 9: Daily energy consumption breakup of five households during peak summer.

As shown in Table 5, the air conditioner consumes a majority of about 4.37 kWh of the daily total energy in a typical household, followed by the refrigerator, which consumes approximately 1.46 kWh daily. The daily average total energy consumption was 10.89 kWh. In addition, during peak summer, the geyser consumed about 1.05 kWh of the total energy, and the washing machine consumed 0.16 kWh daily. During the peak hours of solar energy, the combined energy usage of these four appliances amounted to approximately 1.96 kWh. In contrast, the energy consumption during the solar off-peak hours was about 5.81 kWh.

Table 5: Electricity consumption in solar peak and off-peak hours.

Appliance	Electrical energy consumption (kWh)	
	Solar peak	Solar off-peak
Air Conditioner	0.83	3.54

Geyser	0.32	0.73
Refrigerator	0.42	1.04
Washing Machine	0.104	0.085
Television	0.24	0.38
Water Purifier	0.05	0.03

4.3. Appliance Load Profiles

4.3.1. Air Conditioner Load Profile

The average usage of air conditioning (AC) per household is depicted in Figure 10. The equipment was predominantly operated during nighttime, around 11:00 PM, and the highest usage was observed at 11:30 PM. A small peak in usage was observed during the day, while most of the consumption was concentrated during solar off-peak hours, accounting for 3.54 kWh daily. The energy consumption during solar peak hours was 0.83 kWh daily.

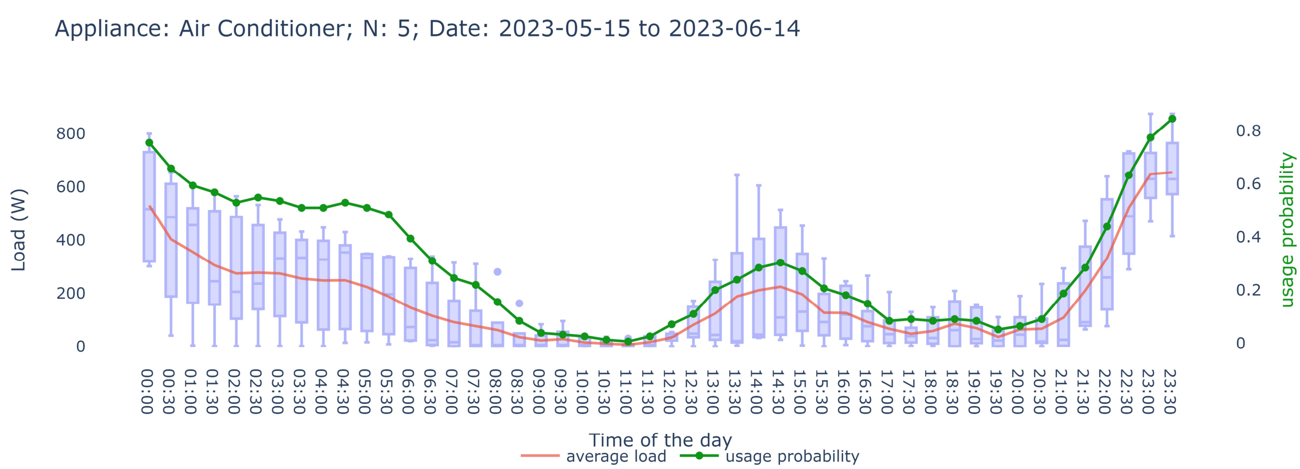

Figure 10: Air conditioner usage profile of five homes during peak summer.

4.3.2. Geyser Load Profile

Figure 11 depicts the probability of geyser usage and the distribution of loads per home concerning the time of day. The majority of geyser usage is concentrated between 8:30 AM and

10:30 AM. The peak usage occurred at 8:30 AM in the morning. A small proportion of homes utilised geysers post-evening as well. This is evident from a brief nighttime spike observed in usage at 10:30 PM. The geyser consumed 0.32 kWh during solar peak hours and 0.73 kWh during solar off-peak hours daily.

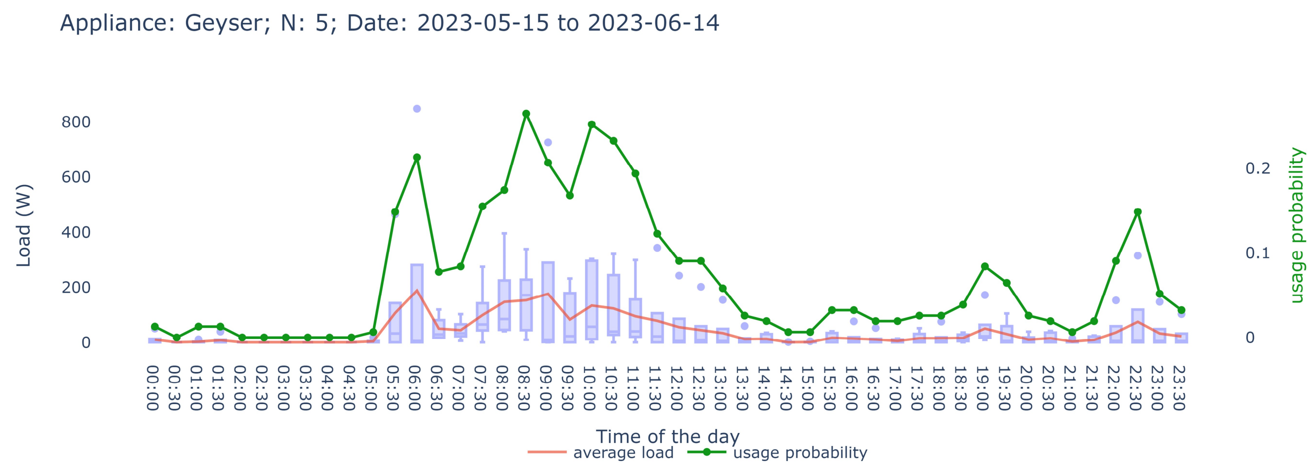

Figure 11: Geyser usage profile of five homes during peak summer.

4.3.3. Refrigerator Load Profile

As illustrated in Figure 12, the load exerted by the refrigerator on each household displays a uniform distribution throughout the day. This outcome is consistent with categorising the refrigerator as a non-shiftable device that remains active throughout the diurnal cycle. The average refrigerator load per household was determined to be 60.14 W. Furthermore, considering that the appliance is intended to remain operative all day, the probability of usage is likely to approach unity at each time increment. Thus, including the probability of usage in the load profile was deemed unnecessary.

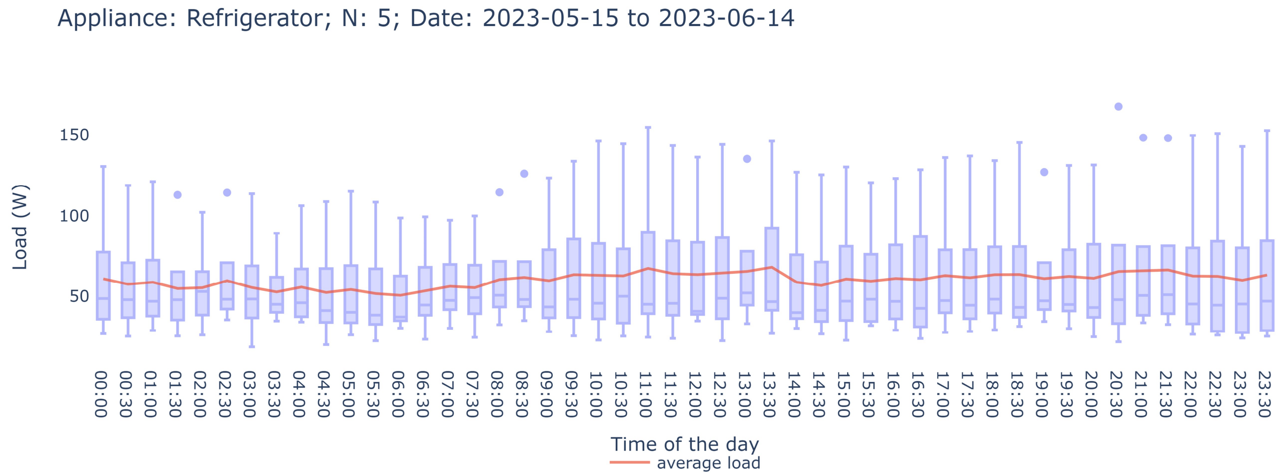

Figure 12: Refrigerator usage profile of five homes during peak summer.

4.3.4. Washing Machine Load Profile

The washing machine's typical load profile is illustrated in Figure 13. Notably, the majority of usage occurred during the 9:30 AM to 10:30 AM timeframe, and the highest usage was observed at 9:30 AM. The appliance was mostly operated close to solar peak hours, consuming 73.8 Wh during solar peak hours and 85.32 Wh during solar off-peak hours daily.

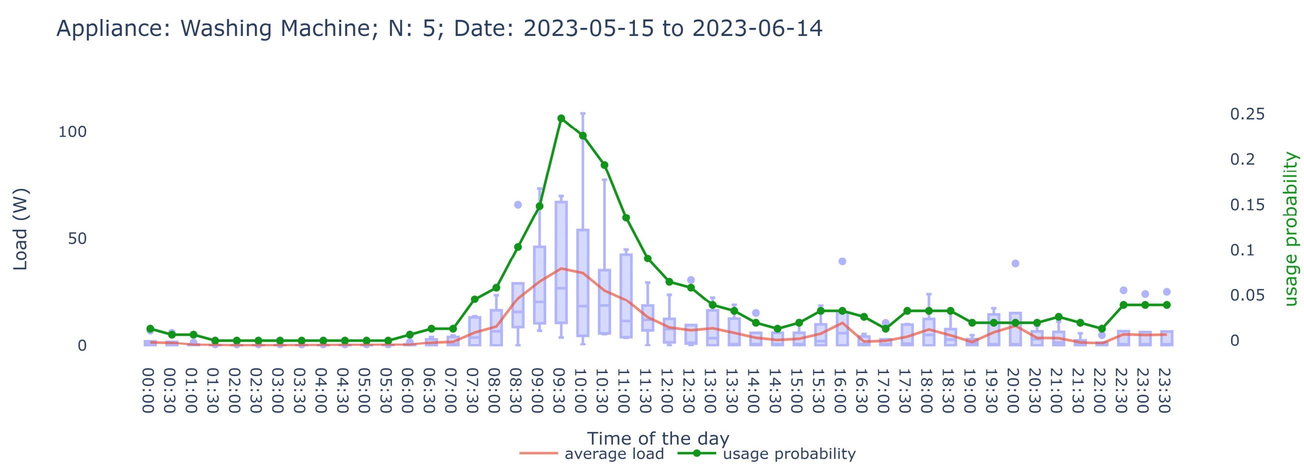

Figure 13: Washing Machine usage profile of five homes during peak summer.

4.3.5. Television Load Profile

The load profile of the television is illustrated in Figure 14. It can be seen that the majority of usage occurred during the daytime. The usage starts around 6:00 AM with few homes, and it spreads till 11:30 PM. The highest usage was observed around 9:00 PM. The appliance consumed 248.1 Wh during solar peak hours and 386.3 Wh during solar off-peak hours in terms of daily electricity consumption.

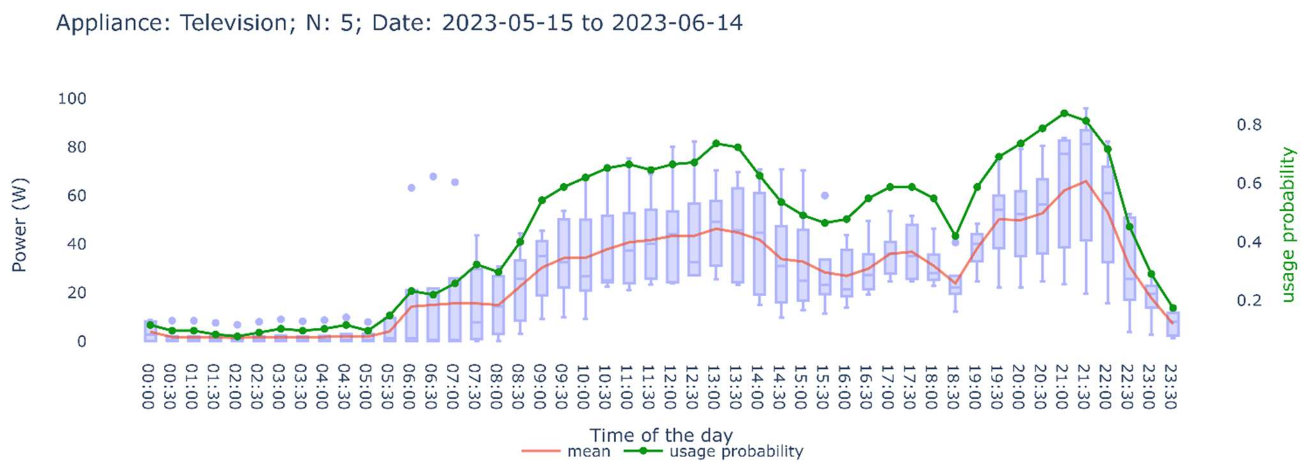

Figure 14: Television usage profile of five homes during peak summer.

4.3.6. Water Purifier Load Profile

The load profile of the water purifier is illustrated in Figure 15. It can be seen that the majority of usage occurred during the daytime. The usage starts around 6:00 AM and continues till 11:30 PM. The highest usage was observed around 11:00 AM. The appliance consumed 0.05 Wh during solar peak hours and 0.03 Wh during solar off-peak hours daily.

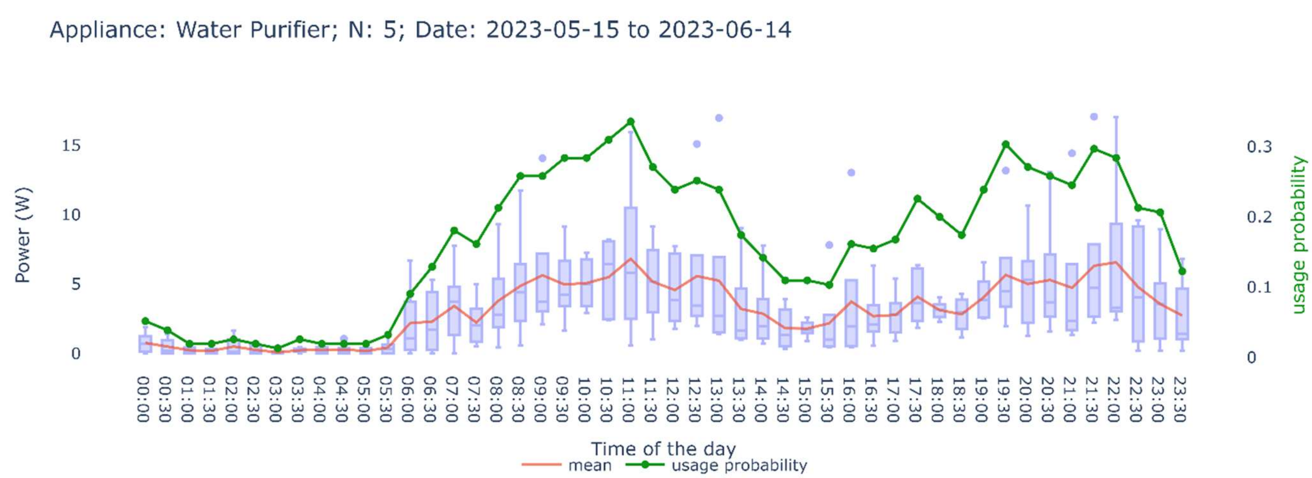

Figure 15: Water purifier usage profile of five homes during peak summer.

4.4. Discussions

In this study, we aimed to understand the electricity consumption patterns of five households during peak summer periods for 30 days through appliance load profiles of major appliances, namely air conditioners, geysers, refrigerators, televisions, water purifiers and washing machines. Our findings demonstrate that these appliances contribute to approximately 71 % of the total electricity consumption in a typical household. Air conditioners (ACs) consumed a major portion of the total electricity, with 3.54 kWh being consumed during solar off-peak hours and 0.83 kWh during solar peak hours daily. It is to be noted that Hyderabad gets 7.48 hours of daily average sunshine, and the peak solar hours generally range from 4 to 5 hours [40], which usually take place between 10 AM and 4 PM. The daily average AC energy consumption can be reduced by approximately 10% (437 Wh) through various measures like operating on higher setpoints, using ceiling fans alongside ACs, and using ACs with better energy efficiency ratios (EERs). The possibility of exploring the district cooling system with thermal storage can also be considered, as it has the potential to shift nearly all AC energy usage to the daytime. It is worth highlighting that residents used geysers and washing machines close to solar peak hours during the peak summer season. The solar off-peak geyser usage was 0.73 kWh per home in peak summer, which can be shifted to solar peak hours. Hence, shifting the entire geyser and washing machine usage will redirect 1.21 kWh per home in daily energy usage to solar peak hours. Moreover, by substituting the geysers with heat pumps, it is possible to decrease geyser energy consumption to one-third of the current daily energy usage down to 350 Wh per home. However, further study is required to understand the actual potential of energy reduction. Additionally, shifting appliance usage close to solar hours needs to be thoroughly investigated for hurdles in practical implementation. Moreover, an extended study can be conducted across different climatic zones to understand the seasonality of these usage patterns. This will further aid in devising demand response and load-shifting strategies for the residential sector.

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Chapter 5

5. AC USAGE PATTERNS

5.1. Introduction

In the ever-changing world of residential living, air conditioning systems are essential in maintaining comfort in different climates. However, using these systems goes beyond personal preferences and includes energy efficiency, cost savings, environmental responsibility, and societal considerations. To fully utilize air conditioning technologies, it is important to understand and analyze how they are used in residential spaces. This understanding allows homeowners to optimize their energy consumption, reduce costs, and promote sustainable practices, efficient infrastructure planning, and the integration of smart technologies. This introduction highlights why understanding air conditioner usage patterns is crucial in modern residential living.

By knowing the timing and frequency at which residents utilize air conditioners, it becomes possible to enhance the efficiency of energy usage. Through understanding the patterns of usage, homeowners can employ tactics that reduce energy wastage, including adjusting temperature controls in a suitable manner and utilizing programmable thermostats.

Understanding how residents use air conditioners in their homes is essential for a variety of reasons:

1. Cost Savings: Efficient use of air conditioners can lead to lower energy bills. By identifying peak usage times and making adjustments to habits or settings accordingly, residents can save money on their utility bills without compromising comfort.
2. Environmental Impact: Excessive and inefficient use of air conditioners can contribute to increased energy consumption and greenhouse gas emissions. Understanding usage patterns helps homeowners make informed decisions to reduce their environmental impact.
3. System Maintenance: Regular and proper maintenance is crucial for air conditioning systems' longevity and optimal performance. Knowing usage patterns can assist homeowners in scheduling maintenance tasks more effectively, ensuring that the system operates smoothly when it is most needed.
4. Comfort Optimization: Understanding when residents are most likely to use air conditioners allows for better planning to ensure comfort. For instance, if occupants tend

to use air conditioning during specific times of the day, homeowners can focus on creating comfortable living spaces during those periods.

5. Load Management: The overall electrical grid can be affected by large-scale patterns of air conditioner usage in a community or region. Understanding these patterns helps utility companies manage peak loads more effectively, reducing the risk of power outages and the need for additional infrastructure.
6. Smart Home Integration: As the popularity of smart home technologies is increasing, understanding usage patterns enables the integration of smart HVAC systems. These systems can learn user preferences and automatically adjust settings, providing a more convenient and comfortable living environment.
7. Policy and Planning: Governments and urban planners can benefit from understanding air conditioner usage patterns to develop effective policies related to energy conservation, sustainability, and urban planning. This information can contribute to the creation of energy-efficient buildings and also promote sustainable practices.

In conclusion, comprehending air conditioner usage patterns in residences is crucial for optimizing energy consumption, saving costs, reducing environmental impact, ensuring system maintenance, enhancing comfort, managing electrical loads, integrating smart technologies, and informing policy and planning decisions.

5.2. Methodology

The AC usage analysis was conducted in the following settings:

- Summer analysis (1 May 2023 to 30 Jun 2023)
  - Number of homes with ACs monitored (N): 13
  - Number of ACs monitored: 15
  - Total number of occupants in the homes: 48
  - Daily average AC usage profile with respect to the time of day created at 30-minute intervals.
- Winter analysis (1 Nov 2023 to 30 Nov 2023)
  - Number of homes with ACs monitored (N): 9
  - Number of ACs monitored: 10

- Total number of occupants in the homes: 31
- Daily average AC usage profile with respect to the time of day created at 30-minute intervals.

- Usage time trends with respect to daily average temperature.
- Electrical energy consumption trends with respect to daily average temperature.

5.3. Summer Analysis

The summer usage profile of the air conditioners monitored in 13 homes is given in figure 16.

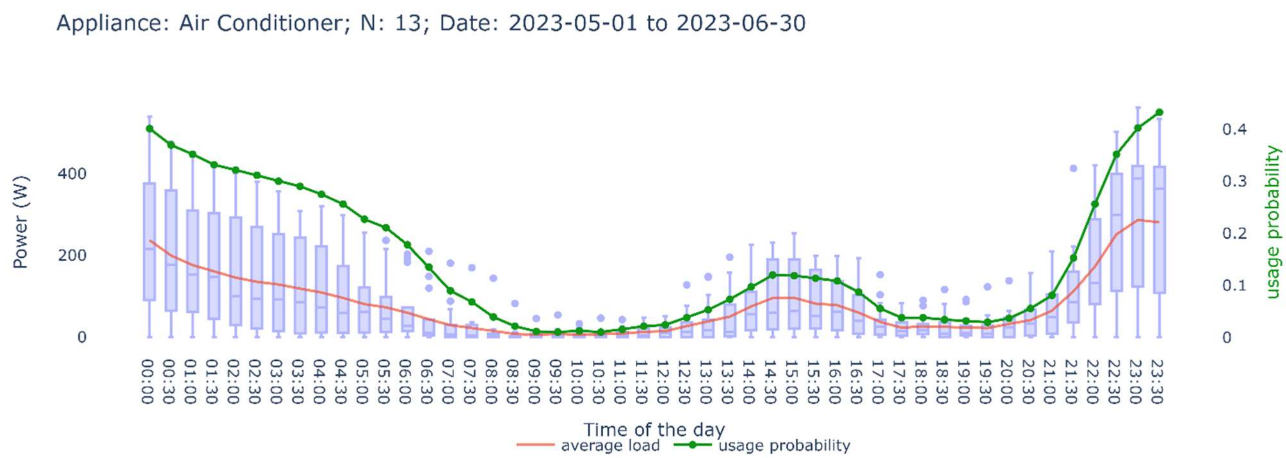

Figure 16: Summer usage profile of ACs (N: number of homes).

From the figure, it can be seen that most of the AC usage is concentrated during the nighttime, and the peak usage occurs around 11:30 PM with approximately 0.4 usage probability. The average load around this time period was found to be approximately 280.5 W per home. A brief daytime peak was also observed between 2:00 PM and 4:30 PM. The peak usage probability during this period was around 0.12, and the peak average load per AC was 95.12 W.

5.4. Winter Analysis

Figure 17: Winter usage profile of ACs (N: number of homes).

Figure 17 shows the usage profile of ACs in nine homes during winter in Hyderabad. It can be clearly inferred from the graph that AC usage significantly declines in the winter. The maximum usage probability was found to be less than 0.05, which is almost negligible. However, there are very few instances when the AC was operated. This can be attributed to Hyderabad's arid climate, where sometimes there are days warmer and more humid than usual. ACs are required to ensure the user's thermal comfort during these conditions.

5.5. Trends in AC Usage Time

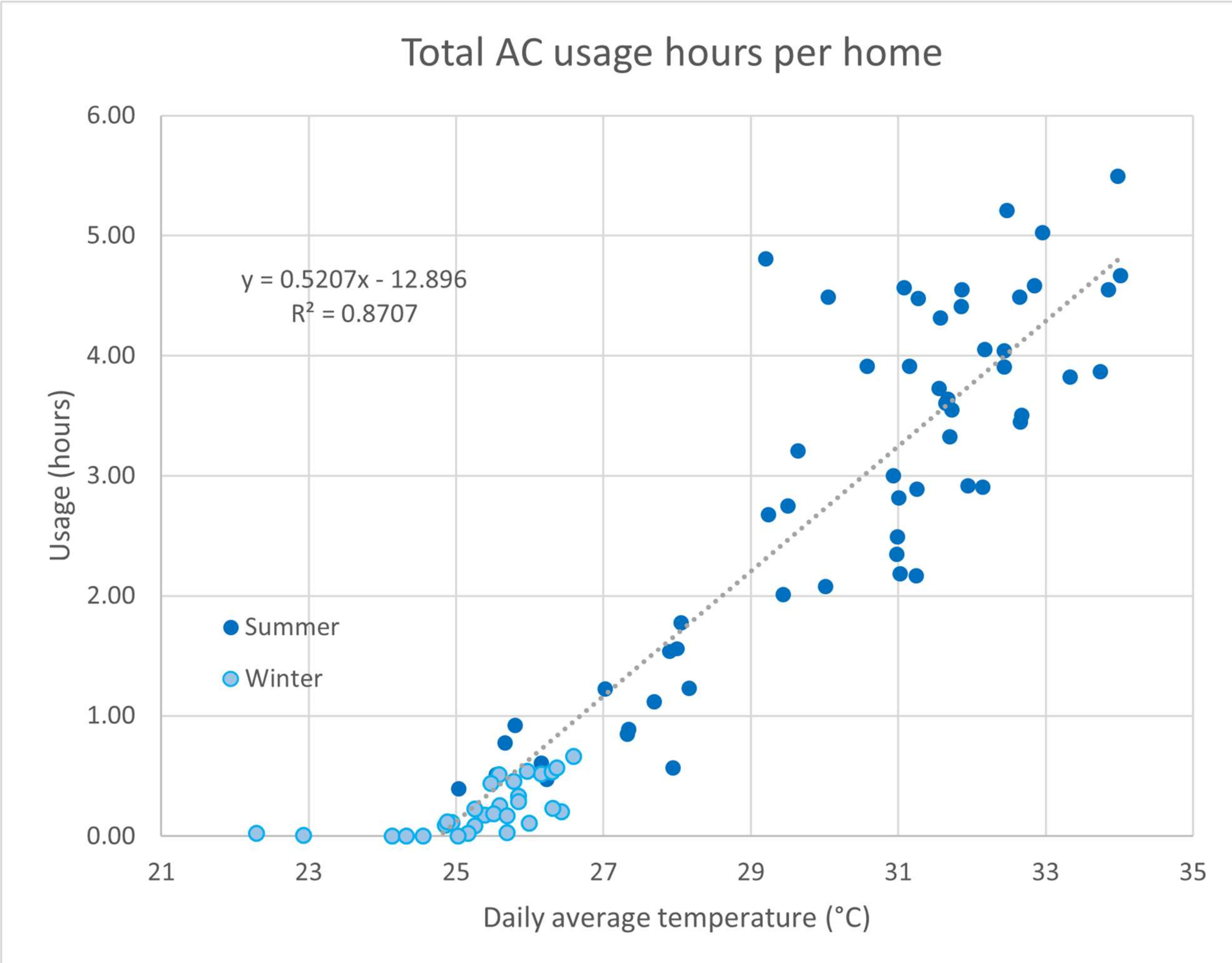

Figure 18: Total AC usage hours per home v/s daily average temperature.

Figure 18 shows the relation between the total AC usage hours per home and the daily average temperature. The trends show a positive correlation between the total usage hours per home and the daily average temperature. The Equation of the regression line in Equation (5) shows a positive slope, stating that a 1 °C increase in daily average temperature results in an increase in AC usage by 0.5 hours per home in Hyderabad. Subsequently, negligible AC usage occurs when the daily average temperature is less than 25 °C.

$$y = 0.5207x - 12.896 \qquad \ldots(5)$$

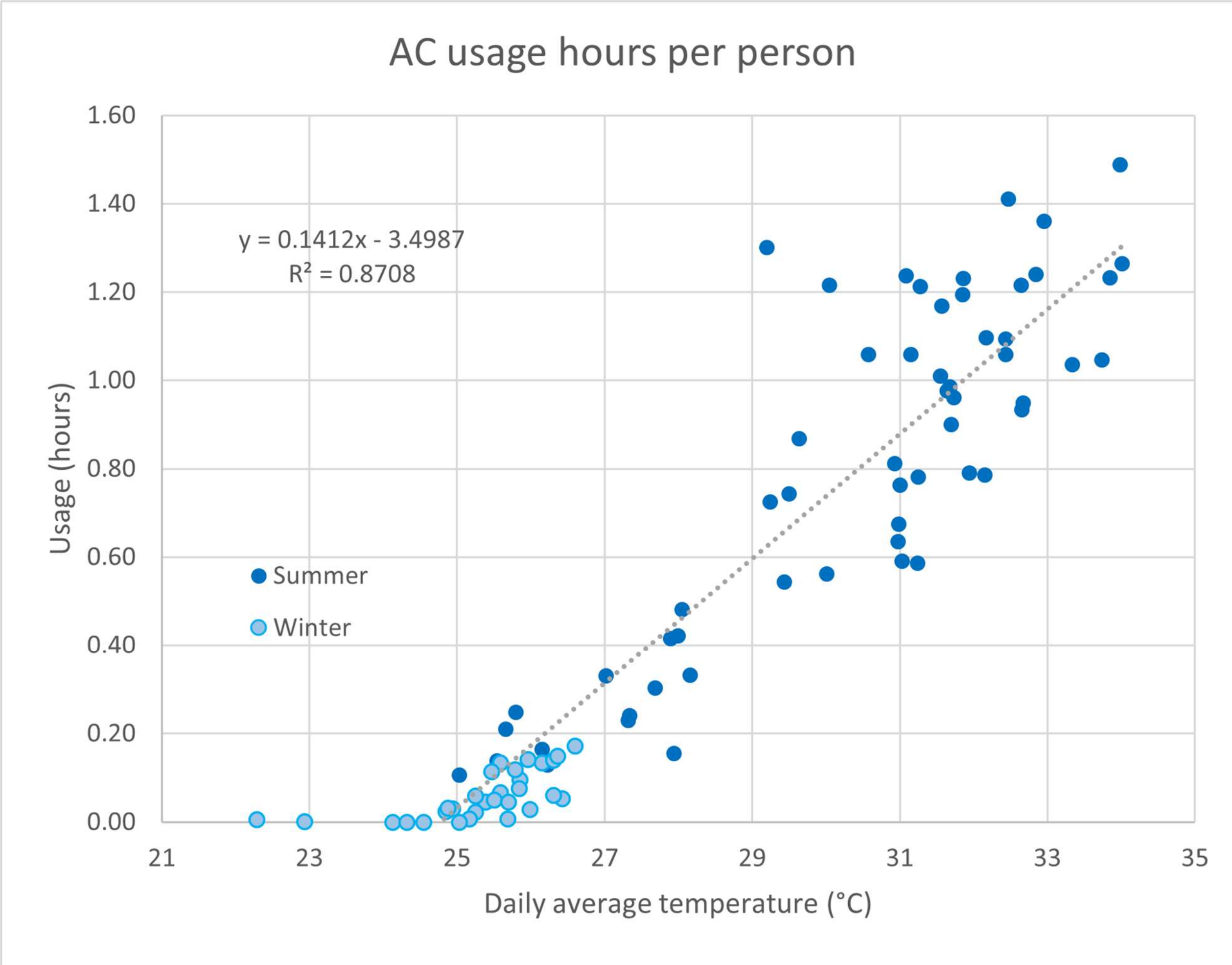

Figure 19: AC usage hours per person v/s daily average temperature.

Figure 19 shows the trends in the AC usage hours per person and the daily average temperature. There is a positive correlation between the total usage hours per person and the daily average temperature. The Equation of the regression line in Equation (6) shows a positive slope, stating that a 1 °C increase in daily average temperature results in an increase in AC usage by 8 minutes per person in Hyderabad. AC usage is approximately negligible when the daily average temperature is less than 25 °C.

$$y = 0.1412x - 3.4987 \qquad \ldots(6)$$

5.6. Trends in AC Energy Consumption

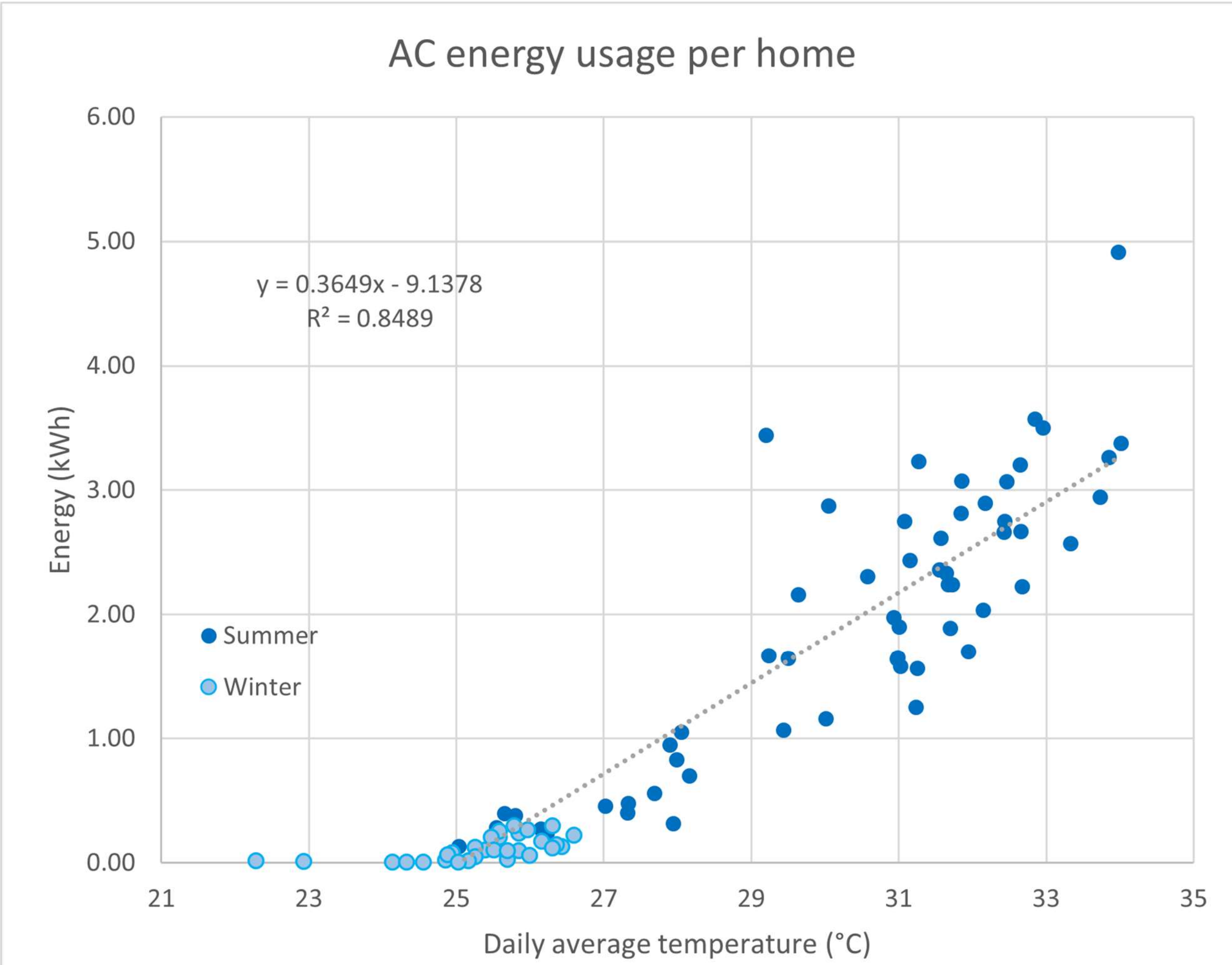

Figure 20: AC energy usage per home v/s daily average temperature

In Figure 20, the daily average AC energy consumption per home exhibits a positive correlation with the daily average temperature. The regression line given in Equation (7) describes the AC energy consumption trends per home. It shows that 1 °C rise in the daily average temperature tends to increase AC energy consumption per home by approximately 0.4 kWh in dwellings in Hyderabad. The figure shows that the AC usage is negligible below the daily average temperature of 25 °C.

$$y = 0.3649x - 9.1378 \quad \ldots(7)$$

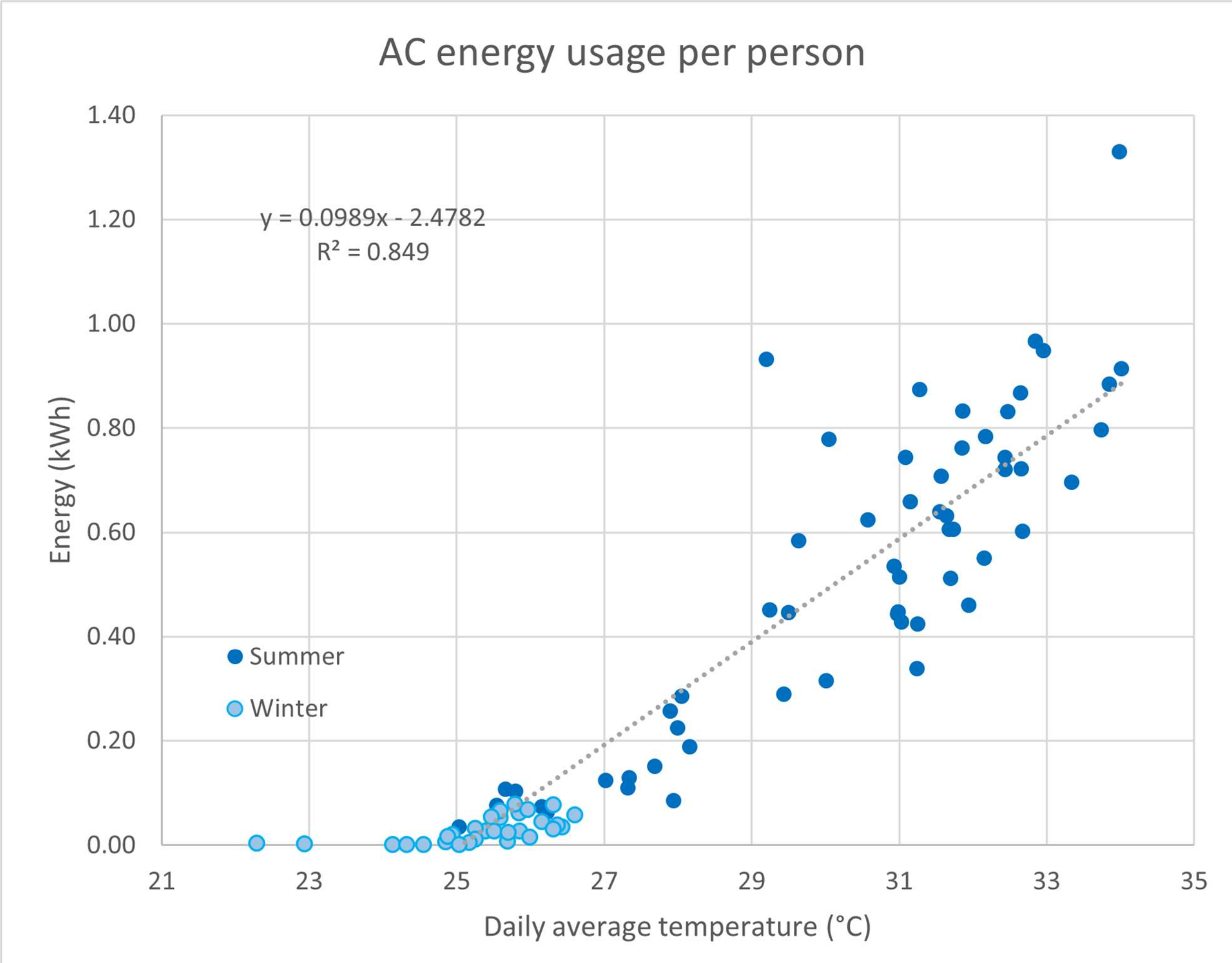

Figure 21: AC energy usage per person v/s daily average temperature.

The daily average AC energy consumption per person exhibits a positive correlation with the daily average temperature, as shown in Figure 21. The regression line given in Equation (8) describes the AC energy consumption trends per person. It shows that 1 °C rise in the daily average temperature tends to increase AC energy consumption per person by approximately 0.1 kWh in dwellings in Hyderabad. The figure shows that the AC usage is negligible below the daily average temperature of 25 °C.

$$y = 0.0989x - 2.4782 \qquad \ldots(8)$$

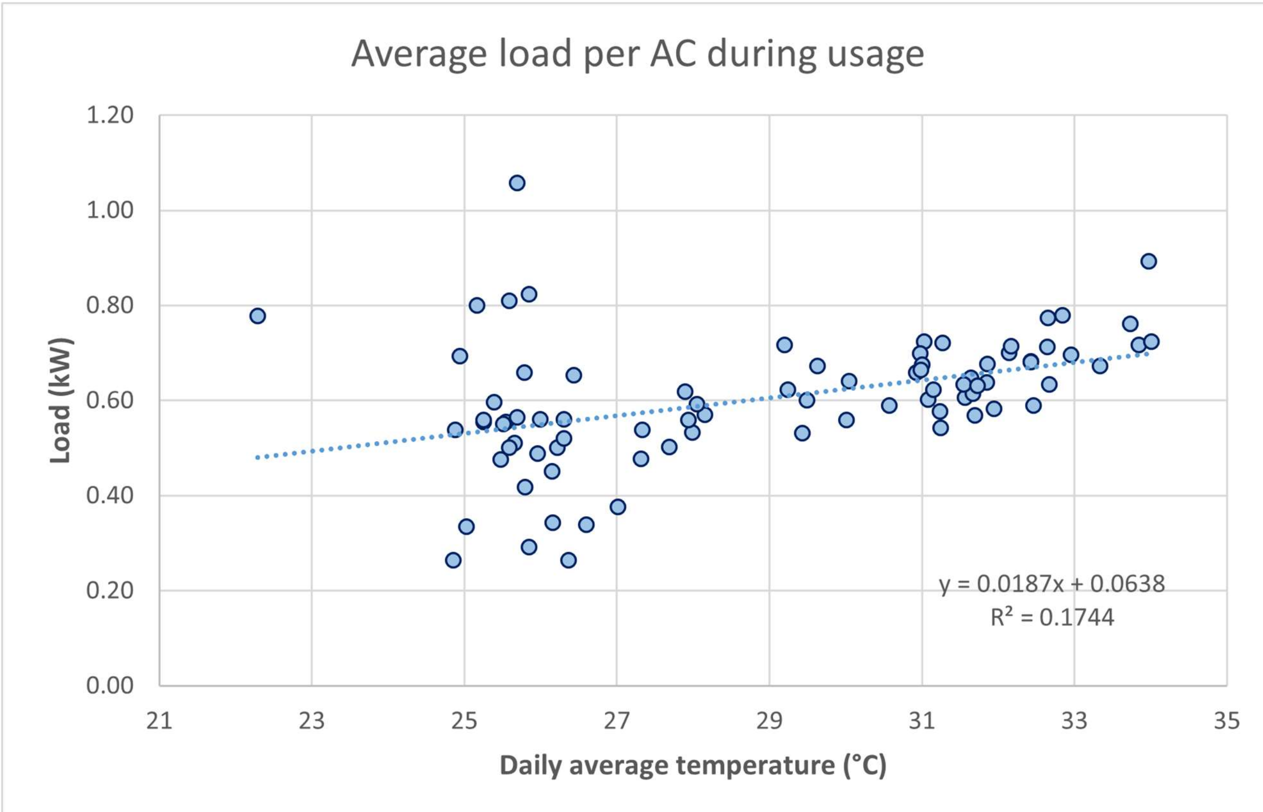

Figure 22: Average load per AC during usage v/s daily average temperature.

Figure 22 shows the average load imparted per AC with respect to the daily average temperature. The regression line given in Equation (9) describes the average load per AC during usage. It shows that an average load of approximately 600 W per AC is observed during usage.

$$y = 0.0187x - 0.0638 \qquad \ldots(9)$$

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Chapter 6

6. GEYSER USAGE PATTERNS

6.1. Introduction

In today's world of residential living, the role of geysers (domestic water heaters) goes beyond just being convenient. They play an important role in saving energy, reducing costs, conserving water, and being environmentally responsible. To use these essential appliances efficiently, it is important to have a deep understanding of when and how residents use their geysers. This knowledge allows homeowners to make informed choices that not only optimize energy consumption and save money but also contribute to broader sustainability efforts. From prolonging the lifespan of appliances to incorporating smart technologies, understanding the usage patterns of geysers is crucial in attaining a sustainable equilibrium between modern comforts and responsible living. This introduction lays the groundwork for exploring the various reasons why understanding water heater usage patterns is crucial in shaping contemporary residential practices.

Understanding how residents use geysers in their homes is crucial for a variety of reasons.

1. Energy Efficiency: Having knowledge of when and how residents use geysers allows for the optimisation of energy consumption. By identifying times of peak usage, homeowners can adjust their habits or explore alternative water heating solutions, resulting in increased energy efficiency and lower utility bills.
2. Cost Savings: Efficient use of geysers can lead to significant cost savings. By understanding usage patterns, residents can implement strategies such as using hot water during less busy times or installing energy-efficient water heaters to reduce their overall energy expenses.
3. Water Conservation: Monitoring geyser usage patterns is closely linked to water conservation efforts. Knowing when there is a high demand for hot water allows residents to adopt water-saving practices, such as using low-flow fixtures or insulating water pipes, which contribute to overall water conservation efforts.

4. Appliance Longevity: Regular and proper maintenance is crucial for ensuring the long lifespan of geysers. Understanding usage patterns helps homeowners schedule maintenance tasks effectively, ensuring that the water heating system operates efficiently and experiences fewer breakdowns.
5. Comfort Optimisation: Understanding when residents typically need hot water enables better planning to meet their comfort needs. Whether it is for morning showers or evening dishwashing, optimising geyser usage patterns contributes to a consistently comfortable living environment.
6. Smart Home Integration: Similar to air conditioning systems, understanding geyser usage allows for the integration of smart home technologies. Smart geysers can adapt to usage patterns, learning when hot water is required and adjusting settings automatically, providing convenience and energy savings.
7. Environmental Impact: Inefficient geyser usage can result in unnecessary energy consumption and environmental impact. For the residents to make informed decisions to reduce their carbon footprint, it is imperative to understand geyser usage patterns. Adapting necessary habits with the help of insights gathered from usage patterns can lead them to contribute to a more sustainable living environment.
8. Load Management: Large-scale patterns of geyser usage in a community can affect the overall water infrastructure. Understanding these patterns helps utility companies manage water supply and distribution more effectively, reducing strain on local water resources.
9. Policy and Planning: Governments and city planners can benefit from understanding water heater usage patterns to develop effective water conservation policies, promote sustainable practices, and plan for resilient water infrastructure.

In summary, comprehending how residents use geysers in their homes is crucial for optimizing energy consumption, reducing costs, conserving water, ensuring the longevity of appliances, enhancing comfort, integrating smart technologies, minimizing environmental impact, managing water infrastructure, and informing policy and planning decisions.

6.2. Methodology

The geyser usage analysis was conducted in the following settings:

- Summer analysis (1 May 2023 to 30 Jun 2023)
    - Number of homes monitored with geysers (N): 19
    - Number of geysers monitored: 27
    - Total number of occupants in homes: 74
    - Daily average geyser usage profile with respect to the time of day created at 30-minute intervals.
- Winter analysis (1 Nov 2023 to 30 Nov 2023)
    - Number of homes monitored with geysers (N): 12
    - Number of geysers monitored (N): 16
    - Total number of occupants in homes: 46
    - Daily average geyser usage profile with respect to the time of day created at 30-minute intervals.
- Usage time trends with respect to daily average temperature.
- Electrical energy consumption trends with respect to daily average temperature.

6.3. Summer Analysis

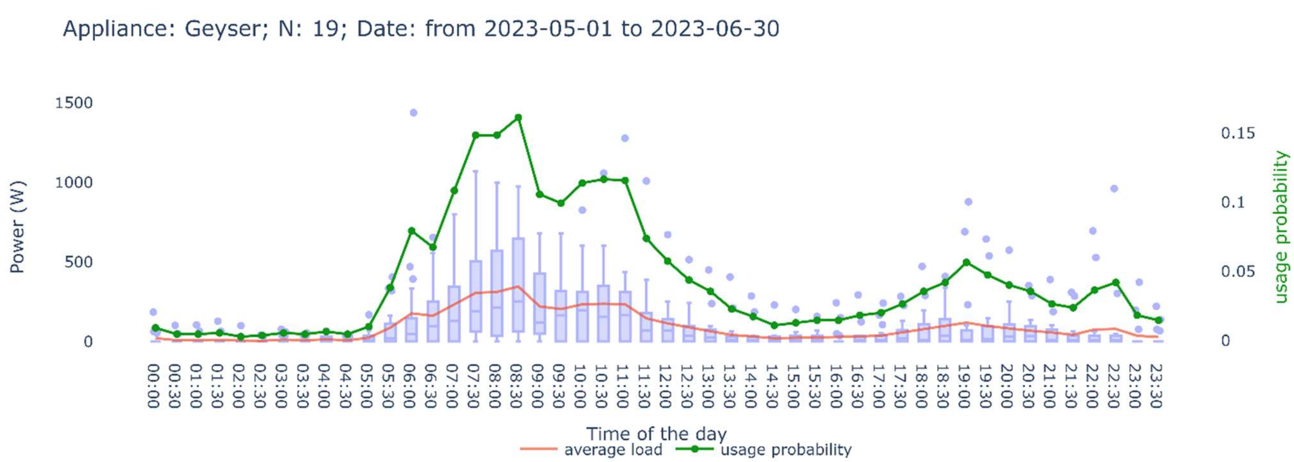

Figure 23: Summer usage profile of geysers (N: number of homes).

Figure 23 depicts the usage profile of geysers in 19 homes during summer in the year 2023. As shown in the figure, most of the geyser usage is concentrated in the daytime between 7:00 AM and 11:00 AM. The peak usage was observed around 8:30 AM, and the usage probability at this time was approximately 0.16. The average load by geysers turned out to be approximately 257.94 W per home during this peak period. A small peak in usage occurred in the evening around 7:00 PM. The usage probability during the evening peak was approximately 0.05, and the average load by geysers was 118.2 W per home. Even though the geyser usage probability seems to be small during peak usage time, the geyser was utilized significantly even during the summers. This can be seen in the usage profile, which shows that the usage is spread between 6:30 AM and 11:00 AM. Hence, it can be inferred that the dwellers prefer to use geysers in this time range. It is to be noted that this usage in consistent in the Hyderabad region and cannot be generalized across India.

6.4. Winter Analysis

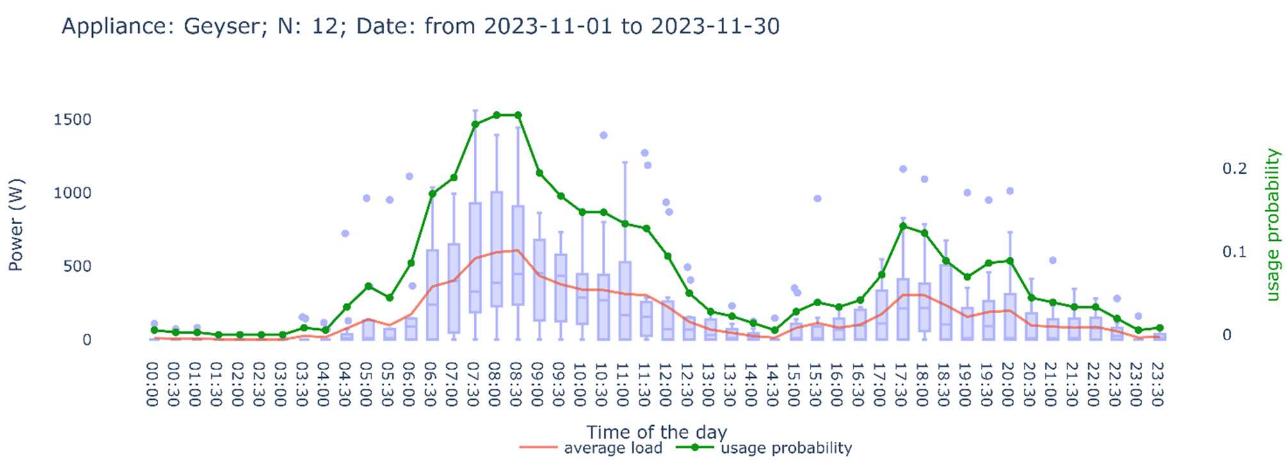

Figure 24: Winter usage profile of geysers (N: number of homes).

The winter usage profile of geysers in 12 homes can be seen in Figure 24. The usage is spread between 6:30 AM and 11:30 AM in the morning. The peak usage in the morning was found at 8:30 AM, with an average load of 606 W per home. The usage probability observed at the morning peak usage was approximately 0.26. Some dwellers also preferred to use geysers in the evening as well between 5:00 PM and 8:00 PM. The evening peak usage was observed at 5:30 PM. The average load during this period was 303.4 W per home, and the associated usage probability was approximately 0.13. A significant increase in geyser usage was observed in the winter as compared to summer, especially in the evening usage. It can be observed from the usage profiles that the spread of usage is almost similar in both winter and summer, even though the usage is increased in winter.

6.5. Trends in Geyser Usage Time

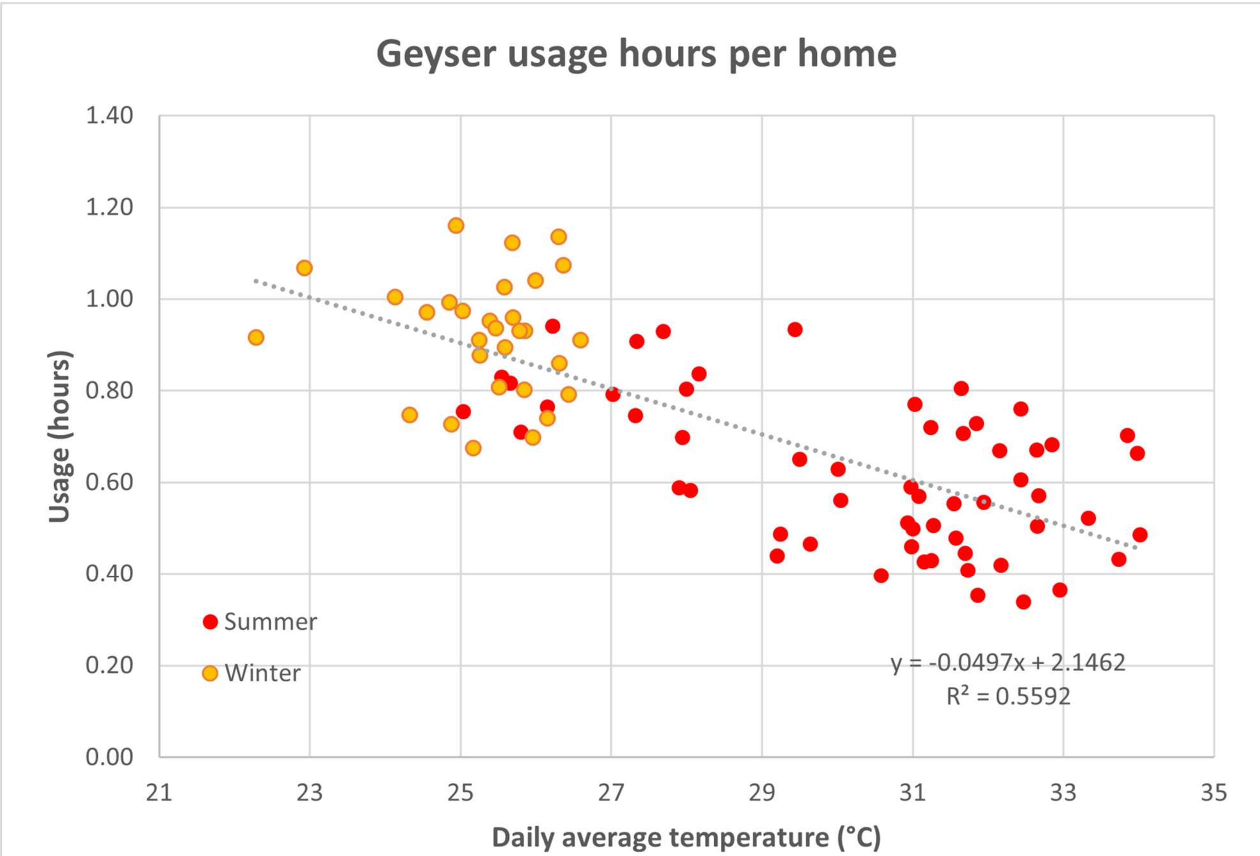

Figure 25: Geyser usage hours per home v/s daily average temperature.

As can be seen from Figure 25, the daily average usage time (hours) per home of the geyser exhibits a negative correlation with the daily average temperature. Hence, it can be inferred that the geyser usage time reduces with the increase in daily average temperature. The usage time trends can be described by Equation (10), which denotes that a 1 °C rise in the daily average temperature can reduce the geyser usage time by approximately 3 minutes.

$$y = -\,0.0497x + 2.1462 \qquad \ldots(10)$$

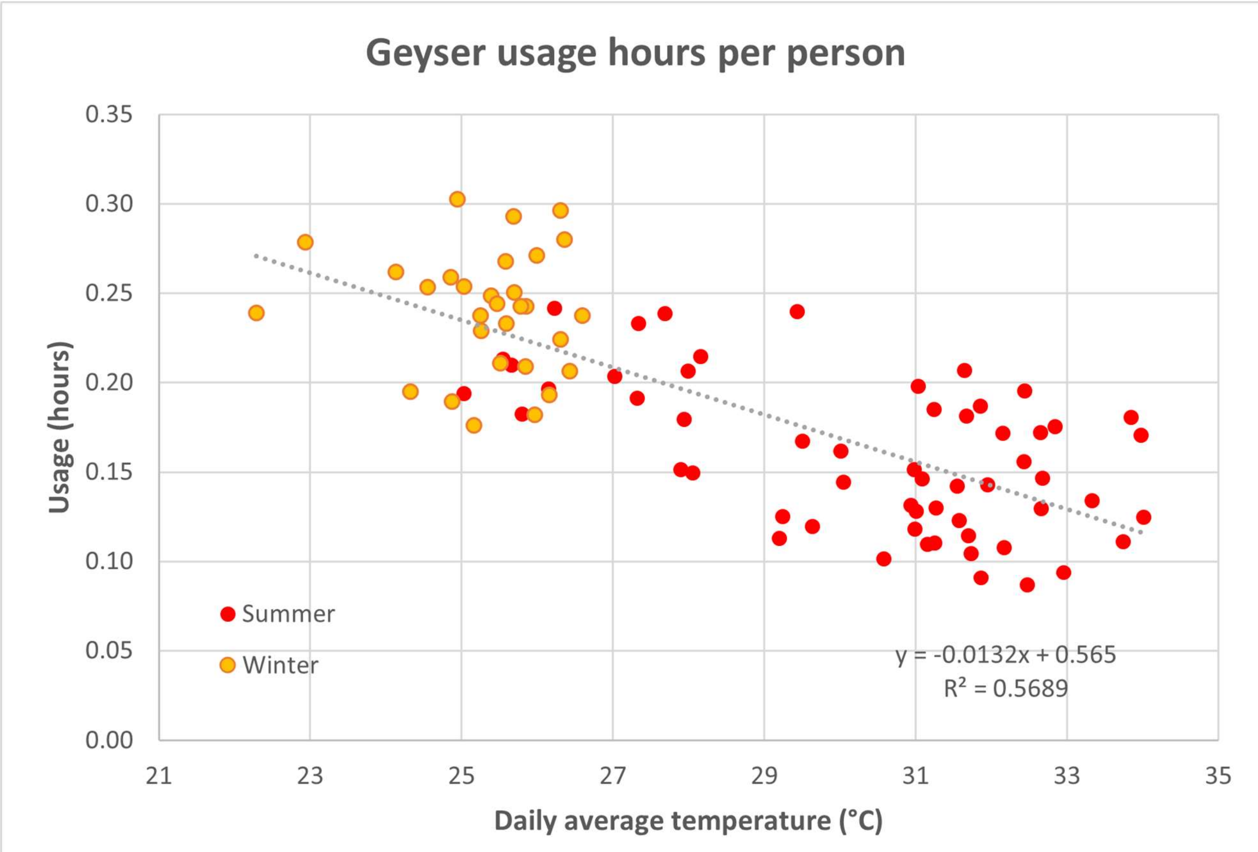

Figure 26: Geyser usage hours per person v/s daily average temperature.

Figure 26 shows the daily average usage time (hours) per person of geyser exhibiting a negative correlation with the daily average temperature. It can be inferred from the figure that the geyser usage time per person reduces with the increase in daily average temperature. The usage time per person trends can be described by Equation (11), which denotes that a 1 °C rise in the daily average temperature can reduce the geyser usage time per person by approximately 1 minute.

$$y = -\,0.0132x + 0.565 \qquad \ldots(11)$$

6.6. Trends in Geyser Energy Consumption

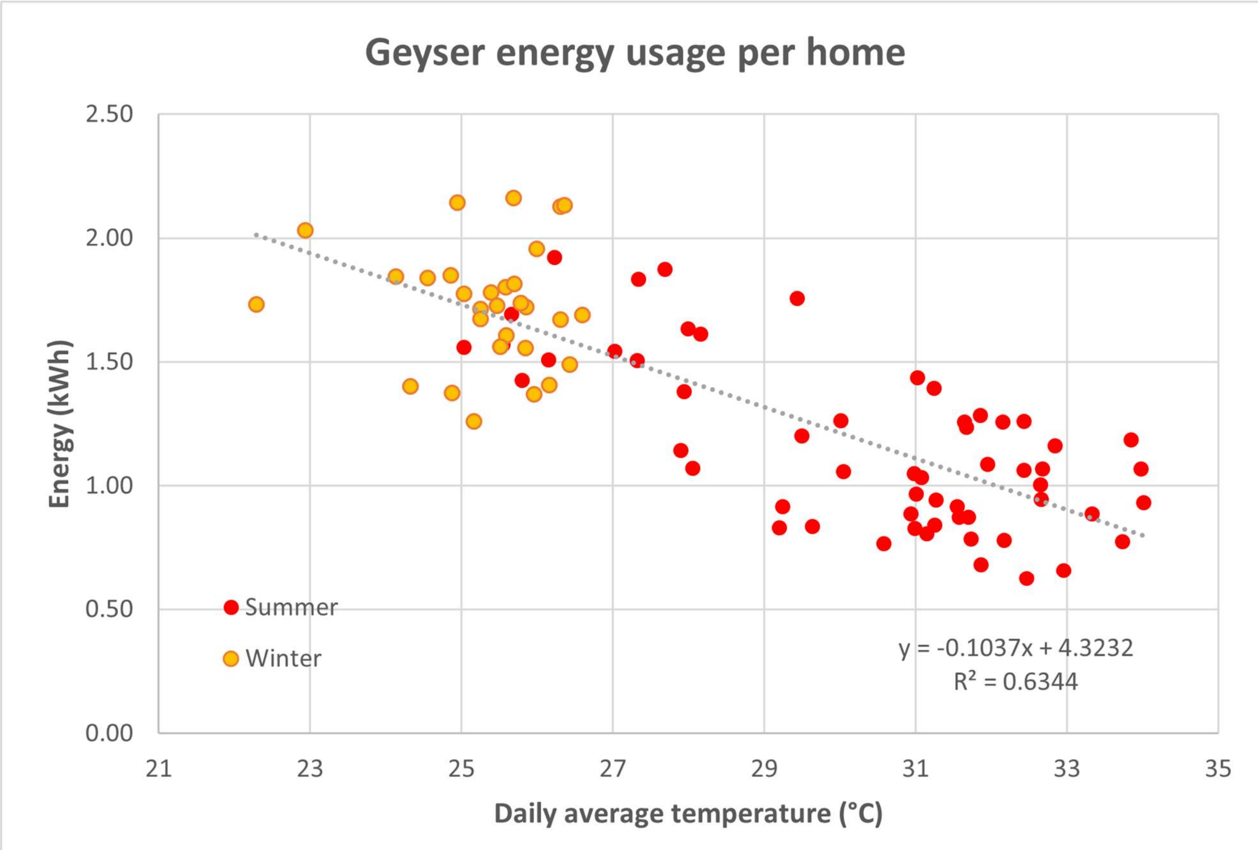

Figure 27: Daily average geyser energy consumption per home v/s daily average temperature.

Figure 27 shows the trends in the geyser energy consumption per home with respect to the daily average temperature. The correlation between the daily average energy consumption and the daily average temperature is negative. Equation (12) represents the regression line of the plot. It suggests that a 1 °C rise in the daily average temperature can lead to approximately 0.1 kWh reduction in the geyser energy consumption.

$$y = -0.1037x + 4.3232 \qquad \ldots(12)$$

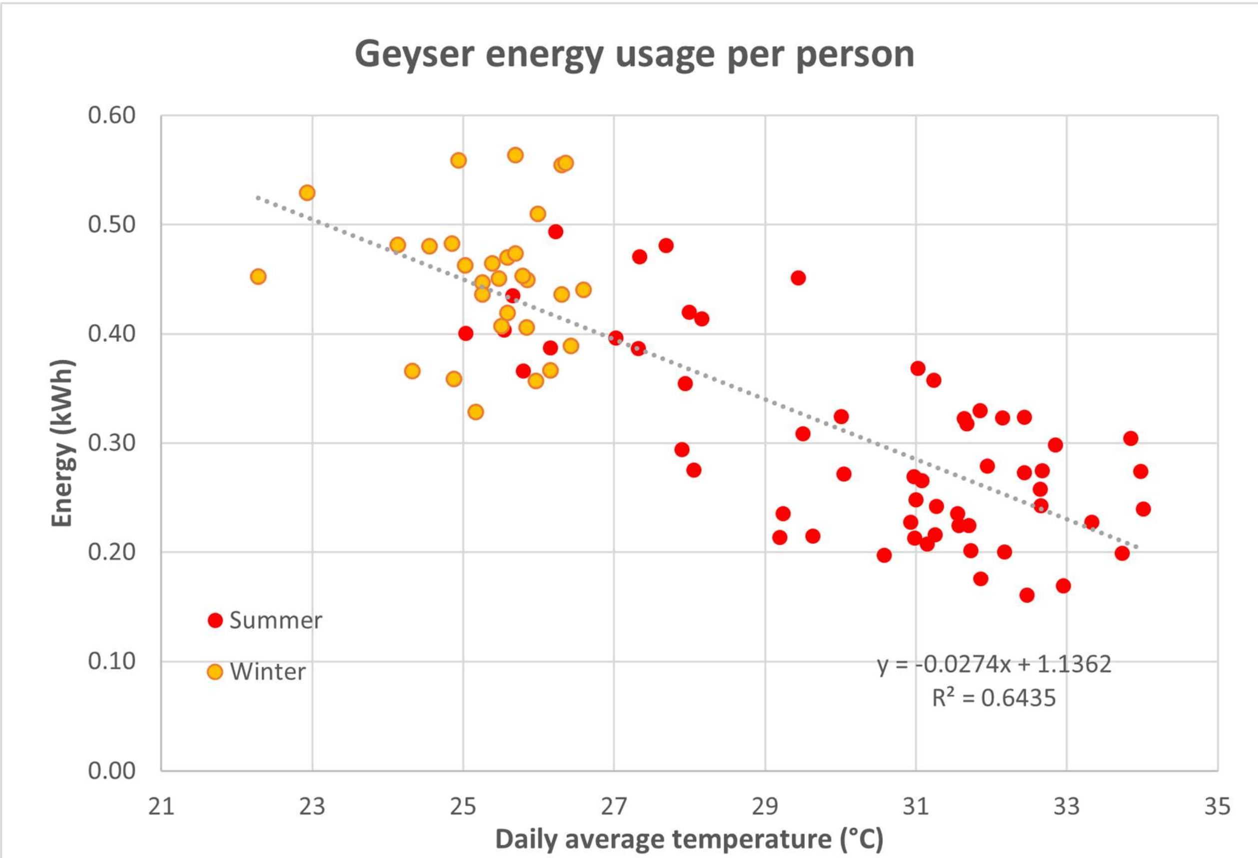

Figure 28: Daily average geyser energy consumption per person v/s daily average temperature.

The trends in the geyser energy consumption per person with respect to the daily average temperature can be seen in Figure 28. The daily average geyser energy consumption per person and the daily average temperature exhibits a negative correlation. Equation (13) represents the regression line of the plot. It suggests that a 1 °C rise in the daily average temperature can lead to approximately 0.02 kWh reduction in the geyser energy consumption per person.

$$y = -\,0.0274x + 1.1362 \qquad \ldots(13)$$

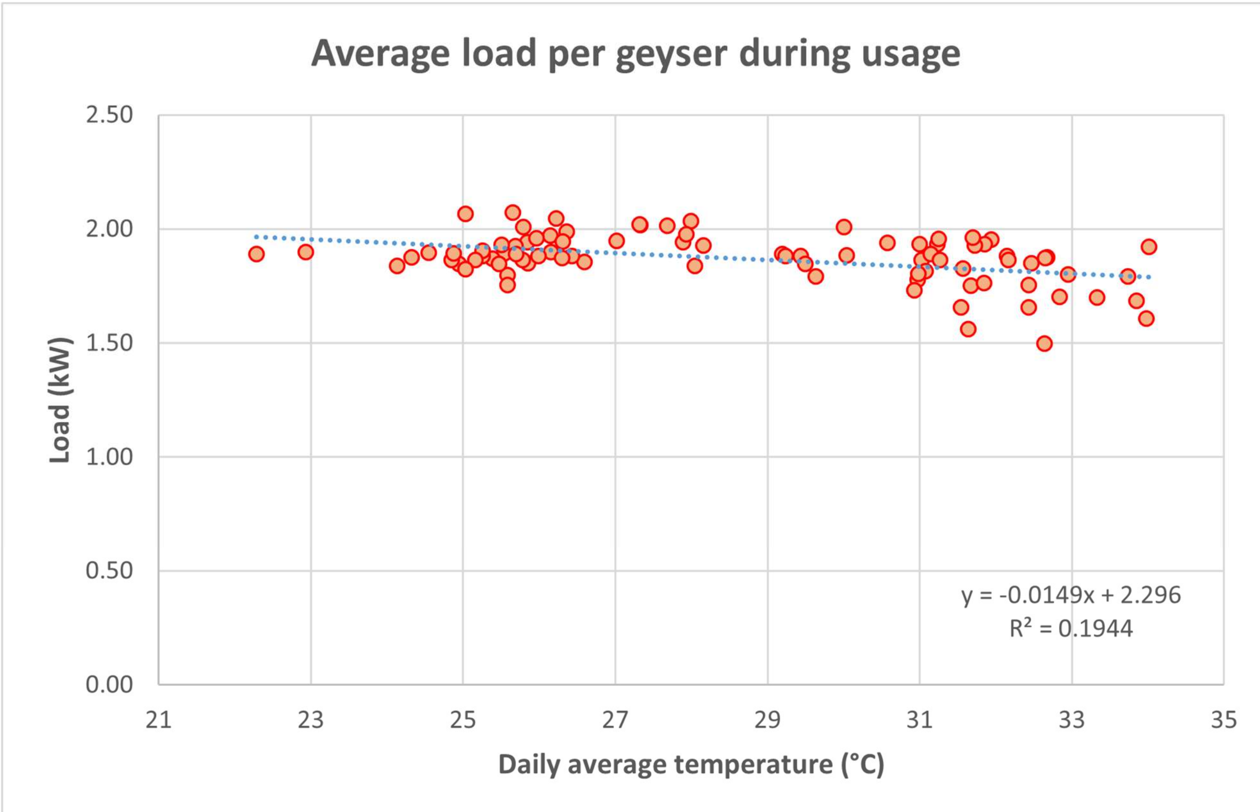

Figure 29: Average load per geyser during usage v/s daily average temperature.

Figure 29 shows the average load imparted per geyser with respect to the daily average temperature. The regression line given in Equation (14) describes the average load per geyser during usage. It shows that an average load of approximately 1.87 kW per geyser is observed during usage.

$$y = 0.0149x - 2.296 \qquad \ldots(14)$$

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Chapter 7

7. APPLIANCE USAGE PROFILES

7.1. Introduction

In the contemporary landscape of residential living, the way households interact with their appliances holds profound significance, influencing factors ranging from energy efficiency to environmental sustainability. This understanding is pivotal for homeowners, guiding them in optimizing energy consumption, minimizing costs, and ensuring the longevity of essential household devices. The intricate patterns of appliance usage also extend their impact to broader societal considerations, influencing policies, smart technology integration, and even the overall efficiency of electrical grids. As we delve into the multifaceted reasons behind comprehending these usage patterns, it becomes clear that this knowledge is integral not only to individual households but to the collective pursuit of a more sustainable, efficient, and technologically advanced future.

Understanding how household appliances are used is of great importance for several reasons:

1. Energy Efficiency: Having knowledge about the timing and manner in which appliances are used enables homeowners to optimise their energy usage. By identifying the periods of highest usage, they can modify their habits, make use of energy-saving configurations, or upgrade to more efficient appliances. This leads to less energy wastage and a decrease in utility bills.
2. Cost Savings: Efficient use of household appliances leads to reduced utility expenses. Understanding usage patterns allows residents to make informed decisions about when to use specific appliances, minimising energy usage during peak rate periods and ultimately saving money.
3. Appliance Longevity: Proper usage and maintenance are vital for the lifespan of household appliances. Understanding usage patterns helps homeowners schedule maintenance effectively, ensuring that appliances operate optimally and have a longer lifespan.
4. Environmental Impact: Inefficient appliance usage contributes to higher energy consumption and environmental degradation. Understanding usage patterns allows

residents to adopt eco-friendly practices, which will eventually reduce their carbon footprint and help them contribute to sustainability efforts.

5. Smart Home Integration: Understanding how appliances are used is essential for integrating smart technologies. Smart appliances can learn usage patterns, automatically adjust settings, and even communicate with other devices to optimise energy efficiency and convenience.
6. Load Management: The patterns of large-scale appliance usage affect local electrical grids. Utilities can manage peak loads more effectively by understanding when certain appliances are commonly used. This reduces strain on the grid and the risk of blackouts.
7. Comfort and Convenience: Understanding usage patterns ensures that appliances are available when needed, enhancing overall comfort and convenience within the household.
8. Data for Improvement: Manufacturers can use data on usage patterns to improve appliance design and functionality, creating more efficient and user-friendly products.
9. Policy and Planning: Governments and energy agencies can utilise data on appliance usage to develop policies, incentives, and regulations which will promote energy efficiency and reduce overall energy consumption at a broader societal level.

In summary, understanding how household appliances are used is crucial for optimizing energy consumption, reducing costs, extending appliance lifespans, minimizing environmental impact, integrating smart technologies, managing electrical loads, enhancing comfort and convenience, fostering product innovation, and informing energy-related policies and planning.

7.2. Summer Usage Profiles

7.2.1. Refrigerator

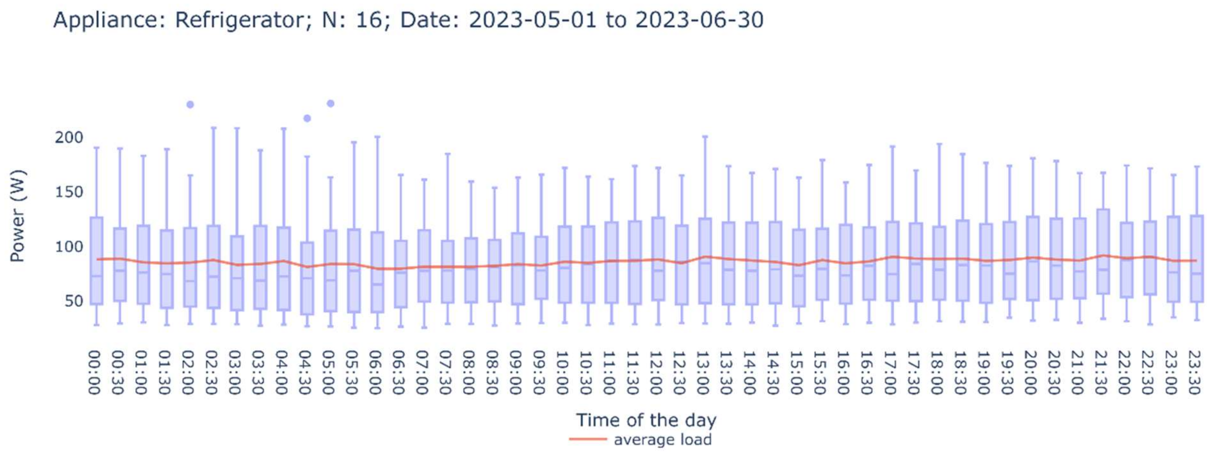

Figure 30: Refrigerator load profile in the summer.

Figure 30 shows the refrigerator load profile during the summer for sixteen refrigerators. It can be clearly seen from the figure that the refrigerator imparts an almost constant load throughout the day. The usage probability of the refrigerator is not calculated as the appliance's power is turned on throughout the day. The average load per refrigerator was found to be 85.94 W.

7.2.2. Television

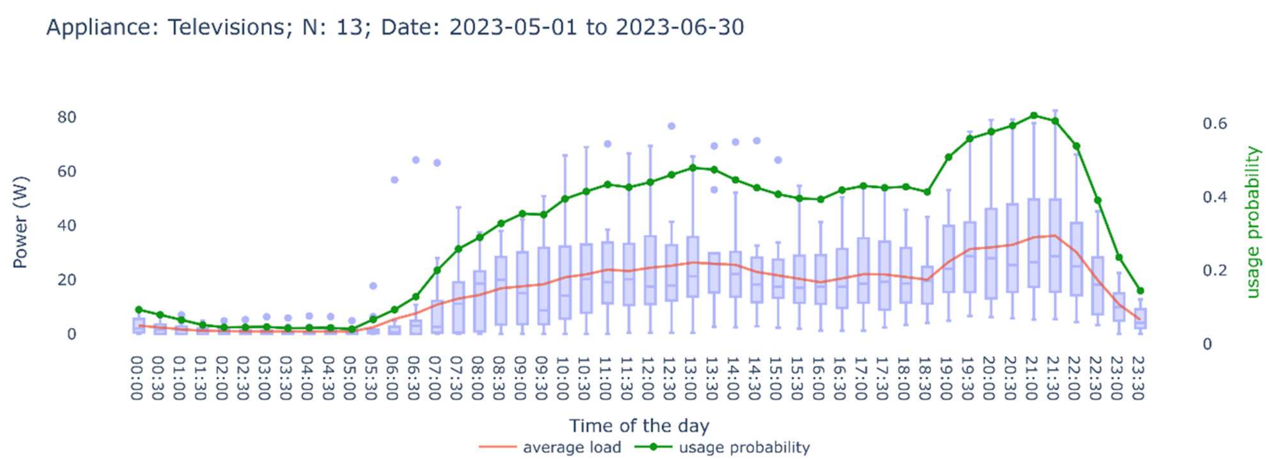

Figure 31: Television load profile in the summer.

The load profile of the thirteen televisions during the summer can be seen in Figure 31. It can be inferred from the figure that the television is mostly operated around 8:30 AM in the morning till 10:30 PM at night. The highest usage was observed between 7:30 PM and 10:00 PM, and the average usage probability was approximately 0.6. The average load was 33.02 W during this period.

7.2.3. Washing Machine

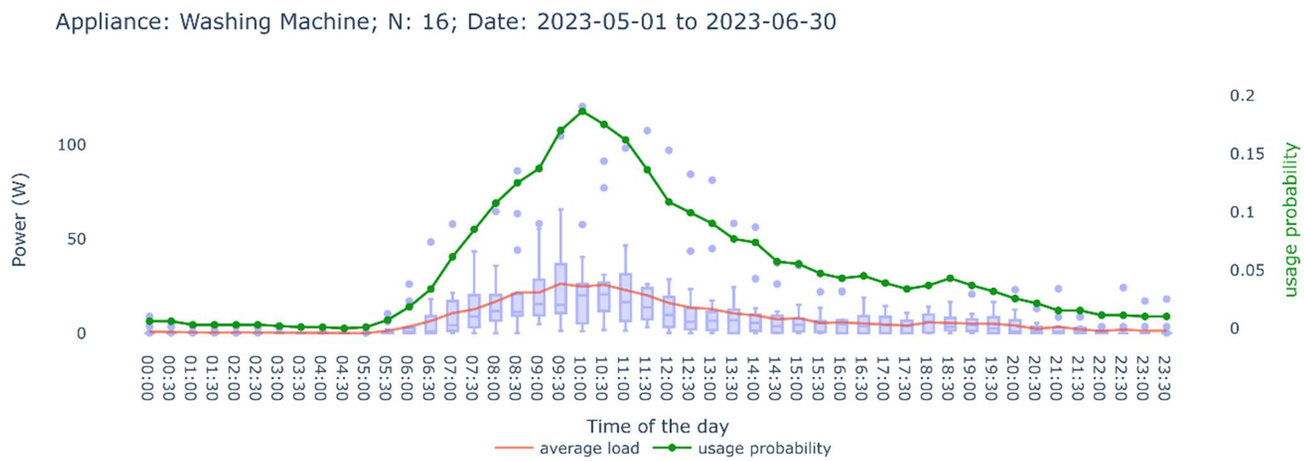

Figure 32: Washing machine load profile in the summer.

As can be seen from the load profile of sixteen washing machines in Figure 32, they are mostly operated in the morning between 9:00 AM and 11:30 AM. The highest usage was observed around 10:00 AM, exhibiting approximately 0.2 probability of use. This indicates that users use washing machines almost every other week.

7.2.4. Water Purifier

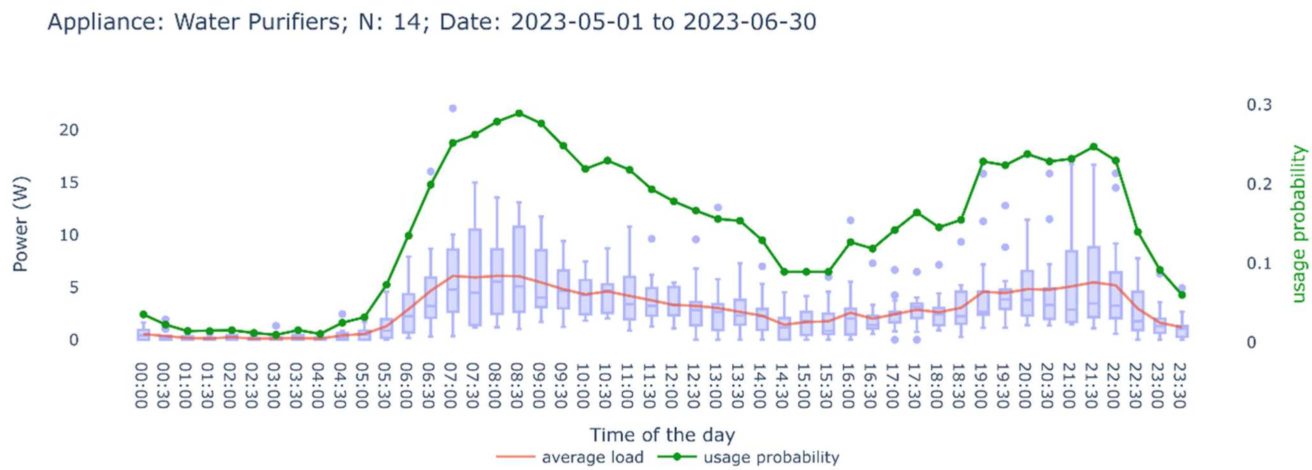

Figure 33: Water purifier load profile in the summer.

Figure 33 shows the load profile of fourteen water purifiers. Although the water purifier usage is spread across the day, two peaks can be observed from the figure during morning and the evening. High water purifier usage is found to be occurring around these peaks. The morning peak is observed around 8:30 AM with approximately 0.2 usage probability. The average load per water purifier was 6.05 W during this timestep. This nearly corresponds to the start of a day in a typical household. On the other hand, the evening peak is observed between 7:00 PM and 10:00 PM, exhibiting an average usage probability of 0.23. The average load per water purifier was 4.9 W during this period.

7.3. Winter Usage Profiles

7.3.1. Refrigerator

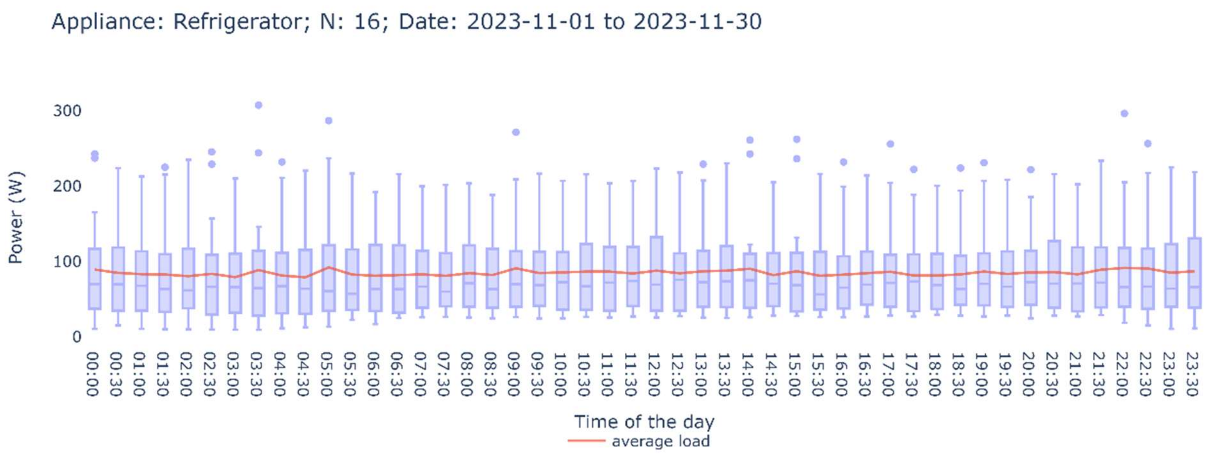

Figure 34: Refrigerator load profile in winter.

Figure 34 shows the refrigerator load profile during the winter for sixteen refrigerators. The average load per refrigerator was found to be 84.76 W. As can be seen from Figure 26 (summer refrigerator), there is no significant difference in the summer and winter usage of the refrigerator. This corresponds with the fact that the refrigerator is a non-shiftable appliance and is operated in the same capacity in the daily cycle.

7.3.2. Television

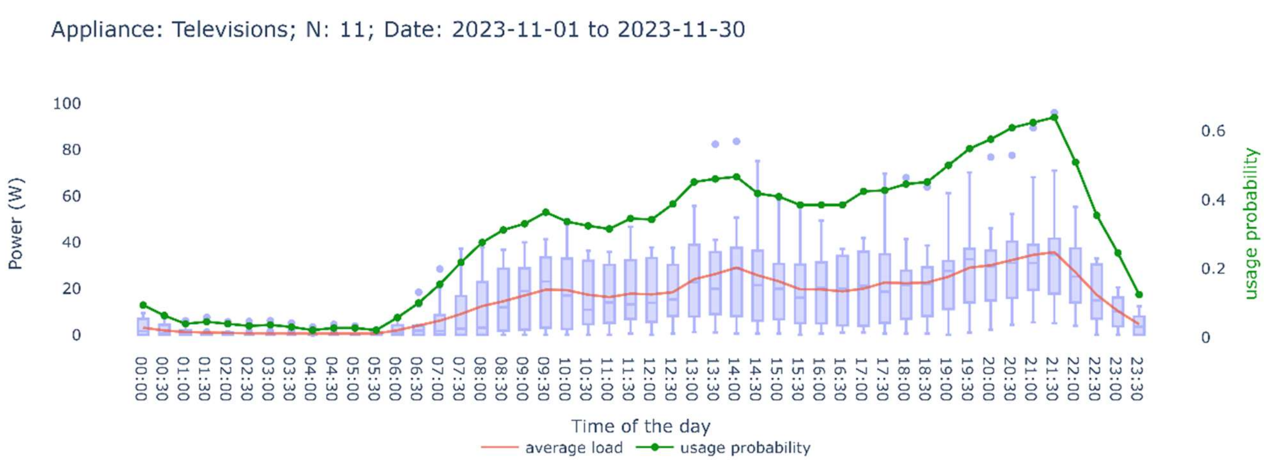

Figure 35: Television load profile in winter.

The load profile of the eleven televisions during the winter is visible in Figure 35. It can be deduced from the figure that televisions are mostly used from 8:30 AM in the morning until 10:30 PM at night. The peak usage occurs between 8:30 PM and 9:30 PM, with an average usage probability of approximately 0.62 and an average load of 34.24 W during this time period. It can be observed that the use of television during both summer and winter is similar, with the only difference being a slight reduction in usage during the nighttime in winter. This is because the residents tend to stop using the appliance a bit earlier during winter compared to summer.

7.3.3. Washing Machine

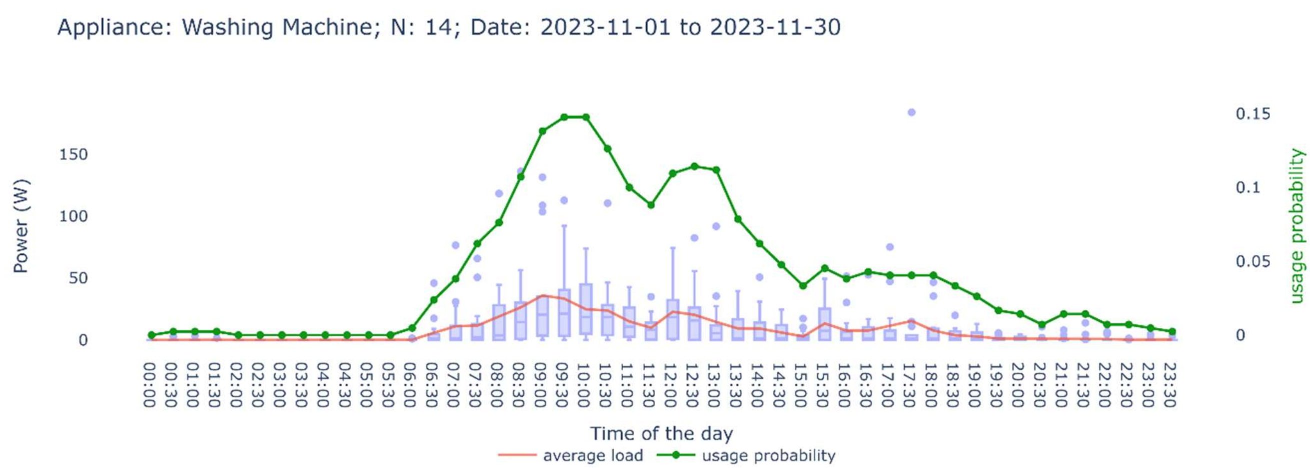

Figure 36: Washing machine load profile in winter.

As evident from the load profile displayed in Figure 36, the usage of 14 washing machines is predominantly distributed during the morning hours, specifically between 8:30 AM and 1:00 PM. The peak usage is observed between 9:30 AM and 10:00 AM, with an approximate probability of use of 0.14. It can be concluded from the figure that the usage of washing machines is slightly lower in winter compared to summer.

7.3.4. Water Purifier

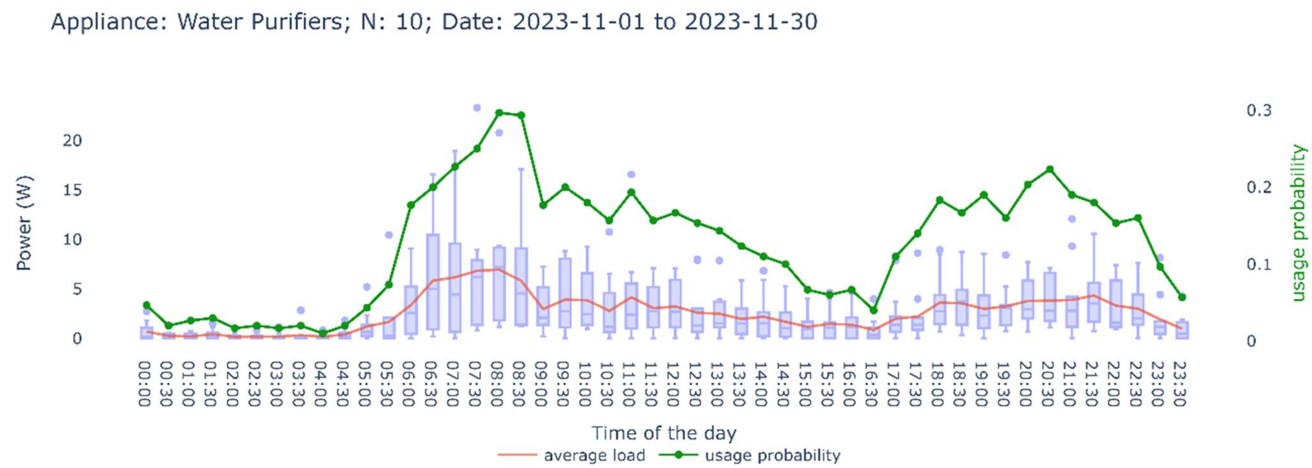

Figure 37: Water purifier load profile in winter.

The load profiles of ten water purifiers are displayed in Figure 37. The figure shows two distinct peaks in the morning and evening. Around these peaks, high appliance usage is observed. With a usage probability of about 0.3, the morning peak is observed at 8:00 AM. During this timestep, 6.9 W was the average load per water purifier. The evening peak, on the other hand, is seen between 6:00 PM and 9:30 PM and has an average usage probability of 0.18. During this time, 3.64 W was the average load per water purifier. The usage of water purifiers is implied to be somewhat higher in the morning and lower in the evening in the winter as opposed to the summer.

Chapter 8

8. DISCUSSIONS AND SCOPE

8.1. Discussions

The thesis depicts a study conducted at the household and appliance level. The objective was to gain insight into the patterns of electricity consumption in households during summer and winter through device level monitoring of home appliances in 21 homes in Hyderabad. At the household level, five homes with larger number of monitored appliances were monitored during the peak summer season for a period of 30 days. We achieved this by analyzing the load profiles of six regularly used major appliances: air conditioner, geyser, refrigerator, television, water purifier, and washing machine. Our findings reveal that these regularly used appliances collectively account for approximately 71% of the total electricity usage in a typical household. Among these appliances, air conditioners consume the most electricity, with 3.54 kWh consumed during off-peak solar hours and 0.83 kWh consumed during peak solar hours on a daily basis. It is important to note that Hyderabad receives an average of 7.48 hours of sunshine per day, with peak solar hours typically occurring between 10 AM and 4 PM. The daily average energy consumption of air conditioners can be reduced by approximately 10% (437 Wh) through various measures such as adjusting the setpoints to higher temperatures, using ceiling fans in conjunction with air conditioners, and utilizing air conditioners with higher energy efficiency ratios (EERs). Another possibility worth considering is the implementation of a district cooling system with thermal storage, as this has the potential to shift the majority of air conditioner usage to daytime hours. It is worth mentioning that residents tend to use geysers and washing machines during the peak solar hours of the peak summer season. The energy consumption of geysers during off-peak solar hours is 0.73 kWh per household, which can be shifted to peak solar hours. By shifting the usage of geysers and washing machines entirely to peak solar hours, the daily energy usage per household can be redirected by 1.21 kWh. Furthermore, by replacing geysers with heat pumps, it is possible to reduce the energy consumption of geysers to one-third of the current daily usage, resulting in only 350 Wh in energy consumption per household.

The study shows that the ACs and geysers significantly influence the residential electricity demand in summer. Meanwhile, geysers significantly influence the winter electricity demand. The

ACs and geysers are the primary energy consumers in a typical home. From the usage analysis of the ACs, it was found that their energy consumption trends are inclined towards the high side more when the daily average temperatures are greater than 29 °C. In winter or below daily average temperature of 25 °C, AC usage is almost negligible, while significant usage can be observed during the summers. The average AC energy consumption per person was 0.52 kWh and 0.03 kWh daily in summer and winter, respectively. On the other hand, geysers were used both in the summer and winter. During winters, the geysers' energy consumption trends were inclined more towards the higher side than in the summer. The geysers consumed 0.29 kWh and 0.45 kW in daily energy per person during summer and winter, respectively. It is to be noted the daily average geyser usage time per home was approximately 37 minutes and 55 minutes in summer and winter, respectively. While the daily average AC usage time per home was approximately 3 hours and 0.2 hours in summer and winter, respectively. The average load per AC and geyser during usage was found to be 0.6 kW and 1.87 kW, respectively.

8.2. Key Outcomes

The key outcomes of this research include the following:

- Load profiles of air conditioners and geysers during the summer and winter months, providing insights into the seasonal usage patterns, probability of use, and consumption trends of these appliances.
- An analysis of the energy usage of a typical household, highlighting consumption patterns and energy breakdowns of regularly used major appliances.
- Load profiles of common household appliances, namely refrigerator, washing machine, television and water purifier.
- A granular dataset on disaggregated residential electricity consumption based on the Indian context was created in this study. The data is collected at 1 second intervals in the months of May, June and November of the year 2023 comprising of more than 1.5 billion data points. This will be beneficial for researchers to train and test their NILM models in Indian scenarios.

8.3. Limitations and Future Scope

There are significant possibilities for further investigation to analyze residential electricity consumption patterns in-depth within the context of this thesis report. More research is needed to fully understand the potential for energy reduction. The feasibility of shifting appliance usage to align with solar hours needs to be thoroughly investigated for any practical obstacles. Moreover, conducting a comprehensive study across different climatic zones would help in understanding the seasonal variations in these usage patterns on a country-wide scale. This would further assist in developing strategies for demand response and load shifting in the residential sector.

In conclusion, a more comprehensive study involving a greater number of appliances and households in different locations could be conducted over a longer period, which will help in gaining a better understanding of household energy usage. Such a study would be beneficial in assisting utilities and other stakeholders in developing residential demand response policies, improving operational efficiency, and reducing associated costs.

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