MANIPAL
ACADEMY *of* HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)

UNDERSTANDING AND MODELING RESIDENTIAL ELECTRICITY DEMAND IN INDIA

A THESIS TO BE SUBMITTED TO

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THE AWARD OF THE DEGREE OF

DOCTOR OF PHILOSOPHY

BY

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UNDER THE GUIDANCE OF

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DECLARATION BY THE CANDIDATE

I declare that this thesis, submitted for the degree of Doctor of Philosophy to Manipal Academy of Higher Education, is my original work, conducted under the supervision of my guide Dr. Kshitija Joshi and co-guide Dr. Tejal Kanitkar. I also wish to inform that no part of the research has been submitted for a degree or examination at any university. References, help and material obtained from other sources have been duly acknowledged.

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CERTIFICATE

This is to certify that the work incorporated in this thesis **"Understanding and Modeling Residential Electricity Demand in India"** submitted by Sashi Kiran Challa was carried out under our supervision, in the School of Natural Science and Engineering at the National Institute of Advanced Studies, Bengaluru. No part of this thesis has been submitted for a degree or examination at any university. References, help and material obtained from other sources have been duly acknowledged.

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Dedicated to my late father, my first teacher,
for always having faith and never letting go

Acknowledgments

This thesis marks a important milestone in the journey that started as an idea almost a decade ago during my masters, from an idea that seems almost non relevant, to the last five years which cover my admission to the PhD program to submission of this thesis. These five years have been both trying and rewarding with steep, steep learning curves and mentally trying times, which on occasion did not seem worth putting up with. This submission therefore would not have been possible without the timely support and help of a several people.

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Chapter 1
Introduction

1. Overview of Electricity Demand

Electricity demand can be defined as the need or use of electricity by various categories of users to meet different end uses. In the context of a large country like India the various end users are constituted by the different sectors of the economy. These include industry, agriculture and domestic among others. The demand and consumption of electricity from these different sectors is not uniform, that is, how much they consume and how they consume what they need is unique to each sector.

In order to analyze how electricity is used, we need to understand the difference between consumption and demand. *Demand* gives us the quantity of consumption, measured in *X-Watts* or *XW*, where *X* is the prefix to indicate kilo (k), mega (M), giga (G), etc. *Consumption* gives us the amount of electricity used over a specific period of time *T* and it is generally measured in *XWatt-hours* or *XWh*. For example, a 10W (10 watt) light bulb will "demand" 10W when it is on, but will consume a total of 100Wh (100 watt hours), when it is on for 10 hours, or will consume 10W/hour, every hour for the 10 hour period it is on.

To get a better understanding of electricity consumption in India, identifying the different sectors (with respect to classifying electricity consumption) and the annual consumption (share) of each sector is important. Figure 1 gives sector wise break up of consumption in 2018-2019.

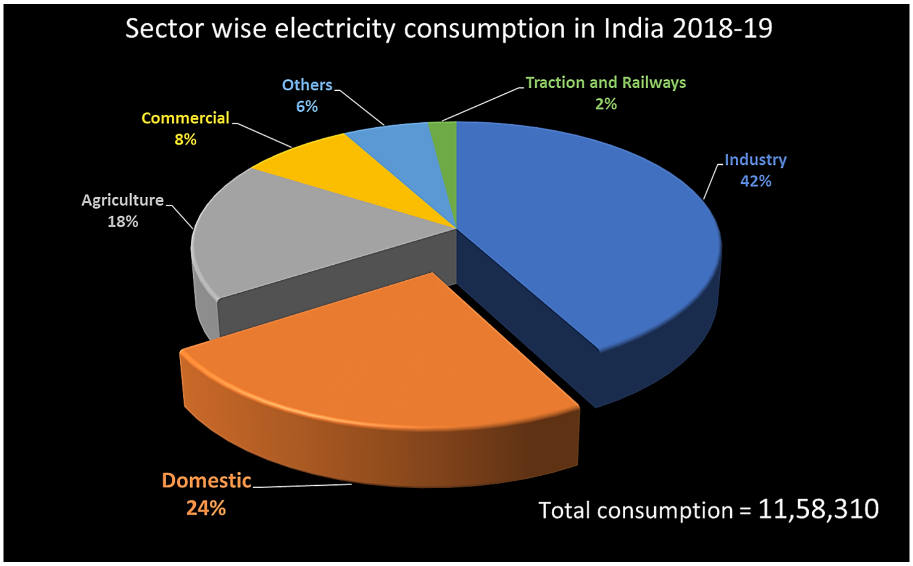

Figure 1: Share of each sector in the total consumption of electricity in India, Energy statistics 2020

From figure 1 that the highest consumption came from the industrial sector, followed by *domestic* and *agriculture*. In terms of growth, industry and domestic were the highest, with CAGRs of 7.4% and 6.7% [1] respectively. The total consumption of all sectors combined, in 2018-19 was approximately 1158.3 TWh (Terra watt-hours), increasing from 612.645 TWh in 2009-10, with a CAGR (Compound Annual Growth Rate) of 6.5% for the decade.

Among the different sectors, residential has seen a CAGR close to 7% over the last decade and an average growth of approximately 7.6% to 8% annually [1]. This rate is projected to increase as all households in the country gets access, quality of supply improves and appliances become affordable [2] [3]. This trend can already be observed. In 2017, close to 40 million households (approximately 20%) in the country did not have access to electricity [4]. By 2019, over to 99% of the households were electrified [5, 6]. Another indicator is the increase in per capita consumption of electricity, increasing from 273kWh in 1990 to just over 1180 kWh in 2018-19. With increasing income, affordability of appliances and overall improvement in the electricity infrastructure, demand for electricity will only increase [7, 8].

Given this growth trend and the heterogeneity in consumption and demand for electricity across different households, owing to size, income and regional locations makes the residential sector interesting and important to study, especially given that residential electricity is projected to grow five to six times by 2030 from to 2016 levels [9].

Considering these factors, we study residential electricity sector closely, understanding and identifying key drivers of residential electricity demand. We look at key data needed to gain a holistic understanding of the sector along with some shortcomings in the current analysis methods and propose possible methodologies to gain a deeper understanding of this sector and its growth to propose frameworks to plan and manage this growth efficiently and sustainably. In the next few sections, a deeper look at the residential electricity sector is presented along with the possible changes that can be made to improve and add to the current methodology of analysis and outline a few ways to approach this problem to try and gain a deeper understanding of the sector.

1.1. A Closer Look at Residential Electricity Consumption (REC)

Residential electricity demand in India has grown by close to 50% since 1970 [10], consuming today close to a quarter of the electricity produced in the country. It is projected that organic consumption from households will grow (growth without any external influences) to between 438 TWh to 623 TWH by 2030 accounting for anywhere between 25% to 30% of the total demand, at a GDP growth rate of 5%-7.8% [11].

Considering this growth, in order to better understand electricity consumption from the residential sector, the first question to ask is what is *residential electricity consumption* and *what constitutes residential electricity consumption*.

Residential electricity consumption (REC) is the total electricity used by households to meet various end use needs. This is calculated by the total electricity units, measured in kWh, consumed by a household over a given period of time (a day, fortnight, month, etc.). The end uses in households consist of various electrical appliances used to meet different needs. They can be categorized broadly into

- **Lighting** : covering various sources of lighting across the household
- **Space comfort**: fans, desert coolers, air conditioners and space heaters
- **Entertainment**: TVs, set top boxes, music systems etc.
- **Productivity**: laptops and desktops
- **Kitchen**: mixers (blenders), refrigerators, microwaves, induction cook tops

- **Utility**: washing machines, motor/pump for water, etc.
- **Water heating**: covers different electric water heating appliances like induction rods, geysers, etc.
- **Transportation**: Electric vehicles - two wheelers and four wheelers

This is not a comprehensive list and is not strict way of classifying the appliances into different categories. This is one of the ways to make understanding and calculating consumption from various appliance categories more intuitive. Electricity consumption of households is a composite of usage from some or all of these appliances.

From list it would seem fairly straightforward that electricity consumption in households can be looked at as a direct function of appliance owned.

$$\mathrm{E_{HH}} = f(\text{Appliances}) \qquad (1)$$

But this is not always the case. First, the ownership of appliances themselves are not uniform across households. For households to own appliances, access to electricity is the primary requirement. As households get access to electricity, there is a gradual growth of appliance ownership . The households tend to move up an *"appliance ladder"*. Once they get access to electricity, households first start by using basic appliances like lighting, followed by fans, TVs, mixers. As they move to the top of the ladder they begin to use appliances like refrigerators, washing machines and electric stoves [12, 13, 14]. This shows us the inherent heterogeneity in consumption of electricity across households at various "rungs" of the appliance ladder.

Access alone though does not drive demand for electricity. In the case of a developing economy like India, there are many socio-economic, demographic conditions among others that influence ownership of appliances [7, 15, 16]. We categorize them as primary, secondary and tertiary influences or drivers. For India, a developing economy, the obvious first driver is electrification. Next, income and/or expenditure play an important role followed by region, broadly disaggregated to urban, rural and state levels, and climatic zones [17, 18, 19, 20, 21]. Some studies have also shown that demand from households is sensitive to price of electricity [22, 23, 24]. All of these broadly can be considered as primary drivers.The secondary drivers include factors such as dwelling type, size of the house, number of members in the household and their age distribution, head of the household and education levels of the head of the households among others [17, 18, 21, 24, 25, 26, 27, 28]. Finally, the tertiary drivers are the appliances themselves whose ownerships are a derivative of the primary and secondary drivers and form the end use categories of households.

These drivers indicate the different set of variables that play a significant role in electricity demand from residences. A hierarchical view of drivers can be summarized as shown in figure 2 . It is important to note that there will be an overlap between different levels (primary, secondary) of drivers and that this hierarchical structure is not a fixed, but is presented to help in understanding how various indicators influence and drive electricity demand of households by orienting them to different appliance profiles.

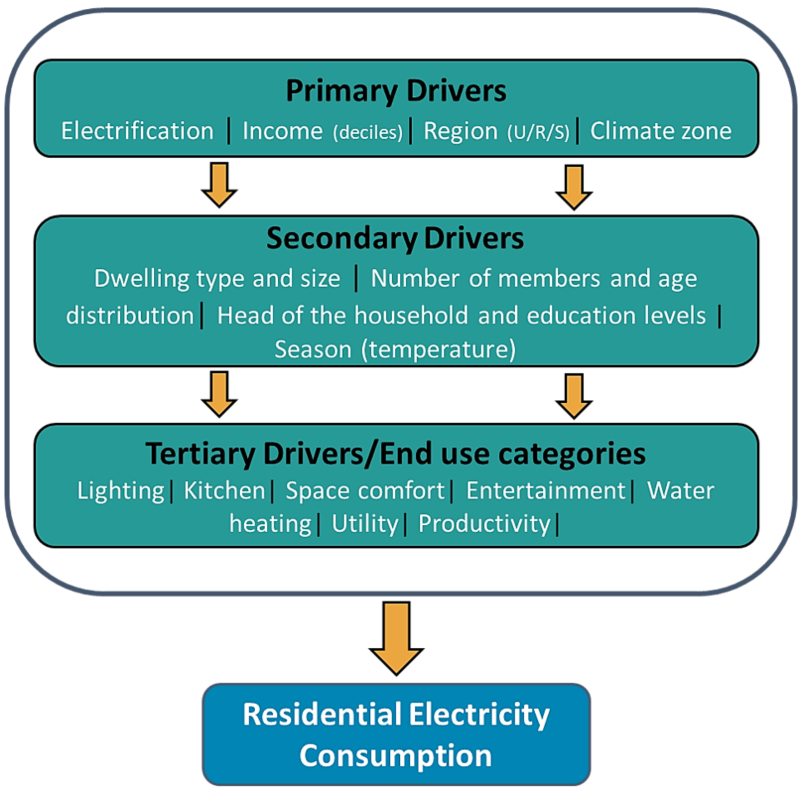

Figure 2: Key drivers of residential demand

From figure 2 it is clear that these drivers influence the ownership of appliances and the overall electricity demand from a household. For a developing country like India, electrification still remains a exogenous factor to the household and is governed by policies from the government. However, the remaining drivers govern the overall electricity demand of household by influencing at various levels the ownership of appliances. Now, ownership of appliances can be considered as a function of these drivers. For example, in the case of space comfort appliances (Fans, desert coolers, air conditioners, space heaters), the ownership of these appliances is influenced by income (fans being cheapest to own), with more expensive appliances owned as households move up income brackets, in line with appliance ownership ladder [26]. But income is not the only driver, Fans are the most primary form of space comfort appliances used, with almost ubiquitous ownership [29]. The need for stronger space cooling appliances is also influenced by the climatic zone that the household falls into. Next, the use of the appliance depends on number of residents in the household, the age demographic and the season among others [13].

We can therefore begin to see a divergence in the drivers of ownership and usage. The determinants of ownership of an appliance A_i can be looked at as

$$A_{O_i} = f\ (I, R, C) \qquad (2.a)$$

where,

A_{O_i} = Ownership of Appliance i,

I = represents the income (or income decile) of the household ,

R = region (urabn/rural/state) in which the household is,

C = Climate zone that the household falls into

Similarly, the use of an appliance can be considered as

$$A_{U_i} = f\ (A_{O_i}, D, T) \qquad (2.b)$$

where,

A_{U_i} = Usage of appliance i,

A_{O_i} = Ownership of the appliance by the household ,

D = Various demographic and dwelling indicators,

T = Temperature (reflection of season, governed by the climate zone the household is in),

With these relationships it become more evident that appliance ownerships and consumption of electricity in households are both derivatives of these various indicators. Based on this, we can rewrite equation 1 to reflect the total energy consumed by a household as

$$E_{HH} = f(A_{O_i}, A_{U_i}) \quad (3)$$

where, A_{O_i} and A_{U_i} are composite variables as defined indicating ownership and usage of an appliance A_i. These composite variables are functions of a subset of drivers from figure 2, which are either unique to each appliance or shared between different appliances.

These relationships show that, one, appliance ownerships across households are not uniform, two, usage of appliances, even if two households have the same appliance profiles might not be the same and are governed by different spatial and temporal conditions. This indicates that even if households have similar profiles of ownerships, their demand and consumption could vary significantly or even if they had similar income and demographic characteristics, their appliance profiles might vary significantly. For example, in cities that fall into different climate zones , the ownerships and usages of air conditioners vary significantly [10, 30]. This is not limited to high end appliances like air conditioners, even everyday appliances like refrigerators see a variation in size of ownership and usage (hours kept on) based on the economic profile of a household [31]. Another good example to consider is that the appliance profile of a household also depends strongly on the sanctioned load (AEH, NON-AEH) [32, 33].

From equations 2, 3 it can be seen that analysis of residential electricity consumption has two components. First, the need to analyze and understand how key drivers influence ownerships of appliances, in-turn influencing electricity consumption and second, how the household's load profile or load curve varies over a period of time (day, month, season etc.). The load curve or profile gives us the variation in demand from a household (or any sector) over a defined period of time (for example, the variation in demand in electricity from a household, collected hourly, for an average day will indicate how demand from the household varies with in a 24 hour period). The first type of analysis gives us a point estimate of consumption (in Watt-hours), while the second aspect gives us temporal estimate of demand (in Watts) for different resolutions of time.

These two analyses are equally important in providing a rounded and comprehensive understanding of electricity demand from the residential sector capturing its variations. The next question is what are the key outcomes from an analysis of this type.

1.2. Need for Analyzing and Understanding Residential Electricity Consumption

Household use of electricity in India has increased by approximately 50 times between 1970 to today. The growth in demand from the residential sector outpaces the other major consumption sectors in the country [33, 34]. Figure 3 shows the trend in growth of residential electricity consumption from 1970.

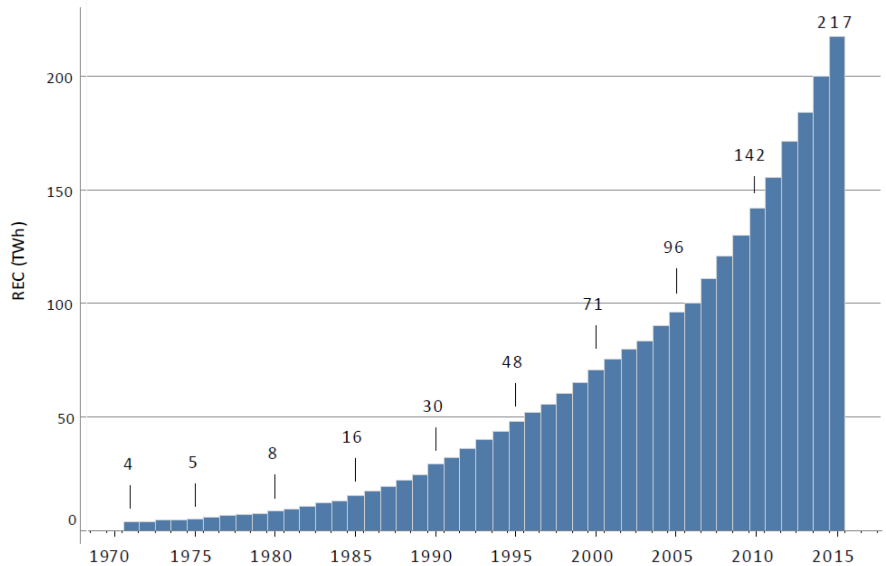

Figure 3: Growth of residential electricity consumption since 2017, *Source: Plugging In: A Collection of Insights on Electricity Use in Indian Homes*

It is predicted that India is moving towards its largest urban transition in the coming decades [33, 35]. This coupled with the over 99% of the households that will see improvement in quality of supply, incomes, affordability of appliances along with access to other electricity based services, is projected to increase demand from the residential sector by 5 to 6 times by 2030. Therefore a better understanding of the residential electricity sector becomes imperative to manage this growth and its impacts efficiently. There are at least three key broad areas where a comprehensive understanding of residential electricity demand will prove beneficial.

1.2.1. Capacity and Dispatch planning, Renewables integration and Better models

Capacity planning in the country has traditionally relied on trend based projections of growth in demand which has also governed capacity increase in the country [10]. CEA has used trend and regression models to project growth in demand [36]. These models work by assuming three different economic growth rates compared to a business as usual (BAU) scenario. These scenarios are applied at national level and regional level (states grouped to regions) [34, 36, 37]. This methodology, over time, will become unsustainable, considering expansion of generation capacity has many tangible impacts on the both society and the environment. [37] highlights the variations in estimates of demand coming from different studies [37]. Therefore there is a need to adopt different approaches based on demand or on end use projections and/or econometric approaches [38].

Next with the rapidly increasing penetrations of renewable, the intermittent nature of renewables becomes prominent. This means there is a need to model more effectively the patterns of end use for different sectors to optimally utilize the renewable infrastructure and enable smooth transitions between renewable and fossil sources with no impacts to end users as generation from renewables go through their daily cycles. With an in depth understanding of patterns of demand from different sectors, the intermittency related issues can be managed efficiently.

The need to understand in depth sectoral variations and intricacies leads to the need of developing better models that consider variations and drivers of different sectors in more detail. Therefore a residential demand model that can model in greater detail the variation in different end uses individually and build up towards how demand from the sector will vary will help in developing more refined models. These refined inputs to overall prediction models can be used to review India's INDC's and impacts on emissions.

1.2.2. DSM, Efficiency and Appliance replacement programs

DSM or demand side management is the process of modifying the normal consumption patterns of end users by shifting their demand to non peak hours or other time periods as suggested by the grid. The DISCOM can use active or passive mechanisms to achieve this change. In active mechanisms, end users can be incentivized to change their consumption patterns or penalized for not changing their consumption patterns, while in passive methods, the users participation is not mandated but left to the user [39, 40, 41].

One of the most common methods of DSM is time of use (TOU) or time of day based (TOD) pricing methods . Here the end users are charged different prices at different times of the day. The idea is that end users will shift their usage patterns to times when the charges are lowest

[40, 42, 43, 44]. The other way to manage load, especially during peak is to curtail electricity usage by force. This is either by choice of the end user, where the user cuts off all usage during this time, or it is forced by the grid either as a management technique or because it is unable to meet the need [45, 46]. Either way causing inconvenience to the end user.

It can also be argued that these mechanisms would not work for a developing country like India. Considering a large population has just recently got access to electricity, any pricing based mechanism that is applied as a blanket policy can be a deterrent to growth driven increase in consumption for these segments. Also currently the residential electricity demand is not very flexible [13, 47], so such programs might not find a lot of success. The alternative to manage demand for a developing grid like India is with efficiency improvement and replacement programs. A good example is the light bulb replacement program (DELP) which sets a good way forward. But this also highlights a key problem, the need for replacement of old stock of inefficient appliances. Appliances like fans have a very long life time and are not replaced very often [29]. There are two key things that need to be done, one, encourage, inform and incentivize new users to buy energy efficient appliances transitioning them directly into an efficient ecosystem while incentivize existing users to replace their existing inefficient stock. The current road block to this is the lack of relevant data on stock of each appliance and its age. With this data, we can better understand ownership and consumption patterns and intensity of demand from households to plan dispatch more efficiently.

1.2.3. Managing emission requirements

In a developing economy like India, as we see more growth, households also require more energy to meet varied end use needs as observed from figure 3. We saw from figure 2 that income and affordability are important drivers influencing changes in ownership of appliance profiles. This has a direct impact on the demand patterns of the households, also reflecting in the national demand patterns [48, 49, 50]. Given that today, over 99% of households in India are electrified, the demand for electricity will only increase as services are made affordable and quality of service is improved. Considering that residential sector constitutes close to a quarter of the total demand in the country and is poised to grow significantly, it is also going to be a key contributor to emission. With studies indicating that especially in developing countries, energy demand is going to come from the residential sector skewed towards urban households, it becomes important to identify intensity of growth and ways of mitigation [51] .

Given that households in the country are undergoing an energy transition across affordability brackets it provides us with a great opportunity to plan a low carbon transition pathway right at the get go to set a proper transition path for these households [52, 53, 54, 55]. This requires a closer understanding of appliance ownership and usage patterns, transition paths, and ownership drivers.

A closer understanding of residential electricity consumption can help address these three broad areas and more. This broad categorization is a representation of the key areas that a deeper understanding of the residential electricity consumption can help address. This categorization is not fixed and each of the subcategories is a major area (ex. dispatch planning and grid expansion are two large areas). They have been grouped in this case, to provide a condensed view of various areas that an understanding residential demand can contribute to. There are still some key limitation that need to be addressed to developed a more comprehensive understanding of the residential sector.

1.3. Current Methodologies and Overview of Few Gaps

With the benefits of understanding residential demand outlined, the current limitations that need to be addressed for development of better models need to be outlined. To improve accuracy of forecasts there are two primary considerations that we need to take into account. Choosing the right modeling methodology and identifying the correct data sets that provide current data on key variables that feed into the models. Any lapse in these two conditions will lead to the inaccurate forecasts. To understand the current approaches a closer look at these two key aspects is necessary.

1.3.1 Model choices

There are multiple modeling methodologies that can be used to predict electricity demand. Some of the models that have been used by different studies to forecast residential electricity demand for the country are highlighted.

1.3.1.1. Trend based analysis

In this method, the variable to be predicted is expressed purely as a function of time and does not take into account its interactions with other variables like economic, demographics, technological, etc. This method has the advantage of ease and simplicity of use. The main disadvantage of this method is that it ignores interactions of the predicted variable with other social and economic factors. The underlying principle of trend analysis is that time is the is the primary factor determining the behavior of the variable, i.e., the pattern of change seen in the variable, in the past, will continue or govern its change in the future.

1.3.1.2. End-use analysis

This method tries to capture the energy use and energy use patterns of various electricity consumption systems (appliances, machines, etc.) to build models for different sectors (residential, commercial, agricultural,etc.). For example, in the residential sector, end uses of electricity are for cooking, space comfort, water heating, lighting among others. The end use method, estimates the demand and consumption from each of these appliances to arrive at the total demand. The basic principle here being electricity is looked at as a service to drive appliance use and not as the final product itself. A basic form of estimation using this idea was presented in equations 2 and 3 in section 1.1. But a alternate way to look at this relationship is

$$E_i = P_i * N * W_i * T_i$$

where,

E_i = Total energy consumed by an appliance i,

P_i = Penetration of percentage ownership of the appliance i,

N = total number of households ,

W_i = wattage (power required) for running the appliance i,

T_i = Amount of time appliance i is used

$\sum_i E$ across all "i" appliances owned will give the aggregate demand of a sector.

This has the advantage of taking into consideration variations in income, efficiencies other policies, etc., as they are reflected through variations in ownership rates, power required by the appliance/system, etc. But this methodology needs data that is collected at high levels of detail to reflect each end use case accurately. This method also can lead to a iterative way of estimation of demand not accounting for social, economic, cultural or regional influences that can cause variations in use. Other than better estimates of demand, another advantage of this method is the collection of detailed data, over time, enabling deeper analysis of interactions of variables that govern end use.

1.3.1.3. Econometric approach

This method uses statistical and economic methodologies to develop a system of equations for forecasting electricity demand. In this approach, electricity demand is expressed as a function of various economic factors like income, population, prices of commodities, etc. So for example,

$$E_D = (I, P, C, N)$$

where,

E_D = Total energy demand

I = Income (or a proxy of income),

P = Price of an appliance,

C = Cost of electricity

N = Total population ,

Several combinations and functional forms of similar economic variables might need to be tried before we find a statistically signification relationship. This methodology requires data on the variables to be collected over a sustained period of time. This ensures both short-term and long-term relationships between variables being evaluated and established. This model though fails to capture any sudden shocks to the system (like the Covid-19 pandemic and its economic impacts we are seeing in 2020), or other immediate changes that can be a result of policy implementations. These will have to be explicitly be built into the model.

1.3.1.4. Hybrid models

A hybrid model is a combination of two or more modeling approaches. Some examples can be end-use and econometric, or time-series and end-use, or a econometric-time series, etc. Hybrid models have the advantage of negating some of the shortcomings of its individual component models, if chosen properly. But at the same time they also need a wider breadth of data compared to individual models.

This is a broad overview of some key model methodologies that can be used to build models to predict residential electricity demand. The type of model choice or approach depends on the problem or question being addressed. In the case of India and its residential demand, currently the primary demand forecast is carried out by the Central Electricity Authority (CEA). They carry out a study called Electric Power Survey used to predict future electricity demand. It uses a mix of methodologies, which includes trend analysis (for most sectors except HT), end use analysis for some sectors (HTl) and econometric models based on larger national indicators to predict sector wise growth in electricity demand [36, 38, 10]. An exercise was carried out by NITI AAYOG who produced scenarios for growth till 2047 [56]. They based their end use analysis on past trends (trend based) and some pre-existing benchmarks. Some independent models have also forecast residential electricity demand using similar methods [8, 57, 58]. There has been variation in forecasts of each of these studies due to variations in assumption, data sources and methodologies. One key point or observation this brings out is the lack of a standardized approach or framework and lack of consistent data availability across the system.

1.3.2. Data availability

Accurate and pertinent data is one of the primary requirements for a model to forecast accurately with low error. In India, there are surveys that are conducted every few years to collect data on consumer expenditure which include a array of appliances (NSSO), this is other than the CENSUS conducted every decade. The limitations of these surveys are that they do not cover all the variables needed to address residential electricity demand. They do not cover all appliances owned, age, efficiency rating and usage patterns. These variables in the very least are required to build a effective end use model to estimate aggregate consumption from the residential sector.

Bureau of Energy Efficiency (BEE) conducts surveys and also has periodic data on the numbers and efficiencies of different appliances sold by various companies. Along with this DISCOMs also conduct surveys and have data from households that can help analyze demand patterns, historical demand changes and success of various efficiency programs. Targeted surveys covering residential electricity demand are common place in many countries. In the United States, the Energy Information Administration (EIA) conducts the Residential Electricity Consumption Survey (RECS) and annually publishes detailed reports on consumption and expenditures of households on electricity for various end uses. Similarly, in the United Kingdom, they conduct The Household Electricity Survey (HES), which covers a variety of variables. The key with these surveys is that data collected is made accessible to researches across the board.

None of the data collected and collated in India by DISCOMS and other governmental or non-governmental agencies agencies is in the public domain currently. There are also no targeted residential electricity use surveys that are conducted [10, 13, 31, 32, 59]. The data that is available in the public domain is not comprehensive to perform detailed end use analysis.

These constraints currently pose a strong challenge when trying to build models to forecast growth or changes in residential electricity demand. Especially the lack of pertinent national or state level data as inputs to the models leads to a variation in assumptions made by different models leading to a wide range in the predictions. In the work presented as part of this thesis, some of these issues are addressed by presenting methodologies that can be replicated to model residential electricity demand.

2. Thesis Outline and Overview

The set of methodologies and limitations presented leads to interesting questions, some of which are addressed through the work carried in this thesis.

The larger questions around this sector can be summarized as *what are the primary drivers of residential demand, how do they vary, what impacts do their variations have on changing end use electricity demand?*

From this several research questions emerge out of which the following are covered and addressed.

1. Given lack of open data, is there reproduceable methodology to design a survey identify-

ing and covering the right set of variables ?

2. With right set of variables and data collected, what are the new insights gained in identifying key demand segments and categories?
3. What approaches can be used to model appliance ownership and load curves to identify variations across different households
4. What would be the right approach to model growth of appliances and load curves for short to medium t erm growth forecasts
5. What are the key policy and amendment suggestions that can be made based on model insights

The thesis is organized around trying to address these questions. Figure 4 gives an overview of this structure and the work carried out as part of the thesis. The thesis is divided into two sections, with work from the one section contributing to the other. The first section covers work carried out in designing, executing, analyzing a primary survey built and targeted specifically to collect data relating to residential electricity use. The data collected was used to gain insights into ownership, usage and purchasing patterns of appliances across different household categories and to build a model to reflecting clearly the usage patterns of households. In chapter 2 the survey design and survey sample identification methodology is outlined. In chapters 3 to 5 results from the survey are presented along with the models built to understand electricity use by households seasonally. The use of electricity by households is presented in the form of load curves.

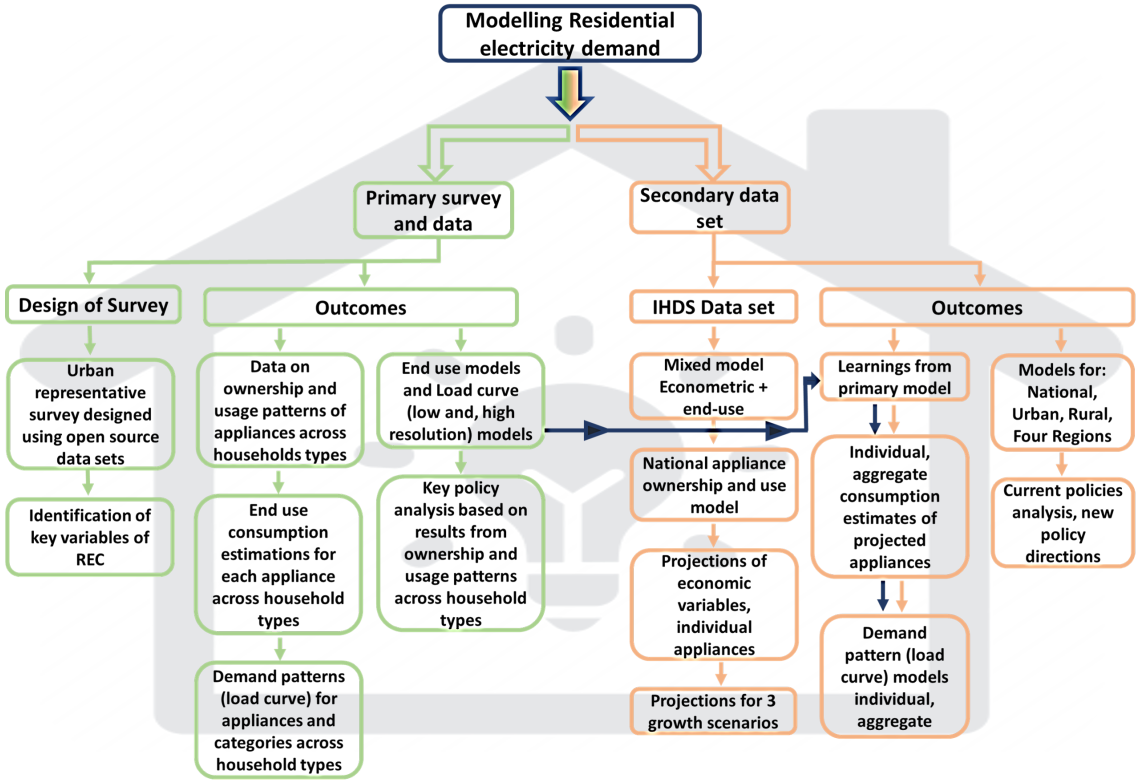

Figure 4: Thesis overview

In the second part of the thesis a national model using secondary survey data is built to project changes in ownership of various appliances to estimate consumption and demand. A mixed model (econometric + end-use) approach is used to project changes in ownership of individual appliances with respect to changes in key socio-economic variables. Using insights from the primary survey and some supportive insights from literature, consumption from individual appliances and the aggregate consumption from all appliances in the panel are estimated. Models were built to generate load curves for this projected data. Secondary survey data was used to build models for consumption and demand patterns nationally, by income decile, for urban and rural areas and the four regions (north, east, south and west) of the country (north east and east regions were grouped). The estimations of demand and consumption were made for three different economic growth scenarios outlined by NITI AAYOG [56] for each of the regional disaggregations. The results indicating growth in residential electricity demand nationally, regionally and by appliance category (as point estimates in TWh), and load curves indicating probable usage patterns along with the methodology for building the model are presented in chapters 6 and 7.

2.1. Chapters Outlines

As shown in figure 4, the thesis is divided into two parts. Part one covers in chapters 2 to 5, outlines the design, execution, analysis and results from a representative urban survey of Bengaluru, with models for appliance ownerships and load curves.

In chapter 2 the need for a survey of residential electricity demand, the current lack of such purpose driven surveys currently in the country is outlined, followed by identifying the set of key variables spanning socio-economic, demographic, dwelling descriptors and usage that need to be covered in the survey to gain a comprehensive understanding of appliance ownership and use/consumption patterns. Next, the process of identifying representative populations, representative in this case of urban Bengaluru's key variables, to identify key areas (wards) to survey is elaborated. The methodology to identify these representative populations has been designed around open access data sets like the CENSUS and city municipal data so that it can repeated for other cities in the country.

Chapter 3 presents key statistics collected in the survey. The first section presents the results of the survey as an aggregate (not divided in quintiles). Identifying response rates of various questions, and key indicators like income that will be used to divide the data into quintiles to identify consumption variations. The need to look at the data not just at aggregate levels but also categorized into different income brackets is outlined. With a significant part the respondents declining to provide income bracket information, different methodologies that can be used to divide data into quintiles are presented along with identifying the most effective method for data sets of this type using different metrics. Results of the data from the survey divided into quintiles is presented, identifying key ownership pattens across various income quintiles for different appliances and appliance categories.

Chapter 4 covers the process of designing a model to identify consumption patterns (load curves) of households by highlighting the need for design of the load curves and demand pattern analysis, followed by designing a model that generates load curves at aggregate levels for the survey at resolution data was collected. The load curves are generated for summer and winter covering two peak hour slots of 4 hours and two non peak hour slots of 6 hours. Based on the preliminary load curves, key trends in demand are identified along with shortcomings and the need for load curves representing different income quintiles being outlined. Following this a model to generate load curves at the above resolutions for each income quintile for summer and winter is built. This is followed by key observations from quintile data. The chapter concludes with an elaboration on a model to design load curves at higher resolutions is needed.

Chapter 5 by outlining the reference data from other surveys that form the base for the assumptions to build a load curve model at hourly resolutions followed by generating load curves for different income quintiles for summer and winter. The appliances are categorized into different categories and the contributions from each of the appliances made to the load curve in each quintiles are presented. Key differences in ownership and usage patterns of appliances across income quintiles is highlighted along with appliances that have seasonal variations and are key contributors to the load curve. Finally, using the insights from the chapters 3,4 and 5, critical analysis of policies and programs is presented, brining out points that can be addressed to improve their efficacy along with highlighting success of some key programs while highlighting how key insights from them can be transferred to current policies and to frame new policies.

Chapter 6 begins with presenting key statistics from the panel of variables from the secondary survey data set, IHDS, that will be used to build to build a national model for projections of appliance ownership and consumptions. A preliminary set of estimations for consumption from each appliance and penetrations of different appliances is presented. This is followed by outlining the methodology to build a national appliance ownership model. A step by step methodology covering identifying and shortlisting key independent variables for each appliances is presented followed by the first round of model building using training and test data sets, iteratively refining the models based on key diagnostic variables. This is finally followed by identifying key socio-economic variables and projecting them to be used with the models to project appliances. These appliance ownerships are projected for three growth scenarios to 2027.

In chapter 7, using projections in key variables and final set of models appliance ownership growth is projected, iteratively refining the models for the new set of input data. With the projections, for three scenarios obtained estimations of the demand from various appliances is presented followed by building a model to generate demand profiles for the projected data set. The estimates for future demand and consumption are calculated nationally, followed by estimation for income deciles, urban and rural areas, and for four regions (north, east, south, west) of the country. Using these estimates, key variations across regions and income brackets are identified along with highlighting key contributors at each level of disaggregation. Load curve models developed for each of these regions along with any additional assumptions made are presented. The chapter concludes by looking at different policies that currently govern the electricity sector making a case for amendments and introduction of new policies where applicable.

3. Summary

In this chapter, an overview of the residential demand and its current contributions vis a vis the total national electricity demand were presented. This was followed by a closer look at the sector and what form the key components and drivers of this electricity demand sector. The various functional relationships that exist between these drivers are highlighted and are categorized as primary, secondary and tertiary, while indicating how each level of drivers influence the other levels. Also highlighted were functional relationships that exist between these drivers and electricity demand and consumption. Next the need to understand this segment, current methodologies used to estimate demand and consumptions from this sector and some of their shortcomings was elaborated. This was followed by the outline of the thesis highlighting how some of these gaps are addressed, presenting methodologies that can be replicated for similar exercises. This was followed by the overview of chapters forming this thesis, outlining each chapter.

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Chapter 2
Survey Design and Methodology

1. Introduction

The demand for electricity in households arises from the need to service various end-uses. These end uses can be broadly grouped into essential and comfort based needs. End-uses like lighting, cooking and some forms of thermal regulation fall into basic or essential services, while needs like food refrigeration, water heating, space comfort, fall under comfort based needs. To meet some of these end uses households use a combination of energy sources. For example, a mix of electricity and gas can be used for cooking or for heating water. The use of electricity to meet these end use needs can be defined as residential electricity consumption or residential electricity demand. Only services that use electricity to meet end use needs are considered under residential electricity consumption.

To estimate residential electricity consumption, it is important to understand the factors that affect and drive it. While income alone is not a strong predictor, income and appliance stock become a strong predictor of demand and consumption [1]. Considering importance of data on the effectiveness of any prediction or projection exercises, there are not many sources of comprehensive open data sets in India to carry out an effective residential demand study. Data on some basic appliances owned in Indian households is collected through nation wide surveys like National sample surveys and the national Census as part of the larger basket of goods and services they cover. But with the current limited attention given to residential electricity consumption, the resolution at which data needs to be collected in order to effectively estimate patterns of residential electricity consumption is missing [2, 3]. It is not only important to collect ownership data but also to gather data on usage times and patters. Ownership information along with temporal data will help us understand in detail how households consume electricity and estimate how consumption (load curve) varies over a 24 hour period. Along with daily temporal variations, consumption also varies seasonally. Appliances like fans, water heaters, space heaters and coolers see more use in specific seasons. Similar information coupled with socio-economic indicators and dwelling spaces based information would help estimate consumption patters more effectively. Such detailed data collection could help in more efficient planning of supply or directed policy interventions for better conservation and efficiency programs among others. But, as highlighted in [2] most of the current work has been limited to papers studying specific aspects of residential consumption like appliance efficiencies, building designs, seasonal variation etc. In order to get a more in depth understanding of residential consumption, there is a need to address this gap of lack of appropriate high resolution data. With this in mind and based on the insights presented in [1, 4, 5], we designed and conducted a survey in Bengaluru to understand urban household appliance ownership and usage patterns. The survey covered 85 variables across 7 categories and 19 sub categories and was designed to cover areas that are representative of distribution of key indices of Bengaluru. In the next section the process of design of the survey, identifying sample size and survey areas using open access data are described.

2. Survey Design

2.1. Design Considerations

To understand electricity consumption better multiple variables need to be considered as income alone is not a strong predictor. Broadly these can be classified as (i)socio-economic variables - income, number of occupants, age distribution, head of the household, (ii) appliance variables - Types, age, numbers of each, penetration of each type of appliance, etc. (iii) Dwelling type - Type of household (independent, apartment), number of rooms, area, etc. These variables influence the usage patterns of the household [6, 7, 8, 9].

As the fist step for the design of the survey, two rounds of the IHDS survey (2005 and 2012) [10, 11] were used to understand which appliances had seen significant changes in ownerships. Given the survey was to be conducted in Bengaluru penetration of appliances for urban India, metros and Bengaluru were compared along with the changes in penetration levels of each income decile for various appliances between the two survey rounds. Changes in penetrations of 7 appliances - Fan, Cooler, AC, Refrigerator, Washing machine, Computer and TVs were compared as these appliances were part of both rounds of the IHDS survey.

Figure 1 compares penetration of these appliances between the two survey periods for urban India. It can be seen that in between these two survey periods, refrigerators, washing machines and ACs have seen significant growth, with more pronounced growth in the last 4 to 5 deciles for ACs.

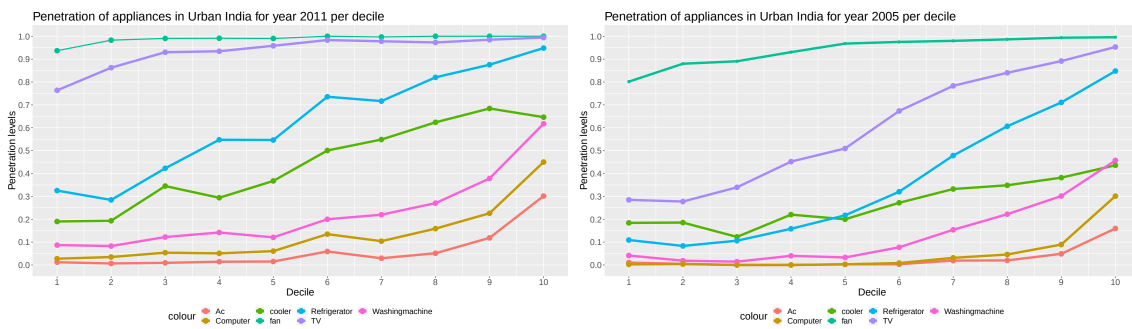

Figure 1: Comparison of penetration for different appliances in 2005 and 2012 for urban India

Figure 1 presents that different appliances saw non uniform growth across deciles for the same appliance. For example refrigerators in the 4^{th} decile saw an increase from approximately 15% to 55% (40 percentage points or 2.6 times) and the 6^{th} decile saw increase from approximately 30% to 70% (40 percentage points again) but a lot more homes in this decile became refrigerator owners, lastly in the 10^{th} decile the ownership only increased approximately from 85% to 95% (10 percentage points), not very significant compared to the other deciles. Similarly, if we look at the AC ownerships, a different trend can be observed. While the lower deciles saw no significant growth, the top three deciles saw the highest growth. The last decile saw the most growth (from 15% to 30%). This indicates two things; correlation to income of some appliances and the intra-decile variations in appliance ownership, bringing to the fore the importance of capturing this heterogeneity in growth of appliance ownerships.

Figure 2 compares penetrations of the same appliances for the 6 metros of the country (Mumbai, Delhi, Kolkata, Chennai, Hyderabad and Bengaluru),covered in IHDS.

Similar to the trends observed in Figure 1 ACs have seen maximum penetration increase in the last decile. While refrigerators saw significant increases in the last 5 deciles. It can also be

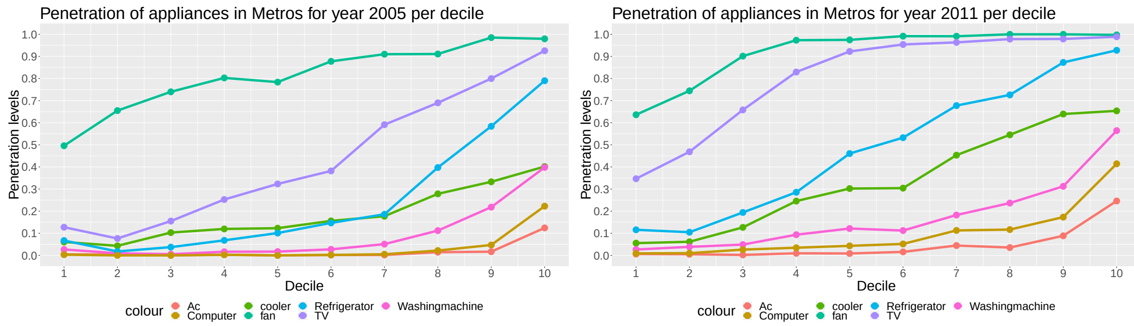

Figure 2: Comparison of penetration for different appliances in 2005 and 2012 for 6 major metro cities

observed that for appliances that come fairly low in the ownership ladder like TVs and Fans, ownerships increased significantly between the two survey periods.
For TVs, the ownerships were significantly low for the first 6 decile, in 2011 these increased significantly with ownerships from 5th decile onward increasing to above 90% the top 3 decile getting close to saturation. Similarly, in the case of fans, in 2005, only the top two deciles had close to 100% ownership, there was significant increase in 2011 with 7 of the 10 deciles going upwards of 95% ownerships.

Figure 3 presents the ownership of these appliances for Bengaluru.

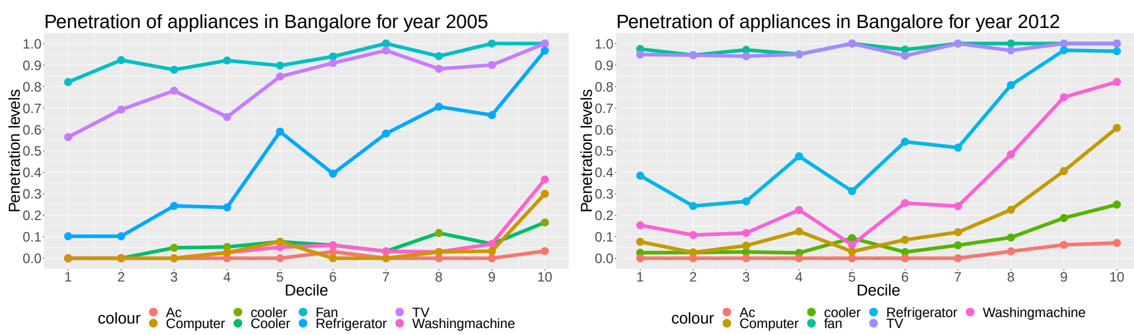

Figure 3: Comparison of penetration for different appliances in 2005 and 2012 for Bangalore

We see trends similar to figures 1 and 2. While the general trend of the ownerships has shown an increase across all appliances, there is a clear indication of inter-decile variation unique to each appliance.

[5], using 2014 NSSO data compared ownerships of different appliances between urban and rural Maharashtra. Comparisons presented in figures 1 - 3 or as shown in [5] present aggregate changes in ownerships of appliances. While this is useful in understanding how total demand could vary based on changes in ownerships appliances, it fails to provide clarity in terms of

how these appliances are used. For appliances like the refrigerator estimation becomes easier if we assume that households using refrigerators do not turn it off, which might not always be the case [9]. With appliances like ACs whose usage exhibits a strong correlation to season, capturing usage with higher time resolution becomes key. As indicated in [4, 12, 13], there is also correlation between operation of the AC and income.

It is therefore important to understand how appliances are used with higher time resolution to identify and address appliances specific peaks. Especially with appliances like fans, coolers, TVs, washing machines and ACs, seeing increased penetrations across various income deciles, usage information becomes important, as it is dependent on multiple variables like income, population, age distribution of the household and seasonality among others.

[3] identified key indicators that need to be captured for an effective residential electricity consumption survey. They identify key indicators that are amiss in other national open access surveys like NSSO and CENSUS. Figure 4 summarizes what a residential electricity use survey should include and the current coverage of some indicators in surveys today.

It is clear that for a residential electricity use survey to be effective the data captured needs to cover more than basic appliance ownership and electricity statistics, collecting data on appliance specifications and usage trends among others. Therefore one of the primary concerns in the design of the survey for Bengaluru was to include questions that capture a broad set of variables to reflect variances brought in by socio-economic, temporal and seasonal factors.

2.2. Questionnaire Design

In order for the survey to be effective in collecting data that helped us gain insights into *time of use patterns* of appliances, data collected from the survey had to cover the following aspects.

- Basic household information
- Household demographics
- Size and income profile of the household
- Basic electricity background of the household
- Appliances owned
- Vehicular ownership - Regular and electric

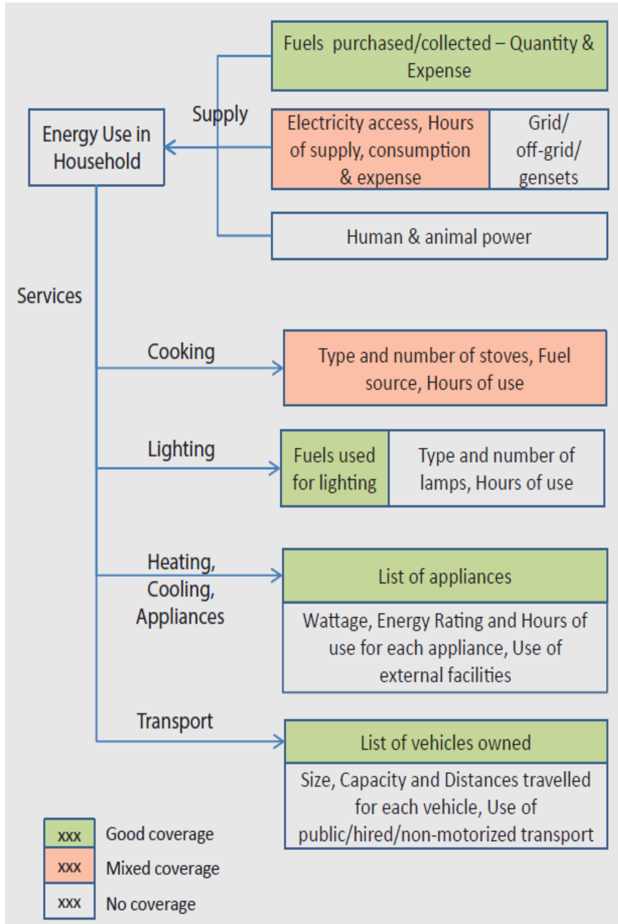

Figure 4: Key indicators for comprehensive Residential electricity consumption survey

- Probability of buying new appliances

To identify which appliances to include in the survey, [1, 2, 3, 4, 10, 11, 13] were also referred. As it is also important to capture time, duration and seasonality of use, the data to be collected included seasonality (Summer and Winter), time of use (time of day) and duration of use (minutes/hours used).

2.2.1. Sections Description

2.2.1.1: Household Information

This section of the survey collected basic household details which covered

1. Area of the household

- BBMP (Bruhat Bengaluru Mahanagara Palike) block number where the household is located. The block is one level lower than the ward.

2. Type of the household

    - Classification into apartment or independent household.

3. Gender of the head of the household

4. Ownership, rental status and rental bracket.

    - Rental households split into 5 rental brackets (table 1)

Code	**Income Range**
R1	less than 5000
R2	Rs.5001 to Rs.10000
R3	Rs.10001 to Rs.15000
R4	Rs.15001 to Rs.20000
R5	Above Rs.20000

Table 1: Rental brackets

5. Residential status of the household

    - If the residents have been in Bengaluru for more than 10 years or not and language spoken at home (mother tongue)

2.2.1.2: Household Demographics

This section collects information on the number of people in the household and their age distribution. Details covered are:

- Total number male, female adults and children (below 18 years)

2.2.1.3: Household Income

This section collects information on income bracket of the household for classifying households to analyze variance between income brackets for appliance ownership profiles and electricity usage. Details covered are:

- Total number of male, female earning members including pensioners in the household

- Total income of the household split into 5 brackets - HHI1 to HHI5 and DND

Code	Income Range
HHI1	less than 200000
HHI2	Rs.200001 to Rs.400000
HHI3	Rs.400001 to Rs.700000
HHI4	Rs.700001 to Rs.1000000
HHI5	Above Rs.1000000

Table 2: Household income code

2.2.1.4: Household Physical Description

This section collects information on the size and number of bedrooms in the households. Details covered are:

1. Size of the household in square feet and number of bedrooms in the household

2.2.1.5: Basic Electricity Information

This section collects information on electricity bills and type of electricity back up system used to identify seasonal variation in bills along with information on hours of power cut observed seasonally.
Details covered are:

5.1. Electricity information

- Approximate electricity bill amount in summer, winter and the survey month
- Approximate hours of power cuts in summer and winter

5.2. Electricity back up information

- Type of electricity Back-up used: UPS/Inverter, Diesel generator, Solar, Number of batteries used
- In the case of apartments: type of common backup: Diesel, Batteries, Solar

2.2.1.6: Appliances Owned

This section collects information on various appliances that the household owns. The appliances are categorized as Living space appliances, Kitchen, Utility appliances, and Bathroom appliances.

Appliances are categorized based on the end use service. Lighting needs for each of these area was captured separately.
For each appliance details captured were

Information collected

Appliance details	Daily usage	Seasonal usage	Time slots
Owned/installed	Total hours used - Weekdays	Usage in Summer	6am-10am, 10am-6pm, 6pm-11pm, 11pm-6am
Number of each	Total hours used - Weekends	Usage in Winter	
Wattage			
Star Rating			
Age of the appliance			
Size/Capacity			

Table 3: Appliance data collected

2.2.1.6.1: Living Space Appliances

Table 4 lists appliances categorized under ”*Living Space Appliances*”. This includes Lighting, Space cooling, Space Heating, Entertainment and Productivity appliances. Table 3 lists the appliances that make up each of these categories.

Lighting	Space Cooling and Heating	Entertainment and Productivity
Incandescent	Fan	TV - CRT
Tube light	Cooler	TV- LCD
CFL	AC	TV-LED
LED	Room Heater	Computer - Desktop
Other	Other	Computer - Laptop

Table 4: Living room appliances and Lighting

Room wise installation	Numbers used simultaneously	Hours of simultaneous use of
Lighting	Fan	Fan
Cooling - Fan, AC, Cooler	Cooler	Cooler
TV	AC	AC

Table 5: Room wise installation and simultaneous use data

The *”other”* category for lighting, cooling and TVs covers appliances other than what has been listed on the questionnaire. This captures at the household level and by room the total number of appliances owned and installed to understand simultaneous use and distribution of appliances in the household (table 5).

2.2.1.6.2: Kitchen and Utility Appliances

Table 6 lists the appliances covered under *"Kitchen and Utility Appliances"*.

Kitchen	**Utility**	**Lighting**
Refrigerator	Washing machine	Incandescent
Microwave	Motor/pump	Tube light
Induction cooktop		CFL
Gas stove		LED
Electric coil heater		

Table 6: Kitchen and Utility appliances and Lighting

Inductive appliances that have the propensity to be used for comparatively long periods have been included. Smaller appliances like Mixer/grinder or toaster have not been included as the duration of their use is not significantly high or regular. Microwaves also does not have significant usage and contribution but has been included also as a asset check.
Under Utility appliances only washing machine and motor/pump for water was included as these are used frequently and for significant periods of time contributing to the load curve. For households that did not know the capacity of the installed pump/motor, a question checking the height to be pumped to is included to get an approximation of the pump capacity.

2.2.1.6.3: Bathroom Appliances

This section we cover the appliances and lighting installed in bathrooms.

Bathroom Appliances	**Lighting**
Geyser	Incandescent
Immersion Rods	Tube light
Instant geyser	CFL
Solar water heaters	LED
Other	

Table 7: Bathroom appliances and Lighting

Table 7 lists bathroom appliances with the *"Other"* option covering any other source of heating water like gas geysers, fire wood, gas stove, etc., not included in the list.

It was also important to cover solar water heaters as a separate category as installation in Bengaluru is mandatory for all houses with area over 1200 square feet. Solar water heaters with heating elements were noted separately. Data on number of each of the appliances installed and used along with the number of bathrooms in the household was also collected.

Capturing these details was important to get a detailed understanding of water heating use in households. Table 8 lists additional information collected for each bathroom in the household.

Bathroom wise appliances	Seasonal use	Additional information	Time slots
Geyser	Usage in Summer	Time geyser switched on daily	6am-10am
Instant geyser	Winter usage	Number of water heaters on simultaneously	10am-6pm
Solar heater	Monsoon usage	if water heating is used more in monsoon	6pm-11pm
Other			11pm-6am
Lighting type			

Table 8: Bathroom appliances and time of use data

Given the mandate to install solar water heaters and considering the fact that Bengaluru has extended monsoons, it is important to capture what households with solar water heaters installed use as an alternate during the cloudy, rainy and low light days through monsoon and winter. To capture this, geyser usage hours for monsoon was recorded separately. For households with solar water heaters, specific questions on other sources of water heating in monsoon compared to other seasons along with simultaneous use of geysers and their duration of use was asked.

2.2.1.7: Vehicle Information

In this section vehicle ownerships divided into two sub sections of non electric vehicles and electric vehicles are covered. The goal of this section was to understand usage patterns of vehicles, propensity of households to buy electric vehicles and as a additional asset indicator.

Table 9 and 10 list data collected for non-electric and electric vehicles covering vehicle type owned (two and four wheeler), numbers of each owned, daily usage of each, type of fuel used (for 4 wheelers only) and preferred public transportation. Specific data on propensity to buy in the next 5 years and charging patterns were captured for EVs. Key reason in collecting propensity to buy electric vehicles was to understand impacts on electricity demand.

Type of Vehicle	Data collected
Two Wheeler	Owned
Four Wheeler	Number of each owned
	Number of times used weekly
	Fuel type (four wheeler only)
	Most used public transport

Table 9: Non-electric vehicle ownership and usage data

Type of Electric Vehicle	Data collected	Propensity to buy EV in the next 5 years
Two Wheeler	Owned	Two wheeler EV
Four Wheeler	Number of each owned	Four wheeler EV
	Hours of charge per day	
	Time of the day charged	
	Number of charges per week	
	Wattage per charge	

Table 10: Electric vehicle ownership and usage data

2.2.1.8: Propensity to Buy Desert Cooler or AC

The last section of the survey collects information on the propensity of households to buy a new air conditioner or desert cooler over a one year period and possible reasons for their decision to buy or not to buy the appliance. This is to get an estimate of change of ownerships in space cooling appliances to identify possible influences on electricity demand.
The reasons for purchasing/not purchasing covered were

- Expensive to own - Can not afford to purchase
- Expensive to use - Can not afford/do not want to incur the additional electricity costs associated with running the appliance
- Not needed in Bengaluru - Given the annual temperature profile of Bengaluru, it is not a necessity
- Difficult to maintain - It is either expensive to maintain or it takes too much effort to use regularly in terms of upkeep
- Other - Any other reasons for not wanting to own the appliance like health, lifestyle choice, etc.

The questionnaire was designed to be generic enough to cover multiple socio-economic profiles leading to the described sectioning, appliances, and variables covered. The final questionnaire is attached at the end of thesis for reference.

3. Sample Size Estimation and Survey Area Identification

In capturing electricity usage pattens across various economic brackets, it is important that the population sample surveyed is representative of Bengaluru's population distribution for identified indices and a given confidence level. It was therefore important to identify the right sample size , income distribution, area(s) that have similar distributions of the households in the city, and randomly survey households from these areas.

3.1. Sample Size Estimation

The survey sample size was estimated using

$$n = \{[z^2 * (p * (1-p))]/CI^2\}/\{1 + [(z^2 * (p * (1-p)))/(CI^2 * N)]\}$$

where,

- N = 8.4 million (est. Census 2011)
- Confidence level (CL (1-α)) of 95% (0.95)
- Confidence interval (CI (α)) of 5% (0.05)
- $z_{\alpha/2}$ value = 1.96
- Assumed population proportion values of p = 0.5, q = 0.5

The estimated sample size to survey was 385, the final sample size decided was 400 households. A detailed description of the formula and each variable is provided in [14, 15, 16] with a simple explanation of the formula and sample size calculator are [17]

3.2. Identification of Areas to Survey

It is important that the areas surveyed were representative of distribution of Bengaluru for identified key indices. It is also important that the households surveyed were random to avoid any biases [surveyor or otherwise]. While true random sampling is not possible, effort was made to randomize the choice of households to survey. There were key primary considerations that were taken into account when trying to identify areas to survey.

Income is a good indicator to identify how households are distributed in the city [1, 4, 6, 18].IHDS provides data on income for households surveyed in Bengaluru. But considering the limitations of IHDS concerning limited representative sample size and geographical resolutions, it was not possible to identify individual areas at city level to survey. The next best option was CENSUS, given its nature, provides data at higher geographical resolutions.

3.2.1. CENSUS Data and Indicators

As there were no open access data sets that gave income information, CENSUS 2011 data was used to estimate distribution of households in Bengaluru. CENSUS online catalogs are hosted under the CENSUS digital library [19]. The library has household data listed for various categories of amenities and assets owned disaggregated to ward level.

The data downloaded for Bengaluru, listed household information for Bengaluru Rural and Urban. Under Bengaluru Urban it covered all the 198 wards listed under Bruhat Bengaluru Mahanagara Palike (BBMP City municipal corporation) along with outgrowths indicating percentage of homes in each ward that owned different assets. The file covered over 26 categories and indicators as classified by CENSUS, out of which the shortlisted indicators and categories were

- Type of Household
- Number of rooms in the household - split into 1, 2, 3, 4, 5 and 6 and above rooms
- Household size (residents) - split into 1, 2, 3, 4, 5, 6-8 and 9 and above residents
- Main source of lighting - Electricity, Kerosene, Solar, Other oil, No lighting
- Assets of the household
  - Television
  - Computer - with and with out internet
  - Telephone - Land line only, mobile phone only and both land line and mobile phone
  - Bicycle, Scooter, Car
  - Households with all the assets listed above
  - Households with none of the above listed assets

Each of these was listed at ward level. While there was no information on income or expenditure it covered key indicators on condition and asset ownership spanning all households in the city presented at ward level. It meant that this data could be used to build a comparative asset based distribution of households at ward levels.

The data was presented in ”percentages of households” that fell into each listed category with no data on total number of households at ward or city level. To accurately build indices to identify household distributions, this information on total number of households in each ward is necessary.

3.2.2. BBMP Data

To address the above gap, we identified BBMP (Bruhart Bengaluru Mahanagar Palike) data collated in 2015 as part of the BBMP master plan [20]. This has data on number of households and population of the wards, based on CENSUS 2011.

The CENSUS file and the BBMP file were merged using central and state constituencies, ward names and ward numbers as primary keys. The number of households and the population of each ward for each indicator were then extracted using the percentages from CENSUS data and actual numbers from BBMP data:

Number of Households in a ward per indicator = CENSUS.Percentage.Value$_i$ * BBMP.Number.Households$_i$, where i = i^{th} ward.

For example in Bytarayanapura, CENSUS indicated 77.5% of households owned a TV in 2011, and from BBMP data Byatarayanapura had 12378 households in 2011. From this data the total households with TV’s in Byatarayanapura in 2011 were 9599.93

It was important to get actual numbers to build asset index to use as a proxy for income to compare wards to Bengaluru’s distribution.

3.3. Indices for identification of distribution of households

To compare distributions of each ward or constituency to Bengaluru common index(s) were needed. Given that CENSUS categorized assets, number of rooms and residents, a total of three indices for assets, room distribution and resident distribution were built to shortlist constituencies/wards that were close to Bengaluru’s distribution.

3.3.1. Asset Index

The idea of using an asset index was to build a proxy for income. Out of the 26 assets listed in CENSUS, we choose the following.

- Television, Radio
- Computer - with and with out internet
- Telephone - Land line only, mobile phone only and both land line and mobile phone
- Bicycle, Scooter, Car
- Households with all the assets listed above
- Households with none of the above listed assets

A monetary value was assigned for each of them to construct the asset index.The asset index is a summation of the monetary values of assets owned by a household categorizing the households into various asset brackets. The monetary values assigned to various assets are listed in table 11

Asset	Monetary value used
Radio	1200
Television	10,000
Computer	15,000
Mobile Phone	1500
Bicycle	1300
Two wheeler	30,000
Four wheeler	2,70,000

Table 11: Monetary values for each asset in CENSUS

This indicates that a household that owns all assets would have a higher asset value falling into a different asset bracket compared to a household that owned fewer assets.

Using the above assets and their indicative values asset indices were built

1. Identifying total asset value for the ward

   The total asset value of each ward was calculated using

   Total asset value of the ward

   $TA_w = \sum A_i * V_i$, Where

A_i = i^{th} Asset owned by the household,

V_i = i^{th} Rupee value of the i^{th} Asset owned by the household

2. Next average asset value for each ward was calculated using

Avg. asset value of the ward

$AA_w = \sum A_i * V_i / HH_w$, where

HH_w = Total households in the ward

3. Weight of each i_{th} ward among all wards in Bengaluru was calculated next using

Weight of each ward

$WW = HH_j / \sum_1^j HH$, where

HH_j = Households in j^{th} ward

$\sum_1^j HH$ = Sum of households in all wards (total households in Bengaluru)

4. Using the weight of the ward, the average weighted asset value for each ward was calculated using

Wt. Avg. Asset value of the ward

$\mathbf{WAA_w} = \{\sum A_i * V_i / HH_w\} * \{HH_j / \sum_1^j HH\}$

or

$AA_w * WW$ ((2)*(3))

5. Finaly using the average weighted asset value of the ward, the average weighted asset value for all of Bengaluru was calculated using

Avg. Wt. Asset value of Bengaluru

$\mathbf{B_{WAA}} = \sum_1^j [\{\sum A_i * V_i / HH_w\} * \{HH_j / \sum_1^j HH\}]$, Where,

A_i = i^{th} Asset owned by the household,

V_i = i^{th} Rupee value of the i^{th} Asset owned by the household,

HH_w = Total households in the ward,

HH_j = Households in j^{th} ward,

$\sum_1^j HH$ = Sum of households in all wards (total households in Bengaluru)

or

$\mathbf{B_{WAA}} = \sum_1^j WAA_w$

3.3.2. Room and Resident Distributions

CENSUS collected information about the number of rooms each household had. The room numbers were categorized from 1 to five and six and above and the data set indicated per ward, the percentage of households that fell into each category.

CENSUS similarly had data on the number of residents living in each household. The residents were categorized from 1 to 5, households with 6 to 8 residents and households with over nine residents. Figure 5 is a snapshot of the data listed in CENSUS in percentages.

Ward No	Area Name	Number of Dwelling Rooms							Household size						
		No exclusive	One room	Two rooms	Three rooms	Four rooms	Five rooms	Six rooms and	1	2	3	4	5	6-8	9+
0008	BBMP (M Corp. + OG) - Ward No.8	12.5	35.9	27.9	13.6	6.6	2.1	1.3	3.1	12.8	23.8	32.6	14.9	10.9	1.9
0009	BBMP (M Corp. + OG) - Ward No.9	3	15.1	25.1	28.2	17.4	6.2	5.1	2.7	12.7	24.9	31.3	15.5	11.2	1.7
0010	BBMP (M Corp. + OG) - Ward No.10	7.4	25	34.9	21.4	8.3	1.9	1.2	3.3	11.3	23.7	33.7	15.8	10.4	1.7
0011	BBMP (M Corp. + OG) - Ward No.11	16.5	38.9	29.5	10.2	3.7	0.8	0.5	2.2	9.3	17.3	31.3	19.1	18.2	2.6
0012	BBMP (M Corp. + OG) - Ward No.12	12.3	40	30.2	13	2.9	0.9	0.7	4.6	12.6	21.3	33.7	15.4	10.8	1.6
0013	BBMP (M Corp. + OG) - Ward No.13	2.7	39.9	43.9	11	1.9	0.3	0.2	6.8	13.2	24	32.8	13.2	8.8	1.1
0014	BBMP (M Corp. + OG) - Ward No.14	4.8	30.4	38.5	18.9	5.4	1.4	0.7	3.5	12.5	24.9	34.3	13.8	9.6	1.3
0015	BBMP (M Corp. + OG) - Ward No.15	2.7	30.5	43.7	16.9	4	1.2	1	5	15.2	24.2	31.1	13.2	9.6	1.7
0016	BBMP (M Corp. + OG) - Ward No.16	3.4	25.8	30.4	26.5	10.3	2	1.6	5	10.2	20.5	32.5	17.1	12.3	2.2
0017	BBMP (M Corp. + OG) - Ward No.17	4.9	26.5	33.8	21.3	8.8	3.1	1.5	4.5	13.5	23.1	29.9	15.2	11.9	2
0018	BBMP (M Corp. + OG) - Ward No.18	6.6	25.6	24	23.8	12.4	3.5	4	4.9	14.6	22.6	29.6	14.7	11.3	2.2
0019	BBMP (M Corp. + OG) - Ward No.19	3.8	21.2	25.3	30.8	13.3	3.5	2.1	4.5	14.5	22.8	28.5	15.1	12	2.6
0020	BBMP (M Corp. + OG) - Ward No.20	3.9	30.2	35	21.5	6.4	2	1	3.5	11.4	20	31.1	16.6	14.4	3.1
0021	BBMP (M Corp. + OG) - Ward No.21	6	34.8	28.7	17.5	6.5	3.2	3.3	4.2	13.4	23.9	30.1	15.1	11.5	1.8
0022	BBMP (M Corp. + OG) - Ward No.22	5.5	23.6	32.7	30.3	5.7	1.2	1	3.9	12.2	20.9	31.7	16.2	13.1	2
0023	BBMP (M Corp. + OG) - Ward No.23	5.4	31	34	23.9	4.2	0.8	0.7	1.4	7	13.2	24.9	22.3	26.3	5.1
0024	BBMP (M Corp. + OG) - Ward No.24	6.2	24.4	30.7	24.3	8.6	3.3	2.6	2.9	11.6	18	27.7	18.7	17.7	3.4
0025	BBMP (M Corp. + OG) - Ward No.25	4.3	19.2	27.5	31.4	12	3.9	1.7	3	13.8	22.6	31.1	15.7	11.9	1.8
0026	BBMP (M Corp. + OG) - Ward No.26	6.1	32.3	30.6	21.9	6.2	1.8	1.1	2.6	13.5	22.2	31	15.6	12.8	2.2
0027	BBMP (M Corp. + OG) - Ward No.27	3	19.9	30.5	27.8	11.9	4.3	2.6	4	13.8	22.1	30.9	15.1	12	2
0028	BBMP (M Corp. + OG) - Ward No.28	2.8	30.1	34.6	24.7	5.7	1.2	0.9	2.9	11.7	19.8	31.5	18.4	13.4	2.3
0029	BBMP (M Corp. + OG) - Ward No.29	1.5	17.9	29.3	30.2	14.1	4.8	2.3	5.3	14.5	21.1	30.3	15.5	11.2	2.1
0030	BBMP (M Corp. + OG) - Ward No.30	3.8	33.2	37.3	19.9	4.4	0.9	0.5	1.6	7.5	14.7	27.1	21.2	23.7	4.2
0031	BBMP (M Corp. + OG) - Ward No.31	3.3	28.6	35.9	26	4.5	0.9	0.9	1.8	6.7	12.7	24.3	20.5	25.6	8.2
0032	BBMP (M Corp. + OG) - Ward No.32	6.8	33	29.9	21.1	5.8	2	1.4	3.5	12.3	20.2	30.2	17	14.1	2.6
0033	BBMP (M Corp. + OG) - Ward No.33	7.9	32.4	34.2	18	4.9	1.5	1	2.3	9.3	16.7	28.1	20.3	19.5	3.8
0034	BBMP (M Corp. + OG) - Ward No.34	3.3	22.1	32.8	25.5	8.4	3.3	4.6	4.3	12	21.5	31.1	15.7	12.7	2.7
0035	BBMP (M Corp. + OG) - Ward No.35	3.8	20.2	25.3	26.9	13.8	5	5	5.7	14.1	22.1	29.4	14.3	12	2.4
0036	BBMP (M Corp. + OG) - Ward No.36	3.3	32	36.4	20.2	5.9	1.4	1	4.9	13.3	23.3	30.4	14.2	11.6	2.3
0037	BBMP (M Corp. + OG) - Ward No.37	4.6	36.1	35.4	17.3	4.2	1.7	0.7	5.4	12.3	21	30.2	15.6	12.9	2.5
0038	BBMP (M Corp. + OG) - Ward No.38	18.1	36.5	24.7	15.4	3.8	0.7	0.8	4.8	13.5	23.2	30.4	15	11.4	1.7
0039	BBMP (M Corp. + OG) - Ward No.39	7.2	40.8	38.2	10.4	2.4	0.5	0.4	7.1	17.5	23.4	29.5	12.8	8.6	1.1
0040	BBMP (M Corp. + OG) - Ward No.40	8	45.9	36.9	6.6	1.5	0.5	0.6	3.7	15.2	23	33.2	14	9.9	1.1
0041	BBMP (M Corp. + OG) - Ward No.41	14.7	50.4	26.8	6.2	1.3	0.3	0.3	10.6	16.1	21.5	28.3	13.2	9.4	0.8
0042	BBMP (M Corp. + OG) - Ward No.42	9.6	52.3	30.8	5.2	1.3	0.5	0.3	4.2	13.8	21.7	31.1	15.6	12	1.5
0043	BBMP (M Corp. + OG) - Ward No.43	20.3	53.1	18.6	6.4	1	0.3	0.3	3.5	12.8	22.5	33.5	15.5	10.6	1.6
0044	BBMP (M Corp. + OG) - Ward No.44	7.6	46.5	33.3	9.4	1.9	0.6	0.7	3.8	11.6	21.4	31.6	15.7	13.6	2.2
0045	BBMP (M Corp. + OG) - Ward No.45	4.3	28.9	34.4	18.4	9	3	2	4.6	14.6	22.1	30.1	14.5	11.7	2.4

Figure 5: Snapshot of room and resident numbers from CENSUS data

Using these, weighted room and resident values were calculated at ward level and for Bengaluru.

1. weight of each room type for the households in a ward was calculated using

   Weight of each room type in the ward

   $WR_i = HH_i/\sum HH_i$, where,

   HH_i = Households with i number of rooms in the ward (ranging from 1-5, 6 and above)

   $\sum HH_i$ = Sum of all households with all room types

   Weighted room number for the ward was then calculated using

Weighted room number per ward

$WR_w = \sum(i * (HH_i/\sum HH_i))$

Or,

$WR_w = \sum(i * WR_i)$, where,

i = Number of room (room category/type of the household, 1-5,and 6 and above)

2. Weight of each resident number for the households in a ward was calculated using

Weight of resident number in the household in the ward

$WM_i = HH_i/\sum HH_i$, where,

HH_i = Households with i number of residents in the households in the ward (ranging from 1-5, 6 to 8 and 9 above)

$\sum HH_i$ = Sum of all households with all resident numbers

Weighted resident number for the ward was next calculated using **Weighted resident numbers per ward**

$WM_w = \sum(i * (HH_i/\sum HH_i))$

Or,

$WM_w = \sum(i * WM_i)$, where,

i = Number of residents per household (resident numbers per household ranging from 1-5,and 6 to 8 and 9 and above)

3.4. Identifying Constituency and Wards to Survey

In India wards are administrative units of cities, and a city is divided into multiple wards. A constituency generally is a collection of wards. Nationally India is divided into 543 constituencies with Members of Parliament as their representatives. Each state has specific number of constituencies represented by elected Members of Legislative Assembly (MLA). Bangalore (Urban) has 198 wards and 27 constituencies at the assembly (MLA) level listed in 6.

3.4.1. Constituency Identification

With asset, room, and resident indices and weighted average values for Bengaluru calculated, the wards were grouped at constituency level. The reasons for this grouping is that calculations at ward level give us a point estimate using which we can not identify the variation within the ward.

It is also important to identify constituencies with wards that have large variation in the asset values (range of the asset values of wards with in the constituency (max(asset_value)-min(asset_value)) because a constituency with large variation in asset values would indicate a diverse set of households (7).

We calculated average weighted asset values at constituency level. Figure 6 shows average weighted asset values for 27 constituencies in Bengaluru and the percentage variation of each constituency as compared to Bengaluru.

From this list, the constituencies that had approximately 10% or lesser variation from the the average Bengaluru value were shortlisted. Figure 7 lists the constituencies that meet this criteria.

From the constituencies with 10% or lesser variation 5 constituencies were further shortlisted that met the following constraints

- An asset value close to Bengaluru's value
- Room and resident average numbers close to Bengaluru's value
- Constituencies with maximum intra-constituency range (Max_asset_value - Min_asset_value)

The final 5 constituencies shortlisted were: *K R Puram*,*Sarvagyna Nagar*,*Bommanhalli*,*Byatarayanapura* and *Bengaluru South*.

Figure 8 below summarizes the asset, room and resident values as compared to Bengaluru along with ranges.

Figure 9 shows plots that compare the room and resident distribution of the shortlisted wards to Bengaluru.

These comparisons were necessary to identify constituencies whose distribution were closest to Bengaluru, and that had the highest intra-constituency variance.

The final constituency shortlisted was ***Byatarayanapura***.

Comparison of % variation of assets with banaglore average and Range (Max-Min) of avg asset value per ward - All Constituencies			
MLA Constituency	Avg.Wt.Asset Value.per.ward	Bangalore Avg asset value	% Variation
Chamarajpet	37071.61	79000.98	-53.07
Dasarahalli	37854.92	79000.98	-52.08
Yeshwantpura	48350.60	79000.98	-38.80
Gandhi Nagar	49204.55	79000.98	-37.72
Pulakeshi Nagar (SC)	63235.19	79000.98	-19.96
ViJayanagar	66134.40	79000.98	-16.29
Rajarajeswari Nagar	66715.86	79000.98	-15.55
Mahalakshmi Layout	69943.41	79000.98	-11.46
Govindaraja Nagar	72257.37	79000.98	-8.53
Yelahanka	73047.88	79000.98	-7.53
K.R. Puram	81334.50	79000.98	2.96
Sarvagna Nagar	81554.10	79000.98	3.23
Rajaji Nagar	82714.93	79000.98	4.70
Bommanahalli	83359.85	79000.98	5.52
Bangalore South	84715.46	79000.98	7.23
Shanthi Nagar	84807.44	79000.98	7.35
Shivaji Nagar	85072.61	79000.98	7.69
Byatarayanapura	**86161.28**	**79000.98**	**9.06**
Chickpet	87737.77	79000.98	11.06
BTM Layout	92694.10	79000.98	17.33
Padmanaba Nagar	92960.49	79000.98	17.67
Mahadevapura	93920.26	79000.98	18.89
Hebbal	95748.98	79000.98	21.20
Basavanagudi	100704.02	79000.98	27.47
Malleshwaram	101022.70	79000.98	27.88
C.V. Ramannagar (SC)	112242.47	79000.98	42.08
Jayanagar	118191.33	79000.98	49.61

Figure 6: List of all constituency average asset index values compared to Bengaluru's asset index value

Comparison of % variation of assets with banaglore average and Range (Max-Min) of avg asset value per ward - Shortlisted Constituencies			
Constituency	Range	Bangalore Avg asset value	% Variation
Mahalakshmi Layout	99211.90	79000.98	-11.46
Govindaraja Nagar	101025.50	79000.98	-8.53
Yelahanka	44767.00	79000.98	-7.53
K.R. Puram	85601.90	79000.98	2.96
Sarvagna Nagar	85990.10	79000.98	3.23
Rajaji Nagar	69983.60	79000.98	4.70
Bommanahalli	114760.60	79000.98	5.52
Bangalore South	63121.20	79000.98	7.23
Shanthi Nagar	124006.60	79000.98	7.35
Shivaji Nagar	126676.20	79000.98	7.69
Byatarayanapura	**72709.40**	**79000.98**	**9.06**
Chickpet	76927.20	79000.98	11.06

Figure 7: List of shortlisted constituencies with 10% variation from Bengaluru's asset values

3.4.2. Identifying Wards to Survey from Shortlisted Constituency

For the survey to be representative, it is not sufficient that the constituency identified was representative to Bengaluru's distribution of the key indices built, it also was important to identify wards within the constituency that are distributed in a similar manner. We compared asset, room, and resident distributions at ward level for Byatarayanapura to identify wards that fell close to the distribution of Bengaluru. Along with this the three constraints to identify the final constituency were also applicable when shortlisting wards. Figures 10 and 11 show the comparison of room and resident distributions of the wards from Bytarayanapura.

Following the comparisons of rooms, residents and assets, the final shortlisted wards from

Assets

Constituency	weighted_assetvalue per ward	Range (Max-Min)	% Variation of assets from Bangalore Value	Range Bangalore	Bangalore Avg asset value
Byatarayanapura	86161.27807	16235.48639	9.064908949	148323.2	79000.98348
Bangalore South	84715.45832	15456.87355	7.234757367	148323.2	79000.98348
Bommanahalli	83359.84827	14130.66598	5.518795276	148323.2	79000.98348
Sarvagna Nagar	81554.09539	13380.65196	3.233032143	148323.2	79000.98348
K.R. Puram	81334.49973	20575.94358	2.955062956	148323.2	79000.98348

Rooms

Constituency	Avg.Wt.Rooms .PerConstituency	Range (Max-Min)	% Variation per constituency comapred to avg. bangalore value	Bangalore Range	AVG Bangalore weighted rooms per ward
Bangalore South	2.452398345	1.098886895	14.06923844	1.626890695	2.149920854
Sarvagyna Nagar	2.293089129	0.699893951	6.659234701	1.626890695	2.149920854
K R Puram	2.243400762	0.682573698	4.34806279	1.626890695	2.149920854
Bommanhalli	2.182243957	0.936343314	1.503455525	1.626890695	2.149920854
Byatarayanapura	2.158456958	1.095178628	0.397042715	1.626890695	2.149920854

Residents

Constituency	Avg.Wt. people/hh	Range (Max-Min)	% Variation per constituency compared to avg. bangalore value of people per HH	Avg. wt.Persons Bangalore	Bangalore Range
Sarvagyna Nagar	4.217646485	1.353097804	2.564980111	4.112170139	
Byatarayanapura	4.094036108	0.531457457	-0.440984443	4.112170139	1.745493493
K R Puram	4.037640917	0.695	-1.812406073	4.112170139	1.745493493
Bangalore South	3.908353985	0.474058474	-4.95641345	4.112170139	1.745493493
Bommanhalli	3.856460151	0.440559441	-6.218370814	4.112170139	1.745493493

Figure 8: Comparisons of shortlisted constituency ranges, asset, room and resident values

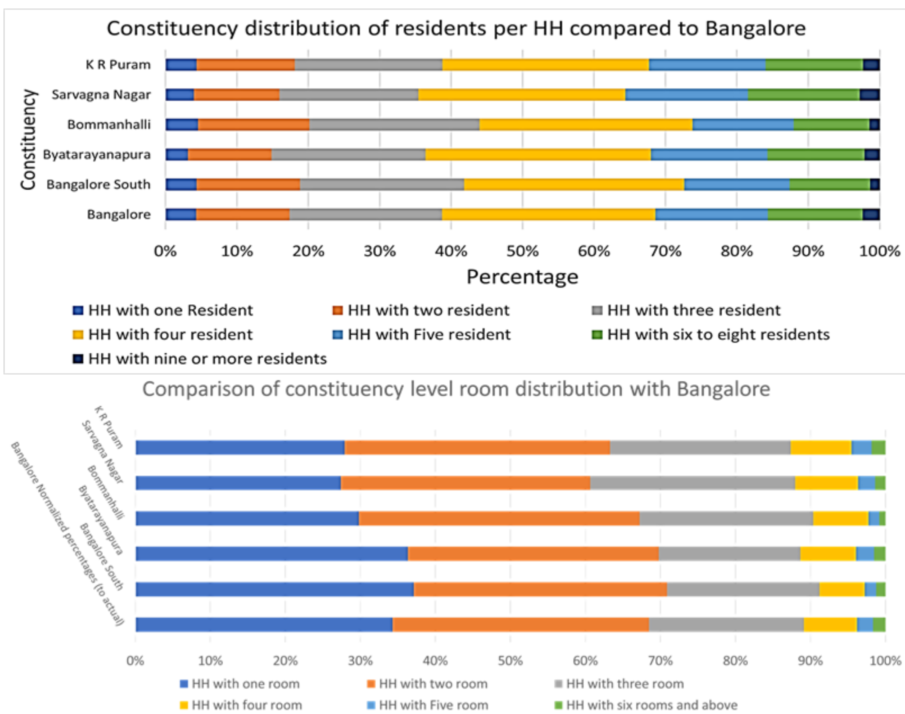

Figure 9: Plot to compare resident and room distributions of shortlisted constituencies with Bengaluru

Byataranayapura constituency were *Vidyaranyapura*, *Byataranapura* (ward) and *Kodigehalli*.

	HH with one room	HH with two room	HH with three room	HH with four room	HH with Five room	HH with six rooms and above
Bangalore Normalized percentages (to actual)	**34.31**	**34.15**	**20.64**	**7.10**	**2.15**	**1.64**
Bangalore South	37.12	33.74	20.34	6.05	1.49	1.26
Byatarayanapura	36.35	33.43	18.89	7.39	2.42	1.52
Bommanhalli	29.81	37.43	23.13	7.35	1.48	0.80
Sarvagna Nagar	27.37	33.27	27.32	8.38	2.27	1.40
K R Puram	27.88	35.42	24.05	8.11	2.69	1.84

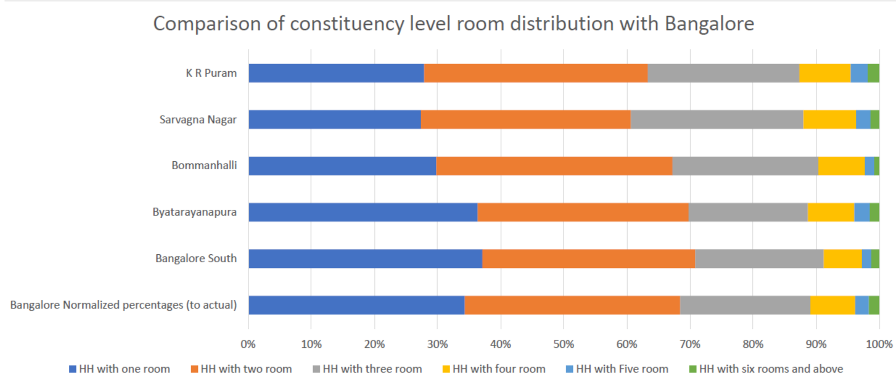

Figure 10: Comparisons of room distribution of wards from shortlisted constituency (Byatarayanapura) with Bengaluru

	HH with one Resident	HH with two resident	HH with three resident	HH with four resident	HH with Five resident	HH with six to eight residents	HH with nine or more residents
Bangalore	**4.31**	**13.06**	**21.35**	**29.86**	**15.74**	**13.26**	**2.41**
Bangalore South	4.38	14.46	22.96	30.85	14.71	11.31	1.33
Byatarayanapura	3.17	11.67	21.56	31.53	16.34	13.60	2.12
Bommanhalli	4.54	15.61	23.83	29.81	14.14	10.60	1.45
Sarvagna Nagar	3.98	11.97	19.50	28.92	17.21	15.59	2.83
K R Puram	4.37	13.76	20.65	28.94	16.31	13.63	2.34

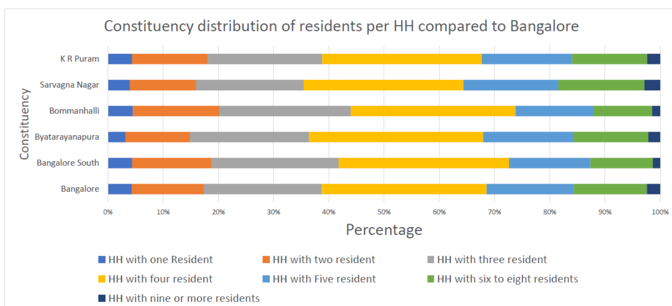

Figure 11: Plot to compare resident distribution of wards from shortlisted constituency (Byatarayanapura) with Bengaluru

3.5. BBMP Data

BBMP on its website lists ward level data further broken down into blocks. BBMP carried out this exercise in 2017 as part of its SWM(solid waste management) program [20].

To get a better understanding of how households were distributed in each of the shortlisted wards, this data was used to compare the distribution of wards to Bengaluru data (aggregated from BBMP SWM data).

Figures 12 gives a snapshot of the type of data that is available from the BBMP-SWM data and the map of Vidyaranyapura ward.

From key information indicated in figure 12, BBMP-SWM data further splits the wards into

DATA	
Total Households	**20688**
Slum HHs	319
HHs in Large Apts. (> 50 units)	1810
Regular HHs	**18559**
HHs - High Income	4729
HHs - Mixed Type	7972
HHs - Low Income	5856
Commerical Establishments	**376**
Small Shops & Clinics	310
Retail Units, Offices & Educational Inst	17
Small Markets & Temples	14
Vgetable vendors	35
Street Sweeping	
Major Roads	6.60
Intermediary Roads	5.00
Minor Roads	124.80

NO OF BLOCKS
26

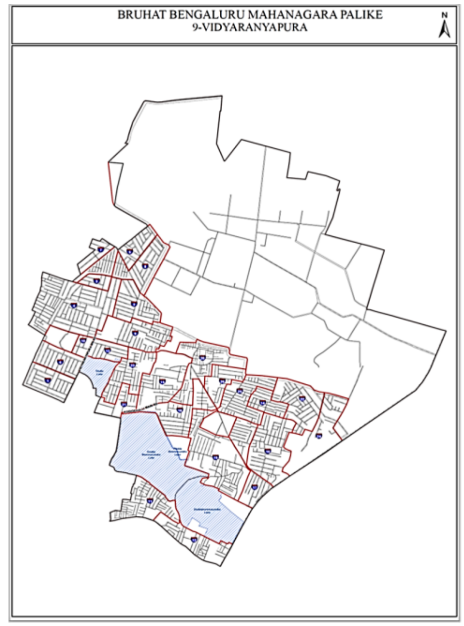

Figure 12: Ward key information and ward map indicating blocks of Vidyaranyapura ward

blocks (26 in the case of Vidyaranyapura). The households in each block are further split into **Dwelling types**; Regular households, Apartments and Slums. The regular households are further split into High income (area more than 2400 sq.ft), Mixed income (area between 1200 sq.ft and 1200 sq.ft) and Low income households (area less than 1200 sq.ft) [21]. Table 12 lists the key statistics for the shortlisted wards.

Ward	Number of Blocks	Total households
Vidyaranyapura	26	20688
Kodigehalli	13	17235
Byatarayanapura	25	24711

Table 12: Wards key statistics overview

Figure 13 lists in percentages, various dwelling types and income categories comparing the 3 shortlisted wards and Figure 14 compares distribution of these categories with Bengaluru's distribution.

NOTE: The distribution of Bengaluru in this case is also from the same data set(BBMP-SWM) calculated by identifying listed information for each ward and aggregating to get values for Bengaluru.

From figure 14 it can be seen that the distributions of the three wards are similar to Bengaluru, while none of the wards independently fell close to the slum percentage of Bengaluru. There-

Category	Bengaluru	Vidyaranyapura	Byatarayanapura	Kodigehalli
Total Slums	7.13	1.54	4.86	2.32
Total Apartments	6.41	8.75	5.79	6.02
Total High income	16.19	22.86	22.00	21.38
Total Mixed income	35.65	38.53	43.98	43.88
Total low income	34.62	28.35	23.38	26.40

Figure 13: Table indicating ward level percentage of each category of households

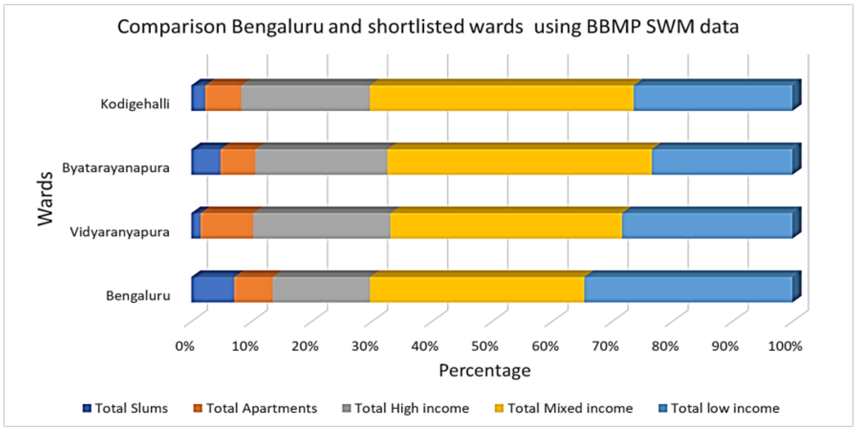

Figure 14: Comparison of distributions of each ward with Bengaluru for categories listed in figure 13

fore in order to cover enough number of slums in the survey, slums from two wards(Vidyaranyapura and Kodigehalli) were surveyed.

3.5.1. Physical Mapping of Wards

The final step was to identify distributions of the households visually to understand the density and type(size, dwelling types, etc) of household distribution in each block of each ward.

To do this block level maps were used to identify key landmarks and cross roads of each block. These key reference points were also used during the execution of the survey to approximately identify the block numbers in which the household surveyed was. Figure 15 shows the block map from the BBMP-SWM data used to map the wards and their blocks .

3.6. Execution of the Survey

The survey was conducted in the second week of October, 2018. The duration of the survey was approximately 2.5 months and was completed in December, 2018. A total of 403 households were surveyed continuously over the period covering independent, apartments and slum households.

Figure 15: Block map of block 16 from ward 9- Vidyaranyapura

4. Summary

This chapter began by outlining the need for appropriate data sets and surveys covering the key variables to enable detailed analysis of residential demand. Given the current lack of open access data sets covering all key variables, a survey design methodology was proposed using open access data sets like the Census and city municipal data. A detailed overview of design considerations was presented outlining the key variables that need to be covered including appliance descriptors, ownership, usage pattern information along with seasonal variations and propensity of households to buy specific appliances. Sample size estimation methodology was outlined followed by a detailed methodology of identifying a representative sample to survey using Census and municipal data by building three indices. The final survey covered 85 variables, across 7 categories and 19 subcategories, with a representative survey size of 403 households.

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Chapter 3
Survey Statistics and Results

In the previous chapter a methodology to design a residential electricity use survey using open access data was outlined. In the sections that follow, presented are statistics and results of data collected in the survey.

The first section presents data and statistics at aggregate levels (data not split into quintiles or deciles). The second section outlines the need for analyzing this data by splitting it into quintiles and the methodologies used to divide the data into quintiles. Finally the last section presents data and statistics of the survey split into quintiles. In each section along with statistics for each variable key observations are presented.

1. Aggregate Statistics from the Survey

This section presents key statistics for the survey data covering the following sections

- Household level statistics
- Electricity and backup statistics of the household
- Appliance and vehicle statistics of the household

The statistics presented in this section are aggregate (data not split into quintiles) and represent statistics of the 403 homes.

1.1. Household Statistics

This section presents statistics of household and demographic descriptors.

1.1.1. Household and Dwelling Types

The survey covered different types of households and dwelling types presented in table 1

Dwelling Types			
Sl. No	**Dwelling type**	Number covered	Percentage of hh
1	**Total Independent households**	364	90.3
1a	**Total Low income/slum households**	41	10.1
1b	**Total non low income/non slum independent households**	323	80.1
2	**Total Apartments**	39	9.6

Table 1: Dwelling types, numbers and percentages of each type covered in the survey

Among the households that were covered in the survey, 90% were independent households, off which 10.17% were slum households and 9.68% were apartments. Comparing this with figure 13 in chapter 2, we find that households covered in this survey fall close to distribution of different household types in Bengaluru.

1.1.2. Ownership and Rental Status

Table 2 presents statistics of household ownership across dwelling types.

Ownership of households and residential status		
Ownership	Percentage of HH	
Total number of households owned	67	
Total number of households Rented	30.7	
Total number of households Leased	2.2	

Table 2: Ownership and rental status of households surveyed

It can been seen from table 2, among the households surveyed 67% were owned, approximately 31% were rented and 2.2% of the households were on a leasing structure.

Table 3 outlines rental brackets that various rental households fall under. The data presented is for households that reported their rental brackets.

We see that the maximum number of households fell into the the 3^{rd} bracket followed by 2_{nd} bracket, with the least number of households in the 5^{th} bracket .

Out of the 124 households that came under rental homes, 25 households (20%) did not disclose their rental brackets.

Rental brackets distribution of rented households	
Brackets	Percentage of hh
R1(<5000)	7.26
R2(>5000, <10000)	17.74
R3(>10000, <15000)	41.94
R4(>15000, <20000)	9.68
R5(>20000)	4.03
Did not disclose	19.35

Table 3: Rental brackets distribution of households

1.1.3. Distribution of Number of Rooms in the Households

Table 4 gives an overview of the distribution of households with different number of rooms.

Household characteristics - Bedrooms		
HH with number of rooms	Values	Percentage of hh
0	1	0.25
1	51	12.6
2	197	48.8
3	110	27.3
4	34	8.4
5	9	2.2
6	1	0.25

Table 4: Distribution of different room numbers

From table 4 it can be seen that 48.8% of households have 2 bedrooms, followed by 3 rooms and 1 room. Approximately 89% of the households have between 1 and 3 bedrooms.

1.1.4. Demographics

Table 5 presents details on the average number of people per households indicating average number of members, adult male, females, and children. For the survey anyone below the age of 18 years was categorized as a child.

Household demographics	
Demographics	Average members
Average number of people/hh	3.8
Average number of Male/hh	1.6
Average number of Female/hh	1.5
Average number of Children/hh (<18 years)	0.73

Table 5: Average number of residents per household

From table 5 it can been seen that the average number of residents per household is 3.8, with more adult male members than adult female and children.

1.1.5. Earning Members

Table 6 gives an overview of the average number of earning members across households. It can been seen that on average the number of earning males is almost 3 times that of earning female members.

Household Income - Earning members	
Type of earning member	Average members
Average number of earning members	1.71
Average number of males earning members	1.26
Average number of female earning members	0.45

Table 6: Average number of earning members in the household

1.1.6. Household Income Reporting and Income Brackets

In the survey information on the income bracket of the household was collected. Household income was the total income earned by all the earning members of the households including pensioners. The income brackets were divided into five brackets ranging from less than Rs.2,00,000 to over Rs. 10,00,000 (table 2, chapter 2).

Table 7 indicates the number of households that disclosed the income bracket they fell into.

Household Income		
Income	Number of HH	Percentage of HH
Total households that did not report income brackets	186	46.15
Total households that reported income brackets	217	53.85

Table 7: Comparison of households that disclosed income VS households that did not disclose income

Table 7 shows that approximately half the households surveyed did not disclose their income bracket.

Table 8 presents the distribution of income brackets among the households that disclosed their income brackets .

It can been seen that the among the households that disclosed income information, the households falling into bracket HHI5 were the highest to disclose their income brackets, closely

Household Income - Brackets break up	
Income bracket	Percentage of hh
HHI1 (<200000)	16.59
HHI2 (>200000, <400000)	22.58
HHI3 (>400000, <700000)	19.35
HHI4 (>700000, <1000000)	17.51
HHI5 (>1000000)	23.96

Table 8: Percentage of households in different income brackets Bengaluru respondents)

followed by households in bracket HHI2.

1.2. Electricity Information

This section covers details of electricity connection and backup used by the households.

1.2.1. Electricity Bill Amounts

Electricity bill amount details were collected for the survey month along with average bill amounts for summer and winter months.

Table 9 below presents average bill amounts collected for three time periods.

Electricity bills	
Electricity bill amounts	Average Amounts
Average bill amount (Previous/Current Month)	1084.8
Average bill amount - Summer	1258.8
Average bill amount - Winter	1085.0

Table 9: Average electricity bill amounts for different times of the year

From the table 9 it can been seen that average electricity bill paid by the households during the survey months and winter was almost the same. This is because the survey was carried out during October to December, which are winter months in Bengaluru.

1.2.2. Type of Backup Used by Households

Electricity back up devices are primarily used to provide electricity during power outages and cuts by the grid. Table 10 presents details about the type of electricity backup appliances used by households.

Electricity backup	
Type of power backup	Percentage of HH
UPS	62.53
DG	0
Solar	0.74
Common Apartment Backup	3.72
Do not have any backup	33

Table 10: Electricity back up device used

Table 10 shows that the most common form of back up used by independent households is UPS/inverter with a very small percentage of households using solar. Common apartment back up for all the apartments surveyed was a DG (diesel generator) with some of apartments using UPS as a source of additional backup. Close to 33% of the households did not own any form of back up appliance.

1.2.3. Electricity Bill Paid to

Electricity bills payment	
Bill Payment	**Percentage of HH**
Paid to ESCOM	95.53
Paid to Owner	4.47

Table 11: Households electricity bill paid to

Table 11 indicates the person/agency households pay their electricity bill to. Approximately 95% of the households paid their bill directly to the ESCOM while approximately 4.5% of the households paid the bills to the owners of their rental households.

1.3. Lighting Use in the Household

This section covers the various types of lighting used in different areas of the household. The household was categorized into three areas: Living, bathrooms and Kitchen. The living areas comprised of all common use spaces like hall/living room, bedrooms and other common use areas.

1.3.1. Lighting Type Used by Area of the Household

Figure 1 below presents the various types of lighting used by households in different areas of the household.

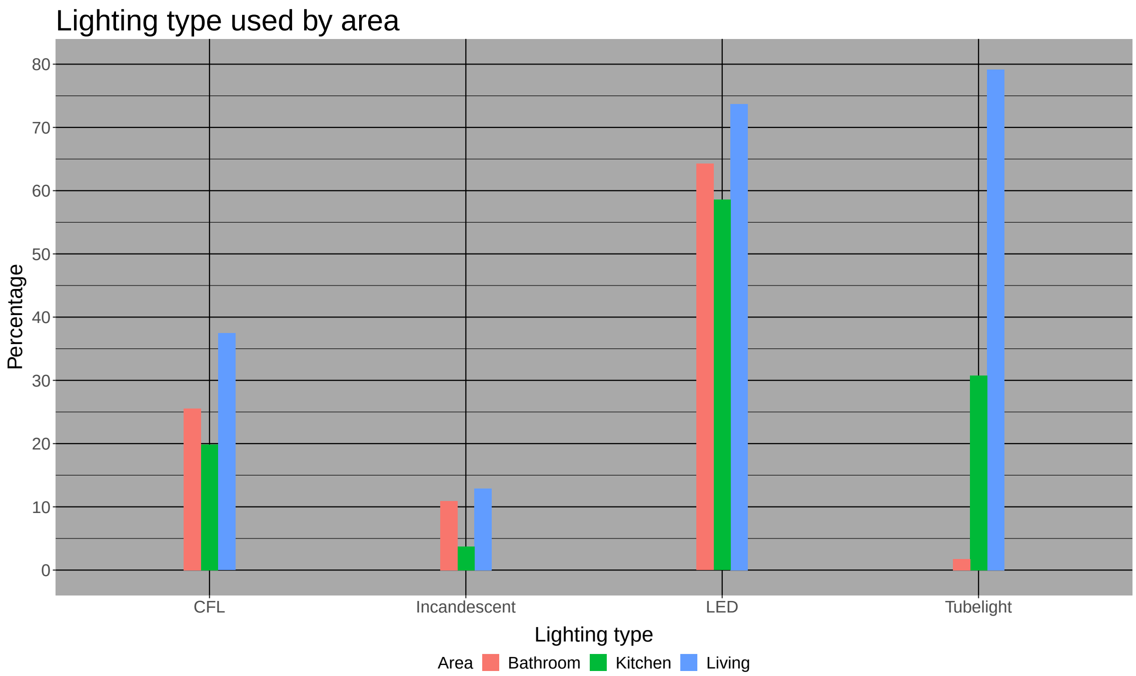

Figure 1: Type of lighting used in different areas of the household

As can be seen from figure 1, primary lighting type used by households in living spaces is tube lights, followed by LED bulbs. LED bulbs are also among the highest used in the kitchen and bathroom areas followed by tube lights in kitchen and CFL in bathrooms. Looking at the use of incandescent bulbs, we see that their usage is highest in living spaces and bathrooms.

1.3.2. Lighting Type by Wattage Used in Different Areas of the Households

Each light type was classified into different wattages, based on data collected in the survey. Their classification and uses in different areas as presented in figure 2.

From the figure 2 we see that the in living spaces, tube lights over 18 watts, ranging from 24-36 watts are used more compared to other wattages. For CFL bulbs, the domaninat wattage ranges from 5-11 watts.

Finally, in the case of LED bulbs, the dominant wattage across all areas of the households is 9 watts. This is probably a result of the UJALA scheme under which the government issued subsidized LED bulbs to all households. In Bengaluru, the wattage of bulbs issued under the scheme were mostly 9 watts costing Rs. 100 (approx.$1.2) or less per bulb.

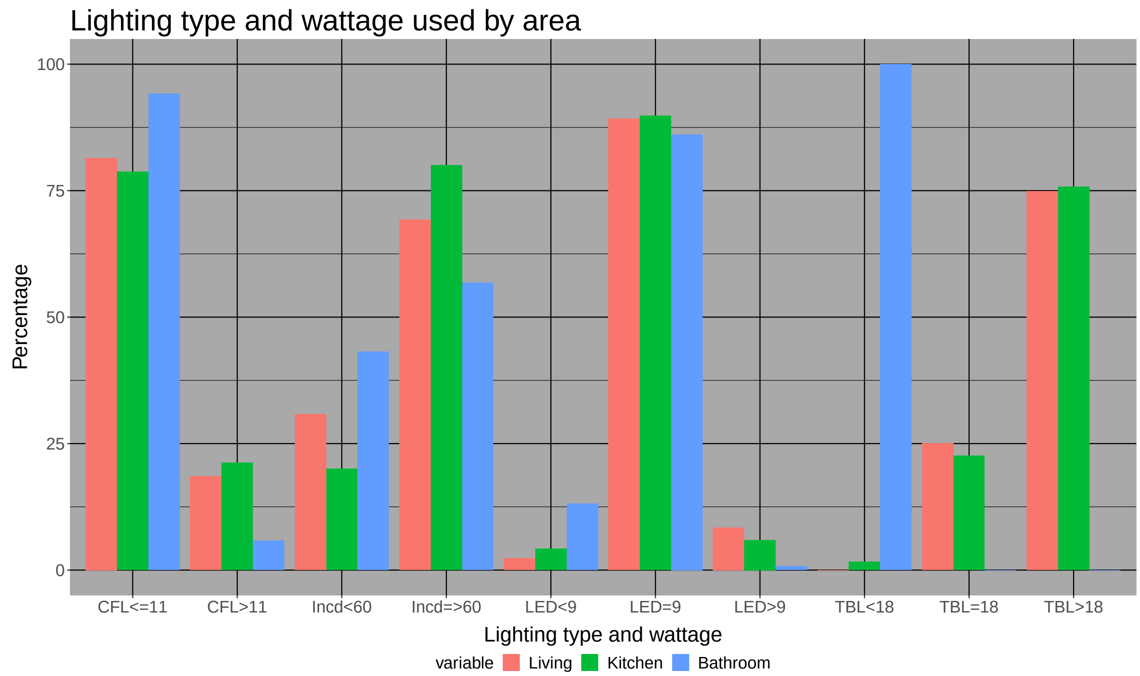

Figure 2: Type of lighting used in different areas of the household

1.4. Appliances Used in the Living Areas

1.4.1. Space Cooling and Heating Appliances

This section covers appliances owned and used for space comfort.

1.4.1.1. Ownership of Space Cooling and Heating Appliances

Figure 3 presents ownership of different space comfort appliances. From figure 3 it can be observed that fans are owned by all the households surveyed, air conditioner ownership is at 20%, followed by desert coolers at approximately 11%. Room heaters do not have a high percentage of ownership, with only 3.2% of the households owning one, considering the climate in Bengaluru the need for a space heating is low.

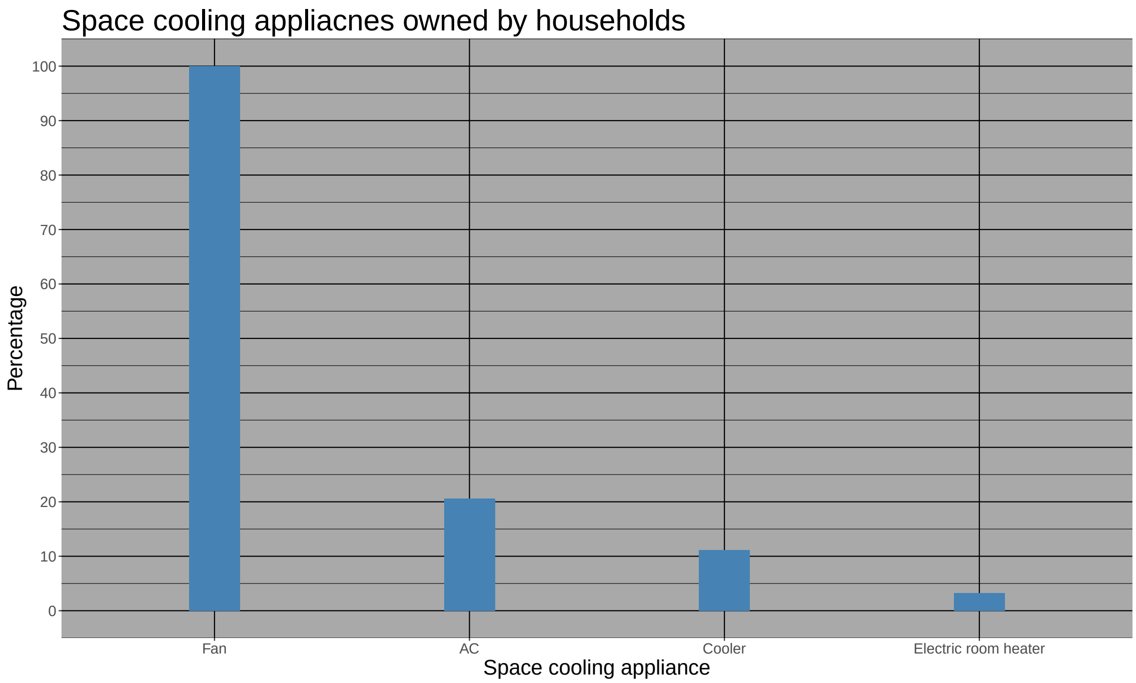

Figure 3: Percentage ownership of different space comfort appliances

Figure 4 presents percentage of households that own more than one of each space cooling appliance. It can be observed that approximately 98% own more than one fan, air conditioners and coolers have very few households that own more than one with 6.2% and 1.2% respectively. None of the households own more than one space heater.

One key observation among households surveyed is, while the number of households that own an air conditioner is only 6.2%. It can be observed that among the households that own an air conditioner close to a third of the households (32.5%) own more than one air conditioner. This observation is important considering the fact that air conditioners are high energy consumption appliances and have high seasonal correlation, indicating demand from these households will be significantly higher.

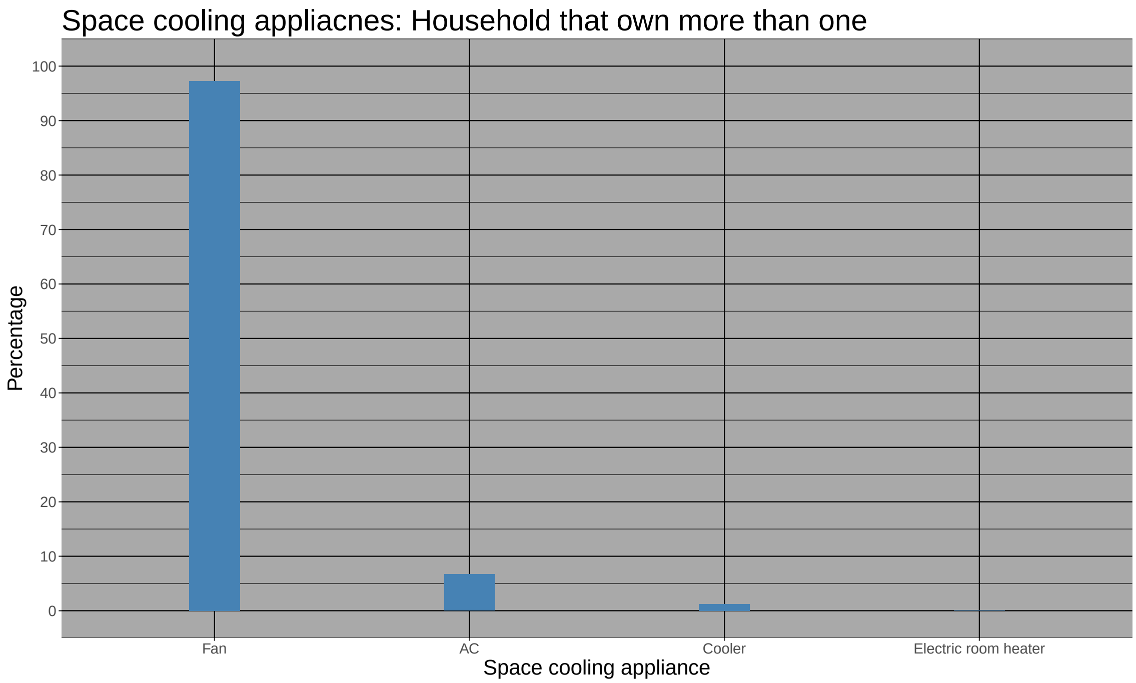

Figure 4: Percentage ownership of different space cooling appliances

1.4.1.2. Star Rating and Capacity Distribution of Air Conditioners

As part of the survey, data on the star rating and capacity of AC's owned was collected. Table 12 below is the distribution of the star rating and tonnage of ACs owned by households.

AC star rating and tonnage			
Star rating	Percentage	Tonnage	Percentage
2	3.6	1	33.7
3	45.7	1.2	1.2
4	10.8	1.5	54.2
5	19.2	2	10.8
NA	20.4		

Table 12: Percentage ownership of different star rating and tonnage of AC's

It can be seen that the dominant star rating of AC's is 3 star with close to 46% of households owning a 3 star AC. The second highest star rating is 5 star. Considering the significant price difference between a 3 star and a 5 star rated AC, it is interesting to that close to 20% of households own a 5 star rated AC. In the case of tonnages It can be seen that the maximum ownership is of 1.5 tons, with close to 54% owning a 1.5 ton AC, followed by 1 ton ACs at approximately 34%.

1.5. Entertainment and Productivity Appliances

This section covers entertainment and productivity appliances. The entertainment appliances covered four types of TV's: CRT, LCD, LED and other TV's. Under other were plasma TV, projectors etc. The productivity appliances covered were desktop and laptop computers.

1.5.1. Entertainment Appliances

Figure 5 presents distribution of different types of TV's owned by households. It can be seen that the highest ownership is of LED TVs with close to a third of the households surveyed owning LED TVs followed by CRT TVs at approximately 20%.

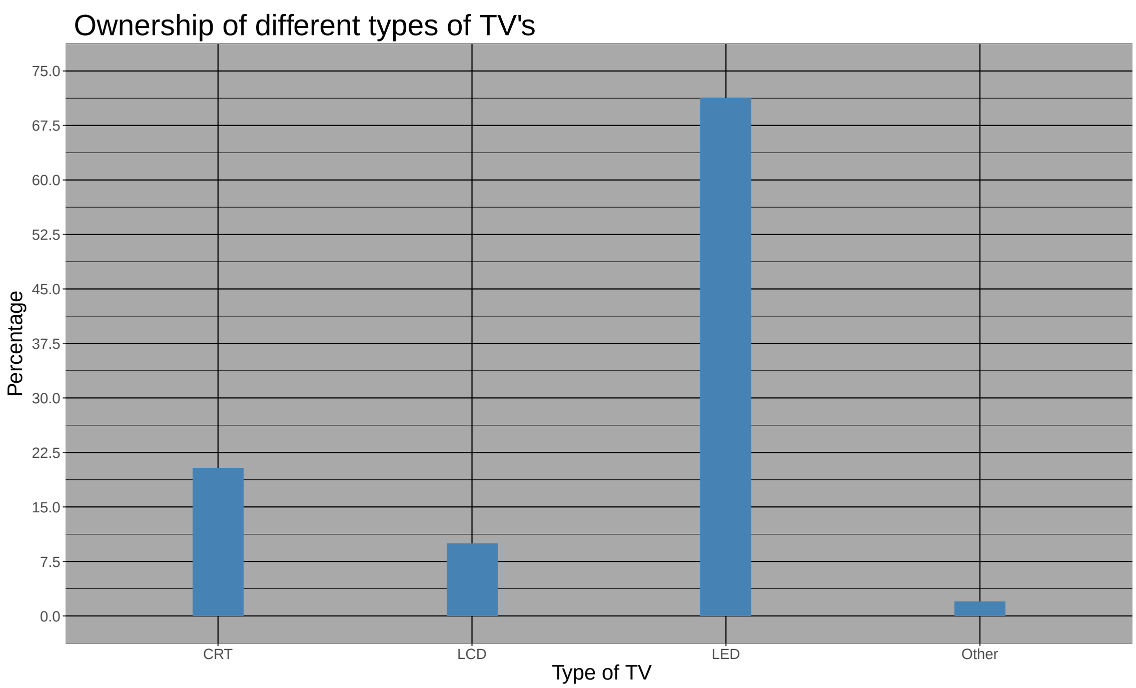

Figure 5: Percentage ownership of different TV types

Figure 6 presents ownership and type of TVs in households that own more than one TV.

It can be seen that LCD TV's are the ones that are owned most in terms of a second TV, followed by both CRT and LCD TVs. It will be interesting to see which income quintiles own what type of TV's and also which ones own more than one TV (next section) considering TV ownerships change with income brackets [1, 2, 3, 4, 5].

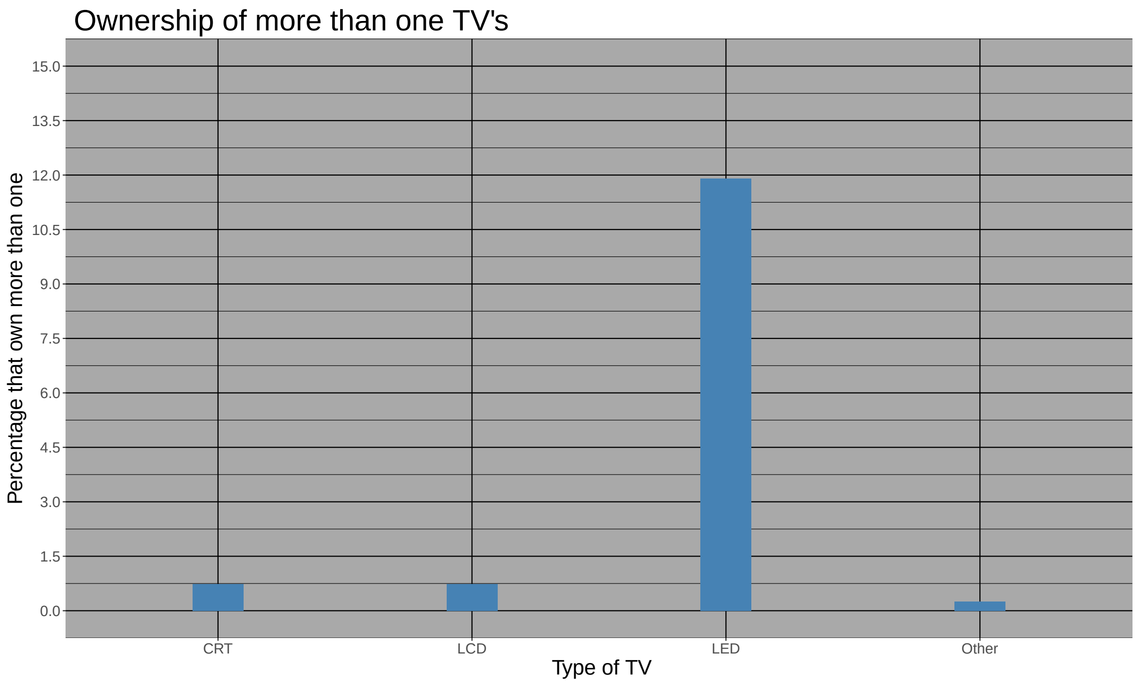

Figure 6: Percentage ownership of more than one TV per household

1.5.2. Productivity Appliances

Productivity appliances were primarily computers covering laptop and desktops. Table 13 presents the percentage of laptops and desktops owned.

Productivity appliances		
Computer Type	Percentage of HH own	Percentage of total HH own more than one
Desktop	27.7	0.74
Laptop	53.3	17.6

Table 13: Percentage of of households that own laptop or desktop and households that own more than one of them

From the table 13 it can be see that almost twice the number of households own laptops (53.3%) compared to desktops (27.7%). A similar trend is observed with households owning more than one laptop compared to desktops.

1.6. Kitchen Appliances

In this section ownerships of different kitchen appliances is presented. The survey covered 5 major kitchen appliances: refrigerator, microwave oven, induction cooktop, gas stove and electric coil stove. These are appliances that are used at least once a day. The refrigerator today forms a part of the base load of most of the households and is rarely switched off, as indicated during our survey.

1.6.1. Ownership of Different Kitchen Appliances

Table 14 lists the ownership percentages of kitchen appliances.

Kitchen appliances	
Appliance	Percentage of HH own
Refrigerator	95.2
Microwave	49.8
Induction cooktop	28.7
LPG stove	100
Electric coil heater	0.9

Table 14: Ownership percentages of different kitchen appliances

It can be seen that all households surveyed own a gas stove, close to 95% of the households own a refrigerator, approximately 41% of the households own a microwave and close to 29% own a induction stove. It is interesting to note the high ownership of microwaves as they are consider a lifestyle appliance [6, 7].

1.6.2. Capacity, Star Rating and Age Distributions of Refrigerators

The amount of energy a refrigerator consumes depends on its capacity, star rating and age. These ratings are revised regularly by BEE [8]. This regular revision would mean that age of a refrigerator has a significant impact on its efficiency. This is because a 5 star rated refrigerator that is 5 years old will be much less efficient to a 5 star refrigerator today, contributing more to the over all demand. Table 15 gives an overview of the distribution of capacity, age and star rating of refrigerators owned.

Refrigerator size and star rating					
Capacity	Percentage of total HH own	Star rating	Percentage of total HH own	Age (in years)	Percentage of total HH own
<=180	26.3	1	0.25	<=3	31.0
<=250	31.0	2	3.2	<=5	20.6
<=350	30.0	3	17.1	<=10	31.0
<=500	5.2	4	29.2	<=15	6.9
>500	2.4	5	20.1	>15	2.9
NA	0.25	NA	25.3	NA	2.7

Table 15: Capacity,. star rating and age distributions of refrigerators owed

From table 15 It can be seen that close to 86% of the refrigerators owned are less than or equal to 350 liters. While approximately 8% only account for refrigerators above 350 liters. It can be observed that approximately 67% of the households own a refrigerator that is at least 3 star or over. Finally, approximately 83% of the households have refrigerators that are 10 years old or lesser and approximately 9% of households only had a refrigerator that was greater than 10 years old.

1.7. Utility Appliances

There were two utility appliances covered in the survey, washing machine and pump/motor for pumping water into the overhead tank.

1.7.1. Ownership of Utility Appliances

Table 16 presents the percentages of households that own each of those appliances.

Utility appliances		
Appliance	Percentage of HH own	Percentage of total HH own more than one
Washing Machine	85.3	1.2
Motor/Pump	89.5	1.4

Table 16: Percentage of households that own utility appliances

It can be seen that close to 85% of the households own a washing machine and approximately 90% of households own a water pump/motor used to pump water to an overhead tank. While it does not directly relate to this study, what this data seems to indicate is that close to 90% of the households surveyed depend on some form of ground level water source (storage sump or bore well) to meet their day to day water needs.

1.7.1.1. Usage of Washing Machine Weekly

Different household tend to use washing machine different number of times a week. Table 17 outlines the distribution weekly usage of washing machines by households.

It can be observed that the a large percentage households use washing machines one and three

Washing machine usage weekly	
Number of days used/week	Percentage of HH
1	12.16
<=3	33.00
<=5	16.38
<=7	22.33

Table 17: Percentage of usage of washing machine weekly

days a week followed by 5 and 7 days. To get a better understanding usage of washing machines, we need to look at usage in combination with households size and age profile.

1.8. Water Heating Appliances

In this section statistics for the various water heating methods used by households is presented.

1.8.1. Water Heating Appliances Owned

Primarily four types of electric water heating appliances were covered, namely, storage geyser, immersion rod, instant geysers and solar water heaters with a heating element. Apart from these households also used gas geysers, firewood and gas stoves to heat water. Data on these methods of heating water was also collected.

Table 18 presents ownership of different water hating appliances and also indicates the percentage of households that own more than one of the same appliances.

Water heating appliances		
Type of water heating appliance	Percentage of HH own	Percentage of HH own more than 1 Bengaluru HH that own)
Geyser	63.52	30.47
Immersion Rod	7.44	0
Instant Geyser	10.67	6.98
Solar water heater	50.37	0
Solar with electric heater	4.96	0
Gas geyser	6.45	0
Gas stove	9.68	0
Fire wood	4.71	0
Other (apartment solar and heat pump)	0.5	0

Table 18: Ownership of various water heating appliances

From table 18 It can be seen that most common type of water heating appliance used is the electric geyser at approximately 63%, followed by solar water heaters at 50%, this is apart

from the households that own solar water heaters with in built heating elements which is at approximately 5%. The data also indicates that among the households that own geysers, approximately 30.5% of the households own more than one. There is also a small percentage using low cost water heating appliances like instant heaters and immersion rods accounting for a total of approximately 18% of households.
There is also use of non-electric water heating methods like gas stoves and firewood. Close to 14% of households surveyed use these methods.

1.9. Vehicle Ownerships

In this section vehicle ownership of households is presented. Information on both electric and non electric vehicles was covered including the type of vehicle owned, weekly usage frequency, fuel type, and charging durations and cycles for four wheelers.

1.9.1. Percentage Ownerships of Different Vehicles

Table 19 lists ownerships of two and four wheeler vehicles for non electric and electric vehicles.

Vehicle ownership		
Type of Vehicle	Percentage of HH own	Percentage of HH own more than 1 Bengaluru HH that own)
Two wheeler	85.61	45.22
Four wheeler	65.76	20.38
Two wheeler EV	0.5	0
Four wheeler EV	0.25	0

Table 19: Percentage ownership of different vehicles

It can be observed from table 19 two wheelers have the maximum ownership at close to 85%, with close to 45% of the households own more than one. Four wheeler ownership was at 65% with households that owned more than one two wheeler at 20%. Among the surveyed population only 0.5% and 0.25% own two wheeler and four wheeler EVs . This is negligibly small compared to number of households that own non electric vehicles.

1.10. Propensity to Own Different Appliances

As part of the survey data on household's propensity to buy specific appliances was collected to identify drivers of future demand. The appliances covered were AC, cooler, electric two wheeler and four wheelers. The households were asked if they will buy a electric vehicle in the next 5 years and if they would buy a AC or cooler in the next one year.

1.10.1 Propensity to Buy Various Appliances

Table 20 below indicates the percentages of households that own the appliances mentioned above.

Propensity to buy	
Appliance/Vehicle	Percentage of HH will buy
AC	8.93
Cooler	0.5
Two wheeler EV	12.16
Four Wheeler EV	11.17

Table 20: Propensity of households to buy various appliances

From table 20 it can be seen that approximately 12% of households mention they will buy an electric vehicle in the next 5 years while approximately 9% of the households say they will buy an air conditioner in the next year with negligibly small amount saying they will buy a cooler in the next year.

2. Asset Index and Quintile based Classification of the Survey

The previous section looked at aggregate statistics of the survey comparing and presenting statistics of the ownership of various appliances in the same category (like cooling appliances, water heating, lighting, vehicles, etc). This gave a perspective of how each appliances with in a category were owned. For example, in cooling appliances we could identify that all households (100%) owned fans while only approximately 30% of the households owned AC's and also that AC's had a higher ownership compared to coolers.

Aggregate levels of comparisons gives us statistics for total populations, but it does not give us the entire picture. This is because electricity consumption is not uniform across households and depends on multiple variables [9, 10, 11, 12].

The electricity consumption of a household can be described as

$$E_H = f(\text{A, C, D}),$$

where

E_H = Total energy consumed by a household,

A = Affordability of the household,

C = Climatic zone the household falls into,

D = Demographics of the household

Each of these variables can be further broken down. For example the affordability of a household could be expressed as a income, or expenditure, assets, or wealth can be used as a proxy for this. The affordability of the households also depends on the number of earning members, etc. Similarly, the climatic zone that the households fall in to influence the type of appliances they own along with affordability of the household. For example, in regions where summers are extremely hot household could own a variety of space cooling appliances. The affordability of the households will influence their ownership and running [3, 13, 14].

Finally, demographics of the household has an direct impact on the electricity consumed. A single resident household versus a household with 3 or 4 residents would see more electricity use. The demography of a household can again be further broken down into secondary variables like age distribution of residents, number of working members, etc. All of which have direct impacts on the way households consume electricity. It therefore is important to look at the survey data beyond aggregate numbers.

One way of dividing survey data into quintile/deciles is to use income or a proxy of income. Dividing the households using income or a proxy is beneficial as income is among the main determinants of electricity consumed by households [15, 16].

Income or expenditure data is difficult to collect and households are not obligated to volunteer this information. To find a work around this, as part of our survey information on income brackets of the households was collected. These brackets were kept wide enough to keep information given by households ambiguous, but be useful enough to categorize the households.

But as seen from table 8, close to 50% of the households did not report their income brackets. Another method was therefore needed to categorizer the households.

2.1. Asset Index

To overcome the shortcomings of the missing income bracket data, assets owned by the households were used as a proxy for income [17]. It is also easier to collect such data as there is comparatively lesser issue in measurement of assets owned [18]. Assets also provide a picture of longterm living standards compared to income as assets are collected over time and last longer[19]. While it is not reliable to use one asset as a indicator of wealth, a set of assets can be used to construct a asset index that reflects the economic standing of a household. Use of these assets to build an asset index works better than expenditure as a proxy for income [18]. There are a few methods of building an asset index for households, a brief over view of three methods that were tried is given below.

Equal Weight Asset Index

In this method equal weights are assigned to an asset A_i. Most common value used is 1. If the household owns the asset then $A_i = 1$. The asset index then is $\sum A_i$, sum of all the assets owned by the household.

This method has one innate flaw, it assigns the same weight to all the assets. So a a car has the same weight as a TV or a two wheeler. This does not reflect the real world situation in many ways. Cars are much more expensive then a two wheeler which is much more expensive than a TV.

Price based asset index

In this method a monetary value P_i is assigned to each asset A_i. The asset index of the households is calculated as $\sum P_i * A_i$ for the *i* assets owned by the household.

Error in this method can creep in when there are some assets which can take up multiple price values. For example, for LED TV's, depending on the brand, the value can range anywhere from Rs.15,000 to Rs.30,000 for the same screen size, or for a car the value can range between Rs.300000 to Rs.600000 for a vehicle of the same class.

Another issue is in the case of second hand / hand me down appliances. In this case the household might have purchased the appliance at a substantially low price than its market value or might have got if for free. In this case the asset adds a higher value to the overall household asset value than it should.

Principal Component Analysis (PCA)

Principal component analysis is a statistical technique that is used to reduce the dimensionality of a matrix with minimum loss of information. This technique is used to get few key orthogonal linear combinations that captures information variability for a set of variables [20]. These set of key orthogonal linear combinations are principal components capturing information on different proportions of variability explained by each principal component, with the first principal component capturing information on highest variability between variables. Using principal components analysis we can determine weights of each variable. The case for PCA as a good option over price based asset index was made by [20]. In this work they empirically show the efficacy of this method over other methods. In order to create a asset index for our survey, we tried both price based approach and principal component analysis.

2.1.1. Price Based Asset Index

For each appliance A_i a price P_i was assigned based on market prices. The asset value of each household was calculated as follows:

$$\sum (A_{i,j} * P_i * N_i) \qquad (2\text{-}1)$$

where,

$A_{i,j}$= i^{th} asset of the j_{th} household,

P_i = Price of the i^{th} asset

N_i = Number of the i^{th} asset owned by the household

Tabl 21 lists the variables considered for the asset index and their.

Using these values the asset index for each household was computed using equation (2-1).

Based on the asset index , the data was split into quintiles and plotted to compare the quintile alignment. Figure 7 presents the alignment of asset index and different income brackets.

Ignoring households that did not report income we see that the asset index was not very accurate

Cooling appliances	Fan	Cooler	AC	
	2500	9000	20000	
Entertainment appliances	CRT_TV	LCD_TV	LED_TV	OTHER_TV
	10000	15000	20000	12000
Productivity appliances	Desktop	Laptop		
	15000	25000		
Kitchen appliances	Refrigerator	Microwave	WashingMachine	
	20000	7500	9500	
Vehicles	Two_wheeler	Four_wheeler		
	30000	450000		

Table 21: Variable and associated prices for price based asset index

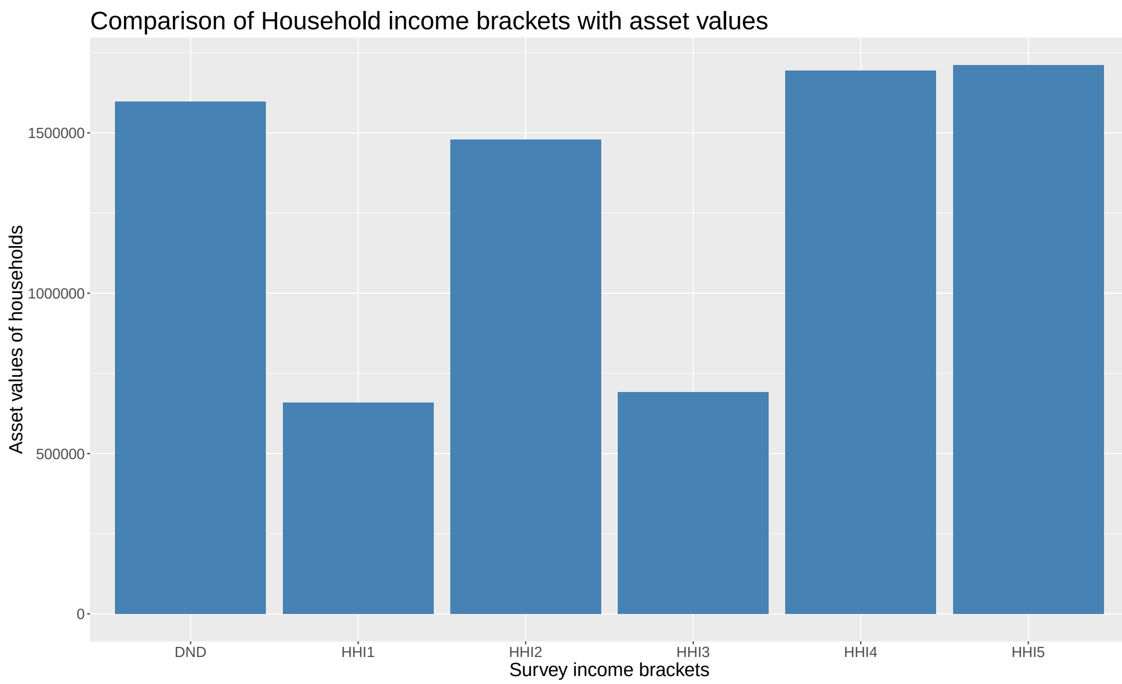

Figure 7: Comparison of alignment of income brackets and asset values

in splitting the data. One reasons for this is that the asset index was the product of the price assigned to the appliance (P_i) and the numbers of that appliance owned (N_i). For example if a household owned 2 CRT tv's but no AC's the index would still indicate that the households were in the same bracket. While in actuality these two assets would in all likelihood be owned by two different income groups. Shortcomings of similar methods have been outlined in [19, 20, 21].

2.1.2. Principal Components Analysis

Principal component analysis (PCA) allows us to summarize and visualize data sets containing multiple variables. Using principal component analysis, we can represent information from multivariate data sets as a set of fewer new variables called ***Principal components***. These new set of variables are a linear combination of the original variables and are always less than or equal to the number of original variables.

The data given by these principal components indicates the total variation of the data set. PCA identifies the directions along which the component's variation is maximum with components orthogonal to each other. Through this process, PCA reduces the dimensionality of a data set to the minimum number of components needed so that the data can be visualized with minimum loss of information.[20] outlined a methodology using PCA to ascertain the weights of households based on assets owned to construct a asset index.

PCA is an good approach because the coefficients have a fairly intuitive interpretation. The coefficient of any one variable is indicative of how much information it provides about other variables. Therefore, if the ownership of any one asset is highly indicative of ownership of other assets, it receives a positive coefficient. If it provides no information on ownership of any other assets, then it receives a near zero coefficient. If the ownership of an asset is indicative that the household will own fewer assets then it receives a negative coefficient. Therefore higher and lower coefficients scores mean that assets/variables convey more or less information about ownership of other assets. This intuitive interpretation makes PCA a convenient methodology to follow in order to construct an asset index [19, 20]. [20] also outlined a way to test the built index by testing ***internal coherence*** and ***robustness*** of the asset index.

2.1.2.1. PCA on Survey Data

Variables shortlisted for PCA

Table 22 lists the variables shortlisted for PCA with their descriptions.

Variables were chosen in a way that they can represent appliances that are good income segment indicators. For example households with higher income would have higher number of four wheelers or lower income households would use appliances like immersion rods for water heating [10, 11].All the variables chosen were assets and no household indicators were selected.

Variables	Description	Variable type
Fan_num	Number of fans owned	Numeric
Fourwheeler_num	Number of fourwheelers owned	Numeric
LED_tv_num	Number of LED TVs owned	Numeric
Microwave_own	If HH owns microwave	Categorical
Laptop_own	If HH owns laptop	Categorical
Geyser_own	If HH owns geyser	Categorical
Washingmachine_own	If HH owns washingmachine	Categorical
Motor_own	If HH owns motor	Categorical
Twowheeler_num	Number of Two wheelers owned	Numeric
LED_tv_own	If HH owns LED TV	Categorical
AC_own	If HH owns AC	Categorical
Desktop_num	Number of Desktops owned	Numeric
CFL_own	If HH owns CFL bulbs	Categorical
Refr_own	If HH owns Refrigerator	Categorical
Cooler_own	If HH owns cooler	Categorical
Solar_heater_own	If HH owns solar water heater	Categorical
LCD_tv_own	If HH owns LCD TV	Categorical
Fan_own	If HH owns Fan	Categorical
Gas_stove_own	If HH owns Gas stove	Categorical
Incand_own	If HH owns Incandescent bulb	Categorical
Immersoion_rod_own	If HH owns Immersion rod	Categorical

Table 22: Variables for PCA

Running PCA and results Using these set of variables, we conducted the PCA in R using ***Princomp*** function. Table 23 presents the results of the PCA and lists the scores from the first principal component along with standard deviations and weights for each variable.

From table 23 we see that number of fans a household owns has the highest weight. This indicates that more number of fans the higher the probability the households own other appliances as well. This is probably because number of fans is a good proxy for the number of rooms in a household indicating a richer household.

Looking at the assets that scored a negative score, the highest negative score was for ownership of CRT TVs, followed by immersion rods and incandescent lights. All of these are energy inefficient appliances and are cheapest to own. [4, 7, 10] indicate that these appliances predominantly are owned in lower income brackets.

These results indicate that PCA gave us better results that the price based asset index.

Variables	Factor scores	SD	Weights (Factor score/SD)
Fan_num	0.902415715	1.521674896	0.593041074
Fourwheeler_num	0.239199669	0.702319967	0.340585033
LED_tv_num	0.181466165	0.677209454	0.267961654
Microwave_own	0.140307355	0.500619963	0.280267199
Laptop_own	0.117302806	0.499496679	0.234842014
Geyser_own	0.1017482	0.481962336	0.211112347
Washingmachine_own	0.095528697	0.353948175	0.269894588
Motor_own	0.091265523	0.305923399	0.298328023
Twowheeler_num	0.085316393	0.805153579	0.105962881
LED_tv_own	0.078820999	0.453319492	0.17387516
AC_own	0.077344547	0.404900661	0.191021044
Desktop_num	0.06687872	0.466049173	0.143501424
CFL_own	0.049199607	0.484644395	0.101516921
Refr_own	0.037513176	0.212215384	0.176769353
Cooler_own	0.033094899	0.315342293	0.104949129
Solar_heater_own	0.025488612	0.217444704	0.117218822
LCD_tv_own	0.007219695	0.299376536	0.024115768
Fan_own	0	0	0
Gas_stove_own	0	0	0
Incand_own	-0.019885226	0.335652341	-0.05924352
Immersoion_rod_own	-0.02424273	0.262814604	-0.09224271
CRT_own	-0.060752654	0.403082453	-0.15072017

Table 23: PCA results

Quintile split and validatoin of PCA Using the weights from PCA the dataset was split into 5 parts(quintiles). We choose to split it into quintiles considering the size of the survey.

Internal coherence test: To check for internal coherence we consider variables that were part of PCA and test their quintile alignment. In this case vehicle ownership was considered. As seen from figure 8 the ownership of two wheelers is almost uniform across quintiles, but the ownership of four wheelers increases as we move up quintiles indicating that PCA holds up well in the internal coherence test.

Robustness test: For the robustness test variables that were not part of the PCA were used to test for quintile alignment. Electricity bill amounts were used to test for robustness.

Figure 9 below presents quintile wise the electricity bill amounts paid by households across seasons.

It can be seen from figure 9 that electricity bill amounts paid by the households increase as

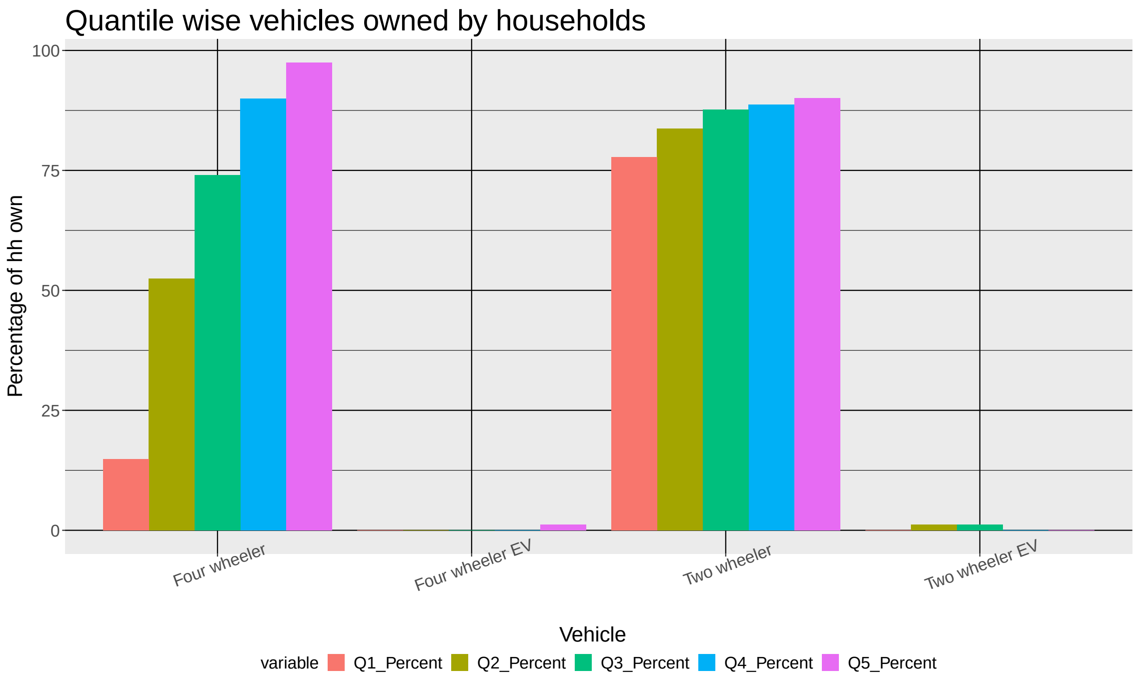

Figure 8: Ownership of different vehicles quintile wise

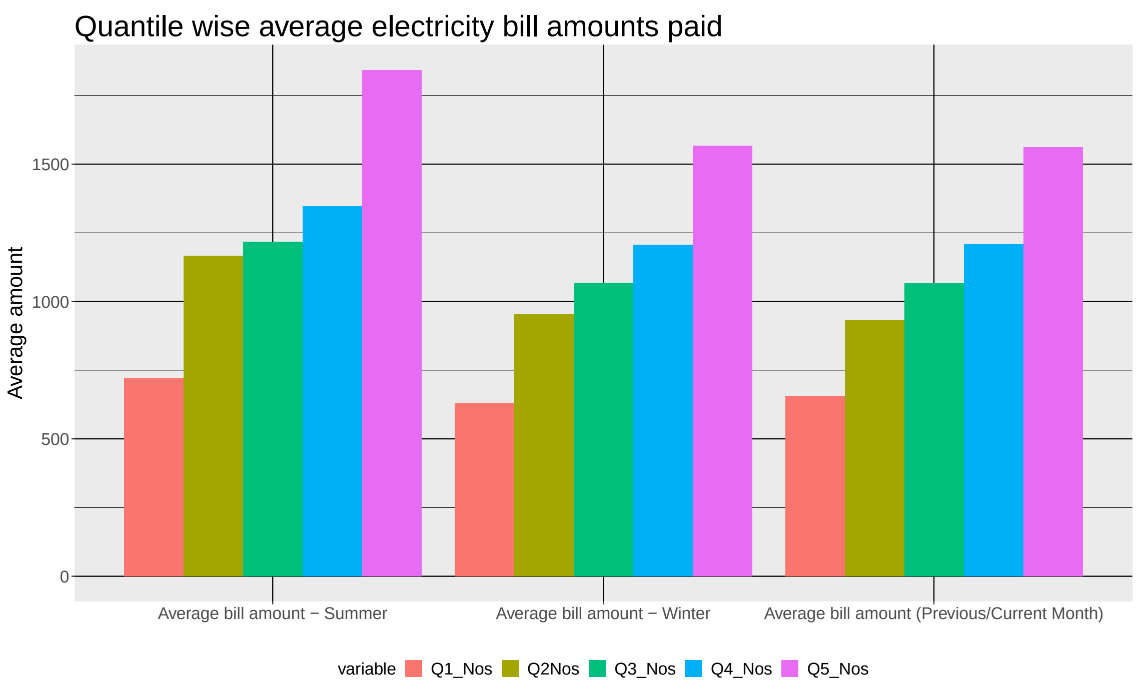

Figure 9: Electricity bill amounts

we move up quintiles. This is expected as appliance ownership is a good proxy for electricity consumed and households in the higher quintiles generally own more appliances.

Finally, we compare the PCA scores against the income brackets. Figure 10 presents the PCA score alignment with the household income brackets.

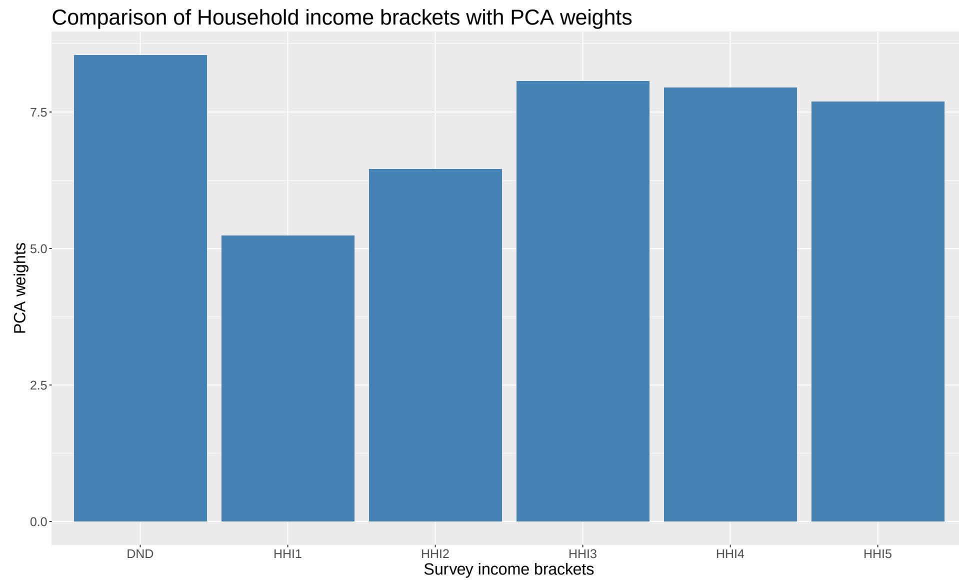

Figure 10: Comparison of alignment of income brackets and PCA weights

We see that the brackets alignment with the PCA scores is much better compared to the price based asset index (figure 7). Based on these results, the weights from PCA were used to split data into quintiles.

3. Statistics of Quintile Wise Data

Section Overview

Section one of the chapter presented survey data at aggregate levels. The aggregate level statistics how ever do not give the distribution of ownership of different appliances. This section presents the survey data divided into quintiles (5 parts) based on asset index calculated in the previous section, with approximately 80 households in each quintile.

3.1. Household Statistics

This section presents statistics covering demographics and physical description of the households by quintile .

3.1.1. Household and Dwelling Types

Table 24 presents types of household in different quintiles indicating independent, low income households and apartments. Multi dwelling units with more than three households was considered as apartments.

Type of household	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
Total independent houses	87.6	86.2	88.8	92.5	96.3
Total low income/slum households	46.9	3.7	0	0	0
Total non low income/slum households	40.7	82.5	88.8	92.	96.3
Total apartments	12.3	13.7	11.1	7.5	3.7

Table 24: Quintile wise dwelling types

3.1.2. Ownership of Households

Ownership	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
Total number of households owned	48.1	50	65.4	78.7	92.5
Total number of households Rented	48.1	46.2	33.3	18.7	7.4
Total number of households Leased	3.7	3.75	1.2	2.5	0

Table 25: Ownership of households quintile wise

Table 25 presents the percentage of households owned, rented or leased by quintiles. As it can be seen the ownership of households increases significantly as we move up the quintiles, with rental households dropping as we go up the quintiles.

3.1.3. Room Distributions in the Households

Figure 11shows the distribution of rooms in households by quintile. It can be seen that across quintiles, most of the households have between 2 and 3 rooms with two bedroom households accounting for the highest percentage in quintiles 2-4. In quintile 1 approximately 59% of households have one room and in quintile 5 approximately 58% of the households have 3.

3.1.4. Demographics

Table 26 is an overview of the number of people per household by quintile. The table covers average number of residents, adult male, adult females and children. Any resident below the age of 18 was considered a child.

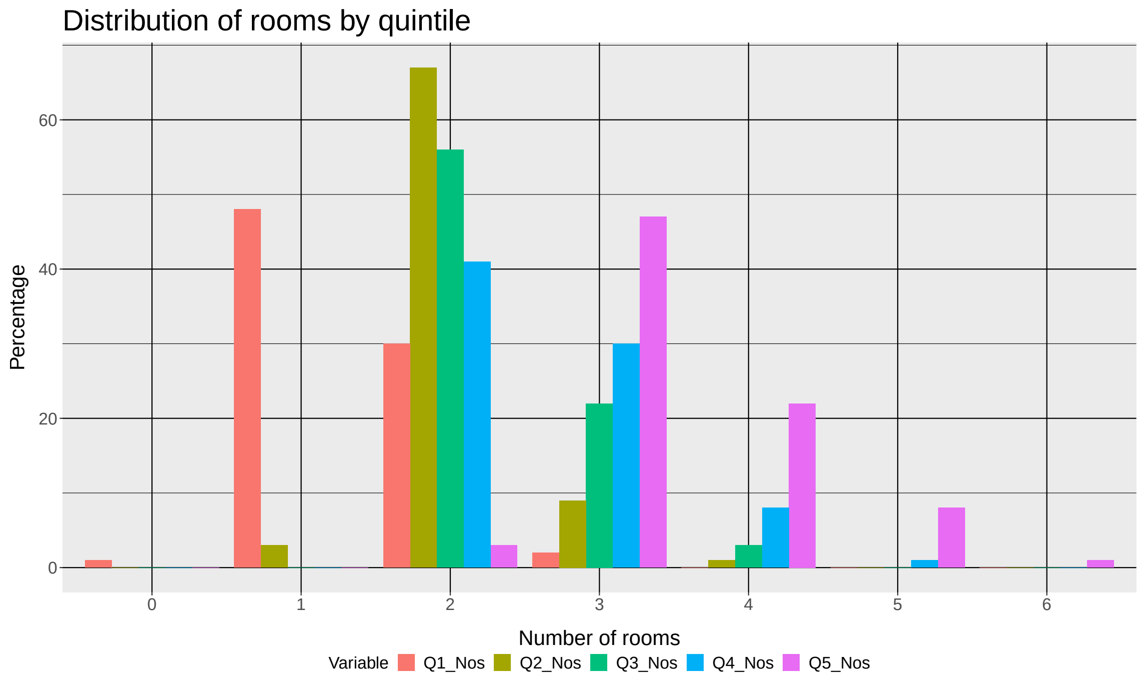

Figure 11: Room distribution quintile wise

One key observation is that as we go up quintiles, the average number of residents, adult males and females increase.

Demographics	Q1_Nos	Q2_Nos	Q3_Nos	Q4_Nos	Q5_Nos
Average number of perople/hh	3.6	3.5	3.7	4	4.3
Average number of Male/hh	1.5	1.5	1.5	1.6	1.8
Average number of Female/hh	1.4	1.4	1.5	1.6	1.7
Average number of Children/hh (<18 years)	0.78	0.59	0.75	0.69	0.82

Table 26: Avreage number of people per household

3.1.5. Earning Members

Table 27 presents the average earning members per quintile along with average number of male and female earning members.

From table 27 It can be observed that as we move up quintiles the number of earning members increase with the number of earning female member also increasing.

Earning members	Q1_Nos	Q2_Nos	Q3_Nos	Q4_Nos	Q5_Nos
Average number of earning members/hh	1.6	1.6	1.5	1.7	1.9
Averge number of males earning members/hh	1.2	1.2	1.1	1.2	1.3
Averge number of female earning members/hh	0.42	0.42	0.36	0.47	0.59

Table 27: Average earning members per quintile

3.1.6. Household Income Reporting and Income Brackets

Table 28 compares the distribution of households that provided income bracket information across quintiles.

Income	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
Did not report	35.8	55	40.7	55	44.4
Reported	64.2	45	59.2	45	55.5

Table 28: Households that reported income

Among the households that reported income, table 28 presents the distribution of income brackets by quintiles.

Income brackets	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
HHI1 (<200000)	30.8	2.5	7.4	3.7	0
HHI2 (>200000, <400000)	20.9	16.2	9.8	8.7	4.9
HHI3 (>400000, <700000)	7.4	6.2	14.8	13.7	9.8
HHI4 (>700000, <1000000)	1.2	12.5	13.5	8.7	11.1
HHI5 (>1000000)	3.7	7.5	13.5	10	29.6

Table 29: Distribution of reported incomes quintile wise

3.2. Electricity Information

This section covers the details of electricity bills and backup system used in the households by quintile.

3.2.1. Electricity Bill Information

Figure 12 presents the distribution of electricity bill amounts for the three periods collected. As expected the higher quintiles pay a higher electricity bill primarily due to the difference in ownership and usage of appliances in across quintiles [9, 13].

We also observe that the bill amounts across quintiles are higher for summer than winter. This is due to the increased use of space cooling appliances in summer.

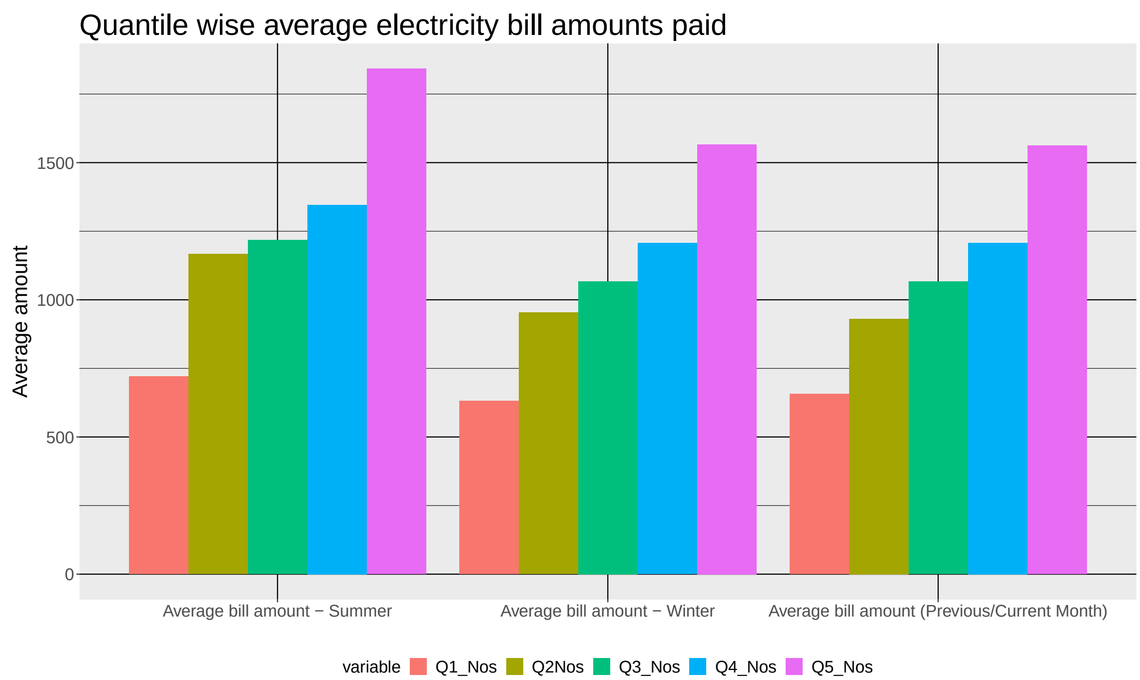

Figure 12: Electricity bill amounts

3.2.2. Electricity Backup Used

Figure 13 presents the distribution of ownership of different back up appliances by quintile. It can be seen that the most common type of back up appliances used across quintiles is UPS/Inverter. The number of households that own a backup appliance increases significantly as we move up the quintiles.

3.1.3. Bill Paid to

Table 30 outlines the percentage of households that paid their bills to ESCOM VS owners. It can be seen that as we move up the quintiles the number of households paying their bills to owners of the households reduces significantly. This correlates with table 25 where the number of rental households reduced as we move up quintiles.

Bill Payment	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
Paid to ESCOM	90.1	91.2	97.5	98.7	100
Paid to Owner	9.8	8.7	2.4	1.2	0

Table 30: Electricity bill paid to

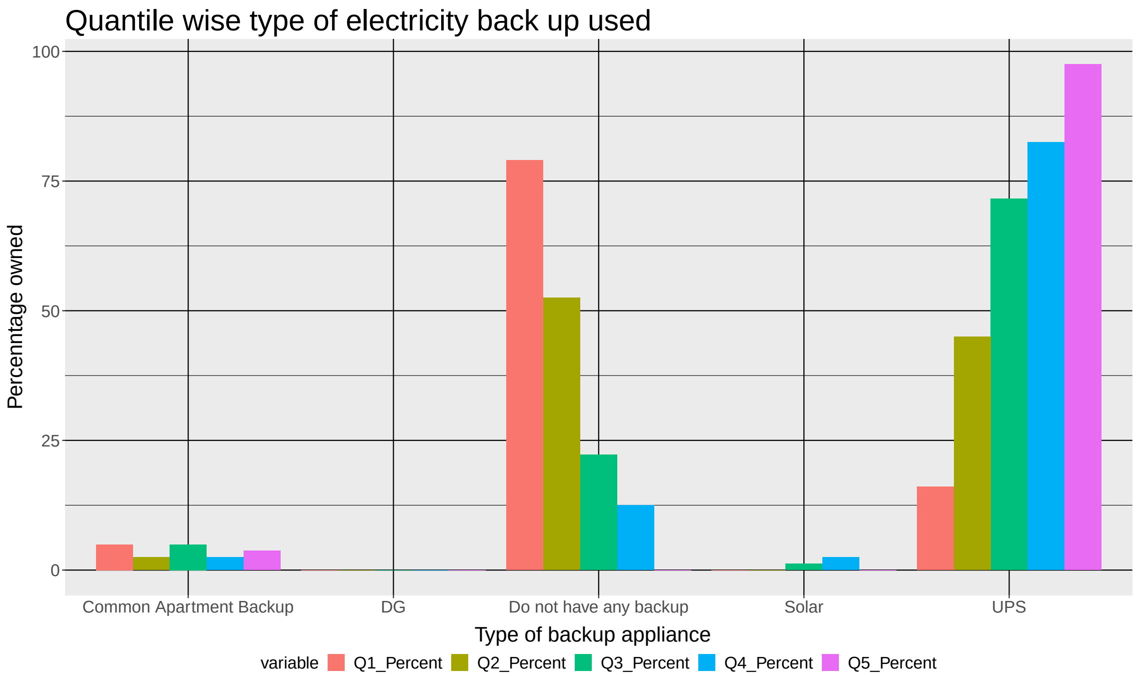

Figure 13: Type of back up used

3.3. Lighting Used in the Households by Quintile

This section covers the various types of lighting used in different areas of the household namely living spaces, bathrooms, and kitchen areas.

3.3.1. Lighting Type by Area

Figures 14, 15 and 16 presents distribution of different lighting types used in different areas of the household. From the figures it can be observed that in living space the preferred lighting type across income quintiles is tube light, followed by LED bulbs while in the lower quintiles we see some use of incandescent bulbs. In the case of kitchens, we see from the figure 15 that the most widely used bulbs are LED bulbs followed by tube lights.Finally, in the case of bathrooms most common lighting type is LED, followed by CFL and in the case of lower quintiles we see an increased use of incandescent bulbs.

One of the reasons LED bulbs are being used in such high numbers across quintiles is because of the *ULAJA* program enabling residents easy access to LED bulbs, by offering lower quintile households a staggered payment plan for the bulbs.

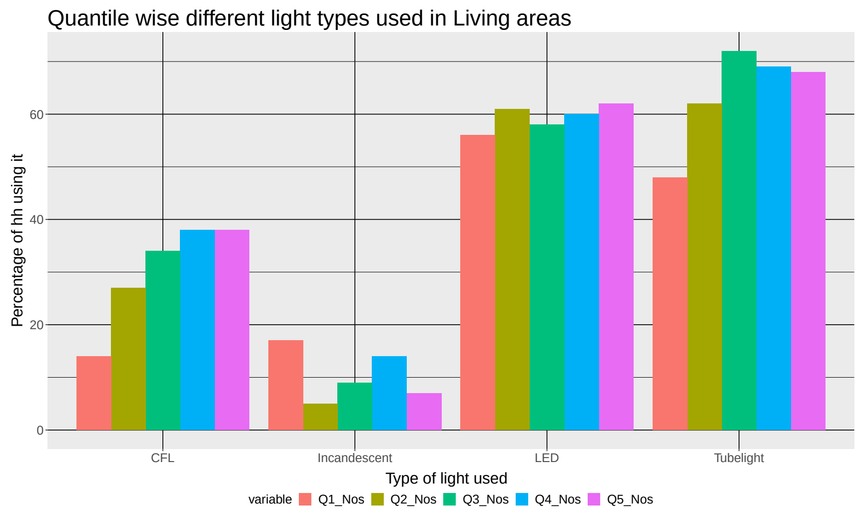

Figure 14: Lighting in living areas

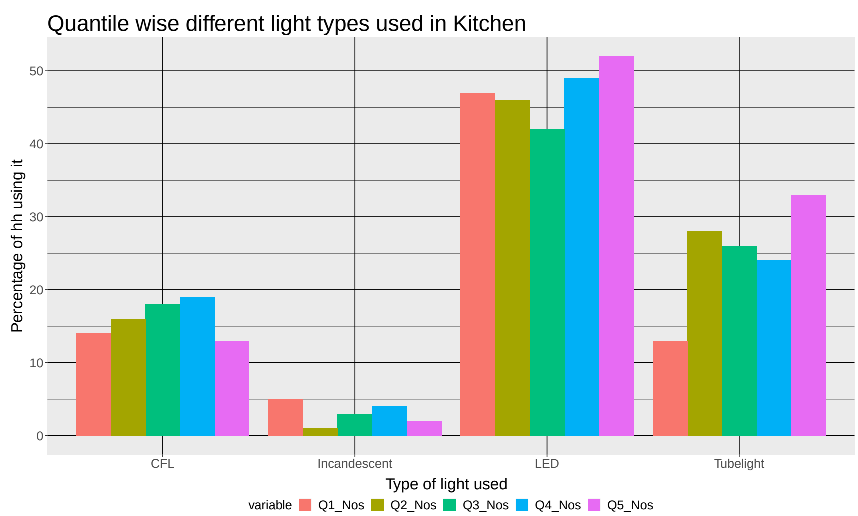

Figure 15: Lighting in kitchen

3.4. Appliances Used in Living Spaces

In this section presents statistics for appliances used in living spaces of the households

3.4.1. Ownership of Space Comfort Appliances

Figure 17 presents distribution of ownership of space comfort appliances.

From figure 17 it can be seen that all households surveyed own fans.The ownership of more expensive space cooling appliances like coolers and AC's are skewed to the top 3 quintiles with the last quintile owning almost twice as many coolers and AC's compared to others. Finally,

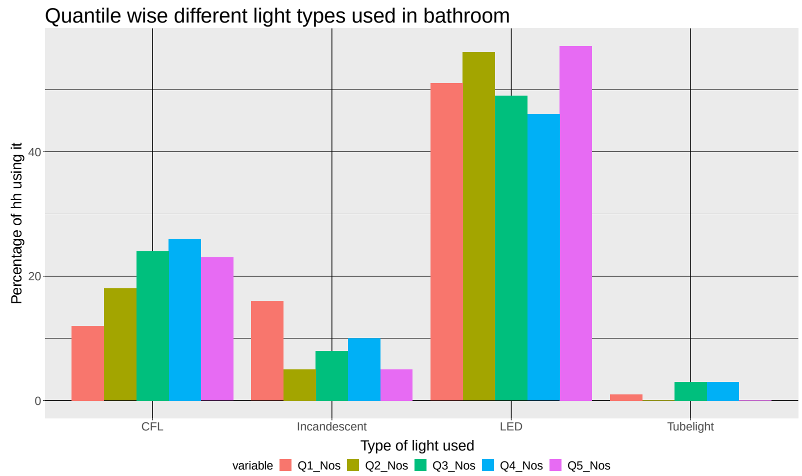

Figure 16: Lighting in bathrooms

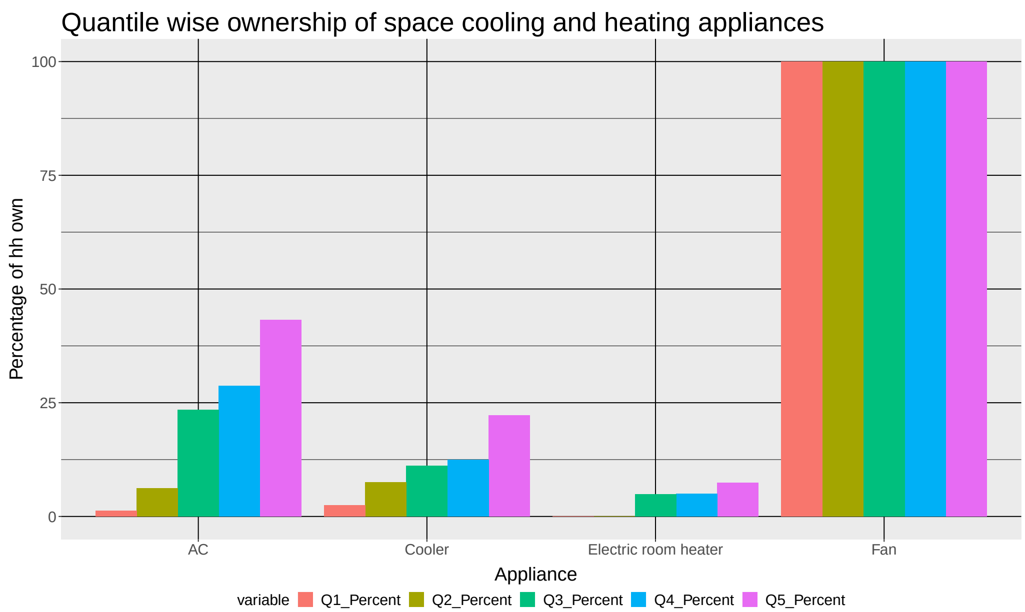

Figure 17: Percentage ownerships of space cooling appliances

ownership of space heating appliances is significantly lower than space cooling appliances owing to the climate of Bengaluru.

3.4.2. AC Star Rating and Tonnage Distribution

Figures 18 and 19 presents distribution of AC's start ratings and tonnage. We see that majority ownership is of 3 star ACs across quintile with a strong preference for 1.5 tons followed by one ton.

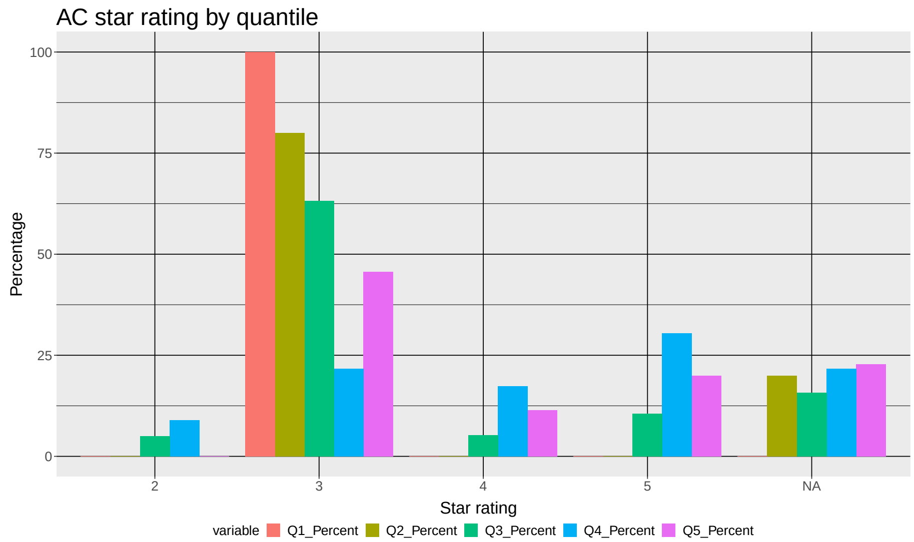

Figure 18: Star rating of AC's

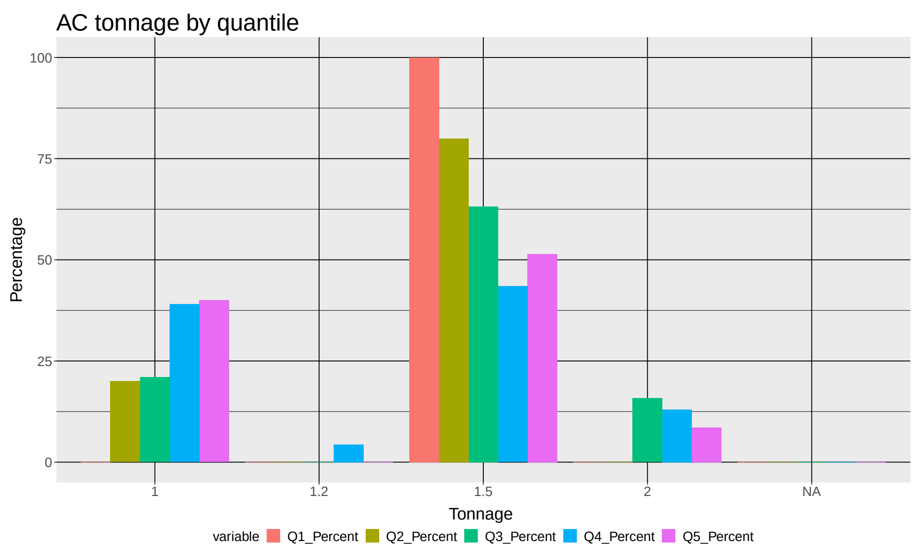

Figure 19: Tonnage of AC's

3.5. Entertainment and Productivity Appliances

This section covers 4 different types of TV's including CRT, LCD, LED and Other. Others included plasma TV's, projectors etc.Productivity appliances were primarily laptops and desktops.

3.5.1. Entertainment Appliances

Figure 20 presents percentage ownership of different type of TVs. It can be observed LED TV's are the highest owned in in quintiles 2 to 5 with quintile 5 having close to 91% ownership of LED TV's. The lowest quintile has the highest ownership of CRT TV's and with the ownership dropping significantly as we move up the quintiles as expected [4, 13].

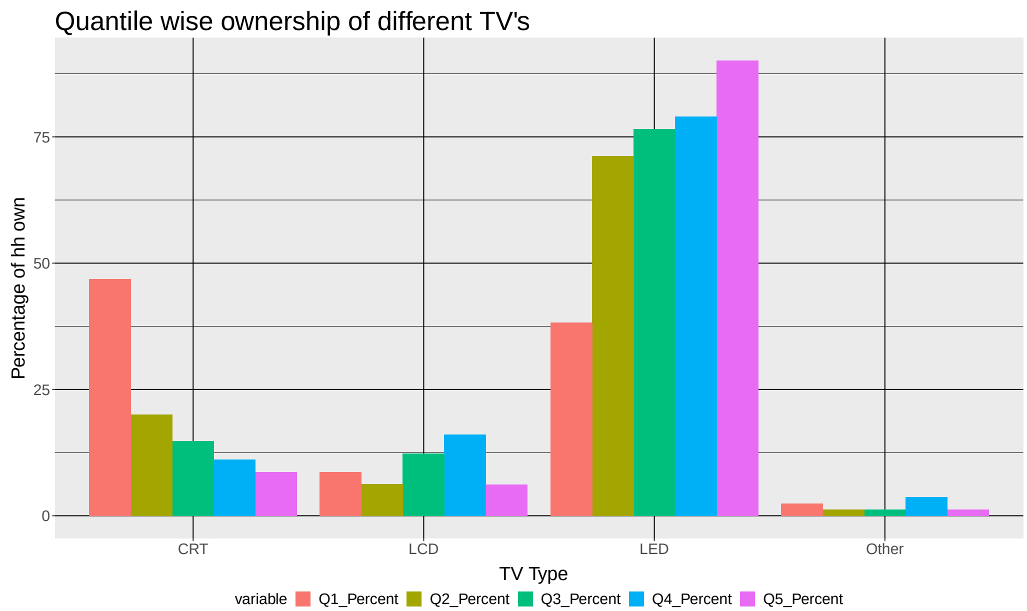

Figure 20: Percentage ownership of different TV's across quintiles

3.5.2. Productivity Appliances

Figure 21 presents distributions of productivity appliances. It can be observed across quintiles, households own approximately twice as many laptops as desktops with ownership increasing as we move up quintiles.

3.6. Kitchen appliances

In this section data on various appliances owned covering refrigerators, microwave ovens, gas stoves, induction cook tops and electric coil heaters is presented.

3.6.1. Ownership of Kitchen Appliances

Figure 22 presents ownership percentages of various kitchen appliances. We can see that, all the households across quintiles own a gas stove. The second most owned kitchen appliance

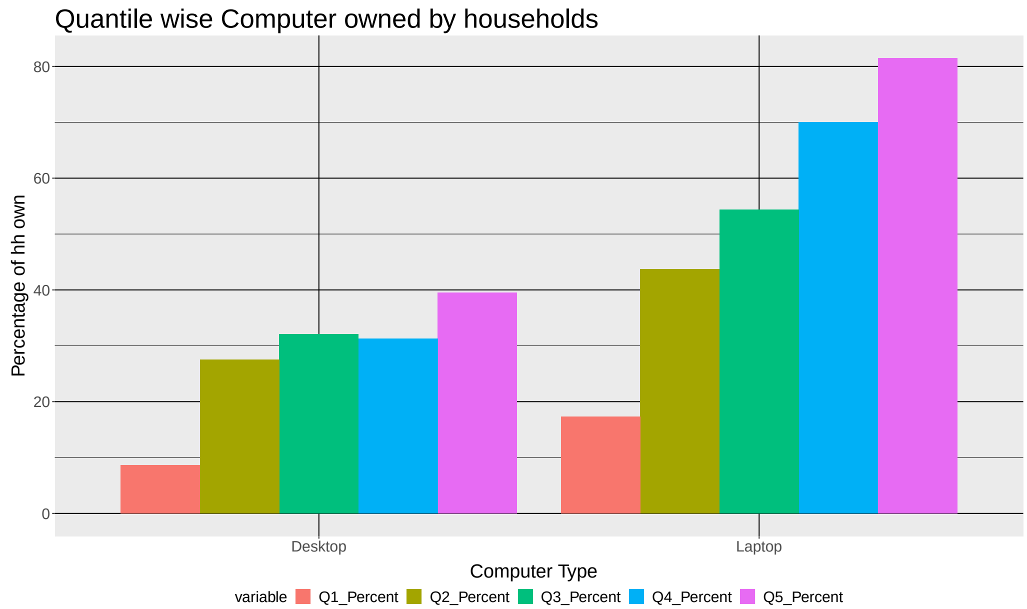

Figure 21: Percentage ownership of productivity devices across quintiles

is the refrigerator, with its ownership increasing as we move up quintiles with only a 20% difference in ownership across quintiles and all households in the 5th quintile owning one. Both microwave oven and induction cook top ownerships are the highest in the last two quintiles. Finally, the ownership of electric coil heaters is negligible.

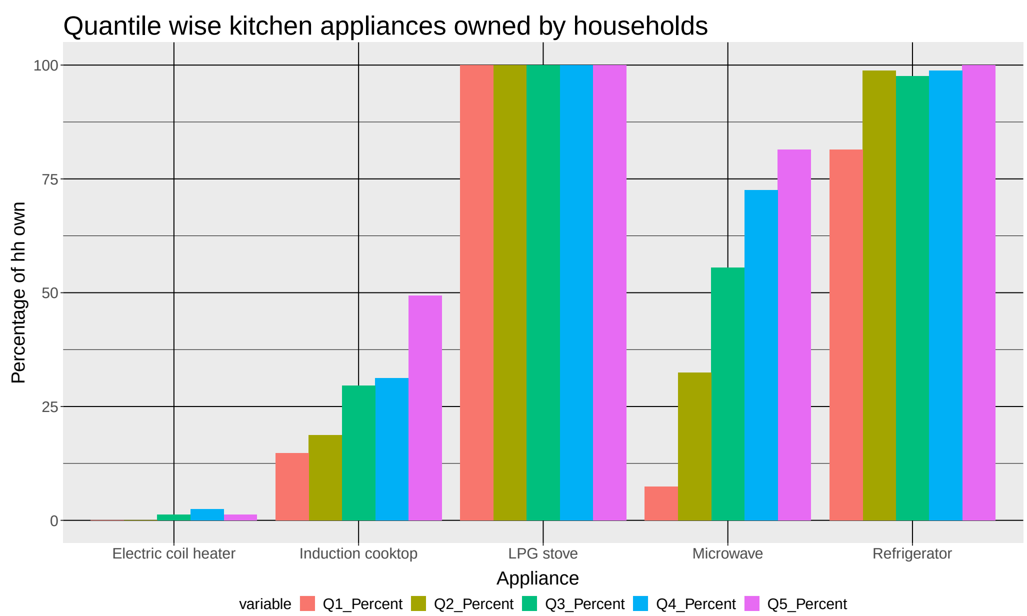

Figure 22: Percentage ownership of various kitchen appliances across quintiles

3.6.2. Refrigerator Capacity, Star Rating

Refrigerators can be considered as part of the base load for any household. The energy consumed by a refrigerator primarily depends on its capacity and star rating. It therefore makes sense to look at the distributions of these parameters.

3.6.2.1. Refrigerator Capacities

Figure 23 gives us the percentages of different size refrigerators owned by households. It can be seen that in the first quintile, the capacity range is 180 liters or lower, for the second quintile this increase to 250 liters with most of the refrigerators owned lying between 180 and 250 liters. In quintiles 3 to 5 highest percentage of households own a refrigerator sized between 350 and 500 liters with the last quintile indicating the highest percentage of households that own a refrigerator of 500 liters or over.

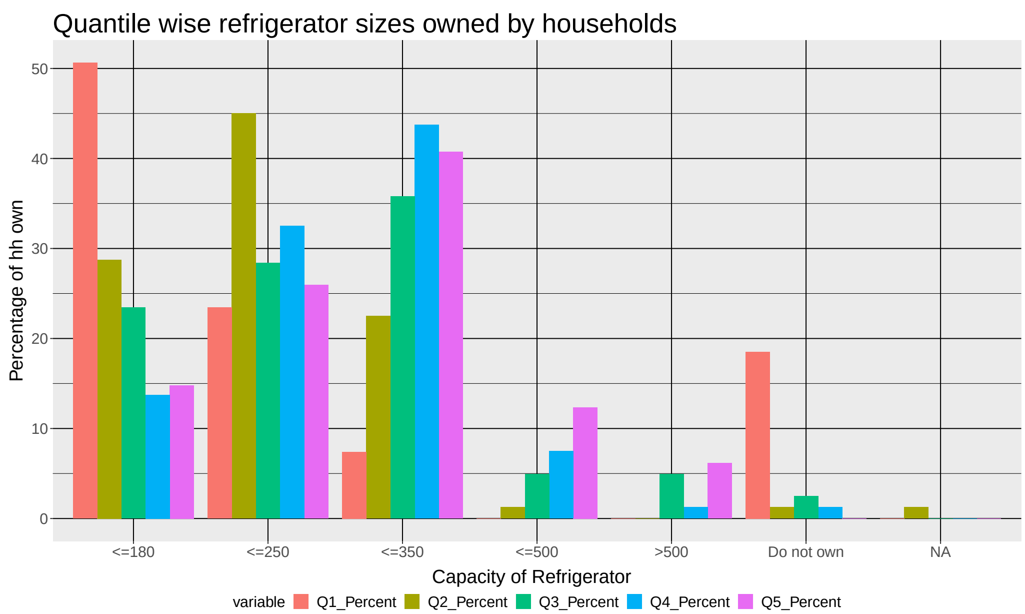

Figure 23: Distribution of different size refrigerator owned quintile wise

3.6.2.2. Refrigerator Star Rating

Figure 24 indicate the distribution of star rating of refrigerators owned for different quintiles. It can be seen that quintiles 1 and 2 mostly own refrigerators rated at 2 or 3 star, with quintiles 3-5 owning more 4 and 5 star refrigerators. Among all the refrigerators owned in quintile 5 the maximum percentage owned are 4 or 5 stars. This indicates that, households in the upper quintiles although own bigger refrigerators, they probably contribute less base load of the household relative to refrigerators owned by lower quintile households.

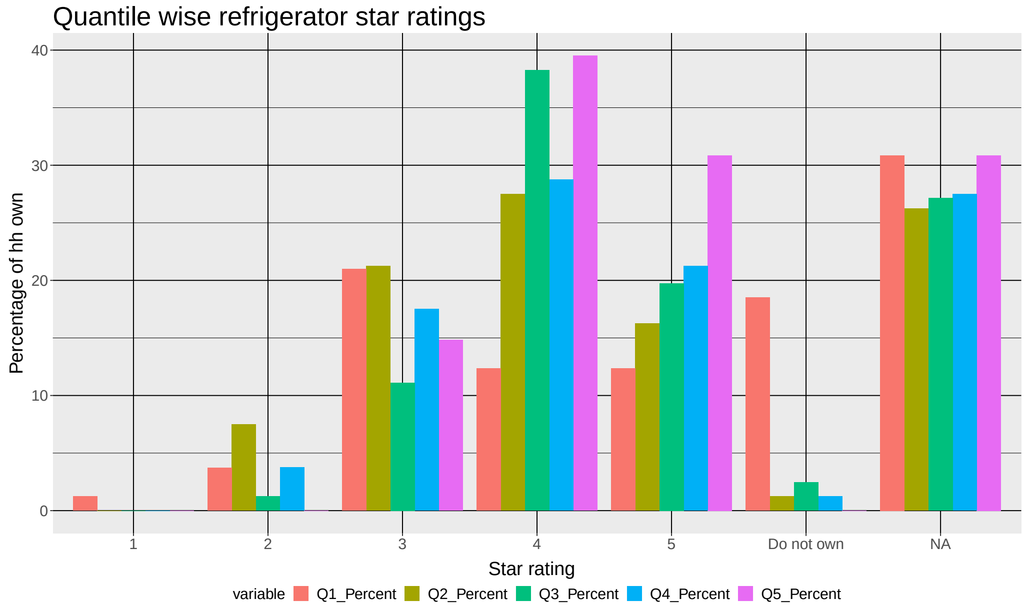

Figure 24: Distribution of different star rating of refrigerator owned quintile wise

3.7. Utility Appliances

This section covers the utility appliances owned by households.Two appliances under this category are washing machines and water motor/pump covering ownerships and usage frequencies.

3.7.1. Ownership of Utility Appliances

Figure 25 indicates the ownership percentages of washing machines and motors. As we see from figure 25 except for the first quintile, the rest own approximately the same percentages of washing machines and motors. In the first quintile approximately only 50% of the households own these two utility appliances.

3.7.2. Washing Machine Usage Frequency

While washing machines are not the highest energy consuming appliances, given their duration of use of approximately 60 minutes, they add to the load profile of households. Therefore getting an understanding of usage frequencies of washing machine usage is important. Table 31 below presents data on the usage frequency of washing machines quintile wise.

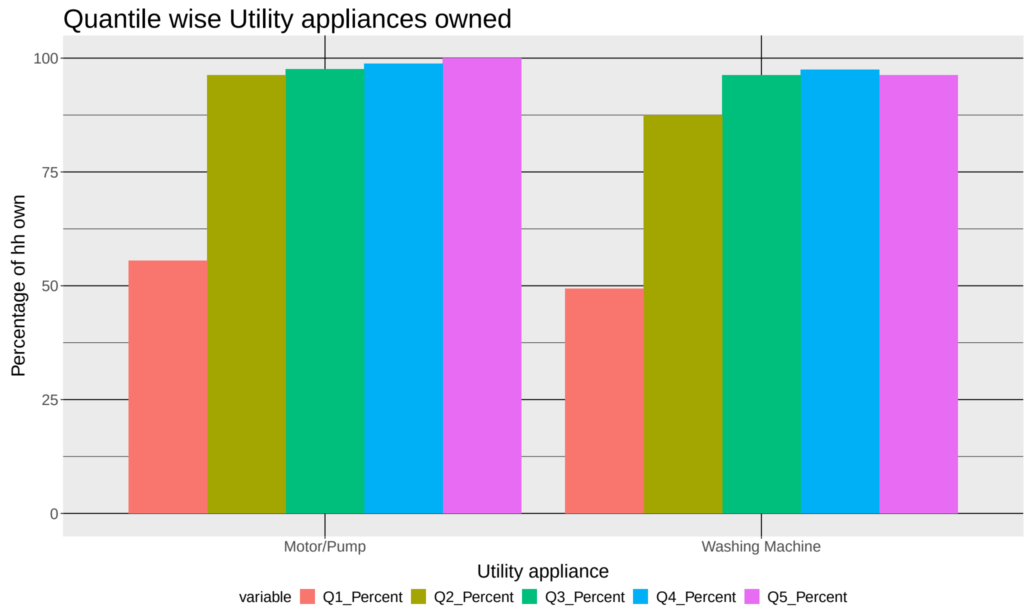

Figure 25: Distribution of different star rating of refrigerator owned quintile wise

number of days used	Q1_Percent	Q2_Percent	Q3_Percent	Q4_Percent	Q5_Percent
1	16.05	15	7.41	13.75	8.64
<=3	18.52	42.5	39.51	36.25	28.4
<=5	6.17	11.25	19.75	13.75	30.86
<=7	7.41	18.75	27.16	31.25	27.16

Table 31: Usage frequency of washing machines per week quintile wise

From the table above it can be seen that the higher quintiles have the highest percentages of households that use washing machines daily. Across quintiles though average usage is between 1 and 3 times a week.

3.8. Water Heating Appliances

Water heating is a high energy, seasonal load. In this section various methods/appliances used by households to heat water are presented by quintile.

3.8.1. Ownership of Water Heating Appliances

Figure 26 presents 9 different water heating methods used across households by quintile.

From figure 26 it can be seen that in the higher income quintiles the most common mode of water heating is electric, using comparatively expensive appliances, followed by solar. In these

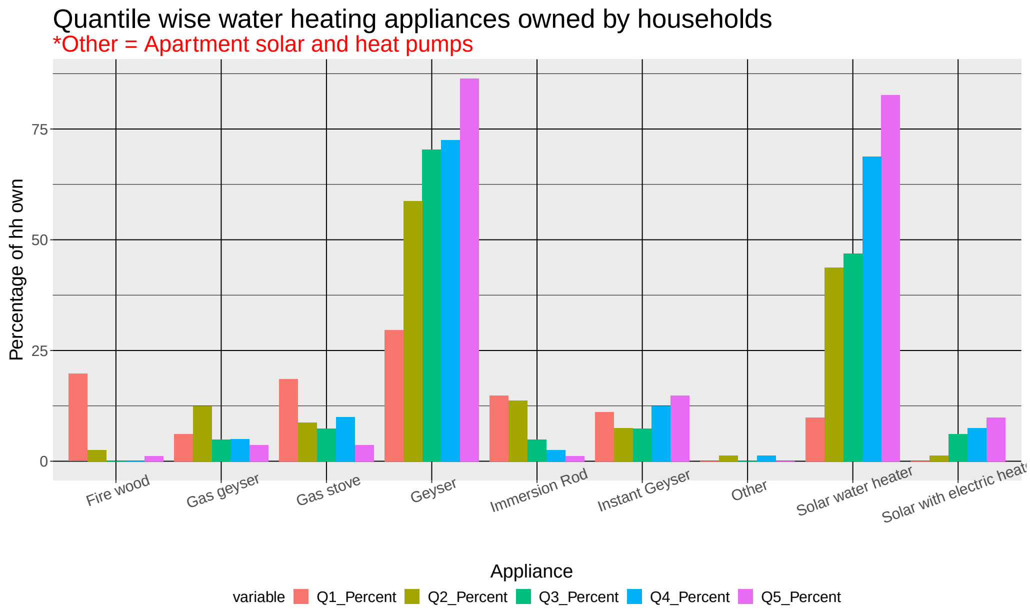

Figure 26: Ownership of different water heating appliances quintile wise

quintiles geysers are the largest mode of water heating closely followed by solar water heating.

In the lower quintiles the most common forms of water heating are non electric, achieved by using firewood or gas stove. This is followed by inexpensive electric heating option of immersion rods. considering the fact that this was a urban survey, we still see close to 22% of households in lower quintiles using firewood. Finally, the other water heating methods that are used are instant geysers and gas geysers which account for a very small percentage across income quintiles.

3.9. Vehicle Ownership

This section outlines the ownership of vehicles across quintiles.

3.9.1. Ownership of Vehicles

From figure 27 it can be observed that two wheeler ownerships are fairly uniform with little difference between quintiles varying between approximately 78% and 90%.

Looking at the ownerships of four wheelers, it is clear that there is a significant difference between the bottom and top quintiles, with quintile 5 showing close to 100% ownership of four wheelers. The difference between two wheeler and four wheeler ownerships is significant in

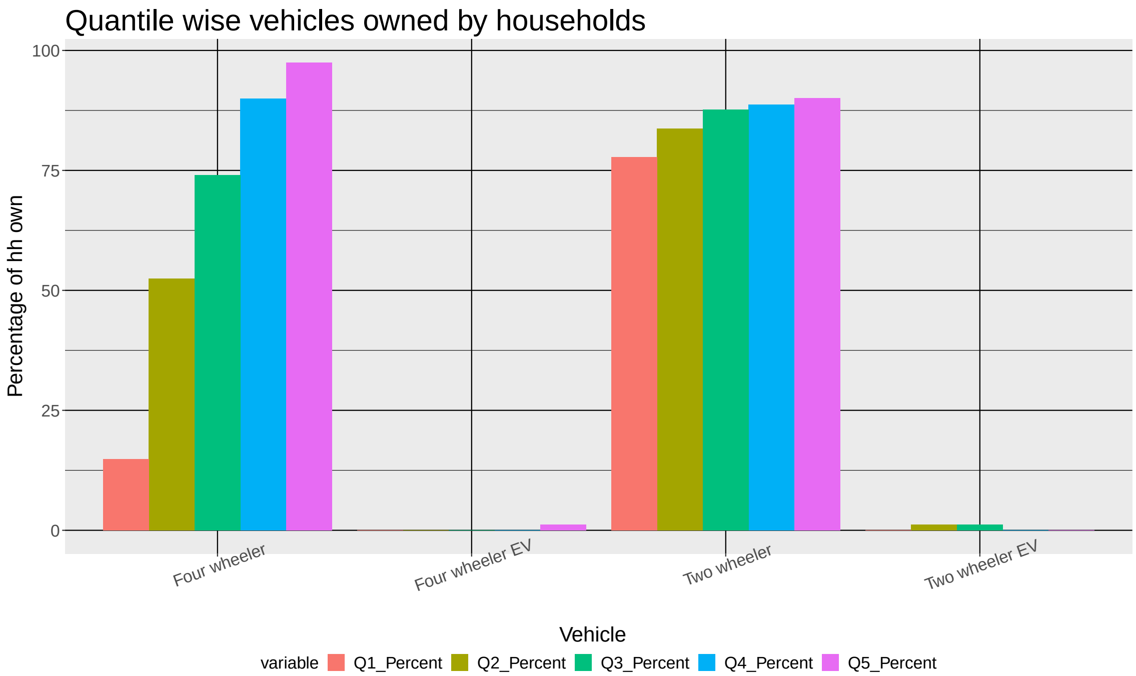

Figure 27: Ownership of different water heating appliances quintile wise

the lower quintiles with ownership of both being similar in the upper quintiles.

In the case of electric vehicles, it can be seen that for four wheelers ownership is seen only in the 5th quintile while two wheelers are owned in the quintile 2 and 3. But a very low ownership percentage of both of these was observed.

3.10. Propensity to Buy

In this section household's propensity to buy cooler, AC, and electric vehicles are presented. This is important as these appliances have a potential to add significantly to the load curve with high peak coincidence probability. The time-frame for the propensity to buy each of these were as follows: for AC and cooler next one year; for Electric vehicles next five years.

Figure 28 presents propensity of households to buy these appliances.

From figure 28 it can be observed that between AC and cooler most of the households indicate they would probably buy an AC in the next year, with the highest percentage (approximately 21%) from the last quintile.

In the case of electric vehicles, quintiles 2 and 3 show the highest propensity to buy electric two wheelers, with close to 25% of the households saying they will buy on in next 5 years. While

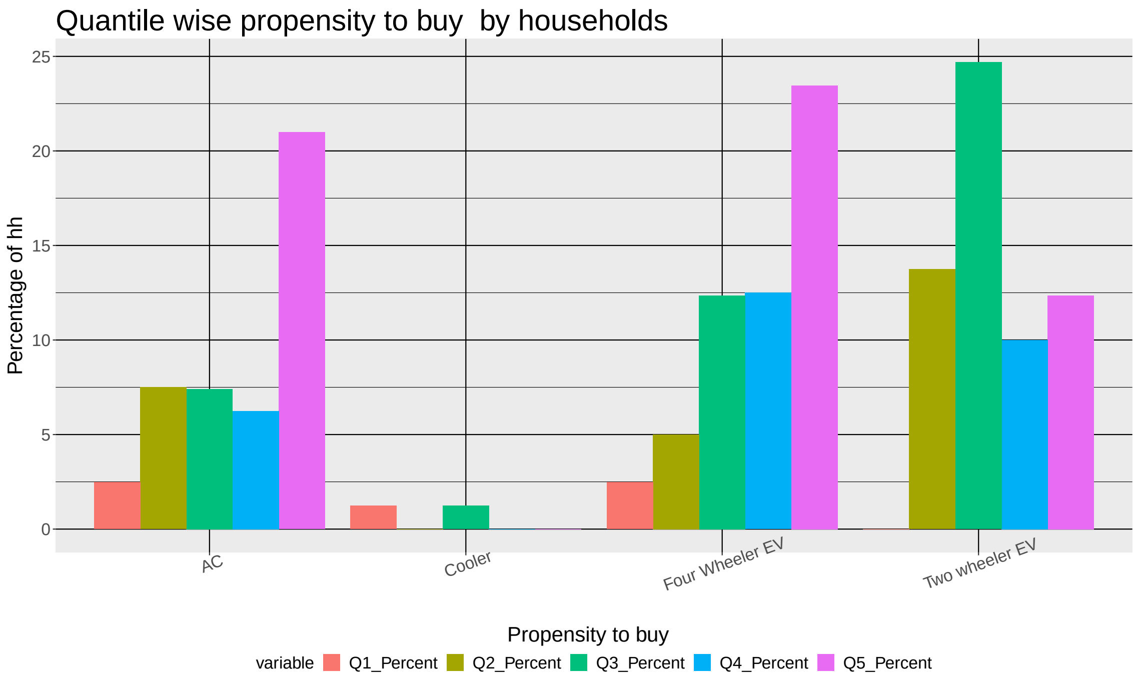

Figure 28: Propensity of households to buy the following

for the four wheelers the last 3 quintiles have the highest percentages of households that could buy a one in the next 5 years, with quintile 5 showing the highest propensity to buy one.

4. Summary

In this chapter we presented at the statistics of the data collected in the survey. The statistics of the entire survey gave us an key insights for different variables of the survey, as presented section 1 of the chapter. But at this level of statistics it was not very clear as to how appliances owned were distributed across different households. To identify variations in the distribution data was divided into quintiles. Two methods to divide the data set into quintiles were presented outlining the methodology that worked on our data set and the shortcomings of the other methods.

With the data divided into quintiles, comparisons of ownerships of different appliances distributed across quintiles were presented. These comparisons gave deeper insights into the ownership patterns of different appliances, identifying the skews in ownerships of different appliances, presented in section 3 of the chapter.

With statistical comparisons and an understanding of distributions in ownership of appliances, the next step is to build load curves. The load curves will be built for all the key appliance categories, at both aggregate and quintile levels for summer and winter seasons to identify variations in usage seasonally and by income quintiles.

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Chapter 4
Load Curve Models

1. Load curves for Survey Data

1.1. Introduction

In the previous chapter key statistics from the survey data was presented, aggregate and by quintile. The statistics helped identify ownership percentages of different appliances at aggregate levels. Dividing the data into quintiles gave insights into distribution in ownership and usage of different appliance across different income brackets. Skew in ownership and usage of specific appliances like coolers, ACs, microwaves, and geysers was observed towards the higher income households, while the skew in ownership and usage of immersion rods, firewood, CRT TVs was observed in the lower income quintile households.This skew in ownership and usage was also reflected in the average bill amounts of each quintile.

In this chapter models for load curves are developed, which give insights into patterns of electricity consumptions of households. The loads curves are are built for aggregate and quintile data to identify variations in patterns of consumption across different quintiles and across seasons (summer and winter). The load curves are built for individual appliances/categories to identify correlations between appliances/categories, quintiles and seasons. These load curves will also help identify peak and non-peak contributions from each appliance/category. The load curves presented in this chapter are built for the time resolution of the data collected in the survey. The data was collected for four time slots, grouping peak and non-peak slots in the morning and evening. These time slots were, 6am to 10am and 6pm to 10pm representing peak slots and 10am to 6pm and 11pm to 6am representing non peak slots for morning and evening respectively.

The sections that follow outline model formulations for the load curves including assumptions made. The load curve formulations are presented for both aggregate and quintile data, presenting load curves for demand from individual appliances first, followed by load curves for total demand from an average household from each quintile for summers and winters.

2. Aggregate Load Curves

This section presents the model to build load curves for each appliance, seasonally, followed by a load curve presenting total average demand for a typical household. The load curves built in this section are for aggregate survey data and are not split by quintiles.

2.1. Model Formulation

For aggregate data, a single load curve is built representing the average demand from a typical household . The total electricity consumed by the households can be considered as

$$E = f(i,j,t,s) \qquad (1)$$

where,

$A_{i,j}$ = i^{th} appliance of the j^{th} household.

i = appliances covered in the survey,

j = households 1 to 403

T_t = t^{th} time slot among the 4 time slots T

T = 6am to 10 am, 10am to 6pm, 6pm to 10 pm, 10pm to 6am

S_s = Season "s" in which the appliance is used. For the survey

s = summer or winter and for specific appliances monsoon.

Then, the electricity consumed by an appliance A_i in the household, for a time slot T is estimated using

$$E_{T,S} = \{\sum(A_i|T_{t,s}=1)*W_{avg\ A_i}\} \quad (2)$$

And the total electricity consumed across all appliances of the households for a given time slot T is estimated by

$$E_{T,S} = \sum_{j,t,s}\{\sum(A_i|T_{t,s}=1)*W_{avg\ A_i}\} \quad (3)$$

Using **(3)** we build aggregate load curves.

2.2. Load curve considerations and load curves

The appliances were categorized into lighting, space cooling and heating, kitchen, water heating and utility. First individual load curves were built for each appliance/category to understand demand patterns.

In total three sets of plots will be presented for each appliance/category covering

- Individual load curves for each appliance that make up a category (ex. one load curve each for fans, coolers, ACs an that make up the space cooling category), comparing their demand for summer and winter
- One load curve presenting the **total demand** from the category (ex. cooling lighting, etc), combining all the appliances that make up the category

These sets of load curves and demands are presented for the entire survey population

- Finally, One load curve indicating the **average demand** for the category from a typical household is presented

At the end of the section load curves presenting the total demand (cumulative demand from all appliances) from all appliances is presented indicating total and average demands from the survey.

2.2.1. Space Cooling Appliances

In this section load curves for space cooling appliances used across living spaces of the household, covering fans, coolers and air conditioners are built. Table 1 summarizes the data considerations for the load curve, ownership percentages, total numbers of each appliance owned, average usage times (weekdays **W.D** and weekends **W.E**), and numbers of each appliance used in different time slots.

Space cooling load considerations - entire survey													
Appliance	**% HH own**	**Total owned**	**Average wattage**	**Average hours**		**Time slot Summer**				**Time slot Winter**			
				W.D	**W.E**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Fan	100.00	1653	75	7.75	7.99	455	1389	1466	1637	56	325	301	1247
Cooler	11.17	49	250	5.35	5.38	2	12	7	39	0	0	0	0
AC	20.60	117	2000	4.98	4.98	0	26	10	110	2	2	0	12

Table 1: Space cooling appliances used

Figure 1 presents hourly demand for cooling during summer and winter from each cooling appliance from the entire survey.

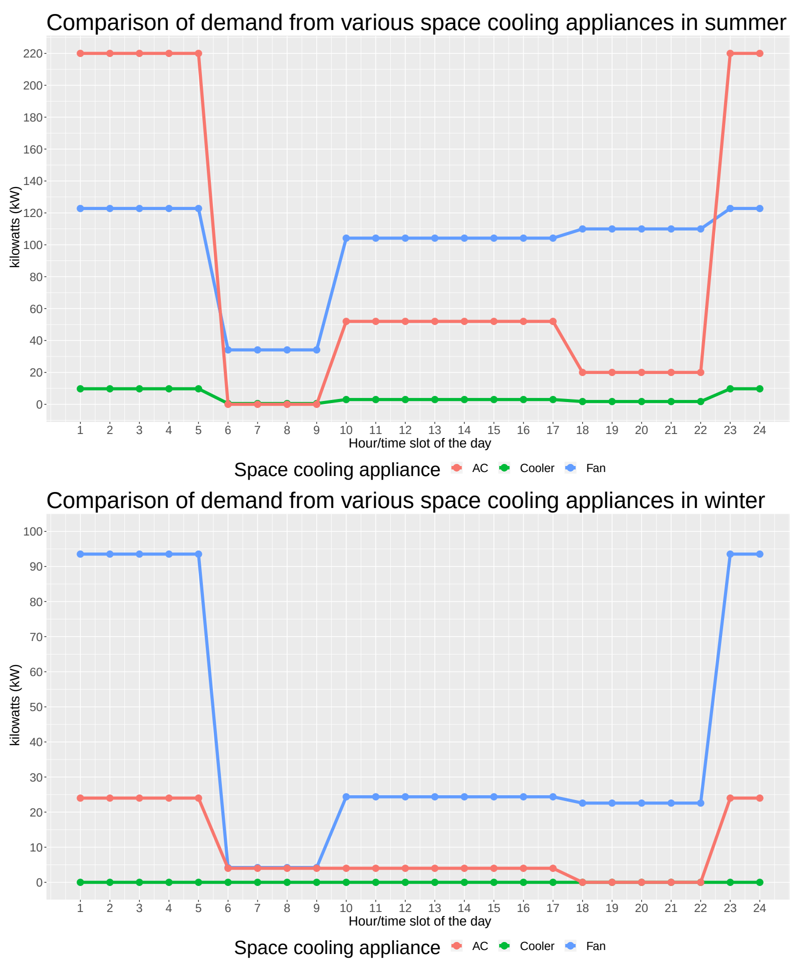


Figure 1: Load curve for different types of space cooling appliances. Summer and Winter

It can be observed that the demand for space cooling is significantly higher in summer than winter. The total peak demands for fans AC and cooler are 122 kW, 220 kw and 9.7 kW respectively in summer and 93.5 kW, 24 kW and 0 kW respectively in winter.These load curves represent of demand for the time slots as covered in the survey. We see from figure 1 that majority of the demand from each cooling appliance is during the evenings and nights in summer and predominantly in the night for winters. The high demand from fans was also observed by [1].

The figure 2 provides insights into total demand difference between summer and winter.

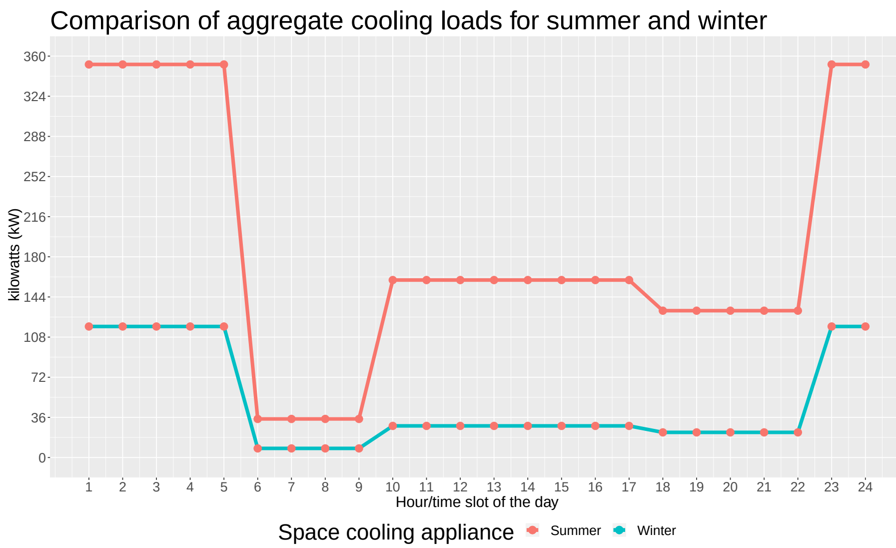


Figure 2: Comparison of total loads from space cooling for summer and winter over 24 hours

It is clear that the peak demand for cooling in summer is almost three times that of winter in the night times and almost 5 times in the afternoons. This is predominantly due to the demand that arising from AC's and fans running throughout the day as presented table 1.

Finally, figure 3 presents average consumption of a household for space cooling.

We can see from the figure 3 that the peak demand during summer nights is approximately 0.9 kw compared to 0.3 kW in winters. Similarly in the afternoon the peak is approximately 0.4 kW compared to 0.1 kW in winters. These load curves indicate a strong seasonal correlation from space cooling appliances. It has to also be noted that demand from fans in winters significantly contributes to night demand, with the drop in demand seen during the day in winters.

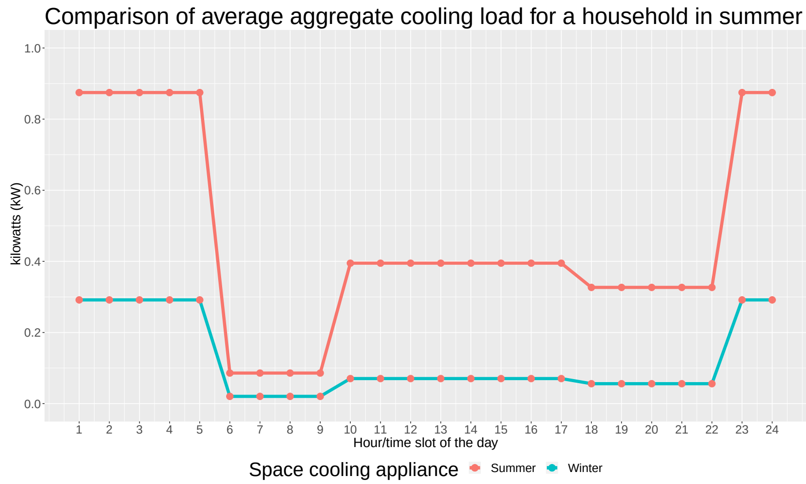


Figure 3: Average space cooling load from a household

2.2.2. Water Heating Appliances

This section presents the load curves for water heating appliances. water heating similar to space cooling has a strong seasonal correlation.

Table 2 presents ownership and usage statistics for water heating appliances.

Water heating load curve considerations - entire survey														
Type of water heating appliance	% HH own	Total owned	Average wattage	Average hours		Time slot Summer				Time slot Winter			
				W.D	W.E	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Geyser	63.52	355	2000	1.87	1.87	177	11	22	3	329	15	33	0
Immersion Rod	7.44	30	2000	8.66	1.55	16	0	0	0	30	0	0	0
Instant Geyser	10.67	46	1000	1.88	1.88	22	1	5	0	37	1	5	0
Solar with electric heater	4.96	19	2000	2.5	2.5	19	0	1	0	19	0	1	1

Table 2: Electric water heating appliances used by households

From the table 2 we see that among the electric water heating appliances, geysers are the highest owned, followed by instant geysers (smaller geysers storing approximately one liter of water), immersion rods and solar water heaters with heating elements built in.

Figure 4 presents a plot of the load from each of these appliances for summer and winter.

We see from figure 4 that the demand is highest from geysers, while immersion rods, instant geysers and solar water heaters are close to each other in terms of demand. We see that during winters the demand from the geysers is almost twice of that of summer. Similar trend is observed with respect to the other three water heating appliances as well.

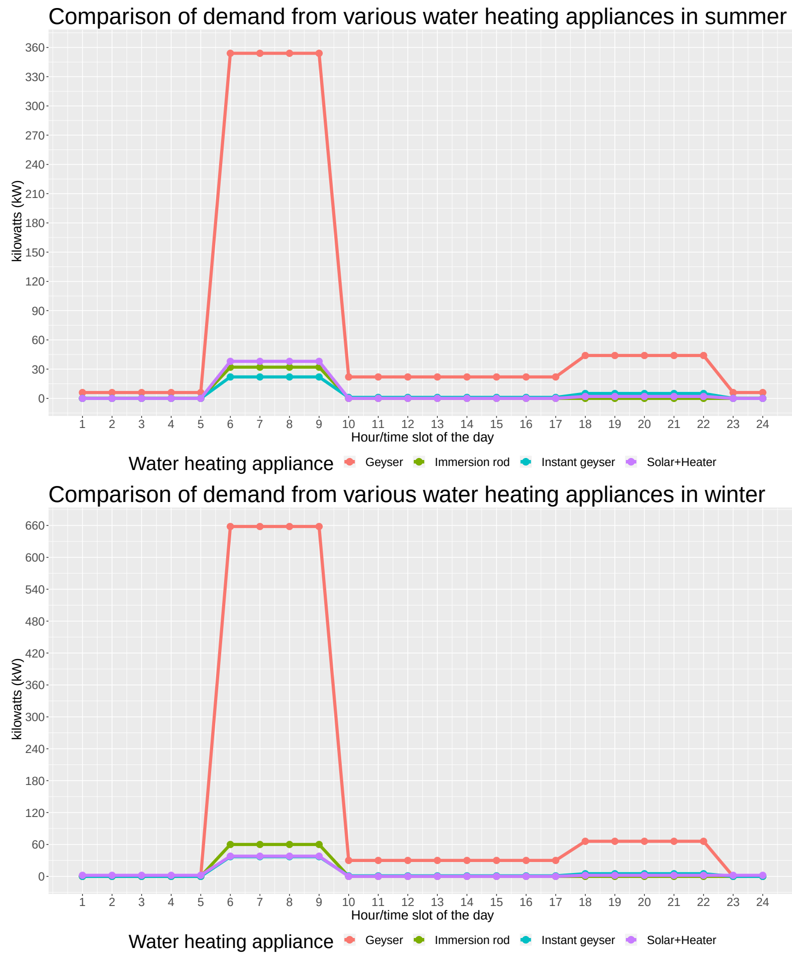


Figure 4: Load curve for different types of water heating appliances. Summer and Winter

Figure 5 shows that the total demand from water heating in winters is almost twice that in summer. It can be observed that the peak occurs during the day and is significantly higher than the peak from water heating in the evening.

Finally figure 6 shows that the during winters the average peak load of a household is close to 2 kW compared to 1.1 kW in summer. The key take away is that the water heating peak predominantly occurs during the day between 6 am to 10 am and the peak load from the surveyed households in winter is almost twice the peak in summer.

2.2.3. Lighting

In this section load curves from lighting in living areas, kitchen and bathrooms for summer and winter are presented.

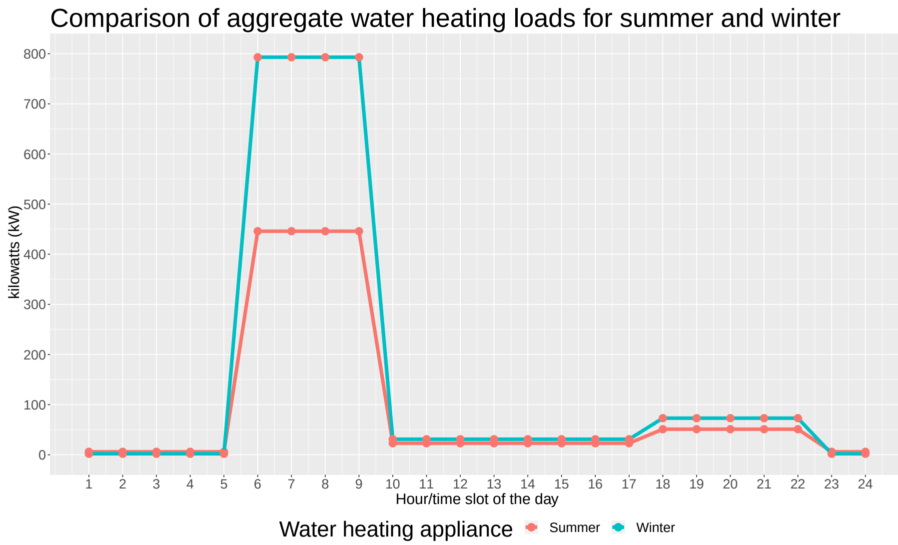


Figure 5: Comparison of total loads from water heating for summer and winter over 24 hours

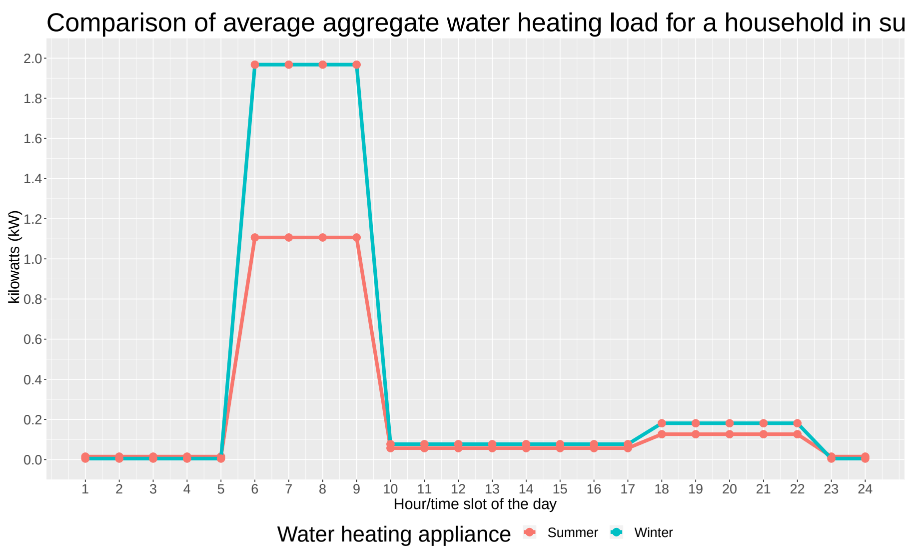


Figure 6: Average lighting load from a household

2.2.3.1. Living Area Lighting

Table 3 presents ownership and usage statistics for lighting used in living areas.

Lighting-Living area load considerations - entire survey														
Type of Light	**% HH Own**	**Total owned**	**Average wattage**	**Average hours**		**Time slot Summer**				**Time slot Winter**				
				Weekdays	**Weekends**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Incandescent	12.90	121	52.69	3.44	3.48	16	9	62	7	16	9	62	7
Tubelight	79.16	1197	30.98	5.67	5.98	384	175	1142	74	444	182	1137	63
CFL	37.47	620	11.29	4.23	4.32	122	57	481	49	134	57	484	46
LED	73.70	1481	9.18	4.57	4.79	380	216	1300	61	418	216	1300	61

Table 3: Lighting types used in living spaces

Figure 7 are load curves for various lighting sources fin summer and winter for living areas.

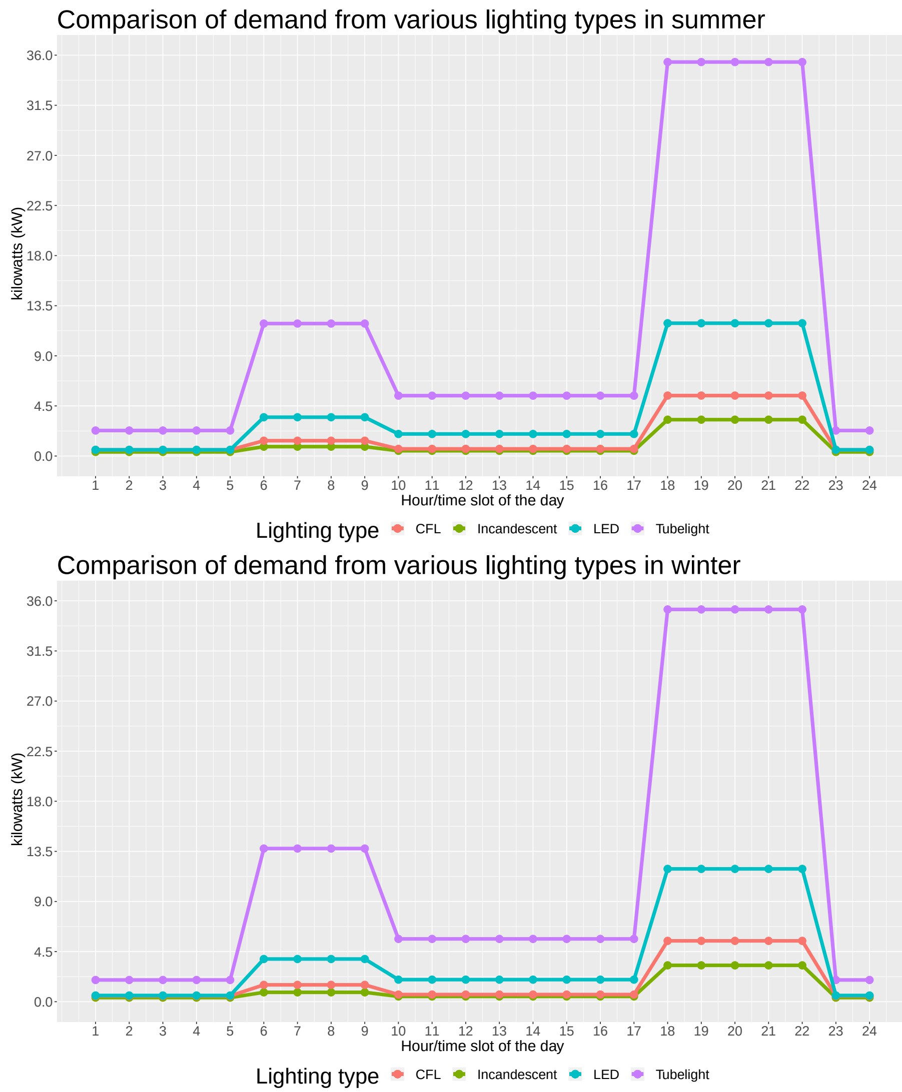


Figure 7: Load curve for different types of lighting. Summer and Winter

No significant difference in the load curves between summer and winter is observed, except during early mornings in winter. This is clearly visible in figure 8 that compares the total load from all lighting sources in living areas.

From figure 7 it can be seen that this is largely due to tube lights and LED bulbs. One reason for this is the late sunrise in winters.

Lastly, figure 9 presents average cumulative lighting demand from a household for summer and winters for living areas.

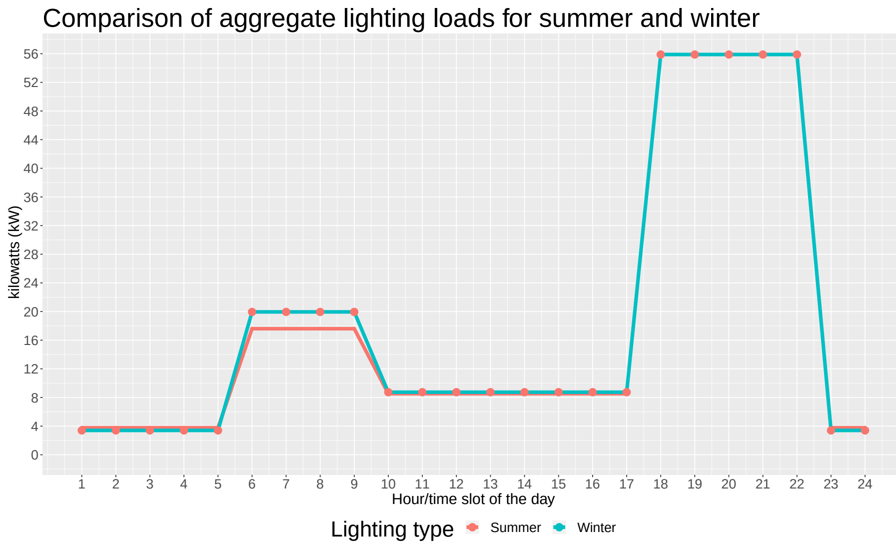


Figure 8: Comparison of total loads from summer and winter over 24 hours

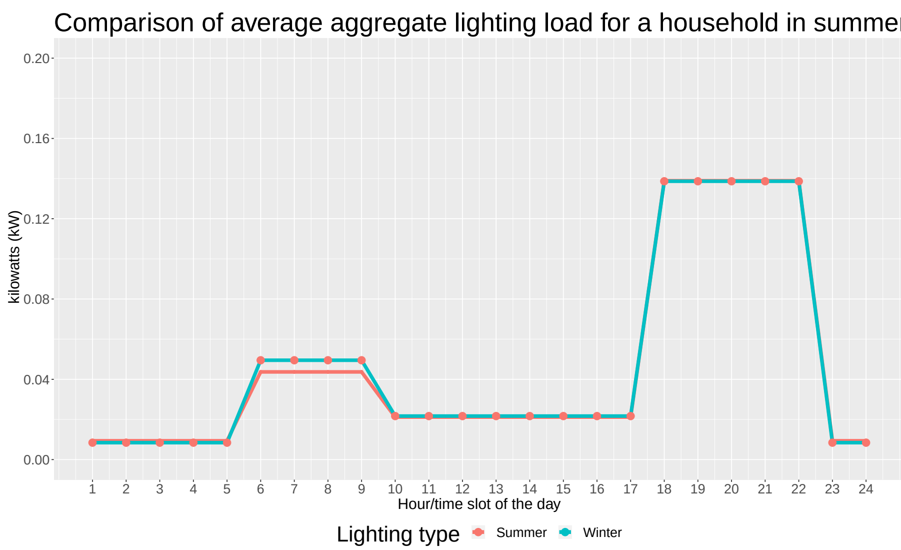


Figure 9: Average lighting load from a household

It can be observed that the average peak load of a household is in the evening (approximately 0.14 kW).

2.2.3.2. Kitchen Lighting

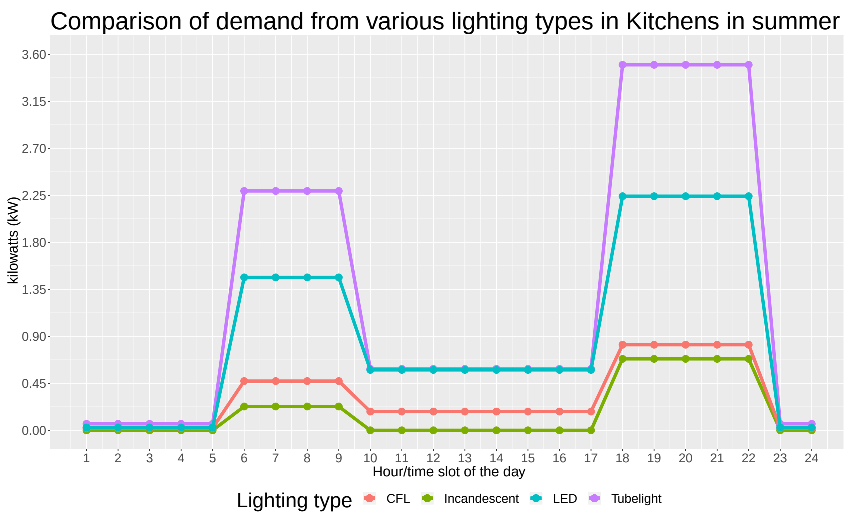
Table 4 presents statistics for ownership and usage of kitchen lighting.

Figure 10 presents the load curves from various kitchen lighting sources for summer and winter.

It can be seen from figure 10 that except for a very small increase in demand in winters, the

Lighting-Kitchen load considerations - entire survey													
Type of Light	**% HH Own**	**Total owned**	**Average wattage**	**Avg hours**		**Time slot Summer**				**Time slot Winter**			
				W.D	**W.E**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Incandescent	3.72	16	57	3.33	3.50	4	0	12	0	4	0	13	0
Tubelight	30.77	125	30.97	4.86	5.01	74	19	113	2	76	18	113	2
CFL	19.85	84	11.23	4.83	4.92	42	16	73	2	46	17	72	2
LED	58.56	281	9.04	4.89	4.97	162	64	248	3	166	64	249	3

Table 4: Lighting types and usage in Kitchens



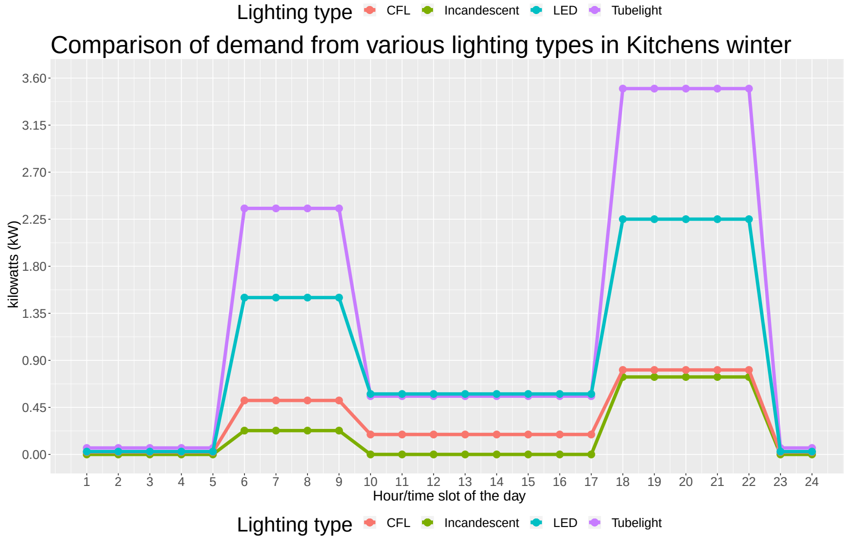


Figure 10: Load curve for different types of lighting for kitchens. Summer and Winter

load curves are fairly similar the observed difference in peak demand compared to figure 7 is primarily due to the duration and the number of bulbs used.

From figure 11 it can be seen that the difference between peak winter and summer demand is not significant.

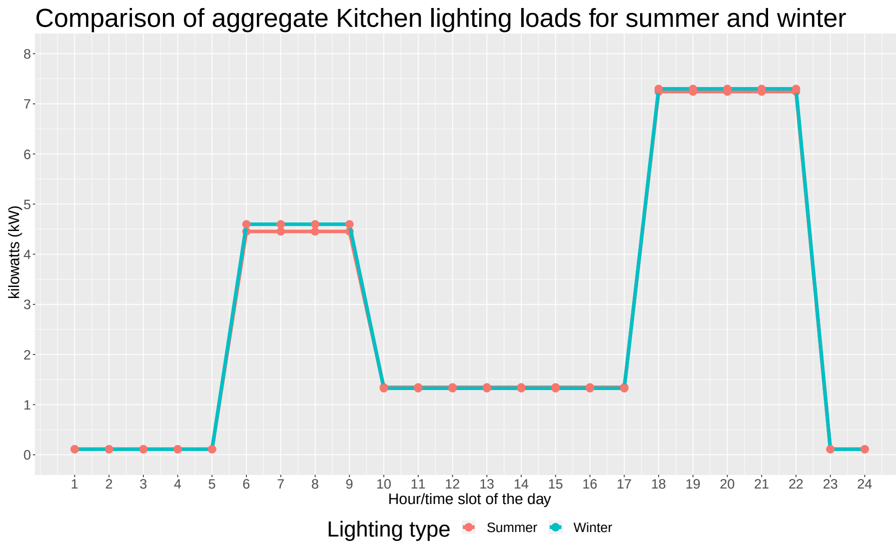


Figure 11: Comparison of total loads from summer and winter in kitchen lighting over 24 hours

Finally from figure 12 it can be seen that the kitchen lighting on average peaks at 0.011 kW (11 w) during the day and approximately 0.018 kW (18 w)during the evening peaks.

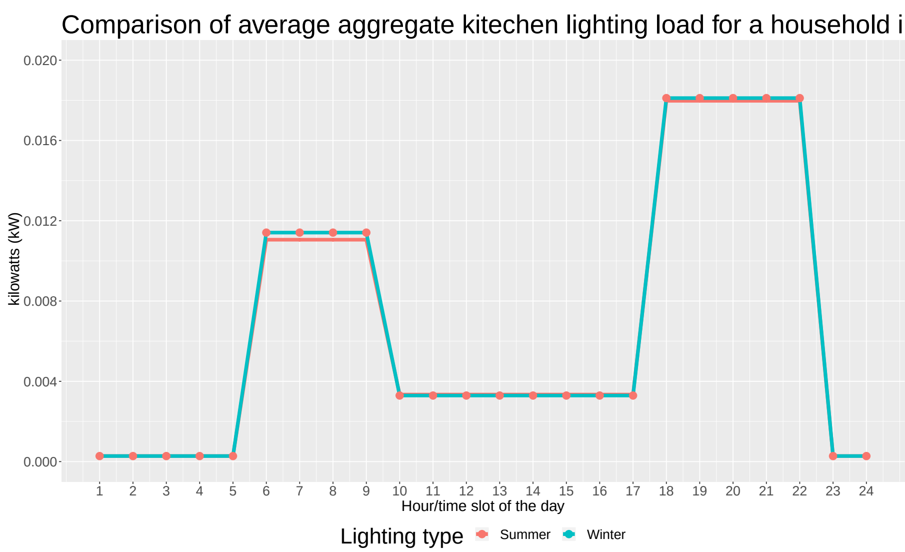


Figure 12: Average kitchen lighting load from a household

2.2.3.3. Bathroom Lighting

Table 5 is a breakup of various lighting types used by households for bathroom presenting ownership and usage statistics.

Lighting-Bathroom load considerations - entire survey													
Type of Light	**%HH Own**	**Total owned**	**Average wattage**	**Average hours**		**Time slot Summer**				**Time slot Winter**			
				W.D	**W.E**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Incandescent	10.92	68	49.32	1.85	1.85	60	33	63	4	58	33	61	4
Tubelight	1.74	10	13.14	1.86	1.86	10	7	10	2	10	7	10	2
CFL	25.56	215	10.09	2.05	2.07	201	149	210	11	195	149	210	13
LED	64.27	518	8.50	2.15	2.17	502	349	510	47	500	349	512	45

Table 5: Lighting types and usage in Bathrooms

Figure 13 presents comparison of the total lighting demand for bathrooms in summer and winter.As seen from figure 14 there no significant difference between peak demand in summer and winter.

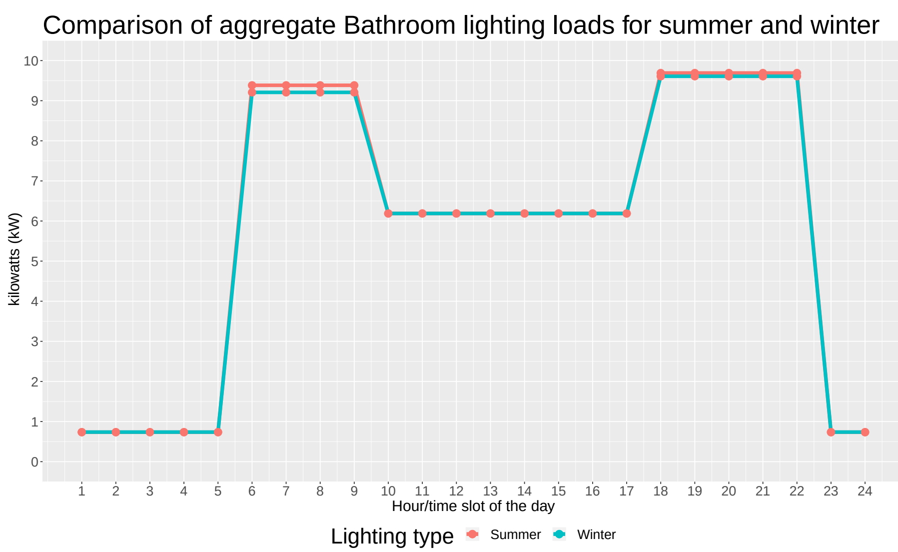


Figure 13: Comparison of total loads from summer and winter in bathroom lighting over 24 hours

Figure 14 presents load curves for bathroom lights. It can be see that the predominant lighting source is LED bulbs, with the maximum demand coming from the same with peak demand in the mornings and evenings almost consistent seasonally.

Finally, figure 15 compares the average load of a household for bathroom lighting. The demand peaks at approximately 0.022-0.023kW (22 W) which is slightly more than the kitchen lighting but significantly lower than the demand from living areas.

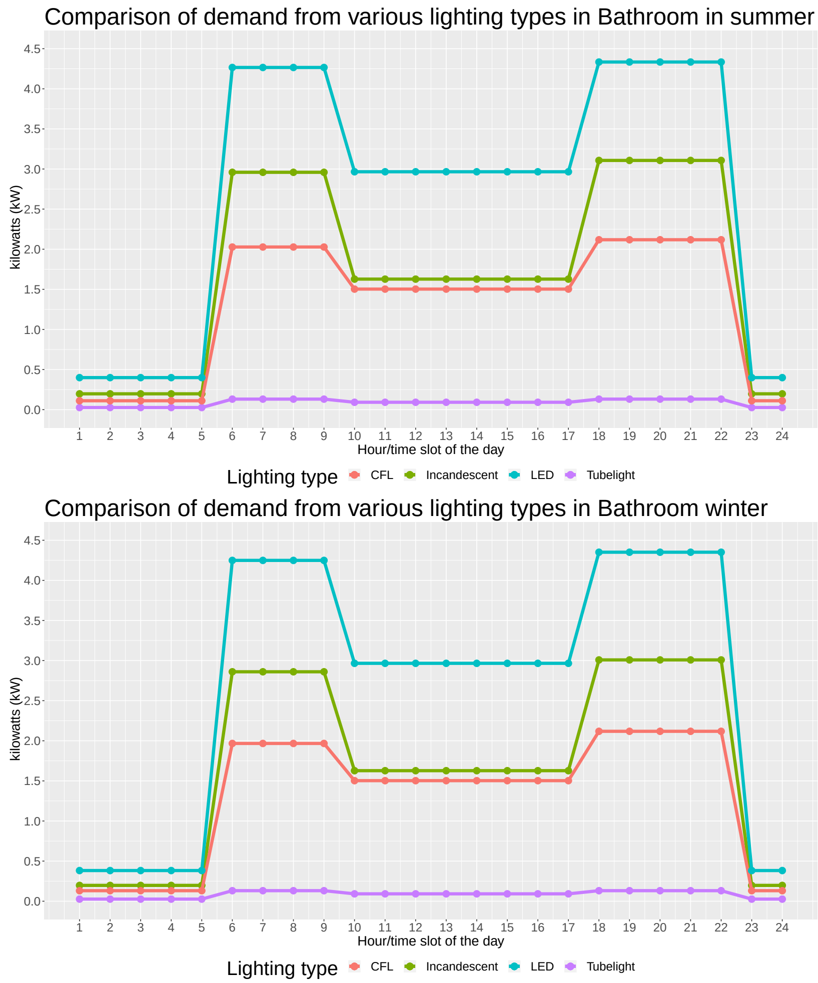


Figure 14: Load curve for different types of lighting used in bathrooms. Summer and Winter

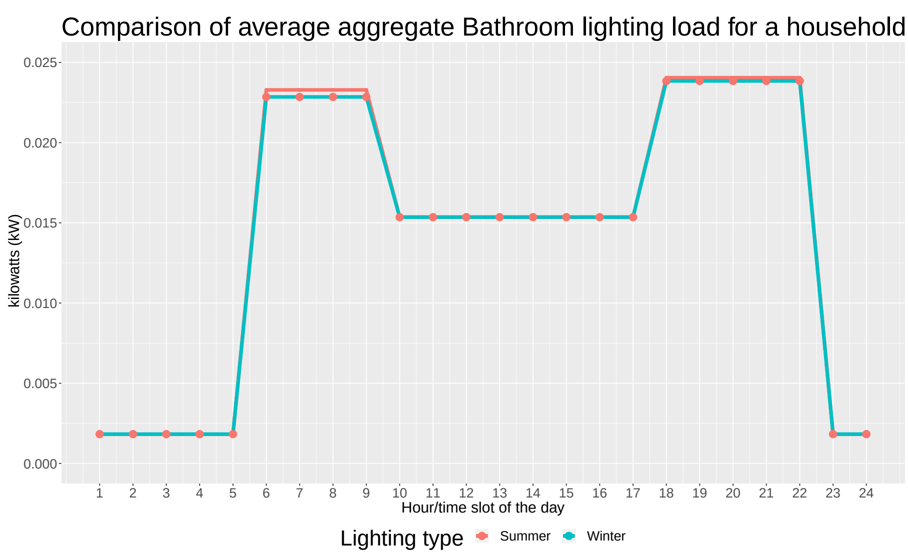


Figure 15: Average Bathroom lighting load from a household

2.2.4. Kitchen and Utility Appliances

This section presents load curves for kitchen and utility appliances covering induction stoves, washing machines and motor/pump. These appliances generally do not have significant seasonal correlation and their usage depends on household lifestyles.

The table 6 presents statistics on ownership and usage for each of these appliances.

Utility and kitchen appliances load curve considerations - entire survey														
Appliance	**% HH own**	**Total owned**	**Average Capacity**	**Average usage/week**	**Average hours**		**Time slot Summer**				**Time slot Winter**			
					W.D	**W.D**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Washing Machine	85.36	349	6.36	3.72	1.13	1.14	165	147	42	11	163	150	42	9
Motor/Pump	89.58	367	0.78	NA	0.53	0.53	157	20	80	0	158	19	79	0
Induction cooktop	28.78	115	2000	NA	1.58	1.58	55	4	34	0	55	4	34	0

Table 6: Kitchen and utility appliances usage considerations

From table 6 it can be seen that close to 85% of the households own a washing machine and approximately 90% of the households own a motor/pump. It can also observed that washing machines are used on average close to 4 times a week, making it a regular load contributor.

Figure 16 presents load curves for these appliances in summer and winter.

As can be observed from figure 16 there is no difference in the load curves between summer and winter indicating no seasonal correlation. Figure 16 shows that these appliances have a coincident day time peak, while the motor and induction stove also have a evening peak. Washing machines have a drawn out demand period across two time slots as washing machines are predominantly day time appliance driven by the need to dry clothes during daylight.

Next the aggregate load curve of these three appliances is presented along with their peak and average demand.

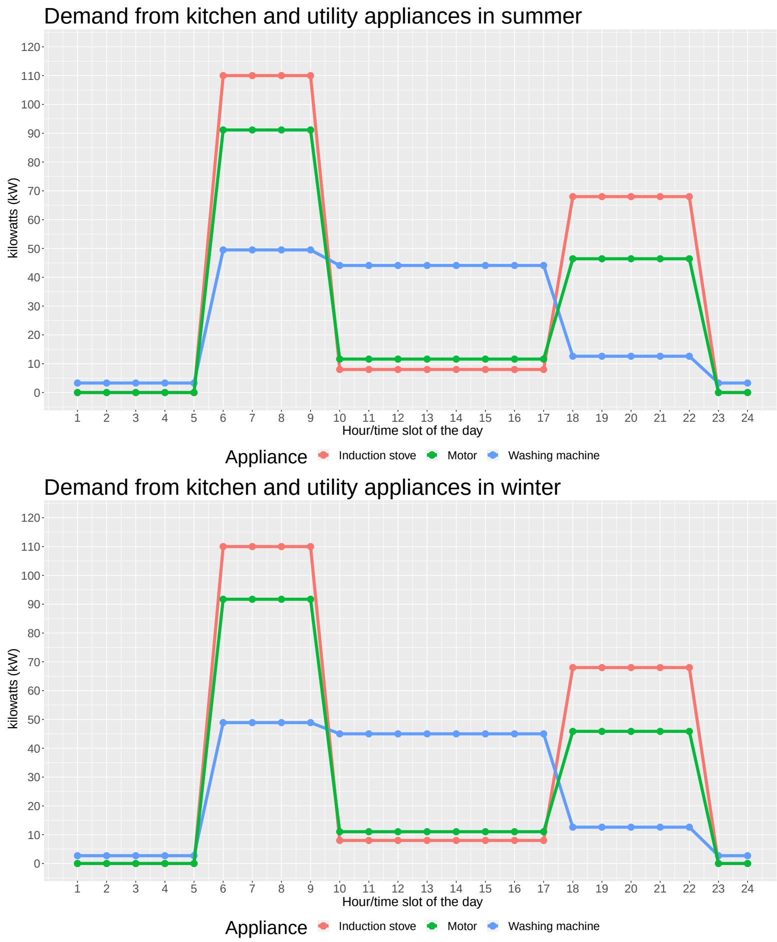


Figure 16: Load curve for different types of lighting used in bathrooms. Summer and Winter

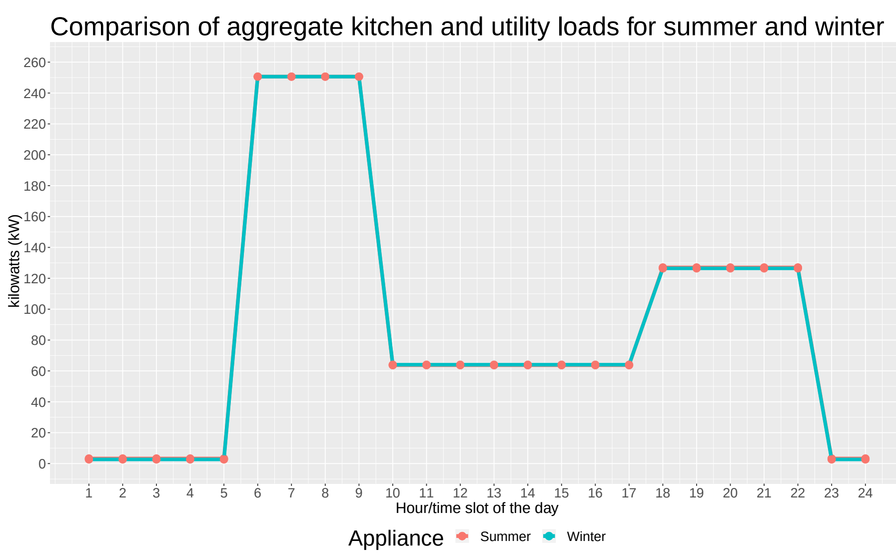


Figure 17: Comparison of total loads from summer and winter in kitchen lighting over 24 hours

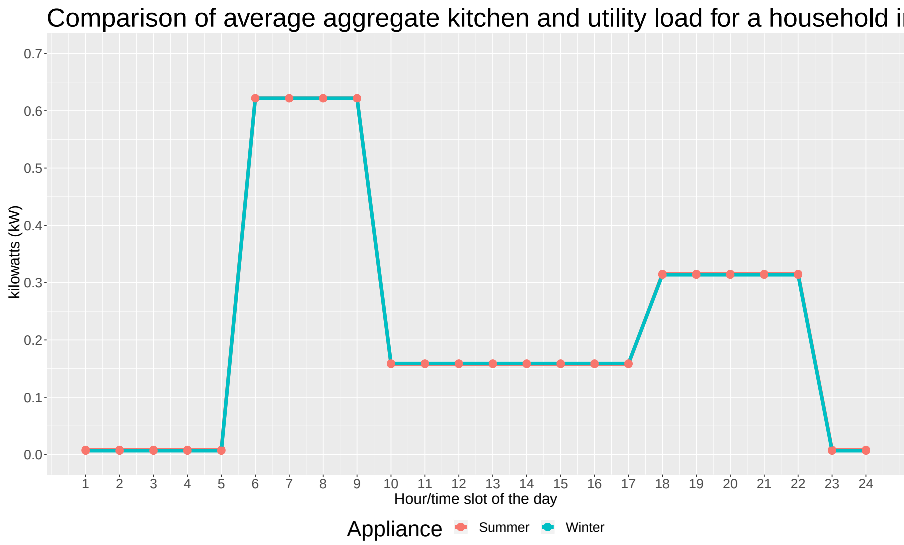


Figure 18: Average kitchen lighting load from a household

As from figure 18 the peak demand per household is approximately 0.62 kW (620 W) during the day and 0.3 kW (300 W) during the evenings, and remains consistent across seasons. Demand from these appliances can be considered a daily major contributor, considering its peak coincidence and consistency across seasons.

2.3. Cumulative Load Curve (All Appliances)

This section will look at the total demand of the households from all the appliances categories presenting overall load curve of the household. Two load curves, one indicating the load curve of all the appliances cumulative and one indicating the average load curve of a household in summer and winter are presented.

Figure 19 presents the cumulative load curve for all the households surveyed including appliance categories.

From figure 19 two peaks can be observed, one during the day and the other during evening/night. In the mornings, in winters, peak is much greater than summer, and for the evenings, summer peak is significantly higher than winters.

Next, figure 20 presents the average (cumulative) load curve for a typical household in the survey for summer and winter together.

We see the same trend that follows from figure 19 with average morning load in winter peaking

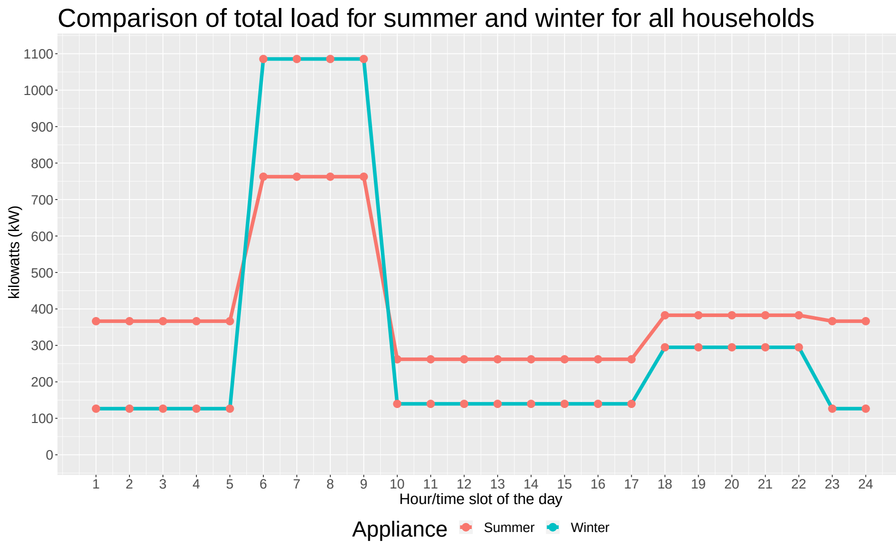


Figure 19: Comparison of total loads from summer and winter in kitchen lighting over 24 hours

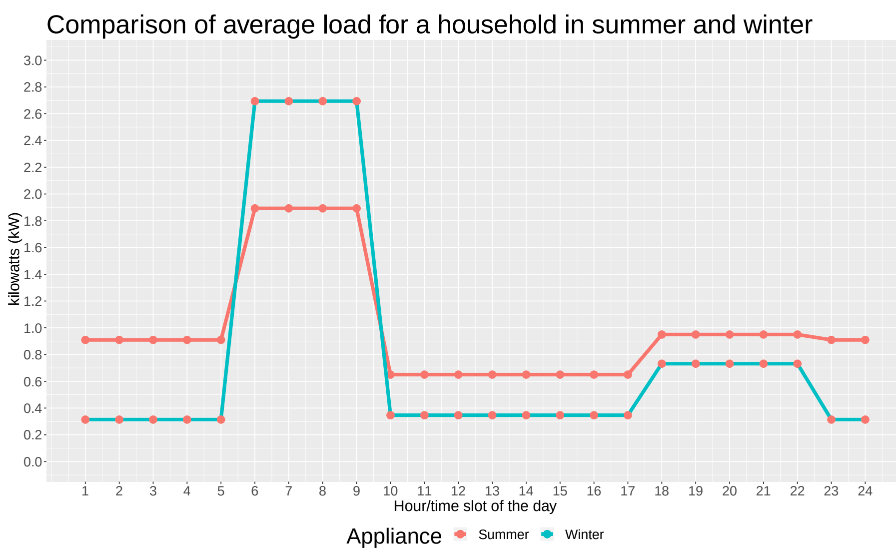


Figure 20: Average kitchen lighting load from a household

at 2.7 kW and 1.9 kW in summers. This is primarily driven by increased water heating load. The evening peak is higher in summer compared to winter at approximately 1 kW compared to 0.7 kW driven increased use of space cooling appliances. Across seasons peaks are almost consistent for categories like lighting and other appliances.

3. Quintile Load Curves

We know that appliance ownerships and usage are not uniform across households [2, 3, 4, 5, 6], and therefore the contributions of different households to the over all load curve also vary. Load curves disaggregated by quintiles will therefore give us a better understanding of how different households contribute to the load curves. To identify these variations, using PCA analysis the survey data was split into 5 income quintiles with approximately 81 households in each quintile. In the sections that follow models for building quintile load curves are presented to identify the variations in demand and from households in different quintiles.

3.1. Model Formulation - Quintiles

The electricity consumed by households in a quintile can be looked at as

$$E = f(i,j,k,t,s) \quad (4)$$

where,

Q_k = is the k^{th} quintile of the household, with k = 1:5.

Other variables are as defined in (1)

The electricity consumed by a household for an appliance in a time slot T_t for a quintile Q_k is estimated using

$$E_{T,S,Q} = \{\sum(A_{i,k}|T_{t,s}=1)*W_{avg\ A_i}\} \quad (5)$$

And the total electricity consumed across all appliances of the households in a quintile for a given time slot T for a season S is estimated using

$$E_{T,S} = \sum_{j,t,s,k}\{\sum(A_{i,k}|T_{t,s}=1)*W_{avg\ A_i}\} \quad (6)$$

Using **(5)** and **(6)** we build the load curves for households in each quintile.

3.2. Load Curve Considerations and Quintile Load Curves

Similar to the previous section, first load curves for 5 quintiles are presented, covering summer and winter, by quintile, indicating average load curves of a typical household for each appliance/category.

Finally an aggregate and an average quintile wise load curve is presented for summer and winter which are cumulative of the load from each of the appliance categories indicating total load from all the households in the quintile. This is followed by an average load curve for each quintile indicating the total consumption from all the appliances for summer and winter.

3.2.1. Space Cooling Appliances

In this section we look at the load curves for space cooling appliances. The load curves presented here are an aggregate of the loads from all three space cooling appliances appliances.Table 7 below indicates the quintile wise statistics of ownership and usage of appliances.

Space cooling load curve considerations - quintile wise															
quintile	Applinace	Total Appliances	% own	Assumed wattage	Average Hours		Time slot Summer				Time slot Winter				
					W.D	W.E	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Q1	Fan	189	100.00	75.00	7.43	7.57	42	123	145	189	8	32	29	150
	Cooler	2	2.47	250.00	2.50	2.50	0	0	0	2	0	0	0	0
	AC	1	1.23	1500.00	8.00	8.00	0	0	0	1	0	0	0	0
Q2	Fan	272	100.00	75.00	7.91	8.10	61	228	223	268	14	34	30	194
	Cooler	6	7.50	250.00	4.75	4.75	0	1	0	4	0	0	0	0
	AC	6	6.25	1500.00	3.20	3.20	0	2	0	6	0	2	0	0
Q3	Fan	323	100.00	75.00	7.41	7.57	102	269	292	320	17	45	46	242
	Cooler	9	11.11	250.00	4.25	4.25	0	3	2	7	0	0	0	0
	AC	23	23.46	1500.00	4.74	4.74	0	6	1	22	0	0	0	2
Q4	Fan	367	100.00	75.00	7.84	8.06	108	340	331	358	9	72	58	250
	Cooler	11	12.50	250.00	6.20	6.20	0	3	2	9	0	0	0	0
	AC	32	28.75	1500.00	5.22	5.22	0	7	2	30	2	0	0	2
Q5	Fan	502	100.00	75.00	8.19	8.67	142	429	475	502	8	142	138	411
	Cooler	21	22.22	250.00	5.88	5.94	2	5	3	17	0	0	0	0
	AC	55	43.21	1500.00	5.14	5.12	0	11	7	51	0	0	0	8

Table 7: quintile wise space cooling appliances considerations

From the table it can be seen that all the households across quintiles own fans and the number of fans used in summer increase as we move up quintiles. This is also observed in the use of AC's. Figures 21 and 22 present quintile wise load curves for summer and winter.

It can be seen that the night peak for space cooling in summer is at least twice the winter demand with a similar trend observed in the afternoon. The peak demand goes up as we move up quintiles. Peak demand is significantly higher is the top two quintiles, primarily due to

(i) Increased number of ACs in the last two quintiles

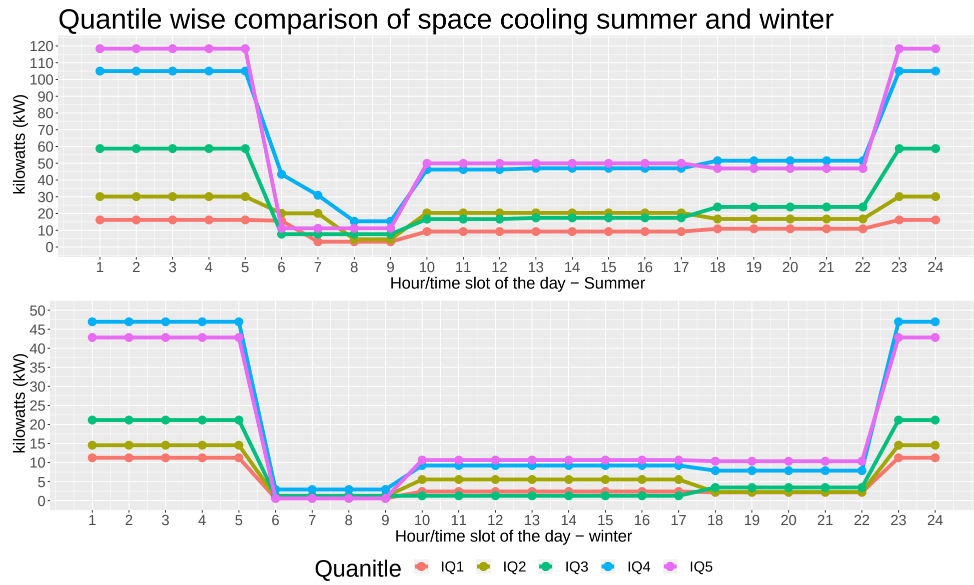


Figure 21: Comparison of total loads from summer and winter in space cooling over 24 hours

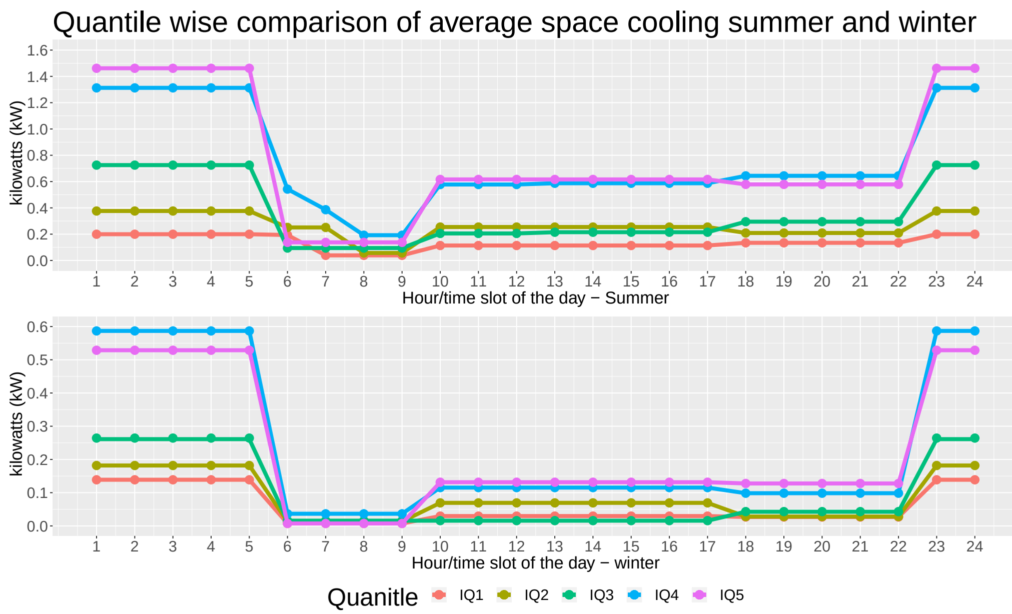


Figure 22: Comparison of total loads from summer and winter in space cooling over 24 hours

(ii) Duration of usage of these appliances, especially AC's

From figure 21 it can be observed that the range across quintiles for aggregate peak demand in summer is 20 kW to 120 kW. Similarly, from figure 22 we seen that the average cooling demand for a typical household in each quintile, in summers ranges from 0.2 kW to 1.5 kW across quintiles with similar distribution being observed in winter.

This indicates that space cooling as a end use has a strong seasonal and income correlation and to identify this relationship with income, it is important to analyze such data disaggregated by income.

3.2.2. Water Heating Appliances

This section presents load curves for water heating appliances. Only electric appliances like geyser, instant geyser, immersion rods and solar water heaters with built in heating elements are considered. Table 8 presents the statistics for water heating appliances by quintile.

Water heating load curve considerations - quintile wise														
quintile	Applinace	Total Appliances	% own	Assumed wattage	Average Hours		Time slot Summer				Time slot Winter			
					W.D	W.E	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Q1	Geyser	24	29.63	2000.00	0.90	0.90	23	0	3	0	23	0	4	0
	Immersion Rod	12	14.81	2000.00	0.48	0.48	8	0	0	0	12	0	0	0
	Instant geyser	9	11.11	1000.00	0.54	0.54	8	0	1	0	8	0	1	0
	Solar with Heater	0	0.00	2000.00	0.00	0.00	0	0	0	0	0	0	0	0
Q2	Geyser	55	58.75	2000.00	1.15	1.15	35	2	5	0	52	2	7	0
	Immersion Rod	11	13.75	2000.00	0.73	0.73	7	0	0	0	11	0	0	0
	Instant geyser	6	7.50	1000.00	0.42	0.42	3	0	0	0	6	0	0	0
	Solar with Heater	1	1.25	2000.00	0.15	0.15	1	0	0	0	1	0	0	0
Q3	Geyser	71	70.37	2000.00	1.21	1.21	49	2	5	0	70	2	11	0
	Immersion Rod	4	4.94	2000.00	0.40	0.40	1	0	0	0	4	0	0	0
	Instant geyser	7	7.41	1000.00	0.61	0.61	2	0	1	0	6	0	1	0
	Solar with Heater	5	6.17	2000.00	0.74	0.74	5	0	0	0	5	0	0	0
Q4	Geyser	84	72.50	2000.00	2.99	2.99	37	4	7	0	80	5	8	0
	Immersion Rod	2	2.50	2000.00	0.73	0.73	0	0	0	0	2	0	0	0
	Instant geyser	11	12.50	1000.00	0.36	0.36	4	0	2	0	8	0	2	0
	Solar with Heater	5	7.50	2000.00	0.98	0.98	5	0	1	0	5	0	1	1
Q5	Geyser	121	86.42	2000.00	2.39	2.39	33	3	2	3	104	6	3	0
	Immersion Rod	1	1.23	2000.00	0.45	0.45	0	0	0	0	1	0	0	0
	Instant geyser	13	14.81	1000.00	0.69	0.69	5	1	1	0	9	1	1	0
	Solar with Heater	8	9.88	2000.00	0.86	0.86	8	0	0	0	8	0	0	0

Table 8: Water heating considerations quintile wise

From table 8 it can be seen that as we go up quintiles, the number of expensive water heating appliances like geysers and solar water heaters increase in number while the number of inefficient water heating appliances like immersion rods decrease.

Figures 23 and 24 below indicate the total load from water heating appliances and average water heating load per quintile.

From figures 23 and 24, peak demand is during the day time in the first time slot of 6 am to 10 am can be observed.

Looking at summer peaks it can be seen that the highest demand is from the 3rd quintile while the top two income quintiles have a relatively lower peak demand. This is likely because the

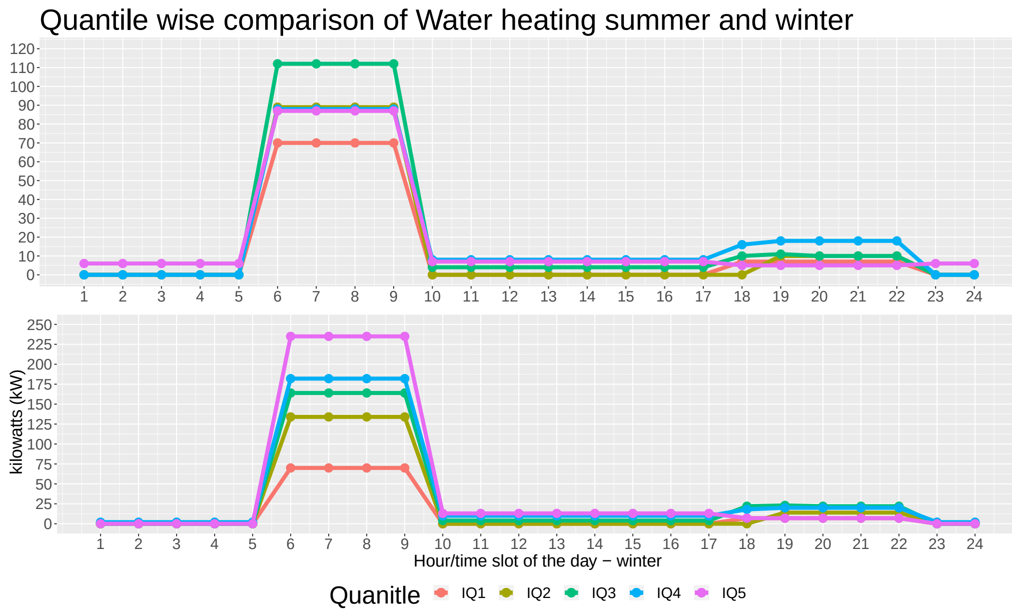


Figure 23: Comparison of total loads from summer and winter in water heating over 24 hours

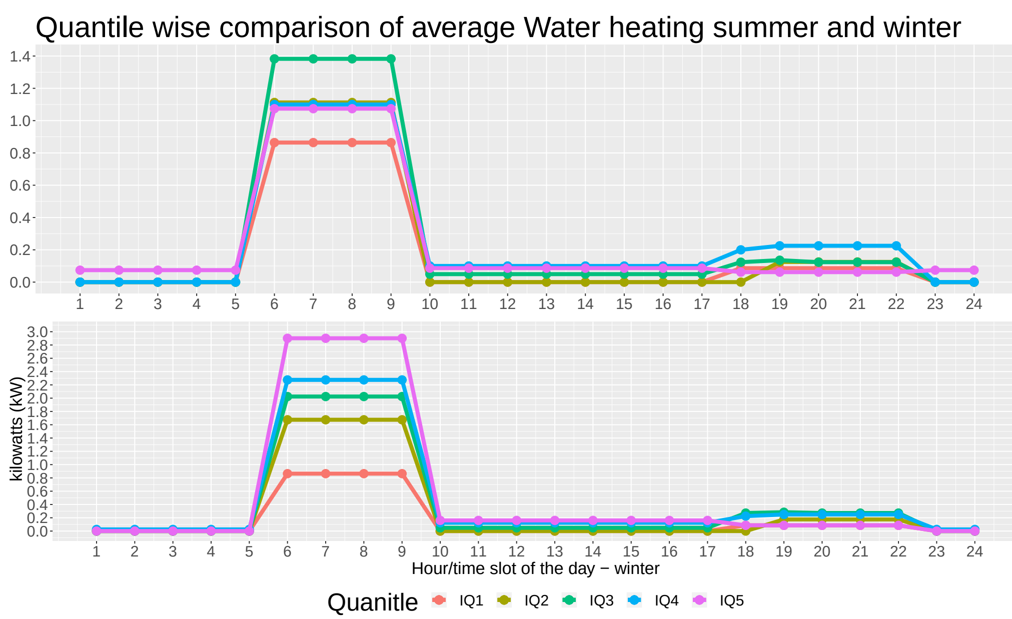


Figure 24: Comparison of total loads from summer and winter in water heating over 24 hours

top two quintiles have significantly higher ownership of a solar water heater indicating a lower probability of usage of electric water heating. From figure 23 it can be observed that the peak demand for water heating in winters is almost twice that of summer, with very little change in demand seen in the first quintile across seasons.

Finally, looking at the average loads for households from each quintile, similar observations follow. The peak demand goes up approximately from 1.1 kW in summer to 2.9 kW in winters. There is significant increase in peak demand from the top 3 quintiles, while demand from the bottom two quintiles remains relatively consistent across seasons. One reason for this is the use of non-electric modes of water heating in the lower quintiles. This indicates that water heating also has a strong seasonal and income correlation that emerges data is disaggregated into quintiles (by income)-.

3.3.3. Lighting

In this section we present the load from lighting divided into three areas of the household - living, kitchen and bathrooms. The load curves presented are an aggregate of the loads from various lighting types for each area as indicated in equation 5. We present 3 sets of load curves that indicate the aggregate loads for each area of the household and a set load curves that are an aggregate of loads from all three areas comparing demand from summer and winter.

3.3.3.1. Living Area Lighting

Table 9 presents statistics of ownership and usage by quintile.

Lighting -living area load curve considerations - quintile wise														
quintile	Applinace	%age own	Total Appliances	Average wattage	Average Hours		Time slot Summer				Time slot Winter			
					W.D	W.E	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Q1	Incandescent	20.99	31	55.29	4.53	4.71	7	7	24	3	7	7	24	3
	Tubelight	59.26	119	34.33	5.85	6.11	67	15	109	6	73	19	110	1
	CFL	17.28	31	11.43	4.25	4.25	4	0	26	0	4	0	26	0
	LED	69.14	159	9.21	4.37	4.42	60	2	149	13	64	2	149	13
Q2	Incandescent	6.25	16	54.00	3.08	3.08	6	0	9	4	6	0	9	4
	Tubelight	77.50	190	31.71	5.53	5.79	58	28	170	5	67	33	170	5
	CFL	33.75	102	11.00	4.86	4.97	15	12	71	15	15	12	71	15
	LED	76.25	241	9.26	4.22	4.73	42	25	207	14	42	25	207	14
Q3	Incandescent	11.11	17	47.78	2.00	2.00	2	2	12	0	2	2	12	0
	Tubelight	88.89	242	32.14	5.74	6.07	82	38	227	5	96	34	227	5
	CFL	41.98	115	10.97	4.74	4.81	30	14	97	9	30	14	100	6
	LED	71.60	267	9.12	4.72	4.82	81	39	235	7	97	39	235	7
Q4	Incandescent	17.50	37	52.86	3.40	3.40	1	0	12	0	1	0	12	0
	Tubelight	86.25	296	29.83	5.13	5.38	73	28	289	22	75	26	289	22
	CFL	47.50	172	11.68	3.50	3.63	34	7	138	15	36	7	138	15
	LED	75.00	291	9.23	4.41	4.57	86	49	274	17	86	49	274	17
Q5	Incandescent	8.64	20	51.43	1.37	1.37	0	0	5	0	0	0	5	0
	Tubelight	83.95	350	27.91	6.11	6.53	104	66	347	36	133	70	341	30
	CFL	46.91	200	11.34	4.04	4.15	39	24	149	10	49	24	149	10
	LED	76.54	523	9.05	5.11	5.40	111	101	435	10	129	101	435	10

Table 9: Living area lighting considerations

From table 9 it can be seen that as we move up the quintiles, use of incandescent bulbs drops and the dominant lighting are tube lights and LED bulbs with the an increase in usage of number lights observed in the morning in winter. Figures 25 and 26 present the load curves for living area lighting. The plots are aggregate(fig25) and average demand(fig26) from lighting in summer and winter.

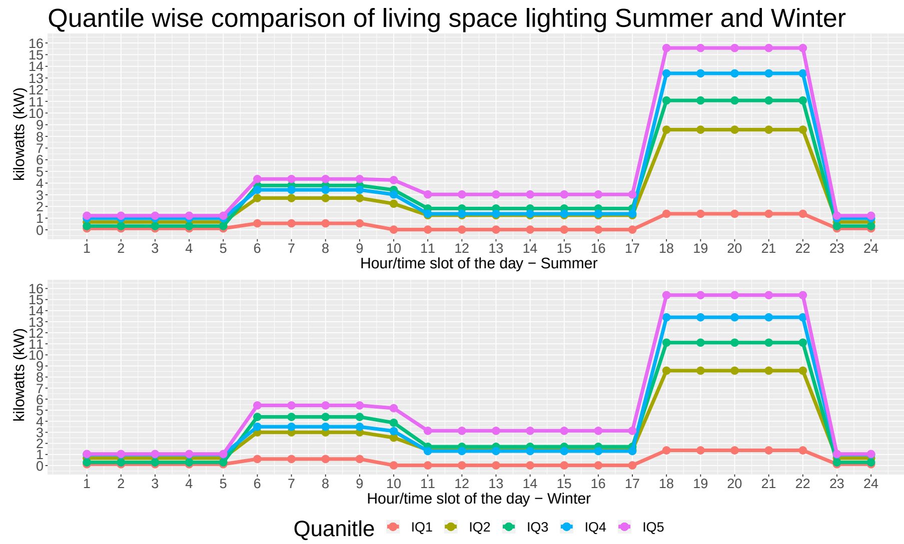


Figure 25: Comparison of total loads from living space lighting in summer and winter over 24 hours

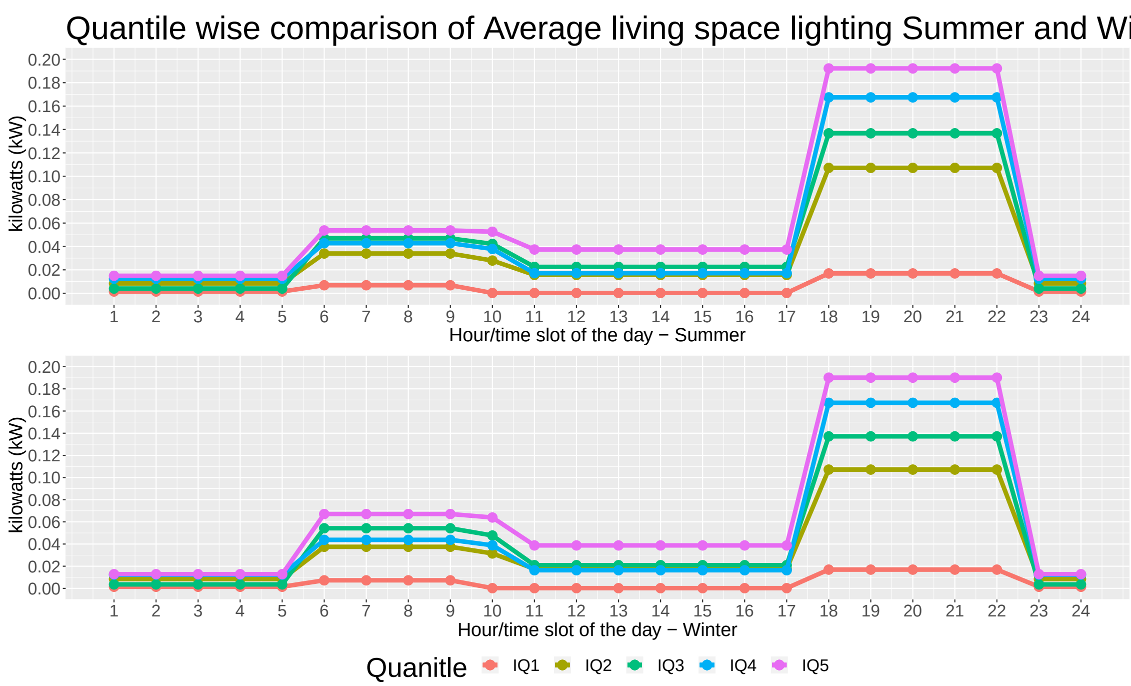


Figure 26: Comparison of average loads from living space lighting in summer and winter over 24 hours

As seen in figures 25 , the peak demand in lighting is in the evening with a lower peak in the morning. The evening peaks do not vary seasonally, significantly across quintiles. One reason for this is increase in the number of lights used as we move up quintiles.

It can be seen from figure 26 that the average peak demand across quintiles in the evening ranges from approximately 0.02 kW to .20 kW. While the lowest quintile's demand remains consistent across seasons, the upper quintiles see an increase in demand. It is important to note that while the number of inefficient bulbs are concentrated in the lower quintiles and the efficiency of lighting increases as we go up quintiles (table 9), the the total electricity consumed increases significantly as we move up quintiles due to the number of lights being used.

3.3.3.2. Kitchen Lighting

Table 10 presents the statistics for kitchen lighting disaggregated by quintile and lighting type.

Lighting -Kitchen load curve considerations - quintile wise														
quintile	**Applinace**	**Total Appliances**	**%own**	**Average wattage**	**Average Hours**		**Time slot Summer**				**Time slot Winter**			
					W.D	**W.E**	**6am**	**10am**	**6pm**	**11pm**	**6am**	**10am**	**6pm**	**11pm**
Q1	**Incandescent**	**5**	**6.17**	**56.00**	**1.80**	**2.20**	**0**	**0**	**4**	**1**	**0**	**0**	**5**	**0**
	Tubelight	**13**	**16.05**	**34.62**	**3.62**	**3.62**	**9**	**2**	**13**	**0**	**9**	**2**	**13**	**0**
	CFL	**14**	**17.28**	**11.21**	**2.95**	**2.95**	**5**	**2**	**13**	**0**	**5**	**3**	**12**	**0**
	LED	**47**	**58.02**	**8.32**	**3.52**	**3.50**	**27**	**6**	**45**	**1**	**27**	**6**	**45**	**1**
Q2	**Incandescent**	**1**	**1.25**	**60.00**	**1.00**	**1.00**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**
	Tubelight	**28**	**35.00**	**31.79**	**4.77**	**4.88**	**17**	**5**	**26**	**1**	**17**	**5**	**26**	**1**
	CFL	**16**	**20.00**	**11.19**	**5.00**	**5.23**	**7**	**3**	**13**	**1**	**7**	**3**	**13**	**1**
	LED	**48**	**57.50**	**9.13**	**5.10**	**5.13**	**27**	**7**	**41**	**1**	**29**	**7**	**42**	**1**
Q3	**Incandescent**	**4**	**3.70**	**65.00**	**4.33**	**4.33**	**2**	**0**	**4**	**0**	**2**	**0**	**4**	**0**
	Tubelight	**26**	**32.10**	**32.00**	**4.83**	**4.96**	**11**	**4**	**22**	**0**	**13**	**3**	**22**	**0**
	CFL	**19**	**22.22**	**11.44**	**5.41**	**5.41**	**9**	**5**	**17**	**0**	**10**	**5**	**17**	**0**
	LED	**57**	**51.85**	**9.36**	**5.20**	**5.43**	**31**	**16**	**53**	**0**	**32**	**16**	**53**	**0**
Q4	**Incandescent**	**4**	**5.00**	**55.00**	**6.50**	**6.50**	**1**	**0**	**2**	**0**	**1**	**0**	**2**	**0**
	Tubelight	**24**	**30.00**	**30.92**	**4.65**	**4.80**	**13**	**2**	**20**	**0**	**13**	**2**	**20**	**0**
	CFL	**22**	**23.75**	**11.32**	**5.38**	**5.44**	**14**	**5**	**19**	**1**	**16**	**5**	**19**	**1**
	LED	**60**	**61.25**	**9.24**	**5.26**	**5.35**	**40**	**19**	**54**	**0**	**40**	**19**	**54**	**0**
Q5	**Incandescent**	**2**	**2.47**	**50.00**	**4.00**	**4.00**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**
	Tubelight	**34**	**40.74**	**28.06**	**5.61**	**5.87**	**24**	**6**	**32**	**1**	**24**	**6**	**32**	**1**
	CFL	**13**	**16.05**	**10.85**	**5.18**	**5.36**	**7**	**1**	**11**	**0**	**8**	**1**	**11**	**0**
	LED	**69**	**64.20**	**9.15**	**5.61**	**5.71**	**37**	**16**	**55**	**1**	**38**	**16**	**55**	**1**

Table 10: Kitchen lighting considerations quintile wise

From table 10 we can see that as we go up the quintiles the use of incandescent bulbs reduces. But, we see that number of LED bulbs used across quintiles does not significantly vary, with only the use of tube lights increasing as we move up quintiles.There is also no significant difference between summer and winter demand with a minor differences in the amount of lighting used in the mornings and evenings.

Figures 27 and 28 reflect these observations presenting aggregate and average demand from kitchen lighting.

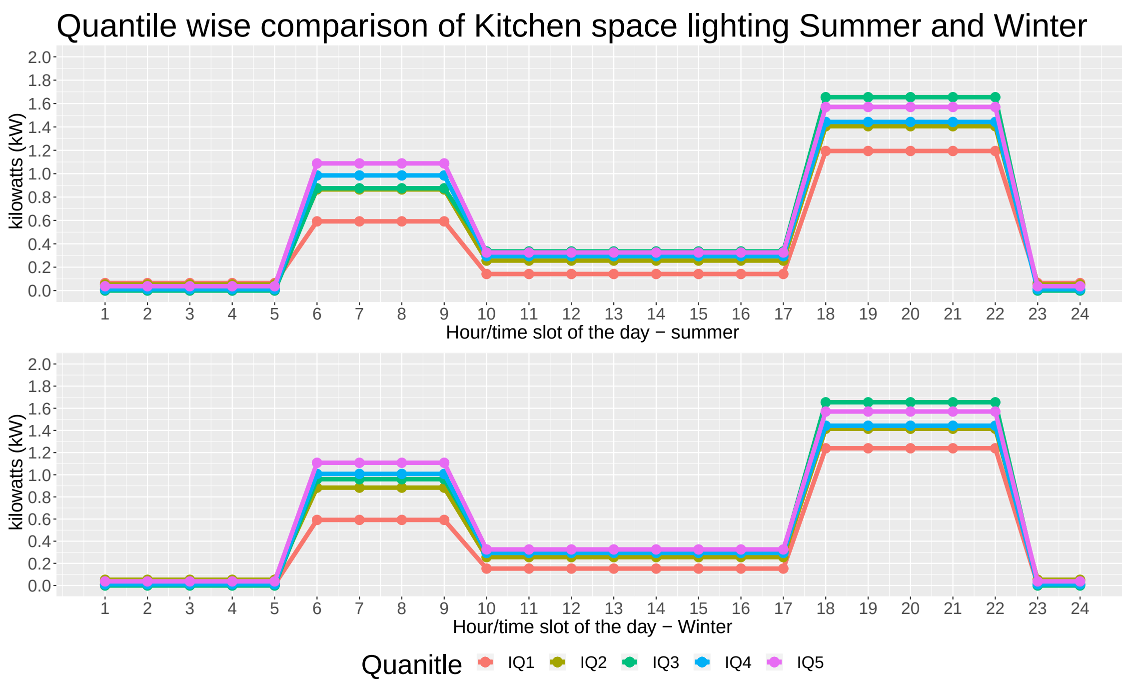


Figure 27: Comparison of total loads from kitchen lighting in summer and winter over 24 hours

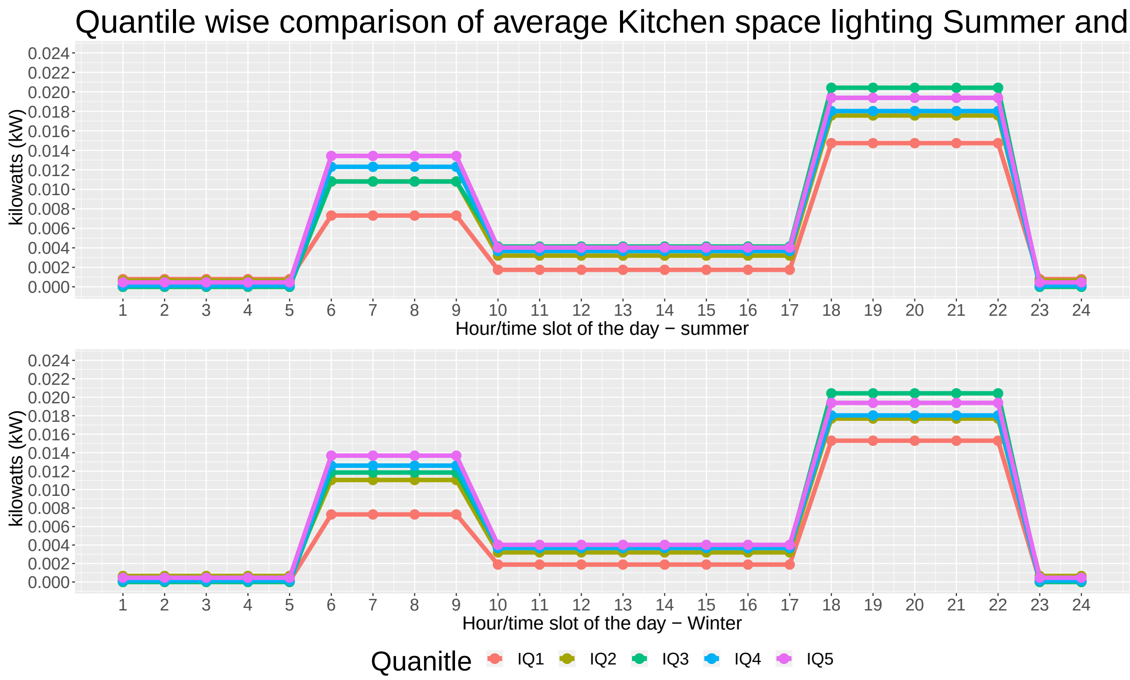


Figure 28: Comparison of average loads from kitchen lighting in summer and winter over 24 hours

From figures 27 and 28 it can be seen that there is no significant difference between the morning and evening peaks seasonally. It can be see that the morning peak in the first quintile is almost half of that of the upper two quintiles, while in the evening this difference is smaller. The average household consumption ranges from approximately 0.007 kW to 0.014 kW during the mornings and 0.015 kW to 0.021 kW in the evenings across quintiles. These ranges remain consistent seasonally.

Finally, even in the case of kitchen lighting it can be seen that the average wattage decreases as we go up quintiles, but demand and peaks increases as we go up quintiles, similar to living area lighting.

3.3.3.3. Bathroom Lighting

Table 11 presents ownership and usage statistics for bathroom lighting by quintile.

From table 11 we can see that CFL and LED bulbs are the dominant lighting types followed by incandescent bulbs. We also see from that there is no significant difference in their usage seasonally. Figures 29 and 30 present summer and winter aggregate and average demand for bathroom lighting.

Lighting -Bathroom load curve considerations - quintile wise															
quintile	Applinace	Total Appliances	%own	Average wattage	Average Hours		Time slot Summer				Time slot Winter			
					Weekdays	Weekends	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Q1	Incandescent	17	19.75	40.63	1.32	1.32	15	5	17	1	15	5	17	1
	Tubelight	1	1.23	12.00	1.00	1.00	1	1	1	0	1	1	1	0
	CFL	14	14.81	8.83	1.63	1.63	14	7	14	0	12	7	14	0
	LED	61	62.96	7.51	1.45	1.45	58	33	61	2	56	33	61	2
Q2	Incandescent	7	6.25	64.00	2.10	2.10	7	3	7	1	7	3	7	1
	Tubelight	0	0.00	0.00	0.00	0.00	0	0	0	0	0	0	0	0
	CFL	31	22.50	10.22	1.81	1.81	29	15	31	0	29	15	31	0
	LED	90	70.00	8.64	2.23	2.24	83	53	90	7	83	53	90	7
Q3	Incandescent	15	9.88	55.00	1.78	1.78	15	10	15	0	15	10	15	0
	Tubelight	4	3.70	13.33	1.33	1.33	4	3	4	0	4	3	4	0
	CFL	45	29.63	10.33	2.22	2.22	40	40	42	2	40	40	42	2
	LED	95	60.49	8.59	2.11	2.13	94	65	93	4	94	65	95	2
Q4	Incandescent	17	12.50	48.00	2.90	2.90	14	12	16	1	12	12	14	1
	Tubelight	5	3.75	13.33	2.67	2.67	5	3	5	2	5	3	5	2
	CFL	51	32.50	10.62	2.04	2.12	46	35	49	4	42	35	49	6
	LED	105	57.50	8.98	2.28	2.34	105	80	105	15	105	80	105	15
Q5	Incandescent	12	6.17	56.00	1.24	1.24	9	3	8	1	9	3	8	1
	Tubelight	0	0.00	0.00	0.00	0.00	0	0	0	0	0	0	0	0
	CFL	74	28.40	9.78	2.33	2.33	72	52	74	5	72	52	74	5
	LED	167	70.37	8.61	2.61	2.66	162	118	161	19	162	118	161	19

Table 11: Bathroom lighting considerations quintile wise

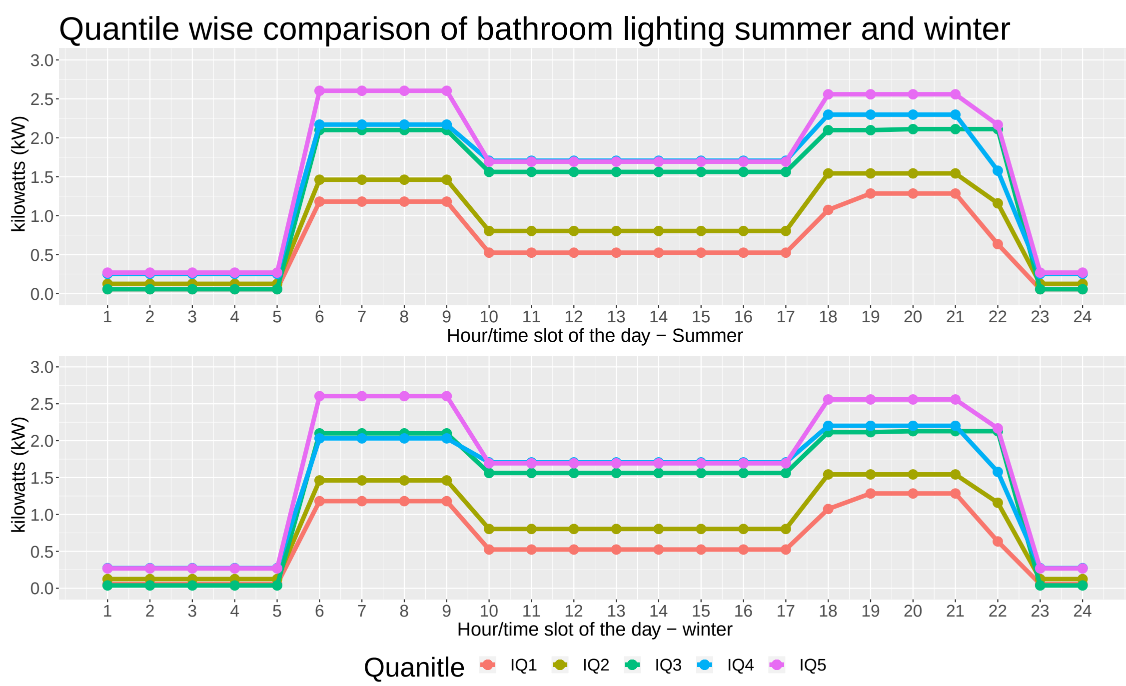


Figure 29: Comparison of total loads from bathroom lighting in summer and winter over 24 hours

From figures 29 and 30 it can be seen that bathroom lighting has two peaks in the mornings and evening, with demand consistent across seasons and across quintiles. The average demand from bathroom lighting is very small peaking between approximately 0.016 kW to 0.032 kW across quintiles for an average household.

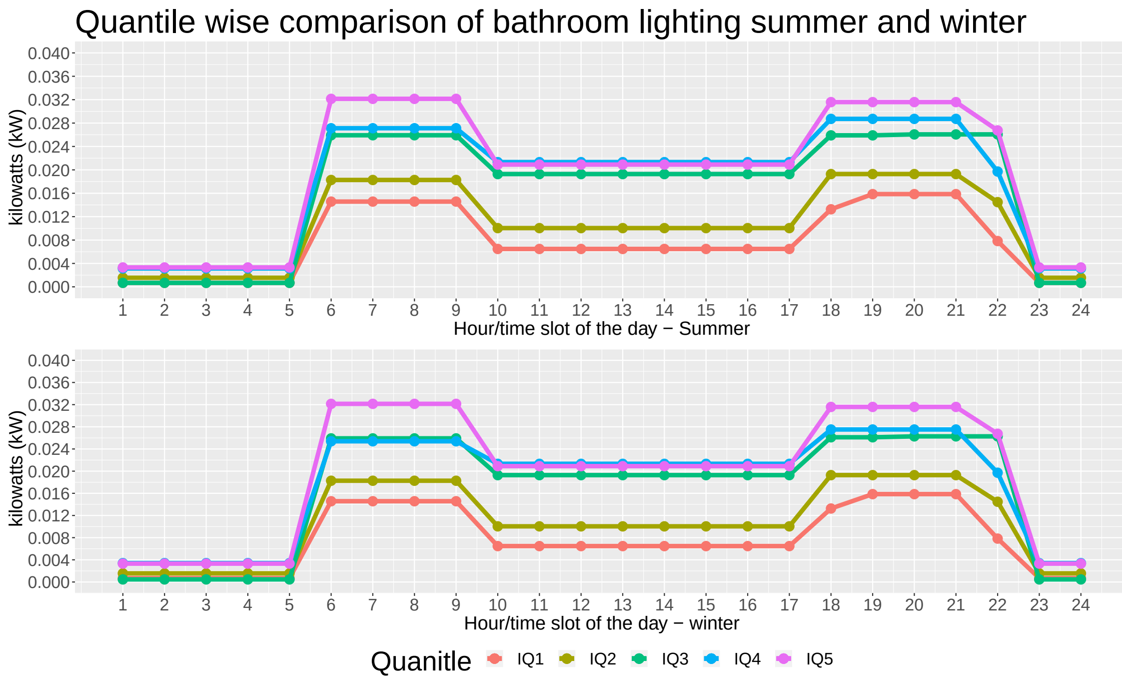


Figure 30: Comparison of average loads from bathroom lighting in summer and winter over 24 hours

3.3.3.4. Cumulative Lighting Load

In this section we look at the aggregate lighting load, cumulative, from the three areas of the household.

From figure 31 it can be seen that the lighting load has a dominant evening peak compared to its morning peak. The main contributors are living space lighting which has a very pronounced evening peak compared to kitchen and bathroom lighting. It can be seen that the summer and winter peaks are almost the same, with slightly higher peaks in winter. The significant difference between the lower and upper quintiles can also be observed.

Looking at average aggregate load presented in figure 32 it can be seen that the range of the peaks is 0.025 kw to 0.10 kW in the mornings and 0.05 kW to 0.025 in the evenings.

Some of the key observations are

(i) Pronounced evening peaks for lighting, especially from living area lighting load

(ii) The inverse relationship between lighting demand and efficiency of lighting as we move up quintiles

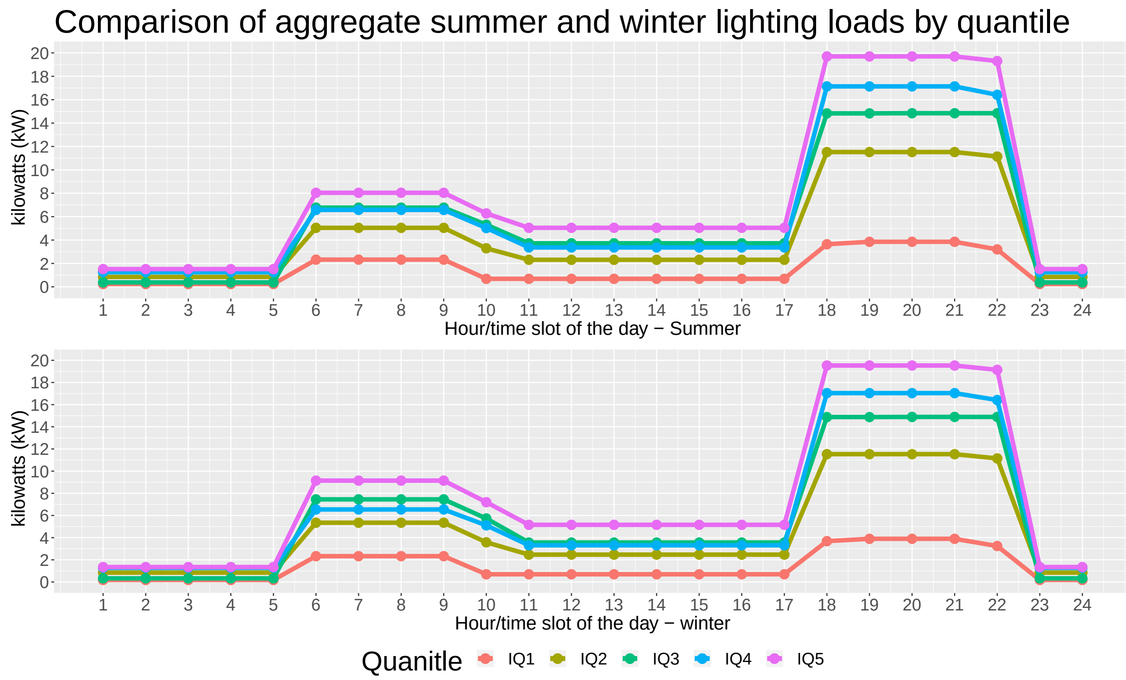


Figure 31: Comparison of cumulative loads from all lighting in summer and winter over 24 hours

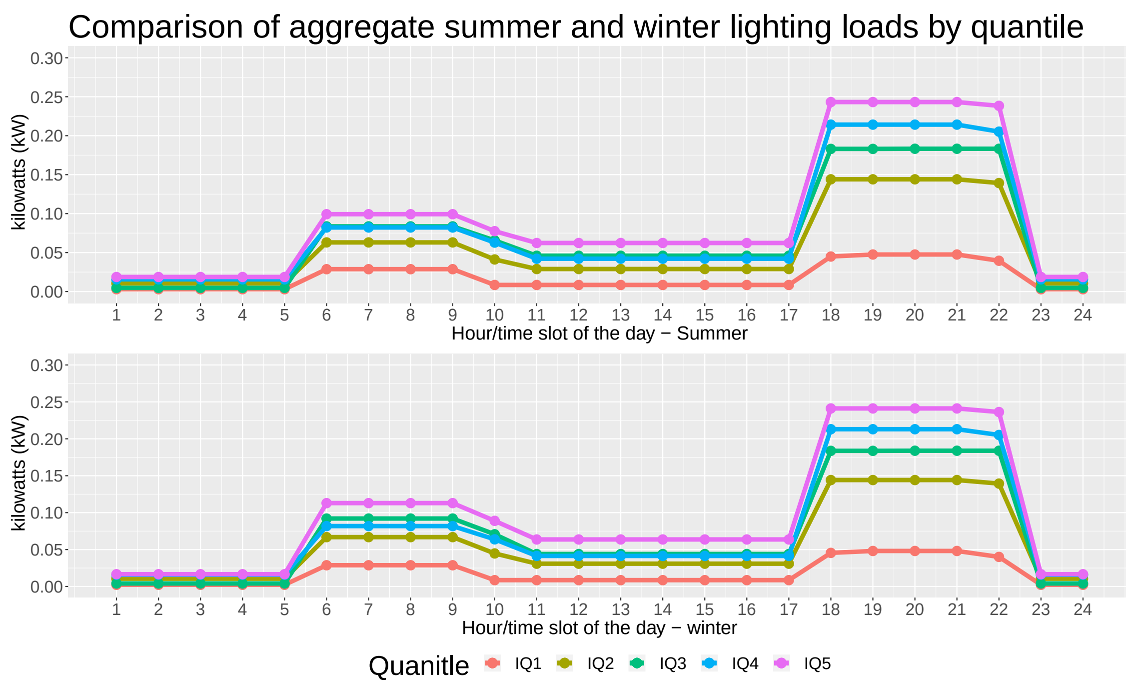


Figure 32: Comparison of cumulative average loads from all lighting in summer and winter over 24 hours

3.3.4. Kitchen and Utility Appliances

The table 12 presents statistics of ownership and usage for kitchen and utility appliances.

Kitrchen and Utility appliances load curve considerations - quintile wise																
quintile	Applinace	Total HH own	Total Appliances	Assumed wattage	Average capacity	Average Hours		Time slot Summer				Time slot Winter			
						W.D	W.E	6am	10am	6pm	11pm	6am	10am	6pm	11pm
Q1	Washing Machine	40	40	300	6.09	0.99	1.00	17	17	6	2	17	17	6	1
	Induction cook top	12	12	2000	NA	1.61	1.61	8	0	7	0	8	0	7	0
	Motor	45	45	580.4	0.62	0.28	0.28	17	1	7	0	17	1	7	0
Q2	Washing Machine	70	71	300	6.26	0.95	0.96	37	27	9	2	37	27	9	2
	Induction cook top	15	15	2000	NA	0.875	0.875	6	0	1	0	6	0	1	0
	Motor	77	77	580.4	0.73	0.35	0.35	29	3	16	0	29	3	16	0
Q3	Washing Machine	78	78	300	6.38	1.17	1.18	39	32	7	1	38	33	7	1
	Induction cook top	24	24	2000	NA	2.14	2.14	11	1	8	0	11	1	8	0
	Motor	79	81	580.4	0.79	0.77	0.78	34	3	18	0	34	3	17	0
Q4	Washing Machine	78	78	300	6.27	1.25	1.25	33	35	9	4	33	36	10	3
	Induction cook top	25	26	2000	NA	1.18	1.18	11	1	5	0	11	1	5	0
	Motor	79	79	580.4	0.71	0.59	0.59	33	8	19	0	34	7	19	0
Q5	Washing Machine	78	82	300	6.49	1.21	1.21	39	36	11	2	38	37	10	2
	Induction cook top	40	38	2000	NA	1.71	1.71	19	2	13	0	19	2	13	0
	Motor	81	85	580.4	0.95	0.50	0.50	30	1	15	0	30	1	15	0

Table 12: Kitchen and utility load considerations

From table 12 it can be seen that the numbers of each appliance owned increases as we move up the income quintiles. translating into probable higher demand from these appliances. It can be also observed that the average capacity and usage duration of both washing machines and pumps increases as we move up the quintile. While washing machines have predominantly day time usage, induction stoves and pumps are used through out the day. Finally, it can also be observed that there is no significant variation in usage between summer and winter.

Figures 33 and 34 present aggregate load curves for all three appliances combined. From figure 33 it can be seen that the morning peak is more dominant than the evening peak even though there are significant number of induction stoves and pumps that are used in the evening (tab.12). One of the key contributors to the morning peak are washing machines. Even though the average wattage of washing machines is lower than both induction stoves and pumps, the numbers used leads to this significant contribution. This trend is consistent across seasons, indicating no seasonal correlation.

Figure 34 presents the average peak loads from households in summer and winter across quintiles. The average peak demand ranges from 0.4 kW to 0.85 kW in the day time while it ranges from 0.1 kW to 0.45 kW in the evening.

The quintile variations can be clearly correlated with table 12 to see how variation in ownerships influence peak demand.

3.3. Cumulative Load Curves (All Appliances)

In this section we present load curves summing up (cumulative) demand from all appliances giving a representation of the total and average demand from each quintile from all appliances

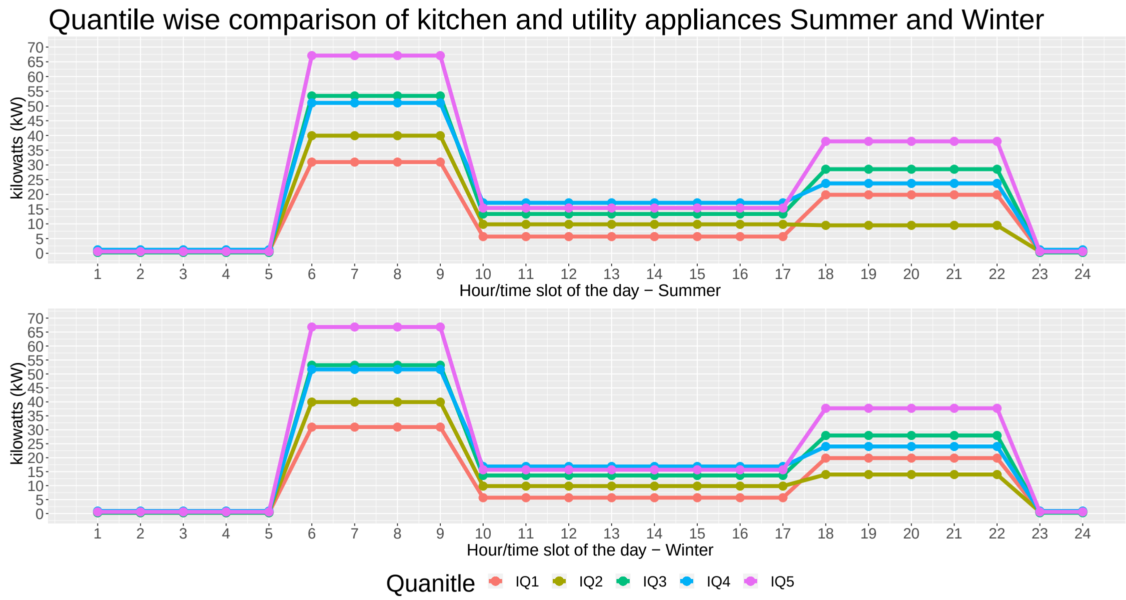


Figure 33: Comparison of total loads from summer and winter for kitchen and utility appliances over 24 hours

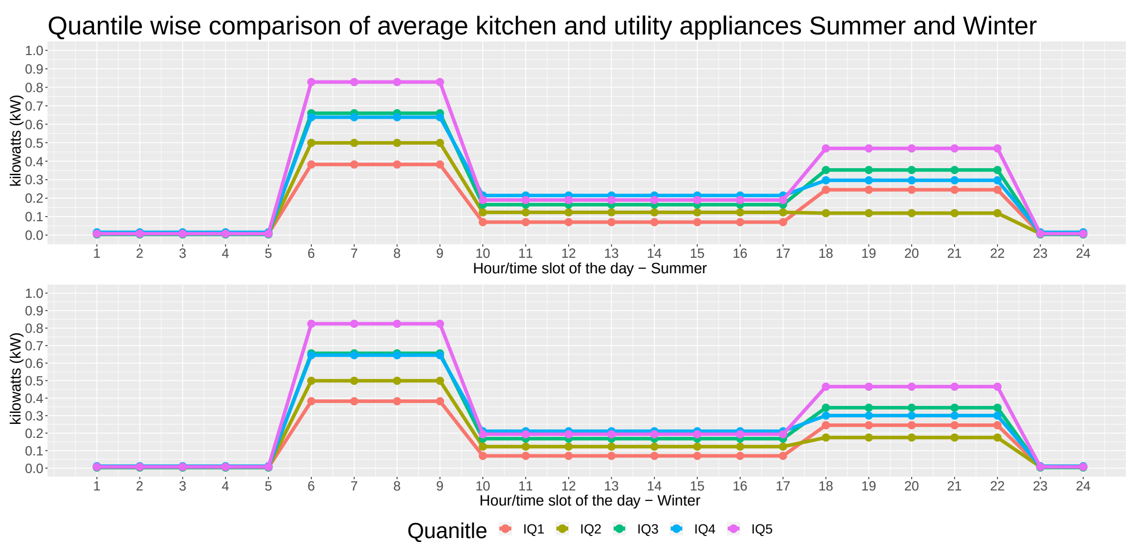


Figure 34: Comparison of total loads from summer and winter kitchen and utility appliances over 24 hours

in the household. Figures 35 and 36 present load curves for total and average demand from all appliances in the household by quintile and season.

The first observation that can be made is the scale of difference between in the day time peaks of summer and winter. Winters are strongly dominated by water heating driving the morning peak, with day peak in winter almost twice that of summer. Similar observation can be made in

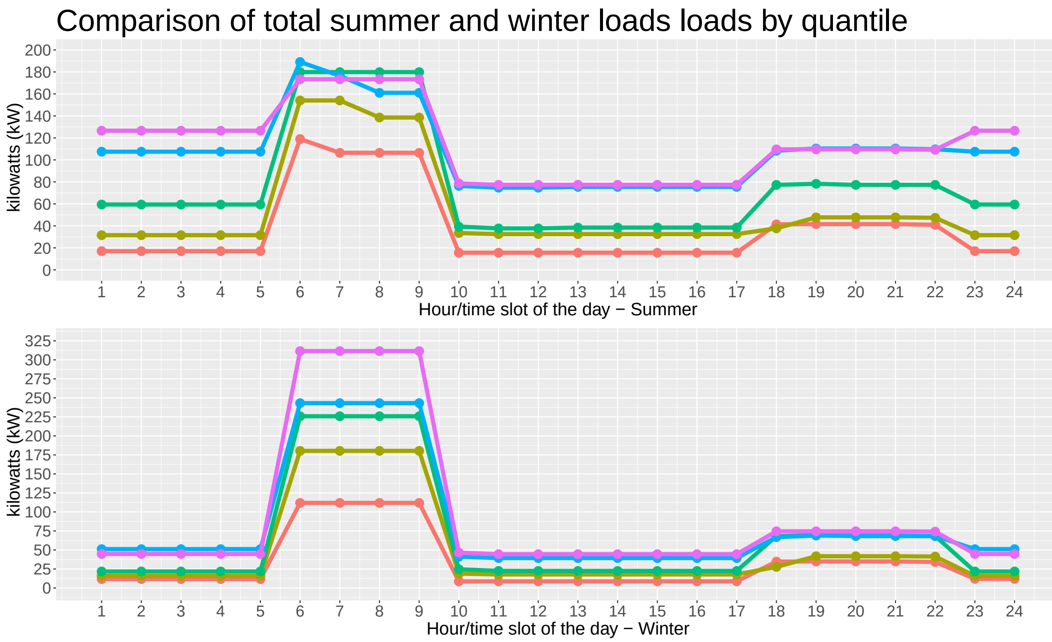


Figure 35: Comparison of average loads from summer and winter from all appliances over 24 hours

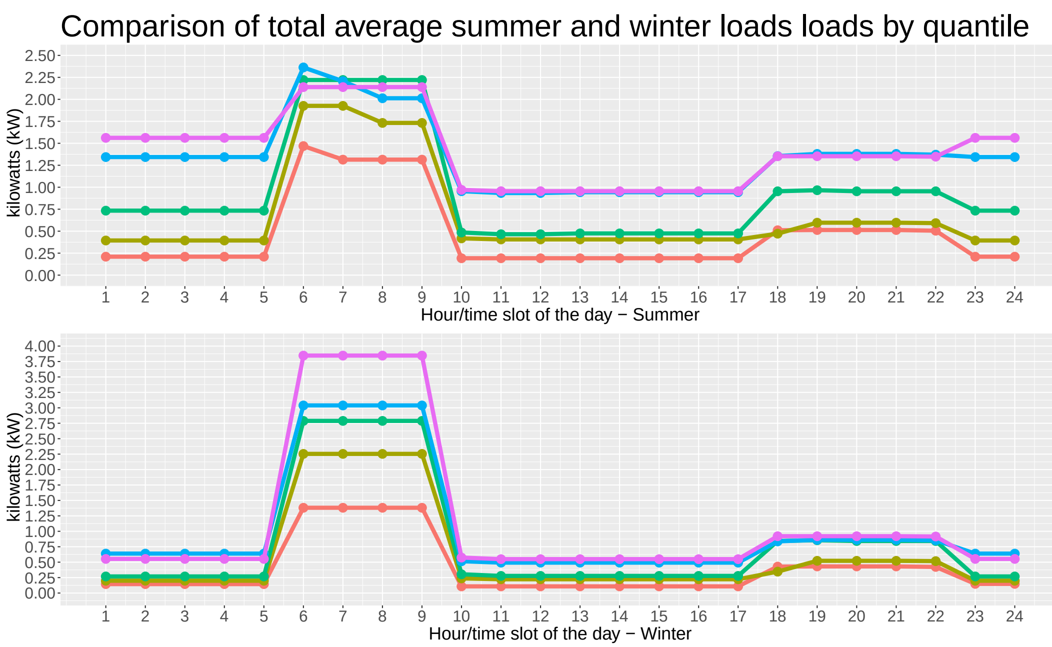


Figure 36: Comparison of total average loads from summer and winter from all appliances over 24 hours

the case of cooling loads and the evening peaks which are significantly higher in summer than winter.

Next, in summers a mid morning/afternoon bump can be observed in demand driven primarily by space cooling demand. Some "*kinks*" in the morning peak in summers can be observed which are caused by reduction in lighting and space cooling loads.

From the average demand load curves it can be seen that there is a significant difference between the peaks across quintiles in winter during the day and in summer during the nights. This is observed in the bottom and top quintiles.This is because in winters, the upper quintiles are more dependent on electricity based water heating appliances compared to the lower quintiles leading to more prominent day time peaks. Similarly, in summer the upper quintiles use appliances like AC's leading to a more prominent peak from these households compare to lower quintile households. Finally, it can also be seen that in the winters there is contribution to the evening/night peak by fan usage, while the lighting load remain consistent through seasons (as observed previously).

As a consequence of this the average household peaks across quintiles during the day in summers range from 0.25 kW to 2.25 kW and in the evenings ranged from 0.5 kW to 1.6 kW approximately. Similarly in winters the peaks ranged from 1.4 kW to 3.85 kW during the day and 0.12 kW to 0.75 kW approximately in the evenings.

4. Summary

We know that demand for electricity by households in not uniform and varies with income. To identify these variations, this chapter outlined the model formulation for load curves, both aggregate and by quintile. The first section presented model formulations to build load curves for aggregate data. Using this model aggregate load curves were built for different appliances followed cumulative load cures that presented total and average demand from all appliances for an typical household. Shortcoming of aggregate load curves were indicated stressing the need for quintile based load curves.

To build quintile load curves, the initial model was modified to account for quintile variations. Based on this modified model, load curves were built for each appliance by quintile identifying variations in ownership and usage and its impacts on the load curve. This was followed by a set of load curves presenting cumulative and average demand from all appliances for a typical household in each quintile.

With quintile load curves variations in demand intensity across quintiles and seasons were identified along with appliances/categories that contributed to this variation in each quintile and for each season. But this analysis still fell short in terms of resolution of the load curves built. These load curves are restricted by the resolution of the data collected in the survey, which was broken into 4 slots of the day. We know demand from households is not as flat as indicated in the load curves presented, especially in the morning and evening peaks. The demand sees significant variations through out the day. To address this, in the next chapter assumptions and methodology to build hourly load curves using the same data set is presented.

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Chapter 5
Hourly Load Curve Models and Policy Suggestions

1. Introduction

The load curves built in the previous chapter presented an over all trend of consumption from households in each quintile, but lacked the resolution to understand and identify hourly variations and appliances contributing to this demand as the data collected in the survey covered 4 and 6 hour slots for peak and non-peak hours. This is important because the consumption patterns are not flat as presented in the previous chapter and vary significantly hour to hour. Good examples for this are the time a household turns on their lights in the evenings in summer versus winter or the time and duration a household might use water heating appliances. To identify these differences we need to build load curves at a higher resolution indicating contributions of each appliance category to the load curve. With an understanding of consumption patterns and contributions from appliance categories identifying the variables that drive ownership and consumption from different appliances is possible.

In this chapter, presented first is the model used to build hourly load curves and the assumption that were made. Next, present ed are the hourly load curves and the contributions made by different appliance categories along with ownership and usage models for key appliances. Finally, key policy interventions based on analysis of survey data and load curves are presented.

2. Hourly Load Curves

This section presents the model developed to build load curves at hourly resolutions from survey data collected at lower resolutions, as presented in the previous chapters. Assumptions and model formulations are first outlined followed by the load curves at hourly resolutions.

2.1. Assumptions to Generate Hourly Load Curves

The data of the survey was not collected at hourly resolutions. Given this limitation, assumptions on how households use their appliances, hourly, seasonally had to be made. To do this data and work carried out by [1, 2, 3] were referred, to get a better understanding of expected observations and outcomes.

2.1.1. NEEM Data

NEEM or National Electricity End use Monitoring dashboard was set up by CLASP and EDS. This was done in collaboration with BEE and included a 5000 household national survey. Along with this they installed NILM (non intrusive load monitoring) meters in 200 households across the country, which included household from Bangalore.

Their dashboard [1] allows users to download data. The data is available at hourly resolution and can be downloaded for specific appliances or for the entire household. This data was the first point of reference. The data was available at an hourly resolution. This was first grouped into monthly data and further grouped into seasonal data, representing three seasons, summer, monsoon and winter. Hourly load curves were generated as the first step to understand consumption patterns (considering the almost fixed patterns of residential demand with morning and evening peaks). NEEM does not specify the income/economic standing of the households that have the NILM meters installed. Considering the details of appliances that the NILM collects, we can assume these are households that fall into the upper income/economic brackets. This is important point to note as the load curves will reflect this. But it is also safe to assume that the general shape of the curve (demand patterns) will remain fairly consistent in shape across various income/economic representative brackets, given the general nature of residential demand.

Figure 1 presents load curves from the NEEM data at hourly resolution for each of the three seasons.

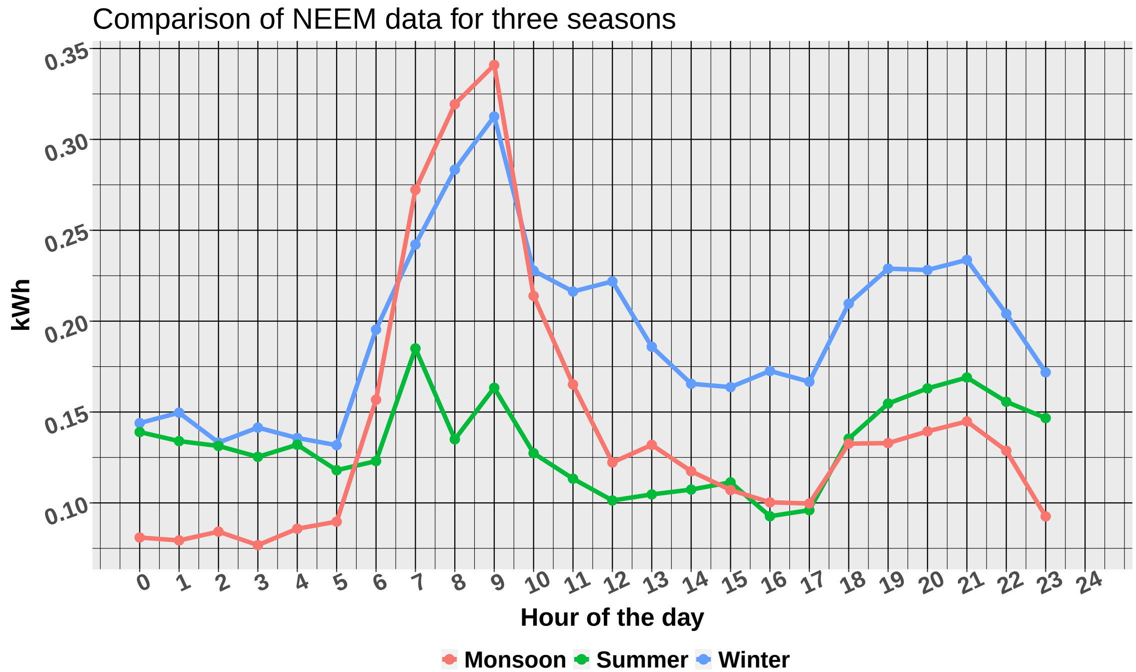

Figure 1: NEEM seasonal reference load curves

From figure 1, the variations, both hourly and seasonal in the shape of demand (pattern of demand) across seasons can be observed. It has to be noted that these load curves are from a sample size of 200 households which are not representative of all income brackets.

2.1.2. PRAYAS Data

The Prayas energy group (PEG) has installed energy monitors in 100+ households in urban Pune, under their eMARC program. They have installed two monitors per household, one at the meter and one at specific appliance like a refrigerator or air conditioner. These monitors provide minute wise data. This has been uploaded on their website [2] and shows load curves from these households monthly, weekly and appliance wise. We can look at load curves of households with air conditioner, or water heaters and compare them to basic load curve of the households. This gives us a good understanding of how consumption varies weekly or monthly. Below is a screen shot from the eMARC website.

From the figure 2 the differences in the patters and intensity of consumption for different appliances compared to the basic load curve can be observed. While figure 2 is an instance of

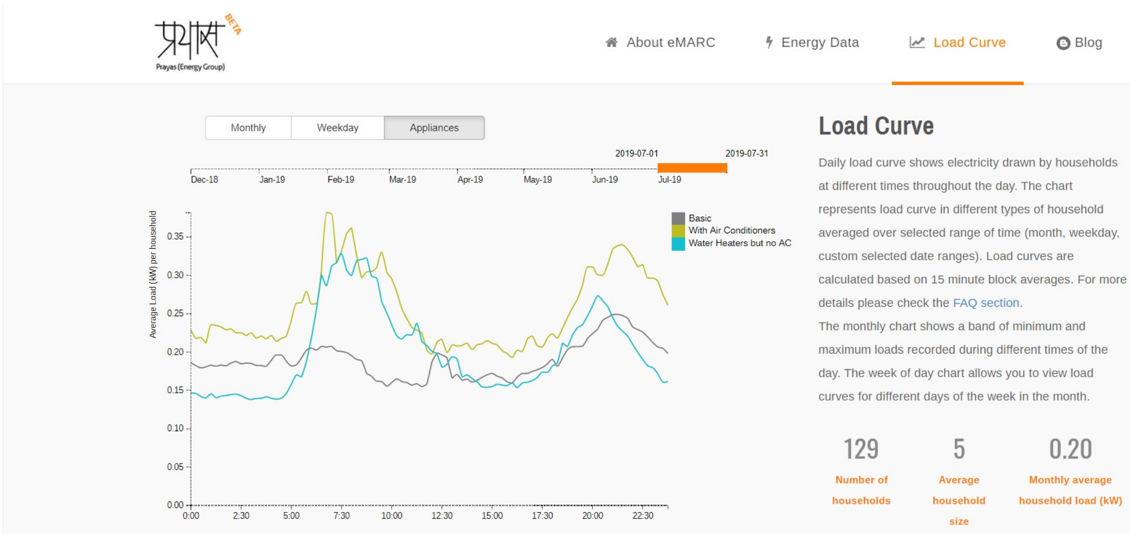

Figure 2: Prayas eMARC load curves

one day, their dash board allows users to look at different time resolutions as mentioned, giving us the ability to compare load curves seasonally. While the load curves are not built at minute level, this data helps us get an understanding of how demand varies hourly.

2.1.3. Garg et al., 2014

[3] carried out a survey in Gujarat covering 400 households across 5 discoms. One of their goals was to estimate residential load curves and contributions from different appliances across different income brackets. Below are figures presented from their work.

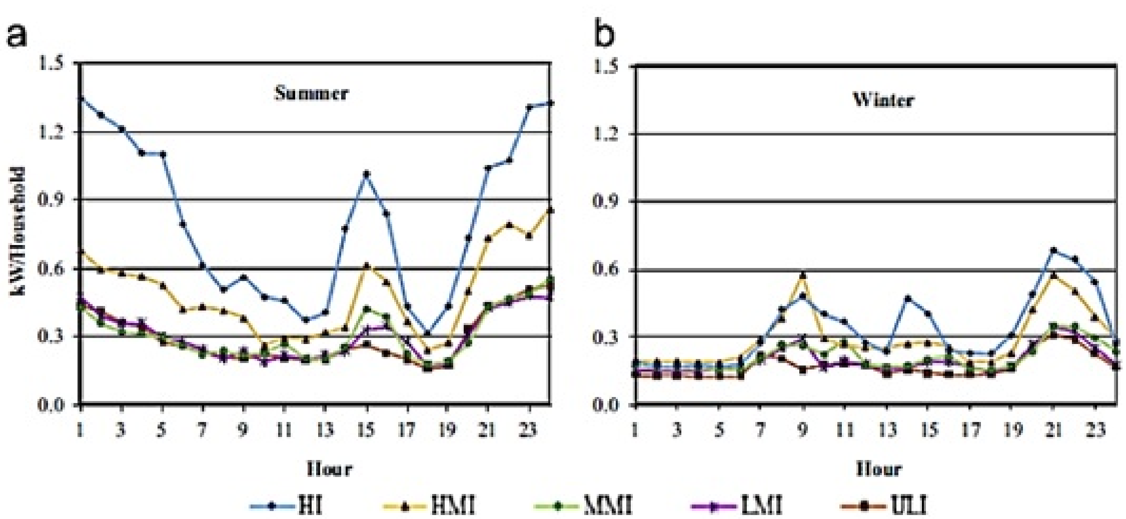

Figure 3: Load curves, Garg et al., 2014

From figure 3 (a and b) the differences between summer and winter demand patterns and intensities (peaks), across income categories can be observed. The paper does not outline the model used to generate load curves and other assumptions that were made by the authors in identifying income brackets. It would therefore lead to additional errors in our model and outputs if we assumed same set of distributions for our data set. Therefore, while these results from Gujrat might not fit our data, assumptions about how overall usage behavior changes depending on time of the day and seasons can be used as reference to build our assumptions.

2.2. Hourly Load Curve Model

2.2.1. Load Curve Model and Preliminary Load Curves

Based on above considerations and observations a model to generate load curves at hourly resolutions was built. The modified model estimates the probability of each appliance being used for each hour. The model to estimate the hourly consumption of a household is given below in equation 1.

$$E_{T,S} = \sum_{j,t,s,k}\{\sum(A_{i,k}|T_{t,s}=1) * P(H_{T,A_i}) * W_{avg\ A_i}\} \quad (1)$$

Where,

A_i = i^{th} appliance

A = j^{th} household

T_t = one of 4 time slots for which usage data was collected (6am-10am, 10am-6pm, 6pm-11pm, 11pm-6am)

$P(H_{T,A_i})$ = Probability of appliance i being used at hour T

$W_{avg\ A_i}$ = Average wattage of the i_{th} appliance

The probability of each appliance being used in the time slot **T** was estimated by estimating

- percentage usage of each appliance in each time slot
- duration of usage of each appliance in each time slot
- information on the duration of use of each appliance was collected for each household (hours/minutes each appliance was used in each time slot), using which the probability of usage of each appliance, hourly, in each time slot was estimated

Based on this model, the load curves were generated at hourly resolution for each quintile for summer and winter. Figure 6 presents these load curves. These load curves indicate the average electricity consumed hourly by a typical household in each quintile. The demand indicated by the load curves is the total load at any given time by all the appliances in use during that hour.

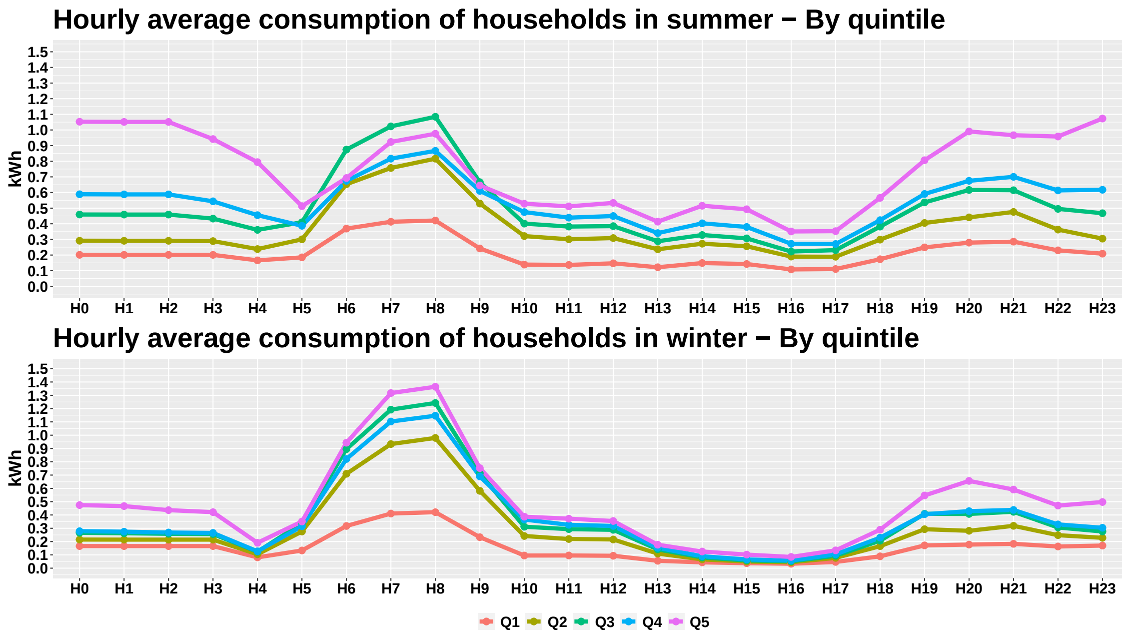

Figure 4: Hourly load curves indicating average consumption - Quintile wise

From figure 4 it can be seen that load curves at a higher time resolution provide a better picture of variations in consumption both across seasons and across quintiles. Taking a closer look at the mid morning periods between seasons, it can be observed that there is a significant drop in demand from households in winter, while in winters there is stronger morning peak whose shape varies compared to demand during the same time slot in summer. A similar trend emerges in terms of evening and night peaks between summer and winter. But this still does not give an in depth view of which appliances are causing these variations. In order to understand this, load curves for each appliance, at an hourly resolution need to be built.

2.2.2. Contributions from Appliances

To get a clearer understanding of how each appliance is contributing to the load curve, load curves at hourly resolutions for each appliances was built and superimposed on figure 4. The model used to build these load curves for each appliance is the same as the model outlined in the previous section. Figure 7 to 11 present these load curves for each of the quintiles comparing summer and winter.

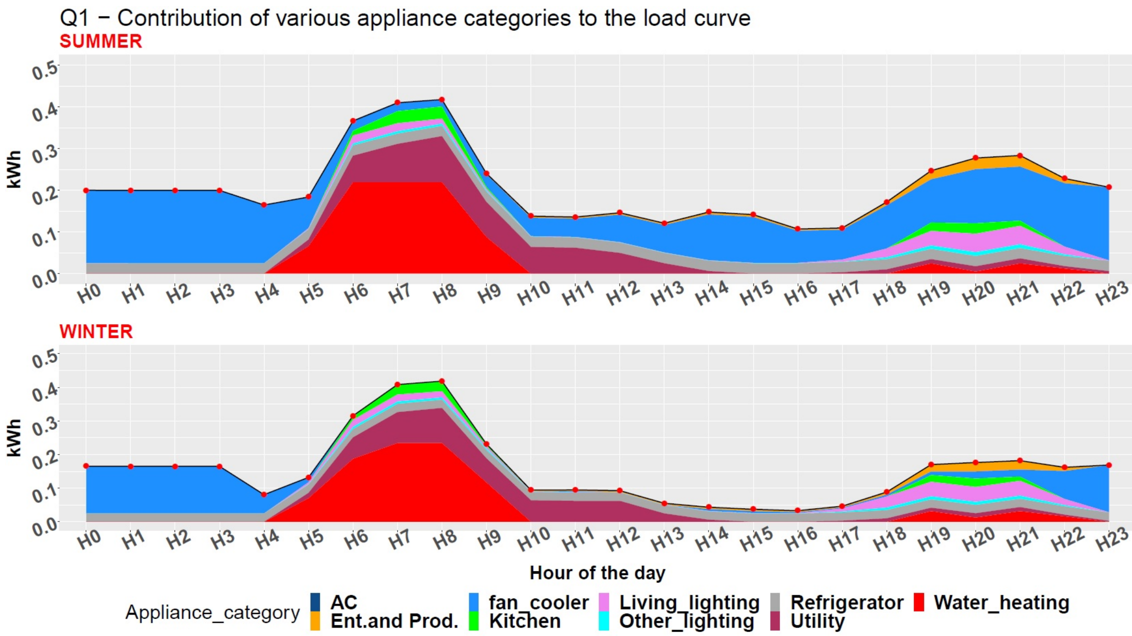

Figure 5: Quintile 1 load curves with appliance contributions for summer and winter

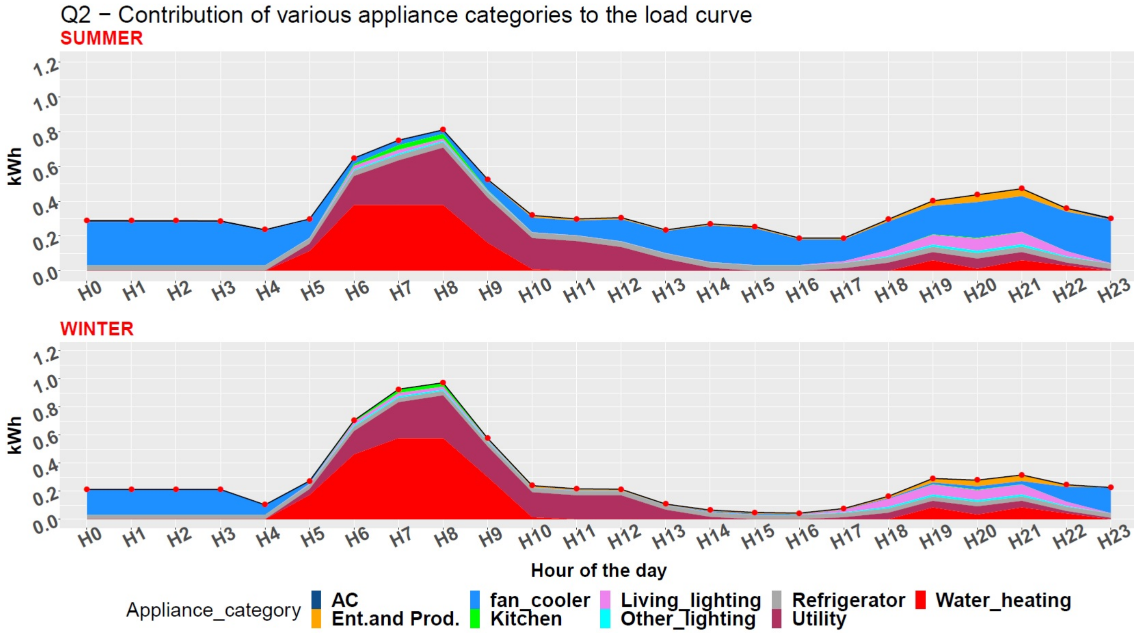

Figure 6: Quintile 2 load curves with appliance contributions for summer and winter

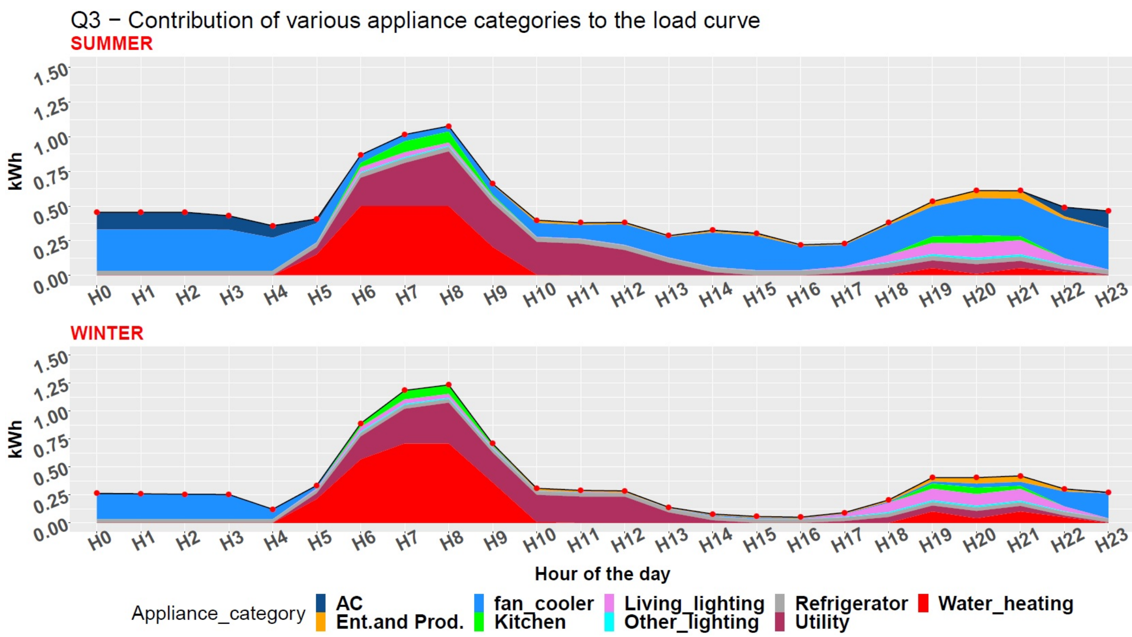

Figure 7: Quintile 3 load curves with appliance contributions for summer and winter

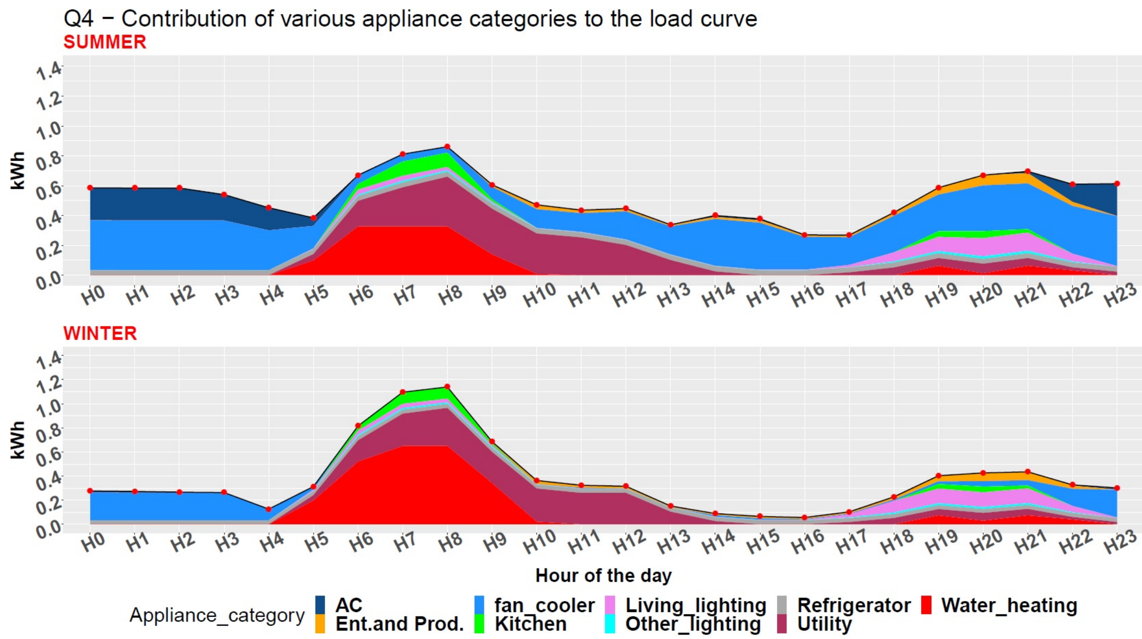

Figure 8: Quintile 4 load curves with appliance contributions for summer and winter

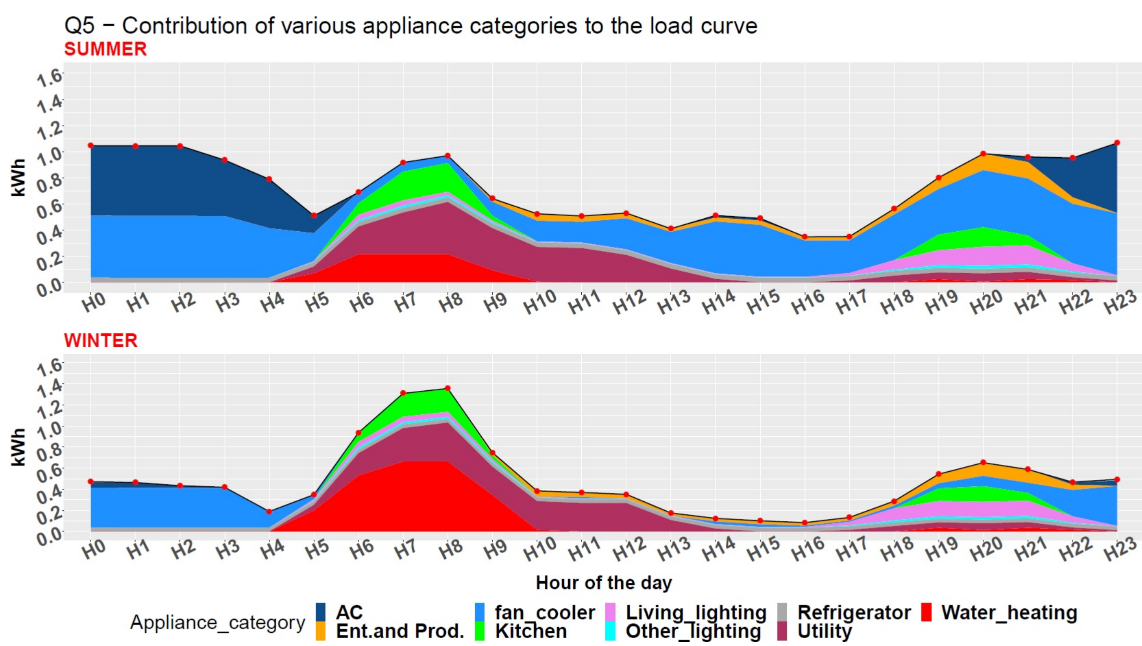

Figure 9: Quintile 5 load curves with appliance contributions for summer and winter

From figures 5 to 9 it can be seen that there is significant difference in the way different appliances are used across seasons and quintiles. A significant contribution from water heating, space cooling and lighting appliances is prominent and clearly observable. While kitchen and entertainment appliances show a significantly high contribution to the load curve in the upper income quintiles. Across quintiles a consistent contribution from utility appliances during the day time can be observed. Comparing summer and winter intra-quintile, it can be seen that in the bottom two quintiles, there is very little variation across seasons. The significant impacts that appliances like ACs and geysers bring become prominent as we move up quintile, as the ownership of these appliances increase. The impacts ACs have on night time demand in summers from the upper quintiles can be observed with close to 50% of the night demand coming from ACs. Similar impacts can be observed from geysers in the upper quintiles, with close to 40% of the morning peak coming from geysers in winters. The impacts from space cooling appliances can also be seen in summers during the mid-morning and afternoon periods. There is a clear **bump** in demand that can be observed in summers compared to winters, primarily due to the demand from space cooling appliances.

With these insights, the next step is to assess the policy implications that these load curves can help guide. In the next section a few key areas where either existing policies can be amended or new policies can be introduced is presented.

3. Policy Interventions

Based on the insights from the previous sections look at some key policies and amendment suggestions that emerge from these observations covering space cooling, water heating and solar PV rooftop.

3.1. Space Comfort Appliances

Three primary types of space cooling appliances were covered in the survey; fans, desert coolers (coolers) and air conditioners. Electric room heaters were the only appliance that was covered under space heating appliances. figure10 indicates the ownership of these cooling appliances.

It can be seen from figure10 that all households surveyed owned fans, this is because as households move up the affordability ladder, fans are among the first appliances procured [4, 5]. The ownership of other space cooling appliances shows an increasing trend with respect to quintiles, with the upper quintiles owning the highest percentages of each. Given Bangalore's climate though, winters do not warrant a significant use of space heaters, which reflects in their

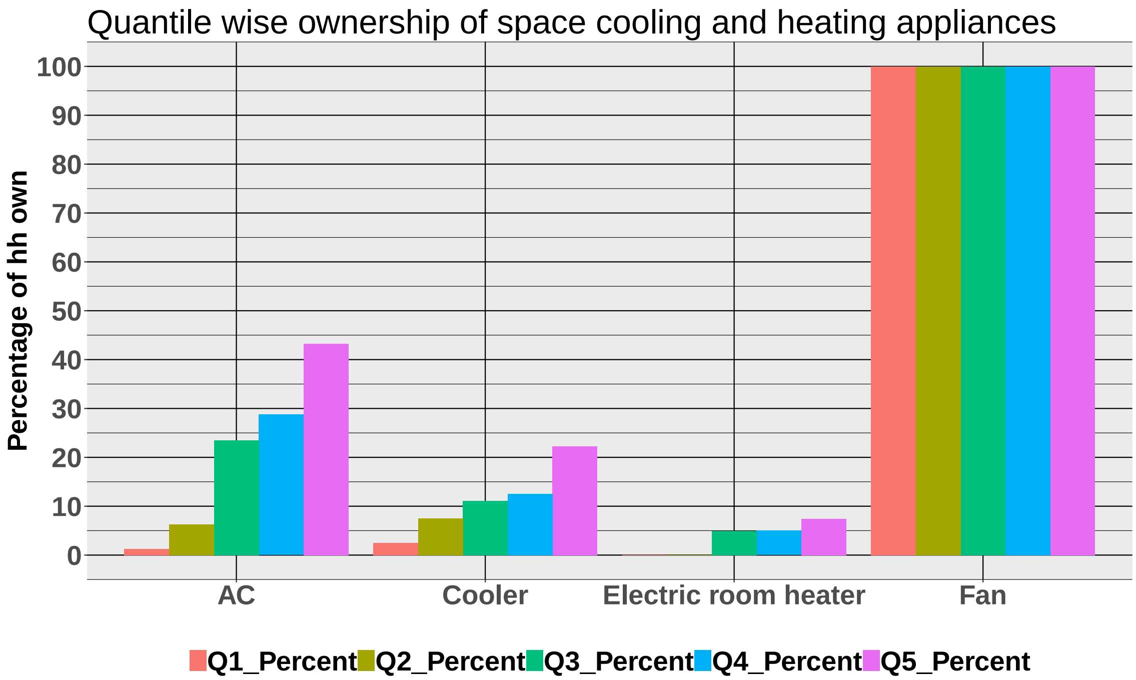

Figure 10: Ownership of cooling and heating appliance

low ownership numbers.

Correlations of ownership of cooling appliances		
	Cooler	**AC**
Income	0.195	0.382
Independent HH	0.009	0.084
Apartment	-0.009	-0.084
Own HH	0.132	0.227
Rental HH	-0.151	-0.207

Table 1: Correlation of space cooling appliances

Table 1 presents Pearson correlation coefficients for ownership of coolers and air conditioners with respect to income and other household indicators. The values highlighted in blue and orange indicate positive and negative correlations respectively at a significance of 0.05. Table 1 shows that both coolers and ACs have a strong correlation to income. Air conditioners ownership also indicates significant correlation (higher than coolers) to ownership of households and a negative correlation to rental households. This is understandable as people who own households would prefer investing the high upfront costs (presented in the last section) entailed with ownership of an AC.

Next presented are usage patterns of each of the cooling appliances, individually, in summer and winter months.

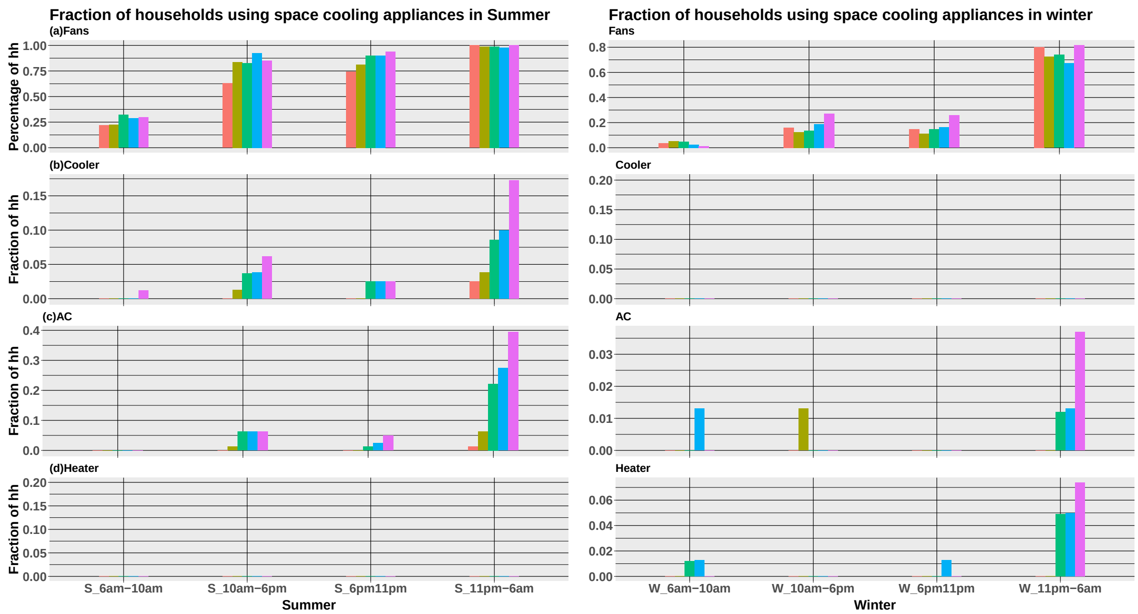

Figure 11: Usage of cooling and heating appliances

Fans

Figure 11(a) shows the usage of fans in summer and winter, across various quintiles, for different time slots of the day. In summer it can be observed that in the night almost all households use fans and during the day times the number of households using them is still significant. In the winters, it can be seen that between 75%-80% of the households use fans, especially during typical sleeping hours. But it is interesting to note that, even in winters approximately 20%-30% of the households continue to use fans throughout the day. As seen clearly in figure 11(a), and space cooling driven by fans is a consistent "hidden" electricity demand creator [6].

Coolers

From figure 10 it can be seen that the highest ownership of coolers is in the top three quintiles and among the three cooling appliances, coolers are the least owned. One of the reasons for this could be the price difference between coolers and air conditioners. The price is of an air conditioner typically is 1.5 to 2 times more. For households that can afford an air conditioner, it becomes a more viable option. Figure 11(b) shows the usage of coolers in summer and winter, across quintiles, for different time slots of the day. It is very clear that unlike fans, coolers have a stronger seasonal inclination, with no usage in winters. In summers it can be seen that maximum usage comes from the top 3 quintiles with significant usage in the nights and some usage mid-mornings.

Air conditioners

Figure 11(c) shows the usage of air conditioners in summer and winter, across quintiles, for different time slots of the day. From figure 10 it can be seen that air conditioners are the second highest owned space cooling appliances, with ownership largely concentrated in the top 3 quintiles. From figure 11(c) it can be seen that in summer the top three quintiles use air conditioning to cool their living spaces, with minimum usage through the day and peaking at between 11pm and 6 am. It can be also seen that in the fifth quintile usage of air conditioners is almost twice the other quintiles. In winters, there some usage of air conditioners in the nights with highest usage coming from the fifth quintile.

Space heaters We can see from figure 10 that space heaters are not owned significantly among the households surveyed. One of the reasons for this is could be the that the average minimum temperature in Bangalore is 17^{o}C, which does not warrant a wide demand for space heating. This is reflected in figure 11(d) which presents the usage of room heaters in summer and winter, across quintiles, for different time slots of the day and shows a strong seasonal trend linked to its use.

3.1.1. Contributions to the Load Curve by Space Cooling Appliances

Figure 12 shows the average demand from various space cooling appliances during summer and winter, for a typical household in each quintile. The load curves do not include space heaters, given very low demand from the surveyed sample. From figure 12 it can be clearly seen that during summers there is a significant demand from fans across quintiles, through the day with demand from ACs peaking in the night but also appearing during the afternoon periods. In winters clear significant demand from fans can be observed during the night times across all quintiles with some demand form ACs still appearing from the higher income households.

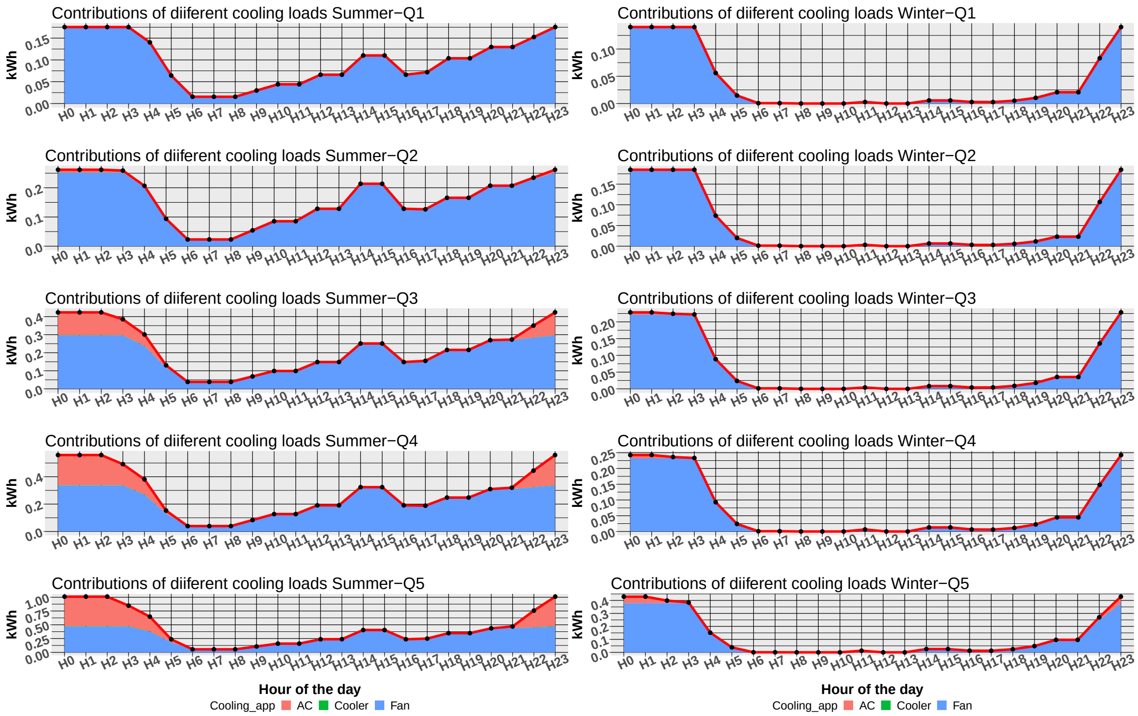

Figure 12: Cooling load curve quintile

3.2. Water Heating Appliances

It can be see from figure 13 that households use 3 broad ways to heat water; electricity, solar energy and non-electric (using firewood or LPG gas).

Under the electricity-based water heating appliances are immersion rods, instant geysers and geysers. Immersion rods are the cheapest and least energy efficient ways of heating water. Its price on average is a tenth that of a regular geyser. Instant geysers are more like traditional storage-based geysers, but heat lesser quantity of water and need to be used for longer durations to cater to the entire family. They are more efficient than immersion rods but not as efficient as storage-based geysers. And cost on average half as much as a larger geyser. Larger storage-based geysers are comparatively the most efficient among the three, have an efficient thermostat based on-off cycle and are the most expensive among the three.

From figure 13 it can be seen that ownership of these three types of water heaters has a correlation with income. It can be seen that immersion rod ownerships reduce as we move up income quintiles and for geysers, the top income quintile has maximum ownership percentage, with increase in ownership as we move up quintiles.

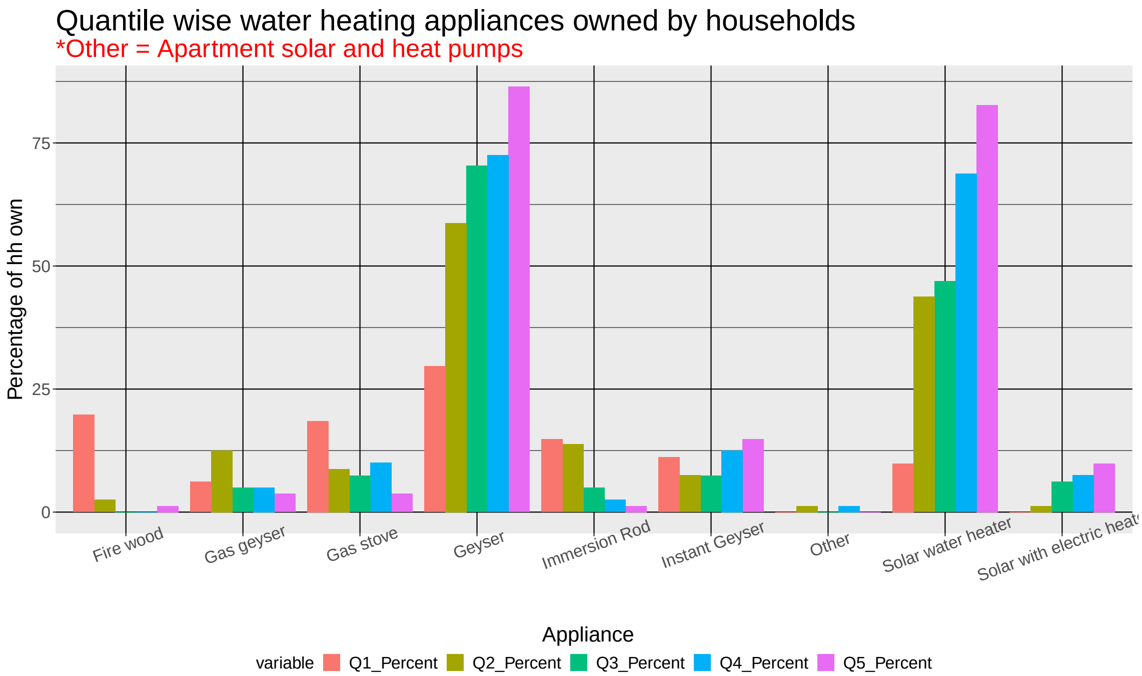

Figure 13: Water heating appliances ownership

Under solar based water heaters, there is primarily just one type with a variation that comes with an in-built electric heating element. These are more expensive than the geysers and therefore from figure 13 can be seen that there is a strong correlation between income and ownership of these. The highest ownership percentage of these can be seen in the top income quintile. The installations of these solar water heaters for residences was mandated by the state government (of Karnataka) in 2007 under the energy conservation act of 2001. A closer analysis of the policy is carried out in the next section.

Finally, looking at the non-electric mode of water heating, there are three main methods households use: fire wood, geysers that run on liquified petroleum gas (LPG) and cooking stoves that run on LPG. It can be seen that for the use of fire wood and LPG to heat water, the lower income quintiles show a higher.

Table 2 presents Pearson correlation coefficients for ownership water heating appliances with respect to income and other household indicators with highlighted in blue and orange indicating positive and negative correlations respectively at a significance of 0.05. It can be seen that in the case of geysers and solar water heaters there is a significant correlation to income, while immersion rods have a negative correlation. This trend can also be observed in figure 5. The

Correlations of ownership of water heating appliances			
	Geyser	Immersion	Solar
Income	0.399	-0.179	0.487
Independent_HH	-0.109	-0.003	0.229
Apartment	0.109	0.003	0.109
Own_HH	0.005	-0.062	0.317
Rental_HH	-0.020	0.077	-0.306

Table 2: Correlation of water heating appliances

ownership of solar water heaters has a significant correlation with households that are owned rather than rented. This can be explained by the comparatively higher upfront costs to install the system.

Figures 14(a)-14(c) indicate the time of use and seasonality of use of the three electricity-based water heating methods, given that the scope is limited to looking at electricity-based water heating methods and estimating impacts on the load curve.

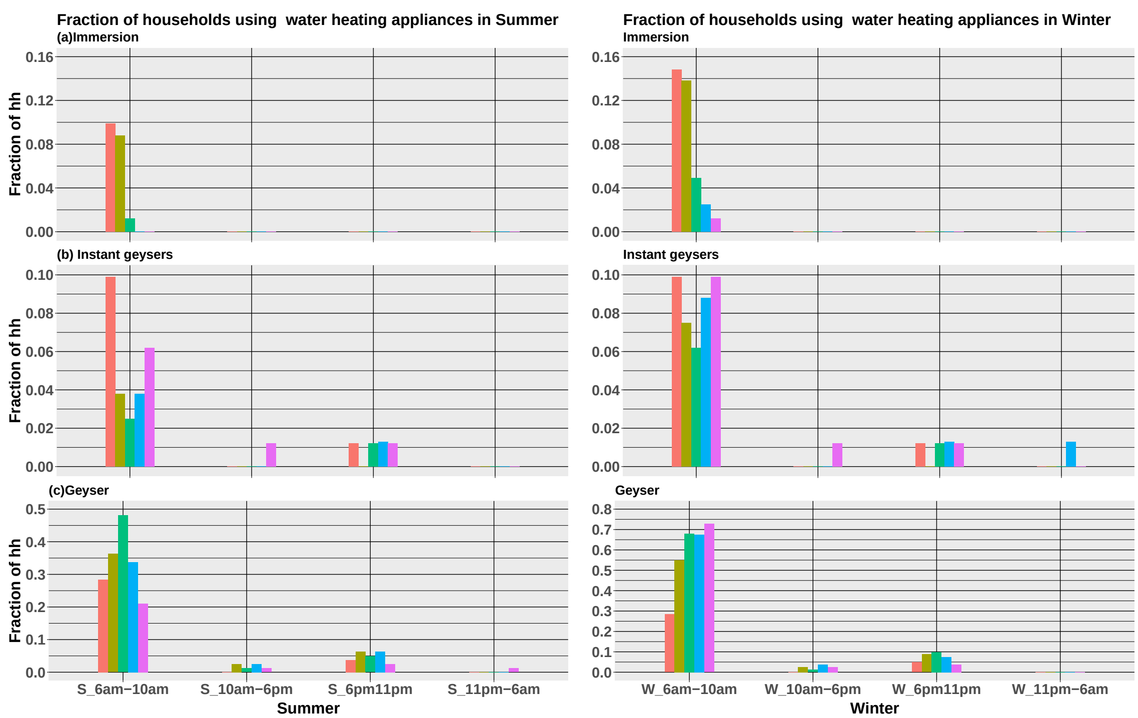

Figure 14: Water heating appliance usage

Immersion Rods

Figure 14(a) shows the use of immersion rods in summer and winter. It can be seen from figure

14(a) that predominantly immersion rods are used by households in the lower income quintiles with a considerable increase in the percentage usage it in winter, mostly in the morning time.

Instant geysers

Figure 14(b) shows the usage of instant geysers across income quintiles for summer and winter. From figure 13 it can be seen that instant geysers have approximately the same percentage of ownership across income quintiles. From figure 14(b) it can be seen that in the lowest quintile the usage is uniform across both summer and winter and as we move up income quintiles usage significantly increases in winter almost doubling in usage.

Geysers

Finally, in figure 14(c) we look at storage-based geysers and their usage in summer and winter across income quintiles. As can be seen from figure 13, geysers are by far the most dominant electricity-based water heating appliances used. We can also see a strong seasonal trend associated with the usage of these, with significantly higher usage in winter from the upper income quintiles. The predominant slot of usage is the morning slot with some usage in the evening slot.

3.2.1. Contributions to the Load Curve by Water Heating Appliances

Figure 15 presents the average demand from various electric water heating appliances during summer and winter, for a typical household in each quintile. Figures 14(a)-(c) indicated the strong correlation that water heating appliances have with respect to seasonality and time of use. This can be seen in figure 15.

Figure 15 shows that there is a significant increase in the usage from the upper quintiles, with demand going up approximately by two times from summer to winter. We can also see from plots 14(b) and 14(c) that the use of instant geysers and geysers jumps significantly in the winter, this follows from figure 13 which indicates that the top two quintiles own a higher percentage of both solar water heaters and geysers (both types). In summer the reduction in demand can be attributed to the use of these solar water heaters (data presented in the next section).

In the lowest income quintile, there is no significant change in demand. From figures 14(a) and 14(b) to 14(c), we see that this is because the ownership and usage of electricity-based water heating appliances is not very high and a significant percentage of households use fire wood and/or LPG stoves as a source of water heating. The penetration of solar water heaters in this quintile is also very low meaning year-round they are either dependent on the inefficient electric appliances or use firewood and/or gas stoves.

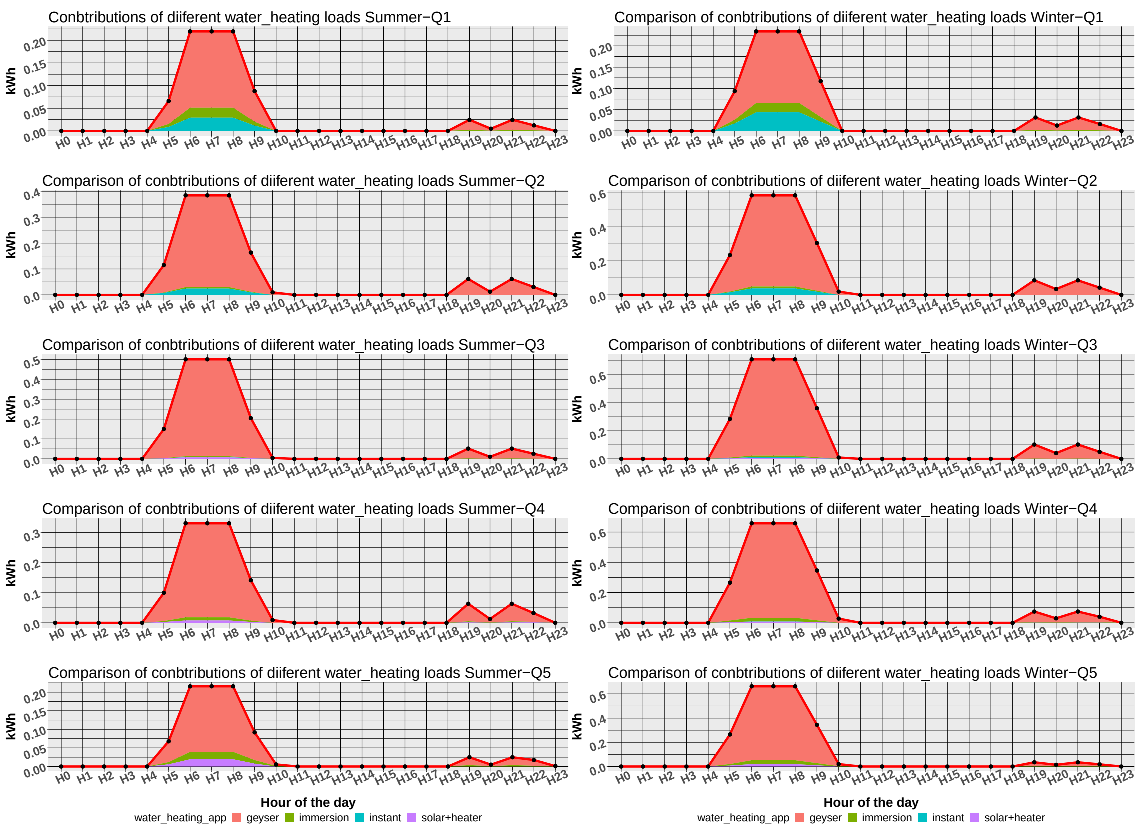

Figure 15: Water heating load curve

3.3. Addressing Demand Trends Through Policy and Programs

Considering cooling and heating loads form a significant part of residential electricity demand, across quintiles, it is important to manage these loads to efficiently handle demand and better plan grid expansion and dispatch [7]. It is important to understand the evolution of this demand given that as households move up income brackets and their lifestyles become more energy intensive[4, 8, 9]. One of the ways of managing some of this demand growth is to have effective policy measures and awareness programs which help efficient management of demand and transitions. Some broad policy interventions and programs are suggested by looking at examples of current schemes, where helpful, that proved to be a success to suggest possible directions.

3.3.1. Managing Demand from Space Cooling and Water Heating Appliances Through Policy Interventions

3.3.2. Cooling Appliances

Fans

Table 3 indicates the penetration of fans and the percentage of households that own more than one in each quintile. From table 3 we see that all the households surveyed own fans, and except for a few households in the lowest income quintile, all households own more than one fan. Figure 13(a) indicates that in summer, during the nights, almost all households use fans with close to 80% usage during the day.

Fan ownership percentages					
Appliance	Q1	Q2	Q3	Q4	Q5
Fan	100	100	100	100	100
HH owing more than one					
Appliance	Q1	Q2	Q3	Q4	Q5
Fan	86.4	100	100	100	100

Table 3: Fan ownership across quintiles

Similarly, in winter 30% of the households use fans through the day, increasing to approximately 80% at night. It can be seen that fans are among the appliances that are used significantly year-round and can be targeted for an efficiency improvement program. This is important considering fans also have a significantly long life cycle and are not replaced frequently.

In the Indian market today, 5-star rated fans are available and are not more expensive when compared to regular fans. On average a regular fan consumes approximately 75 watts. A conservative estimate of a 5-star rated fan's average consumption is 50 watts. From figure 11(a) it can be seen that on average a household uses fans for approximately 12 hours every day.

Based on these estimates, on average savings of close to 110 units/year/fan can be achieved. This translates into significant savings to the households and reduction of load on the grid.

Currently private energy providers like Tata power and Reliance Energy in Mumbai provide services to exchange old fans for new efficient ones at lower prices [10]. Considering the larger urban population, a good scheme to follow for fan replacement is the DELP or Domestic Efficient Lighting Program [11]. This is joint venture of state run power companies and the government. DELP offers energy efficient LED bulbs at 20-40% of the price and also offers some consumers the option to pay for the bulbs in monthly installments. This program has currently seen close to 350 million bulbs distributed across the country. From our survey data also it can be seen that on average close to 70% of lighting used across households is LED (table 4). Similar schemes can be set up for the exchange and installation of energy efficient fans across the country, especially considering the success of the DELP program.

LED Lighting installed percentages					
Type of Light	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
LED	69.14	76.25	71.60	75.00	76.54

Table 4: LED lights ownership across quintiles

The India cooling action plan (elaborated in the next section), with one of the key points being tackling residential demand from cooling. While there is a mention of making efficiency labeling mandatory for fans and stricter operating efficiency norms, there is no outline indicating how penetration and replacement of old stock will be achieved. As an example, it is currently mandatory for refrigerators and air conditioners to have efficiency labels (star rating). But as indicated in table 5, this does not always lead to consumers buying the highest rated appliance. One of the reasons is the fact that higher efficiency appliances are more expensive, meaning higher initial costs.

Just an availability of more efficient fans is not incentive for consumers to shift to new fans, given their long life cycles. One way forward to see increase in purchase of efficient models and higher replacement rates of old stock could be to follow the template that is set by the DELP, considering its success.

Air conditioners

From figure 11(c) it can be seen that in the top 3 quintiles over 90% of the households that own air conditioners use them during the night time slots in summers. This adds significantly to the summer load curve as seen in figure 14. Table 5 lists the distribution of tonnage and star rating of these air conditioners.

AC star rating and tonnage					
Star rating	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
2	0	0	5.26	8.70	0
3	100	80	63.16	21.74	45.71
4	0	0	5.26	17.39	11.43
5	0	0	10.53	30.43	20
NA	0	20	15.79	21.74	22.86
Tonnage	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
1	0	20	21.05	39.13	40
1.2	0	0	0	4.35	0
1.5	100	80	63.16	43.48	51.43
2	0	0	15.79	13.04	8.57
NA	0	0	0	0	0

Table 5: AC tonnage distribution across quintiles

As it can be seen from table 5, most of the air conditioners owned are largely between 2 and 3 stars with very few households owning 5-star air conditioners and most of the air conditioners owned are 1.5 ton in capacity. Studies carried out by [12, 13] have highlighted the impacts on the grid by using energy efficient air conditioners and [14] indicates that as we move up income categories, people tend to run air conditioners at lower temperatures. This is another area where efficient air conditioners would make a difference. In most cases, as seen from table **??**, the households might not size the air conditioner effectively and might end up over or under sizing the unit.

Figure 12 showed the significance of air conditioner's demand, therefore creating an intervention here would help. Though there are no strict policies in place yet, the government has a outlined a National Cooling Action Plan which targets space cooling across all sectors, including residential. The report outlines to establish a range of temperature set points that lie between 24C to 27C. The target for this program is to come to full action by 2030. Along with this, programs to educate end users on identifying proper sizing of air conditioners and incentive programs for potential buyers to buy higher star rated air conditioners would have significant impact on demand from air conditioners, especially considering findings in [12, 14]. Considering air conditioners are also appliances that have long lifecycles, programs to exchange old air conditioners along with offering new units for discounted prices would aid in removal of inefficient stock. For older air conditioners there is no easy way to implement the new temperature caps placing more importance on a replacement plan.

3.3.3. Water Heating

The government of Karnataka has a policy under the energy conservation act of 2001, mandating among others, residences to install solar water heaters. The policy mandates for residences, any building with a minimum floor area of 600 sq.ft to install solar water heating systems.From table 6 it can be seen that all households in quintile 2 to quintile 5 have a minimum built up area of at least 600 sq.ft, with 65% of households in quintile 1 falling under this category.

Household characterstics					
Variable	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Average built up area	667.41	938.75	1154.48	1262.24	1740.44
Min builty up area	200	600	600	620	800
Max built up area	1100	1600	2400	2500	4000

Table 6: Built up areas of households

All of the households above 600 sq.ft therefore have to install solar water heaters as per the policy. From figure 13, it can be seen that in the first quintile approximately 10%, quintiles 2 and 3 have approximately 45%, quintile 4 has 68% and quintile 5 has 82% of the households with solar water heaters installed. None of the quintiles have 100% installation, but as per the data in table 6 above, all independent households that fall in quintile 2 and over must have installed solar water heaters.

In the lower income quintiles one of the reasons for the low percentage of installation of solar water heaters, as mentioned by respondents, was the price of the system. The price of the system begins on average at Rs.35,000 which is a significantly high. Other reasons stated by the respondents of other income quintiles were, not enough sun light area on the roof, houses were built before the policy was enforced among others. In the latter case as the approval of the construction was not contingent on the installation of the system, therefore they choose not to do it.

The next point of failure of the solar water heater is in the usage of the system itself. Table 7 below indicates the usage statistics of solar water heaters in summers and winters across quintiles.

Percentage usage - Solar					
Quantile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Summer	8.64	38.75	33.33	51.25	20.99
Winter	6.17	15.00	16.05	17.50	18.52
Percentage usage - Geyser					
Quantile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Summer	28.40	36.25	48.15	33.75	66.67
Winter	28.40	55.00	67.90	67.50	72.84

Table 7: Usage of solar water heaters VS Geysers

From table 7 it can be seen that, first, all the households that have solar heaters installed do not use it irrespective of summer or winter and use geysers. Second, in winters when there is higher demand for hot water, people use more geysers and the use of solar water heaters drops. One of the reasons for this as survey respondents mentioned, is the inefficiency of the system in providing desired temperature of water. On inquiring about the regularity of service to mitigate these issues, most common replay was servicing of the system was not carried out as households did not have the right information on authorized channels. From the survey, some key points of failure in terms of installation and usage of solar water heaters were, price, especially for the lower quintiles, lack of information/options for maintenance to keep the system performing efficiently in terms of heating water, no checks on installation status for households built before the policy was implemented and finally no mitigation for households with high shade areas on rooftops leading to insufficient space for installation.

Some of the steps that can be taken to mitigate some of these concerns could be (one or a combination of) subsidies/soft loans to increase affordability(68% of the households in the lower quintile have built areas of 600 sq.ft, with only 9.8% installation), periodic outreach programs for servicing and maintenance, stringent checks to implement retrofitting on older households.

While this addresses the issue of the usage of solar water heating systems, if we look at the lower two income quintiles, we can see that close to 20% of the households use firewood and the less efficient immersion rods to heat water. The government needs to evaluate and identify the best plan of action to transition them to more efficient electricity based water heating systems, if not solar water heating systems. Programs like DELP should be designed to make efficient electric and solar based water heating systems affordable and accessible. The key to the success of DELP was the involvement of the government and the state utility boards which brought down the costs significantly. In order to achieve scale therefore, the government and/or state utility boards need to intervene with the right policy framework and process.

3.4. A Closer Look at Domestic Solar Rooftop Program in Karnataka

From the load curves presented it was observed that, in general the residential curves have two peaks, one in the morning and one in the evening. This is the standard pattern that is observed from general household demand. But as we move up income quintiles, in figures 8 and 9, one can observe that, especially in summer, the load curve of the households in the 4th and 5th quintiles show a comparatively flatter curve with less prominent morning and evening peaks. If we take a closer look at Fig. 10 and 11, between 10am and 5 pm, the significant contributor to demand is space cooling load, mostly driven by fans. This trend can be observed in the other quintiles as well, but the intensity in demand is lower compared to quintiles 4 and 5.

3.4.1. Solar Profiles for Bengaluru

This mid-day demand from cooling can be met locally using solar rooftop installations. Figures 16 and 17 below present the average daily generation profiles for a 1kW solar roof top system with 14.5% assumed systems losses. The plots indicate the output of the AC system. These profiles have been generated based on data from PVWATTS Calculator from NREL [15].

The profiles in figures 16 and 17 are daily averages for the seasons of summer and winter for Bangalore along with an indication of variation in generation. The months considered for summer were March, April, May and June, and for winter, November, December, January and February were considered. The average peak production in summer is approximately 0.6kW, with an average range of approximately 0.5kW to 0.7 kW. In winter, the average peak production is slightly higher at approximately 0.7kW, with an average range of approximately 0.55kW to 0.8 kW. The time band between 9 am and 3pm is when we see most of the generation taking place. While it clear that there is a mismatch in the peaks of demand from households and peak

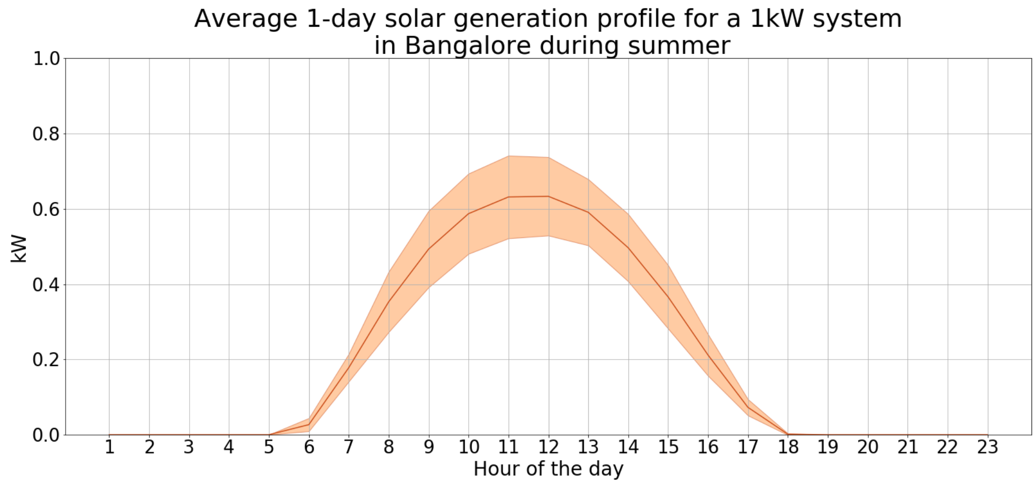

Figure 16: Solar profile for 1kW system in summer for Bengaluru

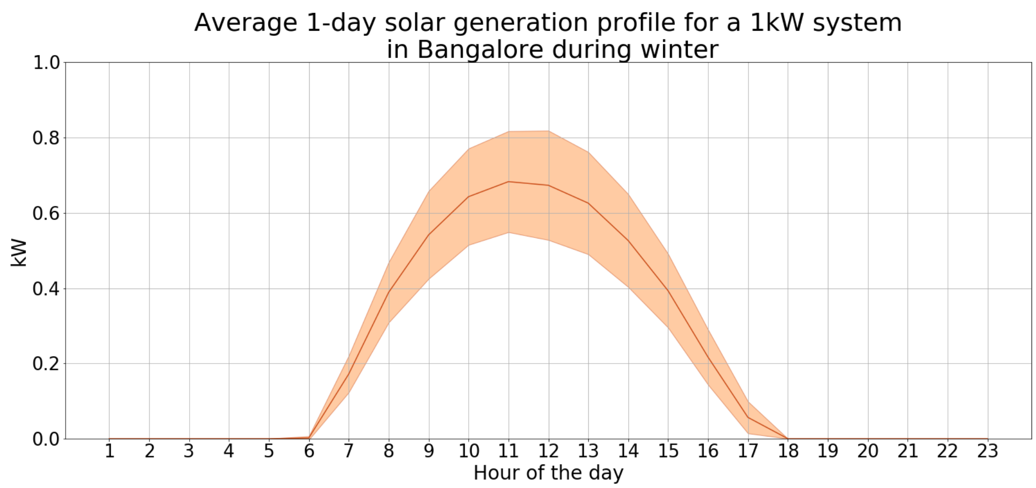

Figure 17: Solar profile for 1kW system in winter for Bengaluru

generation from solar PV, it can be seen that this generation is still sufficient to meet the significant mid-day cooling load in summer along with additional entertainment loads. In winters this can still meet some of the additional morning demands from lighting as well as lighting and demand from entertainment and productivity appliances in the afternoon. As a note, the possible reason for slight increase seen in production from the panel; in winter might be due to lower ambient temperatures leading to incremental efficiency lost during higher ambient temperatures in summers [16].

3.3.2. Rooftop Solar Policy in Karnataka

The solar rooftop policy outlined by the Government of Karnataka [17], sets a target of 2.4 GW of solar rooftop to be installed by March 2021. But figures in the same policy state that as of March 2018 we have seen only 145 MW of rooftop solar PV installations, which is not even 10% of the targeted capacity. If this set target needs to be achieved, the government needs to incentivize end users to increase adoption rates. As per the policy, the subsidized cost has been set at Rs.48,000 /kW $700/kW) and the unsubsidized cost is between Rs.65,000 $900) to Rs.75,000/kW ($1100/kW) for units below 5kW. The feed in tariffs suggested currently is Rs.3.08/kW for a unit bought with subsidy and Rs.4.15/kW for a unit bought without subsidy.

3.4.3. Target Households and Suggested Policy Amendments

Considering the type of households that need to targeted for a successful rooftop program, we need to consider two primary conditions – affordability and availability of roof top space. Given the price of both the subsidized and non-subsidized systems, it is safe to assume that households that can afford these systems have a higher probability of being in the top two may be three quintiles. Table 6 presents data on average built up areas of households across income quintiles.

Assuming approximately 120-150 square feet for the installation of 1 kW system, it would be safe to assume that households in the top 3 quintiles would also have the required usable rooftop space. As a point of reference, considering the ownership of solar water heaters,figure 13, it can be seen that the last two quintiles own significantly higher number of solar water heaters compared to even the third quintile. It is also important to note that the average cost of solar water heaters is close to the cost of a subsidized 1kW solar PV system. These observations therefore help us narrow down the possible households that can be targeted for rooftop PV programs.

Next, looking at the cost of procurement and available financial options as outlined by the policy. The policy allows for a loan facility of up to 70% of the cost of the system at 10% interest with an annual depreciation of 5.38% spread over 13 years, with the rest being spread over the life of the plant, considered 25 years. Finally, looking at the feed in tariff which is set at Rs.3.08 ($0.04) for PV systems procured with subsidy while for units without subsidy get a feed in tariff of Rs.4.15 ($0.05)

3.4.4. Suggested Policy Amendments

While the price of the system is fixed by the government and might not have much room to change, the financial options can be modified to make installing solar PV systems more inviting. Reducing interest rates on loans or setting up subsidized interest rate loan options specifically for incentivizing adoption of solar PV could be one option.

For larger installations of solar PV, including rooftop installations have the benefit of accelerated depreciation of 40% the first year, while domestic installations see a depreciation of 5.38% for the first 13 years, totaling to 70% with the rest of the 30% spread over the next 12 years. Increasing this benefit and providing better tax incentives for domestic consumers as well could be one more point that could help incentivize the adoption of roof top PV.

Next, we look at the feed in tariff (FIT) and net metering set in place for grid tie consumers [18, 19].When we look at the tariff for FIT/net metering, they stand at Rs.3.08 ($0.04) for PV systems procured with subsidy and Rs.4.15 ($0.05) for units without subsidy. The tariff of Rs.3.05 is lower than the cost for the first 30 units of electricity supplied by the local electric utility, while tariff of Rs.4.15 for non-subsidy units is not significantly more than the charges for first 30 units and is lower than the charges for the next slab of 31 to 100 units table 8. This is not encouraging for users who want to opt for grid tie solar PV system. This needs to be addressed. Table 8 below presents the comparison of tariffs [19] charged by the local electric utility for different consumption slabs and the current FIT/net metering tariffs for subsidized and unsubsidized rooftop systems.

Units	Tariff charged for different slabs (INR)	FIT Subsidized (INR)	FIT Unsubsidized (INR)
0-30	**3.75**	**3.08**	**4.15**
31-100	**5.2**	**3.08**	**4.15**
101-200	**6.75**	**3.08**	**4.15**
Above 200	**7.8**	**3.08**	**4.15**

Table 8: Slab wise per unit cost of electricity consumed

Based on the above prices a look at return on investments ROI) for rooftop PV installations is provided. Two cases for calculation of ROI and two scenarios for each are presented. First case (S1) considers a direct deduction of the units fed into the grid from the consumer's bill (Total units billed = Total units consumed Total units fed back). This effectively gives the consumer a variable price-based return as indicated in table 8. This is not the situation currently in Karnataka [18], and therefore case two (S2) presents a fixed tariff-based ROI calculation where the tariff is as indicated in table 8 for subsidized and unsubsidized roof top installations. In table 9, ROI calculations for the above two cases are presented based on two scenarios for each of 100% consumption and 50% consumption to feed back ratio.

ROI based on net metering					
S1: 100% fed to grid					
Size	Average Units Per Month	Subsidized Price (INR)	ROI Subsidized (Years)	Unsubsidized Price (INR)	ROI Unsubsidized (Y)ears
1 kW	150	48000	4.91	70000	7.17
1.5 kW	200	72000	5.21	105000	7.60
2 kW	250	96000	6.64	140000	9.69
50% - 50% consumed - feed in					
Size	Average Units Per Month	Subsidized Price (INR)	ROI Subsidized (Years)	Unsubsidized Price (INR)	ROI Unsubsidized (Y)ears
1 kW	150	48000	11.54	70000	16.84
1.5 kW	200	72000	12.59	105000	18.36
2 kW	250	96000	12.40	140000	18.08
ROI based on Fixed feed in tariff (FIT)					
S1: Fixed tariff					
Size	Average Units Per Month	Subsidized Price (INR)	ROI Subsidized (Years)	Unsubsidized Price (INR)	ROI Unsubsidized (Y)ears
1 kW	150	48000	8.66	70000	9.37
1.5 kW	200	72000	9.74	105000	10.54
2 kW	250	96000	10.39	140000	11.24
S2: 50%-50% consumption - feed in					
Size	Average Units Per Month	Subsidized Price (INR)	ROI Subsidized (Years)	Unsubsidized Price (INR)	ROI Unsubsidized (Y)ears
1 kW	150	48000	17.32	70000	18.74
1.5 kW	200	72000	19.48	105000	21.08
2 kW	250	96000	20.78	140000	22.49

Table 9: Comparison of ROI for net metering and FIT-2scenarios

From table 9 it is clear that net metering is most effective with a significantly lower ROI period where cost per unit follows a variable structure (table 8). Looking at figures 8 and 9 (estimate average monthly units consumed from daily consumption), on average depending on the size of the system installed, it would account for approximately 40%-60% of the units consumed by the target household groups. This percentage of savings will remain consistent even if the utility increases the prices per unit, given the variable payback tariff structure presented above.

While this may not seem viable to the utility if it reaches large scale adoption, given the relatively short ROI and the consistent savings potential, we can make a case for either increased FIT with a revision of FIT scheme that stays in line with consumption tariff increases or/and the option of end users to choose from either a FIT or variable net metering structure. If a few or all of these points ranging from structuring of loans to tariff revisions, can be addressed in future policy revisions, it would possibly incentivize users to more readily install rooftop solar PV systems.

4. Summary

This chapter outlined the need for hourly load curves to overcome some of the shortcomings observed in the load curves developed in chapter 4. Formulation of a model to generate hourly load curves, assumptions and considerations to generate hourly load curves was outlined. The hourly load curves presented patterns of consumption in more detail. Contributions from each appliance/category were identified at hourly resolution, and included in the load curves to identify key contributors in each quintile, seasonally. Significant seasonal variations were observed across quintiles, in both consumption patterns and contributing appliances/categories in the hourly load curves.

With the understanding of key drivers of consumption, across quintile, two policies areas were identified. The first policy framework was built around use of passive demand side management methods to manage peak seasonal loads arising from space comfort and water heating demand. Suggestions on addressing demand from year round appliances like Fans and seasonal appliances like ACs and geysers were made. Specifically, critical analysis of the current ICAP and solar water heater program (in Karnataka) was carried out and key shortcomings were identified and amendments were suggested along with inclusions that can be made to increase access and aid in transition of lower income households into efficient consumption practices.

Next a critical analysis was carried out on the domestic solar roof top policy in Karnataka, identifying some issues with the policy and mismatch between so,ar production and residential demand. Suggestions were made on how to make the policy more attractive to target households and incentivize households to install solar roof top with amendments to feed in tariff structures.

In the last 3 chapters an understanding of ownership, consumption and peak demand patterns of households across income quintiles, seasonally was developed through data collected in the primary survey carried out in Bengaluru. The next part of the thesis, in chapters 6 and 7, build a bottom up, end use, national residential electricity demand model is built using secondary survey data and key insights gained through the last 3 chapters.

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Chapter 6
National Appliance Ownership Models

1. Introduction

In chapters 2 to 5 a methodology to design a representative survey to understand residential electricity consumption in urban Bangalore was presented. Ownership and consumption patterns were identified across income quintiles and seasons. A model was developed to generate load curves at an hourly resolution. Key insights were identified in terms of differences in consumption across income quintiles indicating contributions of different appliance categories to the load curve. From the data it was observed that space cooling and water heating were primary drivers of demand from residences with strong income and seasonal correlation.

The next logical step is to build a national model to understand drivers of residential electricity demand nationally, their changes and its impacts on both demand and patterns of demand using where applicable observations from the primary survey analysis.

Residential demand in India has seen consistent growth over the last couple of decades with growth in the economy improving income and access, increasing urbanization and affordability of goods and services. Residential electricity consumption has grown at 9% per year in the period 2000-2016 [1, 2]. While high, this growth rate is expected to increase as newer population is expected to get access. Households with access will significantly increase consumption due increased used of space comfort appliances and water heating. Residential electricity use per capita in India is only 205 kWh per year (2016 est.), significantly lower than the global average of 739 kWh per year (2014 est).

Among the population that has access to electricity there has been an evolution in the pattern of electricity consumption influenced largely by the types of appliances that are owned [3, 4, 5]. For households in higher income groups, there is higher penetration of lifestyle appliances like ACs, geysers, and space heaters. Lower and middle income households are seeing ingress of appliances like televisions, refrigerators, coolers, washing machines etc. This has led to changes in demand. With the country projected to continue on the growth path, it is important to understand these changes from the residential sector and identify the key drivers to project how residential demand growth and its impact India's demand profile.

The primary questions that arise when approaching a problem like this are: What are the drivers of residential demand? What are the scenarios in which they change? How do these changes impact residential demand? A very important set of questions are related to the contribution from increase demand to climate change, and the role of new technologies like rooftop solar PV in meeting this rapidly increasing demand. In order to answer these questions we will need to develop a model that will estimate changes in demand bottom up by taking into account various socio-economic, regional and weather conditions. For a large and varied country like India the residential demand model should also have sufficient spatio-temporal detail to capture the impact of different seasons, urbanization and climate change related impacts. As surveyed in recent review, such residential electricity demand studies have never been carried out in India [6, 7]

Some recent studies partly address the questions raised above. The World Bank study [8] used the National Household and Consumer Surveys (50th round 1994, 55th Round 1999 and 61st Round 2004) to estimate electrification rates, appliance ownership curves and urbanization rates. This study [9] uses a very similar approach on the JONSON 61st round survey of household consumer expenditure to project India's residential energy demand in 2050 according to the COED Environmental Outlook Scenario of 2008.

Some obvious gaps in these studies remain: These studies use expenditure data as a proxy for income. While this is an accepted methodology, given that IHDS collected income data at national level, this data can be used. These studies give only a point estimate for appliances. While this is useful, it is also important to analyze appliances usage and their patters. This will help understand peak and non peak variations, helping dispatch planning. Next understanding how different appliances/appliance categories contribute to the load will help plan and manage the uncertainty that is introduced into the grid with addition of renewables. Finally, the understanding of the time, intensity and seasonality of demand, can help introduce policy frameworks that can be used to design efficient demand response programs with narrower scope and targeted implementation to manage appliance level demand, varying across income/consumption brackets.

2. Data, Initial observations, Methodology for Model Building and Diagnosis

2.1. Data Sources

In the previous chapters, primary survey data was analyzed to understand appliance ownership and usage patterns of Urban Bangalore. In order to build a national model for appliance ownership and usage, a larger representative data set was required, covering the entire country.

Various surveys like NSSO, CENSUS, IHDS, were considered, with the IHDS survey data set being finally used. The **Indian Human Development Survey (IHDS)**[10, 11] is a nationally representative survey covering 1503 villages and 971 urban neighborhoods across the country. The survey had two rounds that were conducted, first in 2005 and second in 2011. The survey covered 42,152 households and over 200000 individuals, weighted to represent the country. The survey covered a wide panel of social, economic, developmental and other indicators.

Out of the 759 variables covered, a total 56 variables which included electricity indicators, appliances(electric), demographic, household and education indicators, and regional (state, urban rural and metro) indicators. This list was further shortened the to 38 to include the panel of 15 appliances and vehicle ownership, income, expenditure, expenditure per capita, state id, urban-rural code, modes of bill payment, bill amounts, demographic and education level of the head of the household. Given climate zone also plays has a role in ownership of certain types of appliances **"climate zones"** were identified and added as an additional variable for each of the data points using district level climate information. There is an over lap between the variables covered in the primary survey (chapter 2) and the variables in IHDS. This was deliberate, to be able to extend some of the observations made in the primary survey to the national model.

2.2. Initial Observations: Trends from IHDS Data

The IHDS survey conducted two rounds of surveys. Presented first are the key statistics, ownership trends and patterns and changes across both survey periods at national, urban and rural levels, aggregated and decile wise.

2.2.1. Key Statistics

Presented first are the key summary statistics of the two rounds of the IHDS survey presented in Table 1.

The first observation is that higher number of variables were covered in IHDS-II compared to IHDS-I. Appliances like microwaves and laptops became a separate variable only in 2011. Similarly in the household demographic variables, there are many more categories in IHDS-II compared to IHDS-I. It is important, when comparing the two surveys for the changes in variables across survey periods to be mindful of the new variables that were added to the second round of the survey to avoid incorrect comparisons. Some key things to note are; for both the surveys the variable **"weights"** is indicative of the number of households that are present at each data point. Next, for income, expenditure and expenditure per capita there are values that are negative. The values given for these variables are annual. The electricity bill amounts indicated are average monthly amounts. All the values given are average for the weights (households) indicated for each data point.

Summary IHDS 2005							Summary IHDS 2011					
Variable	**Minimum**	**Median**	**Mean**	**Maximum**	**NA's**		**Variable**	**Minimum**	**Median**	**Mean**	**Maximum**	**NA's**
state.id	1	Na	NA	34	0		state.id	1	NA	NA	34	0
dist.id.01	0	12	NA	NA	0		dist.id.01	0	12	14.8	68	0
metro.code	0	NA	NA	1	NA		metro.code	1	3	2.98	6	NA
urbrur	0	NA	NA	1	0		urbrur	0	0	0.3483	1	0
total.residents	1	5	5.192	38	0		total.residents	1	5	4.862	33	0
total.adult	0	2	2.797	18	0		total.male.adult	0	1	1.43	9	0
total.teen	0	0	0.7469	8	0		total.male.elderly	0	0	0.2487	3	0
total.children	0	1	1.648	17	0		total.male	0	1	1.679	11	0
highest.education.hh	-4	8	7.543	15	0		total.female.adult	0	1	1.492	9	0
highest.educaton.male	-4	8	6.812	15	0		total.female.elderly	0	0	0.2694	4	0
highest.educaton.female	-4	4	4.612	15	0		total.children.female	0	1	1.761	11	0
weights	220	3704	4623	308216	0		total.teen.male	0	0	0.2845	5	0
total.income	-108328	31626	53922	6520261	1		total.teen.female	0	0	0.2911	5	0
expenditure.percapita	-6	685	953.6	39273	0		total.children.male	0	2	1.94	21	0
electrified	-1	1	0.7701	1	0		highest.education.hh	0	9	8.316	16	6
hours.supplied	-1	14	12.57	24	0		highest.educaton.male	0	9	7.9	16	3060
bill.payment	-1	1	0.639	5	0		highest.educaton.female	0	5	5.658	16	672
bill.amount	-3	90	142.6	9000	0		weights	154.1	4741.8	6039.9	156647.5	0
fans	-1	1	0.6416	1	66		total.income	1006	75000	130209	11360000	0
cooler	-1	0	0.1289	1	131		total.expenditure	180	87231	118014	4080760	15
AC	-1	0	0.0063	1	2380		expenditure.percapita	180	19442	27082	1461484	15
black.tv	-1	0	0.2604	1	128		electrified	0	1	0.8741	1	152
color.tv	-1	0	0.2981	1	106		hours.supplied	0	16	15.26	24	5444
computer	-1	0	0.0134	1	2425		bill.payment	1	2	2.508	8	5519
mixer	-1	0	0.258	1	89		bill.amount	0	180	281.1	9000	5572
refrigerator	-1	0	0.1776	1	141		fans	0	1	0.755	1	17
washingmachine	-1	0	0.0467	1	2407		cooler	0	0	0.1792	1	29
generator	-1	0	0.0137	1	101		AC	0	0	0.02102	1	27
two.wheeler	-1	0	0.1873	1	109		cooler.ac	0	0	0.1855	1	28
four.wheeler	-1	0	0.0228	1	2352		tv	0	1	0.656	1	18
mobile.phone	-1	0	0.08734	1	153		black.tv	0	0	0.05052	1	31
credit.card	-1	0	0.0163	1	2524		color.tv	0	1	0.6162	1	19
							computer	0	0	0.07037	1	26
							laptop	0	0	0.02664	1	27
							desktop	0	0	0.0558	1	26
							mixer	0	0	0.3365	1	22
							refrigerator	0	0	0.2806	1	21
							washingmachine	0	0	0.09886	1	29
							microwave	0	0	0.01735	1	70
							generator	0	0	0.0195	1	23
							any.vehicle	0	1	0.6662	1	17
							any.motor.vehicle	0	0	0.3	1	18
							two.wheeler	0	0	0.2875	1	20
							four.wheeler	0	0	0.0499	1	43
							mobile.phone	0	1	0.8061	1	19
							credit.card	0	0	0.01735	1	70
							cable.dish	0	1	0.5279	1	23

Table 1: Summary of variables for IHDS-I and IHDS-II

From table 1 we observe the changes in average ownerships of each of the appliance categories along with changes in household numbers (weights). Figure 1 compares the penetration percentage (percentage ownerships) of each appliance for both the survey periods at three levels of disaggregation; National, Urban and Rural and indicates percentage changes of each appliance between 2005 and 2011. Figure 1 helps identify rate of change of ownerships between 2005 and 2011. These levels of disaggregation give us an understanding of how the urban and rural areas contribute to various appliance ownerships and the difference in growth rates.

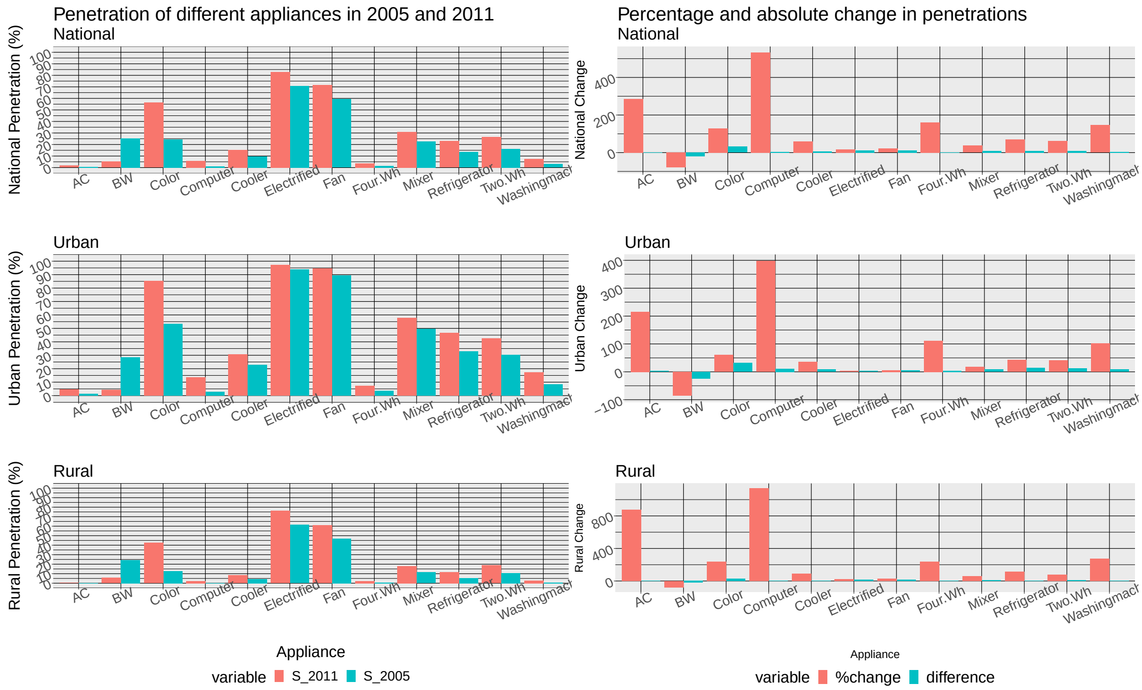

Figure 1: Ownership of appliances and percentage changes between survey periods - National, Urban and Rural

From figure 1 it can be observed that appliances like fans have not seen significant changes in ownership, unlike appliances like refrigerators, washing machines and televisions that have doubled in ownership. It can be seen that across the board, all appliances have had a much more significant growth in the rural areas compared to urban areas. One reason for this is that the urban areas already had a higher ownership base across appliances. But this also indicates that there is a high probability of the demand from rural areas increasing significantly compared to urban areas owing to the scale of appliance growth observed.

2.2.2. Appliance Totals and Consumption Estimates for IHDS

For the given panel of appliances in IHDS 2005 and 2011, table 2 presents by appliance, penetration, consumption and the total demand estimated for the respective years from these appliances.

The penetration for an appliances $\mathrm{A_i}$ is calculated using
$(\sum_{j=1}^{n}(\mathrm{A_i} * \mathrm{WT_j}))/\sum \mathrm{WT}$
where, $\mathrm{A_i} = \mathrm{i^{th}}$ Appliance,

IHDS 2005 Data				IHDS 2011 Data			
Appliance	**Penetration**	**Numbers**	**Consumption(TWh)**	**Appliance**	**Penetration**	**Numbers**	**Consumption(TWh)**
Fans	0.643	1.21E+08	28.61	**Fans**	0.755	1.89E+08	44.86
Cooler	0.130	2.43E+07	4.03	**Cooler**	0.179	4.49E+07	7.43
Ac	0.006	1.19E+06	0.78	**AC**	0.021	5.26E+06	3.47
Color TV	0.300	5.62E+07	11.25	**ColorTv**	0.616	1.54E+08	30.86
Computer	0.014	2.54E+06	0.61	**Cable**	0.528	1.32E+08	15.87
Mixer	0.259	4.86E+07	1.90	**Computer**	0.07	1.76E+07	2.29
Washingmachine	0.047	8.81E+06	1.29	**Desktop**	0.056	1.40E+07	3.35
Refrigerator	0.178	3.34E+07	13.19	**Mixer**	0.337	8.43E+07	3.29
Two Wheeler	0.189	3.53E+07	0.00	**Washingmachine**	0.099	2.48E+07	3.61
Four Wheeler	0.023	4.30E+06	0.00	**Refrigerator**	0.281	7.03E+07	27.7
Total			**61.65**	**Microwave**	0.017	4.34E+06	0.1
				TwoWheeler	0.288	7.20E+07	0
				FourWheeler	0.05	1.25E+07	0
				Total			**142.83**

Table 2: Penetrations and consumptions of appliances for 2005 and 2011

WT = Weight of the data point,

j = j_{th} household

Ownerships data was noted as a **"1"** or **"0"** indicating if an appliance is owned or not respectively. The weights, numeric values, indicated the total number of households represented by that data point.

The total consumption from each appliance is estimated using
W_{avg}*Hr_{annual}*$(\sum_{j=1}^{n}(A_i * WT_j))$
where
W_{avg} = Average wattage of appliance A_i
, Hr_{annual} = Total hours of annual usage of the appliance A_i
, $(\sum_{j=1}^{n}(A_i * WT_j))$ = Total numbers of the appliance A_i

From table 2 we see that that the panel of appliances covered changed between the survey periods and not all appliances that are part of the household are included in the panel covered. Appliances like Cable/dish/set top box, laptops and microwaves part of the 2011 data are in the 2005 data set. Key high energy appliances like geysers, space heaters and domestic water pumps have also not been included. A major exclusion is load from domestic lighting, which forms a significant part of the demand from domestic sector.

Table 3 presents the assumptions made to estimate the consumptions presented in table 2. The first key assumption was that the usage hours of appliances remain uniform across the two time periods along with their wattage. For appliances like fans, coolers ACs the life of the appliance is high and the replacement rate low, therefore wattages can be considered to remain consistent. Next for appliances like Tv and laptops refrigerators, the efficiency improves with time, while for washing machines and microwaves they do not vary significantly. This would indicate that estimates, for 2005 data, would be on slightly lower than actual.

Appliance	Avg watt per hr	hours per year
Lighting	45	2555
Fans	65	3650
Cooler	230	720
AC	1800	550
ColorTv	100	2000
Cable	60	2000
Computer	65	2000
Desktop	120	2000
Mixer	650	60
Washingmachine	400	365
Refrigerator	45	8760
Microwave	600	37
Geyser	1500	400
TwoWheeler	0	0
FourWheeler	0	0

Table 3: Assumptions for wattages and duration of annual use

Looking at the domestic consumption, from estimates of CEA in 2005-06 [12] the consumption from domestic sector was approximately 100,090 GWh or 100 TWh and for 2011-12 CEA estimates were 171,104 GWh or 171.10 TWh [2], While the estimates for the IHDS 2005 and 2011 come up to 61.65 TWh and 142.83 TWh respectively (table 2). This variation in estimation is due to the fact that the survey does not collect the numbers of each appliances owned, but only collects the status of ownership. Also, there is no data on appliances like water heaters or lighting, which can be a significant contributor to the peak demand.

In the sections that follow, a methodology to estimate ownership of geysers and lighting, to make more reliable predictions for future demand scenarios is outlined.

2.3. Appliance Ownership Model

With the understanding of appliances penetrations, consumptions and changes in ownership between the two survey periods, the next step is building a regression model for each appliance to project changes in ownership. To build the best fit model the steps are:

- Identifying and choosing the right regression model
- Identifying the right set of independent variables (IV) to pass to the model
- Identifying the correct split for training and test data sets
- Running multiple iterations of model and performing diagnostics

- Through elimination of independent variables and using diagnostic measures arrive at the best combination of independent variables giving the best prediction on the test data set

Using these steps models were built for each appliance identifying optimal set of independent variables for the best fit predictions on the test data.

2.3.1. Identifying Regression Methodology

Regression is the statistical method to determine the strength and nature of relationship between a dependent variable (DV) and one or multiple independent variables (IV). The type of regression method used depends on the nature of the dependent variable.

In the case of IHDS, the dependent variables (ownership of appliances) are categorical or binary variables, assigned one of two values, **"1"** if an appliance A_i is owned and **"0"** if an appliance A_i is not owned by the household. For these types of variables, the apt method is **Logistic Regression** making the problem a classification problem, to classify households into two bins of "own" or "do not own" for each appliance A_i.

2.3.2. Identifying Independent Variables

Considering that there are close to 40 variables shortlisted from the IHDS data set, it is important to short list the right set of independent variables that have the maximum influence or predictive ability for an appliance A_i. To shortlist the set of IV from the set of variables **Correlation** and **Information Value** methods were used.

2.3.2.1. Correlation

Correlation denotes an association between two variables, either positive or negative. The correlation coefficient gives the degree of association varying between -1 and 1. -1 and 1 indicate perfect correlation (-ve or +ve) and 0 indicates no correlation. Pearson correlation was used at a significance of 0.05.

The Pearson correlation is calculated using $r_{x,y} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum {x_i}^2 - ({x_i}^2)}\sqrt{n\sum {y_i}^2 - ({y_i}^2)}}$

where,

$r_{x,y}$ = Pearson r correlation coefficient between x and y

n = number of observations

x_i = value of x_i

y_i = value of y_i

Table 4 presents a snapshot of correlations for some variables from IHDS 2011 data.

Correlations															
	Income	**Exp**	**EXP_PC**	**fans**	**cooler**	**AC**	**color.tv**	**laptop**	**desktop**	**mixer**	**Fridge**	**Washer**	**microwave**	**2.W**	**4.W**
Income	1	.435**	.292**	.206**	.259**	.255**	.262**	.267**	.292**	.289**	.345**	.330**	.202**	.323**	.346**
Total.Exp	.435**	1	.785**	.266**	.314**	.248**	.327**	.270**	.308**	.340**	.416**	.368**	.194**	.400**	.337**
EXP_PC	.292**	.785**	1	.222**	.229**	.231**	.262**	.231**	.246**	.307**	.342**	.305**	.181**	.279**	.268**
fans	.206**	.266**	.222**	1	.251**	.081**	.590**	.092**	.131**	.383**	.328**	.171**	.069**	.323**	.117**
cooler	.259**	.314**	.229**	.251**	1	.190**	.322**	.155**	.219**	.296**	.473**	.328**	.122**	.365**	.217**
AC	.255**	.248**	.231**	.081**	.190**	1	.110**	.285**	.300**	.170**	.227**	.367**	.321**	.153**	.342**
color.tv	.262**	.327**	.262**	.590**	.322**	.110**	1	.124**	.176**	.512**	.439**	.233**	.100**	.417**	.161**
laptop	.267**	.270**	.231**	.092**	.155**	.285**	.124**	1	.282**	.173**	.236**	.328**	.266**	.186**	.308**
desktop	.292**	.308**	.246**	.131**	.219**	.300**	.176**	.282**	1	.249**	.346**	.423**	.255**	.262**	.319**
mixer	.289**	.340**	.307**	.383**	.296**	.170**	.512**	.173**	.249**	1	.484**	.318**	.159**	.440**	.214**
Fridge	.345**	.416**	.342**	.328**	.473**	.227**	.439**	.236**	.346**	.484**	1	.480**	.194**	.481**	.296**
washer	.330**	.368**	.305**	.171**	.328**	.367**	.233**	.328**	.423**	.318**	.480**	1	.289**	.318**	.372**
microwave	.202**	.194**	.181**	.069**	.122**	.321**	.100**	.266**	.255**	.159**	.194**	.289**	1	.131**	.259**
2.W	.323**	.400**	.279**	.323**	.365**	.153**	.417**	.186**	.262**	.440**	.481**	.318**	.131**	1	.231**
4.W	.346**	.337**	.268**	.117**	.217**	.342**	.161**	.308**	.319**	.214**	.296**	.372**	.259**	.231**	1
**. Correlation is significant at the 0.01 level (2-tailed).															

Table 4: Correlations for IHDS 2011 variables

In table 4, * indicates correlations at significance level of 0.05 and ** indicates correlations at significance level of 0.01.

2.3.2.2. Weight of Evidence and Information Value

Weight of evidence (WOE) and information value are techniques used in logistic regression to identify the importance of a independent variable with respect to a dependent variable. Weight evidence gives us the predictive power of an independent variable in relation to a dependent variable.

This is calculated using

$$WOE = ln(\frac{"Event"Percentage}{"Non-Event"Percentage})$$

Information Value gives a list of variables, ranked by the "importance" of each independent variable with respect a dependent variable, calculated by

$$InformationValue(IV) = \sum("Event"\% - "Non-Event"\%) * ln(\frac{"Event"\%}{"Non-Event"\%})$$

OR

$$InformationValue(IV) = \sum("Event"\% - "Non-Event"\%) * WOE$$

Table 5 presents the information values for one appliance. The table has been truncated to show 15 variables and their related information values for the variable **AC ownership**. The full table lists 34 variables.

AC	
Variable	**IV**
Washingmachine	2.933049
Refrigerator	2.904577
ExpenditurePercapita	2.361711
TotalExpenditure	2.164575
BillAmount	1.968013
Computer	1.951632
TotalIncome	1.899879
HighestEducationHh	1.894218
FourWheeler	1.841405
Mixer	1.707974
Desktop	1.514491
CableDish	1.401032
Cooler	1.300564
ColorTv	1.197403
Urbrur	1.124832
TwoWheeler	1.109564

Table 5: Information value for AC ownership variable - IHDS 2011

The order in which the column "IV" is listed, is the rank order of importance of the independent variables in relation to the dependent variable (the title of the table, AC in this case).

2.3.2.3. Shortlisting Variables for Model Building

Based on results from correlations and information value, a final shortlist of independent variables was obtained. To do this, first the correlations were ordered. Next, the information value list and the correlation data were compared and overlapping variables were first shortlisted along with a few other variables based on evidence from literature and our primary survey. For example in the case of ac/microwave Urban/rural variables did not show a high correlation and was not in the top 10 in the information value list. But it is has been shown that ownership of these appliances has a skew to urban areas. Such variables were included in the final shortlist. A list of 10 independent variables were shortlisted for each appliance, for the first iteration of the model.

2.4. Appliance Ownership Models - Round 1

To build a model with good predictability, multiple iterations of the model need to be executed for each combination of dependent variable and independent variables further shortlisting the set of independent variables.

2.4.1. Training and Test Data Sets

To build appliance ownership models, the IHDS 2011 data set was used. The data is first divided into two subsets, one for **training** the model and one for **testing** the trained model. The training data set is used to build models with different combinations of independent and dependent variables. These models are then tested using the test data set, assessing its predictability using different diagnostic metrics. This process is iteratively run till the best combination of independent variables is obtained.

The division of the parent data set into training and test data subsets is not random and needs to be done carefully. To do this the data frist needs to be tested for class bias. In the best case scenario, the proportions of event to non events will be approximately same. If it is not, data needs to be sampled so that the observations are split approximately in equal proportions.

Considering the data being used is of appliance ownership, there is very little probability that the ownership(1) to no-ownership (0) ratio will be even. Bias was observed across all appliances, therefore addition care was taken when generating training and test data subsets to try and maintain proportions. The final data split of the parent data set was a 70-30 ratio with 70% of the data being used for training and 30% of the data being used to test model strength.

2.4.2. Building Training Model and Testing

With 70%-30% split for training and testing respectively, models for each appliance were built using the shortlisted variables.

Example, for "Fans" the set of independent variables shortlisted were *Expenditure, Expenditure Per Capita, Income, Urban/Rural, Electrified, Hours of supply, Climate Zone, Bill Amount, Cooler, Color TV and Mixer.*

The model was first run with all of these variables included. The Logistic Regression model was run in R using the ***GLM*** function. The function call is

Model_parameters = glm(formula = **Appliance (dependent Variable) ~set of Independent**

Variables, family = binomial(link = "logit"), data = app_train_data, weights = Weights)

The first set of inputs to the **GLM** function were the shortlisted independent variables. Using the output of the function, saved in the variable *Model_parameters* and the ***Predict*** function was run on the test data set (30% of the original data set) to predict the outcome of the dependent variable.

To check the predictability of the model the following diagnostics were used

- VIF: To check for multi-collinearity between independent variables
- AIC: Is a estimator of out of sample prediction error for models of a given data set. The lower the AIC score the better the model compared to other models.
- AUCROC: Receiver operating characteristic (ROC) curve in simple terms is a probability curve and its area under the curve (AUC) that tells us how well the model is able to distinguish between classes (0 and 1).
- Confusion matrix: The confusion matrix gives us information about the total predictions made, the actual positives and negatives and the predicted positives and negatives. From the confusion matrix we get the following metrics:
  - Accuracy: This is the sum of true predictions divided by the total predictions. Tells us how often the model is right. Higher the value better the model.
  - Sensitivity : When it is actually "yes" (actual positive) how often does the model predict "yes" (predicted positive). Higher the value better the model.
  - Specificity : When it is actually "no" (actual negative) how often does the model predict "no" (predicted negative). Higher the value better the model.
  - Misclassification error/rate : sum of false predictions divided by the total predictions.Tells us how often the model predicted wrong. Lower the value better the model.

Using these diagnostic methods, the independent variables were iteratively dropped until the best possible set of independent variables were identified. The primary guiding diagnostic method was the AUC-ROC plot, which is a part of the standard SOP when trying to identify the best logistic model.

2.5. Data for projection of Ownership of Appliances

Considering the variations observed in residential electricity consumption and appliance ownerships [5, 8, 13, 14, 15], a long term projection would not be very reliable. A short to medium term model would be more apt considering this. The 19th electric power survey (EPS) brought out by the Central Electricity Authority (CEA) makes projections for demand from various sectors to 2027, and for specific cases to 2030. Taking into account these factors, the projection time line for the appliance ownership and demand based on the above models was to 2027.

2.5.1. Scenarios, Assumptions and Economic Variable Projections

2.5.1.1. Scenarios for Economic Growth

To project appliances growth to 2027, three growth scenarios (low, medium and high) were considered. For the economic (GDP [16]) growth rates, rates suggested by NITI Aayog were considered. NITI Aayog in their report *India Energy Security Scenarios, 2047*, they offer three economic growth rates to be used. The NITI Aayog lists CAGR of 5.8%, 6.7% and 7.4% GDP growth to be considered till 2047, with the CAGR of 7.4% being considered as the default scenario.

2.5.1.2. Projecting Income and Expenditure Data

Projecting of income data

The key reason for using IHDS data was the availability of information on household annual income. GNI-per capita (GNI-PC) or Gross national income (GNI) [17] is an apt index to use for projections of income data. Considering that the NITI Aayog provides GDP growth rates, it had to be converted to GNI-PC.

Conversion from GDP to GNI-PC

To convert GDP to PC-GNI a two step methodology was followed. First, a model to convert GDP to GDP-PC (GDP per capita) was built followed by another model to convert GDP-PC to GNI-PC. The data for both these steps and for model validation was obtained from World Bank's database [18].

Figure 2 is a scatter plot of the GDP VS GDP-PC data. The regression line, equation, and the r^2 value are presented in the figure. The r^2 value 0.9663, indicating a good fit.

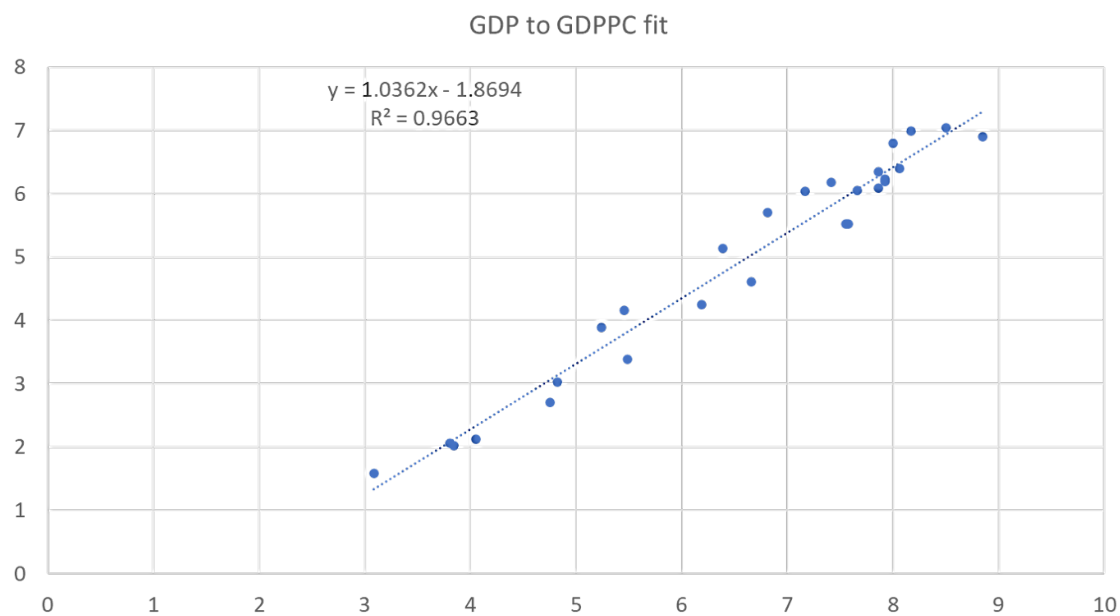

Figure 2: Model to convert GDP to GDP-PC

Figure 3 shows the plot and model for GDP-PC VS GNI-PC.

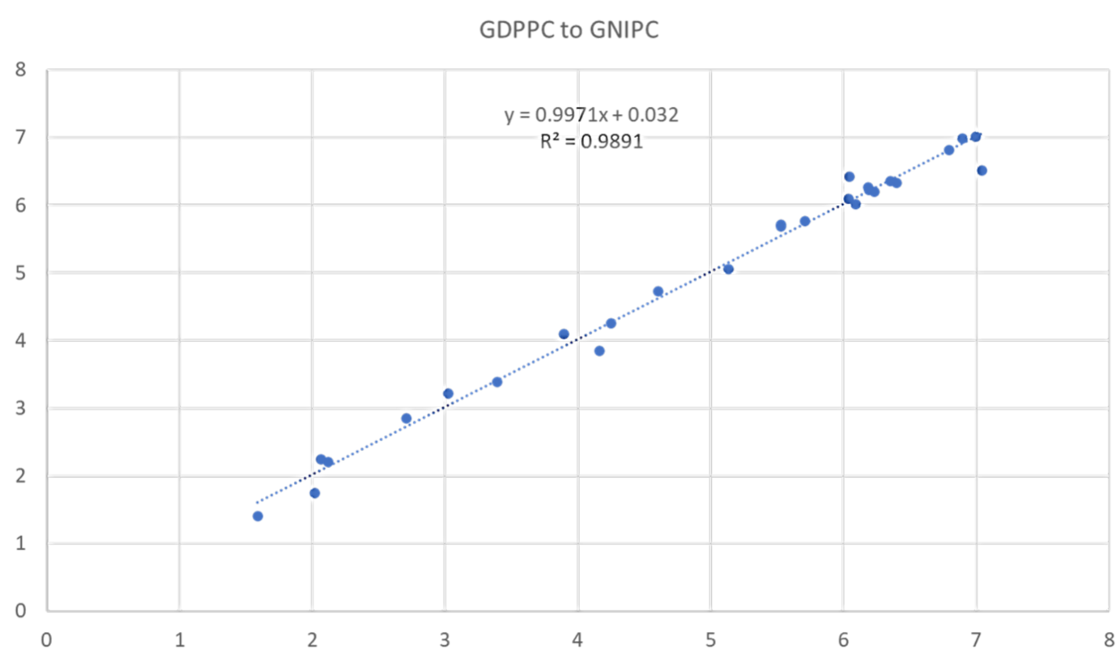

Figure 3: Model to convert GDP-PC to GNI-PC

Figure 3 presents the regression equation and the r^2 value of 0.9891, again indicating a good fit. Table 6 presents the actual GDP, GDP-PC, and GNI-PC values from World Bank along with predicted values using the models shown in figures 2 and 3.

Year	Actual GDP	Predicted GDP-PC	Actual PCGDP	Squared Error	Actual GNI-PC	Predicted GNI-PC	Squared Error
2005	7.9234	6.3409	6.2319	0.0119	6.2056	6.3545	0.0222
2006	8.0607	6.4831	6.4033	0.0064	6.3350	6.4963	0.0260
2007	7.6608	6.0687	6.0482	0.0004	6.4201	6.0831	0.1135
2008	3.0867	1.3290	1.5876	0.0669	1.4052	1.3572	0.0023
2009	7.8619	6.2771	6.3511	0.0055	6.3529	6.2909	0.0038
2010	8.4976	6.9358	7.0423	0.0114	6.5169	6.9477	0.1856
2011	5.2413	3.5617	3.8939	0.1104	4.0974	3.5834	0.2642
2012	5.4564	3.7845	4.1655	0.1452	3.8504	3.8055	0.0020
2013	6.3861	4.7479	5.1350	0.1498	5.0625	4.7661	0.0878
2014	7.4102	5.8091	6.1867	0.1426	6.2704	5.8242	0.1991
2015	7.9963	6.4163	6.7970	0.1449	6.8195	6.4297	0.1519
2016	8.1695	6.5959	6.9970	0.1609	7.0095	6.6087	0.1607
2017	7.1679	5.5580	6.0352	0.2277	6.0979	5.5738	0.2747
2018	6.8114	5.1885	5.7091	0.2710	5.7692	5.2055	0.3177
			Mean squared error (GDP to GDP-PC)	**0.1039**		**Mean squared error (GDP-PC to GNI-PC)**	**0.1294**

Table 6: GDP to GNI-PC conversion table with actual and predicted values and mean square error

As seen, the models performed well in predicting the GDP-PC and GNI-PC data indicated by the mean squared error values. Using these two models GDP growth rates were converted to GNI-PC growth rates.

Prediction for 2027		
GDP from NITI aayog	**Predicted PCGDP**	**Predicted PCGNI**
5.8	4.14056	4.160552376
6.7	5.07314	5.090427894
7.4	5.79848	5.813664408

Table 7: NITI Aayog GDP growth rates converted to GNI-PC

Using the GNI-PC predicted values in table 7, three scenarios of projected income were generated for 2027.

Projecting expenditure and expenditure per-capita

IHDS also collected data on expenditure and expenditure per-capita. Two regression models were built to project expenditure and expenditure per-capita (to 2027) using projected income values.

The fit for the model is presented in the figure 4 followed by the r^2 value and model summary in table 8.

As we it can be seen from table 8, both the variables are significant and the r^2 value is 0.7628 indicating a good fit.

2.5.2. Population and Household Projections

Population and household numbers were the next set of key variables to project. These are important variables as household numbers and population have a direct impact of the stock

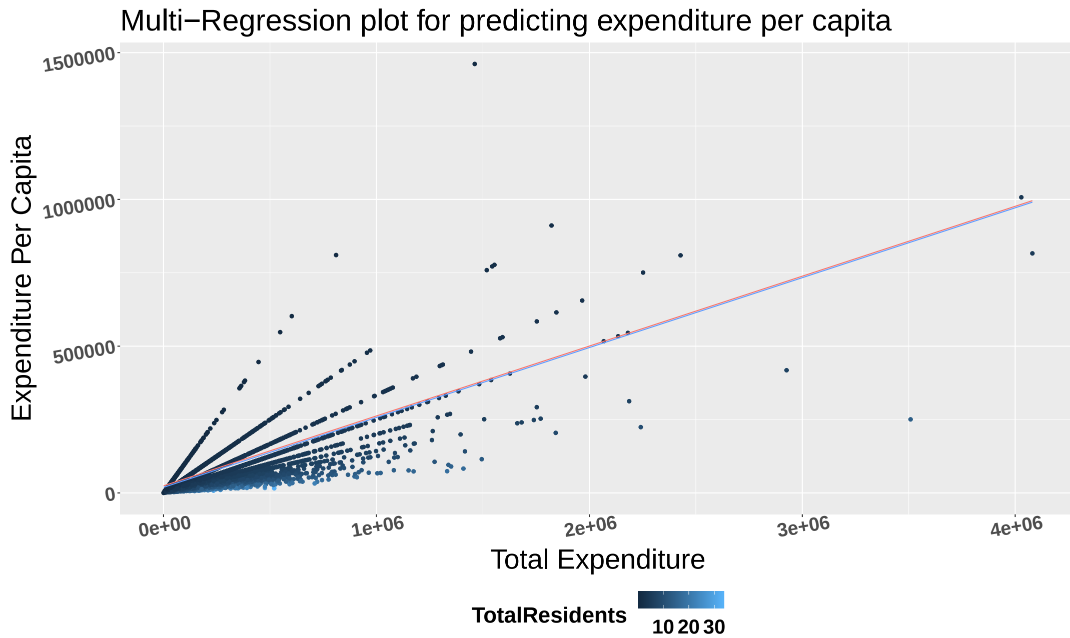

Figure 4: Model to predict Expenditure per-capita given Expenditure

Coefficients					
	Estimate	Std.Error	t-value	Pr(>|t|)	
(Intercept)	2.28E+04	1.60E+02	142.6	<2e-16	***
TotalExpenditure	2.48E-01	7.06E-04	351	<2e-16	***
TotalResidents	-5.06E+03	3.04E+01	-166.5	<2e-16	***
—					
codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '
Multiple R-squared:	0.7628				
Adjusted R-squared:	0.7628				

Table 8: Model expenditure to expenditure per-capita coefficients

of appliances. Office of registrar general and Census commissioner of India published a report projecting population growth [19] from 2011 to 2037, indicating annual population values. [19] projects that the population in 2027, nationally will be 1.4 billion up from 1.2 billion.

IHDS lists weights for each data point indicating the number of households and the household size for each point. Given this structure of data set, a point estimate of 1.4 billion is not sufficient to identify variation in household and population numbers for each data point. To identify this, a growth rate for gross population from 2011 to 2027 needs to first be established and then applied to each data point. This was estimated by

Growth rate = $((\frac{Population_{2027}}{Population_{2011}})^{(\frac{1}{Period})})$ - 1

Which gave a growth rate of approximately 1.2% annually. This value was used to project the population for each data point in the IHDS to get the new household number for 2027. This was done using

$(\text{Population}_{2027})_{\text{i}}$ = $\text{for}_{\text{i=1:N}}\{(\text{Population}_{2011}) * ((\frac{Growthrate}{100})+1)^{\text{Period}}\}$, where
i = i_{th} data point in the IHDS survey

With the above method we arrived at a total population (summation of all data points) for 2027 of 1.41 billion compared to CENSUS projected population of 1.43 billion.

To estimate the number of households one key assumption made was that household sizes would remain unchanged in 2027. The number of households at each data point was then estimated using

$\text{HH\_numbers}_{\text{i}}$ = $\frac{Projected\_population_{\text{i}}}{Persons_n umbers_{\text{i}}}$

Giving number of households at each data *i*.

With the projected values of income, expenditure and expenditure per capita, population and households, the next step was to use this data to project appliance ownership changes to 2027.

3. Model Refinement and Projections of Appliance Ownerships

3.1. Model Refinement and Best Case Models

The best case models built in the previous section for each appliance were run iteratively again with the new set of projected income, expenditure, expenditure-per capita, population and household numbers, optimizing them (where needed) using diagnostic metrics. With this final set of best case models that included projected values for economic and demographic indicators, the ownerships of each appliance was projected to 2027.

3.2. Obtaining Projected Appliance Stock

Logistic regression models give the probability of ownership, for each appliance, for each data point based on which the average probability of ownership is calculated for an appliance nationally. This average probability is calculated for each appliance for each of the three growth rate scenarios. Table 9 presents the average ownerships/penetrations for each appliance in 2027 as estimated by the models.

Average ownerships				
Appliance	**IHDS data**	**NITI 5.8**	**NITI 6.7**	**NITI 7.4**
Fans	0.755	0.854	0.864	0.872
Cooler	0.179	0.272	0.293	0.310
AC	0.021	0.068	0.075	0.080
ColorTv	0.616	0.736	0.762	0.782
Cable	0.528	0.639	0.668	0.690
Computer	0.070	0.131	0.148	0.163
Desktop	0.056	0.111	0.126	0.139
Mixer	0.337	0.432	0.456	0.476
Washingmachine	0.099	0.111	0.135	0.153
Refrigerator	0.281	0.345	0.374	0.395
Microwave	0.017	0.042	0.044	0.044
TwoWheeler	0.288	0.310	0.349	0.379
FourWheeler	0.050	0.082	0.094	0.105

Table 9: Average ownerships/penetrations of each appliance projected

Table 9 compared the penetration of appliances in 2011-12 (IHDS, column 2) with the projected appliance penetration for the three growth scenarios (columns 3 to 5).

Significant growth across all appliances was observed. Comparing growth of appliance by categories, in the space cooling appliances we see that AC's and coolers see a significant growth compared to fans. In the case of entertainment and productivity appliances both laptops (computer) and desktops more than double in ownership while there is a significant growth in color TV ownerships. Next, in the kitchen and utility appliances a significant increase is observed in ownerships across all appliances. Finally, in the case of two and four wheelers, four wheelers show a doubling in ownerships as indicated by the penetration percentages.

These projections are still missing two key appliances, lighting and water heating. Electric vehicles also today are poised to become a major contributing category especially in personal transportation with high peak coincidence factor. It is important to include these appliances as they are key contributors to the load curve [20, 21]. A methodology and the assumptions made to estimate these appliances is presented in the next section.

3.2.1. Estimating Appliances and Future Demand Cases

Lighting and water heating while are integral parts of domestic electric demand and electric vehicles are becoming the new category adding to domestic demand with a high probability of peak coincidence. It is therefore important to estimate the penetration of these appliances and estimate the demand from them.

3.2.1.1. Lighting and Water Heating

Lighting and water heating loads form a significant part of the domestic load and peak demand [8, 20, 21]. It is important to identify and include estimates for these appliances into list of projected appliances. Government estimates and statistical methods were used to estimate the probable stock of these appliances in 2027 for the three growth scenarios.

3.2.1.1.1. Lighting

To estimate the lighting loads for the household, Government's estimates of households electrified were considered. We know that as a household gets electrified, the first electric good installed is a source of lighting, followed by fans and so on [13, 22].
The number of households currently electrified is provided by the government on the **Soubhagya** dashboard [23]. As of June 2020, 99.93% of households have been electrified. Based on this, that assumption that all the households in 2027 would be electrified and have basic lighting was made.

3.2.1.1.1. Water Heating

Electric geysers were not included in IHDS data set. An applicable statistical method needed to be used to estimate the penetration percentage of geysers.

To first understand which are the households are most probable to own a geyser, there are two primary considerations: cost and electricity consumption. In India the electric geyser ranges on average between Rs.15,000 to Rs.20,000 (\$200 to \$300). This price bracket would indicate that only households that are above a certain income bracket could afford it. Next, given that the geyser on average consumes approximately 1200 watts the household would need a three phase/AEH connection (able to run loads of 16A) and a higher sanctioned load. Identifying households that own other appliances that need a AEH connection is a appropriate filter to use. These two constraints (economic and electric) were the starting point to identify a method to estimate geyser penetration percentages.

Association Rule Based Mining

One applicable technique for identifying geyser ownerships based on the two constraints is *Association rule based classification or mining*. In this method, rules of association are established with a confidence for an item B based on the number of times the item B is found when item A is owned. There are three parameters that give the importance of the association ***Support, Confidence and Lift***.

Support Tells us how frequently the item set A,B occur together
Support(A=>B) = $(\frac{frequency(A,B)}{N})$,

where,
A = Antecedent,
B = Consequent, frequency (A,B) = Number of times A and B occur together
N = Sample Size

Confidence Is the conditional probability of occurrence of consequent (B), given antecedent (A)
Confidence(A=>B) = $(\frac{P(A \cap B)}{P(A)})$ **OR** $(\frac{frequency(A,B)}{freequency(A)})$

Lift or Lift Ratio Is the ratio of confidence to expected confidence
Lift(A=>B) = $(\frac{Support}{Support(A)Support(B)})$

The primary survey data (chapter 3, covering the same set of variables as IHDS) which also included geysers was used to identify the set of appliances, that if owned would indicate probable geyser ownership.

Table 10 presents a snapshot of the rules of association for the ownership of geyser, run on the primary survey data.

Rule.no	LHS		RHS	Support	Confidence	Lift	Count
[1]	AC=1,Microwave=1,FourWheeler=1	=>	Geyser=1	0.1265509	0.8225806	1.294922	51
[2]	AC=1,Refigerator=1,Microwave=1,FourWheeler=1	=>	Geyser=1	0.1265509	0.8225806	1.294922	51
[3]	Fan=1,AC=1,Microwave=1,FourWheeler=1	=>	Geyser=1	0.1265509	0.8225806	1.294922	51
[4]	Fan=1,AC=1,Refigerator=1,Microwave=1,FourWheeler=1	=>	Geyser=1	0.1265509	0.8225806	1.294922	51
[5]	AC=1,Microwave=1	=>	Geyser=1	0.1364764	0.8208955	1.292269	55
[6]	AC=1,Refigerator=1,Microwave=1	=>	Geyser=1	0.1364764	0.8208955	1.292269	55
[7]	Fan=1,AC=1,Microwave=1	=>	Geyser=1	0.1364764	0.8208955	1.292269	55
[8]	Fan=1,AC=1,Refigerator=1,Microwave=1	=>	Geyser=1	0.1364764	0.8208955	1.292269	55
[9]	AC=1,Microwave=1,FourWheeler=1,WM=1	=>	Geyser=1	0.1215881	0.8166667	1.285612	49
[10]	AC=1,Refigerator=1,Microwave=1,FourWheeler=1,WM=1	=>	Geyser=1	0.1215881	0.8166667	1.285612	49
[11]	Fan=1,AC=1,Microwave=1,FourWheeler=1,WM=1	=>	Geyser=1	0.1215881	0.8166667	1.285612	49
[12]	Fan=1,AC=1,Refigerator=1,Microwave=1,FourWheeler=1,WM=1	=>	Geyser=1	0.1215881	0.8166667	1.285612	49
[13]	AC=1,Microwave=1,WM=1	=>	Geyser=1	0.1315136	0.8153846	1.283594	53
[14]	AC=1,Refigerator=1,Microwave=1,WM=1	=>	Geyser=1	0.1315136	0.8153846	1.283594	53
[15]	Fan=1,AC=1,Microwave=1,WM=1	=>	Geyser=1	0.1315136	0.8153846	1.283594	53
[16]	Fan=1,AC=1,Refigerator=1,Microwave=1,WM=1	=>	Geyser=1	0.1315136	0.8153846	1.283594	53
[17]	AC=1,FourWheeler=1	=>	Geyser=1	0.1364764	0.7534247	1.186055	55
[18]	AC=1,Refigerator=1,FourWheeler=1	=>	Geyser=1	0.1364764	0.7534247	1.186055	55
[19]	Fan=1,AC=1,FourWheeler=1	=>	Geyser=1	0.1364764	0.7534247	1.186055	55
[20]	Fan=1,AC=1,Refigerator=1,FourWheeler=1	=>	Geyser=1	0.1364764	0.7534247	1.186055	55

Table 10: Rules of association for the ownership of a Geyser

Over 100 rules of association were generated indicating confidence levels of ownership of geysers given the combination of appliances owned by the household. 20 rules are presented in table 10. Out of this list the rule with the highest confidence and lift values was chosen which was rule [2] from table 10,

{AC=1,Refigerator=1,Microwave=1,FourWheeler=1} => {Geyser=1}

This indicates that if the household owns an AC, refrigerator, microwave and a four wheeler likelihood of owning a geyser has a confidence value of 0.82. It should be also noted that four wheelers are good asset indicators to identify the relative income bracket of household. With this rule, we estimated the penetration of geysers for each of three growth scenarios.

3.2.1.2. Electric Vehicles

Another category that is quickly becoming a key area to study are electric vehicles. The government has been making a steady push for increased use of electric vehicles to address a wide variety of issues including emissions [24, 25]. As part of this push there is also a focus on integrating electric vehicles into personal transportation, with the government offering incentives to purchase new electric vehicles [25, 26]. It therefore becomes imperative to also estimate the numbers of these vehicles that we will see and the additional demand that they will lead to. It is also a fair assumption that the charging cycles of these vehicles will have fixed patterns given their daily use, with a high probability to contribute to peak coincidence and cause a bump in the peak demand from domestic loads.

The estimation of electric vehicles in the population of all domestic vehicles is comparatively easier. NITI Aayog has scenarios on EV growth in the country by category(2W, 4W). SIAM (Society of Indian Automobile Manufacturers) also cites these estimates in their projection of growth of the electric automobile market [27, 28]. We consider the same scenarios outlined by NITI Aayog to estimate the EV stock in the total automobile population in 2027. One key assumption is that the EVs will replace fossil fuel vehicles. NITI Aayog projects, under the current policy push with a transformative scenario, 50% of all two wheelers by 2026-27 will be electric. From the projection of two wheelers made from IHDS data, 50% are considered to be electric in 2027. Similarly, for the transformative scenario for four wheelers, it is projected that by 2026-27, 20% of four wheeler stock will be electric. Off the projected four wheeler numbers in 2027 for the IHDS data, 20% are taken to be electric.

3.2.1.3. Estimates of Lighting, Geysers and EVs

Average penetration percentages			
Appliance	**NITI 5.8**	**NITI 6.7**	**NITI 7.4**
Lighting	1	1	1
Geyser	0.088	0.092	0.095
TwoWheeler EV	0.155	0.174	0.190
FourWheeler EV	0.016	0.019	0.021

Table 11: Projected penetration percentages of Lighting, Geysers and EVs

Table 11 presents the penetration of the three appliances assuming that all households will be electrified and will have lighting, indicated by 100% penetration. In the case of geysers for the 7.4% growth scenario the penetration percentage stands at 9.5%. For EVs, in the case of two wheelers, approximately 19% of the households will own a two wheeler EV. Similarly in the case of four wheelers, 2.1% of households will own a electric four wheeler.

With estimates of penetration of each appliance for three different scenarios obtained, the next step is to estimate the demand from each of these appliances and the total domestic demand for each scenario in 2027 for this panel of appliances.

4. Summary

This chapter outlined the methodology to build a national bottom up appliance ownership projection model. The data set used for this was the IHDS data set. In the first section of the chapter, descriptive statistics of the data set and the ownerships of appliances and their changes across two survey periods were presented. Next, a methodology to identify the right regression technique and the subset of variables to use to build models was described, followed by the methodology to train and test the model, outlining the methodology to generate training and test data sets from the parent data set. Next, models were built to project key economic and demographic variables namely income, expenditure, population and household numbers. The appliance models were built going through multiple iterations using diagnostic metrics to arrive at the best fit models. Given that IHDS did not include data on lighting, water heating appliances and electric vehicles, we presented statical methods used to estimate these and project them to 2027. With projections of penetration for all key appliances and appliance categories estimated, in the next chapter estimations of appliance stock (for each appliance) and demand from each appliance and total demand from the residential sector in 2027 for the three growth scenarios is presented along with load curves. These are presented for national, urban, rural, regional levels of disaggregation and for different income deciles.

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Chapter 7
Projected Appliance Stock, Demand Estimates and Load Curves

In the previous chapter a methodology to build a national appliance ownership model and project appliance ownerships to 2027 was outlined. In this chapter we present projected estimates of total number of appliances likely to be owned (appliance stock), demand from the given panel of projected appliances, a model to generate load curves from the given data, as an extension from chapter 4 and 5 and finally some key policy directions are presented. This data will be presented first nationally, by decile, then disaggregated by urban and rural, finally disaggregated by 4 regions (North, east, south and west) to identify how appliances ownerships are split across different disaggregated levels and their contributions to the load curve at these levels. This exercise is carried out because the ownership of appliances and the distributions of specific appliances like ACs, geysers, etc., are not uniform across income groups or regions of the country. This therefore would mean each income bracket or region would have different load curves with contributions from different appliances and appliance categories. It is important to identify these from a supply management perspective and for disaggregated policy formulation framework , because a "one size fits all" approach might not be effective as evidenced from the primary survey analysis (chapter 5).

1. National Data

1.1. Appliance Stock

To estimate total demand from residences for the panel of appliances in IHDS, appliance stock needs to be calculated. Appliance stock is the total number of appliances owned by households. To calculate the stock of each appliance the penetration data presented in tables 9 and 11 of the previous chapter is used. The stock of each appliance for each of the scenarios is calculated using

$$\textbf{Stock\_appliance}_{(i,j)} = \textbf{Penetration}_{(i,j)} * \textbf{households}_{2027\ projected}\ )$$

Where,

i = ith appliance,

j = jth growth scenario

Table 1 presents the appliance stocks for each appliance for each of the growth scenarios along with the penetration percentages.

	Average ownerships				Appliance Numbers			
Appliance	**IHDS**	**NITI 5.8%**	**NITI 6.7%**	**NITI 7.4%**	**IHDS**	**NITI 5.8%**	**NITI 6.7%**	**NITI 7.4%**
Lighting	0.7	1	1	1	1.75E+08	2.95E+08	2.95E+08	2.95E+08
Fans	0.755	0.854	0.864	0.872	1.89E+08	2.52E+08	2.54E+08	2.57E+08
Cooler	0.179	0.272	0.293	0.310	4.49E+07	8.02E+07	8.64E+07	9.14E+07
AC	0.021	0.068	0.075	0.080	5.26E+06	2.00E+07	2.20E+07	2.37E+07
ColorTv	0.616	0.736	0.762	0.782	1.54E+08	2.17E+08	2.25E+08	2.30E+08
Cable	0.528	0.639	0.668	0.690	1.32E+08	1.88E+08	1.97E+08	2.03E+08
Computer	0.070	0.131	0.148	0.163	1.76E+07	3.85E+07	4.36E+07	4.80E+07
Desktop	0.056	0.111	0.126	0.139	1.40E+07	3.27E+07	3.72E+07	4.09E+07
Mixer	0.337	0.432	0.456	0.476	8.43E+07	1.27E+08	1.34E+08	1.40E+08
Washingmachine	0.099	0.111	0.135	0.153	2.48E+07	3.28E+07	3.97E+07	4.51E+07
Refrigerator	0.281	0.345	0.374	0.395	7.03E+07	1.02E+08	1.10E+08	1.16E+08
Microwave	0.017	0.042	0.044	0.044	4.34E+06	1.25E+07	1.28E+07	1.31E+07
Geyser	0.070	0.088	0.092	0.095	1.75E+07	2.58E+07	2.70E+07	2.79E+07
TwoWheeler EV	0.003	0.155	0.174	0.190	7.20E+04	4.57E+07	5.14E+07	5.58E+07
FourWheeler EV	0.000	0.016	0.019	0.021	6.25E+03	4.81E+06	5.55E+06	6.21E+06
TwoWheeler	0.288	0.310	0.349	0.379	7.20E+07	9.14E+07	1.03E+08	1.12E+08
FourWheeler	0.050	0.082	0.094	0.105	1.25E+07	2.40E+07	2.77E+07	3.11E+07

Table 1: Appliance stock for each appliance in each growth scenario

Table 1 compares the appliance stock for IHDS appliances. Estimations for IHDS data on the ownerships of geysers and lighting along with electric vehicles. NITI Aayog suggests that the 7.4% GDP growth rate be considered as the default scenario. Comparing the IHDS penetrations to penetration changes in 2027 for the 7.4% growth rate scenario it can be observed that specific appliances have significant increase ownerships. In the case of space cooling appliances, coolers almost double in ownerships while air conditioners (AC) sees close to 4 times increase. While the penetration percentages of AC might be less than 10%, close to 4 times increase in ownerships will add significantly to the demand. Similarly, it can be seen that ownerships of laptops (computer) and desktops both more than double. Refrigerators also show a significant growth along with geysers that will have close to 10% penetration.

The new segment of Electric Vehicles needs to be looked at closely. In 2011 the penetration of all EV stock was less than 2% of the total vehicular stock in the country. This grows to approximately 20% and just over 2% of the total four wheeler stock will be electric vehicles. The demand for charging a two wheelers consumes approximately 600W to 700W and for four wheeler is approximately 3500W per hour with the average charging time between 5-8 hours for both. This is an extended duration of demand and both the vehicle categories can be considered as high energy appliances.

As a point of reference, the electric two wheeler consumes close to 1.3 times the energy of a washing machine for 5-7 hours while the electric car consumes almost double of an air conditioner's demand for 6-8 hours. If we consider a scenario where the EV is plugged in and AC/geyser or other high energy demand appliances are running, it creates the perfect situation for significant peak coincidence.

1.2. Demand Estimates

In order to estimate demand from different appliances, assumption were made for wattages and hours of use based on literature, our primary survey and market data available on appliances. A summary of these considerations is presented in the table 2 [1, 2, 3].

It has to be noted that considering the assumed wattages and usage hours are from the Urban primary survey, average of market data available for each appliance and from literature, the estimates presented are prone to overestimations, and must be taken as an indication of one of the possible set of demand values and not as absolute figures expected in 2027.

Table 2 shows that for some appliances, the daily and annual usage hours are fairly low. This is because annualized usage hours of appliances with strong seasonal skew (AC, cooler) or appliances that do not have daily usage (EV, washing machine) or appliances that have very small usage durations daily (mixers, microwaves) will show low daily/annual usage durations.

Appliance	Avg watt/hr	Hours/day	Hours/year
Lighting	60	8.2	3000
Fans	75	11.0	4015
Cooler	250	2.2	800
AC	1900	1.6	600
ColorTv	120	6.0	2200
Cable	60	6.0	2200
Computer	90	5.5	2000
Desktop	200	5.5	2000
Mixer	600	0.2	60
Washingmachine	450	0.8	310
Refrigerator	50	24.0	8760
Microwave	600	0.1	37
Geyser	1500	1.5	547
TwoWheeler EV	600	2.6	950
FourWheeler EV	3500	2.6	950
TwoWheeler	0	0.0	0
FourWheeler	0	0.0	0

Table 2: Wattages and assumptions of hours of use

A separate note on refrigerators. These are appliances that are run through the year, and with an average assumption 1.2 units consumed per day, indicating 50W of usage per hour, used 24 hours a day or 8760 hours a year. Using these values for wattages and usage hours, annual estimates were calculated for each of the three growth scenarios are presented in table 3.

			Consumption from each appliance in TWh			
Appliance	**Avg watt/hr**	**Hours/year**	**IHDS**	**NITI 5.8%**	**NITI 6.7%**	**NITI 7.4%**
Lighting	60	3000	31.55	53.03	53.03	53.03
Fans	75	4015	56.93	75.76	76.63	77.31
Cooler	250	800	8.98	16.05	17.27	18.29
AC	1900	600	6.00	22.78	25.06	27.00
ColorTv	120	2200	40.74	57.27	59.30	60.84
Cable	60	2200	17.45	24.83	25.96	26.84
Computer	90	2000	3.17	6.93	7.86	8.65
Desktop	200	2000	5.59	13.07	14.90	16.37
Mixer	600	60	3.03	4.59	4.84	5.05
Washingmachine	450	310	3.45	4.58	5.54	6.29
Refrigerator	50	8760	30.78	44.51	48.20	50.96
Microwave	600	37	0.10	0.28	0.28	0.29
Geyser	1500	547	14.32	21.20	22.16	22.91
TwoWheeler EV	600	950	0.04	26.06	29.27	31.83
FourWheeler EV	3500	950	0.02	15.98	18.45	20.65
TwoWheeler	0	0	0	0	0	0
FourWheeler	0	0	0	0	0	0
Totals			**222.17**	**386.89**	**408.75**	**426.30**

Table 3: Point estimates of demand from three growth scenarios

Column 4 in table 3 presents the estimate of demand from IHDS appliances including estimations of lighting, water heating and electric vehicles. The assumptions are 70% of the households use lighting, considering that in 2011-12 approximately 68% of the households were electrified in India 4. The penetration of two wheeler EVs at approximately 1% and four wheeler EVs at 0.5% based on number of vehicles and estimates provided by [5, 6, 7] between 2014-2016. Finally, the number of geysers owned by households were estimated based on the association rule based mining.

To verify if projections and estimations of demand made were accurate, demand estimates of the IHDS data was validated against CEA's estimated of demand met for 2011-12. From [8], we see that demand met for domestic/residential sector was approximately 172 TWh. Referring to the load generation balance report of 2010-11 and 2011-12 [9, 10] we see that CEA on average estimates the difference between energy demand and energy met is approximately 11% and peak demand to peak met at approximately 12%. Considering this difference an approximation of actual demand is approximately 192 TWh. The IHDS data including estimates of lighting, water heating and EVs is approximately 222 TWh. The difference between CEA's estimates and our estimates for 2011 is off by approximately 12%. This is in the acceptable range of deviation from the actual demand data to consider this model to be good in projecting and estimating appliance stock and demand.

The demand from the three growth scenarios ranges from 387 TWH to 427 TWh between the three scenarios. CEA's estimate for 2027 from the 19th EPS report is approximatel 532 TWH. But this number alone is not sufficient to understand the growth in demand. We need to look at different appliance categories to see where demand growth is coming from.

NATIONAL Appliance Category wise demand				
	Demand (TWh)			
Category	**IHDS**	**NITI5.8%**	**NITI 6.7%**	**NITI 7.4%**
Lighting	31.55	53.03	53.03	53.03
Cooling	46.74	114.58	118.97	122.60
Entertainment/ Productivity	43.52	102.09	108.01	112.70
Kitchen and Utility	26.44	58.38	64.16	68.57
Water heating	9.31	21.20	22.16	22.91
EV	0.06	42.04	47.72	52.48

Table 4: Category wise demand from appliances

Table 4 gives a better picture of contributions to demand from the various appliance categories. Break up of the appliance categories is as follows. Cooling includes Fans, coolers and ACs, Entertainment and productivity appliances are TV, set top box, laptops and desktops, Kitchen and Utility are made up of Mixers, Refrigerator, microwave and washing machines, finally EV's have two wheelers and four wheelers vehicles.

It can be observed that demand from cooling sees the highest increase and also the highest contribution as a segment. Breaking this up further we see, from table 3 ACs by far see the most increase in demand that almost increasing 5 times from 2011 levels, followed by coolers that double in demand. But demand from Fans is the highest in this category. This is because it is the appliance with the most penetration following lighting at approximately 87%.

The next high consumption category is entertainment and productivity appliances. This also see almost a 3 fold increase in demand. Breaking down individual appliances in the category we see from table 3 with most growth seen from computing appliances. In the case of kitchen and utility appliances consistent growth can be observed in appliances penetration and resultant demand, which is also the case with geysers that fall under water heating.

The biggest jump is seen in electric vehicles. It can almost be considered as the creation of a new category that did not exist in 2011. Electrical vehicles can be seen as becoming a prominent category with demand as high as demand from lighting. This is a significant part of demand especially given the nature of charging these vehicles. They are primarily plugged in for charging in the nights or in the mornings for a short period before being used for commute. This would mean they have the potential for significant peak coincidence. The extent of this and impacts on demand from other appliances on the load curve are presented in the next section.

1.3. Load Curve Model and The National Load Curve

With demand estimated from each appliance and appliance category, next step is to understand patterns of use of appliances and their contribution to the overall and peak demand. To identify patterns of demand we build load curves. These load curves will present domestic demand at an hourly resolution indicating cumulative demand and deconstructed load curves that indicate demand from each appliance/appliance category. In the following subsections, presented first is the model to generate load curves and assumptions made to generate load curves at national level, seasonally. Seasonal segregation is important because there are key appliances that have strong seasonal correlation. The load curves will need to reflect these difference in order to understand usage patterns variations.

It has to be noted that given the assumptions, the load curves presented in this section are prone to overestimations and must be taken as an indication of the growth in scale and patterns of demand across seasons and not as an absolute representation of expected residential demand in 2027.

1.3.1. Load Curve Model and Load Curves

The model used to generate load curves is presented below. This is an extension to the model built for the primary survey carried out in Bangalore. This iteration of the model is for generating seasonal load curves at the national level for the IHDS data set. The model gives us a cumulative load curve at an hourly resolution for a given season.

$$E_{S,T} = \sum_{j}\{\sum_{i}(A_i)^{*}\, P(T_{A_i} \mid S)^{*}\, W_{avg\ A_i}\} \qquad \textbf{(1)}$$

where,

$E_{S,T}$ = Total energy demand at any given hour A_i = i^{th} appliance

A = j^{th} household

T_t = any given hour (time)

$P(T_{A_i})$ = Probability of appliance i being used at hour T

$W_{avg\ A_i}$ = Average wattage of the i_{th} appliance

S = Season (summer or winter)

Along with the cumulative load curves, we also present load curves for each category of appliances. The categories are indicated in table 4. The model to develop these load curves is a modification of the above model, outlined below.

$$C_k = \sum_{j}\{\ \sum_{c=1}^{n}[(A_{C_i}) * P(T_{A_{C_i}}|S) * W_{avg\ A_i}]\} \qquad \textbf{(2)}$$

where,

C_k = k^{th} category of appliances

A_{C_i} = i^{th} appliance in category C

j = j^{th} household

Based on this model, the load curves were generated at hourly resolution, for summer and winter, nationally based on the appliance projections. To understand present demand trends, data from three different sources were compared. The first source was from the Energy analytics lab from IIT-Khargpur [11]. They have load profiles for the country listed by day, month and year. From this data we get to see the general shape of the curve and demand variations across seasons. National data from NEEM [12] for the period of 2018-19 and data from Prayas EMARC [13] were the other two sources (presented in chapter 4). The data from [11] and NEEM were divided into seasons and plotted, presented in figure 1 and figure 2 respectively.

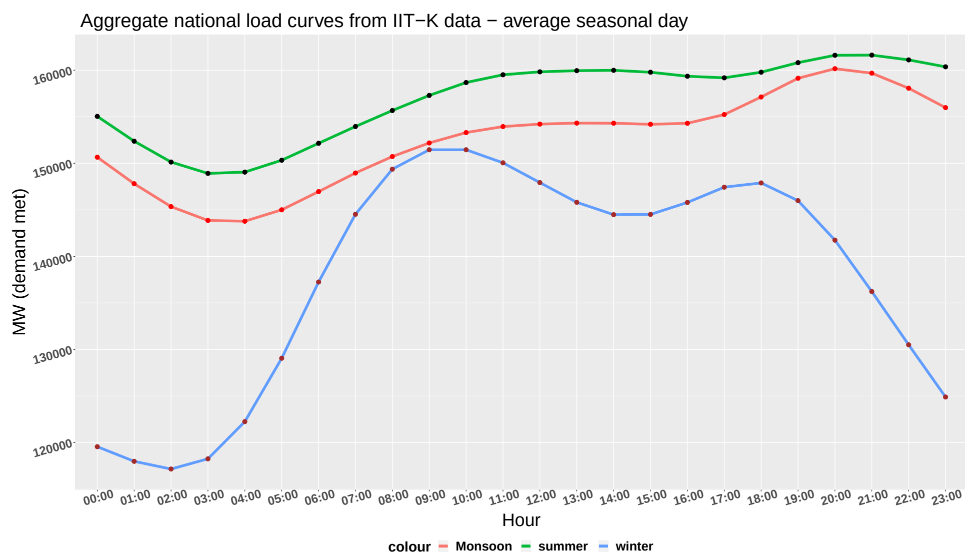

Figure 1: Aggregate national load curves-Averaged seasonally - IIT-K EAL

From figures 1 and 2 the generic shape of the load curve along with the seasonal variations can be seen. It has to be noted the the load curve in figure 1 includes demand from all sectors, while figure 2 is average demand from a household in the country from NEEM data set. We observe from both the plots, common seasonal trends with summer and monsoon following similar trends, while winter has a more distinct peak. Based on observations from these trends and data from our primary survey we generated load curves for the projections from the IHDS data set.

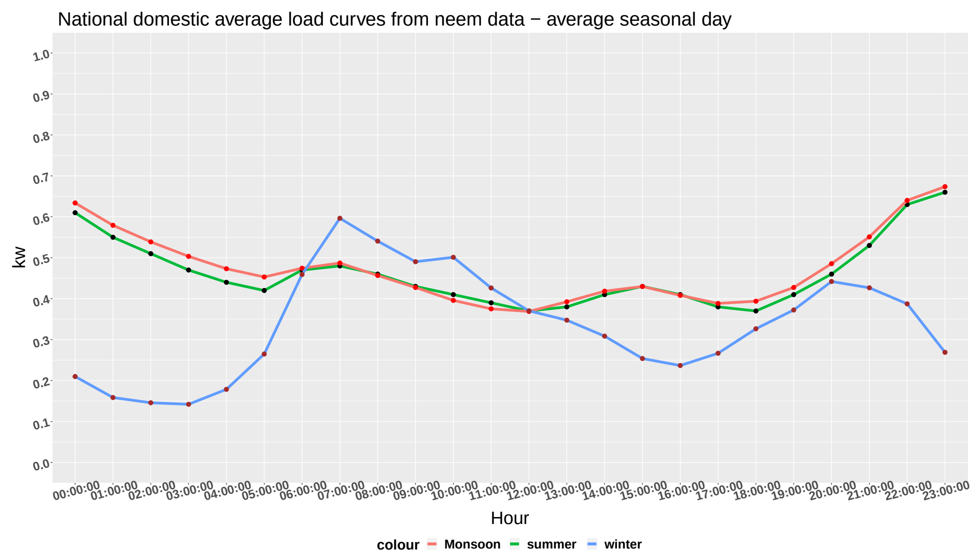

Figure 2: National domestic average load curve - Averaged seasonally - NEEM

Figure 3 presents the load curves for the default growth scenario of 7.4% as outlined by NITI Aayog. The load curves presented are for Summer, Winter and cumulative load curves. The summer and winter load curves present contributions from different appliances while the cumulative load curve present the total demand at each hour.

To get a better understanding of how each appliance/appliance category contributes to the load curve, presented in figure 4 are percentage contributions of each appliance/appliance category at each hour

From figure 4 seasonal dominance from cooling appliances in summer and water heating appliances in winter is clearly observed. Looking at the contributions, it can be seen that in the night the close to 50% of the contribution to demand comes from a combination of fans, coolers and ACs (dark blue and light green colors). Next, we see a prominent difference in the noon to evening periods, where in winters we see a drop in demand during this time, which in comparison to summers is significant. While in summers during this period, the demand almost remains flat, continuing almost at the same level post morning peak. Contributions to this difference are primarily from space cooling appliances with a small bump coming from entertainment appliances. In winters, especially in the mornings, over 40% of the contribution to the morning peak comes from water heating appliances. There is also a significant drop in the noon to evening periods, followed by evening peak mainly driven by entertainment appliances, lighting, some water heating and space cooling. From figure 4 it can be seen that due to the significant drop in

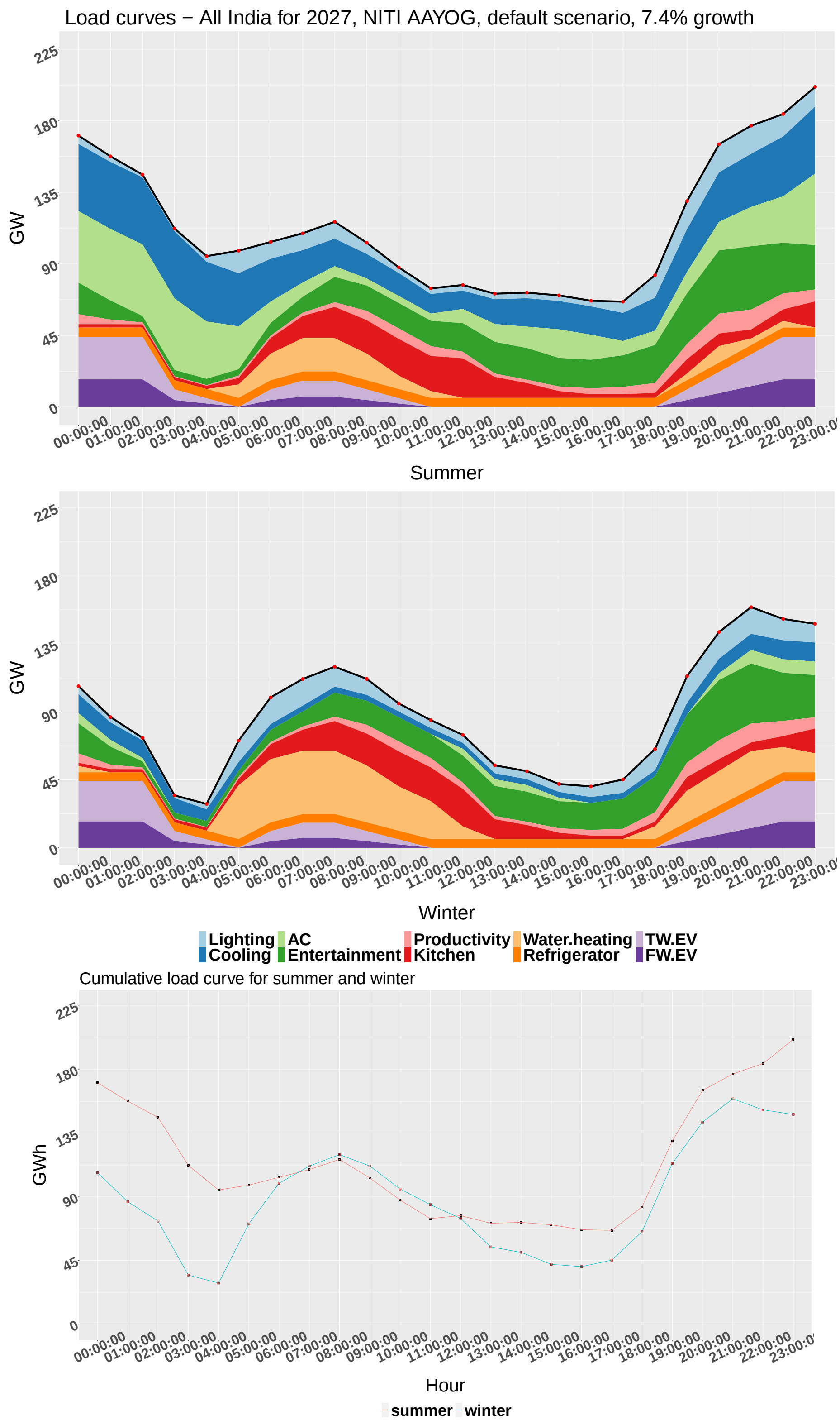

Figure 3: Load curves for NITI Aayog's 7.4% growth scenario

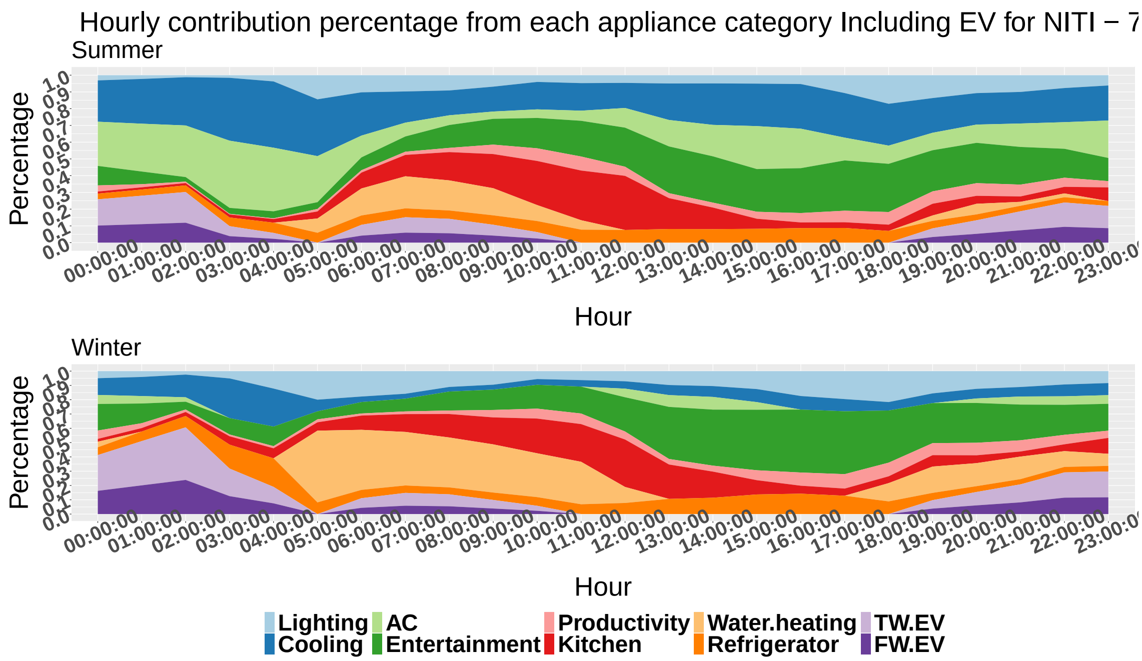

Figure 4: Percentage hourly contributions from appliances/appliance categories

space cooling demand in the evenings/nights in winters, there is a relative increase in demand from kitchen, entertainment and water heating. In the case of entertainment, productivity and kitchen appliances, there is no significant variation in their demand between seasons.

The other category that remains consistent throughout are electric vehicles. At peak, it can be seen that their contribution to demand ranges from approximatly 30% in summer to 50% in winters with an average demand ranging between 15% to 20% round the year. Considering that this a new category which is just gaining traction, an average demand of 15% to 20% is significant and as the population of EVs increase, this demand would only increase especially considering that charging cycles of personal vehicles can currently take place in two prominent slots - nights or mornings. But if there is a significant improvement in the public access charging networks, this demand from EV has a significant chance of becoming an integral part of the base load.

1.4. Decile Demand Trends

Analysis of primary survey data in chapters 4 and 5 showed the variations in ownership and usage of appliances that emerge when data is analyzed by dividing it into quintiles. To identify variations in trends of ownership and demand that could emerge at national level, projected data was divided into deciles based on income data (income deciles).

Tables 5 and 6 present decile wise penetrations for IHDS data and the 7.4% growth scenario. From the table, trends of ownerships of different appliances can be observed. Even low cost appliances like fans are not owned by all households in the lower deciles. For key lifestyle appliances like ACs, coolers and microwaves, a strong skew is observed towards the upper deciles. In the case of refrigerators and geysers, we see that there is a uniform increase in ownership across deciles.

IHDS 2011																
Decile	**Fans**	**Cooler**	**AC**	**TV**	**Cable**	**Computer**	**Desktop**	**Mixer**	**Washingmachine**	**Refrigerator**	**Microwave**	**Twowheeler**	**Fourwheeler**	**Geyser**	**TWEV**	**FWEV**
1	**0.44**	**0.04**	**0.00**	**0.24**	**0.19**	**0.01**	**0.01**	**0.11**	**0.01**	**0.06**	**0.00**	**0.08**	**0.00**	**0.06**	**0.04**	**0.00**
2	**0.49**	**0.04**	**0.00**	**0.28**	**0.19**	**0.01**	**0.01**	**0.10**	**0.01**	**0.04**	**0.00**	**0.08**	**0.01**	**0.04**	**0.04**	**0.00**
3	**0.58**	**0.06**	**0.00**	**0.36**	**0.27**	**0.01**	**0.01**	**0.14**	**0.01**	**0.07**	**0.00**	**0.11**	**0.01**	**0.05**	**0.06**	**0.00**
4	**0.67**	**0.09**	**0.00**	**0.47**	**0.37**	**0.01**	**0.01**	**0.20**	**0.02**	**0.11**	**0.00**	**0.14**	**0.01**	**0.06**	**0.07**	**0.00**
5	**0.74**	**0.10**	**0.00**	**0.54**	**0.43**	**0.02**	**0.01**	**0.23**	**0.03**	**0.13**	**0.00**	**0.17**	**0.01**	**0.06**	**0.09**	**0.00**
6	**0.79**	**0.13**	**0.00**	**0.62**	**0.51**	**0.02**	**0.02**	**0.31**	**0.04**	**0.18**	**0.00**	**0.23**	**0.02**	**0.07**	**0.12**	**0.00**
7	**0.86**	**0.18**	**0.01**	**0.74**	**0.62**	**0.04**	**0.04**	**0.39**	**0.06**	**0.27**	**0.01**	**0.32**	**0.03**	**0.09**	**0.16**	**0.01**
8	**0.91**	**0.23**	**0.02**	**0.82**	**0.70**	**0.07**	**0.05**	**0.49**	**0.10**	**0.37**	**0.01**	**0.42**	**0.04**	**0.10**	**0.21**	**0.01**
9	**0.95**	**0.34**	**0.03**	**0.89**	**0.81**	**0.14**	**0.11**	**0.63**	**0.18**	**0.55**	**0.03**	**0.57**	**0.08**	**0.13**	**0.29**	**0.02**
10	**0.97**	**0.49**	**0.12**	**0.94**	**0.89**	**0.34**	**0.26**	**0.74**	**0.37**	**0.75**	**0.09**	**0.75**	**0.23**	**0.17**	**0.38**	**0.05**

Table 5: Decile wise penetrations IHDS 2011

7.4% growth -2027																	
Decile	**Lighting**	**Fans**	**Cooler**	**AC**	**TV**	**Cable**	**Computer**	**Desktop**	**Mixer**	**Washingmachine**	**Refrigerator**	**Microwave**	**Twowheeler**	**Fourwheeler**	**Geyser**	**TWEV**	**FWEV**
1	**1.00**	**0.596**	**0.032**	**0.000**	**0.398**	**0.329**	**0.001**	**0.002**	**0.154**	**0.001**	**0.005**	**0.001**	**0.367**	**0.017**	**0.014**	**0.184**	**0.003**
2	**1.00**	**0.702**	**0.146**	**0.000**	**0.510**	**0.403**	**0.003**	**0.005**	**0.183**	**0.052**	**0.074**	**0.001**	**0.630**	**0.020**	**0.045**	**0.315**	**0.004**
3	**1.00**	**0.788**	**0.210**	**0.001**	**0.615**	**0.481**	**0.005**	**0.008**	**0.246**	**0.082**	**0.112**	**0.001**	**0.839**	**0.024**	**0.054**	**0.420**	**0.005**
4	**1.00**	**0.857**	**0.282**	**0.020**	**0.715**	**0.567**	**0.013**	**0.024**	**0.329**	**0.135**	**0.142**	**0.002**	**0.947**	**0.030**	**0.062**	**0.473**	**0.006**
5	**1.00**	**0.898**	**0.344**	**0.023**	**0.797**	**0.645**	**0.021**	**0.027**	**0.344**	**0.155**	**0.181**	**0.003**	**0.991**	**0.035**	**0.070**	**0.496**	**0.007**
6	**1.00**	**0.933**	**0.394**	**0.035**	**0.878**	**0.740**	**0.032**	**0.050**	**0.415**	**0.223**	**0.240**	**0.007**	**1.000**	**0.044**	**0.083**	**0.500**	**0.009**
7	**1.00**	**0.966**	**0.446**	**0.061**	**0.940**	**0.837**	**0.062**	**0.080**	**0.531**	**0.310**	**0.327**	**0.008**	**1.000**	**0.059**	**0.098**	**0.5**	**0.012**
8	**1.00**	**0.984**	**0.503**	**0.094**	**0.981**	**0.925**	**0.093**	**0.174**	**0.694**	**0.408**	**0.475**	**0.013**	**1.000**	**0.088**	**0.123**	**0.5**	**0.018**
9	**1.00**	**0.996**	**0.623**	**0.171**	**0.997**	**0.983**	**0.232**	**0.403**	**0.873**	**0.589**	**0.778**	**0.046**	**1.000**	**0.175**	**0.170**	**0.5**	**0.035**
10	**1.00**	**1.000**	**0.773**	**0.359**	**1.000**	**0.999**	**0.644**	**0.618**	**0.994**	**0.786**	**0.979**	**0.183**	**1.000**	**0.622**	**0.239**	**0.5**	**0.124**

Table 6: Decile wise penetrations 7.4% growth rate scenario

Table 7 presents decile wise total consumption and percentage contribution of each decile to the total demand, comparing IHDS and projected data.

	IHDS 2011		**7.4% Growth - 2027**	
Decile	**Total consumption (TWH)**	**Percentage consumption (%)**	**Total consumption (TWH)**	**Percentage consumption (%)**
1	10.4	5.7	17.8	4.9
2	**10.1**	**5.5**	**24.3**	**6.7**
3	**12.5**	**6.8**	**29.5**	**8.2**
4	**14.7**	**8.0**	**33.0**	**9.1**
5	**13.6**	**7.4**	**29.9**	**8.3**
6	**16.6**	**9.0**	**33.8**	**9.3**
7	20.0	10.9	37.6	10.4
8	22.4	12.2	41.0	11.3
9	28.4	15.5	51.2	14.2
10	35.1	19.1	63.5	17.6

Table 7: Decile wise cumulative demand comparison

The highlighted deciles (2 to 6) see significant growth compared to the other deciles. This is evident from the increase in their percentage contributions to the total demand. This is driven by the increase in appliances like TVs, computers, washing machines and refrigerators to a large extent indicating that it is the lower income deciles that will drive the demand increase as they move up the appliance ladder and gain access to newer electricity based end use services.

The upper deciles continue to see increases in demand with the demand almost doubling in each of the top deciles. But their contributions to the total demand drops. One reason for this is that the top deciles start at at higher base of ownership. These deciles see a significant increase in appliances like ACs and EVs and the total demand (TWH) from these deciles is still significantly higher than the lower deciles.

1.5. Regional Demand Trends

The national data set was divided into 4 regions, North, East, South and West to identify variations in ownership and demand regionally. The national grid is generally represented by a 5 regional grids with the separation between east and north east, for this anlysis east and north east regions have been merged into one region.

It is important to analyze each region separately because each region has variations in population densities, average incomes, climates and cultural practices [14]. As a result of these variations, ownerships of appliances and the nature of electricity demand also varies.

North Region	**East Region**	**South Region**	**West Region**
Jammu and Kashmir	Sikkim	Andhara Pradesh	Chattisgarh
Himachal Pradesh	Arunachal Pradesh	Karnataka	Madhya Pradesh
Punjab	Nagaland	Kerala	Gujrat
Chandigarh	Manipur	Tamil Nadu	Daman and Diu
Uttrakhand	Mizoram	Pondicherry	Dadar and Nagar haveli
Hariyana	Tripura		Maharashtra
Delhi	Meghalaya		Goa
Rajasthan	Assam		
Uttar Pradesh	Bihar		
	West Bengal		
	Jharkhand		
	Orissa		

Table 8: State grouping for regional breakdown

Table 8 shows grouping of states for each of the four regions. IHDS state and district classification was based on data from CENSUS 2011, the grouping reflects this. Projected data was grouped into four regions and average ownerships of each appliance, consumptions and demands for each of the regions was re-estimated.

Projected Regional Data										
			North Region		East Region		South Region		West Region	
Appliance	**Avg Watt**	**Hours/year**	**Avg Own**	**Consumption**	**Avg Own**	**Consumption**	**Avg Own**	**Consumption**	**Avg Own**	**Consumption**
Lighting	60	3000	1	14.69	1	13.78	1	12.60	1	11.96
Fans	75	4015	0.888	21.83	0.781	17.99	0.953	20.09	0.851	17.01
Cooler	250	800	0.384	6.27	0.135	2.07	0.151	2.12	0.518	6.88
AC	1900	600	0.175	16.33	0.015	1.34	0.020	1.61	0.065	4.91
ColorTv	120	2200	0.825	17.78	0.707	14.29	0.830	15.34	0.744	13.05
Cable	60	2200	0.738	7.95	0.609	6.16	0.739	6.83	0.648	5.69
Computer	90	2000	0.225	3.31	0.138	1.90	0.129	1.63	0.132	1.58
Desktop	200	2000	0.175	5.72	0.132	4.03	0.123	3.43	0.111	2.96
Mixer	650	60	0.473	1.51	0.373	1.11	0.635	1.73	0.417	1.08
Washingmachine	600	438	0.190	4.08	0.131	2.64	0.145	2.67	0.129	2.25
Refrigerator	50	8760	0.429	15.33	0.350	11.74	0.457	14.00	0.328	9.55
Microwave	600	37	0.064	0.12	0.034	0.06	0.043	0.07	0.028	0.04
Geyser	1500	547	0.157	10.51	0.128	8.02	0.131	7.55	0.114	6.20
TwoWheeler EV	600	950	0.228	10.62	0.143	6.26	0.208	8.30	0.159	6.03
FourWheeler EV	3500	950	0.029	7.76	0.016	4.18	0.021	4.84	0.015	3.34
TwoWheeler	0	0	0.456	0.00	0.287	0.00	0.416	0.00	0.319	0.00
FourWheeler	0	0	0.143	0.00	0.082	0.00	0.104	0.00	0.076	0.00
Totals				**143.80**		**95.56**		**102.80**		**92.52**

Table 9: Appliance wise consumptions in different regions

With regional disaggregation of data variation of demand from region to region can be clearly observed, presented in table 9. Specific appliances like ACs and coolers have a significantly higher ownership in North and West regions followed by the south regions. This trend can be seen with other appliances where the ownership of appliances is higher in the north region followed by west or south depending on the appliances.

A part of the explanation for this can be given using data presented in table 10.

Regions	**Avg income**	**Avg expnditure**	**Avg expenditure-PC**	**Total households**
North	382483.21	170698.78	37679.01	81632115.68
East	276712.42	114900.35	26655.72	76562424.48
South	316342.01	150032.78	37511.73	69974369.12
West	282337.71	132955.53	30853.82	66417159.37

Table 10: Region wise average income, average expenditure and total households

Table 10 gives us average income, expenditure, expenditure per-capita and total households for each region. The north region is the highest in income, expenditure and expenditure per capita followed by the southern region and the west region. The eastern region, considering the number of states included (8), has lesser households, income and expenditure compared to all the other regions. Looking at table 8 we can see that the north and west include states that see either very high temperature in summers or are closer to the coastline with humid weather. As a result we can see significant ownership of Coolers and ACs in these two regions compared to the southern states.

The differences due to ownership of appliances owing to regional disaggregation and variation in income and expenditures should also reflect in the load curves for each of these regions.

1.5.1. Load Curve Model and Load Curves

1.5.1.1. Modified Regional Load Curve Model

To develop the load curves at regional level, the load curve model was modified slightly from the national model. The modified model is

$$E_{R_{S,T}} = \sum_{jR} \{ \sum_{i} (A_i) * P(T_{A_i} \mid S) * W_{avg\ A_i} \} \qquad \mathbf{(1\text{-}a)}$$

where,

$E_{R_{S,T}}$ = Total energy demand at any given hour in region R

R = Regions:North, East, South and West

A_i = i^{th} appliance

j = j^{th} household

T_t = any given hour (time)

$P(T_{A_i})$ = Probability of appliance i being used at hour T

$W_{avg\ A_i}$ = Average wattage of the i_{th} appliance

S = Season (summer or winter)

This is a small modification to the national, where the data is split into 4 regions and energy demand is estimated for each region iteratively going through each of the four regions for all appliances, for each season.

1.5.1.2. Regional Load Curve Model

Using model 1-a and 2, models for each of the four regions were built to study variations in demand. Analyzing the load curves along with tables 9 and 10 give a better understanding of the variations in the intensity of demand.

Figures 5 to 12 are presented in pairs. Each pair of figures present the load curves followed by the percentage contribution from each appliance category in summer and winter for each region.

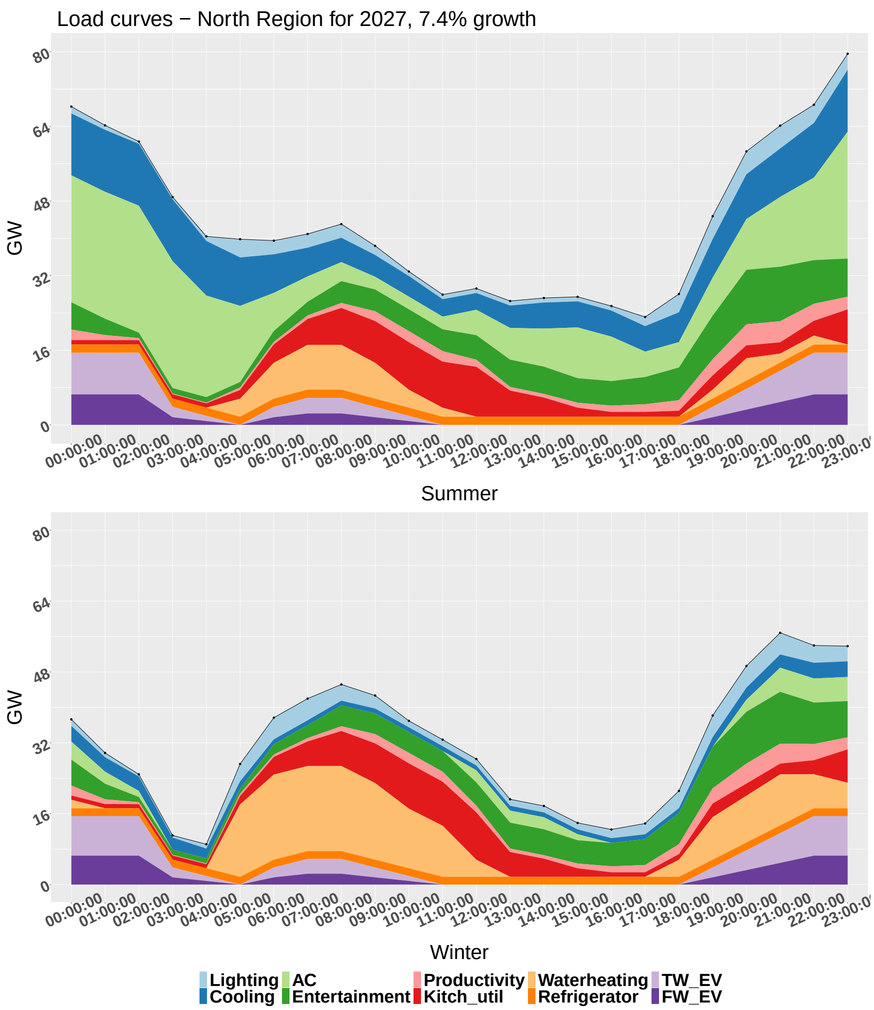

Figure 5: Load curves for North Region, NITI Aayog's 7.4% growth

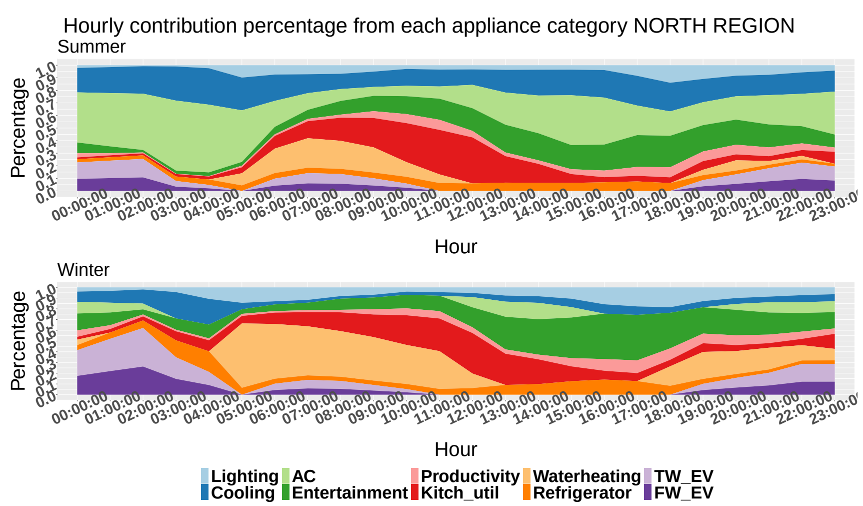

Figure 6: Percentage contributions from different appliances and categories for North region

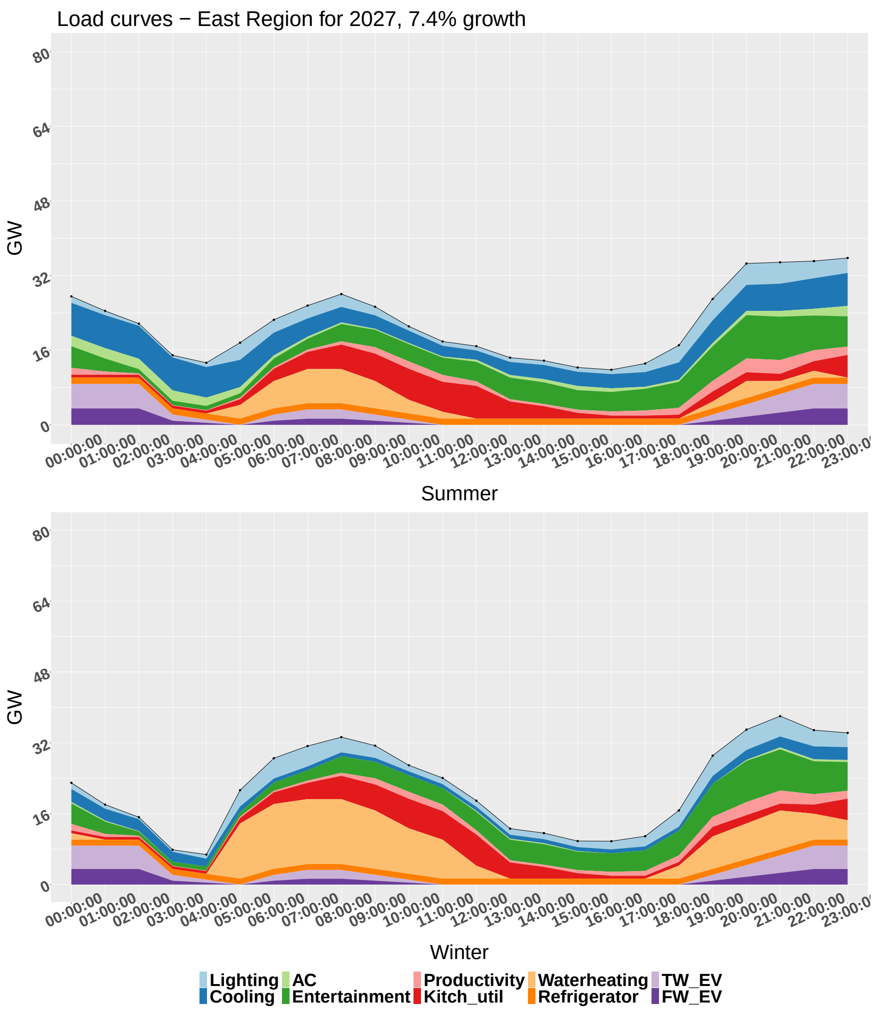

Figure 7: Load curves for East Region, NITI Aayog's 7.4% growth

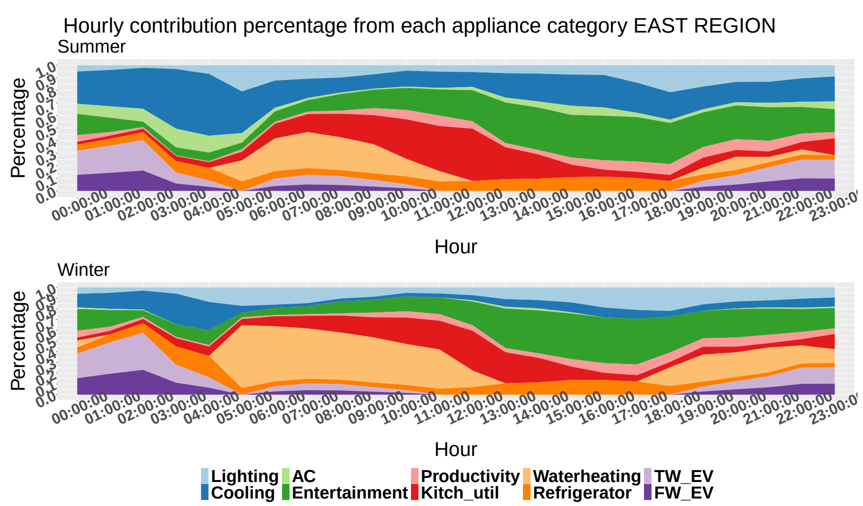

Figure 8: Percentage contributions from different appliances/categories for East region

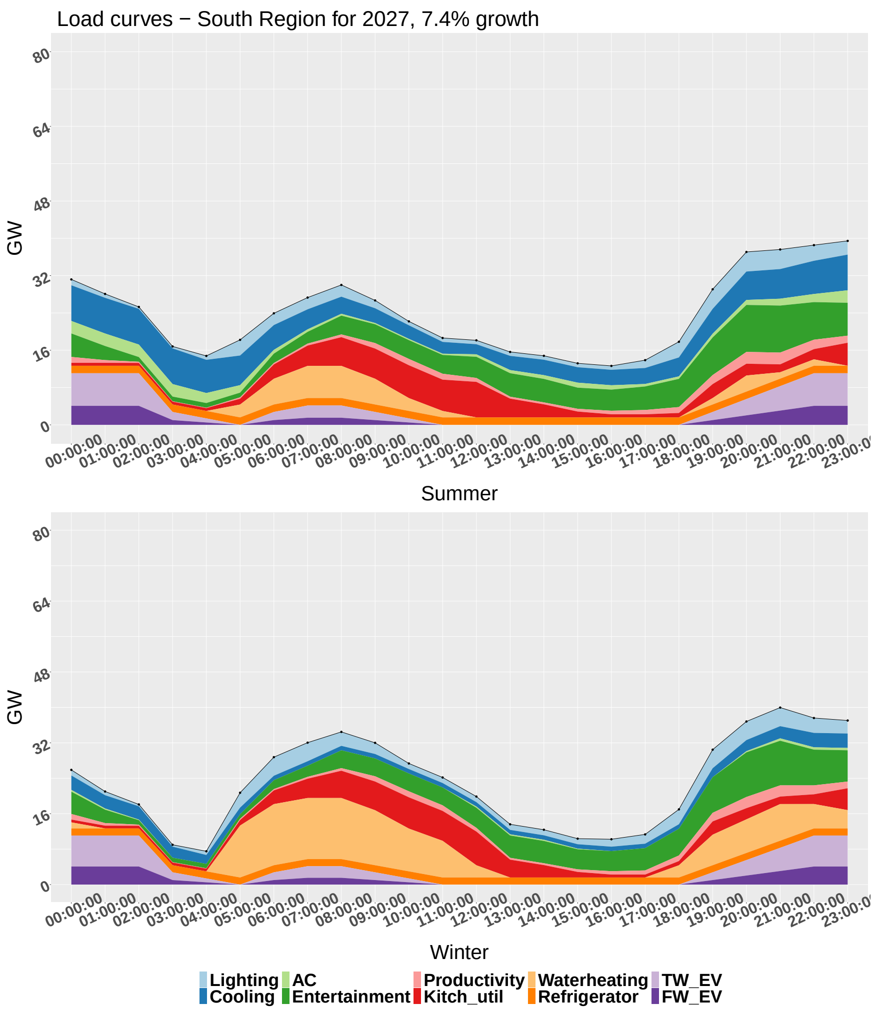

Figure 9: Load curves for South Region, NITI Aayog's 7.4% growth

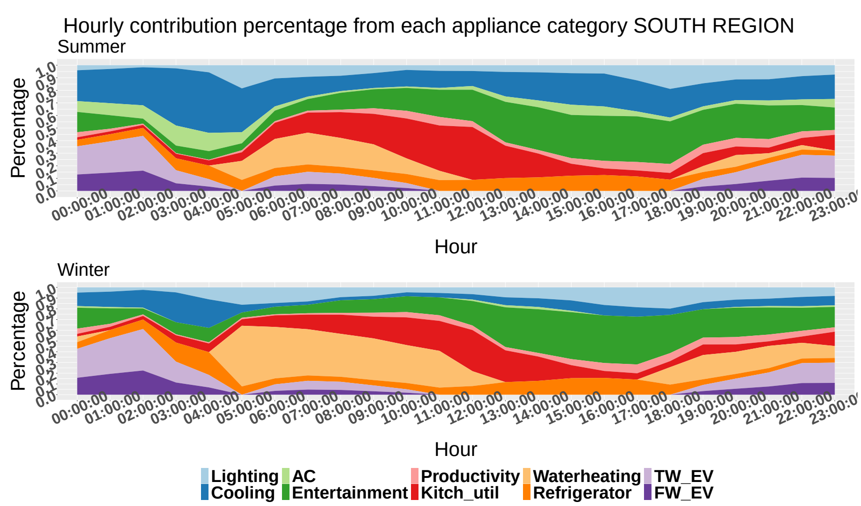

Figure 10: Percentage contributions from different appliances/categories for South region

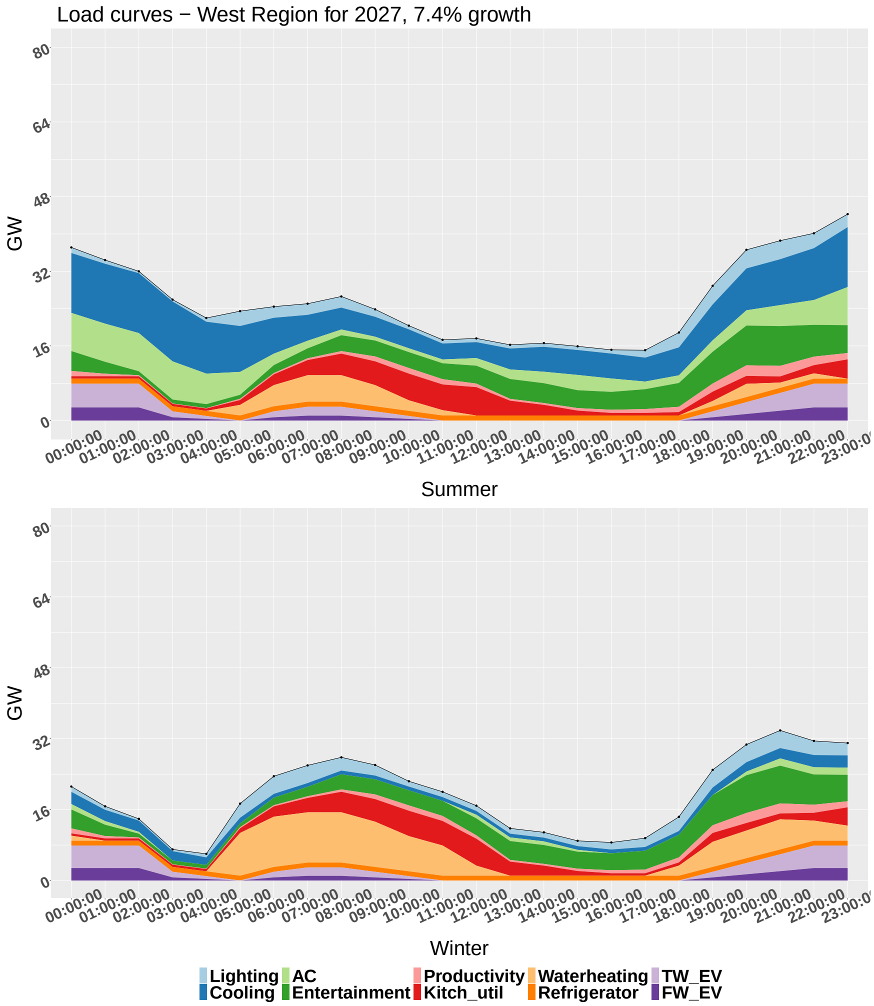

Figure 11: Load curves for West Region, NITI Aayog's 7.4% growth

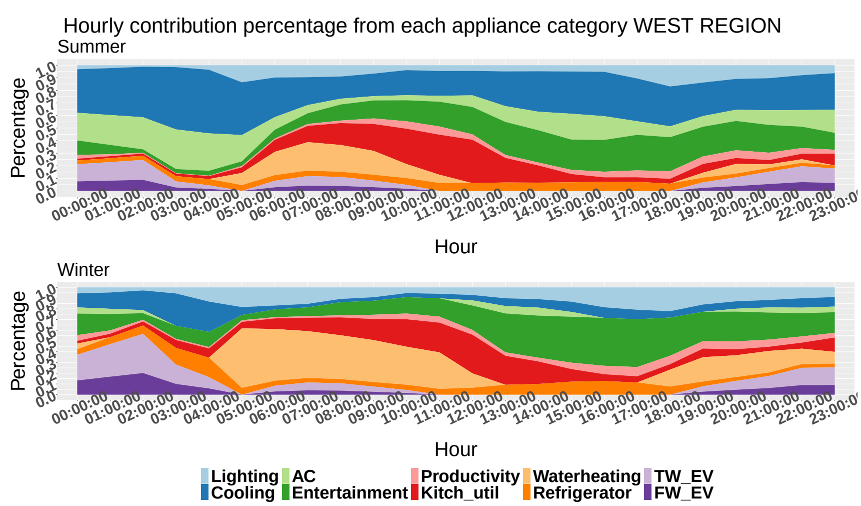

Figure 12: Percentage contributions from different appliances/categories for West region

Looking at figures 5 to 12 we observe that the north region has significantly higher deamand compared to all the other regions. This can be attributed to the fact that the northern region has the highest number of households and significantly higher average incomes. When looking at the contributions from each appliance/appliance categories across all regions, we observe that demand from categories like lighting, entertainment or productivity appliances, the difference is not significant. The first significant variation in intensity of demand can be observed when from the cooling appliances.

The demand from fans does not indicate variations that are significant. When coolers and ACs are compared, significant differences can be observed between regions. While this can be attributed to the skew in ownerships as seen in table 9, a valid additional consideration is the climate aspect. Northern India sees on average the hottest and driest summers compared to most of the country, and includes cities/states that fall under desert climates (table 8). This drives the need for additional cooling especially in summers. Next in line in terms of demand from ACs specifically is the western region. This region has richer cities in states like Maharashtra, Gujarat and Goa that dot that coast line with Gujarat also experiencing hot and dry summers in cities that are in the north east regions of the state. Studies have indicated the correlation of income and increased cooling demand especially from ACs [15, 16].

In order to understand some of the climate zones that overlap these states and and correlate ownerships of key appliances with climate, figure 13 presents climate zones in India and the states that fall under each zone. It can be observed that states like Maharashtra and Gujarat have more than one climate zone as we move through the state. Looking at tables 8, 9, 10 and figure 13, we can correlate the skew in ownership and usage, especially of space cooling appliances.

Next considering water heating appliances, the other appliance with a strong seasonal correlation of use. We see that the usage of water heaters is almost uniform across all regions, with ownerships ranging between 11% to 15% across the country. What this statistic does not reflect though is the difference in the ownerships of solar based water heaters.

The adoption of solar water heaters is significantly higher in the southern and western states compared to other regions of the country [17]. This would indicate that there might be a probability of over estimation of demand from water heaters, especially in the southern and western regions. But considering the usage patterns of geysers and solar water heaters observed from our primary survey, evidence suggests that in winters, usage of solar water heaters drop and

Figure 13: Climate overlay india

usage of geysers increase, indicating that the overestimations (if any) will not be significantly high.

Finally when considering EVs, the northern region indicate the highest penetration numbers and demand followed by the southern region. Considering the projections of personal non-EV transport (table 10), this trend is expected as these are the regions that see significant increase in two wheelers and four wheelers.

These trends disaggregated regionally presents more insights compared to data at just national level. This also presents a perspective of why policy formulations need to be re-looked and why a one size fits all mode might not work and why a disaggregated approach might be more effective.

1.6. Trends from Urban and Rural disaggregation

Data from world bank [18] indicates that in 2018 approximately 66% of India still lived in rural areas. Data from IHDS (figure 1 chapter 6) shows that between the two survey periods rural areas have seen significant growth in appliances penetration compared to urban areas. Considering that the government under the *Saubhagya* scheme has electrified approximately 99.93% [19] as of June 2020, which is significant rate of electrification, given approximately 34% country was not electrified in 2011-12 [4]. With this rate of growth, it becomes important to see how demand is going change in urban and rural ares and how each of these regions will contribute to the demand. To identify the changes for these two regions, we began by splitting the projected data first into urban and rural areas based on census 2011 urban and rural markers and re-estimated the average ownerships for each of these regions.

1.6.1. Ownerships and Consumptions

Table 11 and 12 present data on ownerships of appliances for urban and rural areas along with estimated consumptions comparing IHDS data. The first thing to note is that the number of households and consumer base in rural areas is much higher. When we see the total consumptions from rural and urban households in 2027 we observe that there is not a significant difference between the two. Total consumption from rural households comes to approximately 206.7 TWh and urban households stand at 206.5 TWh. In order to put these numbers into perspective, it is important to remember that rural households are higher in number. They see a higher growth in appliances compared to urban households that start off at a higher base ownership. Even at a conservative estimate of rural population at 60% in 2027, down from 66%, this is still relatively lower per household demand compared to urban households.

Rural Data								
			Penetratoins		**Numbers**		**Consumption**	
Appliance	**Avg watt/hr**	**Hours/yr**	**ihds**	**NITI 7.4%**	**IHDS numbers**	**NITI 7.4%**	**IHDS**	**NITI 7.4%**
Lighting	60	3000	1.000	1.000	1.70E+08	2.00E+08	30.58	35.97
Fans	75	4015	0.658	0.824	1.12E+08	1.65E+08	33.66	49.56
Coolers	250	800	0.110	0.259	1.87E+07	5.18E+07	3.74	10.37
AC	1900	600	0.005	0.044	9.18E+05	8.76E+06	1.05	9.99
ColorTv	120	2200	0.493	0.732	8.37E+07	1.46E+08	22.10	38.60
Cable	60	2200	0.399	0.631	6.78E+07	1.26E+08	8.95	16.65
Computer	90	2000	0.027	0.021	4.61E+06	4.12E+06	0.83	0.74
Desktop	200	2000	0.020	0.013	3.43E+06	2.60E+06	1.37	1.04
Mixer	600	60	0.224	0.270	3.81E+07	5.40E+07	1.37	1.94
WM	450	310	0.044	0.049	7.42E+06	9.89E+06	1.03	1.38
Refr	50	8760	0.169	0.133	2.86E+07	2.66E+07	12.55	10.49
MW	600	37	0.004	0.025	7.49E+05	5.07E+06	0.02	0.11
Geyser	1500	547	0.047	0.051	8.04E+06	1.01E+07	6.59	8.29
TW EV	600	950	0.002	0.113	3.71E+05	2.26E+07	0.42	12.91
FW EV	3500	950	0.000	0.013	2.56E+03	2.61E+06	0.01	8.68
TW	0	0	0.218	0.227	3.71E+07	4.53E+07	0	0
FW	0	0	0.030	0.065	5.13E+06	1.31E+07	0	0

Table 11: Rural ownership of appliances

Urban Ownership								
			Penetratoins		**Numbers**		**Consumption**	
Appliance	**Avg watt/hr**	**Hours/yr**	**ihds**	**NITI 7.4%**	**IHDS numbers**	**NITI 7.4%**	**IHDS**	**NITI 7.4%**
Lighting	60	3000	1.000	1.000	8.05E+07	9.47E+07	14.50	17.05
Fans	75	4015	0.937	0.961	7.54E+07	9.11E+07	22.72	27.42
Coolers	250	800	0.308	0.406	2.48E+07	3.85E+07	4.97	7.69
AC	1900	600	0.050	0.149	4.05E+06	1.41E+07	4.61	16.07
ColorTv	120	2200	0.847	0.877	6.82E+07	8.31E+07	18.02	21.94
Cable	60	2200	0.769	0.801	6.19E+07	7.58E+07	8.18	10.01
Computer	90	2000	0.151	0.430	1.22E+07	4.07E+07	2.19	7.33
Desktop	200	2000	0.122	0.374	9.86E+06	3.55E+07	3.94	14.19
Mixer	600	60	0.546	0.860	4.40E+07	8.15E+07	1.58	2.93
WM	450	310	0.202	0.347	1.63E+07	3.29E+07	2.27	4.58
Refr	50	8760	0.490	0.885	3.95E+07	8.38E+07	17.29	36.71
MW	600	37	0.042	0.080	3.35E+06	7.57E+06	0.07	0.17
Geyser	1500	547	0.096	0.144	7.73E+06	1.36E+07	6.35	11.16
TW EV	600	950	0.0004	0.332	3.36E+04	3.15E+07	0.02	17.94
FW EV	3500	950	0.0000	0.036	3.50E+03	3.42E+06	0.01	11.36
TW	0	0	0.417	0.664	3.36E+07	6.29E+07	0	0
FW	0	0	0.087	0.180	6.99E+06	1.71E+07	0	0

Table 12: Urban ownership of appliances

In rural areas, significant increase in demand comes from Fans, coolers and ACs, with ownerships going up from 65% to 82%, 11% to 25% and 0.5% to 4% (Approx. 8 times increase) respectively. This is followed by entertainment appliances where we see the demand from TVs and set top boxes almost doubling. The contribution from the rest of the panel of appliances is not as high as these two categories. Based on the appliances that saw an increase in penetration, this indicates a probable transition of low income households to mid income and mid income households to high income

In the case of urban households, we see that fans already had high penetrations, with coolers and ACs seeing significant growth. The demand from ACs almost grows four times and ownership increasing from 5% to 15%. This is followed by the productivity appliances of (laptops and desktops) with demand from these appliances also increasing about 4 times and penetrations increasing from 15% to 43% and 12% to 37% respectively. The demand from refrigerators also almost doubles. Finally, we can see that the electric vehicles almost become a new category with ownership of two wheeler EVs at approximately 33% and four wheeler EVs at approximately 3.6%. We can see that in total this category adds close to 28TWh to the total urban residential demand.

1.6.2. Load Curve Model and Load Curves

The model for the generating load curves for urban and rural areas is the same as the four region load curve model presented in section 4.2.1.1 of this chapter. In this case the regions are two: urban and rural. The load curves and the percentage contributions from each appliance/category is presented below in figures 14 to 17

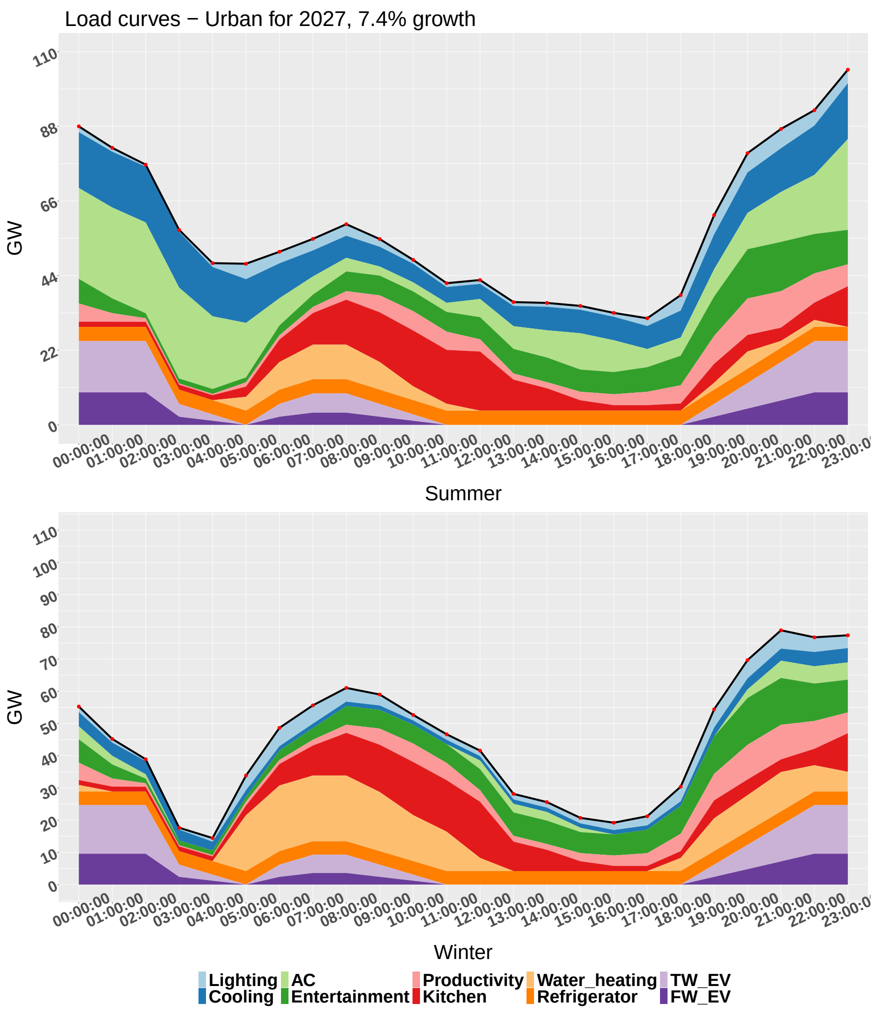

Figure 14: Load curves for Urban areas , NITI Aayog's 7.4% growth

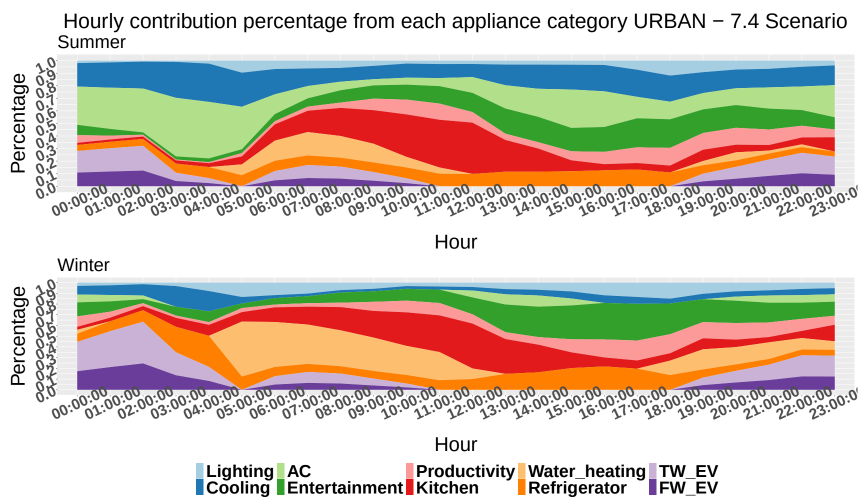

Figure 15: Percentage contributions from different appliances and categories for Urban areas

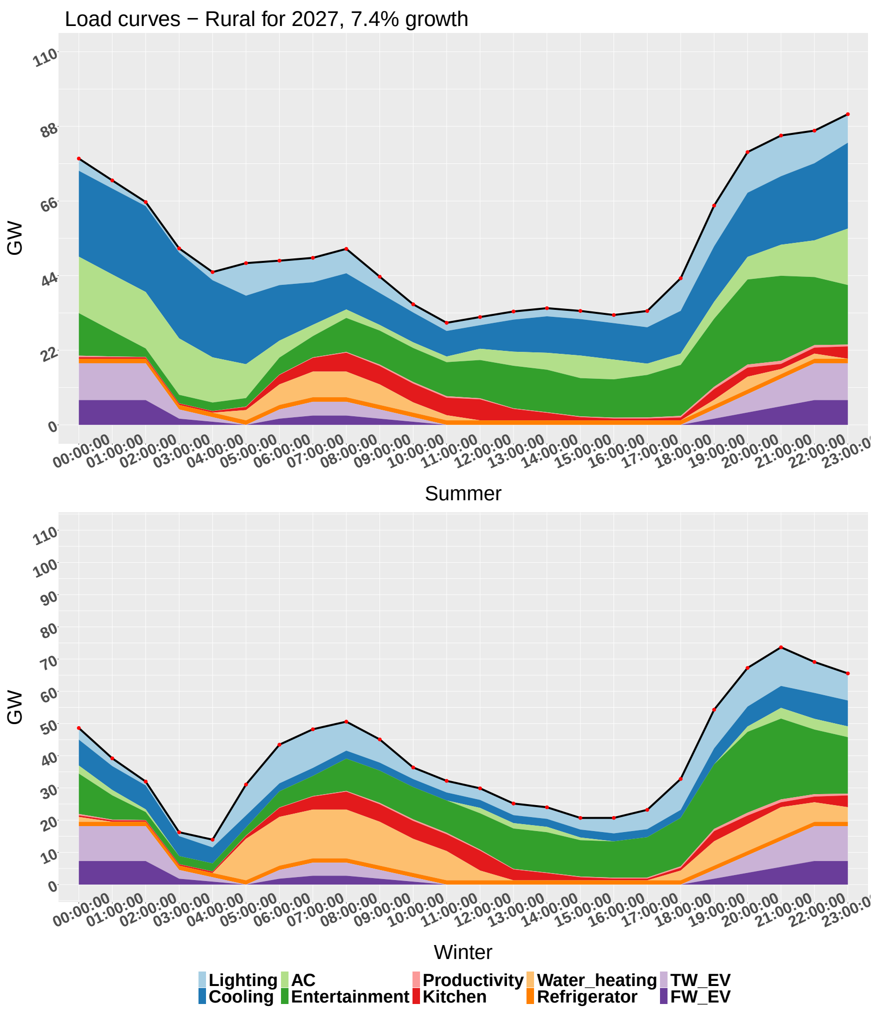

Figure 16: Load curves for Rural areas , NITI Aayog's 7.4% growth

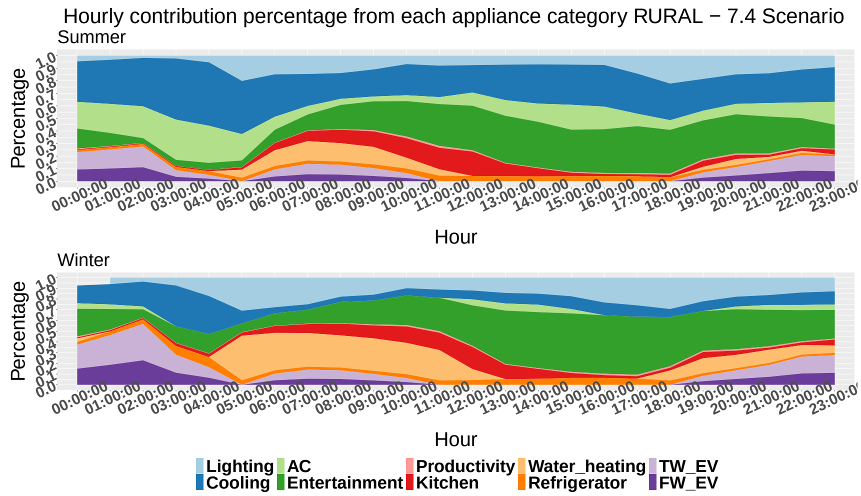

Figure 17: Percentage contributions from different appliances and categories for Rural areas

Looking at the load curves and percentage contribution plots, it can be clearly seen that difference in demand from these two regions. Considering rural areas have more households compared to urban areas, demand from rural areas across seasons (base and peak) is lower than urban areas. There are also differences in the contributions from the different appliance categories across. First, the demand from lighting across seasons is higher compared to other appliance categories in rural areas. This could be due to the skew in ownership of other heavy appliances towards urban areas. Next, in summers demand from air conditioners dominates the cooling load in urban areas compared to the other two cooling appliances combined. Next, the relative demand from entertainment appliances is significantly higher in rural areas. In the case of productivity appliances, the demand from them is very small in rural areas. Similarly the other appliance that has a lower demand in rural areas are refrigerators. In urban areas demand from refrigerators form a constant and significant part of the base load along with more prominent water heating peaks. Though EV's form a significant part of demand from both the regions, the scale of demand is higher in urban areas which is expected given the comparative penetration of vehicles in both these regions.

Section Summary

Analyzing appliance ownership data by deciles and disaggregated regionally (4 regions and urban and rural) significant variations in ownership and usage patterns can be observed. Correlations between climate and ownership of different appliances was observed with the hotter parts of the country seeing higher ownerships of appliances like coolers and ACs. This also had direct impacts on the peak intensity of demand from each of the regions, seasonally.

There were also similarities in trends that were observed across various disaggregations. The shape of the demand curve showed some consistency in shape across different regions with only season driven shape variations. On closer examination, while differences were observed in terms of contributions from different appliance categories, what remained consistent is the two-peak structure of the load curve, due to morning and evening peaks. The peaks showed seasonal variations in intensity, but the structure of two peaks remained consistent. This is very typical of a residential demand curve and does not vary much. This can pose a challenge from a supply perspective [20], especially during the evening peaks. The overlap between renewable drop off (around 4pm) and ramping up of base load plants coincides with the steep increase in residential demand driven by lighting and space cooling loads, with a significant spike in summers, with a minor shift in demand from lighting in winters. Looking at percentage contributions from different categories, we see that there is significant contribution to the morning peak from water heating appliances in both summer and winter with space cooling adding significantly in summers. The demand from entertainment and productivity appliances is very significant and can not be overlooked. The projected growth of this segment indicates that it will contribute significantly, especially to the evening peak, with no significant variations seasonally. Finally, EVs emerge as the **"new category"**. Even with conservative estimates in growth in EVs, we see that there is a high probability of peak coincidence with significant addition to peak demand, as evidenced by the load curves.

But the most important take away is the importance of disaggregated analysis of demand. All of the insights presented were possible because the model was a bottom up, end use disaggregated model. It is especially important considering the variations we saw especially across income deciles. Identifying how different income deciles experience growth is key in designing tailor made policy structures, not just for different income brackets but also regionally.The next section outlines some key policy directions, suggestions and amendments based on the national model and analysis.

2. Some Policy Insights and Directions

2.1. Regularized Surveys and Push for Smart Meters

The need to identify variations in consumption patterns is important to design relevant and effective policies and policy framework. The key is to collect relevant data covering key appliances owned and their descriptors, purchasing patterns, replacement patterns and usage patterns. There are two broad ways of doing this. **Surveys** and **Smart meters**. Data from them can be used to analyze usage patterns across all electricity consumption sectors.

2.2.1. Surveys

There are a variety of surveys conducted by the Government of India covering appliance ownerships, but none specifically targeting residential electricity consumption. Countries like USA, UK have dedicated to enable information driven policy making.

India currently does not have any such *purpose driven surveys* covering energy consumption. The work presented chapters 2 to 5 highlights the benefits of such surveys. They key aspects that these surveys need to cover are

- Types of appliances owned and their descriptors (size, wattage, star rating, etc.)
- Electricity supply patterns
- Consumption patterns of electricity through various end uses
- Gross electricity consumption information through bill amounts and units consumed
- Purchase patterns of households and time line of purchase of various appliances in the households
- Replacement rate of different appliances in the household
- Propensity of households to purchase specific appliances that have significant impacts on demand
- Information/knowledge exposure of current policies and efficiency improvement practices

This is not a exhaustive list but provides a template to identify key areas that need to be covered. For example gaining an understanding of the replacement rate and purchase patterns of appliances can aid in proposing a frame work that encourages domestic consumers to replace appliances that have long life cycles (Refrigerators, ACs, Fans, etc.) keeping in tune with efficiency improvements. Frequent replacements are not carried out for many appliances as they expensive. But with the right incentive program driven policy these rates could be improved.This is one instance of how *purpose driven data collection* can aid in formulating policies aiding efficient demand management (as outlined in chapter 5).

2.2.2. Smart Meter Programs

Surveys are good to capture an annual snapshot of appliance ownership trends and usage patterns. But it fails when it comes to collecting regular data or real time information. To get real time information on usage pattens at higher time resolutions the country's smart meter infrastructure needs to be increased.

In the India, the Energy Efficiency Services Limited is the primary agency installing smart meters. As of May 2020 EESL has installed just over 1.2 million smart meters in four states and one union territory [21]. The current smart meter count is less than 1% of the total households in the country. This is both good and bad. Bad because implementation pace needs to be improved. Good because, it gives us room to plan the installation of these meters to benefit policy planning based on data obtained.

One strategy for their installations is to begin with households that are high consumers of electricity. This can serve as a good pilot program to gauge responses of end users to various demand response programs. High consumption households are a good target because they add significantly to demand and are in the economic bracket that can afford increases in prices. This pilot can help identify price sensitivity for these users and set threshold level prices for different price based DSM programs and see which work.

Another benefit with real time monitoring is the ability to set dynamic pricing framework with varying ***peak slabs***. Just like households are put into "sanction loads slabs" and are charged a base fee in their bills, with smart meters we can implement ***peak demand slabs***. These peak demand slabs would be based on the intensity of the peak demand seen from that meter. For example a household using an air conditioner would see a different peak demand in summer afternoons compared to households that are only using fans. So if a threshold was set to change pricing based on peak demand values, a staggered price mechanism for peak demand can be implemented that sets different price points for different groups of households.A real world case for this is the data we can see in table 7. We can see as we move up income demand changes significantly. Using this method these households can be targeted with different peak demand price structures for DSM programs.

These examples outline how a policy and DSM programs would benefit from smart meters opening up avenues for creative mechanisms of policy formulation with the added benefit of smart meters to stop theft and other losses that plague the system right now.

2.2. Policies Around EVs

The FAME II program (Faster Adoption and Manufacturing of Hybrid and Electric Vehicles in India) implemented by the government, under the NEMMP (National Electricity Mobility

Mission Plan) is pushing for faster adoption of EVs across all vehicle ranging from 2, 3, 4 wheelers to all modes of public transport [22]. In the personal vehicles segment the government if offering subsidies to all users who adopt EVs [23].

Assuming NITI Aayogs projections of increase in ownerships of EVs holds, we see from load curves in figures 3, 5, 7, 9, 11, 14, that demand from EVs become an integral and significant part of the household demand in 2027. They also show peak coincidence, in the nights during the summers and add to the morning peaks during the winters. This is observed because personal transportation is used to commute to and form work leading to EVs being charged at nights or during the day leading to peak coincidence.

One way to manage this peak coincidence is to provide ***economical*** charging infrastructure as an alternative. If a part of this load can be moved to utilize the expanding solar infrastructure from 10 am onward, this will bring down proportionally the demand during nights and early morning hours, while depending lesser on base load plants meeting most requirements.

The key to this, is ***economical pricing*** of the charging infrastructure along with rapid increase in the number of third party charging stations. The pricing structure for this charging infrastructure, especially for personal vehicles, needs to be on average lower than or on par with what users pay for domestic consumption. If the prices are any higher it could de-incentivize users from using this charging infrastructure.Especially in urban areas the need for shared common charging infrastructure needs to be a real consideration given the rate pf expansion which is also more vertical to maximize space available. This would indicate that there could be high density charging needs from each of the high rises creating significant demand spikes. Large number of charging stations geographically spread out across the city at key areas would provide a good alternative and lead to a high possibility of seeing reduction in concentrated charging demand spikes from high density residential establishments.

Given the push with FAME-II, incentives and the current low adoption of EV across there still is opportunity to plan the installation of infrastructure that is decentralized and at key points across urban areas, meeting charging needs from this sector before the demand outweighs the capacity. With proper planning and pricing mechanisms this infrastructure can be integrated to leverage the growing solar capacity in the country.

2.3. Advantages of Passive Architecture and Energy Conservation Policy Impacts

In India, approximately a quarter of the electricity produced is consumed by residential buildings. A significant part of this demand goes to meeting lighting and space cooling demand (table 3). One way of effectively managing this is by using passive and energy efficient building design methods. Passive design methods include designs to providing better light and ventilation, managing building orientation to minimize thermal foot prints, using of thermally insulating material for building shells, using different types of window designs, inclusion of green cover, etc. Estimates indicate that approximately 25% to 30% of energy on average can be saved by using passive methods [24, 25].

India has a variety of initiatives to implement energy efficiency standards for residential buildings including National Building Code (NBC), Energy Conservation Building Code (ECBC), Indian Standard SP:41 modified Leadership in Energy and Environmental design (LEED) homes, Small Versatile Affordable Green Rating Integrated Habitat Assessment (SVA-GRIHA). But studies have shown that these standards are not strictly implemented in all residential constructions [26]. While the standards are strictly formulated at the center and state levels implementation is found to be lacking on ground. This is a key point of failure.

Stricter measures need to be put in place to make following these norms mandatory. For example, in the case of non compliance to building codes, approvals of building plans should be withheld. In case post approval, the norms are not followed, fines and other penalty structures need to be put in place, similar to what is followed in countries like USA and Europe. Strong policy framework incentivizing passive designs for both high rises and independent houses needs to be put in place. Along with policy, awareness programs need to be put in place in government offices and websites to enable consumer to gain easy access to information during planning and approval phases of their homes/buildings. The awareness program needs to highlight potential savings, ROI periods for solar and other energy saving installations along with a approved list of vendors that can provide these services at government approved rates. One way to ensure these norms are followed is to enable a stricter framework of auditing systems that monitor and penalize buildings not following norms.

2.4. Time Zones in India

In the report titled ***"Options for Adjusting Indian Standard Time for Energy Savings" (IST)*** [27, 20, 28], the authors present a valid case for either introducing a ***day light savings time*** or ***advancing IST*** by half an hour or ***introducing two time zones***.

[28] suggest that the most advantage is achieved by advancing IST by 30 minutes from the current time zone of 5.30 + GMT to 6 hours + GMT. It is estimated that there would be over 2 billion units saved year on year coming largely from the evening hours when the utilities find it difficult to manage the rapidly rising evening peak.

Primary reason for change in standard time is to make more use of the daylight in the evening, thus reducing the amount of lighting energy needed, which is a major contributor to evening peaks.This was observed in the load curves presented in figures 3 to 17. Report further elaborates based on studies conducted, that the evening bumps seen in the aggregate load curves are much like the ones seen in residential curves.

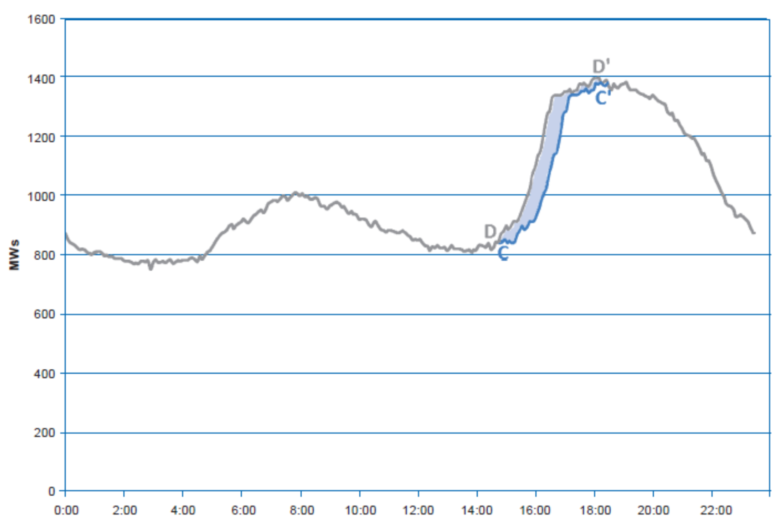

Figure 18: Reduction in demand from time shift

Figure 18 (source: *(Options for Adjusting Indian Standard Time for Energy Savings, D.P Sen Gupta, Dilip R. Ahuja)*) shows the savings potential by shifting IST by thirty minutes in MW.

This is a valid proposal considering the fact that commercial load like malls and office building do not vary much through the day. All the lighting load coming up post sunset can be pushed ahead by 30 minutes. This not only provides significant savings of 2 billion units year on year but also brings down the stress on plants needing to keep up with the quick rise in demand for the evening peak.

3. Summary

In this chapter we presented appliance stock, demand from the projected appliances, total demand and a model to generate load curves, followed by a few key policy directions.

The first section of the chapter presented the appliance stock nationally projected to 2027. Assumptions to estimate demand from each appliance, appliance category and total demand was presented followed by demand estimates. Next, in order to identify the patterns of consumptions and contributions from different appliances, the load curve model was outlined followed by national load curves.

Considering the insights observed in chapters 4 and 5 by splitting the data into quintiles, the projected IHDS data was divided into deciles, four regions, and urban and rural to identify variations in appliance ownership and usage patterns. The deciles data presented insights into how different deciles saw changes in percentage contributions to total demand. Deciles that saw significant changes were identified followed by appliances that lead to this. It was observed that significant contributions were not from the upper deciles but the lower deciles, which saw the most growth in appliance penetrations.

Next, the consumptions and load curves were developed for four regions. Correlations between specific appliances ownerships, region and the climate zone were observed. The skew in ownership of key appliances like space cooling were observed in some regions and this skew in ownership was also reflective in the load curves built for each of the regions, with the north region showing the maximum demand and the east region showing the least demand. This was followed by dividing the data into urban and rural areas. It was observed that rural areas saw significant growth across all appliances compared to urban areas, but the demand from the rural areas was approximately on par with urban areas. This was because the urban areas started off at a higher based of ownership and also had the skew of heavier appliances (like ACs, geysers and EVs). Across all disaggregations EVs stood out as the "new sector" that became significant contributors to the load curve with significant peak coincidence.

With the disaggregated analysis and load curve observations, key areas to address with policy were outlines. These policy directions covered surveys, smart meters, EV demand management, passive buildings and novel way to manage evening peak demand rise with significant savings.

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Chapter 8
Conclusions and Scope for Future Work

Residential electricity demand, especially in a developing country like India, is a segment that has seen significant growth of approximately 8% year on year over the last decade. Electrification has also increased to over 99% with the rate of electrification seeing exponential growth over the last 5 years. Coupled with improvements in quality of supply, it has increased the aggregate consumption potential of this sector. This is because households that previously did not have access have now become new consumers and with increase in affordability and access to appliances increasing, electrified consumers are consuming significantly higher and transitioning into newer electricity services. Categories like space comfort are becoming more prominent with influx of ACs, new categories of electric vehicles are set to also become key demand segments. Added to this, variations in consumption and demand from households owing to social, economic, demographic and regional contributions makes this an interesting area to analyze. Currently to gain a deeper understanding there some key limitations and gaps, including lack of pertinent data that is open access, regularized purpose driven data collection methods and fixed modeling approaches to forecast changes in demand. The thesis is organized around trying to address some of these key questions.

Beginning with the larger set questions spanning this sector, which are *what are the primary drivers of residential, how do they vary, what impacts do their variations have on changing end use electricity demand?*

Among these,the questions distilled to address in this thesis were

1. Given the lack of open data, is there a reproducible methodology that can be followed to collect data required to gain an in-depth understanding of electricity demand from the residential sector and what are they key variables that need to be covered?
2. What are the insights we gain if the right set of variables are covered and the right survey is designed?
3. What approaches can be used to then model ownership and usage patterns (load curves) to bring out accurately the variation we expect to see across different households?
4. With these insights, among the various modeling approaches, which approach could be used to model the growth of end use categories (appliances) and changes in demand and consumption patterns (load curves) for short to medium term scenarios?
5. Using the forecast and consumption patterns (load curves) data, what are the key policy insights we can generate and what amendments can be suggested for the current policies and frameworks?

The thesis was organized around these primary questions and sectioned into two parts. The first part of the thesis covered survey design including identifying key variables that can be covered to get pertinent data to optimally model ownership and usage patterns of appliances across different households. This section addressed the first three questions raised. The second part covers building a national model to project changes in end-use segments using a mixed model (econometric+end-use), to model and project national, urban, rural and regional (north, east, south west) changes in ownership and end-uses along with variations in demand patterns (load curves). In both sections, based on the analysis, success and shortcoming in current policy frameworks were identified and suggestions were made for amendment and formulation of new policies.

1. Chapter Conclusions

The **first chapter** of the thesis presented an overview of the electricity sector in the country, highlighting the contributions of various sectors looking at why residential electricity sector is interesting to study as problem. Key growth statistics of the sector were presented indicating that this sector saw the most growth over the last decade. Some key limitations and gaps in the methodologies currently used to understand this sector and its demand trends weew highlighted. The overarching question covering this sector were identified. Questions around addressing some key aspects of the sector were listed to be covered as part of the thesis work.

Chapter 2 addressed the lack of relevant and purpose driven surveys covering this sector and the lack of appropriate data in the public domain needed for multiple studies. The need to identify a methodology that can be easily be replicated to design surveys that can collect data along with listing the key variables and categories that needed to analyze residential demand were outlined. Some open access data sets and surveys were identified that can be used to design a representative survey covering a wide variety of households. Statistical methods that can be used to design the survey sampling methodology were presented. City level data from the municipal website was used to validate the survey areas and samples identified indicating the simplicity of this approach. The chapter concluded by outlining the areas covered and the time-line of survey execution.

Chapter 3 looked at the statistics of the data collected in the survey. The first section of the chapter presents key statistics at aggregate levels looking at the various social, economic, demographic, end use categories and usage hours. The need to divide the data into quintiles and compare statistics was highlighted followed by the methodologies tried. The next section of the chapter presented the data and key statistics in quintiles, indicating key trends and insights for the observed variations in ownership patterns of appliances across households in each quintile.

Chapter 4 identified the need to build models that look at usage patterns or load curves. A load curve model at the aggregate level for the survey were developed followed by load curves for each appliance category. These load curves were developed for summer and winter, at the time resolutions that the data was collected in (4 and 6 hour time resolutions covering peak and non-peak hours). Shortcomings of aggregate load curves were highlighted followed by a model developed to generate load curves by quintiles for summer and winter identifying key variations in the demand patterns of each quintile. The limitations of these load curves with low resolutions were highlighted and the need for higher resolution load curves was outlined.

The **Fifth chapter** presented the need to look at load curved at least at hourly resolutions considering household show variations in use both seasonally and across income brackets. Therefore the generalized load curves developed in 4th chapter were modified and a model to generate load curves at hourly resolutions was developed, preceded by the assumptions made, including some key data that was considered. Using this model hourly load curves were generated, by quintiles, for each appliance, appliance categories along with cumulative and average load curves representing a household in each quintile, for summer and winters. The differences across quintiles and seasons and the observations that emerge with higher resolution load curves were listed. The chapter was concluded by analyzing some key policies built around the residential sector highlighting some successful policies and programs as reflected from the survey data.

In the **sixth chapter**, using secondary data national model was developed to project changes in demand patterns and consumption from the residential electricity sector. A mixed model approach using econometric and end use analysis was used to build this model. An overview of the IHDS survey and the key statistics from both the rounds of the IHDS survey for ownerships of appliances and other key variables were presented followed by the methodology of building the model to project ownerships of appliances. Elaborate step by step procedure was presented on how to identify key variables to for the model and steps to refine the model using various diagnostic metrics. Key variables like populations, households, income and expenditures for three growth scenarios were projected to 2027 to be used as input to the model. To fill gaps of some appliances that were not included in the IHDS data set, statistical methods were identified and used. Three additional appliance/categories were included and estimated which were lighting, water heating and electric vehicles.

Finally in **chapter 7** based on model built in chapter 6, appliances ownerships were projected for each of the three growth scenarios to 2027. Based on the projections of appliances, consumptions for each appliance and appliance category were estimated. To identify variations in ownership and use of appliances due to variations in regional habits, climate zones and population variations, projected data was disaggregated into deciles, urban, rural and 4 regions building models for load curves for each of the different levels of dissagregations. With projections of consumption and demand, few key policy directions that can be taken to manage growth in demand from key appliance categories were outlined.

2. Future Directions

In the previous sections summarizing the work carried out in this thesis, few key questions that are a part of the larger part of analysis of electricity demand were addressed. There are many areas that need equally close analysis, a few are highlighted as part of the future work and as a natural follow on to what was covered in this thesis.

2.1. Long Term Models with Significant Technological Improvements and Automation:

The projections made in this thesis, to 2027, can be considered shot to medium term projections. There is a need to develop a long term model to estimate demand from this sector and model impacts of significant efficiency improvements and automation. As outlined in chapters 5 and 6 switching to LED bulbs in India have had a significant reduction in demand from lighting. This has been in part due government interventions and active participation of DISCOMs. With home automation becoming more affordable it is a matter of time that these technologies become a staple in Indian households. It is a useful exercise to model impacts of automation and efficiency improvements of high energy appliances like ACs, geysers, washing machines with the ability to remotely manage their use.

The other aspect that automation has enabled is the centralized management of HVAC demands from buildings in the west. Building and services management companies in the west work in close coupling with DISCOMs in real time alter HVAC demand from buildings to aid grids manage peak demand. With the trend of vertical housing becoming commonplace in India centralized automation and management will lead to peak management from the residential sector. This also applies to the demand that will come from high penetrations of EVs contributing to these concentrated demand islands.

Modeling these scenarios to estimate potential benefits of technology ingress, enables the government to incentivize implementation of systems and foster an ecosystem of such energy management services.

2.2. Multi-Sector Modeling for An Integrated Energy Demand Analysis:

As we saw through this thesis, the demand from the residential sector is driven by a variety of variables and a bottom up analysis provides better insights into how demand varies. Similarly, other sectors also have drivers that are unique to them that drive their electricity demand patterns. But, across sectors there are also many variables that are common. There are inter sectoral dependencies that drive demand across sectors. A bottom up model for each sector can help identify the demand trends and drivers of each sector, and also aid in understanding inter sectoral dependencies. These insights can be used to build a integrated sectoral demand model that can be used to more accurately forecast demand growth based on variations of common and unique variables across sectors. The first step to this identify and address roadblocks like data availability and modeling approaches. Bottom up approach of policy formulation targeting multiple sectors also then brings in the simplification of the dynamics of peak management and peak shifting across sectors with minimum strain on the supply network and to manage demand growth across sectors with maximum efficiency.

2.3. Household Transition and Energy Demand Impacts Model:

Results presented in chapters 4,5 and 6 indicates how as households that transition into higher income brackets, their consumption and demand patterns changed. Income is not the only factor that drives this energy transition. There are other variables like access, availability of appliances, quality of supply, educational and awareness levels of residents, age demographic of residents among others that drive these transitions. It is critical to analyze these transitions more closely. This gives us a multivariate view of household transitions and the possible trajectory of changes in demand and consumption patterns. This is important for policy formulations and establishing awareness and efficiency programs that are tailor made to target specific household brackets based on their probable transition paths. For example for households transition to using electric water heating appliances as a new service because of improvement in access and/or affordability, provisioning of energy efficient options that are affordable can nudge these households to use them right from the get go, rather than slowly move up the appliance ladder. Simply put, packaging access, affordability, efficiency and nudging transitioning households to a more efficient pathway. A transition model of this type can enable building efficiency directly into the system bottom up and outline potential savings (or lack of) by modeling various transition paths. This can significantly impact policies, pricing and incentives programs.

2.4. Multi-City Survey and Models:

Not all cities grow equally. There are few cities that are identified to be the next growth centers and some currently that are at the peak of growth and modernizing. Considering the repeatability of the primary survey conducted, metro and non metro cities that have seen similar growth over the last decade or two decades need to be surveyed with larger sample size of approximately 1000 households with the right set of variables and questions collecting data on growth dynamics (social and economic) of the cities. This exercise will gives insights into how development in different cities have taken place. This model will help in planning the need for access, growth in demand and bottom up efficiency mechanisms that can be put in place at step one to plan and manage growth efficiently.

3. Conclusions

The thesis started with trying to address a few key questions around understanding residential electricity demand, its divers, current approaches and some gaps. Through the thesis these gaps have been addressed and approaches were suggested that help gain better insights into ownership, use and usage patterns of appliances across a variation of households. The methodologies implemented in collection of data, analysis and model development were demonstrated to be repeatable. Through various exercises carried out in the thesis, efficacy of purpose driven data collection methods and surveys to enable key insights into electricity use behaviors across households spanning income, social and regional brackets were presented. Benefits of purpose driven surveys and data analysis methods in providing insights into analyzing policy and policy frameworks was elaborated using current policies as examples.

Using a mixed model approach a possible outcome of how appliances, consumptions and demand patterns could evolve in the future was presented. Using these projections, current policies were analyzed identifying some key shortcomings and possible areas to address. A set of policies and policy directions were listed to efficiently manage the growth of demand. Through work carried out in chapters 2 to 6 a strong case for data driven, bottom up policy formulation approaches and benefits of such an approach were elaborated on.

Finally, directions for possible future work that can be carried out either by building on this of work or by using the approaches outlined in this thesis work were highlighted covering aspects of data generation, growth planning and policy formulation.

Before concluding, I acknowledge that the work carried out in this thesis is a small contribution to overall domain of electricity analysis, and has scope to be built on in multiple directions. But this work presented in this thesis makes a strong case showing the benefits that a data driven, bottom up, modeling based analysis can bring to a problem of this nature, both in clarity of direction that can be taken in formulating and analyzing it and the real world implication it can have for technology, policy, awareness and outreach programs that can be formulated.

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Survey book No.

NIAS Residential electricity demand survey

National Institute of Advanced Studies, Indian Institute of Science campus

Objectives of the survey

- This **survey is part of the PhD thesis work of C Sashikiran**, who is a student in the Energy and Environment research program at NIAS, IISc
- This survey is being conducted to understand the ownership and hourly usage of electric appliances of a household
- The data collected will include ownership of various appliances, times of the day they are turned on/used at two different points of the year – summer and winter

Declaration

- We are not requesting any personal information as part of this survey (Email, Phone number, Address, Names of residents, exact income etc.)
- All the information collected as part of the survey will only be used for academic purposes and will not be shared with any other non-academic parties
- All the information before use/sharing will be anonymized further by not revealing the area where the data was collected or the type of the household that was surveyed

Surveyor

- The surveyor conducting the survey will carry with him a his official NIAS student ID and/or an authorization letter from the institution, on the institution letterhead that indicates that the student is part of/has been authorized by the institution to carry out the survey.
- You can request to see the ID card/authorization letter any time of the survey in case this has not been presented to you before beginning the survey

Section 1. Household Information

1.1 HH	Household number/Survey number	
1.2 HHA	Area of the Household	
1.3 HHT	Type of the household	**Independent** ☐ **Apartment** ☐
1.3 HHG	Gender of head of household	**Male** ☐ **Female** ☐
1.4 HHS	Ownership of the household	**Own** ☐ **Rent** ☐
1.41 HHRP	If rental, Rent bracket	**R1** ☐ **R2** ☐ **R3** ☐ **R4** ☐ **R5** ☐ **Don't want to say** ☐
1.5 HHLR	Are you from this city? (Living in the city for less than 10 years – non-local)	
1.52 HHOR	If not local, your original city of domicile	
1.53 HHSL	What is the language spoken at home	

Rental Range reference chart					
Rental Ranges	**Less than 5000**	**5000 to 10000**	**10001 to 15000**	**15001 to 20000**	**Above 20000**
Rental Codes	**R1**	**R2**	**R3**	**R4**	**R5**

Section 2. Household Demographics

2.1 HHT	Total Number of people in the household including children	
2.2 HHMT	Total Number of Male members	
2.3 HHFT	Total Number of Female members	
2.4 HHCT	Total number of children (<18)	

Section 3. Household Income and earning members (include people earning pension also)

3.1 EMT	Total Number of earning members	
3.11 EMMT	Total Number of earning members **– Male**	
3.12 EMFT	Total Number of earning members – **Female**	
3.2 RT	Total Household income Range	**HHI1** ☐ **HHI2** ☐ **HHI3** ☐ **HHI4** ☐ **HHI5** ☐ **Don't want to say** ☐

Section 4. Household physical description

4.1 HHSFT	Size of the home in square feet	
4.2 HHBHK	BHK of the household	

Income reference Chart					
Income ranges	**Less than 2 lac**	**2 lac to 4 lac**	**4 lac to 7 lac**	**7 lac to 10 lac**	**Above 10 lac**
Income code	**HHI1**	**HHI2**	**HHI3**	**HHI4**	**HHI5**

Section 5. Electricity information

5A. Electricity bill details

5A.1 EBL	Approximate previous/current month electricity bill	
5A.2	Average monthly bill in	
5A.21 EBS	**Summer**	
5A.22 EBW	**Winter**	
5A.3	Average hours of power cut in	
5A.31 PCS	**Summer**	
5A.32 PCW	**Winter**	
5A.4 EBPY	Electricity bill paid to	**ESCOM** ☐ **Owner** ☐ **Fixed** ☐

5B. Electricity Backup information

Which of the following devices do you use for electricity backup – Make note of number of batteries used.

5B.1	**Appliance**	**Owned**	**Capacity**
BP1	UPS		
BP2	DG		
BP3	Solar		
ABP	Common Back up (only in case of apartments)		
BPB	Batteries		

5B.2 Only for apartments, if common backup is provided

What is the backup power source (Solar/Batteries/DG) | BPCA | |

Section 6. Appliances owned

6A. Living space appliances Owned (totals)

	Appliance	**Owned/ Installed**	**Num.**	**Watt**	Star rating	Age/ When was it bought	Size/ capacity	Total hours used per week day	Total house used per week end day	Usage in Summer (Apr/May)				Usage in Winter (Dec/Jan)			
6A.1	**Lighting**									6am-10am	10am-6pm	6pm-11pm	11pm-6am	6am-10am	10am-6pm	6pm-11pm	11pm-6am
L1	Incandescent																
L2	Tube light																
L3	CFL																
L4	LED																
L5	other																
6A.2	**Space cooling**																
SC1	Fan																
SC2	Cooler																
SC3	AC																
SC4	Other																
6A.3	**Space Heating**																
SH1	Electric Heater																
SH2	Others																
6A.4	**TV**																
ET1	CRT																
ET2	LCD																
ET3	LED																
ET4	Other																
6A.5	**Computer**																
EC1	Desktop																
EC2	Laptop																
EC3	Both																
EC4	Other																

6A.6

On a summer night how many of these appliances are on simultaneously (Fill AC and cooler section only if they have more than one)

6A.6	**Space cooling**	Numbers on simultaneously	Approx. Hours on simultaneously
SCOS1	Fan		
SCOS2	Cooler		
SCOS3	AC		

6A.7

If you have more than one TV and Computer, how many of them are on simultaneously

6A.7	**Appliance**	Numbers on simultaneously	Approx. Hours on simultaneously
ET1	CRT		
ET2	LCD		
ET3	LED		
EC1	Desktop		
EC2	Laptop		

6A.8

If the household has more than one AC/cooler installed, at what times of the day are each of them on?

6A.8	Appliance	Nos. in Living room	Nos. in Room 1	Nos. in Room 2	Nos. in Room 3	Nos. in Room 4	Usage in Summer (Apr/May)				Usage in Winter (Dec/Jan)			
							6am-10am	10am-6pm	6pm-11pm	11pm-6am	6am-10am	10am-6pm	6pm-11pm	11pm-6am
FOR	Fan													
ACOR	AC													
COOR	Cooler													
TVOR	TV													
L1OR	Incandescent													
L2OR	Tube light													
L3OR	CFL													
L4OR	LED													

6B. Kitchen and Utility appliances Owned. Enter room name

	Appliance	**Owned/ Installed**	**Num.**	**Watts**	Star Rating	Age/ When was it bought	Size/ capacity	Total hours used week days	Total house used week ends	Usage in Summer (Apr/May)				Usage in Winter (Dec/Jan)			
										6am-10am	10am-6pm	6pm-11pm	11pm-6am	6am-10am	10am-6pm	6pm-11pm	11pm-6am
6B.1	**KITCHEN**																
K1	Refrigerator																
K2	Microwave																
K4	Induction cooktop																
K5	LPG stove																
K6	Electric coil heater																
6B.2	**Lighting**																
KL1	Incandescent																
KL2	Tube light																
KL3	CFL																
KL4	LED																
6B.3	**UTILITY**																
U1	Washing machine																
U2	Motor/ pump																
6B.4	**Lighting**																
UL1	Incandescent																
UL2	Tube light																
UL3	CFL																
UL4	LED																

6B.5 If you do not know the power of the water pump/motor, Do you know the height of the tank (how many floors)?

	Height
Pmpht	

6C. Bathrooms appliances Owned.

	Appliance	**Owned/ Installed**	**Num.**	**Watts**	Star rating	Age/ When was it bought	Size/ capacity	Total hours used week days	Total house used week ends	Usage in Summer (Apr/May)				Usage in Winter (Dec/Jan)			
6C.1	**Water heating**									6am-10am	10am-6pm	6pm-11pm	11pm-6am	6am-10am	10am-6pm	6pm-11pm	11pm-6am
WH1	Geyser																
WH2	Emersion Rods																
WH3	Instant heaters																
WH4	Solar water heater																
6C.2	**Lighting**																
BL1	Incandescent																
BL2	Tube light																
BL3	CFL																
BL4	LED																

6C3. How many bathrooms in the household

TBHH	

6C.4 If the household has more than one Bathroom with Geyser installed, what times are they on?

6C.4	Appliance	Nos. in bathroom 1	Nos. in bathroom 2	Nos. in bathroom 3	Nos. in bathroom 4	Usage in Summer (Apr/May)				Usage in Winter (Dec/Jan)			
						6am-10am	10am-6pm	6pm-11pm	11pm-6am	6am-10am	10am-6pm	6pm-11pm	11pm-6am
WH1OB	Geyser												
WH3OB	Instant geyser												
WH4OB	Solar												
WHOOB	Other (mention)												

6C.5 **Water heating use in Monsoon**

Usage in Summer (Apr/May)			
6am-10am	10am-6pm	6pm-11pm	11pm-6am

(Ask if they own/use electric water heaters)

6C.6 For how many minutes/hours is the geyser/water heater on daily

WHHO	

(Ask only if more than 1 water heater)

6C.7 How many water heaters are on at the same time in your home

WHOS	

(Ask only if the household has solar water heater)

6C.8 Do you use more of electric water heat in the monsoon compared to Summer/Winter months? (record(y/n))

WHMU	

Section 8. Ownership of Vehicles

8A. Ownership of vehicles

8A	Vehicle	Currently own (Y/N)	Number of each vehicle owned	Number of times used weekly	Fuel type (P/D)	Approximate distance travelled daily (KM)	Most frequent mode of public transport used when not using the vehicle
VH1	Two-Wheeler						
VH2	Four-Wheeler						

8B. Ownership of electric vehicles

8B	Vehicle	Currently own	Buy one in the next 5 years	Hours of charge per day	Time of the day charged	Number of charges per week	Wattage/power per charge
EV1	Two-Wheeler						
EV2	Four-Wheeler						
EV3	Both						

Section 9. Which will you buy in the next year

9.1	Appliance	Response	
ACO	Will you buy an AC in the next one year?		
COO	Will you buy a cooler in the next one year?		
9.2	**Appliance**	**Response code**	**Response code choices**
NACR	Why have you not bought an AC yet?		1 - Too expensive to own 2 – Expensive to use 3 – Not needed in Bangalore climate 4 – Difficult to maintain 5 - Other
NCOR	Why have you not bought a cooler yet		