A Study on Electricity consumption in a typical urban residential building in India

Abstract

Understanding the energy usage of buildings is crucial for policy making, energy planning, and achieving sustainable development. Here, we analyze the energy data from smart meters installed in a residential building inside the campus. In doing so, we demonstrate the impact of weather on energy usage, the correlation between different age groups of people and their energy usage. Also, we have presented the results of a survey that we conducted at the building mentioned above to check the knowledge of people on their electricity usage and a possible way of improving their awareness through an Android application.

1.Introduction

Buildings consume about 40% of global energy and the share of residential sector is 23%.The building sector is the largest contributor of GHCG emissions.Due to the rapid economic expansion, India has one of the world's fastest growing energy markets and is expected to be the second-largest contributor to the increase in global energy demand by 2035, accounting for 18% of the rise in global energy consumption. As a result, it is crucial to understand the usage pattern and optimize the energy usage in buildings.

The availability of cheap smart meters in the market that can monitor buildings energy usage with good granularity in order of seconds is a great advantage. Studying the energy usage with high resolution can help us to gain insights into how the energy consumption of a building varies due to different factors. This is, in turn, important for better energy management plans and identify potential ways of reducing energy wastage.

Here, we analyse the data collected by 60 smart meters deployed at a residential building inside the campus of IIT, Bombay for a 6 month period of time.We try to answer some of the following questions such as how to i) improve the energy efficiency ii) find out different consumer load profiles iii) quantify influence of weather on energy consumption iv) find a relationship between age of the occupants and their usage v) improve the awareness.

Background of the study

The study mainly focuses on understanding the energy usage of a residential building, both at the building level and apartment level by using the data collected from the smart meters and by conducting a survey. A smart meter is an internet enabled device that measures energy, natural gas or water consumption of a building or a home with fine granularity, whereas traditional meters measure only total consumption.We have gathered the smart meter data for a 6 month period from June 2016 to November 2016 from the Aravali building consisting of 60 apartments, where data is collected at a resolution of 7 seconds.The demographic information is obtained by conducting a survey to the mentioned building.

2.Clustering the Consumers

Identifying the different types of load profiles is important to determine the patterns of electricity usage. The usage behavior is dependent on many factors such as the income, occupation, age of the occupants, type and number of appliances, the size of the apartment, etc. The building under study comprises of people from a similar academic background, similar occupation and the size of the apartments are also the same. Hence the different load patterns is due to the remaining contributing factors. Here, we took one-month data for all the apartments normalized to one day with one-hour granularity. The data was then passed to a k-means algorithm, which clusters the apartments into different groups. The k-means algorithm requires the number of clusters to be pre-decided, i.e, it forces the data into similar groups with whatever number you have mentioned.We can make use of different scoring parameters to decide the optimal number of groups. We did a few trial runs and found out k=6 to be suitable for our requirement.

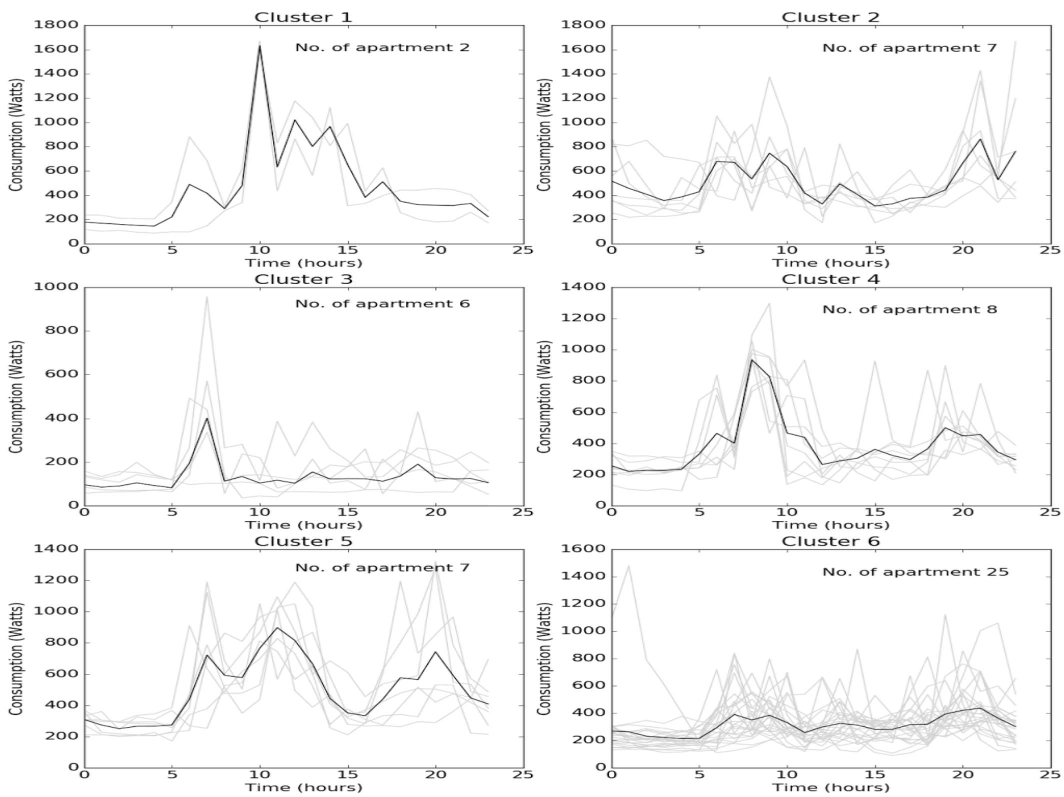


Figure1 : Load profile clusters of apartments over the entire dataset

Figure 1 shows the 6 clusters(consumer groups) that we got from the analysis.The light shaded lines represent the apartments in each of cluster and the bold line represents the centroid of the load pattern within the cluster.There are two unimodal with a single peak usage period and four bimodal with two peak usage periods of varying degree over the course of the day

Clusters 1 and 3 denote unimodal graphs with a single peak at the morning between 7 am and 10 am.This customers show a typical working class section.In clusters 4 and 5, we can find two peaks in the graph, a sharp high peak in the morning and comparatively smaller peak in the evening.Where as in clusters 2 and 6,the evening peak is more prominent than the morning peak.The position and magnitude of the peaks denote the usage of appliances in a day i.e taller morning peaks denote the usage of appliances more at the morning time(such as usage of geysers for heating water,electric ovens,laundry machines etc) and evening peaks denote a nocturnal lifestyle where people prefers to do their work in the evening.The cluster 6, which is the largest among the other clusters, has a constant usage throughout the day with smaller peaks at the morning and evening, denotes occupancy in the household throughout the day.

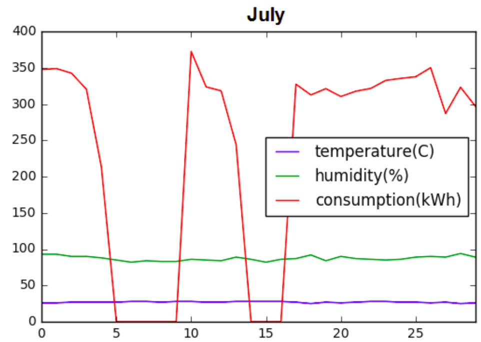
With this grouping, we can say that about 85% of the households have a bimodal usage, along with a 50% of households with a nocturnal energy usage.

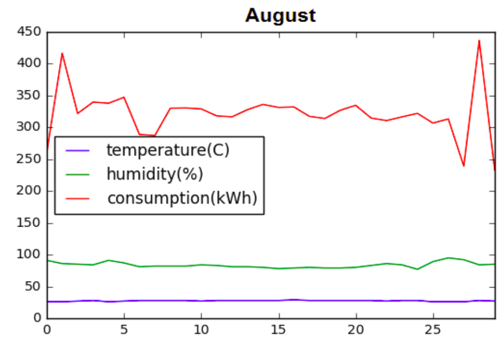
3.Weather-Consumption Correlation

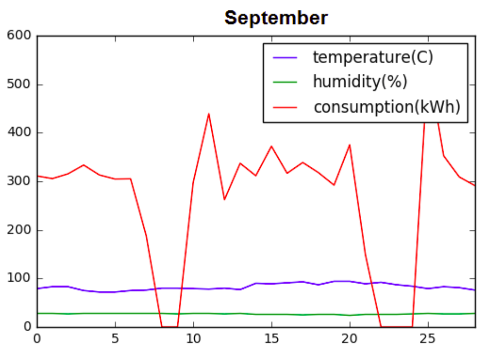
We will see the impact of weather conditions on the energy consumption on the building level.We have divided the dataset into two parts- July 2016 to October 2016 as rainy days and November 2016 as winter days.

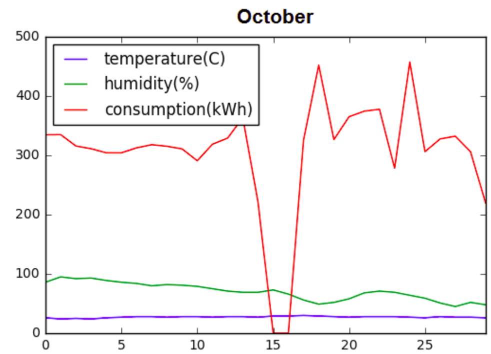
We have tried to find out the correlation of power consumption at a building level with temperature and humidity.In the month of July, there is a negative correlation of -0.50 with the temperature, whereas as a positive correlation of 0.60 with the humidity.As we move across the months upto October, correlation with temperature increases and correlation with humidity decreases.July to October is marked as the rainy season in Mumbai area and people tend to use more electricity for heating water.Hence, the increased consumption is marked by the use of geysers.

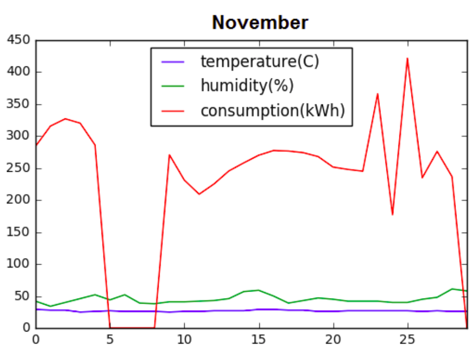
There is a positive correlation of 0.306 between temperature and power consumption, negative correlation of -0.12 between humidity and power consumption in November.November denotes a transition month from rainy season to winter, which is not rainy yet humid.

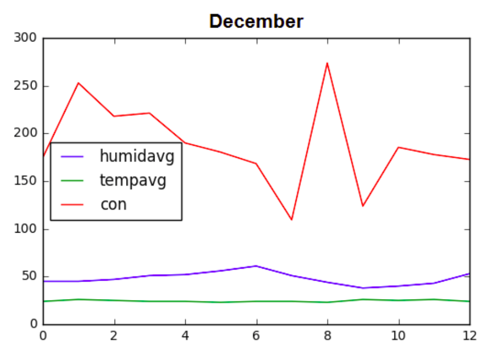

July
temperature(C)
humidity(%)
consumption(kWh)

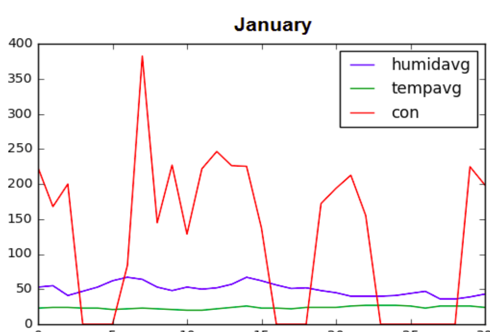

August
temperature(C)
humidity(%)
consumption(kWh)


September
temperature(C)
humidity(%)
consumption(kWh)


October
temperature(C)
humidity(%)
consumption(kWh)


November
temperature(C)
humidity(%)
consumption(kWh)


December
humidavg
tempavg
con


January
humidavg
tempavg
con

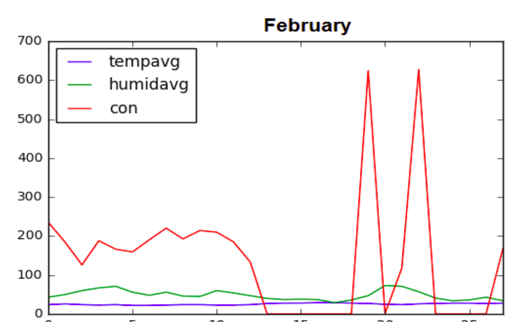

February
tempavg
humidavg
con

Figure 2: Variations in daily energy consumption, temperature,humidity at the building level from July, 2016 to November, 2016

Month	Minimum Consumption(kWh)	Maximum Consumption(kWh)	Variation(kWh)
July	372.52	213.30	159.22
August	436.70	232.99	203.71
September	543.24	149.66	393.59
October	457.35	219.21	238.14
November	421.68	177.06	244.63
December	273.76	109.41	164.35
January	382.50	83.93	298.58
February	627.33	118.21	609.19

Table 1: Maximum and minimum consumption from July 2016 to November 2016

4.Age-Consumption Correlation.

From the study, we have found that age of occupants also affect the power consumption in a household. A high positive correlation value between power consumption and age groups above 60 points to the fact that the apartments with senior citizens consume more, since those households can be marked with occupancy throughout the day and senior citizens use geysers more for hot water. Similarly, the age group 0 to 20 falls to the second position. Hence, we can say that households with children also consume more.

	zeroto20	twentyto40	fortyto60	above60	total	power
zeroto20	1.000000	0.029429	0.020339	0.087429	0.738352	0.161909
twentyto40	0.029429	1.000000	-0.902201	0.043905	0.007667	0.039390
fortyto60	0.020339	-0.902201	1.000000	0.000000	0.211955	-0.027388
above60	0.087429	0.043905	0.000000	1.000000	0.615004	0.419429
total	0.738352	0.007667	0.211955	0.615004	1.000000	0.331173
power	0.161909	0.039390	-0.027388	0.419429	0.331173	1.000000

Table 2: Correlation matrix constructed using power consumption and different age groups in a household

5.Lack of awareness of people on their energy consumption and how to improve it.

In the survey we conducted prior to the analysis, we have found out that only 39% of the consumers know their average monthly electricity bill and 17% of the consumers can identify their daily energy consumption pattern.The reason for the ignorance of the people about their electricity bill can be possibly due to the fact that the bill is getting deducted from their salary, which is a very small percentage.The people tend to notice it with less probability unless it deviates a lot from the average bill they were getting.Whereas the unawareness of the load profile from the clusters created sheds light to the fact that even educated people need energy awareness programs.Understanding the basics of energy consumption makes it easy to follow utility programs, because a good understanding makes it easy for the consumer to find the possible ways of reducing their consumption.

To improve the understanding of the energy usage, there should be a platform to give regular updates on their energy usage, so that they can find out any abnormalities in their usage and take decisive actions.For doing so, we have developed a preliminary version of an awareness application.

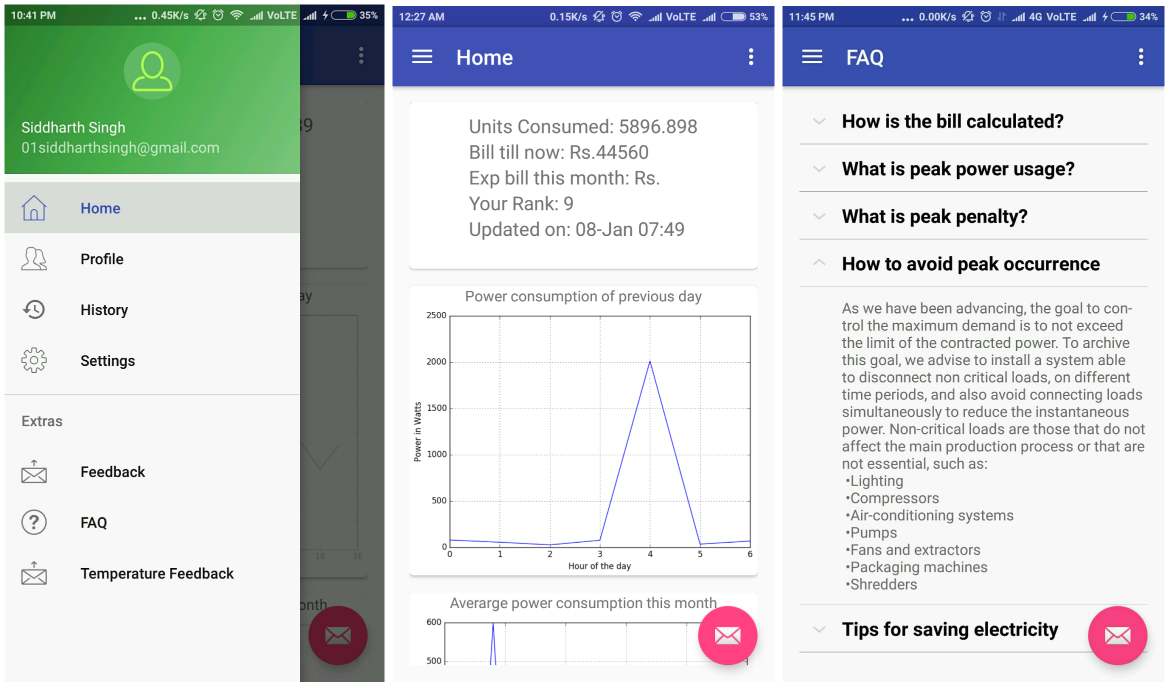


Figure 3: Screenshots from the app.

The app creates a profile for each of the consumer. In the home page, they can view the number of units of electricity they have consumed till now, expected bill and also their rank among the others in the clusters they are belonging.The clusters are created using the distribution of people in different age groups, owing to the fact that other factors such as size of household,number of bedrooms,income and education level of people remains the same.The rank is a metric to decide the efficiency of a home among similar households. Hence a lower rank depicts the usage of electricity inefficiently or some malfunctioning in the usage of the appliances.They can also see their energy consumption pattern for previous day and current month. By getting a detailed report on their usage, the people will have a better awareness of their usage and spend energy wisely.

6.Future Work

The next stage of the work is to make a prediction model for each of the cluster created. Creating accurate models for the load forecasting is important for the electric utility to make decisions on purchasing and generating electric power,load switching and infrastructure development.There are three main types of load forecasting : short-term forecasts, medium forecasts and long-term forecasts.It is very important to predict a load with 1-3% accuracy approximately. Because of the constant Demand-Supply fluctuations and changing weather conditions, load forecasting is vitally important. With the short-term load forecasting, we can estimate load flows and make decisions that can prevent blackouts.

When the app is deployed, we can include a prediction model that can do short-term load forecasting for each of the customer in every half an hour/one hour and give alerts to them if they are crossing the limit of peak power allotted to them. This can also be done in the building level, to check whether the consumption breaks the peak power allotted.This provides an opportunity to the consumers to play an effective role in the operation of the electric grid by reducing/shifting their usage if a peak usage is predicted

7.Conclusion

The accuracy of load forecasting is important for utility companies as well as the consumers. So it is very essential to identify the factors and how they influence the way the consumer use the power.In this study, we tried to find out an empirical relationship between the power consumption and its contributing at a typical urban household in India. We have observed that 85% of the households have a bimodal usage, along with a 50% of households with occupants with a nocturnal lifestyle. Also, there is a strong correlation between weather events and the energy usage.The age of the occupants in a household also affect the consumption, where households with senior citizens and children consume more. We also found out that even people with a good educational background tend to know less about their usage and need awareness programs. As a part of educating people on their energy consumption, we also suggest an android application that can act as an interface to the people to give them insights on their usage.

8.Acknowledgement
We would like to thank all SEIL lab members for their immensive support and residents at Aravali in IIT, Bombay for cooperating and actively participating in the survey.

9.References

[1] Srinivasan Iyengar, Stephen Lee, David Irwin, and Prashant Shenoy: Analyzing Energy Usage on a City-scale using Utility Smart Meters.BuildSys November, 2016