ANNEX 21: SCRUTINY OF ELECTRICITY BILLING AND SUPPLY DATA AS A PROBABLE PROXY FOR ECONOMIC ACTIVITIES: AN ANALYSIS OF POWER CONSUMPTION OF DHAKA, BANGLADESH (DRAFT)

Zaber, Moinul;Ali, Amin A;Bhyiyan, Farhad;Sayeed, Abu;Islam, Samiul;Rakib, Nibras;

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Scrutiny of Electricity Billing and Supply Data as a Probable Proxy for Economic Activities: An Analysis of Power Consumption of Dhaka, Bangladesh

Moinul I Zaber, Amin A Ali, Farhad Bhyiyan, Abu Sayeed, Samiul Islam, Nibras Rakib
Data and Design Lab, University of Dhaka, Bangladesh
Email: zaber@du.ac.bd
https://dndlab.org
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Key Points

- Energy is a basic need for modern Human beings. Hence governments require to ensure unhindered availability of energy. Energy is scarce resource. Hence it demands efficient management. Bangladesh has 160 million populations. Bangladesh is aspiring middle income country. Hence the energy need is high and ever growing. Bangladesh acknowledges this need. Promises 100% coverage. Has improved in last few years. Managing public utility is a major challenge. Prerequisite of better management of public utility is:

  i. Understanding the consumers (Their consumption behavior, do the poor behave the same way as the rich? how their behavior changes over time, what is the difference among different demographic zones?). Granular information about consumption behavior can help ascertain how much energy is required and at different parts of the year.

  ii. Understanding how regulatory decisions impact their behavior. Regulators disrupt consumption behavior through various shocks such as price hikes. How does that impact the behavior? How fair is the hike?

  iii. Forecasting short, mid and long-term demand.

  Utilities and regulatory organizations ensure these using their domain knowledge, use surveys, statistical methods to manage and understand the users. However, most of these mechanisms are very expensive, time consuming, and in many ways fraught by perception. Moreover, these methods are seldom granular. Granularity may help better management. Advancement in computational social science and machine learning (ML) for understanding data, may help harness insight from the data generated at the supply and consumption level. This project uses demand: monthly household consumption and supply: hourly load variability data to cater to the management need. We use data from DESCO (Dhaka Electricity Supply Company Limited), that caters to Northern part of Dhaka city of Bangladesh. This paper tries to answer questions related to the three queries stated above in the context of Dhaka North focusing residential users.

  Our Findings indicate:

- The consumption pattern analysis gives more granular level picture of urban economic health. We observe zone wise consumption variation indicating and confirming the wealthy areas of the city (assuming that people in more wealthy are would have more to spend on consumption). We observe that Consumers from other tariff brackets tend to increase or reduce their consumption to find themselves in the [76-200]. Consumers seem to gravitate towards [76-200] bracket However, it is quite a big tariff bracket and people in this bracket do not tend to change state much. This may indicate that it is time to redesign the tariff bracket. Dhaka is getting populated and the pattern of consumers' settling down in most of the zones is similar. However, at the wealthy zones such as Baridhara, Gulshan the rate is low. Finding Electricity consumption data may be a real-time indicator of the growth of households in the urban Dhaka.

Price hike on average do not have impact in short term. People may reduce usage intensity to cope. However, the impact is not homogenous. Consumers in bracket [1-50], [51-75] seem to have kept their upward propensity to consume more. While [76-200] stays in their position. However, most of the high-level consumers of bracket [401-600] seem to shift down to the lower level. Long term data of price impact is required to understand long term effect. In short term people may not stop using the device but may reduce the propensity. People in low tariff brackets may already use the devices at the minimum. While the people in high tariff brackets may reduce their propensity of use and hence we see this reduction in consumption. Short term tariff hike may induce people in higher tariff brackets to check their usage (by impacting on their propensity of using the devices). More extensive research on short term and long-term price and income elasticity may help to understand the impact better

- Dhaka is getting populated and the pattern of consumers' settling down in most of the zones is similar. However, at the wealthy zones such as Baridhara, Gulshan the rate is low. Finding Electricity consumption data may be a real-time indicator of the growth of households in the urban Dhaka.
- We also find that, hourly electricity load data augmented with demand side data can be a potential data for short term forecasting. Load data from the supply stations have potential for better load forecasting at the substation levels. More digitized data on hourly load can help build better models. User billing data, supply data (load data), load shedding data in conjunction with socio-economic data such as census, survey data, weather and environmental data such as temperature, dew point, data may help understand people's consumption behavior, understand impact of price change on consumption and help build better forecast model.

Abstract

This report is a case study of electricity consumption pattern of Dhaka city dwellers of Bangladesh. Electricity is a vital resource for country's development. Efficient management of electricity production, distribution and supply is vital for not only the economy but also for the environment. Bangladesh as a developing country needs well managed electricity-energy eco system to ensure continuous economic development. The prerequisite of a well-managed electricity eco system, are policies driven by robust knowledge of the demand and supply needs. Bangladesh lacks data driven research that sheds light on various aspects of electricity eco system and may help the policy makers. The gap between the need for evidenced based research and policy initiatives is ever increasing. This report aims at reducing the gap.

In order to reduce the gap, the report aims to harness uniquely built dataset based on monthly

billing data and hourly supply data at the household level. The underlying assumption of the report regarding better management of public utility requires fulfillment of prerequisites: a. understanding the consumers and their economic health, b. understanding how regulatory decisions impact their behavior and c. forecasting short, mid and long-term demand of the public utility. The uniquely built dataset is examined via various statistical and computational tools to help policy makers gain more insight on these prerequisites.

By analyzing the consumption pattern, we try to indirectly understand the economic health of the households. The report shows, it is possible to use electricity consumption data as a heterogeneous data source for better understanding of country's economy. The approach can be an effective measure of household level economic condition, especially because various other direct methods such as survey may be expensive and time consuming. This research finds that the number of electricity consumers are rapidly increasing over the year. However, most of them belong to specific groups that have predictable patterns. High consumption users belong to mainly in two specific zones where total numbers of users are very low with respect to other zones. It is found that household consumption pattern is impacted by weather fluctuations. The impact of regulatory intervention is measured by scrutinizing impact of price hike at the household level. Electricity price has been increased multiple times in Bangladesh and this paper is intended to find out the impact of the price hike and impact of weather change on the residential users. Preliminary research indicates that short term impact of price hike on electricity consumption is very small (inelastic). However, impact varies among tariff groups. The research also proposes a computational approach to forecast short term electricity demand at household level.

This report is seminal in the context of Bangladesh energy eco system because of the use of large dataset and pertinent computational tools used to find the policy relevant outcomes.

1. Introduction

Bangladesh is one of the developing countries in the world and is blooming in economic development. According to a 2016 report published by the International Monetary Fund (IMF), Bangladesh is now ranked among the top ten 'fastest growing economy' nations (World Economic Forum, 2017). Economic development of a country and usage of electricity are strongly correlated (Ferguson, R., Wilkinson, W. & Hill, R. 2000; M. Golam Ahamad, M. G., & Islam, A. N. 2011). Supply of electricity is vitally important to meet the growing demand for electricity and to improve the country's economic condition (Altinay, G. , & Karagol, E.2005).

However, the impact may vary depending on the context of a certain country. Thus, consumption and supply pattern can indirectly indicate the country's economic health. Direct methods of understanding economic health of a country, such as a census entails colossal expenditure and is highly time-consuming. Thus, these methods can be the benchmark but fail to be a real-time indicator of macro(?) level economic health. With the advent of machine learning algorithms and high performing computing devices, use of indirect methods to understand macro level socioeconomic conditions are gaining popularity. Two most frequent approaches are - using secondary data sources as proxy indicators (Steele, J. et al. 2017; Xie, M., Jean, N., Burke, M., Lobell, D. & Ermon, S., 2017; Blumenstock, J., Cadamuro, G., & On, R., 2015; Falkingham, J., & Namazie, C., 2017) and processing satellite images to understand economic health of an area (Mellander, C., Lobo, J., Stolarick, K., & Matheson, Z., 2015).

In this work, we make use of electricity consumption as a proxy indicator of economic health. Electricity is a prerequisite for economic prosperity. If the current global energy consumption pattern continues, by 2030 overall consumption will be increased by 50% (Pachauri, R., 2007). These energy transitions are more visible in a country experiencing an economic shift. A country while in its developing phase, should ensure efficient use of its resources, proper management, prioritization of needs, forecast the demand etc. In a developing country, the industrial sector generally consumes 45% to 50% of the total commercial energy (Suganthi, L. , & Samuel, A. A., 2012). Electricity as one of the fuels of the development thus needs to be managed in an organized fashion.

Researchers favoring the notion of 'energy justice' argues that justice principles should be applied to 'energy policy, energy production and systems, energy consumption, energy activism, energy security and climate change' (Jenkinsa, K., McCauleya, D., Heffronb, D., Stephanc, H., & Rehnera, R., 2016). In order to ensure energy justice, energy security must be achieved. (Ang, B., Choong, W., & Ng, T., 2015, Mansson, A., Johansson, B., & Nilsson, L., 2014) argues that 'energy security' means i. the security of production and supply, ii. Availability and pricing ensuring safeguard of energy supply and 'indigenous' production capabilities. According to Middlemiss, L., & Gillard, R., (2015) a similar concept, 'fuel poverty' means energy vulnerabilities in community's due to distributional unfairness. They argue that such inequity may be alleviated by shaping the ability of the consumers to access and consume the energy.

The issues related to electricity can be explained via discussions on energy need. The theoretical discussions of energy justice, security and poverty points to the fact that management inefficiency is one of the facts of ineffective energy eco system. One way to do it is to change the legacy 'system centric energy policy approach'. Some researchers have stressed on the point that policies need to be more 'human centric' and social scientific explorations of energy development is imperative (Sovacool, BK., 2014). Jenkins point out that, in order to understand how to circumvent the 'injustice', the policy makers should be able to ' i. identify the concern- distribution, ii. Identify who is affected - recognition and only then iii. Identify strategies for remediation - procedure'. Consumption based researches such as of

Boardman, B., (2013) & Liddell, C., & Morris, C., (2010) show the extent of energy poverty of various marginalized sections of the society. Researchers such as Eames, M. & Hunt, M., (2013) have pointed out that 'evidence of inequality' should be explained with argument of 'fair treatment'.

The issue of ensuring energy and in our context electricity for all is a very difficult one - mostly because it is a basic need that has environmental repercussions. Hence the policy makers have sought solution for efficient energy management. In line with the theoretical research, many countries around the world have recognized 'energy justice' as a part of their management policy. (Walker and Day 2012) reports that UK's policy on 'fuel poverty acknowledges the specific needs of social groups such as 'the elderly, the infirm, and the chronically ill – and their reliance on higher-than-average room temperatures'. On the other end of the spectrum, the energy strategy of Germany titled "Energiewende" puts emphasis on environmental issues. However, along with various environmental issues such as gradual removal of nuclear power plants the policy framework also encourages them to understand financial burden on lower income communities Jenkinsa, K. et al., 2016.

One of the earliest works on understanding urban electricity consumption behavior was based on western USA by Rand Corp (Berman, M.B., Hammer, M.J., & Tihansky, D.P., 1972). The researchers tried to ascertain the price impact on consumption. In the developing world side, a number of research has tried to ascertain the consumption behavior of urban dwellers (Moreira, João M. L., & Charfuelan, M.J., (Year??)), the impact of tariff subsidies on urban health (Tongia, R., 2017), and some have looked at the connections between income and electricity consumption (Tongia R., 2017). However, most of these works are based on surveys or secondary sources of data. With recent improvement of computation social sciences, a number of machine learning tools have been incorporated as well. However, to the best of our knowledge, two most frequent approaches use secondary data sources as proxy indicators (Steele, J. et al., 2017; Xie, M. at al., 2017; Blumenstock, J. et al., 2015; Falkingham, J., & Namazie, C., 2017) and processing satellite images to understand economic health of an area (Mellander, C., 2015).

With advent of the field of computational social science, processing power to harness data and machine learning approaches to recognize patterns, the researchers are now able to harness large datasets from heterogeneous sources. Researchers are scrutinizing data from Internet, social media, transportation and utility consumption etc. to find insights for public policy. However, the field is still developing and has challenges to overcome.

A number of studies have shown the potential of various indirect data sources such as satellite images, cellular telephony calls records, bank transaction records etc. to understand temporal changes in the economic activities, social-behavioral pattern, the standard of living and even growth of cities (Steele, J. et al., 2017; Xie, M. at al., 2017; Blumenstock, J. et al., 2015; Falkingham, J., & Namazie, C., 2017; Mellander, C., 2015). Sundsøy, R., et. al. (2017) have found a possible way to estimate and monitor economic growth rate at a high spatial resolution which can support countries, which have limited provision for conducting a survey for data collection. This new approach is also harnessed to understand energy consumption and prediction. However most of the work done was focused in forecasting and prediction accuracy (Grolinger, K., 2016).

Xie, M., et. al. (2015) used machine learning to mine socioeconomic indicators from raw satellite imagery. Nighttime light intensities were used as a proxy for economic activity. Blumenstock, J., et. al. (2015) have used Call Details Record (CDR) and have constructed the asset distribution for small areas consisting fewer household and extend the model to reconstruct the country's wealth distribution.

Falkingham, J. et al. (2012) have shown that that asset based measures have been considered as a better proxy for the long-term status of households as they are thought to be more representative of permanent income or long-term control of resources.

The literature describing the state of the art of energy sector or Bangladesh is not vast enough. One of the most recent work on electricity marketplace found via our exhaustive search in various scholarly avenues, is (Islam, S., & Khan, M., 2016). The authors give a tacit review of the energy sector, comments on energy research, initiatives, policies and discusses issues related to supply and demand scenario. Most of the works that came in the exhaustive search are mostly qualitative, driven by data from secondary sources, and surveys. The ones that took more quantitative approach have mostly used survey data from Bangladesh Bureau of Statistic's HEIS data as primary source to understand impact of technology on the socio-economic condition of the country. Unfortunately, the population census[1] data (2011) , HEIS[2] data (2014) and any other secondary sources are quite old to understand the dynamic changes that happened the last few years [FIG – econ dev BD].

Some researchers have harnessed the power aggregate data from mobile operators with geospatial data to understand poverty rate in urban and rural Bangladesh (Steele, J.E. et al., 2017). Similar works were done to understand mobile consumption pattern during cataclysmic weather in the costal belt of the country[3]]. Data from the mobile operators was also used to understand commuting behavior of Dhaka dwellers (Iqbal, M., Choudhury, C., Wang, P., & González, M., 2014) and GPS data was harnessed to understand traffic pattern of the city (Sayed, M.A., Rahman, M.M., Zaber, M.I., & Ali, A.A., 2017).

This report intends to show a pathway that elaborates the use of computational social scientific approach to harness data for the public good in the context of energy sector of LMIC (Lower Middle-Income Countries) like Bangladesh.

2. Background

2.1. Electricity sector of Bangladesh

This section provides a brief study of the existing electricity eco-system in Bangladesh. The emphasis is given on Dhaka, more precisely on Dhaka north as the report is based on data from DESCO-the electricity company catering to that region.

The Power Division (PD)[4], of the Ministry of Power[5], Energy and Mineral Resources (MPEMR), oversees the whole electricity utility. Electricity is generated by the Bangladesh Power Development

[1] http://bbs.portal.gov.bd/site/page/47856ad0-7e1c-4aab-bd78-892733bc06eb/Population-and-Housing-Census
[2] http://203.112.218.65:8008/WebTestApplication/userfiles/Image/LatestReports/HIES-10.pdf
[3] https://link.springer.com/article/10.1007/s10584-016-1753-7
[4] http://www.powerdivision.gov.bd/
[5] https://www.mpemr.gov.bd/

Board (BPDB)[6], a company spun off from BPDB, Independent Power Producers (IPPs) and private power producers. Generated electricity is supplied via the Power Grid Company of Bangladesh's (PGCB)[7] power grid to the capital area and then distributed by Dhaka Power Distribution Company (DPDC)[8] and Dhaka Electricity Supply Company (DESCO)[9]; local areas are supplied by BPDB and West Zone Power Distribution Company Limited (WZPDCL)[10]; and farming areas are supplied by Palli Bidyuit Samity (PBS)[11].

A handful of generation plants (SIPPs) are directly distributing to the distributors while others are delivering through the national power grid. Under these distributors, there are several substations from where power goes area specific feeders. Feeders are directly responsible for consumer-end distribution. A very general path of generation to consumption is as follows: Generation to Transmission (PGCB) to Distribution (Substation) to Feeder to Consumer end.

The present installed electricity generation capacity barely meets the current demand. Despite the fact that production increased considerably since 2010 Figure 2.1, lack of efficient management in the supply and distribution is still a severe hindrance to the growth in power sector.

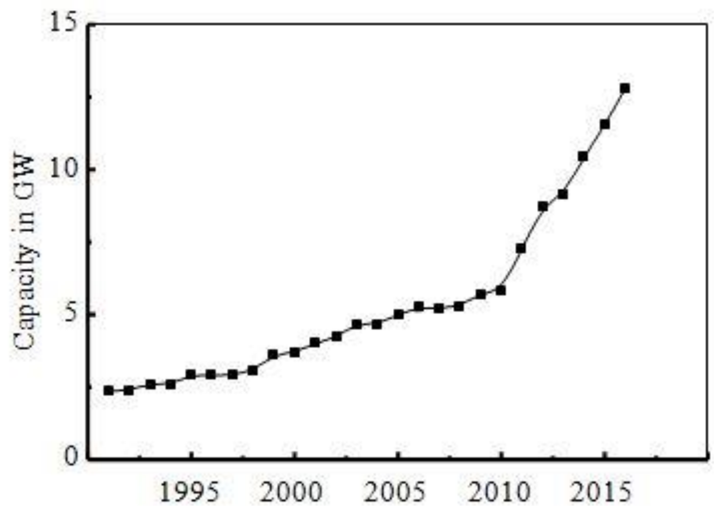


Figure 2.1 Installed power generation capacity (Kaikaus, D.A. & Khatun, J., 2016)

According to Power system master plan (Resources, M., & Board, D., 2016), Bangladesh mainly produce their electricity from natural gas. Other sources include, hydro, coal, heavy furnace oil, diesel and wind[12]. The growth in maximum demand from 2005-2017 is shown in figure 2.1. It is evident from the figure 2.1 that the demand increased rapidly after 2010. During this time, installed capacity has also increased as shown in Figure 2.1. However, even after much effort to reduce demand and supply curves since 2010, the consumers are still suffering from severe black outs and brown outs. This is evident from the figure in the context of Dhaka north. Figure 2.2 Indicates that in percentage of total consumption

[6] *www.bpdb.gov.bd*
[7] https://www.pgcb.org.bd/PGCB/
[8] *https://www.dpdc.org.bd*
[9] *https://www.desco.org.bd/*
[10] *www.wzpdcl.org.bd*
[11] http://www.dhakapbs1.org.bd/
[12] https://www.adb.org/

will increase in the residential sector while in the industrial sector may reduce its dependencies on the grid. This shows the importance of the need for understanding the residential sector.

The power management sector is fraught with distributional system loss. System loss in a distribution system refers to both technical loss and non-technical/distribution. It is reported that distribution loss reduced from 35.79 % in 1990-91 to 11.17% in 2014-2015 Figure 2.2 Governmental reform projects helped. However, as this research shows, system loss is not uniformly distributed and varies among zones.

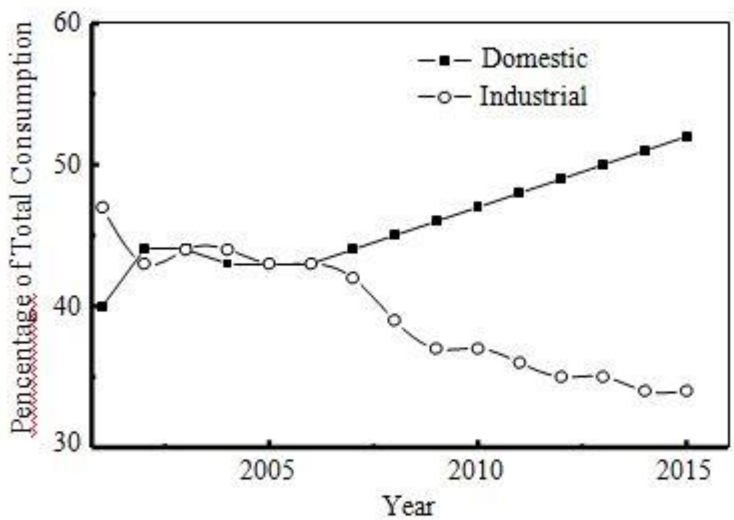


Figure 2.2 Energy Consumption ("Key Statistics", BPDB)

The schematic diagram in figure 2.3 explains the production, distribution and supply of electricity in the context of Bangladesh.

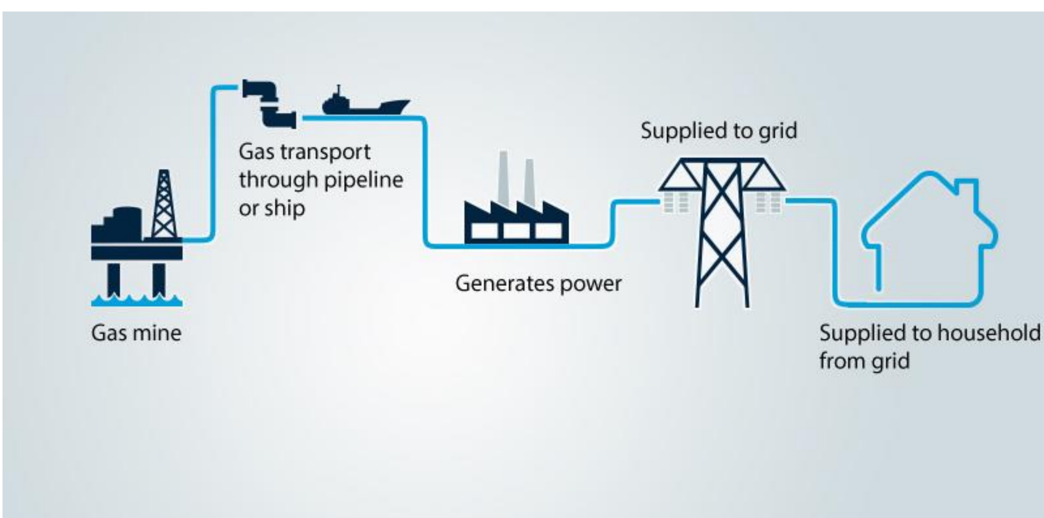


Figure 2.1 Process to supply electricity household (Source: *(Resources, M., & Board, D. (2016)*)

According to power system master plan in order to become an advanced country in 2041 the goals to be achieved the in energy sector is following: (Resources, M., & Board, D., 2016)

Goal 1: Enhancement of imported energy infrastructure and its flexible operation

Goal 2: Efficient development and utilization of domestic natural resources

Goal 3: Construction of a robust, high-quality power network

Goal 4: Maximization of green energy and promotion of its introduction

Goal 5: Improvement of human resources and mechanisms related to the stable supply of Energy

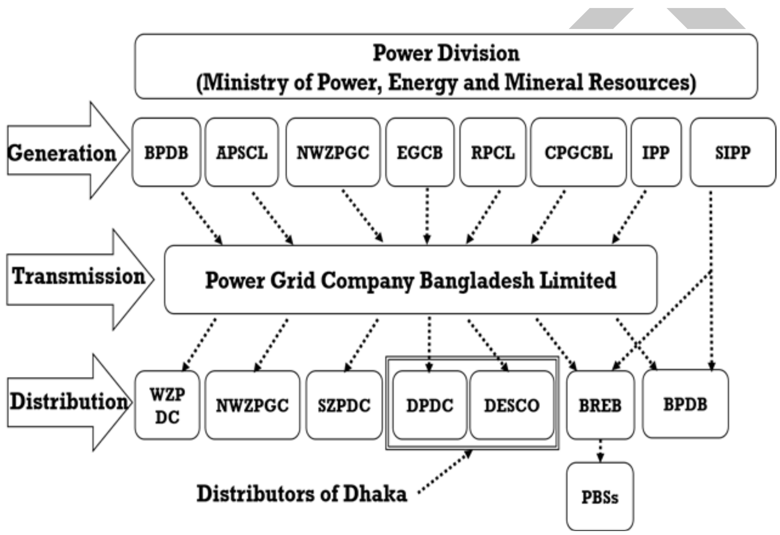


Figure 2.4 Electricity sector structure in Bangladesh (Redrawn by the authors from : Resources, M., & Board, D., 2016)

Figure 2.5 shows installed capacity, available capacity and maximum demand for the year 2013 to 2015 (Survey on Power System Master Plan, 2015). Approximately 30% of installed capacity was not available. The primary reasons include decreases in the output and thermal efficiency and failures of power generators mainly due to the insufficient periodic maintenance etc. However, it is clear that in the year 2015, available capacity was sufficient to satisfy maximum demand. However, load shedding is still a huge concern here in Bangladesh. Without knowing area specific demand, even if with available resources, demand cannot be satisfied. Thus, aggregated data and legacy method needs to be restructured. Moreover, In Dhaka, electricity consumers are increasing day by day. 3 DESCO zones: Pallabi, Shah Ali and Baridhara, , number of connections has almost doubled from 2010 to 2015.

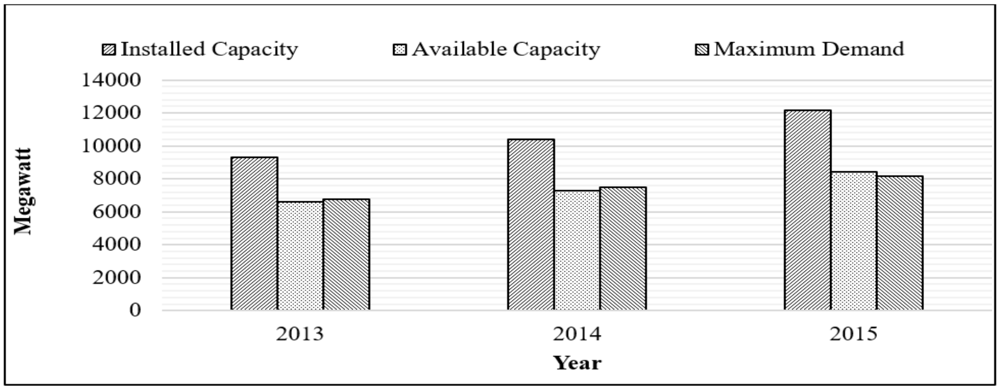


Figure 2.5 Supply/Demand (Max) Balance in a Day: in 2015, available capacity was enough to satisfy maximum demand. Source: Survey on Power System Master Plan, 2015

In Dhaka, Electric Supply Company Limited (DESCO) and Dhaka Power Distribution Company LTD (DPDC) supply electricity to the consumers. DESCO supplies to the northern part of Dhaka while DPDC supplies to the consumers in the southern part of Dhaka. of the analysis of this research is conducted on data from the year 2005 to 2015, collected from DESCO.

2.2 Change in the price of Electricity in Bangladesh

Currently, (as of January 2018) There are 8 different tariff categories in Bangladesh. From However, this report focuses on residential consumers that constitutes approximately 90% of overall consumers (Appendix table 1). Since 2005, tariff categories has not been changed. However, the tariff brackets in the residential category was changed in 2012 (DESCO, 2017). Tariff rate differs among these brackets. Low consumption bracket incurs less per-unit price and relatively upper brackets costs more. The figure 1 details the changes in the tariff brackets.

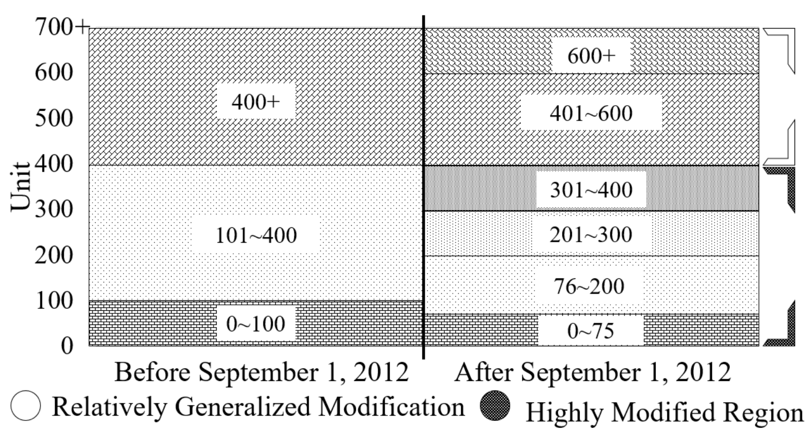


Figure 2.6 Residential Tariff Brackets. (Source: (DESCO, 2017))

Figure 2.6 Change in Residential Tariff Brackets on September 01, 2012. Before 2012, there were three brackets in terms of unit consumed in a month; 1) 0~100 unit, 2) 101~400 unit and 3) 400 and above unit. After 2012, first two brackets have been broken down as 1) 0~75 unit, 2) 76~200 unit, 3) 201~300 unit and 4) 301~400 unit. 400+ bracket was divided into another two blocks; 5) 401~600 unit and 6) 600 and above unit.

In the new tariff brackets, 0 to 400 units range (low to mid consumer range) was completely redesigned. However, 400+ bracket was just divided into two parts. We are highlighting 0~400 range as highly modified region and the rest as general modification. To understand, follow the tables 3 and 4.

In Bangladesh, residential tariff is highly subsidized. However, the amount of subsidy has decreased over the years. Electricity Tariff and cost vs. price gap of our research area is shown in Table 2.1, Table 2.2 and Table 2.3. We take the average cost of per unit electricity production in table 2.1. In Table 2.2, year wise electricity retail price is given. And in Table 2.3, the gap between cost and price is shown. Here we see that the government is subsidize electricity generation for balancing expenditure of citizen.

Table 2.1 Unit Cost of Electricity Generation in Bangladesh in Tk/KWh (2015). Source: Tariff and Governance Assessment, (n.d.), Tariff Rate, BPDB

Source	**BPDB Plants**	**Rental Plants**	**Public Plants**	**IPP**
Hydro	1.49			
Wind	25.45			
Gas	2.07	4.21	2.10	2.18
Coal	6.30			
HFO	17.86	16.46		18.69
Diesel	37.35	24.76	28.24	
Average Unit Cost	15.09	15.14	15.17	10.44

BPDB=Bangladesh Power Development Board, HFO = heavy furnace oil, IPP = independent power plants.

Table 2.2 Per Unit (KW/Hour) Electricity Retail Price. Source: Tariff Rate, BPDB

Category	**Rate Type**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Domestic	Average	3.633	3.633	3.633	3.633	3.997	5.076	5.076	6.320	6.435
Agriculture		0.000	1.930	1.930	1.930	1.930	2.260	2.260	3.390	3.820
Small Ind	Flat	4.020	4.020	4.020	4.020	4.560	6.020	6.020	7.420	7.660
Non Res (Charitable Ind)		3.350	3.350	3.350	3.350	3.350	3.920	3.920	4.980	5.220
Commercial	Flat	5.300	5.300	5.300	5.300	5.850	7.790	7.790	9.580	9.800

Table 2.3 Residential Electricity supply cost per KW vs Price per KW. Source: Source: Tariff and Governance Assessment, (n.d.), Tariff Rate, BPDB

	2010	2011	2012	2013	2014	2015
Avg. Supply Cost	2.37	2.61	4.02	5.43	6.27	5.55
Avg. Price	3.64	3.93	5.01	5.01	6.33	6.58
Net Profit/Loss	1.27	1.32	0.99	-0.42	0.06	1.03

Though there were just a single change in tariff brackets, tariff rate has been changed 6 times from 2005 to 2015; three of these were before September 1, 2012 and three were after 2012. Although, it seems before and after period of bracket change have a similar impact, it is not, and rather there is a significant difference and interesting findings. Table 2.4 and 2.5 show the changes in tariff rates.

Table 2.4 Change in Tariff Rate Before September 01, 2017. (Source: (DPDC, 2017))

Unit	**0 to 100**	**101 to 400**	**Above 400**
March 1, 2007	2.5	3.15	5.25
March 1, 2008*	2.5	3.15	5.25
February 1,2011	2.6	3.46	5.93

Table 2.5 Change in Tariff Rate After September 01, 2017. (Source: (DPDC, 2017))

Unit	**0~75**	**76~200**	**201~300**	**301~400**	**401~600**	**600 +**
Sept 01, 2012	3.33	4.73	4.83	4.93	7.98	9.38
Mar 13, 2014	3.53	5.01	5.19	5.42	8.51	9.93
Mar 13, 2015	3.8	5.14	5.36	5.63	8.7	9.98

These tariff rates are in nominal values; inflation adjustment is not reflected here. From the tabular view of these changes, significances are hard to be seen. To understand, please follow the line graphs of Figure 2.7 and 2.8.

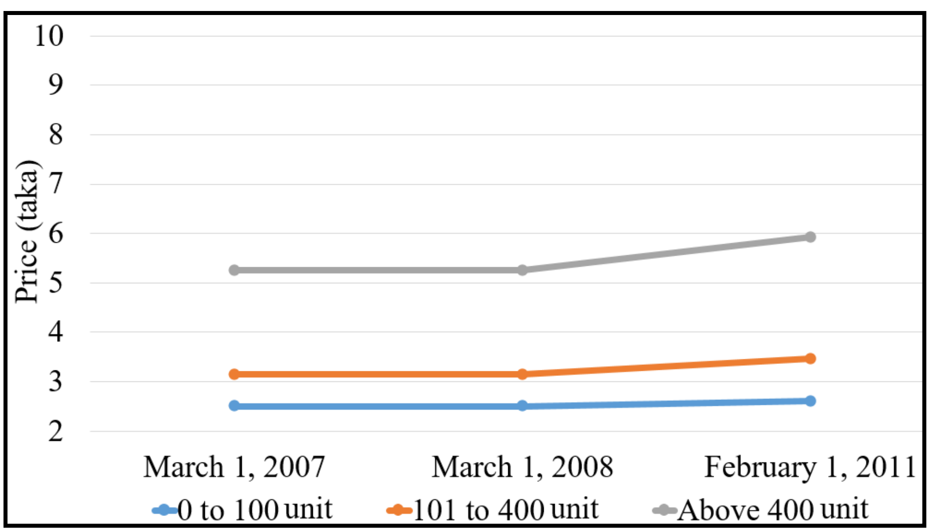


Figure 2.7 Price change from March 1, 2007 to September 1, 2012: More impact on mid to high consumption users. Source: Made by the authors using data used in this research

Figure 2.7 and 2.8 represents tariff rate change over the years. Before tariff bracket change, in figure 2.7, it is shown that price change had relatively more impact on high consumption users while in figure 2.8, we can follow that, low to mid consumption brackets are affected more by the change. And, Pricing almost gets doubled from 2007 to 2015. Though we have not considered inflation adjustment, such increment is hardly the reason of inflation.

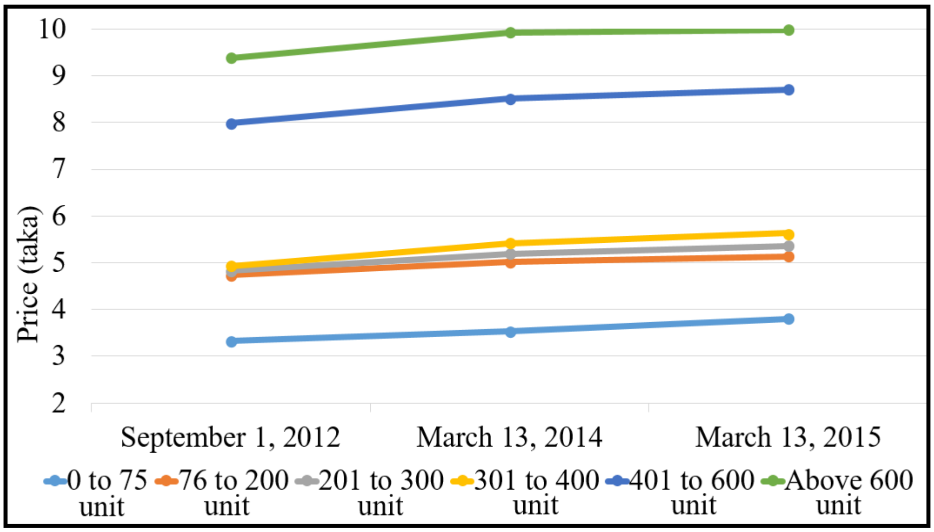


Figure 2.8 Price change from September 1, 2012 to March 13, 2015: More impact on low to mid consumption users. Source: Made by the authors using data used in this research

As most of the consumers fall under 'highly modified region' and as these brackets have more impact of tariff change after September 2012, changes in usage pattern can be a good indicator for community detection and how different people handle these incremental changes. Figure 2.9 and 2.10 are the bar graph representations of these rate changes. Both of these graphs are drawn to the same scale to show the visual differences in changes and it has been seen that the price has been almost doubled in 2015 compared to the tariff pricing of 2007.

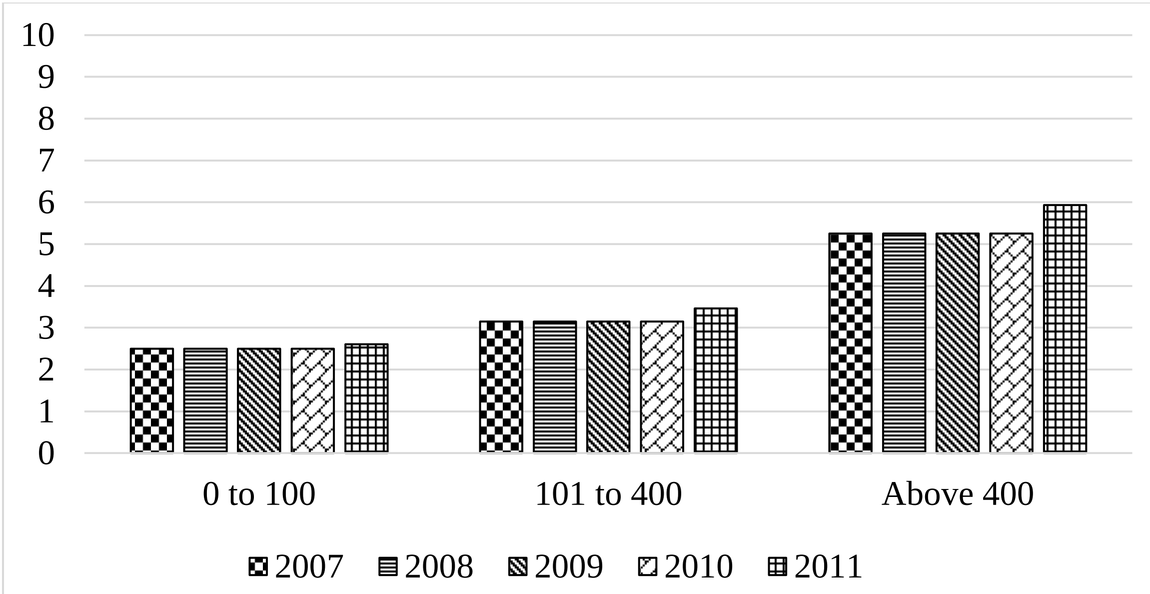


Figure 2. From 2007 to 2011, in residential tariff brackets price changes once, on 2011. (Source: Made by the authors using data used in this research)

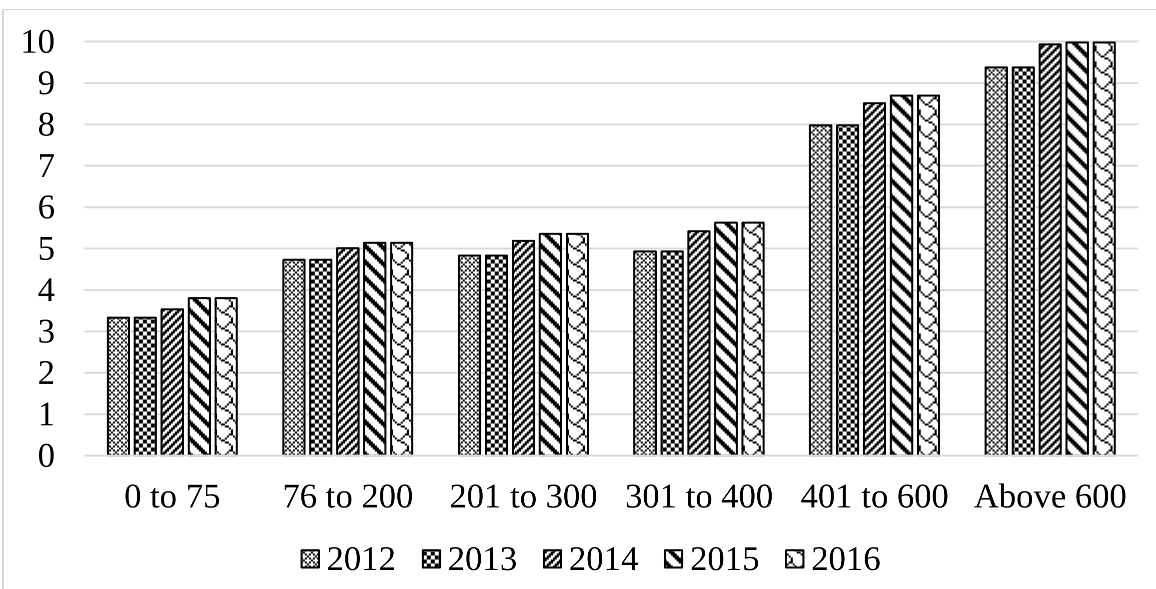


Figure 2.10 From 2012 to 2016, in residential tariff brackets price change occurs in 2012, 2014 & 2015. (Source: Made by the authors using data used in this research)

2.3 Description of Dhaka City (North)

Dhaka district (zila) was established in 1772. Dhaka city is the capital of Bangladesh consisting 41 metropolitan thanas[13]. Dhaka contributes 35% of Bangladesh economy with Gross Domestic Product of US $37 billion according to Cambridge University's 2014 analysis (Cambridge Centre for Risk Studies, 2016). It has two City Corporations[14], Dhaka North and Dhaka South City Corporation.

Total area of the two city corporations is 126.34 sq. km., where Dhaka North City Corporation consists of 36 wards with 82 sq. km. (approx.) which is 65% of Dhaka metropolitan city area. Total population of Dhaka North City Corporation is 3.9 million (approx.). Our research data is from Dhaka Electric Supply Company Limited (DESCO) which operates in the Dhaka North City Corporation area in Dhaka. For our research, we looked into the household, population, area, number of poor living in those zones and economic establishment data of our research area. From these data, we observe that the administrative division of these areas and DESCO zonal areas is not same. Figure 2.11 shows the map of thanas of Dhaka City and DESCO zones in Dhaka (Dhaka District, 2014). Hence, thana wise mapping of DESCO area is important to understand statistics presented here. Table 2.6 shows the mapping of thana to DESCO zone. As we can observe from the table the each of thanas contain one or more DESCO zones. For example, Badda thana area is divided into Badda and Baridhara zones in DESCO and Gulshan thana is divided into Gulshan and Joar shahara Zone, whereas Uttarkhan and Dakshinkhan thana corresponds to Uttarkhan and Dashinkhan zones respectively. Bimanbandar thana can be mapped to Uttara East zone and Uttara thana area is same as Uttara West zone. Tongi East and Tongi West zones are outside of Dhaka Metropolitan area, and are north of Uttara west thana.

Dhaka is the center of Bangladesh and all administrative, educational facilities, medical facilities etc. are mostly concentrated in Dhaka. People all around the country come to the city for different purpose daily. Dhaka North City Corporation (DNCC)[15] has 37 universities, 191 colleges and 721 schools according to the information where total university in Dhaka is 51, colleges 210, school (all kind) 1600 and madrasa is 180. It shows that Dhaka North City Corporation is the core of Dhaka.

Table 2.6 Thana wise DESCO zone mapping. Source: Population & Housing Census, 2011.**Thana**	**DESCO Zone**
Badda	Badda+ Baridhara
Gulshan	Gulshan+ Joar shahara
Kafrul	Kafrul+ Agargaon
Mirpur	Monipur+ Shah Ali

[13] 'Thana' means "police station" in Bangladesh and can also mean the district controlled by a police station, later it is called Upazila
[14] http://203.112.218.65:8008/WebTestApplication/userfiles/Image/PopCen2011/Com_Dhaka.pdf
[15] www.dncc.gov.bd

Pallabi	Pallabi+ Rupnagar
Uttarkhan	Uttarkhan
Dakshinkhan	Dakshinkhan
Bimanbandor	Uttara East
Uttara	Uttara West
Tongi East	Not included in Dhaka Metropolitan area
Tongi West	Not included in Dhaka Metropolitan area

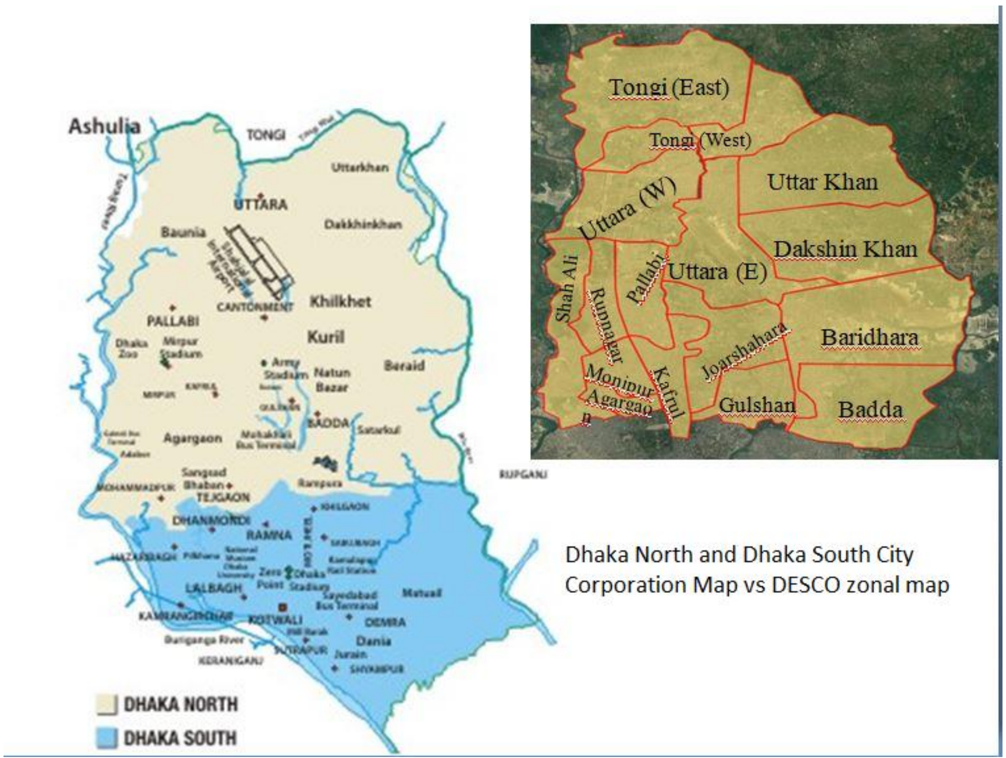


Figure 2.11 Dhaka Thana Map and DESCO Zonal Map. Source: The Daily Star &Google Map

From Table 2.7, we see that the largest thana of our research area is Badda (34 sq. km. approx.) with population of 5 lacs (0.5 million) approx. (in 2011) and literacy rate is 70 (approx), where smallest thana is Shah Ali (4 sq. km. approx) with population of 1 lac (0.1 million) (2011) and literacy rate is 71%. The population assumption for 2011 is made by the authors considering the difference between 2001 and 2011.

From Bangladesh Bureau of Statistics's Population & Housing Census, 2011 we observe that that the average household size is decreasing from 1991. It was 5.5 in the year 1991, 4.6 in the 2004 and 4.33 in the year 2011 [Table. 2.7].

Table 2.7 Thana wise Area, Household, Population & Literacy Rate. Source: Population & Housing Census, 2011.

Thana	DESCO Zones	Area (sq. km.)		Household		Population			Literacy Rate (7yrs+)
		2011	2001	2011	2001	2021*	2011	2001	2011
Badda	Badda+ Baridhara	34.31	49.85	129673	79359	713986	536621	359256	72.3
Bimanban	Uttara East	15.47	4.46	2262	1021	16173	10626	5079	82.7
Dakshinkh	Dakshinkhan	21.62	-	63899	-	511862	255931	-	76.8
Gulshan	Gulshan+ Joar shahara	8.67	10.28	59149	43481	315510	253050	190590	74.8
Kafrul	Kafrul+ Agargaon	7.47	8.85	95575	63299	502378	396182	289986	74.8
Mirpur	Monipur+ Shah Ali	6.42	14.22	117450	122431	439579	500373	561167	80.2
Pallabi	Pallabi+ Rupnagar	9.97	17.96	143332	95611	762413	596835	431257	70.6
Shah Ali	Shah Ali	3.85	-	28127	-	230978	115489	-	71
Sher-E-Bangla	Agargaon	4.45	-	29652	-	275146	137573	-	78.2
Turag	Tongi East +Tongi West	30.56	-	38660	-	314632	157316	-	63.5
Uttara	Uttara East +Uttara	8.95	58.3	39123	78618	14717	179907	345097	80.2
Uttarkhan	Uttarkhan	20.51	-	18297	-	157866	78933	-	68.8

*Projected by authors

Among the DESCO zones highest establishment in Shah Ali zone with 9 thousand (approx.) establishments and total person engaged is 30 thousand (approx.). The lowest is Uttara East with 2.5 thousand (approx.) establishments and total person engaged is 15 thousand (approx.) [Fig. 2.8].

Table 2.8 Establishments and Total Persons Engaged (TPE) by Type, Thana and Location, 2013. Source: Economic Census, District Report: Dhaka, 2013

Thana	DESCO Zone	Establishments	Total Persons Engaged (TPE)
		Total	Total
Rupnagar	Rupnagar	3901	19171
Shah Ali	Shah Ali	8991	29735
Sher-E-Bangla Nagar	Agargaon	6594	56680
Turag	Tongi East +Tongi West	8531	30405
Uttara West	Uttara West	5413	39557
Uttara East	Uttara East	2747	15384
Uttar Khan	Uttar Khan	7169	22612

According to the poverty map 2010 in Table 2.9, the highest poor live in Dakshinkhan with 36.4% poor and the lowest poor live in Gulshan with 4.1% poor.

Table 2.9 Poverty Map 2010. Source: Bangladesh Poverty Maps (Zila Upazila), 2010

Thana	DESCO Zone	% Poor (Upper poverty line*)	% Extreme Poor (Lower poverty line*)	Total %Poor
Badda	Badda+ Baridhara	13.4	1.2	14.6
Biman Bandar Thana	Uttara East	1.3	0.3	18.6
Dakshinkhan	Dakshinkhan	24.6	11.8	36.4
Gulshan	Gulshan+ Joarshahara	3.3	0.8	4.1
Kafrul	Kafrul+ Agargaon	7.0	0.4	7.4
Mirpur	Monipur+ Shah Ali	6.7	0.5	7.2
Pallabi	Pallabi+ Rupnagar	12.0	1.8	13.8
Uttara	Uttara East + Uttara West	3.7	0.8	4.5
Uttarkhan	Uttarkhan	24.9	4.3	29.2

2.4 Related Research

In this section we use electricity monthly billing data and hourly supply data to understand the economic condition, impact of price hike and propose a model to forecast short term electricity need at the granular level.

2.4.1 Use of Electricity Data to understand socio economic condition

Understanding household electricity consumption pattern has been an important field of study in the energy policy and economic policy domain. A number of authors have studied electricity consumption pattern to understand economic condition (Joyeux, R., & Ripple, R., 2007). A number of authors have tried ascertain causal relationship between energy consumption and aggregate income. Some have also tried to propose electricity consumption as an indicator of economic condition. The literature is quite robust ranging from the seminal work of Kraft and Kraft (1978) works of (Joyeux, R., & Ripple, R., 2007). Kraft and Kraft tried to understand how energy conservation policies may inhibit economic growth. They found that income impacts consumption habit. In the developing world context, similar work is done by (Moreira J., Charfuelan M., Year) where the authors find that the correlation between income and consumption of electricity is higher for high consumption values than lower ones.

United nation's sustainable development goal[16] indicates the importance of energy security. Altinay, G., & Karagol, E. (2005) argued in the context of Turkey attaining demand of electricity consumption, it is absolutely important to have smooth electricity process to achieve sustainable economic development. This study used annual observations of electricity consumption and real Gross Domestic Product (GDP) from 1950-2000. Authors have used two different methodologies to understand the casual relationship between electricity and economy: - standard Granger causality test and Zivot and Andrews test. Number of studies tried to monitor economic growth and establish causal relations between electricity consumption and income (Altinay, G., &Karagol, E. (2005), Ferguson, R., Ghosh, S. (2002), Wilkinson, W. et. al. (2000), Ciarreta, A., & Zarraga, A. (2010), Masuduzzaman, M. (2012)). A range of other works in the same domain, are by Akarca and Long (1980), Yu and Choi (1985), Erol and Yu (1988), Abosedra and Baghestani (1991), Hwang and Gum (1992), Yu and Jin (1992), Masih and Masih (1996, 1997), and Soytas and Sari (2003). The authors of these works have varied view on the existence of causal link between income and energy consumption.

A number of authors have tried to use energy as an indicator or standard of living (Sanghvi, A., & Barnes, D., 2001;, Dzioubinski, O., & Chipman, R., 1999). However, (Joyeux, R., & Ripple, R., 2007) argue that typical per capita income is a poor proxy of residential electricity consumption. This is because the available per capita income measures are the result of 'the division of national income aggregate by the national population'. Hence do not directly reflect on residential level income. This also indicates the importance of understanding the household at a more granular level which is difficult to achieve by traditional research methods involving surveys that are always bounded by the sample size and quality.

Advent of large and heterogeneous data centric research initiatives popularly termed as 'Big Data' opened up new mechanisms to aid public policy. Authors have come up with new ways to

[16] United Nations General Assembly. 2015 Transforming our world: the 2030 Agenda for Sustainable Development.

understand the population with high spatial resolution that can complement traditional researches based on surveys and census.

Most recent work in Bangladesh context was conducted by (Sundsøy, R. et al., 2017). They have used Call detail record (CDR) data and geospatial data for the purpose. Using Voronoi diagram, authors conducted a spatial analysis on area of mobile tower coverage. This Voronoi diagram showed a wide variety of (Voronoi polygon size) mobile tower coverage from rural to urban areas. All other dataset used in this study are projected into the Voronoi polygon, and the mean, sum or mode of CDR data were taken. For each Voronoi polygon, the mean wealth index (WI) was taken from sampled population (207 in urban areas & 393 in rural areas).

The aggregated average WI was taken from 2011 Bangladesh Demographic and Health Survey. Household assets and housing characteristics e.g. floor type, ceiling material are used for calculating WI which explains the difference between urban and rural area (Rutstein, S. O. (2008)). Household Income and Expenditure Survey (HIES) in 2010 (Bangladesh Bureau of statistics, statistics division Ministry of planning. (2015)) was used to understand whether or not a certain the household lives below or above the poverty line. The authors have collected producer price Index (PPI) from this survey. This was supplemented with data from a mobile operators' survey where respondents where directly questioned about income. Authors successfully matched 76000 phone number out of 90000 thousand respondents. Basic phone usage, top up pattern, social network has been collected from CDR data. Bivariate Pearson's correlations were computed for CDR and RS data to found out the highest correlation. Non-spatial generalized linear models (glms) used to found every combination of covariates. Hierarchical Bayesian geostatistical models (BGMs) used across the population to predict poverty metrics. CDR-RS model performed well ($r^{2=}$ 0.76) in the study along with stand-alone RS model. Combining CDR-RS model with DHS WI provided the best result ($r^{2=}$ 0.78).

Another study was conducted to examine the connection between economic activity with night-time-light (NTL) emission (Mellander, C., Lobo, J., Stolarick, K. et. al. (2015)). Demographic data of residential and industrial area in Sweden used in this study. While the correlation between NTL and wages is weaker, authors found strong correlation between NTL and economic activity and can be used as a proxy for demography information (e.g. population and establishment density). Nighttime lights Data was collected from U.S. National Oceanographic and Atmospheric Administration (NOAA). On the other hand, population and establishment counts had been collected from Statistics Sweden[17] and then spatially matched with NTL dataset. These geocoded data were divided into square grids and matched with light-emission data.

Authors conducted an empirical analysis to find out the significance level for radiance light and saturated light with number of people, wage, establishments variables. This empirical analysis shows slightly strong correlation between people count and radiance light-emission than saturated light. Authors ran Geographically Weighted Regressions (GWR) and then single Ordinary Least Square (OLS) regression to compare beta values. Authors produced a map based on each GWR regression to illustrate the GWR estimations for people and establishment wage density. While the discussions continue to exploring the proxy indicators for capturing economic activity and urbanization and growth, questions remains about the capturing of exact artificial light emissions at micro-level, the exact mechanism for light-emission and process of satellite to measure these emissions.

[17] Statistics Sweden (Swe: Statistiska Centralbyrån) available at: www.scb.se

2.4.2 Understanding impact of price on consumption behavior

The economic theory of price elasticity[18] of demand is frequently invoked to understand the impact of price hike on consumption behavior. However as discussed earlier in the previous section, causal link between income and energy (and vice versa) consumption is not well established in the literature. Hence, it is not the certain how people at different level of economic status would react to sudden price hike.

It is firmly believed that increasing energy price is an effective policy tool to reduce energy consumption (Finn, M., 2000; Birol, F., & Keppler, JH. 2000;, Wing, I.S., 2008; Valadkhani, A., Babacan, A., & Dabir-Alai, A. 2014). On the other hand, Martinez and Ines (2011) find that energy prices are not a key factor in improving energy efficiency. Authors in (He, L., Ding, Z., Yin, F., & Wu M., 2016) argue that, most of the literature try to measure 'direct effects of absolute energy prices on energy consumption'. They argue that inflation cost resulting from rising energy price should be a better matric to ascertain the impact on energy price. They point out that in the context of China, 'energy prices cannot reflect supply and demand in the energy market' simply because of the 'administrative energy-pricing mechanism in the country'. They term it 'relative energy price'. The authors empirically test the direct, indirect and time-varying effects of energy prices on energy consumption. Among other findings, they also conclude that, low energy prices is the 'main factor hindering energy saving'. The literature thus indicates that, higher energy price should reduce energy use.

A seminal research conducted by RAND corporation (Berman, M. et al., 1972) tried to ascertain short and long term impact of price on consumption in the context of western United States and California. The authors found that the short term impact on 'residential consumption of a particular fuel is very small (inelastic) for even relatively large changes in its price.' The reason, they argue is large 'capital investment in energy consuming devices. These devices create 'locked-in' effect and hence the consumers 'would only be able to react by reducing the intensity of use'. In the long run, according to the authors, residential demand for electricity is price sensitive[19].

In the context of developing world most recent work by (Tongia R., 2017), scrutinizes impact of price subsidy in the power sector. The author concludes that Delhi's subsidies are regressive where the middle class (indicated by mid-level consumers of power) enjoy more benefits on a percentage basis than the lowest consumers. The author find that the lowest tier, on average, gets under 33 percent net billing subsidy, the mid-level users get over 40 percent net subsidy. The findings related to subsidy

[18] In economics, elasticity is the measurement of how an economic variable responds to a change in another. Price elasticities are almost always negative, although analysts tend to ignore the sign even though this can lead to ambiguity. Only goods which do not conform to the law of demand, such as Veblen (types of luxury goods for which the quantity demanded increases as the price increases, an apparent contradiction of the law of demand.)and Giffen goods, (a product that people consume more of as the price rises and vice versa—violating the basic law of demand in microeconomics. For any other sort of good, as the price of the good rises, the substitution effect makes consumers purchase less of it, and more of substitute goods; for most goods, the income effect (due to the effective decline in available income due to more being spent on existing units of this good) reinforces this decline in demand for the good.)

[19] Price sensitivity is the degree to which the price of a product affects consumers' purchasing behaviors. In economics, price sensitivity is commonly measured using the price elasticity of demand.

maybe used to interpret asynchronous pricing among tariff groups, to find whether or not the impact of tariff change varies across tariff groups.

(Moreira J., Charfuelan M., Year) used an about 30 years long time series data over Brazil, to conclude that household electricity consumption over time is sensitive to tariff but elasticity of consumption with respect to tariff is not high.

2.4.3 Forecasting electricity consumption

Electricity demand forecasting or consumption behavior prediction is an essential tool for energy management. As indicated earlier, electricity consumption differs between short and long term. A number of authors also argue that there is a midterm consumption pattern as well[20] .This section gives a technical review of some research related to demand forecasting. The existing literature in this field is quite robust. However, as demand depends on the various exogenous variables such socio-economic condition, regulatory regime, environment, weather etc., expected outcome of forecasting methodologies differ on the basis of the input data. This trigger changes in the models as well. Hence forecasting models cannot be context independent. Our exhaustive search did not find any research work related to forecasting in the context of Bangladesh. Hence, we planned to study previous works that may be more pertinent to developing world context. For this research around 10 research works were preliminary selected among which 4 are being discussed to maintain brevity. Selected papers differ in both long and short-term prediction and also in space and context. This helps us understand the applicability of different algorithms in various context.

Suganthi L, Samuel A.A. 2012 review several models of load prediction highlighting their applicability. They review, econometric estimations such as time-series regression, computational estimations such as genetic algorithms. They conclude that models should reflect the change in demand.

Kaytez F. et al. conducts comparative analysis of regression models, neural networks and least squares support vector machines . They used Turkish electricity transmission data from 1970 to 2009. They tried to predict the net electricity consumption as a function of population, installed capacity, gross electricity generation and total subscription. Data for total installed capacity and gross electricity generation was from the Turkish Electricity Transmission Company (TEIAS) statistical database and the demographic data was obtained from the Turkish Statistical Institute (TIE) database . Both the number of subscribers and the net electricity consumption values for Turkey were taken from Turkish Electricity Distribution Company (TEDAS) and other private electricity distribution companies [16]. Data were split into 2:1 ratio for training and testing purposes respectively while the process was validated using 2010~11 data. A multilayer feed-forward backpropagation neural network, multiple linear regression model and the least square support vector machine (LS-SVM) to estimate the target class. The predictive accuracy of all the model was impressive but the LS-SVM outperforms other models in various performance indicators .

A short-term forecasting research work performs on Korean hourly electricity load data . . The challenge was to find a model that can forecast load one day ahead. Authors used Korean electric

[20] See: https://www.sciencedirect.com/science/article/pii/S0360544205000393.

load data set sourced by Korea Electric Power Corporation. This has been carried out on a sample set of two weeks of data where weekdays' data was used for forecasting load for another immediate weekday and likewise, weekend data was used to predict the load of another subsequent weekend.

The data was classified before making a forecasting model using K- means and k-NN to eliminate error from calendar- based classification. Then Artificial neural network (ANN), Group Method of Data Handling (GMDH) in addition to Simple Exponential Smoothing (SSE) were used to design the predictive model. GMDH uses Kolmogrov-Gabor polynomial which is an inductive self-organizing data-driven approach that provides scintillating performance in modeling small data set. In this study, the data set was very small as mentioned earlier and other than historical load data no other sources were used to predict the load. GMDH had the least Mean Absolute Percentage Error (MAPE). GMDH had the best predictive accuracy in compared to other model proving to have the most strength for small data set-driven predictive design.

Another short-term load forecasting research was done by Lee C.M, and Ko C.N . Electric load data set from is from Taiwan, 2007. Authors aimed to forecast load twenty four hours ahead. Three different patterns of load data are utilized to evaluate the effectiveness of the proposed algorithm. Working days were considered from Monday to Friday, Saturday as weekends and Sunday and other national holidays as holidays. Whole year's data was divided into these 3 groups and different training and testing data have been selected from each group to perform and evaluate forecasting efficiency

Previous 41 days of weekdays data used as an indicator to predict the load of the 42nd date. Likewise, few weekends and holidays data were used to predict a load of the subsequent weekend and holiday. They propose a model to improve the accuracy of short-term load forecasting by integrating support vector regression (SVR), and adaptive annealing learning algorithm (AALA) with radial basis function neural network (RBFNN). The proposed method performed better in MAPE reduction in comparison with other existing methods.

TABLE I????? summarizes the reviewed researches. The table shows, in the last two models, scope is further subdivided into some groups to ensure better forecasting and to accommodate seasonal impacts and occasional impacts (subgrouping column of TABLE I). The timespan of dataset also matters. Therefore, a detailed study of the available data requires finding pattern, understanding the relevance of heterogeneous sources etc. The short review of forecasting literature helps to ascertain the data and model to examine for our load data analysis.

3. Data Description

3.1. Billing data

Dhaka Electric Supply Company Limited (DESCO) and Dhaka Power Distribution Company LTD (DPDC) maintain electricity distribution at the user level in Dhaka. For this work monthly electricity consumption data (i.e., bill records) from the year 2005 to 2017 (up to June) was collected from DESCO (distributor of Dhaka north region). DESCO is responsible for electricity distribution to sixteen zones in northern regions of Dhaka. There are 8 Tariff Categories (namely, A, B, C, D, E, F(11KV), and F(33KV)) in the billing system. From these 8 different types of connections, residential users or the "A" category have been chosen for this analysis. Approximately 90% of overall users are from this residential category. We find a total of 50,365,058 bill records in the dataset.

There are 8 columns in this billing dataset. "ACCOUNT_NO" is the unique id for a user, "LOAD" is an integer Unit (kW) which indicates maximum allowed load for an account. "UNIT" is consumption in kWh per month for an account. Each user account belongs to a "ZONE" and "BLOCK" indicates the area inside a ZONE where the user account is located. Each ZONE has a number of BLOCKs. "ADDRESS" is the exact address of a user under a block inside a ZONE. "MONTH" and "YEAR" are specific time for which a bill is generated. Readers are referred to Appendix 3A for a detailed description of the bill records.

Table 3.1 The total consumption in each year

Year	Total (kWh)
2005	497,627,633.00
2006	567,214,395.00
2007	710,650,880.45
2008	731,592,360.79
2009	945,485,109.37
2010	1,019,777,331.71
2011	1,073,762,792.57
2012	1,174,766,833.72
2013	1,297,665,259.89
2014	1,453,680,380.22
2015	1,566,953,286.93
2016	1,730,382,878.75
2017 (up to June)	708,846,494.00

3.2. Load Data

As described earlier DESCO supply area is divided among 16 zones. At each zone there are at least 2 sub stations from where electricity is supplied to the households through a number of feeders. Each substation keeps a log book where hourly load at each feeder is recorded. This means 24 entries per day per feeder. As this data is not digitized, a summarized report is sent to the DESCO management for their load prediction purpose. The summarized report do not carry vital information such feeder wise load, difference in peak hour-load across different feeders etc.

3.2.1 Digitization of Load data

At the power stations the DESCO officers take note of hourly load at each feeder. We took image of these handwritten data. To use the data for further analysis we needed to go thorugh costly and time consuming digitization process.

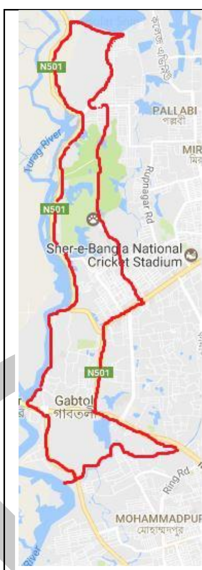
Figure 2.1 Load data sample. Source: Photo taken by the authors

The data was converted to csv format for further use:

Ahmed Na	Section-7	S.Ali Bag	Stadium	Darussala	RM Indust	Gabtoli	J.Housing	M.Sharif	Section-2	S Buddizit	MP RMU
110	175	140		60		65	100	150	80		
115	145	145		70		75	110	160	90		
120	160	160		90		120	135	200	110		
120	155	155		90		110	125	185	90		
110	115	115		90		100	120	180	80		
110	150	150		90		105	130	170	80		
120	150	150		110		95	115	170	80		
120	150	150		110		90	125	180	90		
120	165	165		120		110	140	185	110		
120	160	165		135		115	150	200	120		
145	150	150		140		105	145	200	110		
125	145	145		120		90	130	185	110		
140	120	120		100		70	115	180	110		
130	100	100		100		55	95	160	100		
110	90	90		90		50	85	150	90		
100	80	80		80		45	80	130	80		
90	80	80		70		40	80	120	80		
90	80	80		70		40	80	120	80		
90	80	80		70		40	80	120	80		
90	80	80		70		40	80	120	80		

Figure 3.2: Data in excel sheet

As digitization of load data is expensive and time consuming, for the purpose of this research we selected two substations Shah Ali and Kalyanpur residing in the Shah ali zone.



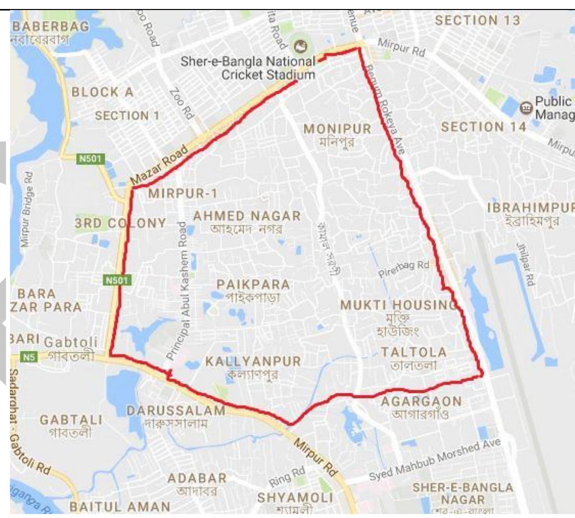


Figure 3.3: Red marked area indicate the Shah Ali region. Source: Made by the authors

Figure 3.4: Red marked area indicate the Kalyanpur region. Source: Made by the authors

Kalyanpur substation caters to 15 sub areas. Each of these areas have individual feeder. The areas are : Ring Road, Gana Bhaban, Adabar, Technical School, Tolarbag, Beri Band, South Bashail, Lal Kuthi, Swearage, Baghbari, Goiter Tek, Monsurabad, Pikepara, BU School, Kallyanpur.

Among these sub areas, Gana Bhaban is the Prime Minister's Residence. In order to avoid load shedding in this area, supply is maintained via two substations. If one of the station is disrupted the other resumes. The feeder from Kalyanpur is designated as the stand by feeder, it only resumes when the main substation at Gana Bhaban fails. For this reason, Gana Bhaban feeder in the Kalayanpur substation do not have any data.

Shah Ali Substation consists 12 sub area each of which has individual feeder. The areas are : Ahmed Nagar, Section-7, Sout Ali Bag, Stadium , Darussalam, RM industry, Gabtoli, J. Housing, Majar Sharif, Section-2, S. Buddhijibi, MP RMU. Among these feeders, our dataset do not have any data from Stadium, RM Industry, S Buddhijibi and MP RMU.

We have digitized a week in summer – 15th to 21st of May 2015, and a week in winter –15 to 21st December 2015.

Descriptive analysis of the data:

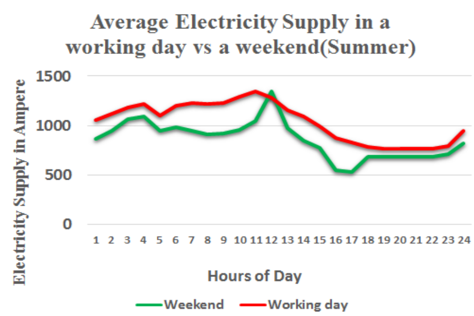


Figure 3.5 Average electricity supply in weekend and working day during summer (3rd week of May , 15th May to 21th May,2015), weekend considering only Friday – ShahAli Substation). Source: Made by the authors

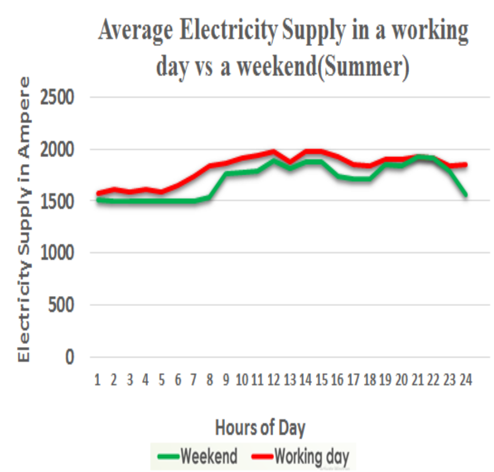


Figure 3.6 Average electricity supply in weekend and working day during (3rd week of May , 15th May to 21th May,2015), weekend considering only Friday – Kalyanpur Substation). Source: Made by the authors

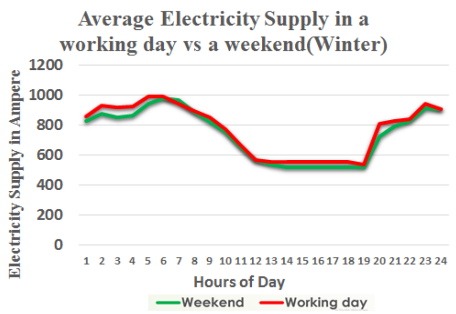


Figure 3.7 Average electricity supply in weekend and working day during winter (2nd week of December, 11th December to 17th December, 2015) weekend considering only Friday – ShahAli Substation). Source: Made by the authors

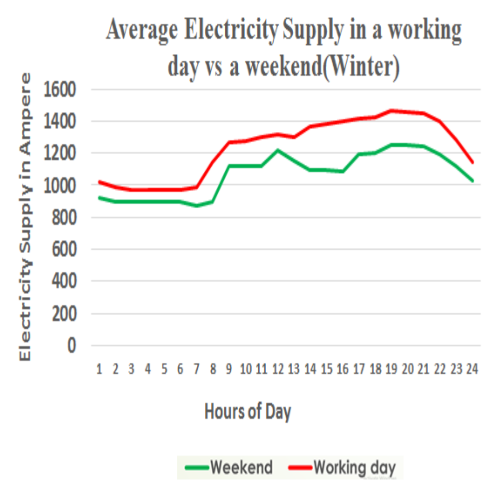


Figure 3.8 Average electricity supply in weekend and working day during winter winter (2nd week of December, 11th December to 17th December, 2015), weekend considering only Friday – Kalyanpur Substation). Source: Made by the authors

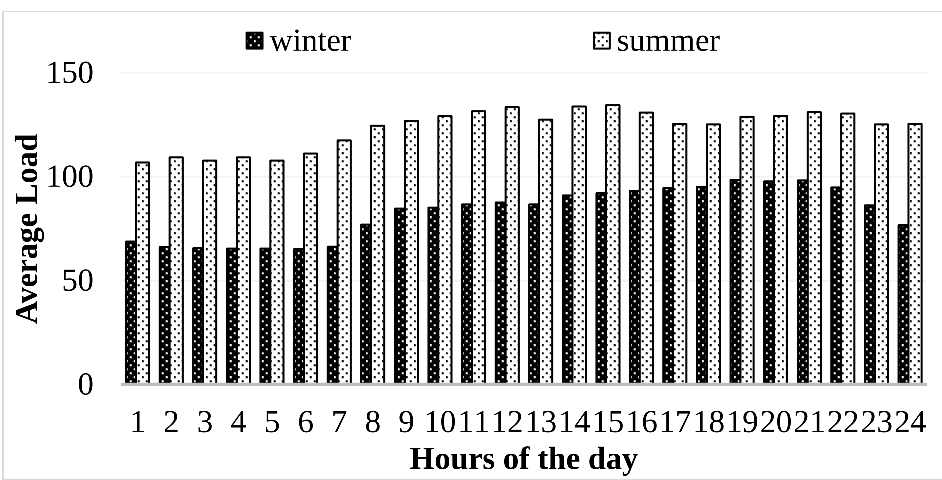


Figure 3.9 Hourly Average Load of Kalyanpur: loads are almost stationary throughout the day where loads in winter are around 40 kWh less than the loads in summer. Source: Made by the authors using data used in this research

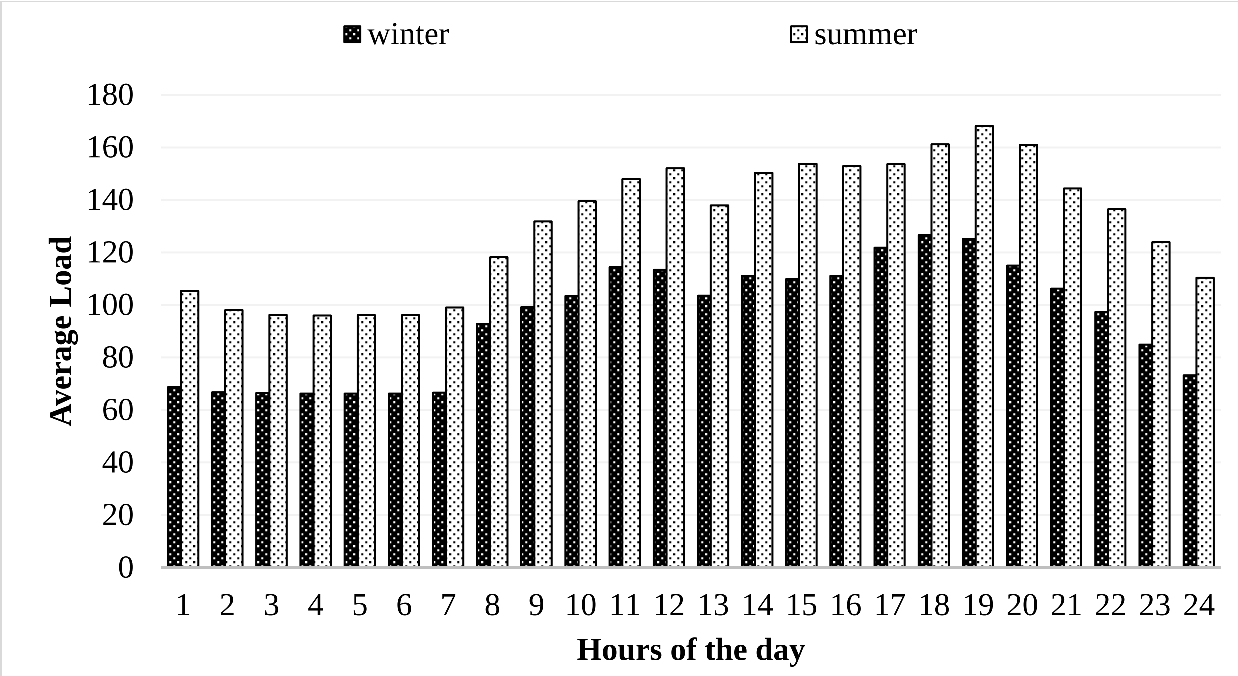


Figure 3.10 Hourly Average Load of Shah Ali: the graph is following a hockey stick pattern. From 12 am to 7 am, the load remains almost stationary and lowest while during 8 am to 11 pm, for half of this range, load rises and then gradually falls. Loads in winter are around 40 kWh less than the loads in summer. Source: Made by the authors using data used in this research

Supply of electricity is lower in weekend compare to weekdays. But in weekend (Friday is considering weekend), supply in Shah Ali increase during Jumma prayer but the supply is almost steadier in Kalyanpur during Jumma.

During winter, there are no changes between weekend and working days in Shah Ali zone. But Kalyanpur have severe changes and the supply is increasing during weekdays.

Midday to late evening has low supply in Shah Ali zone:

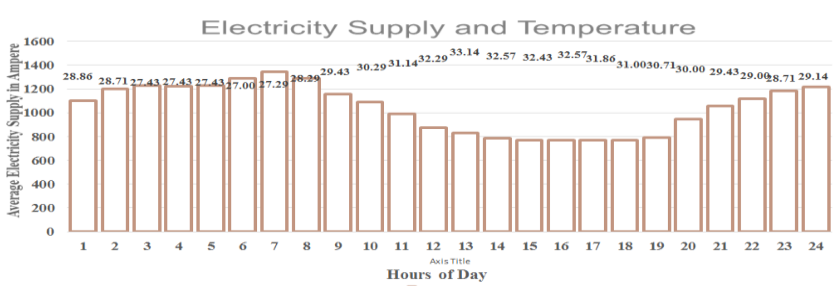


Figure 3.11 Average electricity supply between mid-day to late evening supply (3rd week of May (15th May to 21th May). 2015, weekend considering only Friday – ShahAli Substation). Source: Made by the authors using data used in this research

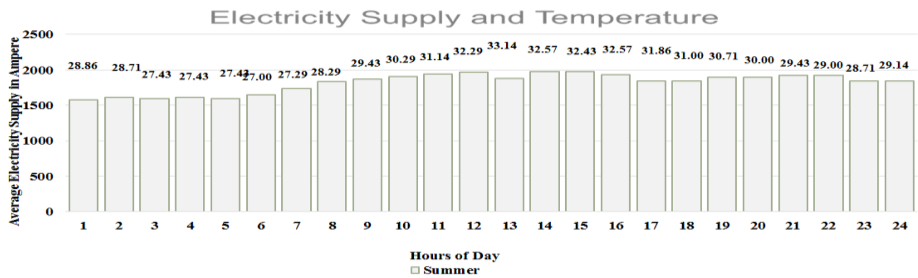


Figure 3.12 Average electricity supply between mid-day to late evening supply (3rd week of May (15th May to 21th May). 2015, weekend considering only Friday – Kalyanpur Substation). Source: Made by the authors using data used in this research

Supply from ShahAli substation dramatically reduce during the mid-day in summer. But no significant changes observed in Kalyanpur substation.

Figure 3.9 and 3.10 gives a comparison between consumptions during winter and summer in Kalyanpur and Shah Ali sub stations respectively. In Bangladesh, use of Air conditioners during the summer is more commonplace than use of heaters in winter. The figures show during summer, the consumption is high. However, the impact of summer and winner is not quite high in Kalyanpur substation, the load varies a little throughout the day while in Shah Ali, from midnight to 7 AM in the morning it remains almost same but then gradually rising till 12 PM, mostly remain constant till 8 PM and then again gradually drops till midnight. The main point of bringing these statistics is to clear the point that even in the same zone, different sub stations act differently. As the load data are available from the logbook of previous years, substation-wise or feeder-wise forecasting could lead to a better management and distribution in the electricity sector.

3.3. Challenges

This research consists of 3 types of data which are electricity billing data, supply/load data and load shedding data for our research. Electricity billing data was collected from zonal offices of DESCO located in the north part of Dhaka city. There are 16 zones in DESCO area. Supply/load data and load shedding data was collected from substations of DESCO located in different zones in Dhaka north. There are 33 substations in DESCO area. The average time required to go to the zonal offices and substations and come back in regular traffic is 2+2 hours (approx.) from Dhaka University. So, to get one data we needed to visit multiple times to one zone/substation. At the same time various reasons like non cooperation, data not good to read, delay in administrative approval creates difficulties in our research. We faced challenges in two spheres,

3.3.1 Collection of Data

The biggest challenges we faced in our project is to collect data from zonal offices and substations of DESCO. We started data collection process in November 2015 by discussing benefits of utility data analysis for better policy making for stakeholders of electricity and government. The lead of Bangladesh team presented his idea to the concern person and top management including Energy advisor to Prime Minister (PM), Access to Information (a2i) program people and United Nations (UN) officials in Dhaka.

After getting some positive response from them, we started collecting electricity billing data by visiting some of the zonal offices including Agargaon, Shah Ali, Pallabi in the first week of January 2017. We handed over official letter from Dhaka University asking for Data for our research. The letter clearly stated that the privacy and security of the Data will be ensured.

We faced difficulties to get the data from zonal offices of DESCO. In every visit to zonal office, we had to explain our research to them and show them written permission from central office. We made official contacts, presented our ideas in meetings and they agreed but the supply and zonal offices (most of them) didn't receive letters that could help them give data. This created problem for us to identify our genuineness. One of our member's experiences during a visit is given below:

"We started our data collection from Agargaon zone. We had to face difficulties to find the office and get the appointment of chief engineer of that zone. After explaining our research goal to the chief engineer, he instructed the IT officer to help us getting data. We had to explain our goal and why we need data to him again. Then he generate a sample file with data for crosscheck if the fields are ok. He also told us to give us data daily as he was busy with his office work and cannot manage time to generate and run query for a long time. Later we could not reach him for data as he was attending an official training. Then we decided to use email for proving us data. We had to knock him every day and he provided us some data. We got data from 6 zones till April, 2017. But the data we got at first was not good. So, we had to restart the process of getting data. This time, they stopped giving us data and we sought help from a2i people. They gave official letter to be sent to all zonal office and supply office. We had several meetings with corresponding authorities that facilitated the process. We were informed to collect data from all zones again as some fields were missing in previous data. We had to collect all zonal billing data again. But for load and load shedding data we faced different challenges. These data are kept in a written format in a book (Figure 3.13). No digital format is available. So, we had to take photos of each page of that book. Till now we are able to take two substations load and load shedding data. From this data, we have digitized only two weeks data involving 3 undergraduate students for 5 days."

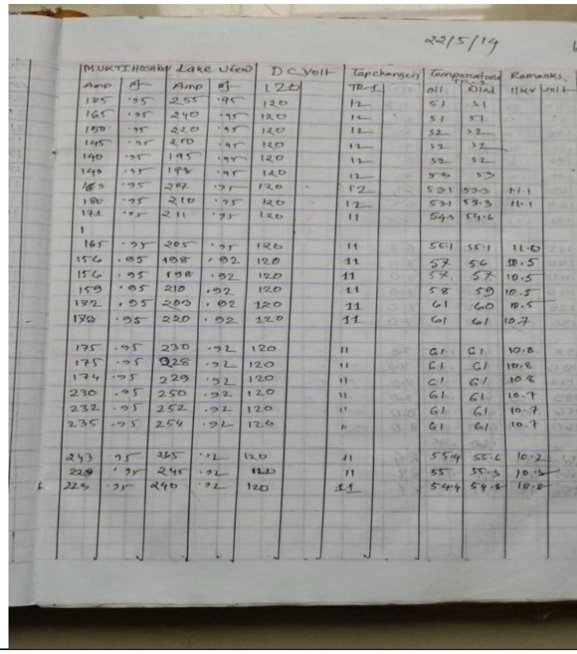


Figure 3.13 : Picture of Load data from a substation.
Source: Photo taken by the authors

We started getting billing data from zones from January, 2017 and till April, 2017 we only collected data from 6 zones. Later on, they informed us that previous data was not complete and we need to collect data from all zones again. Then after several meetings and mutual understanding with the help of a2i people, we started collecting billing data from September, 2017. It took 3 months to collect all billing data again till October, 2017. The data preprocessing and cleaning were performed as soon as we got the data. We got only November & December, 2017 to work with the analysis. Analyze this huge data during this short span of time was very challenging. For data collection we had to make 154 visits, 172 phone calls and 63 email. Month wise communication is presented in figure 3.14.

We also collected population, housing and economic census data from Bangladesh Bureau of Statistics (BBS). They have an arrangement to sell data for organizations. At the same time, University can get the data at a minimal charge for research purpose. We have communicated them and get data at a minimal price with the reference of Dhaka University.

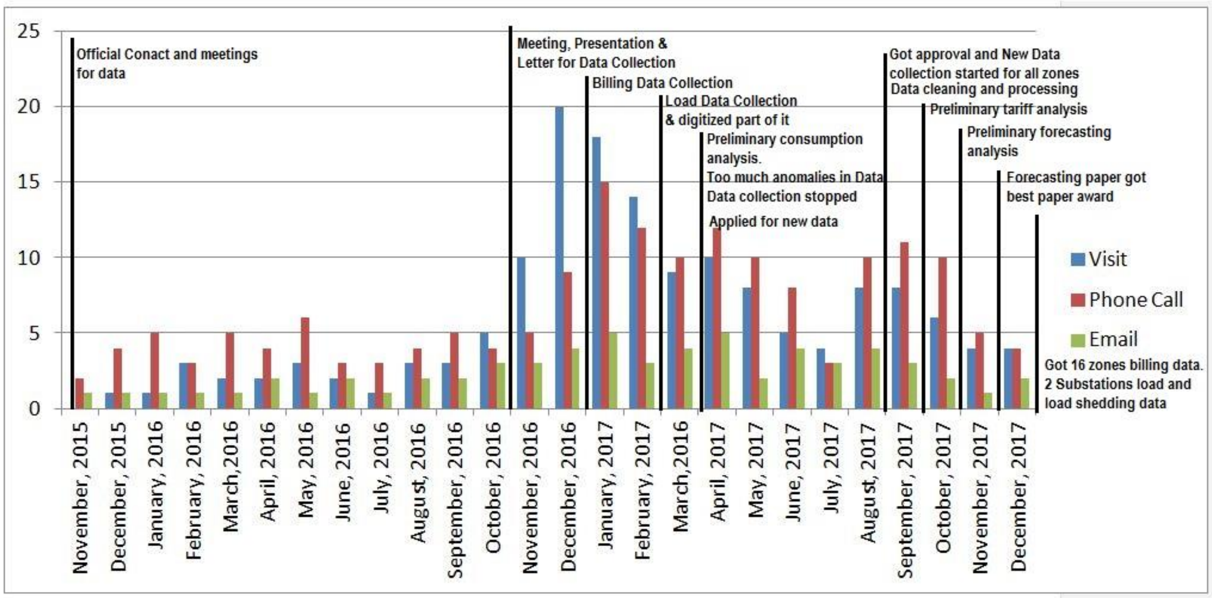


Figure 3.14 Project timeline with task schedule. Source: Made by the authors using data used in this research

3.3.2 Cleaning Data

The data used had a number of problems, from missing data, to misrepresentation of data and misspelling. We had to tackle some of those issues. Also, for our price impact research, we had to find consistent users.

In this analysis, the consistent users' data from 2012-2016 has been considered. The term “consistent users” means, users having bills (UNIT > 1 kWh) in every single month during 2012-2016 time line. In order to understand the impact of tarrif hike a proper trend analysis is required. Hence, we wanted to analyze the impact on users who will be available all through the analysis period. Among these consistent users, 3.67% users are consuming 3000 kWh or above and 4.92% users are consuming 2000 kWh or above in a single month. With respect to consumption per month of most of the users these high consumption-users are outliers. Hence, we have excluded the accounts that consume above 2000 kWh and perform all analysis on rest of the 95% consistent users. Also, this analysis is at the ZONE level granularity. As, there is no data on the exact boundaries of BLOCKs on maps. We faced address resolution problem while doing it.

The problems we faced on plotting the address on map are as follows

There is no exact format of address in Dhaka city. The address wrote on each bill of a particular ZONE, do not have the correct name of that ZONE. As example, we see the addresses of Shah Ali Zone. There were , 8-9 versions of ShahAli name in addresses, like - “ShahAli”, “Sha-ali”, “shah-ali”, “sahali”, “Shahale”, “Shaha Ali”, “Shaha-Ali” etc. And these are only ZONE name problems. So, it is so much difficult to correct the full address. As, the whole address is having the same kind of spelling mistakes.Still, we corrected 100 random addresses from “Shah Ali” Zone and tried to call the Google’s Map API to point those. But, the problem is - Google map API still does not support reverse geocoding for Dhaka. As, we tried to plot those 100 addresses, they all plotted in a single point named as "Shah Ali".

While cleaning the dataset and dealing with the outlier values, a single consistent user couldn't be found in **Badda and Baridhara** zone. So, the whole Badda and Baridhara zone is excluded from the price hike impact analysis. After Cleaning the dataset, dealing with the outlier values and after cleaning the dataset and dealing with the outlier values (>2000 kWh), the number of consistent users are 2,52,173.

4. Data Analysis

4.1. Understanding the User's Consumption Behavior

4.1.1. Consumption Pattern

As mentioned before in this analysis, we considered only those users who have UNIT consumptions between 0 and 2000 kWh. Table 4.1 presents the descriptive statistics of the consumption.

Table 4.1 : Descriptive statistics of consumption (using bill records with unit consumption between 1 and 2000 kWh). Source: Made by the authors using data used in this research

Consumption Statistic	Unit (kWh)
Mean	267.61
Standard deviation	244.86
25th percentile	124
Median	200
75th percentile	324

We can observe from the table that the mean is approx. 267 kWhs and 50% of the bill records show a consumption level less than or equal to 200 kWhs. Also 75% of all records show consumption of less than 324 kWhs. We believe this figure can be deemed to be the higher-middle class consumption level in Dhaka. Whereas, we observe that in the bottom 25% of the bills records the consumption level less than equal to 124 kWhs. There is a considerable gap between these quartile values, which seems to correspond to the different income levels of the residents of Dhaka. This can be further analyzed and validated using economic census data.

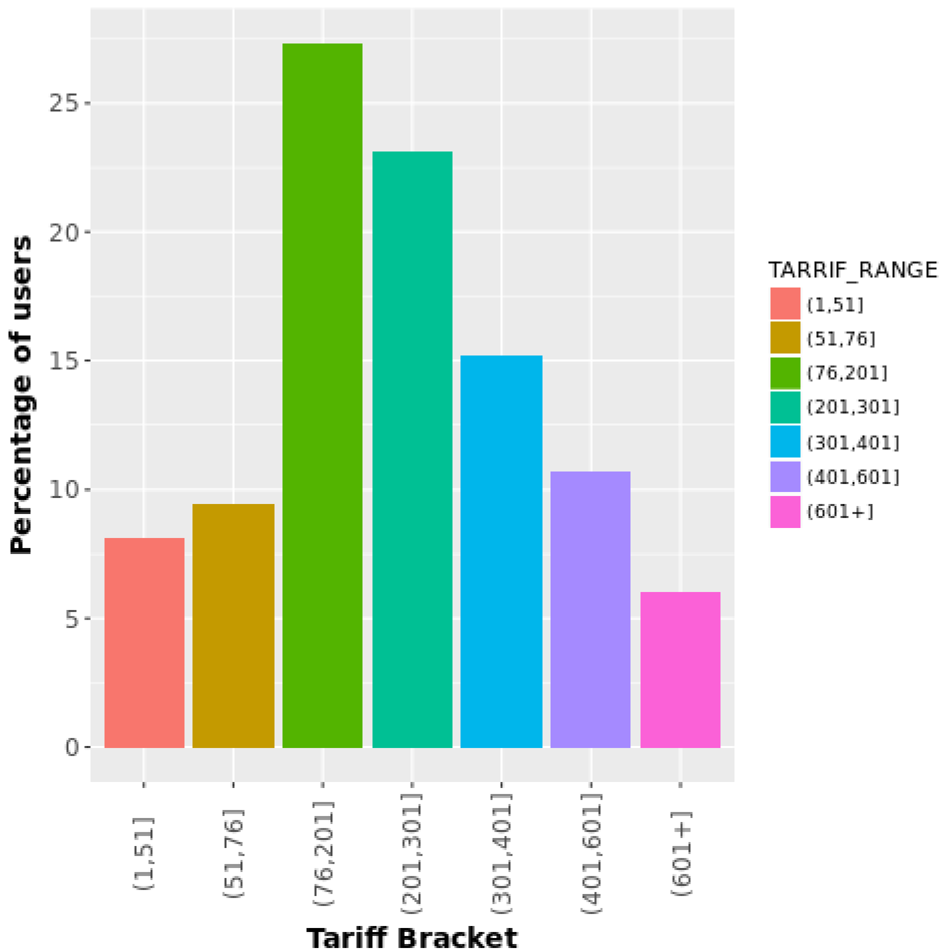


Figure 4.1 Distribution of consistent users of 2015 into different tariff brackets. Source: Made by the authors using data used in this research

Figure 4.1 presents the distribution of consistent users into different tariff brackets. Here, the average consumption of each consistent (those who have all bill records in the year) user is considered. It can be observed that more than 25% of the users belong to the [76-200] bracket and together with users in [201-300] bracket they account for the majority of users in Dhaka north region.

4.1.2 Impact of Weather on Consumption Pattern

Figure 4.2 shows the monthly consumption pattern of 2016. Here the number of users in each month (numbered 1-12) are plotted for each tariff bracket. We observe the consumption pattern is almost similar for other years under analysis. From the figure it is clearly visible that, in the first three tariff brackets ([1-50], [51-76], and [76-200]), there is "U" shape in the middle of the bar diagrams of each of the tariff brackets. That indicates, in the months of January, February, and also December there are significantly higher number of users on these three tariff brackets. These are the months in the winter season Bangladesh [See Appendix C]. The U shape also indicates that the users in these tariff brackets are shifting to the upper tariff brackets in as the weather gets wormer. This results in a reverse U shape between February and October in the middle of the bar diagrams of the rest of the tariff brackets. The likely reason is that in the summer the users are using more appliances or the using the appliances for a longer period of time. We observe that almost 60% users shifts from lower brackets to different upper tariff brackets during the summer months. Figures of zone wise shifts can be found Appendix.

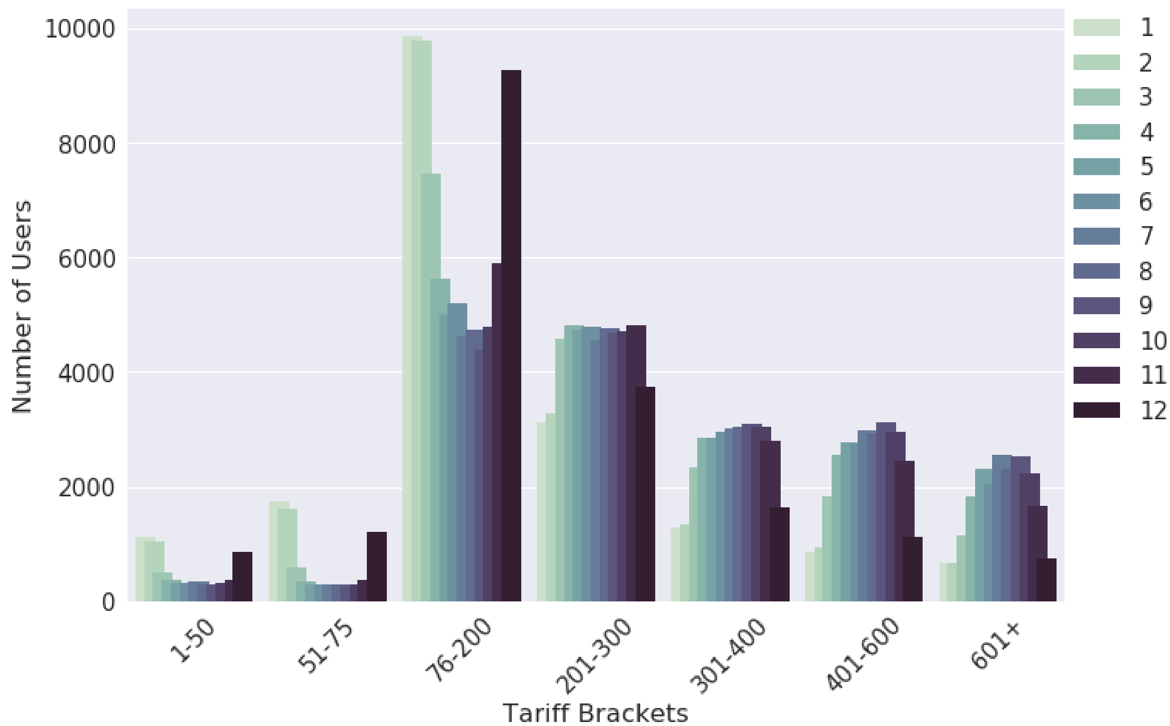


Figure 4.2 Traffic bracket wise monthly consumption in 2016. Source: Made by the authors using data used in this research

4.1.2. Appliance Usage Pattern and their Consumption

In order to collect data on the appliance usage and usage patterns we conducted a survey. The survey collected appliance usage data from a stratified sample (randomly selected from each tariff brackets). The survey questionnaire is available in Appendix ??. Table 4.2 presents the most popularly used 8 appliances based on the survey. Based on the usage data collected from the survey we construct eight possible usage patterns of appliances that map to the eight different tariff brackets. For example, pattern 3 corresponds to a household that has 3 CFL bulbs, 2 ceiling fans and a TV and using these appliance according to the usage levels presented in Table 4.2 the monthly consumption will fall in to the [76-200] tariff bracket.

Table 4.2 Summary of data collected from survey on appliance usage. Source: Made by the authors using data used in this research

Appliances	**Watt**	**Min. Runtime (hour/day)**	**Avg. Runtime (hour/day)**	**Max Runtime (hour/day)**
CFL bulb	15	8	14	18
Ceiling fan	60	4	12	20
Refrigerator (165 liters)	180	24	24	24
Refrigerator (210 liters)	250	24	24	24
Television (small)	110	4	7	12
Television (big)	220	4	7	12
Oven	1000	0.5	1	2
AC (1.5 ton)	2250	2	5	8

Table 4.3 Mapping usage pattern to tariff brackets. Source: Made by the authors using data used in this research

Patterns	**Appliances**	**Tariff bracket**
1	2 Bulbs, 1 Ceiling fan	0-50
2	3 Bulbs, 1 Ceiling fan	51-75
3	3 Bulbs, 2 Ceiling fans, 1TV	76-200
4	3 Bulbs, 2 Ceiling fans, 1 Refrigerator (165 l), 1 TV	201-300
5	3 Bulbs, 2 Ceiling fans, 1 Refrigerator (165 l), 1 TV, 1 Oven	201-300
6	5 Bulbs, 4 Ceiling fans, 1 Refrigerator (165 l), 1 TV, 1 Oven	301-400
7	5 Bulbs, 4 Ceiling fans, 1 Refrigerator (210 l), 1 TV, 1 Oven	301-400

8	5 Bulbs, 4 Ceiling fans, 1 Refrigerator (210 l), 1 TV, 1 Oven, 1 AC (1.5 ton)	600+

As discussed earlier, with exogenous shock, the consumers at each tarrif brackets may change their usage behavior. They may fully cease to use the devices or reduce the propensity of usage. To underdertand the scenarios we conducted a sensitivity analysis. We examine the impact of changes in appliance use due to weather or price hikes. Figure 4.3 shows the box plot of possible consumption level for each usage pattern using the min/max and average use of appliances in each pattern. For example, in pattern 3, the 5 number summery of the consumption is as follows: max = 135.9 kWh, min = 38.4 kWh , median = 85.2 kWh, upper quartile = 110.55 kWh and lower quartile = 61.8 kWh.

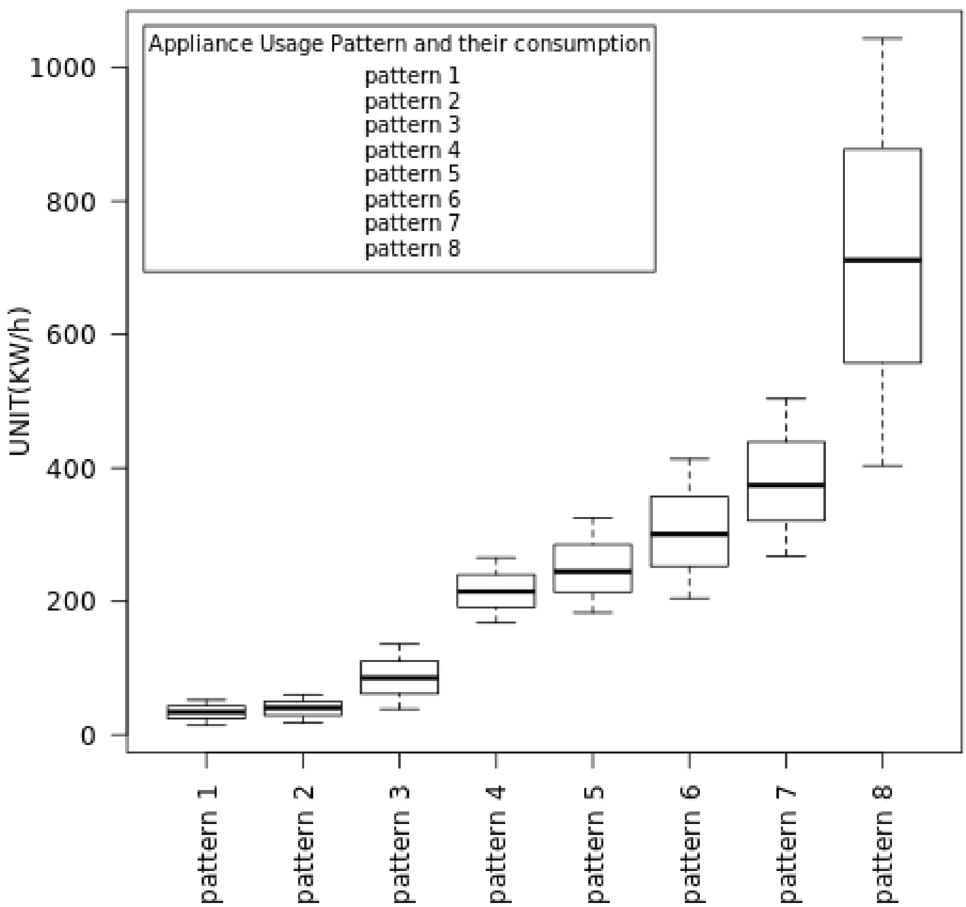


Figure 4.3 Sensitivity analysis of consumption of different usage patterns. Source: Made by the authors using data used in this research

Facing price hike, a consumer can a. stop using an appliance or b. reduce the intensity of using the appliance (for 16 hours use to 8 hour use etc.) in order to keep the monthly bill amount fixed. However, most of the electrical/electronic appliances can work fine for 5/10 years so stopping the usage is not real option in short term.

So we may see with affordable price people might increase the intensity of use, and with high price they may reduce it. From box plots in Figure 4.3 we see that it is fairly easy to hop from one tariff bracket to another (i.e., from one pattern to another) by just reducing or increasing the intensity of the use of devices. Hence if we see this movement, we may assume that the users in these patterns are increasing or decreasing the use and it is very easy to cross the tariff bars by doing so.

From this figure we also see three different clusters. Patterns 1,2, 3 form a cluster, pattern 4, 5, 6 and 7 form the 2nd cluster and pattern 8 is in a separate cluster. It seems it is easy to navigate patterns 1, 2 and 3, with a bit difficultly to do so in the 2nd cluster.

4.1.3 Temporal Change in Consumption Behavior

In this section, we examine the temporal change in consumption pattern of users in different tariff bracket. In Table 4.4 we find in which tariff bracket the percentage of users that fall in a certain tariff bracket at the start of 2005 end up in after 7 years (i.e., in January 2012). Table 4.5 also finds the percentages of such shifts after 12 years (i.e., in January 2017). The diagonal entries of the table indicate the percentage of users in a certain tariff bracket remaining in that tariff bracket and the off-diagonal entries indicate the amount of shift observed. For example, in Table 4.4 we observe that 56.34% users in the [51-76] bracket move to [76-200] bracket at the start of 2012.

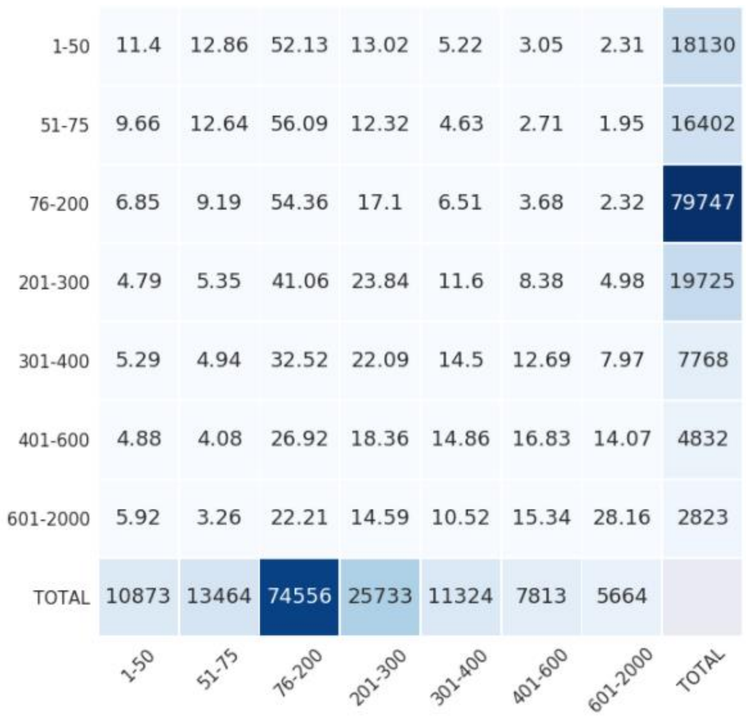
Both tables show similar trend in usage pattern changes. From the tables we observe, more than 50% of users who consume at [1-50] or [51-76] level in January 2005 end up in the [76-200] tariff bracket after 7 years as well as 12 years. Also 55% of the users in the [76-200] tariff bracket remains in that consumption level. We can conclude that majority of low consumption users (who belong to the first 3 tariff brackets) have increased their consumption level over the years.

A little over 50% of users in the [201-300] tariff brackets actually lowered their consumption level, with almost 24% users remained in the same tariff bracket at the start of 2017. Significantly more users actually lowered their consumption level in all three higher tariff brackets and significant number of them ended up in the [76-200] bracket. We can assume that this relates to decrease in usage of appliances or the impact of a couple of electricity price hikes during this period. However, we also see significant increase in consumption of users in [201-300] , [301-400], [401-600] tariff brackets. We observe approximately 25%, 21% and 14% of users increase their consumption in those tariff brackets respectively. We can assume income level and appliance use of these users have risen.

Table 4.4 Shift of users in different tariff bracket from January 2005 to January 2012

	1-50	51-75	76-200	201-300	301-400	401-600	601-2000	TOTAL
1-50	12.92	12.77	51.09	11.86	5.26	3.5	2.59	18562
51-75	8.62	12.49	56.34	12.22	5.03	3.02	2.29	16849
76-200	4.93	6.9	54.99	18.36	7.29	4.85	2.69	82302
201-300	3.32	3.26	34.06	27.26	15.37	10.8	5.92	20463
301-400	3.16	2.74	24.95	22.89	18.91	17.15	10.21	8240
401-600	2.98	2.61	19.74	17.9	17.01	21.17	18.58	5167
601-2000	3.17	1.54	17.54	12.77	9.86	18.59	36.54	3125
TOTAL	9097	11230	74826	28159	13715	10443	7238	

Table 4.5 Shift of users in different tariff bracket from January 2005 to January 2017.



4.1.3. Understanding Socio-economic Variability of Different Zones of Dhaka.

4.1.3.1 Consumption pattern in each zone

In Table 4.6 we present the consumption level at each zone. There are a couple of observations that can be made about the zones. Most notably the consumption level at Gulshan zone is significantly higher than all other zones, this can be observed from the median (324 kWh) and 75th percentile (629 kWh) statistics of this zone. Baridhara and Joar Shahara zones are also higher relatively to other zones except Gulshan.

Table 4.6 Statistics of consumption (using bill records with units consumed between 0 and 2000 kWh) of each zone. Source: Made by the authors using data used in this research

ZONE	Bill record count	Mean	Std. Deviation	25th percentile	Median	75th percentile
Agargaon	3935135	236.59	204.91	121	187	286
Badda	693774	268.17	226.18	120	207	350
Baridhara	1057075	335.47	298.12	146	244	421
Dakshin Khan	3129376	227.33	203.08	107	176	282
Gulshan	2429646	465.42	414.22	173	324	629
Joar Shahara	3166369	351.99	317.92	149	253	439
Kafrul	5317896	245	204.92	128	194	296
Monipur	4562831	232.23	205.18	119	182	277
Pallabi	4404494	233.57	202.41	117	184	284
Rupnogor	4579892	244.59	204.72	126	196	298
Shah Ali	3469400	250.52	209.75	126	197	307

Tongi East	2826701	286.07	231.36	134	227	370
Tongi West	3505173	239.62	214.75	108	181	302
Uttara East	2451121	314.33	280.4	137	232	395
Uttara West	2151272	285.21	254.98	128	219	357
Uttar Khan	2684903	237.07	204.59	112	186	300

Figure 4.4 depicts the average consumption in each zone over the years 2005 - 2016. Source: Made by the authors using data used in this research

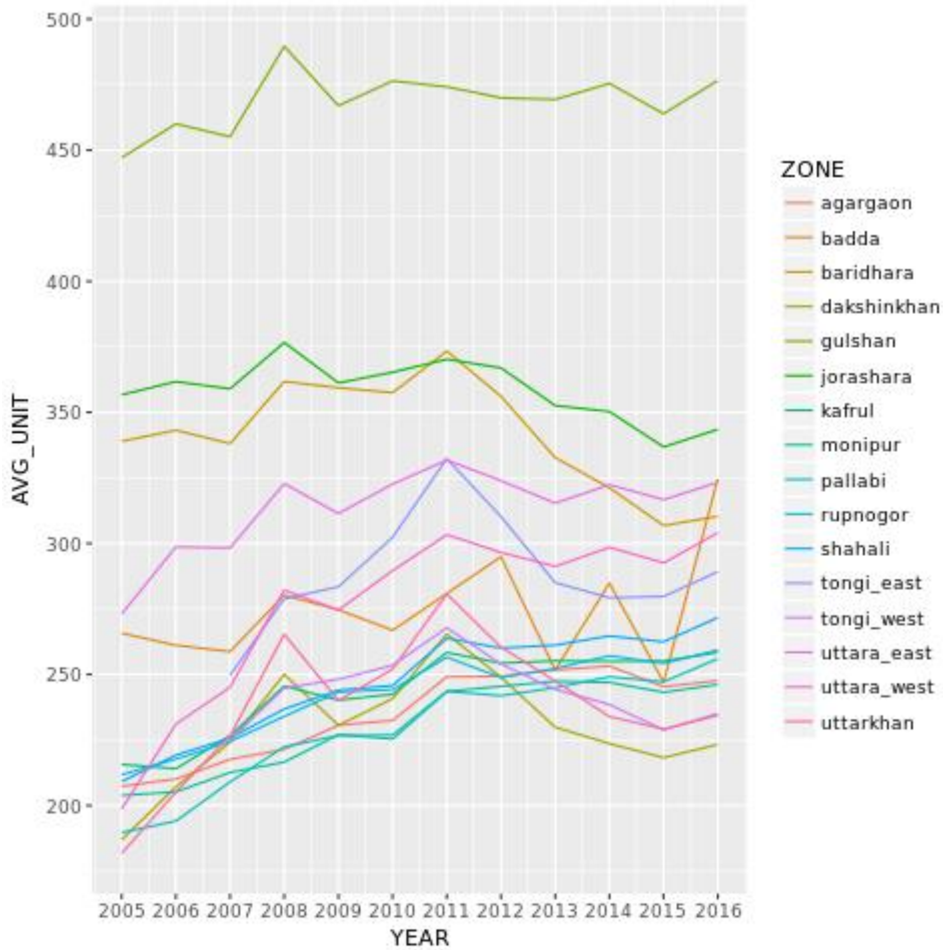


Figure 4.4 Average consumption in each zone from 2005-2016. Source: Made by the authors using data used in this research

In order to investigate the consumption patterns in each zone more closely we examine the distribution of users in each tariff zone. In Figure 4.5 we show the percentage of consistent users in different tariff brackets. It can be observed, that percentage of users is highest for [76-200] units in all zones, except for Gulshan zone. In Gulshan the highest percentage of users are in the [600+] bracket. The next highest percentage of users are those who consume [201-300] units.

We may assume users in tariff bracket [0-50] and [51-75] range have a lower income. We observe Dakshinkhan and Tongi west has higher number of such low consumption users. The percentage of users in [300-400] units are relatively same in all the zones. We assume these are the users who are in the higher-middle income class.

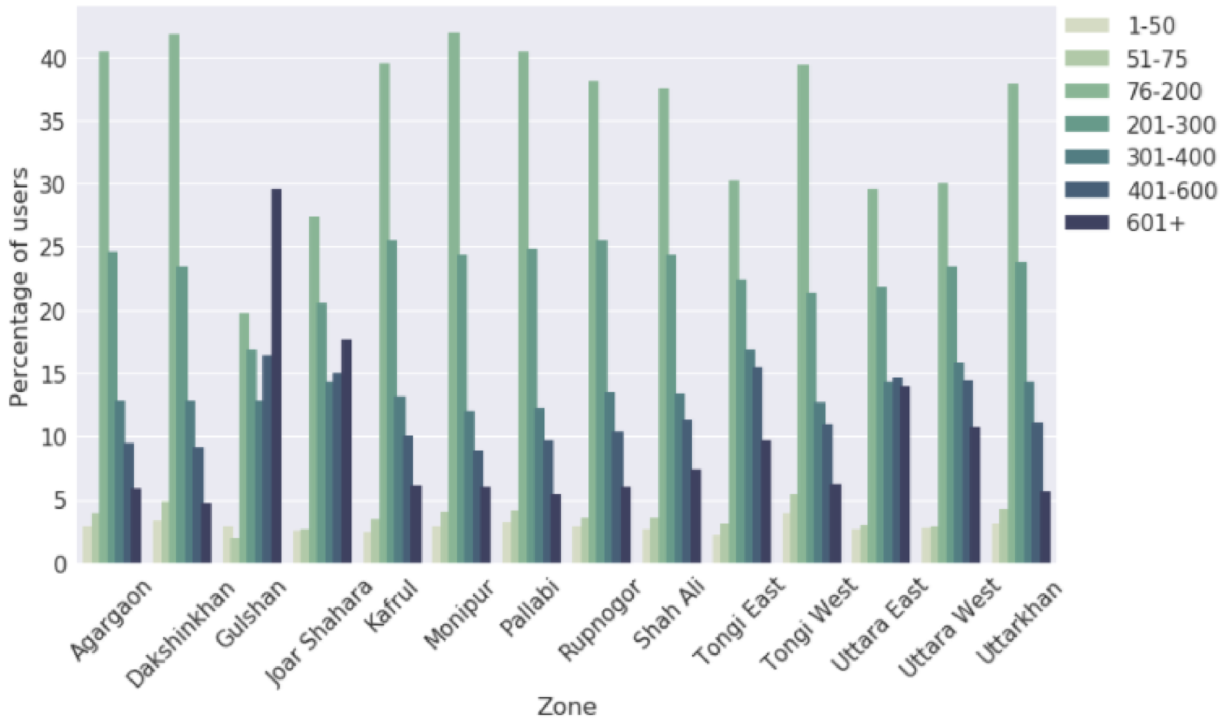


Figure 4.5 Percentage of consistent users in different tariff brackets in different zones. Source: Made by the authors using data used in this research

We can observe that based on these statistics, Agargaon, Dakhshin Khan, Kafrul, Monipur, Pallabi, Rupnagar, Shah Ali, Tongi west, and Uttar Khan has the similar mixture of users. Similarly, Tongi West, Uttara east, and Uttara west also form another cluster.

We can also assume users who consume 600+ units are economically solvent. Gulshan, Baridhara, Jorashara and Uttara_east has the maximum percentage of users in [600+] bracket, with the highest percentage of users in this bracket are from Gulshan zone. This can be more clearly observed in Figure 4.6. Here we each group of 15 bars correspond to each tariff bracket and each of these bars represents the percentage of users in that live in a certain zone. Average consumption of each user in 2015 is considered here. For example, among all consistent user that belong to [76-200] bracket 10% of them live in Kafrul.

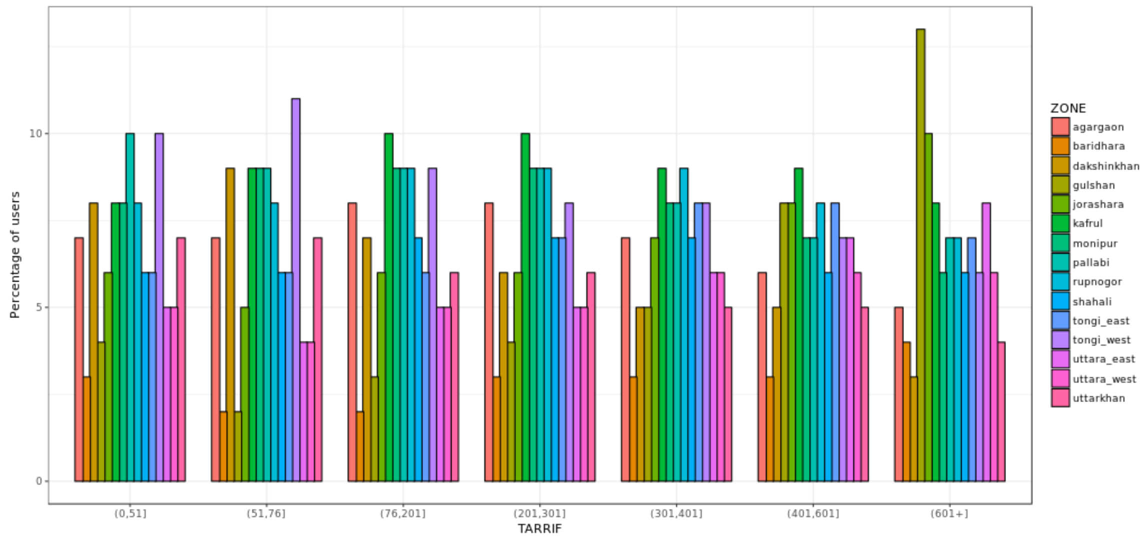


Figure 4.6 Distribution of consistent users of 2015 in each tariff bracket in to different zones.
Source: Made by the authors using data used in this research

4.1.3.2 Increase in number of users in different zones

Table 4.7 and Figure 4.7 presents the percentage increase of number of user accounts in each zone in each year from 2012 to 2016. It should be noted that the new comers or new connections to a zone can possibly due to people migrating from outside of the 15 zones in to one of the zones or it may be due to people moving from one zone to another. We observe that in every year the number of users have increased in all of the zones (as shown in figure 4.8 for Uttara West zone, for other zones see Appendix) and in most cases the increase is well over 15%. However, we also a downward trend in this rate of increase over the years, especially if the initial rate of increase was high.

If we look into the actual number of new user accounts in each zone, we find that the zones that have most number of new accounts are Rupnagar in 2012 and 2016, Pallabi in 2014 and 2015, and Agargaon and Kafrul in year 2012 and 2013 respectively.

Table 4.7 Total number of users and the number of new users in each zone from 2012-2016. Source: Made by the authors using data used in this research

Zone	2012		2013		2014		2015		2016	
	Total users	New-Comers (%)	Total users	New-Comers (%)	Total users	New-Comers (%)	Total users	New-Comers (%)	Total users	New-Comers (%)
Agargaon	29665	17.68	32010	15.49	37017	20.48	40233	15.93	42818	14.72
Baridhara	9138	26.17	10907	22.41	12208	18.38	13866	20.24	38697	15.81
Dakshin Khan	24539	22.80	29467	19.57	32726	17.43	35735	16.07	24956	17.78
Gulshan	20725	22.81	21379	23.24	23015	19.45	24072	18.21	36567	15.82
Joar Shahara	25680	17.17	28389	21.65	31553	18.45	34150	16.58	55161	12.60
Kafrul	40549	15.36	45704	17.69	49110	14.18	52133	13.01	48917	15.63
Monipur	33849	15.29	37623	16.93	42206	18.26	45599	17.08	52070	16.12
Pallabi	32642	16.03	36671	18.46	41944	21.05	47483	18.59	52038	17.44
Rupnogor	36843	20.69	40363	16.86	44167	17.48	47551	16.31	38021	15.41
Shah Ali	25618	18.33	29178	20.22	32573	17.60	35009	14.55	37206	15.89
Tongi East	23664	22.71	28532	20.38	31648	16.40	34376	15.15	49161	15.20
Tongi West	29385	19.89	34187	18.78	40044	19.87	44808	16.45	31030	19.54
Uttara East	20892	18.38	23639	22.65	25901	19.73	28130	18.49	30363	19.53
Uttara West	19381	32.10	22790	21.18	25318	23.52	28088	22.15	33825	16.72
Uttar Khan	20529	22.14	24461	21.76	28176	19.14	31074	18.93	36336	14.05

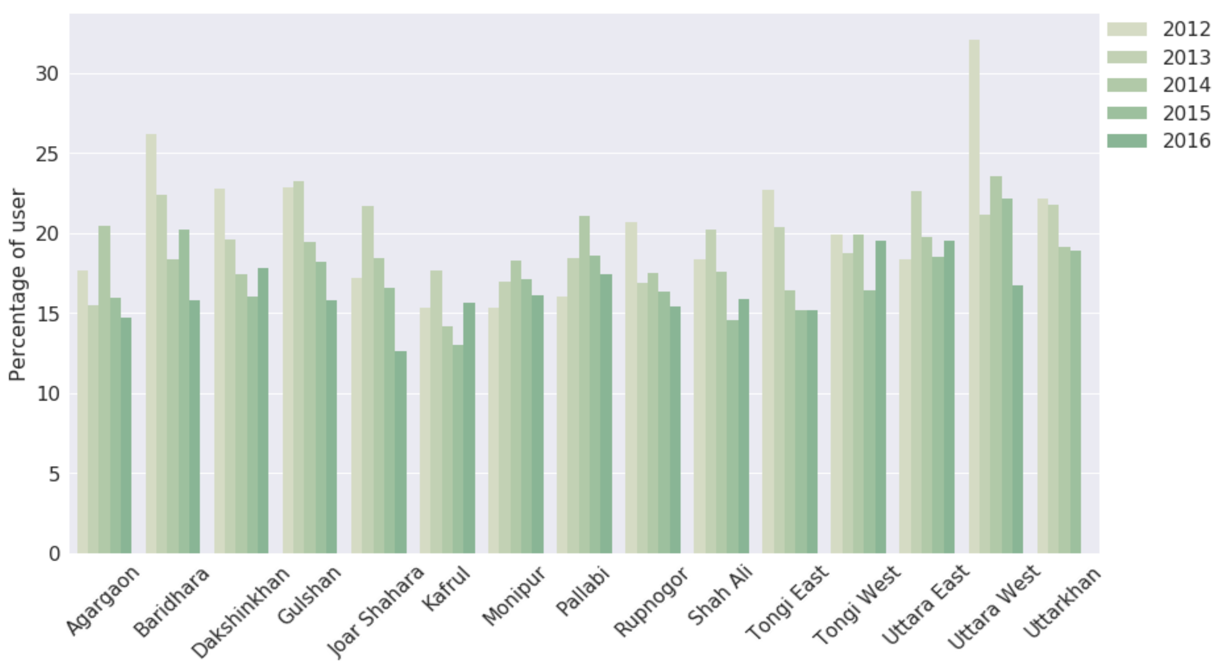


Figure 4.7 Percentage increases of new user accounts in each zone in each year between 2012 and 2016. Source: Made by the authors using data used in this research

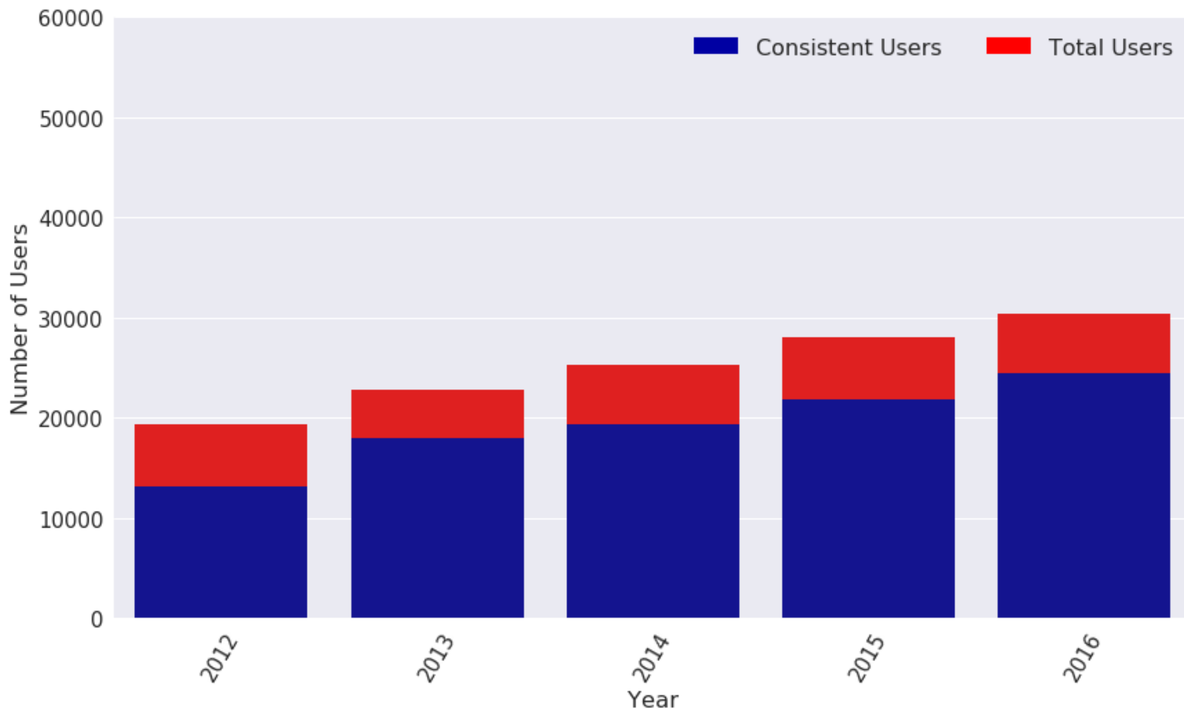


Figure 4.8 Number of consistent users and total number of users in years 2012-2016 in Uttara West zone. Source: Made by the authors using data used in this research

4.2. Understanding how regulatory decisions impact user consumption behavior

4.2.1 Impact of price hike on consumption

In this section we analyze the impact of price hike on consumption patterns of the users in different tariff brackets. Latest two price hike was on 13th March, 2014 and 13th March, 2015. So, we observe the consumption behavior changes of those 2,52,173 consistent users on between April 2014 and April 2015, and between April 2014 and April 2016. We couldn't not ascertain the impact in the long run because of limited data (price hike happened in 2015 and we have data till June 2017). We anticipate in the short term the impact will be very little. We conducted the same analysis to observe the change after a month, 3 months and 6 months. As discussed above weather affects change consumption behavior. So, impact of price hike after 1, 3, or even 6 months may not be appropriate as the price is not exorbitantly high, people may not immediately decrease consumption or the reduction would be so low to notice any change in the aggregate indicator.

Figure 4.9 represents a confusion matrix where the rightmost column is the distribution of users in each tariff brackets on April, 2014 and the bottom row represents the distribution of users in each tariff brackets on April, 2015. Only looking into the bottom row and the rightmost column it is difficult to track the consumption patterns of users. Each row represents a tariff bracket and the last column entry of the row represents the number of consistent users in the tariff bracket in April 2014. Each entry of a row of the table represents the distribution of these consistent users into different tariff brackets in April, 2015. Thus, the diagonal of this confusion matrix shows the users who stays in the same tariff brackets after 1 year. Figure 4.10 shows confusion matrix after 2 years. That is, how the users are distributed after 2 years of the price hike.

We observe price hike on average do not have impact in short term. However, the impact is not homogenous. Consumers in bracket [1-50], [51-75] seem to have kept their upward propensity to consume more. While [76-200] stays in their position. 60% users of [76-200] bracket stay in the same bracket and shifted users jump mostly to the [201-300] bracket in both April 2015 and April 2016. However, most of the high level consumers of bracket [401-600] seem to shift down to the lower level. Around 35% users of [301-400] bracket stay in their own bracket, rest of users in this bracket mostly shift to the immediately lower bracket (i.e., [201-300] bracket) and the upper (i.e., [401-600]) tariff brackets. And, more than 50% users of [600+] tariff bracket stay in their bracket and 25% of them dropped in to the [401-600] tariff bracket.

	1-50	51-75	76-200	201-300	301-400	401-600	601+	TOTAL
1-50	28.6	11.24	38.36	11.22	4.95	3.4	2.23	4671
51-75	12.8	21.04	51.93	8.81	2.62	1.79	1.02	4814
76-200	2.62	3.8	70.52	18.16	3.1	1.37	0.42	79105
201-300	1.18	0.92	29.26	50.77	13.51	3.58	0.78	67740
301-400	0.79	0.51	10.22	31.66	39.36	15.55	1.9	39750
401-600	0.67	0.48	5.69	11.85	25.75	45.7	9.86	35027
601+	0.84	0.4	3.75	4.8	6.19	24.73	59.29	26168
TOTAL	5597	5648	86934	67700	38247	32413	20736	

Figure 4.9 Shift of users in different tariff brackets during April 2014 to April 2015. Source: Made by the authors using data used in this research

	1-50	51-75	76-200	201-300	301-400	401-600	601+	TOTAL
1-50	19.15	9.54	40.63	15.18	6.75	4.93	3.82	4664
51-75	8.93	14.13	54.53	12.86	4.93	2.91	1.71	4805
76-200	2.53	3.14	60.74	24.64	5.46	2.56	0.93	79079
201-300	1.28	1.14	26.4	44.47	18.32	6.8	1.59	67707
301-400	0.87	0.67	11.65	26.16	34.13	22.27	4.24	39716
401-600	0.83	0.59	7.25	12.52	20.27	41.55	16.98	34990
601+	1.07	0.51	4.92	6.36	7.09	20.45	59.61	25906
TOTAL	5102	4985	78867	67333	39756	35684	25140	

Figure 4.10 Shift of users in different tariff brackets during April 2014 to April 2016. Source: Made by the authors using data used in this research

4.3. Forecasting short, mid and long-term demand

Pioneer of flexible design Richard de Neufville commented "The forecast is always wrong" [Flexibility in Engineering Design by Richard de Neufville, Stefan Scholtes]. They argue that, "after-the-fact comparisons routinely demonstrate a big gap between the forecast and the reality. Any model of Electricity demand forecasting also suffers from 'uncertainty' because of several 'frequently changing' input variables such as, weather, macro and micro economic conditions, market dynamics, consumption behavior of the consumers, regulatory environment etc. However, fortunately it has been seen that, consumption behavior may follow some pattern. Hence with sufficient data and robust modeling a reasonable prediction is possible. From the machine learning perspective, a model that reduces the error term in the predictor function may have better forecasting accuracy.

In order to find a short term forecasting model we conduct analysis over a week long data base from Shah Ali substation (15th May 2017 to 21st may 2017). Daily temperature was obtained from Weather Underground website [R25] . We have assumed a normal distribution of hourly temperature.

Data is divided between training and testing parts. Two different forecasting models are examined. These two models are denoted as '5 input model' and '8 input model'. The 5 input model has hour of the day, binary variable denoting peak and off peak hours, load of the previous hour, hourly temperature, dew point are features for predicting demand. In 8 input model, along with these variables, load of t-24 Hour (where t = 1 to 24) , average load of the previous day and load at peak hour of the previous day are used as predictors.

We then run a neural network from (15th May 2017 to 21st may 2017) of which 70% data was used for training, 15% data for validation and 15% data for testing. Data of 21st may 2015 was used for validation.

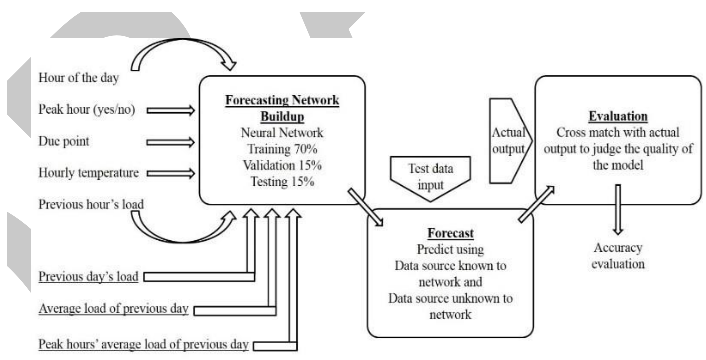


Figure 4.11 Workflow of the load forecasting network buildup and performance evaluation. Source: Made by the authors using data used in this research

Fig 5 shows the flow diagram of the proposed model. Underlined input sources are only for 8 input model. Both the training data and a separate test data has been run through the model. Fig 6 and 7 represent actual and predictive output comparison.

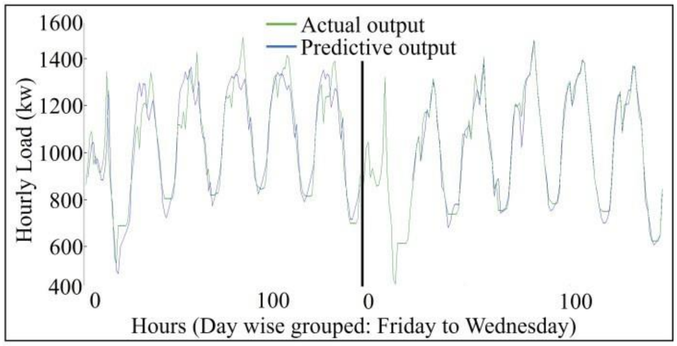


Figure 4.12 Performance of the training set that has been used to train the network in 5 (left) and 8 (right) input model. Source: Made by the authors using data used in this research

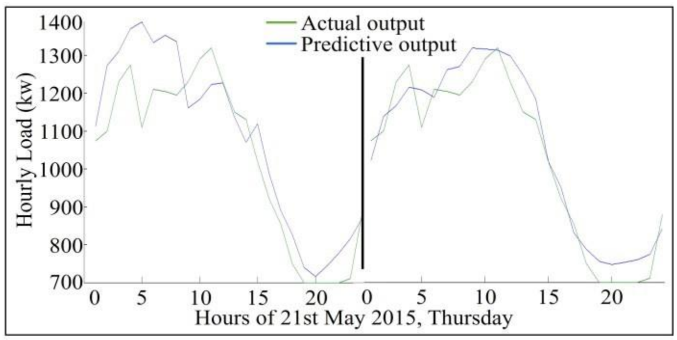


Figure 4.13 Performance of the test set that has not been used to train the network in 5 (left) and 8 (right) input model. Source: Made by the authors using data used in this research

We have computed accuracy using MAPE formula (table 8) and it turns out our 8 input predictive model is performing better. We have achieved around 95% of accuracy while in 5 input model, this is around 90% for unknown datasets (those not have been used to train the network). Few more sources have been used in 8 input model which results in a better forecasting. Table 11 represents the accuracy of the models and comparison shows that 8 input model performs better.

Table 1. Performance analysis.

	5 input model	**8 input model**
Accuracy	Dataset known to model: (100-6.4817) = 93.5183% Dataset unknown to model: (100-8.0615) = **91.9385%**	Dataset known to model: (100-2.0672) = 97.9328% Dataset unknown to model: (100-5.1488) = **94.8512%**

The data used to train the above model is very small. However, the accuracy result is very high. There is a high probability that the model may not generalize well. This means that the model maybe over-fitting the data.

5 Policy outcomes and Future work

Energy is a basic need for modern Human beings. Hence governments require to ensure unhindered availability of energy. Energy is scarce resource. Hence it demands efficient management. Bangladesh has 160 million population. Bangladesh is aspiring middle income country. Hence the energy need is high and ever growing. Bangladesh acknowledges this need (MoPEM, 2016). Promises 100% coverage. Has improved in last few years. Managing public utility is a major challenge. Bangladesh has a history of poor utility management.

Prerequisite of better management of public utility is: Understanding the consumers, their consumption behavior, how consumers at different economic state consume electricity, how this behavior changes over time, and across regions. Information of consumption behavior can help ascertain how much energy is required at which part of the year. This helps planning.

Most of the utilities, regulatory organizations ensure these using their domain knowledge, use surveys, statistical methods to manage. This legacy method can be complemented with computational methods that can harness high volume datasets of heterogeneous nature. The method is cheaper than the legacy methods. Hence can be frequently invoked. It also gives the policy makers to see the impacts at more granular level. Granularity may help better management.

In order to assist policy makers to understand the need of the consumers this research uses consumer level billing data, power satiation level supply data such as load variability and load shedding data. The aim is to understand how regulatory decisions impact their behavior. Regulators disrupt consumption behavior through various shocks such as price hikes. This report tries to ascertain, how that shapes the behavior of consumers at different economic level. Lastly the report gives a load forecasting model that can help to ascertain short demand at regional level. This project uses demand: household consumption and supply: load, load shedding data to cater to the management need. We use data from DESCO, that caters to Dhaka North. Various techniques and granular data is used in this purpose. This paper tries to answer questions related to the three queries stated above in the context of Dhaka North focusing residential users.

The consumption pattern analysis gives more granular level picture of urban economic health. We observe zone wise consumption variation indicating and confirming the wealthy areas of the city (assuming that people in more wealthy are would have more to spend on consumption). We observe that Consumers from other tariff brackets tend to increase or reduce their consumption to find themselves in the [76-200]. However, it is quite a big tariff bracket and people in this bracket do not tend to change state much. This may indicate that it is time to redesign the tariff bracket.

Dhaka is getting populated and the pattern of consumers' settling down in most of the zones is similar. However, at the wealthy zones such as Baridhara, Gulshan the rate is low. Finding Electricity consumption data may be an real time indicator of the growth of households in the urban Dhaka Consumers seem to gravitate towards [76-200] bracket

Price hike on average do not have impact in short term. However, the impact is not homogenous. Consumers in bracket [1-50], [51-75] seem to have kept their upward propensity to consume more. While [76-200] stays in their position. However, most of the high-level consumers of bracket [401-600] seem to shift down to the lower level

Long term data of price impact is required to understand long term effect. IN short term people may not stop using the device but may reduce the propensity. People in low tariff brackets may already use the devices at the minimum. While the people in high tariff brackets may reduce their propensity of use and hence we see this reduction in consumption. Short term tariff hike may induce people in higher tariff brackets to check their usage (by impacting on their propensity of using the devices).

We believe further analysis is necessary. Following are few possible research directions

1. Inclusion of Various census and survey data from Bangladesh Bureau of Statistics and other Governmental sources , GIS Data, to understand the household economic conditions in order to do possible cross sectional regression analysis to understand consumption.
2. At the moment, we can only observe the patterns uptil the sub-zonal level. In order to conducting more granular level estimations we need to solve the problem of address resolution.
3. Digitize the supply level hourly load data to understand the impact of load variability and load shedding on consumption and also to use it as a variable to understand impact on consumption.
4. Conduct research on tariff bracket variability so that near optimal tariff brackt could be proposed for short and midterm.
5. Conduct extensive survey on electric appliance consumption behavior at household level to better understand the tariff brackets.
6. Including non-residential consumption data to understand the consumption behavior holistically.
7. Use of various other environmental data to build models for robust short and midterm forecast model that will be able to anticipate demand at the zonal level. This will aid the regulators to calculate the total consumption need of the Dhaka dwellers- crucial for electricity eco system management.
8. Using various computational social scientific, machine learning methods of unsupervised learning to bring forth more insight from the data.

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Appendix

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