Electricity Infrastructure in Rapidly Developing Cities

Bangalore case study

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I hereby declare that, this dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration, except where specifically indicated in the text.

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Abstract

Emissions contributing to climate change are expected to increase rapidly as electricity use increases in developing cities, fuelled by population and economic growth. Accounting for sustainability is hampered by rapid city development, since infrastructural provision for the current populace is outpaced by growth. Present instability of electrical supply must be addressed while considering future requirements and this paper hypothesises that **decentralised, local electricity supply in the context of a rapidly developing city is key to meeting growing demand in a flexible and sustainable manner**. To test this hypothesis, a city electricity demand profile is required, since spatial demand variation will affect supply placement, while temporal variation will favour different supply systems.

This paper investigates demand for electricity in a rapidly developing city, using Bangalore, India as a case study. Bangalore has experienced unprecedented growth in recent years, now considered the ‘Silicon Valley’ of India, but suffers from daily power outages across the city. To create a spatially disaggregated, high time resolution city demand profile, two approaches are analysed in this paper: the production of a bottom-up engineering energy model and the mapping of power interruption events.

Energy use analysis

Following a review of modelling techniques, the bottom-up engineering energy model was chosen. Aggregation of electrical use from lighting and appliances in the residential sector is used to validate the use of this model, taking income as the explanatory variable for variation between households. Disparity between sources of information on ownership of appliances and light fixtures, and their subsequent Unit Energy Consumption, leads to low confidence in the results. Due to the degree of unknown uncertainty and the lack of available studies to extend a bottom-up model to other sectors at a high time resolution, it is recommended that sampled surveys and building electricity metering is undertaken throughout the city.

Power interruption analysis

Areas affected by power interruptions are mapped across Bangalore and its surrounding areas, using data published by the city utility provider. Interruptions are concentrated in the north of the city; ward 49 experiences the most interruptions, followed by wards 24 and 7. However, interruptions correlate weakly to currently available ward information. Temporal analysis reveals that building end-use sector may affect interruption events and that similarity exists between event frequency and electricity supply profile. The results offer a novel way to disaggregate city-scale electricity demand, can be used to concentrate higher spatial analysis efforts, and highlight explanatory variables for future research consideration.

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Contents

List of Figures

List of Tables

Acronyms

BBMP Bruhat Bangalore Mahanagara Palike.

BESCOM Bangalore Electricity Supply Company Ltd..

BMAZ BESCOM Bangalore Metropolitan Area Zone.

BMP Bangalore Mahanagara Palike.

BRAZ BESCOM Bangalore Rural Area Zone.

BUD Bangalore Urban District.

BUM Bottom-up Modelling.

CDD Cooling Degree Days.

CTAZ BESCOM Chitradurga Area Zone.

HH Household.

IIHS Indian Institute for Human Settlements.

INR Indian Rupees.

MPCE Monthly Per-Capita Consumer Expenditure.

NSSO Government of India National Sample Survey Office.

TDM Top-down Modelling.

TERI Government of India Energy and Resources Institute.

UA Urban Agglomeration.

UEC Unit Energy Consumption.

Chapter 1

Introduction

Our currently changing climate is a phenomenon that is understood to be caused primarily by human activities (Pachauri *et al.*, 2014) and is seen as one of the greatest global threats to mankind (Carle, 2015). Moving towards a “low carbon" future is an agenda on which developed nations have been expected to take the lead since “the largest share of historical and current global emissions of greenhouse gases has originated in developed countries" (UN, 1992). The emissions contribution from developing nations has historically been lower than from developed nations, indeed, per-capita emissions still are (Baumert *et al.*, 2005, Ch. 4). However, developing nations account for approximately 80% of the human population and their total annual emissions have recently overtaken those of developed nations (Olivier *et al.*, 2013, pp.16-17). As nations develop, their per-capita emissions are expected to increase, doubling between the year 2000 and 2050 (Narasaiah, 2001, p. 60). Population increases are likely to exacerbate the problem, with developing city growth accounting for the majority of population growth over the coming 40 years (UN-DESA, 2015). As such, the fight for emissions reductions is increasingly becoming the burden that developing cities must bear. The challenge is thus of sustainable development of cities, such that sufficient population and economic growth is possible without realising drastic increases in per-capita emissions. However, the rate at which cities are growing leaves little time to plan for the future, especially since provision for the current populace is already a strain on resources (Colenbrander *et al.*, 2015; Cohen, 2006).

1.1 Energy in Rapidly Developing Cities

Cities act as the economic powerhouse of the world, with a collection of 600 providing for over half of global GDP (Dobbs *et al.*, 2011). Over the next fifteen years, 136 rapidy growing cities from developing nations will enter into this top 600. Economic growth increases energy requirement, to provide for “transport, industrial and commercial activities, buildings and infrastructure, water distribution, and food production" (UN-Habitat, 2012), while commuting and distribution of commodities becomes more widespread with sprawling infrastructure (UN-Habitat, 2010, p.11). Once this sprawl stabilises, the primary energy end-use sectors are expected to move from industry and transport to the developed nation model of building occupants consuming the majority of energy, in the form of electricity (UN-Habitat, 2008, Section 3.4).

Cities require a constant supply of electricity, but those that are rapidly developing are unable to match infrastructure construction rates with city growth (Cohen, 2006). Frequent power outages occur due to a lack of sources to meet the growing demand, or simply a lack of adequate infrastructure to convey sufficient electricity to the areas of demand. In response to this, inhabitants maintain backup solutions, particularly in the form of diesel generators (Adenikinju, 2005; Reinikka and Svensson, 2002; Romero, 2012). Generators require an economic outlay to purchase and maintain, making them prohibitive to low-income domestic settings or smaller businesses. Even where funds are available, the cost of diesel fuel is more expensive than electricity from an operational grid (Reinikka and Svensson, 2002). Environmentally, a small, 2-5kW diesel generator produces in the range of 1.22-1.94kgCO_2/kWh (Jakhrani *et al.*, 2012) while a coal-fired power station[1] in India produces 0.91-0.95kgCO_2/kWh (Mittal *et al.*, 2012), half the emissions intensity of diesel in some cases. Environmental and economical concerns are compounded by the local nature of generator emissions; noxious gas inhalation and particulate matter ingestion from diesel generator exhausts can cause adverse health effects, such as lung cancer (Olsson *et al.*, 2011).

When electricity supply is available, losses during transmission and distribution (T&D) are often high, exacerbating the occurrence of power outages by reducing available supply. Average T&D losses in 2012 were as high as 30% in Nepal, 17% in India, and 18% in Kenya and Cambodia. Conversely, the United Kingdom, United States of America and Japan experience losses of only 6%, 8% and 4%, respectively (The World Bank, 2012). A reduction in transmission losses is achieved by minimising the distance between electrical supply and demand, while transformation losses can be reduced through the production of low voltage electricity, to avoid transformation requirements. Unconventional energy sources may provide for both of these loss reduction requirements with cities in Africa, Asia, and South America standing to benefit the most compared to their developed city counterparts. For instance, geothermal electricity has the highest potential along the West coast of South America, through the Himalayas, and in Burma, Malaysia and Singapore (Barbier, 2002). Solar irradiation is highest in the North East and South West of Africa, as well as the Middle East (World Energy Council, 2013, Ch. 8), while Russia, China and Argentina are among the top six countries in the world for potential wind energy production (Lu *et al.*, 2009, fig. 2). Although wind patterns in cities tend to be considered sub-optimal for efficient wind energy production, the design of urban areas to channel wind could create higher mean wind speeds than the surrounding environment (Aziz and Elmassah, 2012). Rooftops offer unused space, if buildings are designed to optimise output, while currently unused land could be developed for energy production, but only if designated as such before the loss of the space to urbanisation. Unlike developed cities, developing cities can still incorporate flexibility and sustainability as an inherent component of their energy infrastructure, by optimising urban design for unconventional energy systems.

[1]Coal-fired power stations are considered the most CO_2 intensive form of large-scale power generation (Center for Climate and Energy Solutions, 2015)

1.2 Aims and Objectives

In an environment in which power outages are expected, and only diesel generation is available to tackle the deficit, **how can electricity infrastructure be designed to maximise availability?** Flexibility is required for energy supply to continually meet a changing quantity and purpose of demand, while alternatives to diesel generation must still be available for use when systems are strained. T&D loss minimisation favours the use of more local sources of electricity, which are small-medium scale and potentially utilise renewable sources of energy. But **designing for local sources requires knowledge of local demand for electricity**, as income distribution, end-use sectors, and density of end-users can all affect supply needs. Time of use also becomes important in the context of intermittency from renewable energy sources, wherein choice of energy source, connection of buildings to district systems, and scale of storage all depends on the demand profile to be met.

1.2.1 Hypothesis

This paper hypothesises that **decentralised, local electricity supply in the context of a rapidly developing city is key to meeting growing demand in a flexible and sustainable manner**. Decentralised electricity consists of building-scale renewable energy (solar, wind, ground-sourced heat, and biofuel); district heat and power networks; and local storage solutions. The variation in local demand can be provided for by alterations in the design of systems, and any changes in the structure of demand can be more rapidly accounted for due to the smaller scale and relative ease of construction of these systems.

However, design for decentralisation requires knowledge of the current electricity demand profile of a city, as demand is expected to vary spatially and temporally. It is necessary to ascertain the most accurate method for producing a spatially disaggregated, high time resolution demand profile, before the hypothesis can truly be tested. Therefore, this paper focuses on the first steps towards the design of an electricity supply solution by mapping electricity demand, spatially and temporally, for the Indian city of Bangalore.

1.2.2 Structure of Paper

This study considers the current electricity infrastructural needs of a rapidly developing city. Bangalore is used as a case study and two approaches are taken to assess current electricity use. Chapter 2 attempts to construct a residential sector data set for inclusion in a bottom-up, spatially disaggregated engineering energy model. Chapter 3 collates data of power outages in the city to determine areas of grid instability. These two methods are compared in the context of Bangalore and further data acquisition is recommended where relevant.

1.2.3 Expected Outcomes

A variation in demand across Bangalore, in time and space, is expected. This study intends to quantify the variation in such a manner that local energy sources can be proposed which are pertinent to a demand profile, as well as local topology and urban layout. Not only is such a result of use to local planning agencies, it also provides an insight into primary causes of electricity infrastructure instability which can then be used by electricity providers in order to ensure that current infrastructure is able to better manage demand.

Further research is expected to be required before a complete demand profile, disaggregated spatially and of a high time resolution, can be produced for Bangalore. However, This study intends to highlight the potential for using various sources of information, both direct and indirect, to create demand profiles for cities which are rapidly developing.

1.3 Bangalore Context

Population

Bangalore, the capital city of the southern Indian state of Karnataka, is one of the largest cities in India and has undergone many changes in image in the past century, from the 'Garden City' of India in the 1920s (Hassan, 1970) to the 'Silicon Valley' of the country at the turn of the 21st Century (Vagale, 2004). This transformation has taken place in tandem with rapid growth of the city, in terms of both population and urbanisation. The population grew from the Garden City's 308,000 in 1931 to over one million in 1961 (Vagale, 2004, p. 35). A population growth of 76% from 1971 to 1981 placed Bangalore as Asia's fastest growing city in that decade (Vagale, 2004, p. 35); another population boom of 46% growth in the decade 2001 to 2011 was the highest in India (Bose, 2011)[2]. The latest reports estimate the population of the city as being over 10 million in 2015 (India Online Pages, 2015), placing Bangalore amongst the Mega Cities of the world and third largest in India. Population estimates and census data for the city follows an annual growth rate of 3.7% over the past 100 years (figure 1.1), overtaking Delhi, Greater Mumbai and Kolkata which have all seen a decrease in growth rate in the 21st Century (MOSPI, 2011, p. 3).

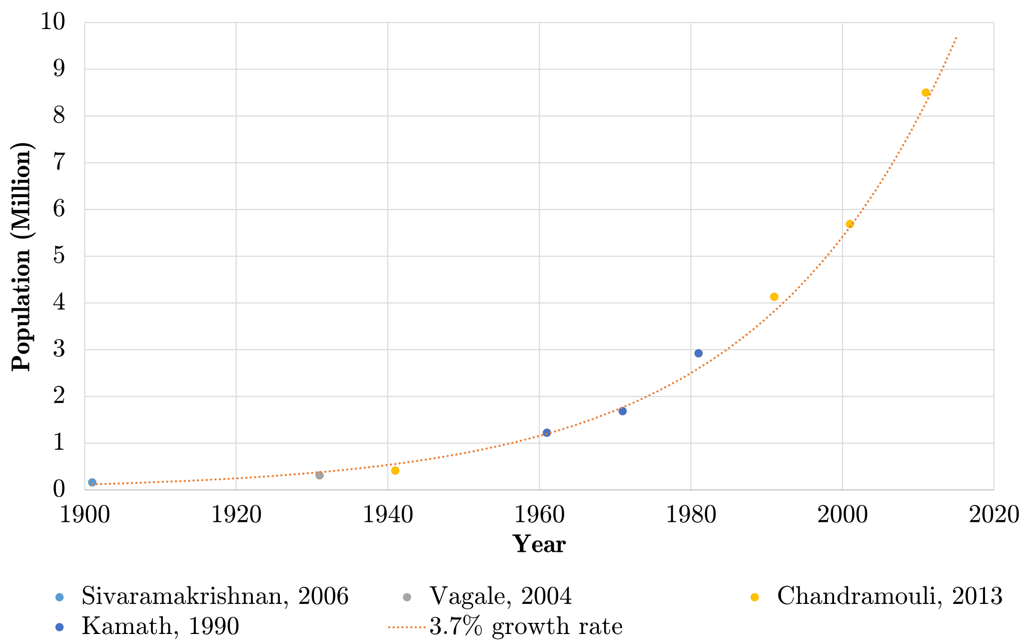


Figure 1.1 Population estimates through time for the city of Bangalore, India, from various sources.

[2]46% growth as highest in India refers to the Bangalore Urban District, the Urban Agglomeration saw a greater growth, of 49%, in the same decade

Infrastructure

Population has not grown at the same rate as infrastructure. The Garden City namesake has been undermined primarily in the 21st Century, with a 100% growth in built-up area between 2000 and 2010 compared to 20% in the period 1990-2000 (IIHS, 2012, p. 21). The rapid loss of green space is visualised in figure 1.2, where infrastructure encroaches on the edges of the the city boundaries between 2001 and 2009, an area previously considered a greenbelt. The sprawling effect of infrastructure has led to migration and settling in the outer wards of the city, depicted in figure 1.5.

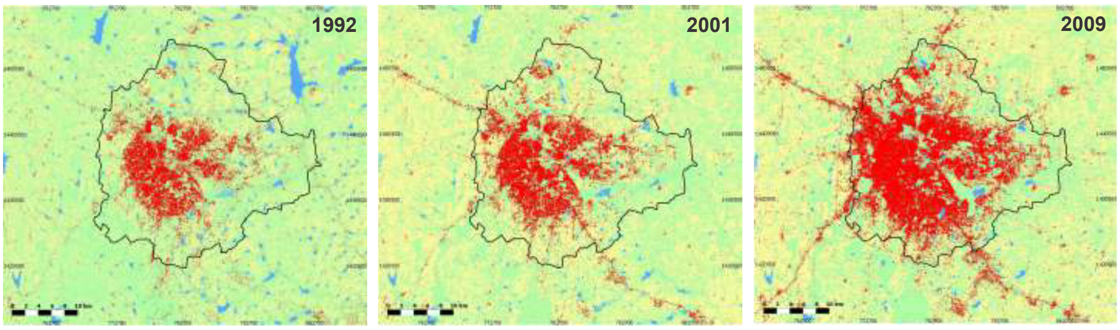


Figure 1.2 Increase in built-up area across Bangalore, 1992-2009. From IIHS (2012)

Electricity

Bangalore has been, and is still, growing rapidly, requiring greater quantities of electricity and associated infrastructure. Its 'Silicon Valley' epithet is testament to its incredibly large IT services industry that requires a steady electrical supply to function and compete in the global market (Vaitheeswaran, 2005, p. 276). Other industries in the city, such as textiles, paper and metallurgy, are equally affected, if not more so. Unscheduled outages can lead to wastage of material along with the halting of manufacturing (Surendran, 2010). Although outages can lead to loss of earnings for businesses, Bangalore is the city that loses the least within India; annual sales are estimated to be reduced by 2% due to outages in the city compared to the country's 5.5% average (Dollar *et al.*, 2005). Electricity has been provided to the city and its surrounding area since 2002 by Bangalore Electricity Supply Company Ltd. (BESCOM) whose supply has increased by an average of 1,450GWh annually, to 26,786GWh in the 2013-14 financial year (BESCOM, 2014a, p. 11). In this same time period, Aggregate Technical & Commercial (AT&C) losses have reduced from 34.25% to 16.97%. AT&C losses include technical losses, those arising during transmission and distribution of the electricity; and commercial losses, where electricity is stolen from the distribution system or metering systems do not correctly capture the actual use of a building (BESCOM, 2014b).

The Sankey diagram seen in figure 1.3 shows the various sources and end-uses of electricity in Bangalore, as provided by BESCOM. "Medium term purchases" refers to private companies that sell their energy to BESCOM, which tend to be, but are not exclusively, fossil-fuelled power stations. "Co-generation" refers to private companies that sell the electricity produced from industrial waste-heat, such as sugar or steel refineries, to BESCOM. Coal and natural gas fired power stations provide over 50% of the city's electricity needs, followed by hydroelectric schemes (often referred to in

Indian literature as Hydel power) and wind power. Solar photovoltaic (PV) power is a negligible contributor to the supply mix, constituting 0.25% compared to 8.5% from wind power and 15.9% from hydroelectric schemes. This result is at odds with a wealth of literature outlining the large potential for PV generated electricity in India (Ramachandra *et al.*, 2011; Ramachandra *et al.*, 2012; Luthra *et al.*, 2015; Khare *et al.*, 2013) and is likely to change over the coming years as BESCOM has been charged with incentivising the installation of 1,000MWp of solar PV on rooftops, farmland and other private settings (Deccan Herald, 2014). Production from solar PV in Bangalore is on average 1,750kWh/kWp (Ransome and Wohlgemuth, 2001, table IV), which would amount to an annual output of 1,750GWh from the latest initiative.

There is a relatively even distribution of electricity supplied to the industrial, commercial, domestic and agricultural sectors. However, there exists an electricity deficit in the state, whereby the demand exceeds supply capacity, which was as high as 13.9% in the 2012-13 financial year in Karnataka state (PwC, 2013). Whether the deficit is distributed proportionally between the sectors is unknown. As previously mentioned, AT&C losses amount to $\sim$17% of the available electricity supply from BESCOM. figure 1.3 shows how the majority of AT&C loss is from transmission and distribution over the electrical lines. “Undelivered" electricity refers to that which is stolen from the distribution system or lost for other, unknown, reasons.

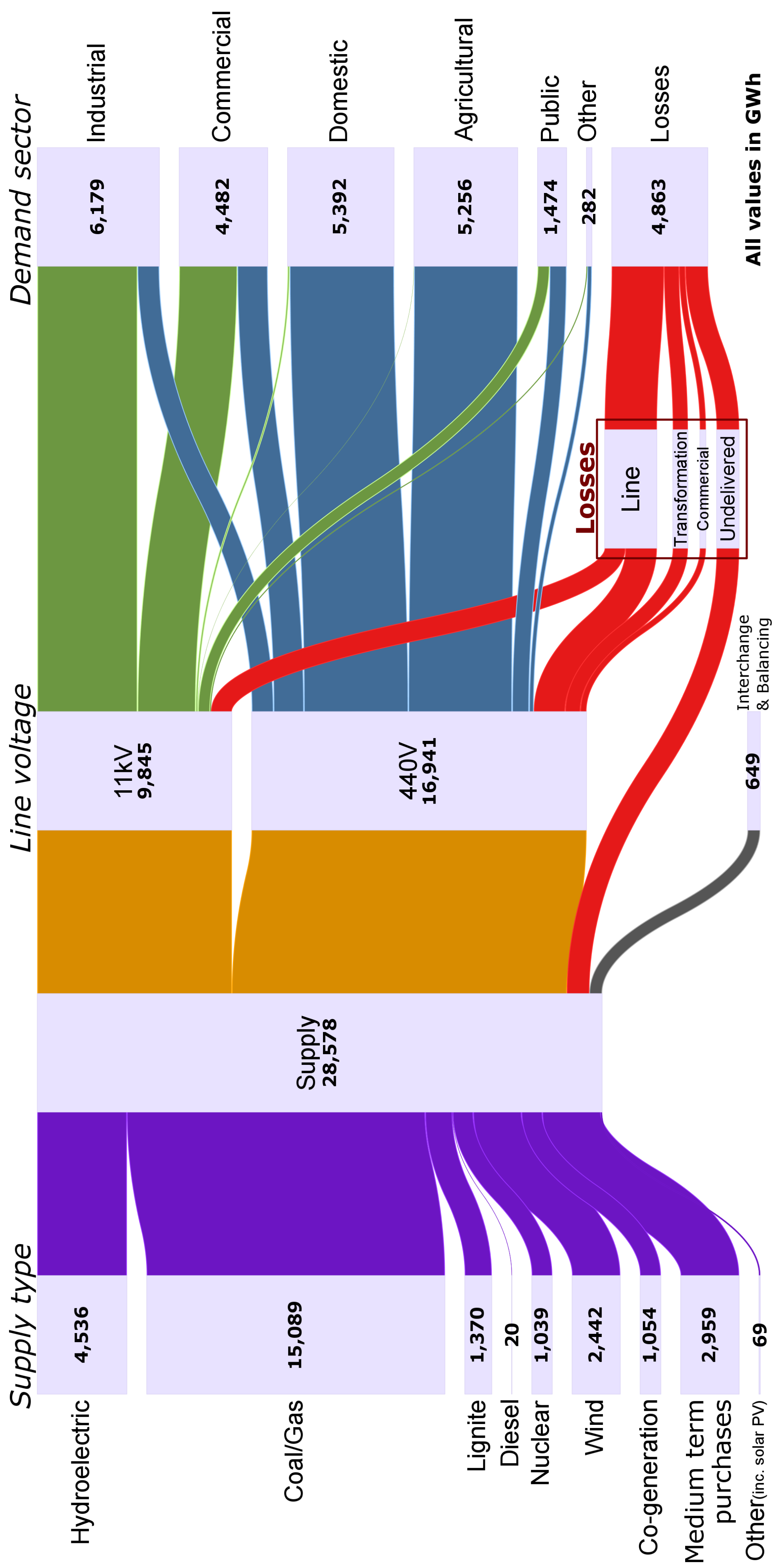


Figure 1.3 Sankey diagram representation of BESCOM electricity production and use for the financial year 2013-14, from BESCOM (2014a)

1.3.1 Defining Geographic Boundaries

This study examines the Bangalore Metropolitan centre, or Bruhat Bangalore Mahanagara Palike (BBMP). BBMP was formed in 2007 by combining the more central Bangalore Mahanagara Palike (BMP) with 7 City Municipal Councils, one Town Municipal Council and 110 villages (Kumara, 2012, Ch.3, p. 85). BBMP consists of 198 wards, which will constitute the maximum resolution of this study (figure 1.5). Boundaries for the city's Urban Agglomeration (UA) have changed over time, to be encompassed by BBMP in the 2011 National census; the area of the UA has increased from 177.30km^2 in 1971 to 709.5km^2 for BBMP (Chandramouli, 2013). Increase in considered area might put the previously calculated population growth into question. For this reason, the Bangalore Urban District (BUD) population growth is considered. BUD covers 2190km^2 and has remained constant as a district for population estimates/censuses since 1901, but it also considers peri-urban areas away from the UA (Kamath, 1990). The UA constituted 41% of the BUD population in 1901 compared to 89% in 2011, with population outside the UA increasing only slightly (figure 1.4). This trend indicates an urbanisation of peripheral areas, and their subsequent inclusion in the UA, rather than arbitrary changes in definition of the UA geographic boundary.

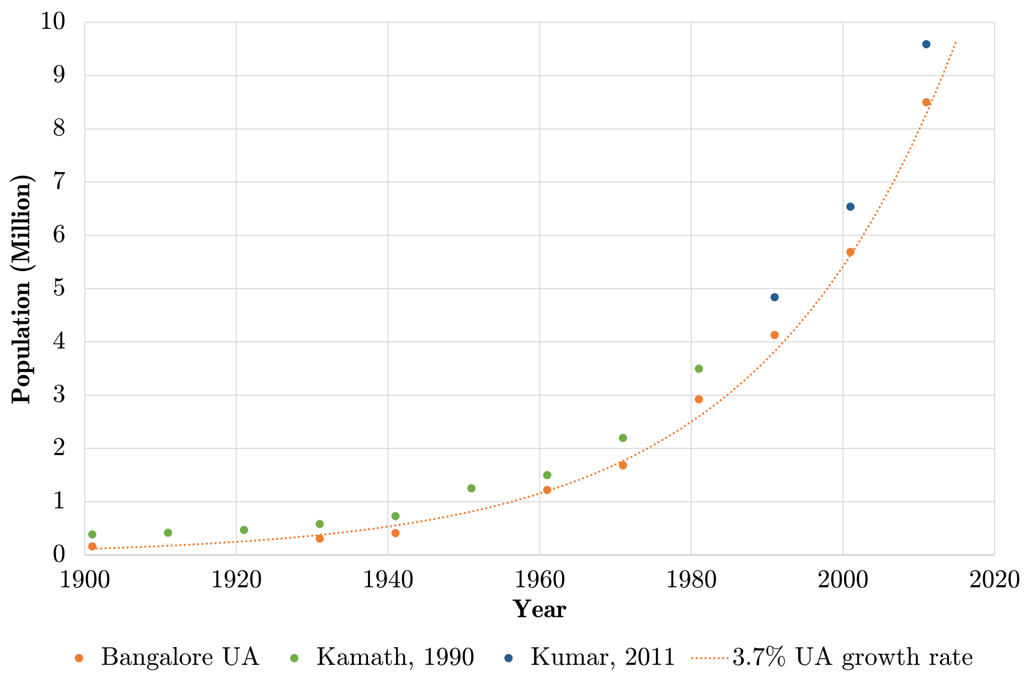


Figure 1.4 Population estimates through time for Bangalore District compared to the Bangalore Urban Agglomeration (UA), from various sources. See figure 1.1 for further information on Bangalore AU population.

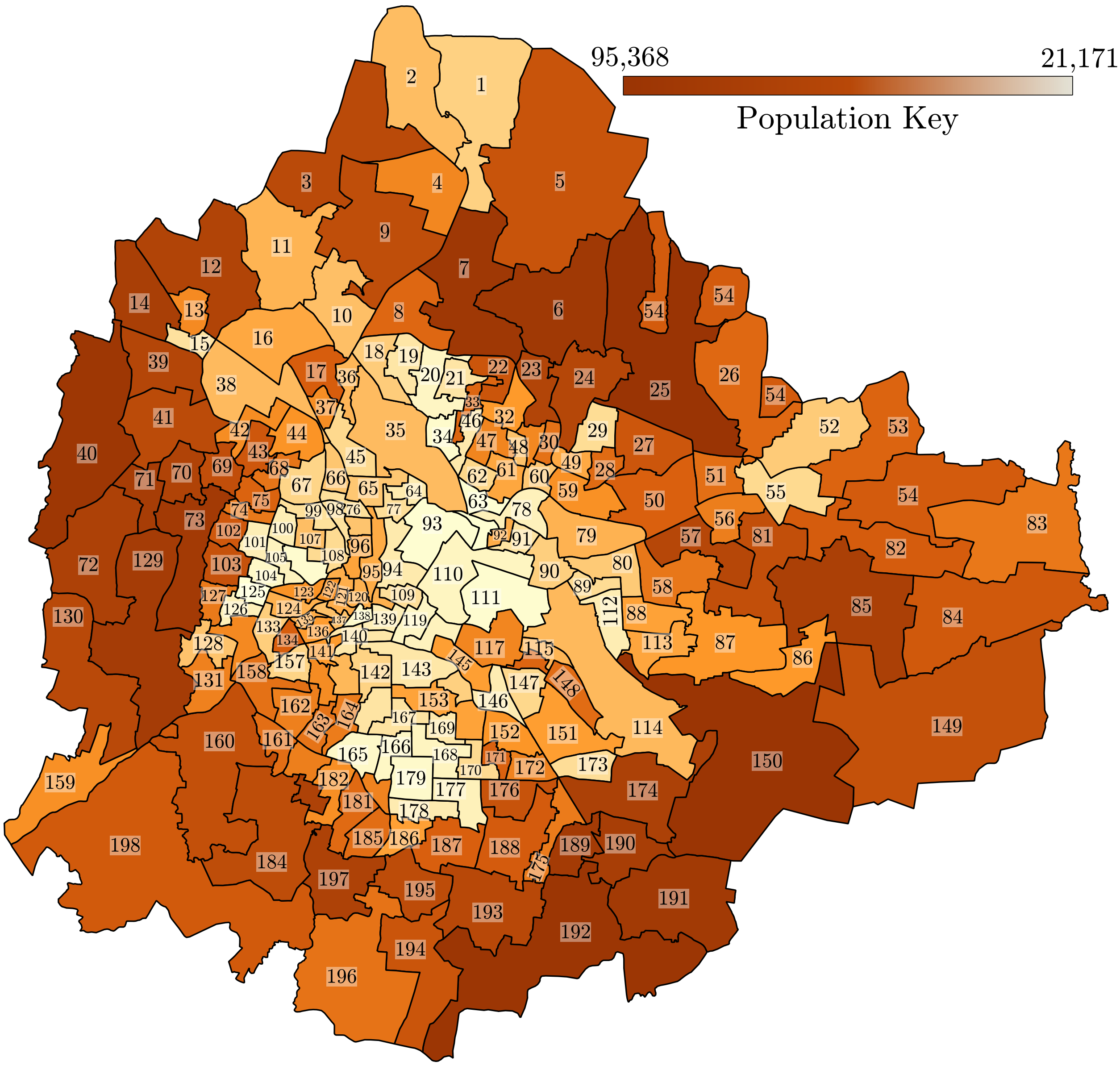


Figure 1.5 Ward number and population for each ward in the BBMP jurisdiction.

BESCOM provides electricity to BBMP, but also to a great deal of the surrounding area. The entire operating area of BESCOM is 41,092km^2, serving a population of 20.7 million. The area is divided into three zones: Bangalore Metropolitan Area Zone (BMAZ), Bangalore Rural Area Zone (BRAZ) and Chitradurga Area Zone (CTAZ) (figure 1.6). The electricity flow found in figure 1.3 refers to the entire operating area of BESCOM, the load from which can be divided between BMAZ, BRAZ and CTAZ at an average ratio of 2.76:1.15:1.00[3]. Figure 1.7 shows how BMAZ covers almost all of BBMP, but also includes sections to the south-west and north of the BBMP boundary. No information is available as to the electrical end-use for BMAZ, but with the high concentration of IT services, there will likely be a higher commercial and industrial electrical load within BBMP and its immediate surroundings.

[3] The given ratio is a result of an analysis into the hourly load curves from BESCOM, studied further in chapter 3.

Figure 1.6 Zonal division of the BESCOM operational area.

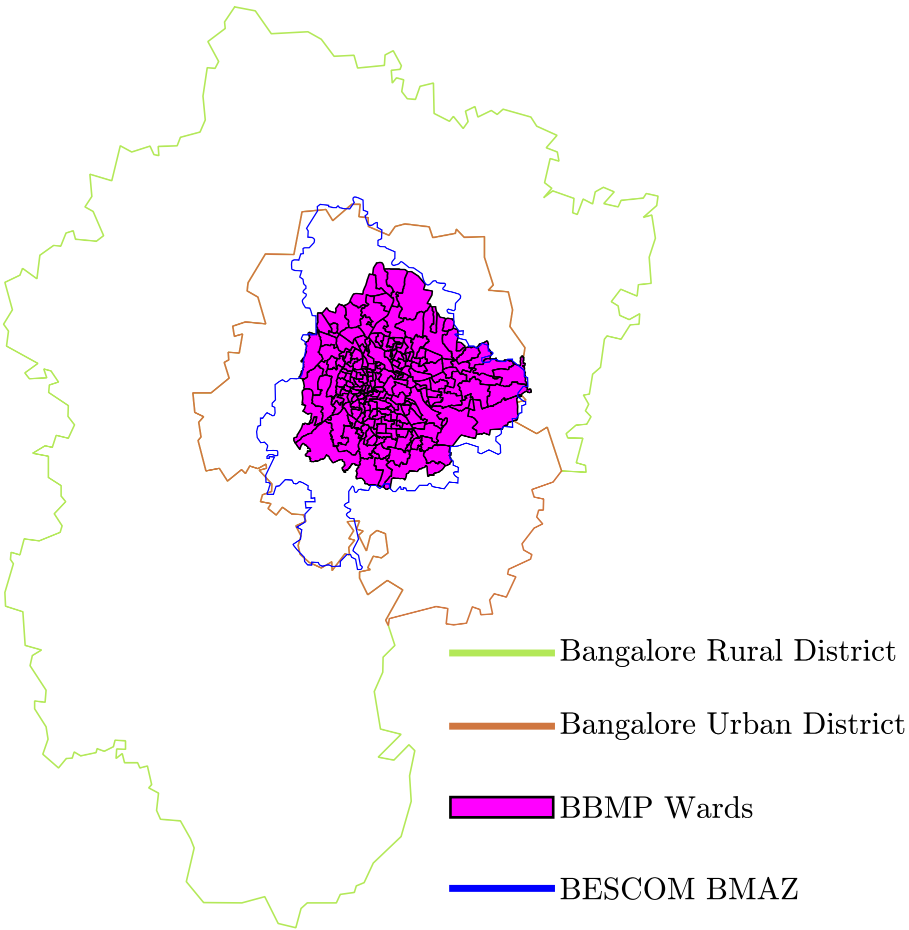


Figure 1.7 Map of various geographical boundaries related to the city of Bangalore.

Chapter 2

Energy Use Analysis

As introduced in the previous chapter, Bangalore is a useful case study into future electricity infrastructure options. Population increases have led to urban sprawl, particularly over the past decade, that has required rapid implementation of infrastructure. No indication of a decline in population growth means there is little time to consider long-term improvements of current infrastructure. The electrical utility company, BESCOM, operates over an area that is much larger than the area of interest, BBMP. For this reason, there is little data published in such a way that makes it possible to satisfactorily ascertain a current spatial and temporal map of the electricity use in BBMP. This chapter will introduce the capability of modelling techniques to map electricity, internationally and in the context of Bangalore, by first studying modelling techniques and then building up the constituent parts for a model from various sources, such as national censuses.

2.1 Energy Modelling

Ascertaining energy demand at a household or city level can be undertaken in a number of ways and has led to the creation of several modelling techniques worldwide in order to aid in the understanding of energy use, project its future change and attempt to design demand reduction schemes in light of emerging policy. Modelling techniques are generally distinguished by the type of data used to produce them. Swan and Ugursal (2009) and Kavgic *et al.* (2010) review available models and separate them into top-down and bottom-up, for which there are several sub-methods that can be used (figure 2.1).

Top-down Modelling (TDM) involves finding relationships between macroeconomic (e.g. price index and income) or climate indicators and energy use, in order to project future demand, while Bottom-up Modelling (BUM) aggregates components of demand to create a picture of the total. TDM is considered to be easier to develop on more limited information streams, but does require a greater deal of historical data in order to predict future energy demand reliably. On the other hand, BUM requires "extensive databases of empirical data" to support component information (Kavgic *et al.*, 2010, p.1684); the BUM statistical method offers something of a hybrid and “bridge[s] the gap between detailed bottom-up end-use energy consumption models and regional or national econometric indicators" (Swan and Ugursal, 2009, p.1832). A number of studies have pointed out

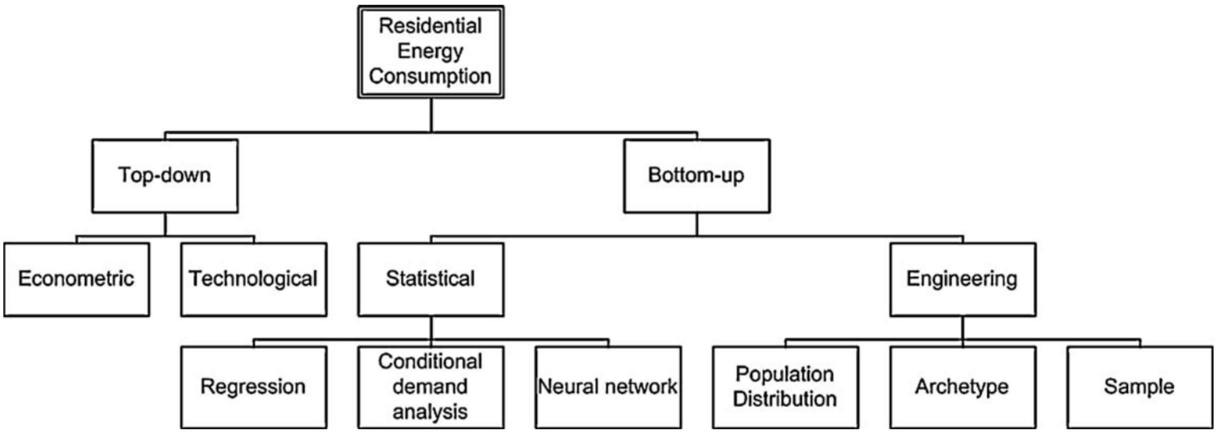


Figure 2.1 Top-down and bottom-up sub-methods for Energy consumption modelling, from Swan and Ugursal (2009).

the disparity between results from TDM and BUM (Koopmans and te Velde, 2001; Klinge Jacobsen, 1998; Heiple and Sailor, 2008; Dai *et al.*, 2015) and although some go on to outline strategies to link the two, TDM can lead the result further from reality in the case of spatial mapping and developed nations. Urban *et al.* (2007) explain how TDM is unable to fully represent the progress of developing countries due to available macroeconomic statistics not accounting for the existence of informal economies nor the lack of relationships between certain market behaviours. Additionally, the rapid development of these countries can lead to discontinuities in energy trends, a phenomenon not inherently visualised by TDM (Swan and Ugursal, 2009; Kavgic *et al.*, 2010). Spatial distribution of energy use is also not readily visualised by TDM; Heiple and Sailor (2008) found that information in a spatial area was oversimplified by TDM, losing the majority of data which differentiated grid cells, such as building density. In light of this, BUM is the preferred approach. Little difference has been found in results from various BUM statistical methods (Neural Network, Conditional Demand Analysis, Decision Tree, Linear Regression) applied to the same data (Aydinalp-Koksal and Ugursal, 2008; Tso and Yau, 2007), but explanatory variables can differ depending on local conditions. For example, Al-Garni *et al.* (1994) found a strong correlation between energy use and relative humidity, as well as solar radiation in Eastern Saudi Arabia, while Ranjan and Jain (1999) found that it was population and temperature that were co-linearly correlated to energy use in Dehli. These studies are indicative of the varying effects of climate, while other studies indicate that socio-economic or political constraints can also be highly correlated with energy use (Bergasse *et al.*, 2013; Green, 2014). This means that statistical BUM methods must be tailored to specific contexts and local conditions. Engineering methods do tend to require more information and yield less behaviour-oriented results than statistical methods (Aydinalp-Koksal and Ugursal, 2008), but they are sufficiently unbiased to be considered for different data sets, in different environments (Swan and Ugursal, 2009; Kavgic *et al.*, 2010).

In choosing an approach to modelling energy use, the consideration of the expected outcome is of great importance. When modelling for the purpose of mapping future demand prospects, undertaken in many studies (Bose and Shukla, 1999; Chaturvedi *et al.*, 2014; Dai *et al.*, 2015; Daioglou *et al.*, 2012; van Ruijven *et al.*, 2011; Fell *et al.*, 2014; Isaac and van Vuuren, 2009; Koopmans and te Velde, 2001; Klinge Jacobsen, 1998), the strategy utilised is that of acquiring a complete and representative view of the current demand and projecting forward by use of explanatory variables such as income, changing climate, or appliance energy efficiency. Explanatory variables may originate from historical evidence and may be implemented at an appliance level. For instance, van Ruijven *et al.* (2011) project that lighting requirement increases with household floor area, while per-capita GDP and cooling degree days are the primary explanatory variables for air conditioning energy use in the country. Current demand may be taken from utility providers (Bose and Shukla, 1999), taken from national surveys (Fell *et al.*, 2014), produced by an engineering model (Chaturvedi *et al.*, 2014; Daioglou *et al.*, 2012; van Ruijven *et al.*, 2011; Isaac and van Vuuren, 2009), or be a hybrid of several data input types (Klinge Jacobsen, 1998). Where data is not available, academic judgement is often used (Chaturvedi *et al.*, 2014; TERI, 2006), but rarely are attempts made to account for uncertainty by such a method.

When modelling to produce spatial energy maps, more local data is required, which tends to lead to the use of census or utility provider data sets. Pereira and Assis (2013) utilise household census data for income and appliance ownership within a city in Brazil, as well as appliance energy use from various local sources, to produce an engineering bottom-up model. Howard *et al.* (2012) initially make the assumption that end-use is primarily dependant on building function (residential, educational, etc.) rather than construction type or building age. It then utilises a wealth of zip-code data from utility providers and surveys in order to map annual energy demand. Heiple and Sailor (2008) use archetypal building models and tend towards a similar accuracy to Howard *et al.*, albeit for a different city in the USA. Utilising spatial energy maps for distributed energy modelling requires further resolution in time compared to that required for demand-only models (Howard *et al.*, 2012). Hourly or daily data is rarely available from utility providers or censuses; here, diaries and metering surveys become useful.

As previously mentioned, a study utilising developed nation energy models in the developing nation environment found discrepancies resulting from differences in the power sector and economies between the two locations (Urban *et al.*, 2007). Aspects of the supply of electricity (such as energy deficits, extent of electrification and the urban-rural divide), as well as the structure for the economy (including investment decisions, the informal economy and subsidies) mean that current models do not correctly represent the situation in developing nations. Since then, van Ruijven *et al.* (2011) have produced a bottom-up model for Indian households based on income dependant ownership of appliances and lights, and their respective Unit Energy Consumption (UEC). This same model has since been extended to several developing nations (Daioglou *et al.*, 2012). The Government of India Energy and Resources Institute (TERI) undertook a similar study in their energy map to 2030 (TERI, 2006), but also included possible variations in energy use depending on GDP growth and considered the commercial as well as residential sector. National census data provides the appliance ownership data used in the 2030 energy map and is also the source for a subset of data used by van Ruijven *et al.* (2011) and a number of more recent modelling studies (Bhattacharyya, 2015; Chaturvedi *et al.*, 2014).

Other, more local, data sets have been used in the past for Karnataka state energy use modelling. Murthy *et al.* (2001) studied survey data using various approaches. The engineering approach is considered to depend too much on user-estimated figures of appliance usage, while a more statistical approach, using regression analysis, is concluded to provide more insightful results in terms of the effect of changing appliance ownership on electricity use. Finally, an example of a different approach to modelling electricity demand can be found in a study of daily load curves undertaken in Karnataka state by Balachandra and Chandru (1999). A partial top-down approach is used to infer end-use categories from changes in load curve base-loads and peaks throughout the day and the year. Determining the exact energy use for a particular end-use is not possible, but the relative importance of different end-use sectors at different times of day can be seen.

2.2 Method

The current trend for modelling energy use in developing countries, and for spatial variation is to use a bottom-up model, often by use of the engineering method. Following this trend, figure 2.2 indicates the process for implementing such a model. First, spatial disaggregation must take place in order to ascertain building end-use, as a bottom-up engineering model for each will be distinct. Second, those buildings within a given end-use sector must be distributed based on a given explanatory variable. This chapter is interested only in the residential sector, due to studies in the field being focussing mainly on it. For the case of the Bangalore residential sector, it is assumed that income is a primary driver for the variation in household electricity use, therefore income distribution must be classified for residential households. Spatial disaggregation of end-use sectors and income distribution is being studied by the Indian Institute for Human Settlements (IIHS) in Bangalore, to which the results of this chapter could be applied.

Within each income class, the number of electrified households must be known, a factor that is important within a developing nation context. For each electrified household within an income class, electricity use is divided between appliances and lighting, for which the number of items and energy use per item is estimated. The time at which appliances are used allows for a high time resolution to be produced for household electricity use, but a lack of data leads to this not being considered further in this chapter. Item energy use estimations are combined to produce a final estimation for electricity use within electrified households of different income classes. This result provides a component of electricity use in the city, which offers an insight into the capability of the bottom-up engineering technique to be used in the context of Bangalore.

Comparison is made to a study of metered data, undertaken in Gujarat state by Garg *et al.*, 2010, self-reported monthly per-capita electricity consumption in urban households of Karnataka state, and electricity supply data from BESCOM. As there is the possibility of data source omissions from a bottom-up model, the comparisons could demonstrate the need to consider more than just appliances and lighting.

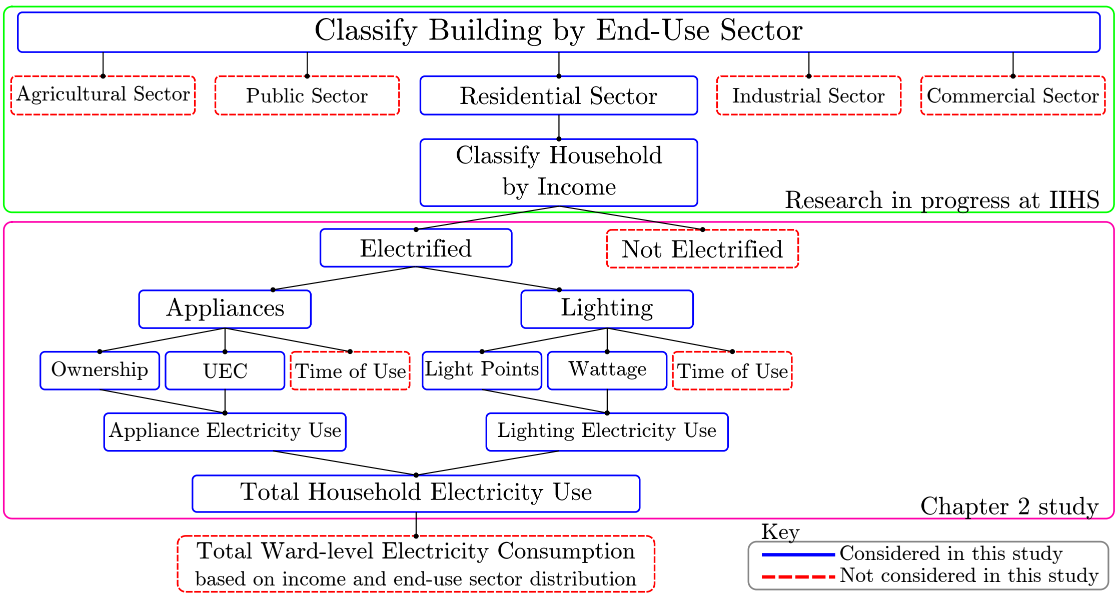


Figure 2.2 Process flow to estimate electricity use across Bangalore by use of a bottom-up engineering model.

2.2.1 Data Sources

Studies and surveys undertaken on a national Indian scale, and on a more local scale within Karnataka, are combined in this chapter to produce an estimation of household electricity use. Table 2.1 provides a summary of data sources alongside the information they provide, which has been used here to estimate household electricity use.

Data Source	**Information provided**
NSSO, 2000	1. Monthly Per-Capita Consumer Expenditure (MPCE) fractiles for income distribution of appliance ownership 2. Appliance ownership in urban Karnataka in 1999-00
NSSO, 2014b	1. Appliance ownership in urban Karnataka in 2011-12 based on MPCE fractiles
NSSO, 2014c	1. Household size in urban Karnataka in 2011-12 based on MPCE fractiles
NSSO, 2014a	1. Primary source of energy for lighting in urban Karnataka based on MPCE fractiles
van Ruijven *et al.*, 2011	1. Appliance energy use 2. Process of defining electrification
TERI, 2006	1. Income classification based on grouping MPCE fractiles 2. Appliance energy use 3. Income distributed light points and wattages
Bhattacharyya, 2015	1. Income classification based on grouping MPCE fractiles 2. Appliance energy use
Reddy and Balachandra, 2006	1. Income distributed light points and wattages
Murthy *et al.*, 2001	1. Appliance ownership in urban Karnataka 2. Appliance energy use 3. Average household light points and wattages
Chaturvedi *et al.*, 2014	1. Appliance ownership in urban India 2. Appliance energy use
Boegle *et al.*, 2009	1. Appliance ownership in urban India 2. Appliance energy use
McNeil *et al.*, 2008	1. Refrigerator and Air Conditioner energy use
de la Rue du Can *et al.*, 2009	1. Appliance energy use
The World Bank, 2015	1. Appliance energy use
Letschert and McNeil, 2007	1. Appliance energy use

Table 2.1 Data sources used to produce income distributed estimates of household electricity use in this study.

2.2.2 Assumptions

Due to the nature of the available data, a number of assumptions must be made. First, results for income class dependant appliance ownership and household distribution are known for urban households in the state of Karnataka, but not for Bangalore specifically. As the only urban area with a population greater than one million, the structure of income classes and appliance ownership may differ in Bangalore to other urban areas in Karnataka. However, due to Bangalore accounting for approximately half the urban population of the state, the dynamics of the city likely have a strong influence on the urban Karnataka data. Second, every household within an income class is expected to use the same amount of electricity, no other explanatory variables for electricity use is assumed. Finally, data sets primarily originate from the period 2010-12. It is assumed here that no great change in ownership within an income class or appliance Unit Energy Consumption has occurred between the 2010-12 period and the time this study was undertaken, in 2015.

2.2.3 Classifying Households

Income distribution

In order to assign an energy use profile to a dwelling, information about the income status of the household is required, as described in section 2.2. the NSSO does not provide income data, since the informal nature of many jobs leads to great uncertainty of an individual's possible income. However, the NSSO collects data on Monthly Per-Capita Consumer Expenditure (MPCE) and uses it to distribute census results into expenditure ranges containing equal fractions of the population, known as MPCE fractiles. The resolution of the fractiles vary depending on the census period; the 1993-94 and 2009-10 census periods utilised 10 MPCE fractiles, the 2004-05 census period utilised 5 MPCE fractiles, while the 1999-2000 and 2011-12 census periods utilised 12 MPCE fractiles, as shown in table 2.2. TERI (2006) grouped the fractiles of the 1999-00 census period into representative 'low', 'middle' and 'high' income classes for the purpose of analysing energy use. The low income class refers to the first 6 income fractiles, the middle income class to fractiles 7 to 11, and the high income class to fractile 12. The rationale behind this distribution is not explained in the TERI report, but a similar choice of distribution is chosen in a later study by Bhattacharyya, who takes the first 6, 7^{th} to 9^{th}, and 10^{th} MPCE fractiles of the 2009-10 census period census as the low, medium and high income classes, respectively (Bhattacharyya, 2015).

MPCE fractile		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Lower bound of MPCE range (in Indian Rupees) for each fractile in NSSO census period	**1993-94**	0	182	219	258	303	351	406	478	581	736		
	1999-00	0	300	350	425	500	575	665	775	915	1120	1500	1925
	2004-05	0	467.29	634.33	945.41	1524.5							
	2009-10	0	733	926	1101	1293	1502	1773	2097	2603	3665		
	2011-12	0	725	860	1090	1295	1510	1760	2070	2460	3070	4280	6015

Table 2.2 Comparison of MPCE fractiles utilised in 5 NSSO census periods.

The MPCE ranges which define fractiles change with time, in order to capture the representative distribution of expenditure within the country. For the purposes of this study, the boundaries of income are consolidated into low, medium and high classes. The MPCE ranges of these classes are taken to be those chosen in the TERI report; for use of the same boundaries in later NSSO censuses, a suitable inflation rate is used. For the case of the 2011-12 census period, the MPCE ranges of income classes do not directly relate to fractiles. Therefore, certain fractiles are split and distributed proportionally to the relevant classes (see table 2.3).

This distribution of MPCE fractiles leads to a household distribution of 24%, 53% and 23% for low, medium and high income classes in urban Karnataka. Household distribution into income classes is used throughout the remainder of this chapter in order to compare income distributed data to average data, where a study does not provide an income distribution.

Income Class	**Low**					**Medium**						**High**		
MPCE fractile	1	2	3	4	5 (20%)	5 (80%)	6	7	8	9	10 (66%)	10 (34%)	11	12
Lower bound of MPCE range (INR$_{1999-00}$)	0	360	427	542	644	665	750	875	1029	1223	1526	1925	2127	2989

Table 2.3 Distribution of NSSO 2011-12 census period MPCE fractiles into three income classes, following adjustment of MPCE to 1999-00 value of Indian Rupees (INR).

Electrification

As traditional fuels are still used for tasks that developed nation models would assume to be electrified, Urban *et al.* (2007) warn that energy modelling in developing countries has to be treated differently. In order to account for the use of traditional fuels, the number of electrified households must be quantified. A measure of electrification can be taken as to whether a household uses electricity for lighting, assuming that once electrified this would be the preferred source of lighting (van Ruijven *et al.*, 2011, p.7752). Based on this assumption, the degree of electrification in Karnataka urban households is 95.3%, 99.7% and 99.6% for low, medium and high income classes, respectively. These results show an increase in electrification from 1999-00 levels, which were 81.4%, 96.7% and 100% for low, medium and high income classes, respectively, and may indicate the progression of Bangalore to use of electricity at a similar scale to fully developed cities.

2.3 Results

2.3.1 Ownership

The ownership of electrical items increases with income and is dominated by light fixtures, space cooling and entertainment & communication appliances (figure 2.3). It is important to understand the distribution of owned items as it is likely that with increasing income of households, ownership of items in low and medium income classes will tend towards that of a household in the middle and high income classes, respectively.

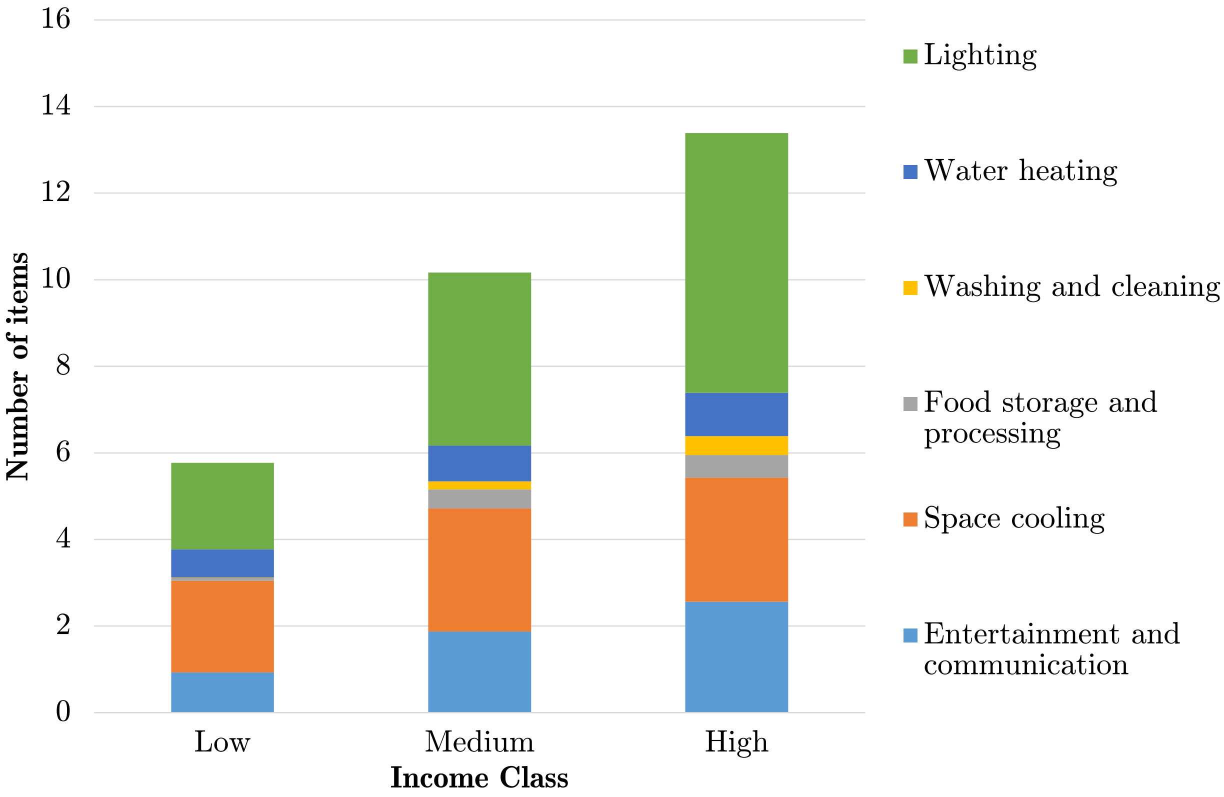


Figure 2.3 Ownership of appliances in income low, medium and high income classes.

2.3.2 Household Electricity Use

When combining ownership with UEC, a shift occurs in the relative contribution of different categories to total household electricity use (figure 2.4); water heating takes precedence, followed by space cooling and lighting. High income household electricity use is twice that of low income households and use in middle income households is closer to that of high income households than low income ones. However, the possible variation is high; an increase in household electricity use of approximately 70% or decrease of 42% is possible in each income class.

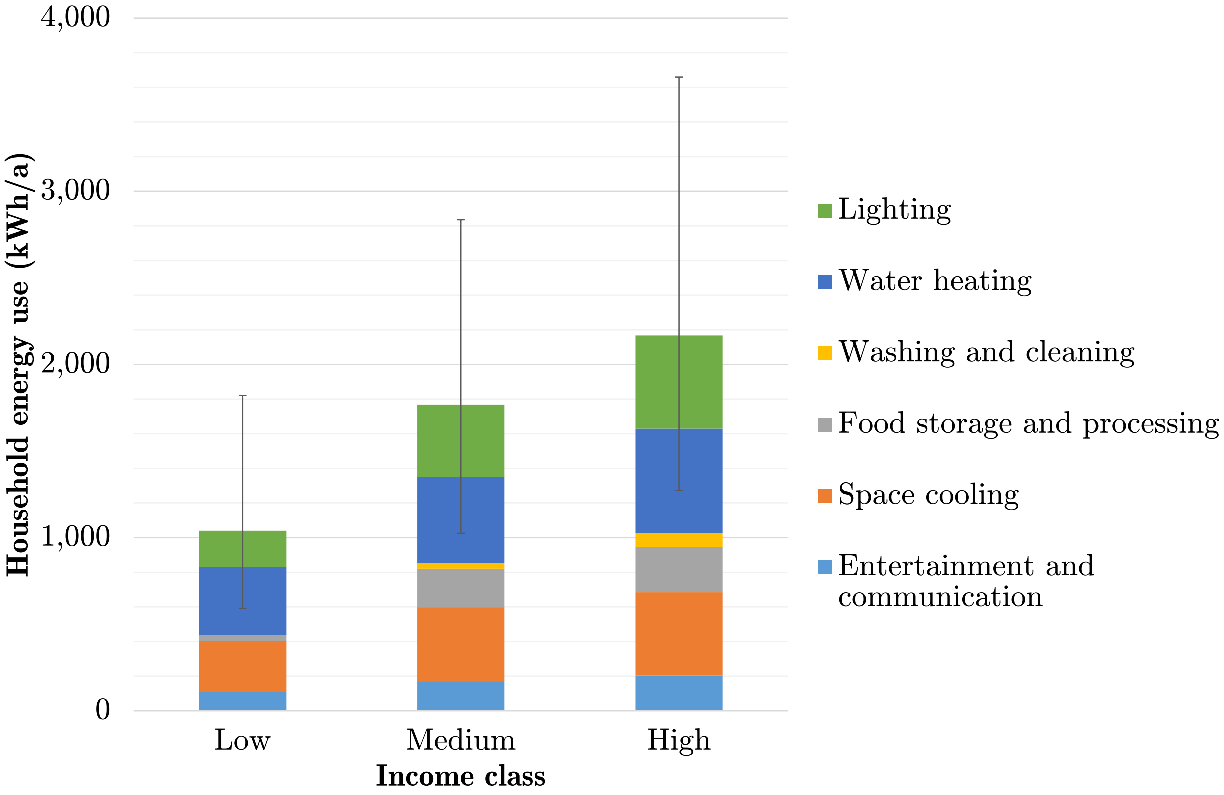


Figure 2.4 Household electricity use from low, medium and high income classes, as estimated by this study.

Comparison with other studies

NSSO reported electricity consumption Based on the Karnataka urban household income distribution of 24%, 53% and 23% for low, middle and high income households, respectively, the average household electricity use from this study is 1685kWh/a. An average of 5, 4 and 3 persons occupy low, medium and high income households, respectively (NSSO, 2014c), resulting in a per-capita electricity use of 455kWh/a from this study, which can vary between 264kWh/a and 751kWh/a over the range of possible results.

The average monthly per-capita electricity use for urban Karnataka was reported as 22.75kWh in the NSSO 2011-12 census period, amounting to 273kWh/a per-capita and placing the reported electricity use at the lower bound of the range given by this study.

Metered data Household data from Gujarat state, given in Garg *et al.* (2010), was corrected for space cooling and lighting electricity requirements to be representative of the climate in Bangalore. Figure 2.5 shows that the corrected metered household data is higher than the results of this study, for all income classes. Metered data sits in the upper bound of possible results from this study for low and medium income households, while metered high income households use 42% more electricity per year than the upper bound of the estimated range from this study. Lighting electricity use is lower in Garg *et al.* (2010) compared to this study, in all income classes. Of individual appliances, food storage and processing shows greatest discrepancy between the two data sets, perhaps caused by the existence of many electrical goods in the kitchen beyond the refrigerator considered in this study.

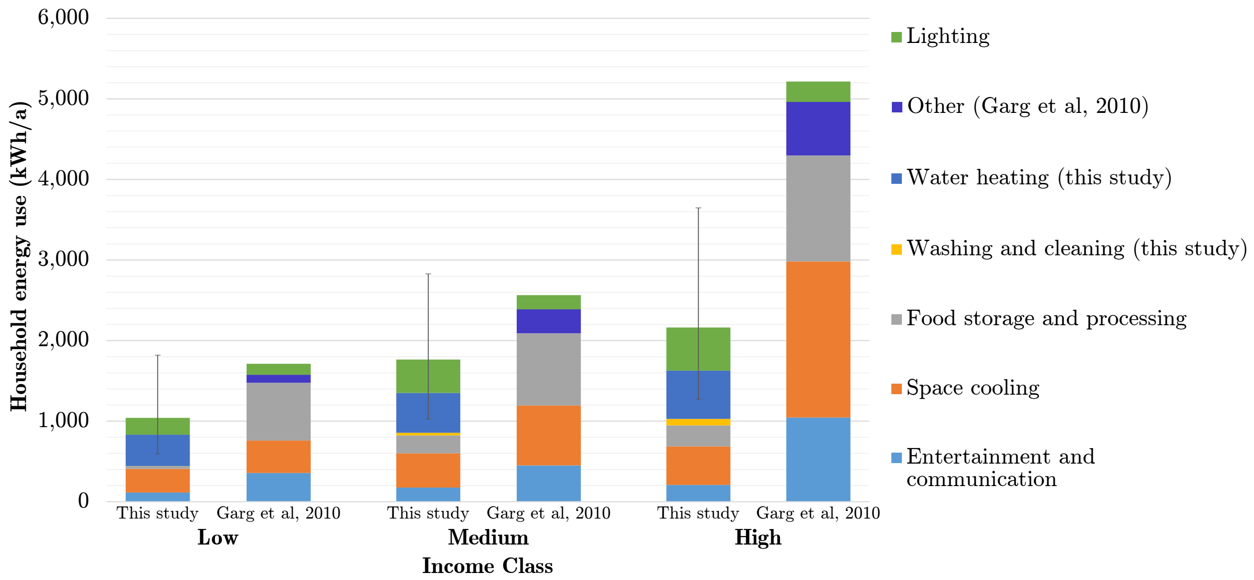


Figure 2.5 Estimated electricity demand from low, medium and high income classes, modified for BBMP climate from results of metering study in Gujarat (Garg *et al.*, 2010).

BESCOM Bangalore Metropolitan Area Zone (BMAZ) electricity supply There were 2,101,831 households reported in BBMP in the 2011-12 NSSO census. Based on the average household electricity use from this study of 1685kWh/a, the annual residential electricity use for BBMP is 3.54TWh, 65% of the provision of electricity by BESCOM to the domestic sector. The supply of electricity to BMAZ is approximately 16TWh, 3.08TWh of which is supplied to the domestic sector if each end-use category receives the same proportion of the supply in each zone of BESCOM. The result is 6.22TWh and 2.3TWh using corrected data from Garg *et al.* (2010) and from reported electricity consumption, respectively.

2.4 Discussion

There exists a great deal of uncertainty in the results of the bottom-up model produced in this chapter, including a large range of possible household electricity use values as well as little agreement with results of other studies. In order to be confident of applying these results to income distributed maps of the city of Bangalore, it is necessary to attempt to understand and bound the uncertainty that exists. This begins by analysing the intermediate steps in the production of the results given in section 2.3, before considering the comparison studies.

2.4.1 Data Source Variation

Lighting

Estimation method The first method for assigning electricity use to lighting involves the estimation of typical light points per household and the energy use per light point. A light point refers to a light fixing in a dwelling and is expected to increase with household income (as a result of larger and more numerous rooms). Conversely, the energy use per light is estimated to decrease with income, as more expensive low-energy light fittings penetrate first into high income households. TERI (2006) and Reddy and Balachandra (2006) offer two differing estimations of the number and type of light points across income categories (table 2.4). Assuming daily usage of 5 hours per light point, irrespective of income class (TERI, 2006, p.89), the household electricity requirement for lighting is shown to be significantly different between the two sources: an increase of 71%, 4% and 27% for low, medium and high income classes, respectively, from TERI (2006) to Reddy and Balachandra (2006) estimations. This degree of variation should be expected from an estimation method on a national scale, wherein assumptions are made and bias is given to certain information. Therefore, it is not possible to assign greater confidence in either result and a range is provided in which lighting electricity use could lie.

	Income Class	**Low**				**Middle**					**High**							
	Lamp type		GLS	GLS		TL	TL	GLS	GLS			TL	TL	TL	GLS	GLS	CFL	
(a)	**Lamp wattage (W)**		60	60		55	55	60	60			55	55	55	60	60	11	
	Light points	2				4					6							
	Energy requirement	210kWh/a/HH				416kWh/a/HH					538kWh/a/HH							
	Income Class	**Low**				**Middle**					**High**							
	Lamp type	GLS	GLS	GLS	TL	GLS	GLS	GLS	TL	TL	GLS	GLS	GLS	GLS	GLS	TL	TL	TL
(b)	**Lamp wattage (W)**	40	60	60	40	40	60	60	40	40	40	40	60	60	60	40	40	40
	Light points	4				5					8							
	Energy requirement	360kWh/a/HH				432kWh/a/HH					684kWh/a/HH							

Table 2.4 Household electricity requirement for lighting, from (a) TERI (2006) and (b) Reddy and Balachandra (2006), based on income class variation in light types and number of light points. GLS – generalised lighting system (incandescent); TL – tube light; CFL – compact fluorescent lamp.

Survey Results Murthy *et al.* (2001) take the result of a 1995 survey in Karnataka state in order to give an average household electricity demand from lighting. The average household electricity requirement for lighting is 363kWh/a/HH. This result lies below the range defined by the estimation method, being 8% lower than the average from TERI (2006) data and 23% lower than the average from Reddy and Balachandra (2006). However, table 2.5 indicates that the 5 hour usage assumed in TERI (2006) may be too high, with no single light point being utilised for more than 2.72 hours.

Appliance category	Wattage	Average appliance no. per HH	Usage (hr/day)	Consumption (kWh/yr)	
				per app	per HH
Table lamp	40	0.1	2.54	37.08	3.71
FL20	20	0.02	1.3	9.49	0.19
FL40	40	4.09	2.63	38.4	157.05
IL15	15	0.22	2.32	12.7	2.79
IL40	40	2.27	1.56	22.78	51.7
IL60	60	2.64	2.36	51.68	136.45
IL100	I00	0.08	2.72	99.28	7.94
IL25	25	0.24	1.27	11.59	2.78

Table 2.5 Light fittings, power requirement and expected household lighting electricity consumption in “all-electric" households of Karnataka state in 1995, from (Murthy *et al.*, 2001).

Appliance Ownership

National censuses Ownership of a range of material items is surveyed by the NSSO, with the relevant electrical items given in table 2.6. As some items were sufficiently relevant or irrelevant in different NSSO censuses (e.g. gramophones in 1999-00 compared to PC/laptops in 2011-12), the items have been categorised and grouped into: entertainment and communication; space cooling; food storage and processing; and washing and cleaning. A similar categorisation is used by van Ruijven *et al.* (2011), Garg *et al.* (2010), and TERI (2006).

Appliance categories	NSSO 1999-00	NSSO 2011-12	No. per owning household
Entertainment & communication	Gramophone & record player		1.2
	Radio, tape rec., 2-in-I	Radio, tape rec., 2-in-1	1
	Television	Television	1
	VCR/ DVD player	VCR/ DVD player	1
	CD, DVD, etc.	CD, DVD, etc.	1
		PC/ laptop incl. soft.	Unknown
		Mobile phone handset	Unknown
Space Cooling	Electric fan	Electric fan	1.54
	Air conditioner, air cooler	Air conditioner, air cooler	1
Washing & cleaning	Washing machine	Washing machine	1
Food storage & processing	Refrigerator	Refrigerator	1
		Water purifier	Unknown

Table 2.6 Appliances present in two NSSO census periods, grouped into appliance categories. The number of appliances owned, per urban household reporting appliance ownership, is given per appliance from the urban Karnataka division of the NSSO 1999-00 census.

Unaccounted appliances National censuses do not cover the complete range of possible appliances owned in the household. For instance, results from Murthy *et al.* (2001) suggest that water heating is a large component of household electricity use in Karnataka. As such, ownership is taken from other sources; Boegle *et al.* (2009) assume a water heater is owned per household, while Murthy *et al.* (2001) find that 29% of households own storage heaters and 36% own immersion heaters, amounting to 65%. For the purposes of this study, the ownership has been taken as being able to range between the results from Murthy *et al.* and Boegle *et al.* The actual ownership levels could be significantly different, especially considering that the survey studied by Murthy *et al.* was undertaken in 1995-96. For the case of new entertainment systems not considered in NSSO 1999-00, data from Boegle *et al.* (2009) suggests that one appliance per owning household is expected, which is the value used in this study.

Finally, although results from NSSO 1999-00 show 1.54 fans on average per owning household, there is disagreement from other studies. Three fans per owning household is assumed in one case (Chaturvedi *et al.*, 2014) and 2.71 fans per household (including those with no fans) in another (Murthy *et al.*, 2001). Both results are analogous as 90% of urban Karnataka households own at least one fan according to the NSSO 2011-12 census (NSSO, 2014b). Once again, without being able to apply a greater degree of confidence to any one set of results, the variation in fan ownership is taken as the possible range.

Appliance Energy Use
Different sources provide different types of information with regards to appliance Unit Energy Consumption (UEC). McNeil *et al.* (2008), de la Rue du Can *et al.* (2009), The World Bank (2015), and Letschert and McNeil (2007) provide UEC for various appliances, with the intention of analysing future energy efficiency improvement possibilities. TERI (2006), Murthy *et al.* (2001) and Chaturvedi *et al.* (2014) begin at a more fundamental level, considering the hours of usage in a day, days of usage in a year and power requirement of an appliance. The latter approach allows simpler analysis of result validity. For instance, in the case of the TERI report, refrigerator data can be discounted since the maximum rated power of the devices was utilised as the average power consumption to ascertain UEC. In reality, a refrigerator operates at maximum rated power for short periods and has an average rated power of approximately 10% of the maximum.

UEC from all studies for primary appliances is given in figure 2.6, showing a great deal of variation in possible values. The median values are used to provide the average household energy use estimate, but the possible values vary as much as four times lower and three times higher than the median value for some appliances. Moreover, the large difference in air cooler and air conditioning UEC leads to their combination into one category in the NSSO censuses difficult to account for.

Variation of UEC through time Appliance ownership is not the only variable which is likely to vary annually and across income classes, UEC is also affected. There is a downward trend in fan UEC through time which may be a result of improved energy efficiency, while larger screen size and resolution may explain an increasing trend in television UEC. Appliance energy ratings have been applied to large domestic goods (refrigerators, washing machines, air conditioning units, etc.) since 2006 (USAID, 2010). It could be assumed that as more efficient appliances penetrate the market, they would be more expensive and thus prohibitive to all but the higher income class, leading to a lower energy requirement in higher income classes. The UEC for refrigerators in the star rating scheme ranges from 400kWh/a (5 star) to 1100kWh/a (no star), leading to some UEC estimations as seen in figure 2.6a being twice as efficient as the most efficient star rated refrigerators. Such a wide variation may be explained by varying sizes of appliances. Refrigerators vary in capacity and exact function, which will change UEC independently of efficiency differences, a trait which is true for all the appliances considered. With currently available data, the most likely UEC for each appliance is not ascertainable.

Comparison to other data sources
Uncertainty exists in all three data sources used to compare the results of this study. Firstly, reported electricity use in urban Karnataka households is taken for one month, at the time of the census. This result has been extrapolated over the entire year due to a lack of knowledge as to seasonal variations in electricity use and no indication as to the month over which the reported value was taken.

Secondly, although the meter results from a study in Gujarat state (Garg *et al.*, 2010) are more objective than survey based results, assumptions made to correct the data are a source of uncertainty. It is assumed that appliance usage is comparable between Gujarat state and Bangalore, only space cooling and lighting will differ as a result of differing climates and daylight levels between the

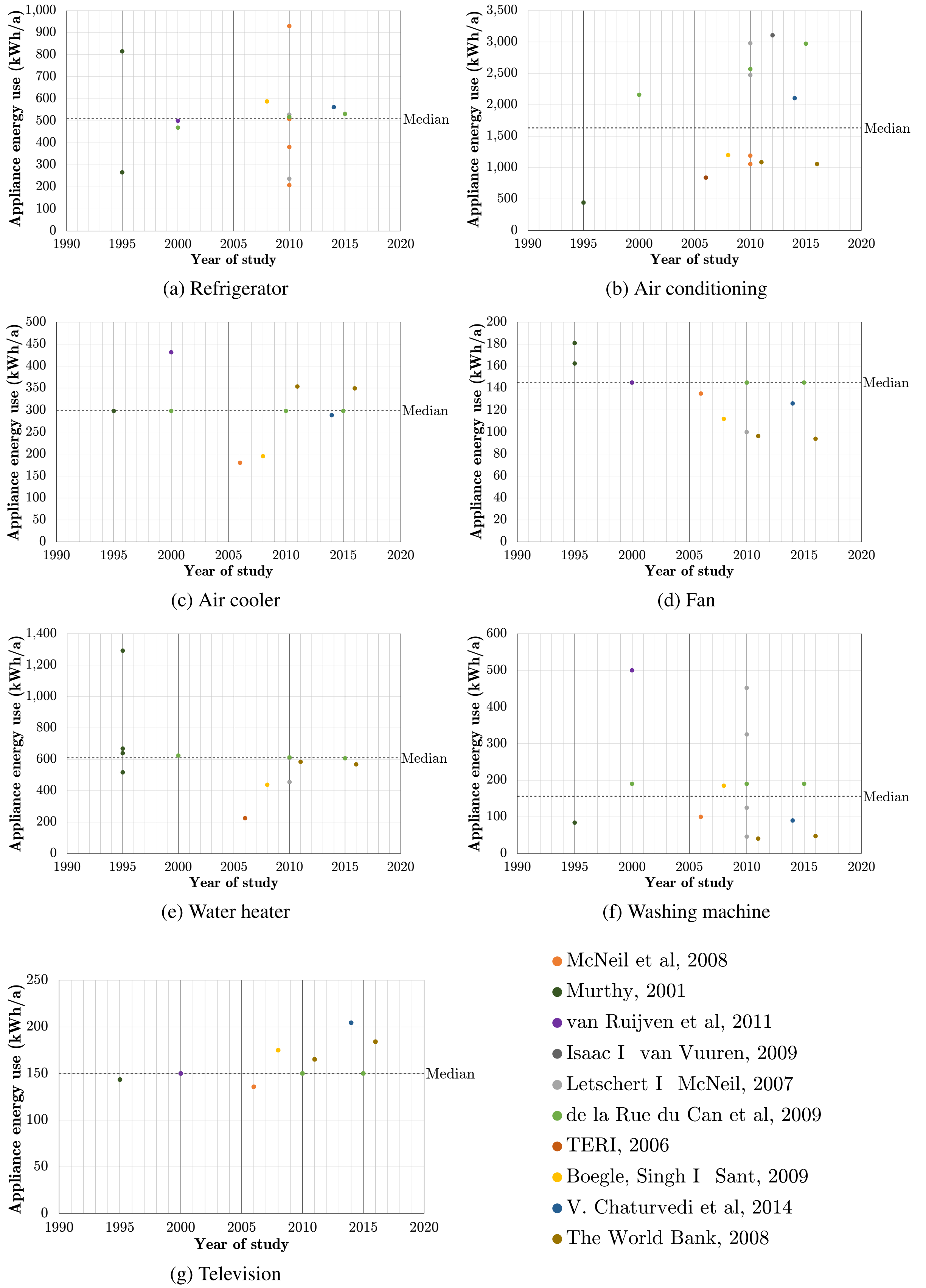


Figure 2.6 Appliance Unit Energy Consumption for 7 primary household appliances, as estimated or calculated in various studies.

two locations. Space cooling is assumed to change alongside the change in Cooling Degree Days (CDD) between the two locations, where CDD are the number of equivalent days in the year that the external temperature is above 15.5°C. Bangalore is a more temperate climate with up to 39% fewer CDD than Surat, a representative city in Gujarat (table 2.7). Lighting is assumed to vary with the change in daylight hours, affected by latitudinal variation. However, these assumptions are simplistic; the degree of correction required is dependant on more than just external climatic conditions. The building fabric, window to wall ratio and density of buildings and population all affect the degree of lighting or space cooling required. Furthermore, taking 15.5°C as the base for calculating CDD is perhaps too low, more pertinent for climates such as that of the United Kingdom than Surat or Bangalore.

	Summer (March to October)	**Winter (November to February)**
daylight hours	+2%	-4%
CDD	-39%	-36%

Table 2.7 Change in daylight hours and CDD from Bangalore to Surat, required for modification of results from Garg *et al.* (2010) to account for Bangalore climate.

Finally, averaging the result of this study over households in Bangalore and comparing to BMAZ electricity supply suggests similarity that lends authority to the result. However, the result for BMAZ is an estimate, assuming that the urban centre of BESCOM's operational area has the same end-use structure for electricity as the rural areas of BRAZ and CTAZ. BMAZ also covers a greater area than BBMP, so the electricity use result for the two areas is not directly comparable. The similarity in results, 3.54TWh from this study for BBMP against the supply of 3.08TWh to BMAZ may provide false confidence in the income distributed results of this study, creating belief in results at a higher spatial resolution which might be incorrect.

2.4.2 Accounting for Uncertainty

When collating information for intermediate values, a range is found based on equal confidence in each result, in the absence of evidence to prove otherwise. When confronted with a similar problem, Booth (2013) undertakes calibration by Bayesian inference, combining uncertain 'prior' data-sets, with pre-defined probability ranges from regression analysis, into a single 'posterior' probability range, allowing the production of a stochastic data-set of representative dwellings to be used in a house retrofit model. Booth's results have a bound uncertainty, giving confidence to the range of possible outcomes and their likelihood. However, such a process cannot be applied here as there is a lack of data sets with which to undertake a regression analysis for the production of 'prior' probability ranges.

Known uncertainty in the electricity use estimate is given as a range in section 2.3, yet there are several unaccountable uncertainties that mean the confidence given to the applied range is low. The bottom-up engineering modelling method requires a level of data accuracy, and situational relevance, that the Karnataka level data and national UEC estimations are unable to reliably supply. Therefore, **the results of this chapter are not recommended for direct application to a spatially disaggregated model of Bangalore**, due to concern that the low level of confidence will be lost in the process. Although there is a clear increase in energy use with income class, the degree to which the income class electricity use differs cannot be confirmed, especially due to the lack of agreement with the differences in income class electricity use given in Garg *et al.* (2010). Moreover, a lack of agreement between the average estimated per-capita electricity use with the NSSO Karnataka Urban per-capita electricity use raises further doubt in the estimation, with no clear indication as to which result to trust.

Improving confidence in results

The current result is based on national, potentially outdated, and varying data sources. In order for an estimation method such as this to provide information with known and low uncertainty it is necessary to undertake local studies of ownership and electricity use (from metering, such as by Garg *et al.* (2010)) with a view to ascertaining the following information:

- Whether an appliance is owned and if so, the quantity of each.
- Electricity use from each appliance that is owned from metered and rated power information.
- Whole-dwelling electricity use, necessary to quantify ‘Other’ electricity use that is otherwise missed.
- Seasonal variation, quantified by metering over a year or seasonally representative weeks throughout the year.

It is useful to obtain both metered and appliance information in order to compare the results from both methods. Surveys may prove unreliable if questions are interpreted differently by different respondents, or inaccurate responses are given. Murthy *et al.* (2001) note a concern with survey results for the running hours of appliances; respondents may not be fully aware of the true operating times of their appliances. Obtaining both data sets could also allow metering data to be correlated to penetration of appliances. Future studies can then record appliance ownership (or purchasing/disposing rates) without needing a new set of metered data.

As such data sets do not currently exist, there are further ways to process the results of this chapter to improve confidence. Once incorporated into an income distributed map for Bangalore, being prepared by the IIHS, the results could be compared to other maps of the city which indicate variations in energy consumption. A lack of agreement between the results of this chapter and other spatially indicative data sets would bring to the fore the need to fully account for uncertainty in order to place confidence in the results. However, agreement could not only reduce result uncertainty, but would also pinpoint parts of the city with interesting energy use profiles, which could direct further research efforts for higher spatial resolution studies (such as metering of dwellings). A map which may indicate variation in energy consumption, based on interruptions to electricity supply, is produced and discussed in the next chapter.

2.4.3 Extending the Scope of Study

Assuming that confidence can be improved in the the result of a bottom-up engineering model, there exists omissions in this chapter with relation to the full data set required to represent electricity use in Bangalore. Figure 2.2 shows that although this chapter concentrated on income distributed electricity use in electrified residential sector buildings, there are several other data sets that must be acquired. Extension of scope will require inclusion of all end-use sectors and inclusion of high time resolution. As few studies can be drawn upon to provide estimations of the electricity use in sectors beyond residential, the need to meter and conduct surveys of samples of each end-use sector is once again highlighted as necessary. Metering by Garg *et al.* (2010) for the commercial sector took account of the type of business (e.g. bank, beauty salon, office), an explanatory variable which must be considered further.

Time resolution can be gained by building an engineering model with time of use data included. This can be compared to metered data in order to disaggregate load curves. Once all end-use sectors are accounted for, the load curve provided by BESCOM for BMAZ (discussed further in chapter 3) can itself be disaggregated based on end-use, similar to that undertaken by Balachandra and Chandru (1999). Future peaks can then be attributed to end-use sectors and end-use appliances without continual need to conduct detailed surveys and metering studies.

Chapter 3

Power Interruption Analysis

In chapter 2, estimations were made for residential sector household electricity use in Bangalore. It was found that current data available for the city is too sparse to provide sufficient confidence in a set of results. Comparison to other indicators of energy use were proposed as a next step to reduce uncertainty in energy use estimations. This chapter analyses a spatially and temporally disaggregated data set produced by mapping the interruptions to power supply that take place in BBMP, and surrounding areas. This data set can be used to highlight explanatory variables for consideration in producing a bottom-up energy model and for comparison to results of a completed model.

3.1 Method

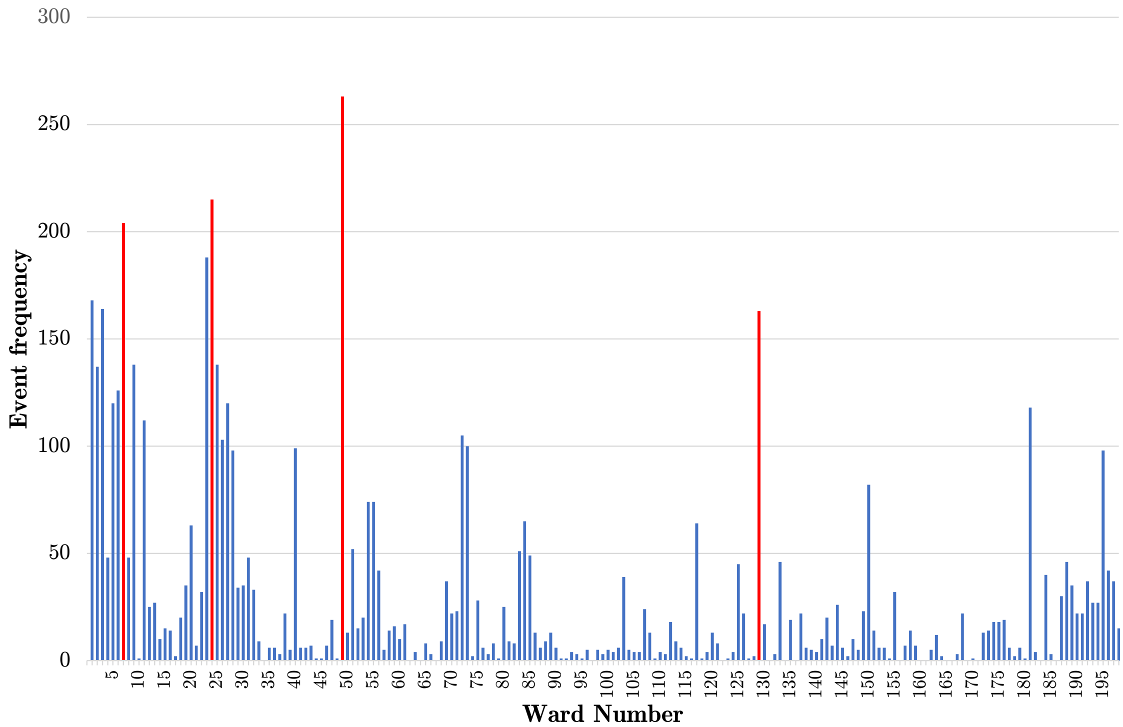
BESCOM publish daily reports on interruptions to the electricity service in the city. These reports specify the time of interruptions, the areas in the city that are affected and the reason for the interruption. Although some interruptions are planned in order to undertake maintenance, others are caused by overload at the transformer stations. It is these interruptions that are of interest in this study: loss of electricity access as a result of demand exceeding that which can be supplied at a given time. Daily reports from 31/12/2015 to 06/07/2015 were acquired from BESCOM and the pertinent information was extracted and cleaned (described in appendix A). A total of 1260 events, affecting 351 unique locations, were mapped across BBMP wards and surrounding areas. Comparisons are made to 2011 census ward-wise population (BBMP-RC, 2015a) and to the results of a survey which ranked wards on degree of liveability (The Times of India, 2011); the goal is to ascertain why any spatial variation occurs in the frequency of events. In order to fully understand temporal distribution, electricity supply load curves to BMAZ have also been evaluated.

3.1.1 Assumptions

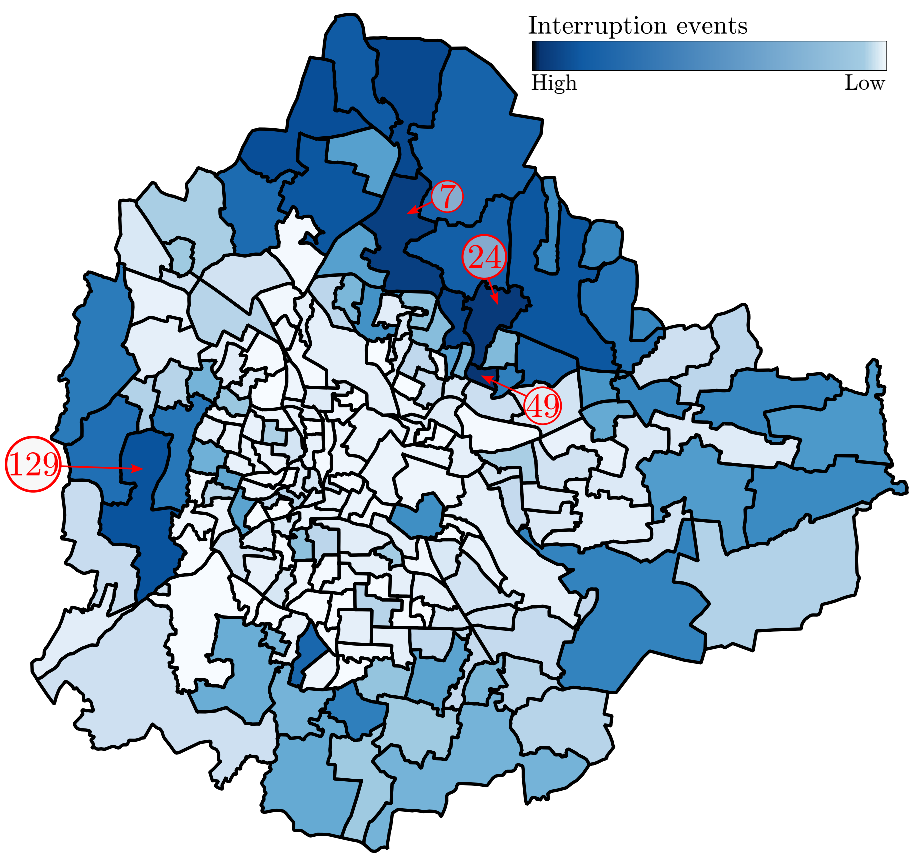
The primary assumption taken in this chapter is that events in which load is restricted due to an overload are unplanned and caused by demand exceeding infrastructure supply capability. It is also assumed that the areas affected are in the locality of Bangalore, to aid geographic location systems which may otherwise find several results of the same name.

3.2 Results

3.2.1 Spatial Analysis



(a) Event frequency per ward.



(b) Spatial distribution of events

Figure 3.1 Ward-wise comparison of power interruption events for BBMP jurisdiction. Highlighted wards refer to those considered further in figures 3.12 and 3.13.

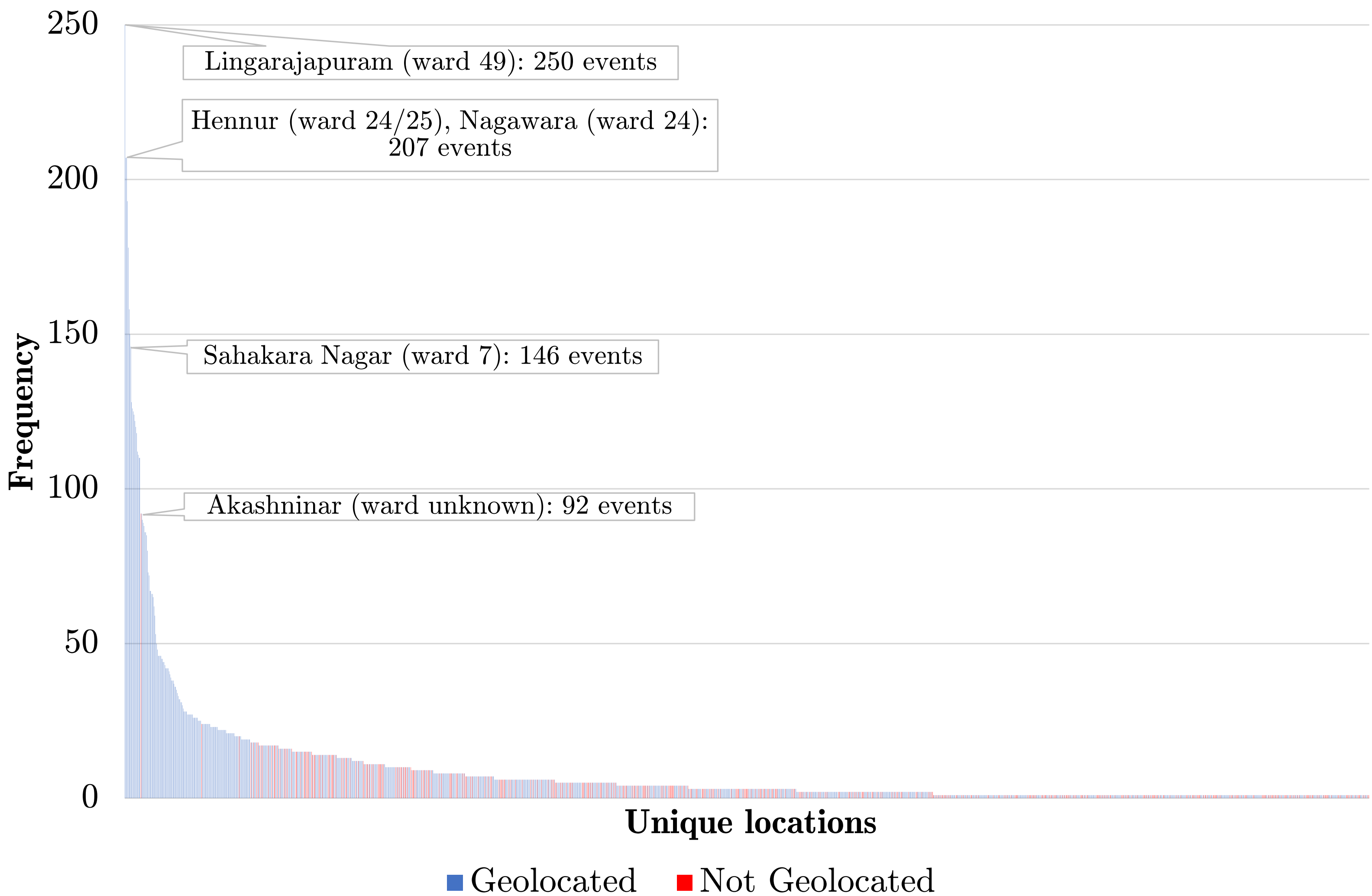
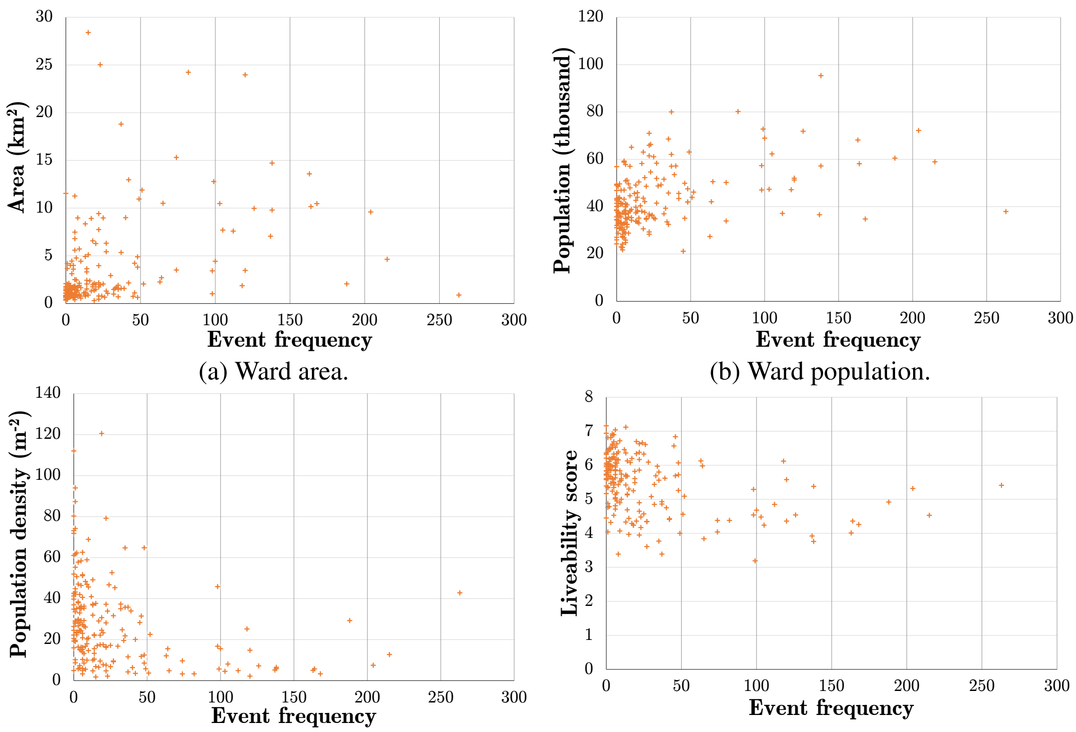


Figure 3.2 All unique locations in data set, ordered by frequency of appearance in primary data set. Non-geolocated unique locations are those which could not be located geographically so were not used in the final data set. Captioned are the three most frequent unique locations as well as the most frequent non-geolocated unique location.

Power interruptions occur across BBMP, with the results in figure 3.1b indicating a greater number of interruptions on the outskirts, particularly to the north of the city. There are distinct peaks in event frequency; 21% of interruption events effect districts within ward 49, while wards 24 and 7 are also affected in over 15% of interruption events (figure 3.1a). Within both wards 49 and 24, there are one or two unique locations which contribute to the total ward event frequency, whereas ward 7 has a greater range of unique locations within the ward contributing to the total, as seen by the lower unique location frequency peak given in figure 3.2. Unique locations which were not successfully geolocated (see appendix A for more information) generally do not appear often in the event data set, except for Akashninar, which appears in 92 events and could viably change the ranking of wards which are most affected by interruptions. Ward 129 is also highlighted in figure 3.1 since it is an outlying peak on the west of the city which becomes particularly prevalent in the temporal analysis of the data (section 3.2.2).

Understanding Ward Distribution

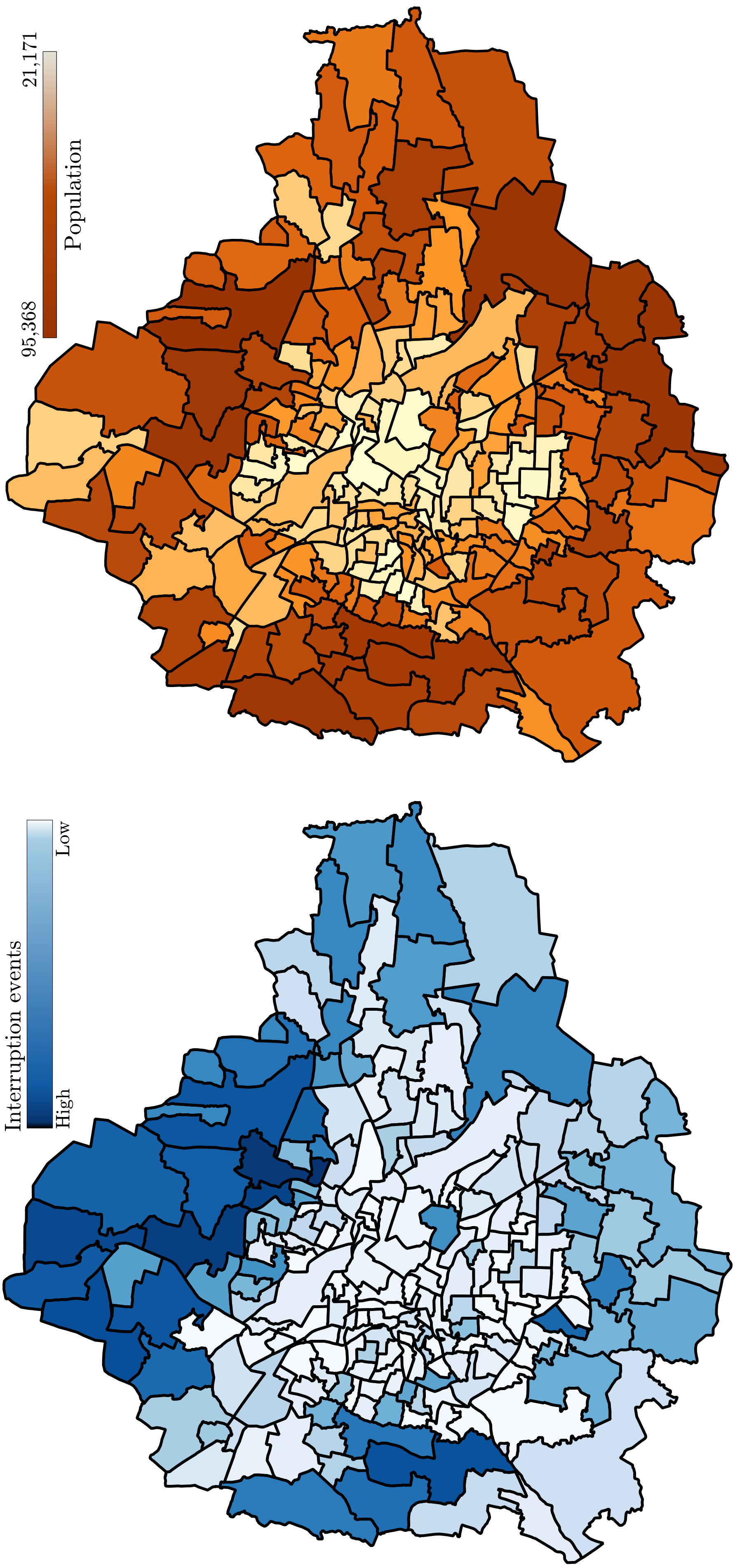
There is a spatial distribution of interruption events which loosely correlates with the increased population and reduced perceived liveability on the outskirts of the city (figures 3.4 and 3.5 respectively). However, when attempting to correlate interruption event data, there does not seem to be a strong correlation with relation to ward area, population, population density or perception of liveability, as seen by the scattered data in figure 3.3. Nevertheless, both population density and liveability score follow a decreasing trend with event frequency increase. The former trend is somewhat counter-intuitive as it suggests that residential sector electricity use is not placing the primary strain on infrastructure, pointing towards the weighted effect of building end-use, i.e. commercial, industrial, residential, etc..



(a) Ward area. (b) Ward population.

(c) Ward population density. (d) Ward liveability score.

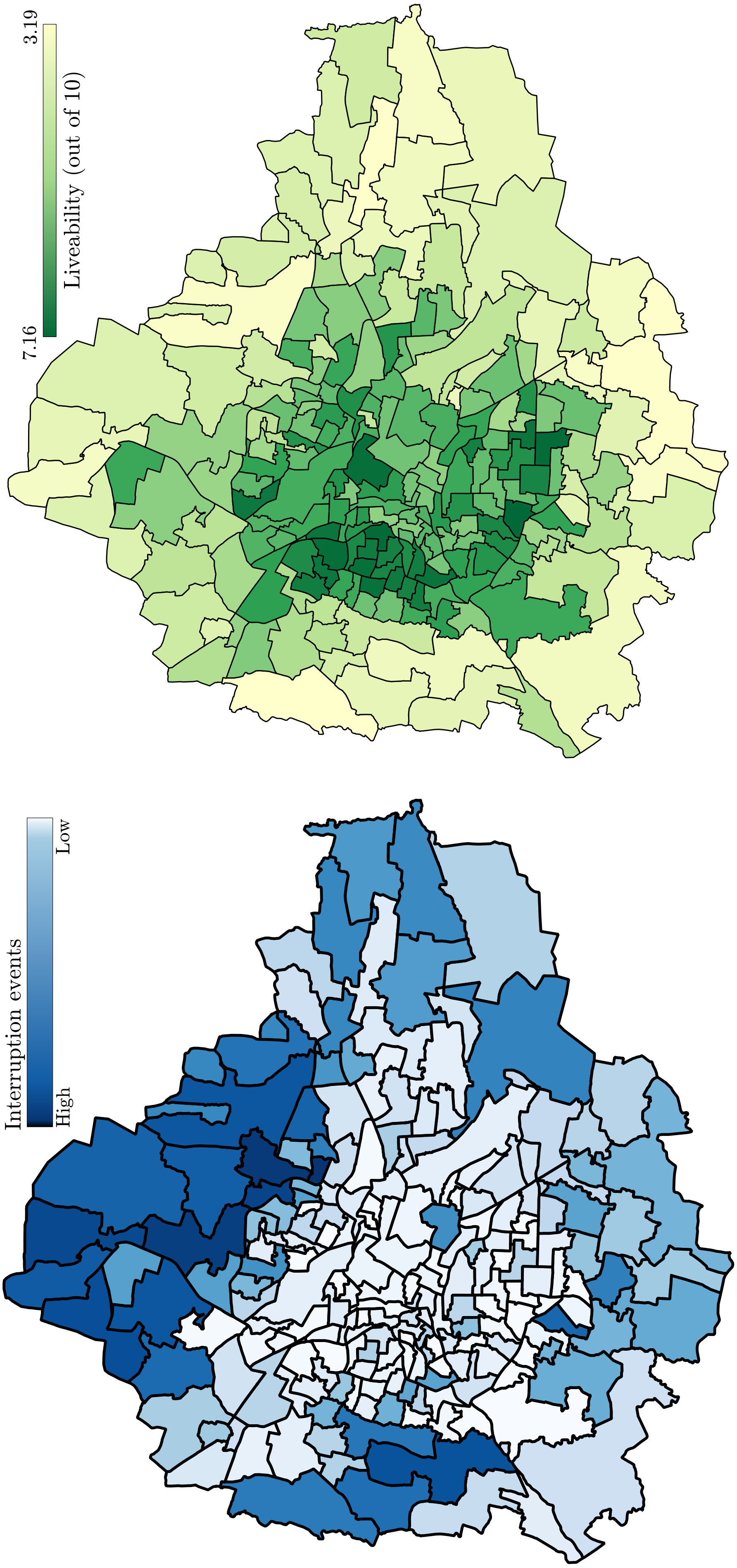
Figure 3.3 Comparison of ward area, population, population density and liveability score to power interruption event frequency.



(a) Power interruption events.

(b) Population.

Figure 3.4 Ward-wise distribution of power interruption events and population for BBMP jurisdiction.



(a) Power interruption events.

(b) Liveability Score.

Figure 3.5 Ward-wise distribution of power interruption events and liveability score for BBMP jurisdiction.

Interruptions Beyond BBMP Boundary

The final data set consists of 180 unique ward locations and 171 unique points outside BBMP. Figure 3.6 shows these interruptions in relation to geographic boundaries, as introduced in section 1.3.1. As with event distribution between wards, the most affected locations outside BBMP are those north of the city. Most events occur within BMAZ while the remainder are within BRAZ; no events took place in CTAZ. The Bangalore international airport is also pinpointed in figure 3.6, to see whether a distinct route exists between it and BBMP. No such route exists, but many interruption events do follow the direction of the city's arterial roads, particularly to the north and south (figure 3.7).

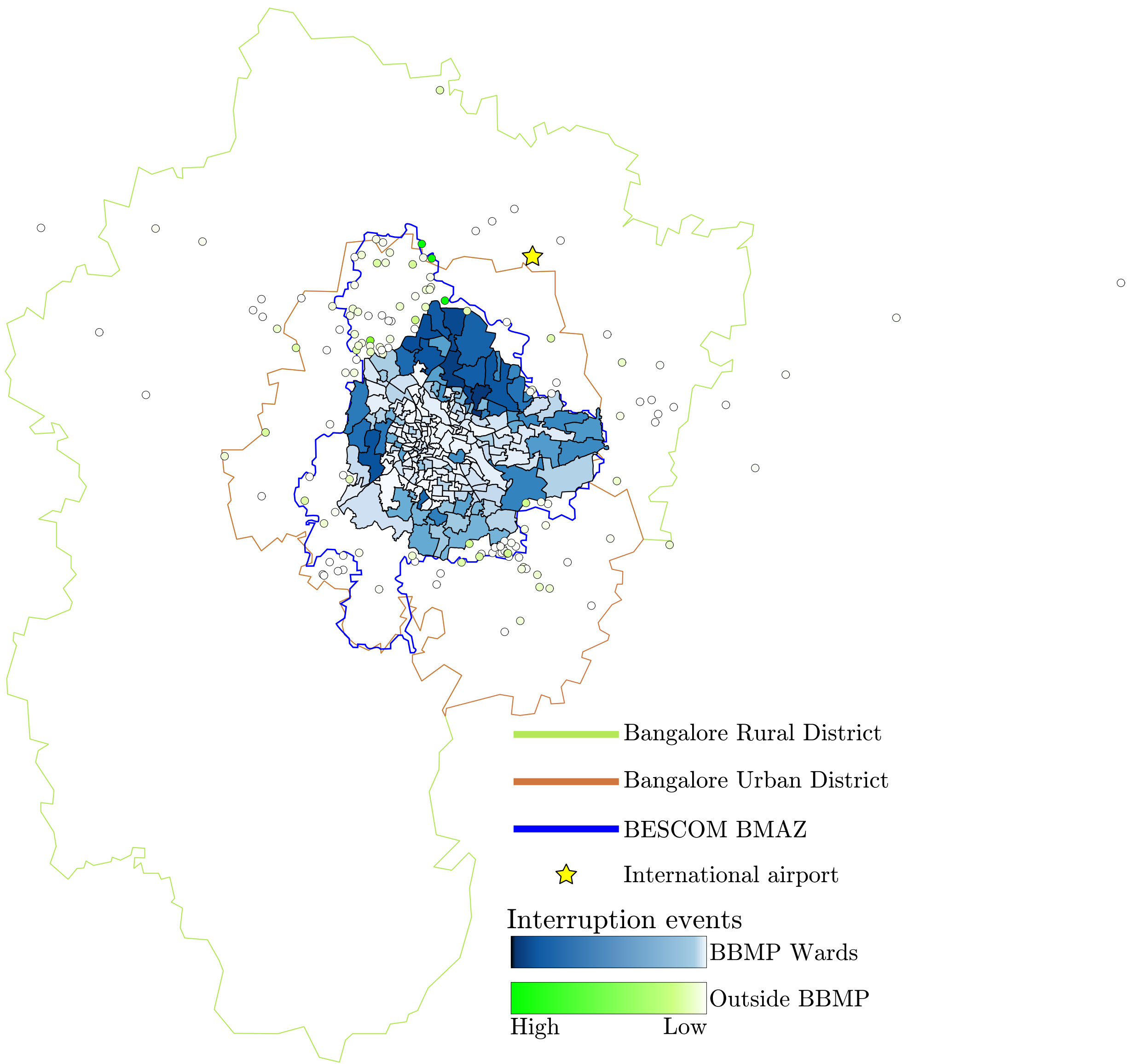


Figure 3.6 Distribution of power interruption events within BBMP wards and surrounding areas, within the context of geographic boundaries. Refer to section 1.3.1 for further boundary information.

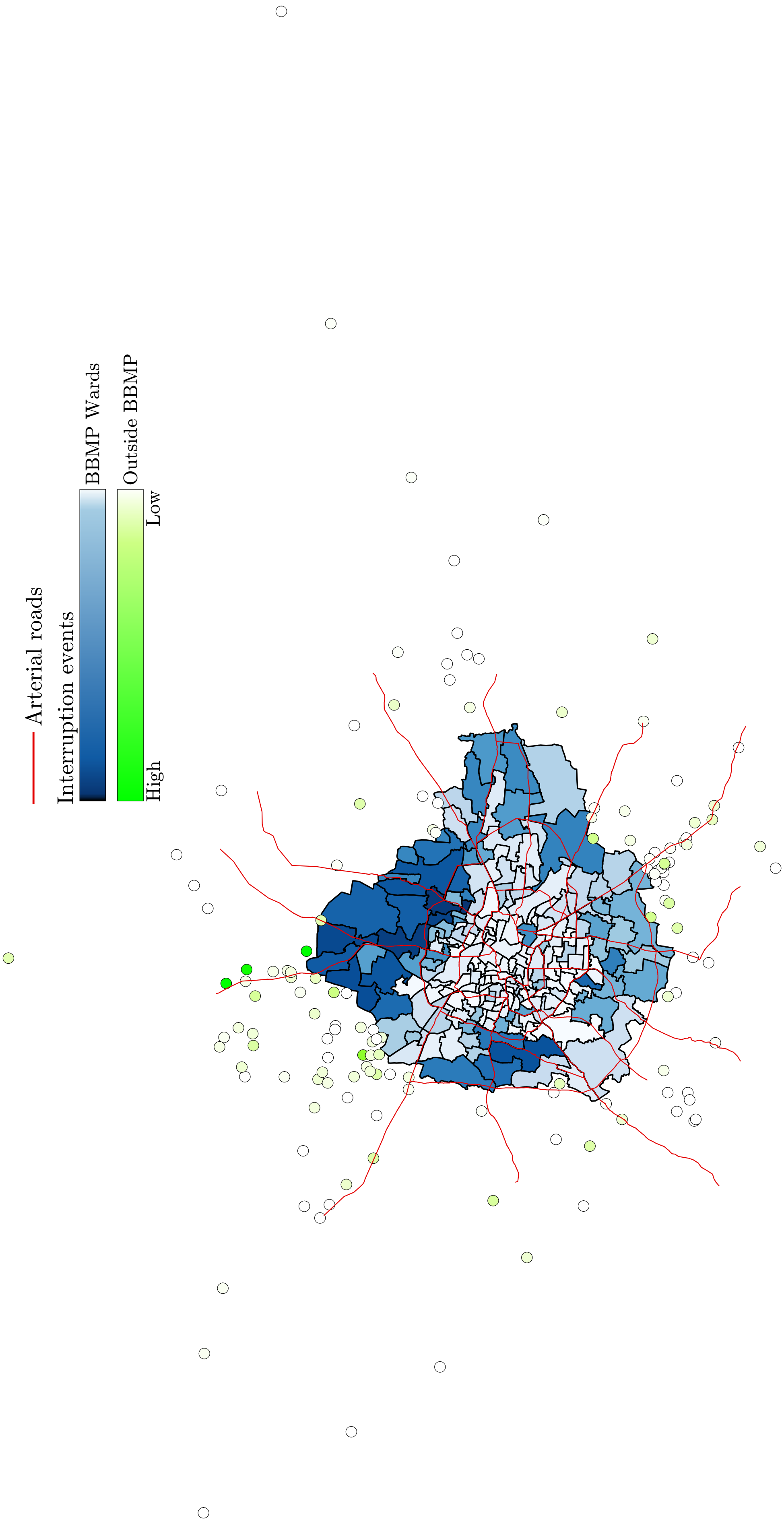


Figure 3.7 Overlay of power interruption events, within BBMP wards and surrounding areas, to the arterial roads of Bangalore.

3.2.2 Temporal Analysis

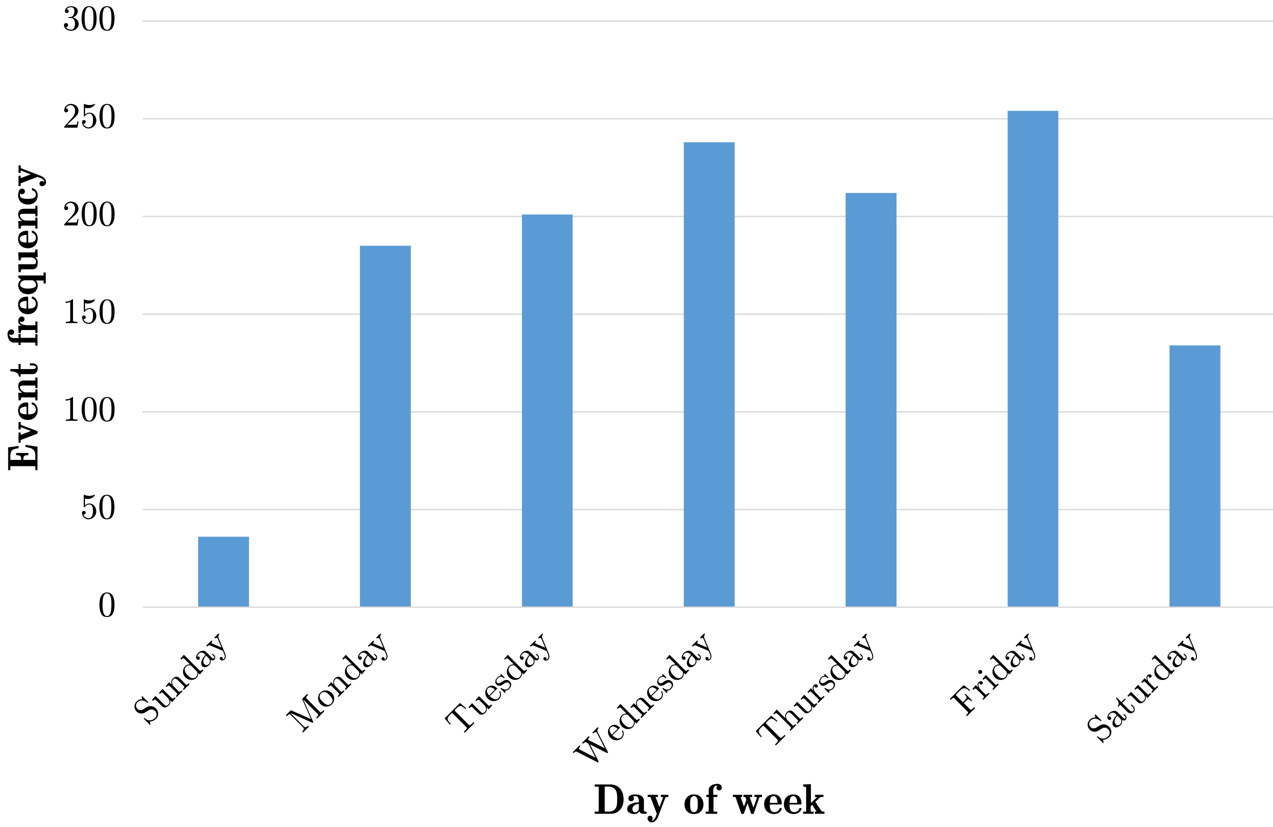
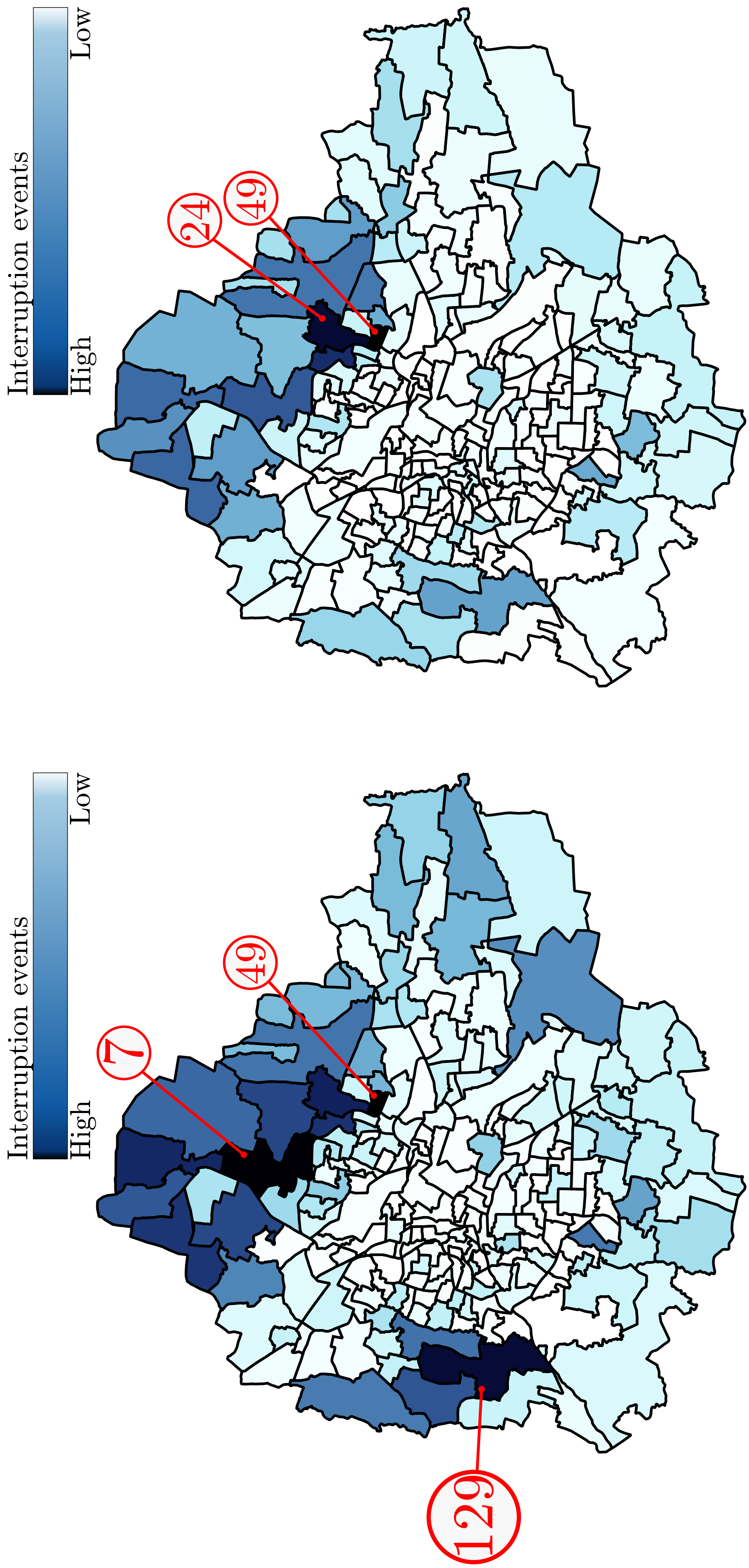


Figure 3.8 Average number of power interruption events on each day of the week.

There exists variation in interruption event occurrence throughout the day and the week. Figure 3.8 above shows that the majority of events occur during the week, particularly on Wednesday and Friday. Ward-wise distribution of events at different times of the day (figure 3.9) shows the change in focus of interruptions between the morning and afternoon. In the morning there is a shift in interruptions towards the west, particularly ward 129; the focus returns east to the most affected ward overall, number 49, in the afternoon. This result justifies the inclusion of ward 129 in more detailed analysis, it is subjected to fewer interruption events compared to wards 7, 24 and 49, but its morning peak is of the same magnitude as those wards (see figure 3.12).



(a) Morning.

(b) Afternoon.

Figure 3.9 Distribution of power interruption events between a) **00:00 and 11:59**, and b) **12:00 and 23:59** within BBMP. Highlighted wards are those with highest event frequency in the given time period.

Hourly resolution

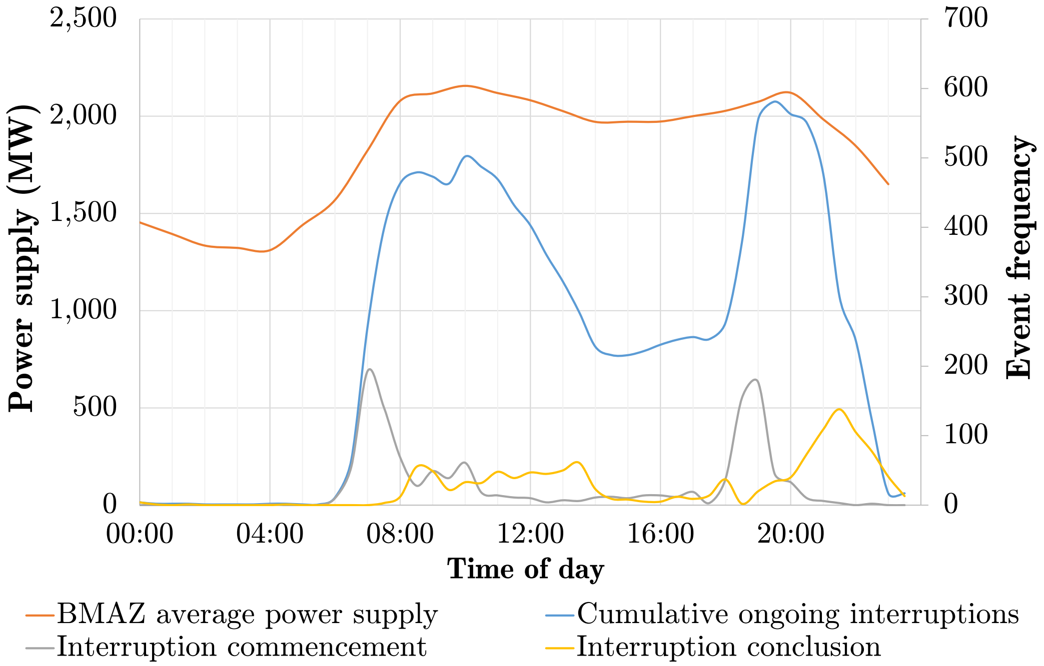


Figure 3.10 Comparison of commencement, duration and conclusion of power interruption events to BESCOM BMAZ power supply.

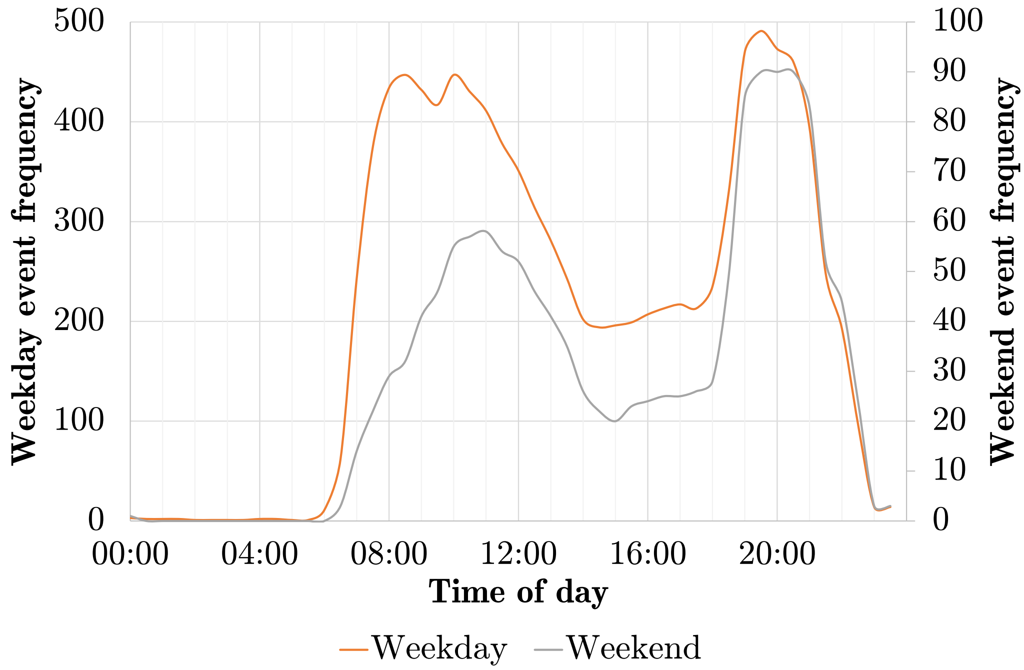


Figure 3.11 Cumulative ongoing power interruption events throughout the day on weekdays compared to weekends.

The commencement and duration of interruption events in the city leads to two distinct daily peaks, which occur in the same time period as the largest increases in power supply to BMAZ (figure 3.10). 07:00 and 19:00 are the two points in the day where the majority of interruption events commence, while the peaks of cumulative ongoing interruptions occur later: 10:00 for morning, and 19:30 for evening peaks. The slow decline from the morning power supply peak is accompanied by a low rate of event conclusions, while a distinct peak in event conclusions accompanies the faster decline from the evening power supply peak. There are two baseload periods, in which very few events commence or conclude: 23:00 to 06:00 and 14:00 to 17:30. The daytime baseload refers to a higher supply of ∼2,000MW compared to the nighttime baseload of 1,300-1500MW. These results all indicate that **it is not the magnitude of supply which dictates the frequency of events, but rather the rate of change of supply**. Results reveal that weekends experience fewer interruptions than weekdays, but the time of day in which the interruptions occur also varies between them. Figure 3.11 shows similar morning and evening peak event frequency on weekdays, while weekends have a much greater evening peak than morning peak, and fewer relative daytime baseload interruptions.

Analysis of notable wards

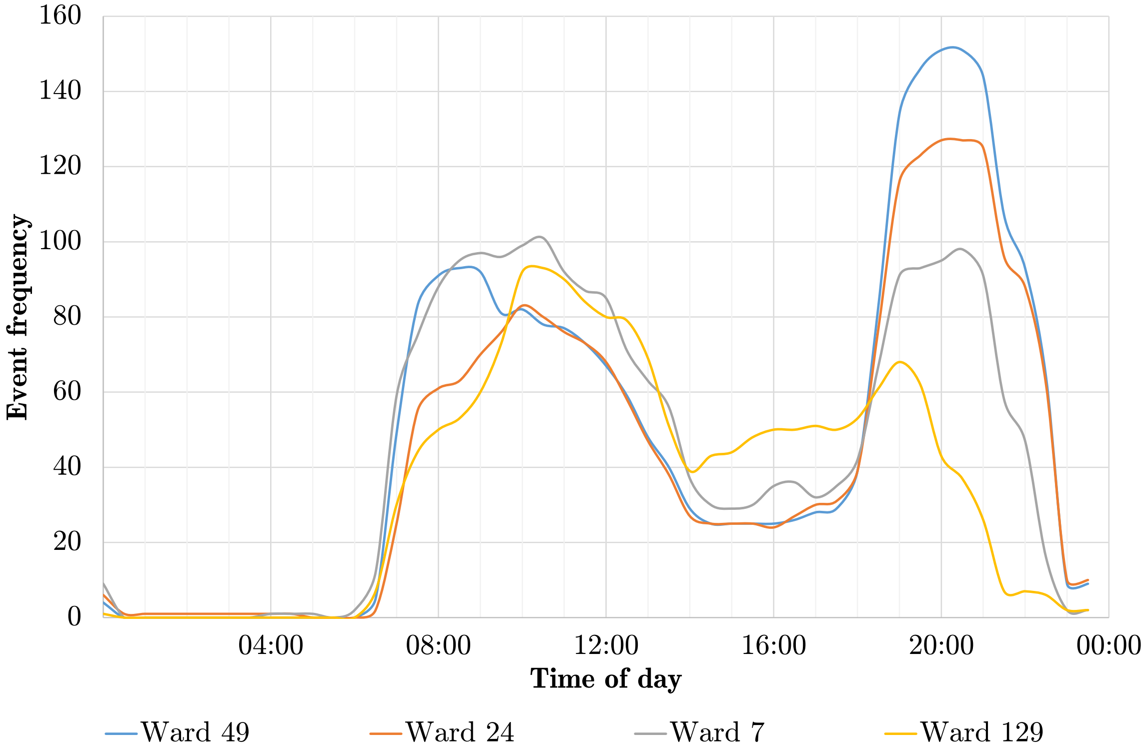


Figure 3.12 Comparison of daily power interruption event duration, for wards with high event frequency and notable event frequency peaking.

Focusing on wards 7, 24, 49 and 129 in figure 3.12, the distinct peaks in the morning and afternoon are still notable. These peaks vary in magnitude and occurrence time between wards, which may be caused by differing prevalence of building end-use sectors. A peak at 09:00 and a much higher peak at 20:30 in ward 49 suggests a more residential nature to the ward, wherein peaking occurs outside business hours and higher evening peak is in agreement with the weekend interruption profile (figure 3.11). Conversely, a peak at 10:00 and a much lower peak at 19:00 suggests more business electricity use in ward 129. The day of the week in which events occur is consistent with proposed end-use sectors as there are more weekend interruptions in ward 49 than ward 129 (figure 3.13). However, this is not so simple for wards 24 and 7, which both have the same morning peak time as ward 129 but the same afternoon peak time as ward 49. Ward 7 then has as many weekend interruptions as ward 129, while ward 24 has as many as ward 49. Nonetheless, the variation in peak times, morning-afternoon peak ratio and weekend event frequency show that building end-use sector is affecting the number of interruptions.

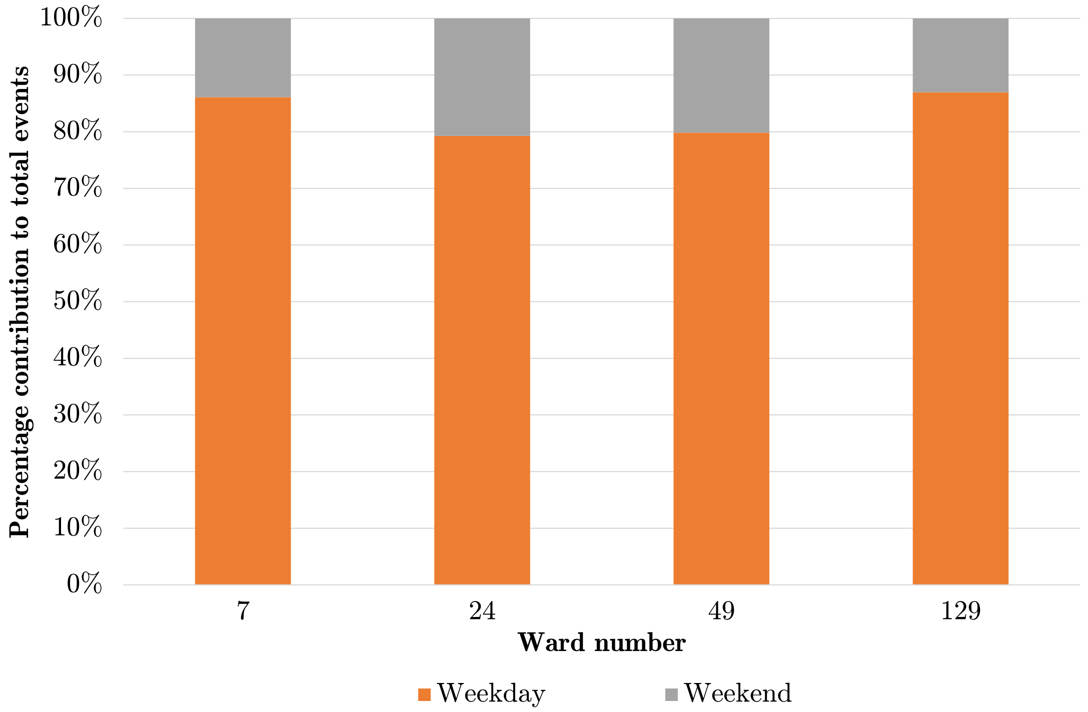


Figure 3.13 Contribution from weekday and weekend events to total power interruption events, for wards with high event frequency and notable event frequency peaking.

3.3 Discussion

The results clearly show a great deal of spatial and temporal variation in power interruptions across Bangalore. It is necessary to understand the cause of these variations, as well as the implications for future research and infrastructural change within the city. The city's rapid urban sprawl witnessed between 2000 and 2010, wherein the urban footprint increased by 100% (IIHS, 2012), will mean less developed infrastructure in the outer wards of the city. Not only has infrastructure sprawled outwards, the residents of the city have also migrated out towards those outer wards. Although no direct data exists for the income distribution within the outer wards, anecdotal evidence suggests that they contain a range of some of the city's wealthiest and poorest residential areas. If BESCOM electricity infrastructure is not related to the wealth of an area, then the greater electricity use from high income dwellings, indicated in chapter 2, may mean that high income residences are more at risk of being affected by interruption events. The need for income distribution is now two-fold: to begin bounding the uncertainty of household energy demand estimations as given in chapter 2, and to confirm the effect of high household energy demand on interruptions in the city. However, this chapter has begun to unravel the importance of other factors beyond income and the residential sector.

Building end-use sector and spatial/temporal variation

No strong correlation exists between interruption frequency and ward area, population, population density or liveability score, but other studies found the greatest electricity use correlation on a spatial scale to be that of building end-use sector (commercial, residential, industrial, etc.) (Howard *et al.*, 2012) or building density (Heiple and Sailor, 2008). Building density cannot be alluded to here, but variation in interruption events may be caused by building end-use. Firstly, there is a weak trend towards decreasing event frequency with increasing population density; commercial and industrial buildings would lead to reduced residential space in a ward, thus leading to lower population density whilst still maintaining high electricity load. Differences in weekday and weekend hourly interruption profiles (figure 3.11) also indicates a difference in end-use categories causing the interruption events, with weekend electricity use expected to reduce drastically in the commercial and industrial sectors as businesses are closed. The study of metered data in commercial and residential properties undertaken in Gujarat state (Garg *et al.*, 2010), used for comparison in chapter 2, provides hourly load curves for the studied end-use sectors. Figure 3.14 depicts the winter[1] load curves for both residential and commercial sectors. Residential sector load sees a peak at 09:00 and again at 21:30, maximum gradient of increasing demand occurs between 06:00 and 07:00 and again between 19:00 and 20:00. Commercial properties do not have the same distinct peaks, with a large increase in demand between 09:00 and 11:00 followed by a relatively steady high load which peaks at 19:00, after another demand increase from 18:00. When considering the result that the rate of change of supply matches interruption frequency, a morning interruption peak between 06:00 and 08:00 followed by a higher peak in the evening, between 19:00 and 20:00, should be expected in the residential sector. In the commercial sector, the morning interruption commencement peak would be expected between 09:00 and 11:00, followed by a much smaller peak between 18:00 and 19:00. This result is in agreement with that which is discussed when comparing ward 129 to ward 49 and with that seen between weekends and weekdays (figure 3.11), except for the late morning peak seen in interruptions on the weekend. Such a phenomenon might be explained by the late start of households on rest days.

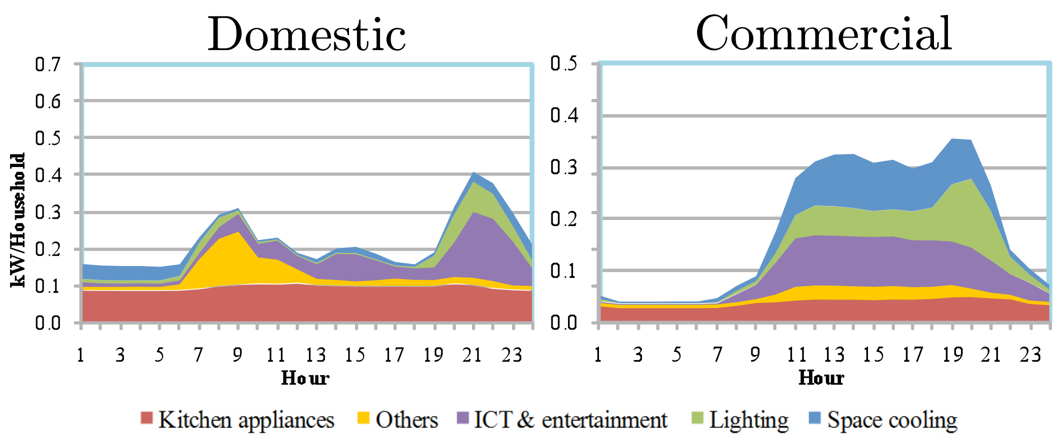


Figure 3.14 Hourly load curve for residential and commercial properties in Gujarat state, India. Figure modified from Garg *et al.*, 2010.

[1]Winter in Gujarat is assumed to be more representative of the Bangalore case due to the more temperate climate; cooling load is the only differing factor between summer and winter load curves.

Defining geographic boundaries and spatial resolution
Restructuring of the city boundaries is constantly ongoing; BBMP was only formed in 2007 with a view to growing further following recommendations of a review committee (BBMP-RC, 2015b). Interruption frequency beyond the BBMP boundary suggests that the study should consider the surrounding areas as equally important to the wards for the provision of reliable energy infrastructure. Additionally, if the urban sprawl of the past decade is expected to continue, a paradigm shift in the design and application of energy infrastructure could still be undertaken in advance of widespread urbanisation in these newly populated areas. Both BMAZ and BUD act to bound the locations with highest event frequency and would be more pertinent for use in future studies. In fact, the structure of electrical infrastructure in the city is unlikely to be built around ward or census boundaries which change, as jurisdictions change, with time. A better analysis might result from use of BESCOM operating areas in the city, which actually divides BMAZ into 139 distinct operation & maintenance areas.

Greater spatial disaggregation may also prove interesting, particularly for larger wards/areas where unique locations could be concentrated in one part of a ward. If sufficiently disaggregated, interesting demand profiles could simply be assessed by visual surveys of an area. At present, wards are too large to undertake such a survey method.

Implications for future research
Attention has been directed to areas of Bangalore which would benefit from improved energy infrastructure, for more reliable electricity provision. It does not, however, aid in the design process of distributed energy solutions, the intended progression of this research. The magnitude and understanding of finer, building scale, distribution of energy demand is still required. Alongside research of viable locations for distributed energy systems, a design for future energy supply can be formed. This process, at such a high spatial and temporal resolution, will be inherently time-consuming and prioritisation of efforts will be necessary. The results of this chapter can not only direct research efforts to areas of the city in which prioritisation is most necessary, but also offer an insight into the data sources, such as building end-use information, which would prove most useful to creating profiles for energy demand. With optimisation of the process of disseminating BESCOM daily reports, the results of this chapter can also be constantly updated in order to maintain focus on primary areas of concern, given that there may be a delay in commencement of future research efforts to continue the objectives of this study.

3.3.1 Limitations

As with chapter 2, there needs to be clarity as to the confidence one should have in the outcome of the results. The primary focus here is on the process of data cleaning, detailed in appendix A.0.4. Several data points are lost, from 13515 to 10792, in order to produce a data set that could be used for the analysis. It may be the case that those lost points would change the outcome of the spatial analysis; as far fewer whole events are lost in the cleaning process, it is less likely that there has been an effect on the temporal analysis. The manual process of cleaning by an individual unfamiliar with the city may have also caused mistaken correction of words considered as ‘misspelt’ or incorrect geolocation being applied to the raw data set. Manual processing also means that, although BESCOM publish daily reports on interruptions, it is not a simple process to continually update the results of this chapter. Ideally, the locations could all be understood without human intervention, which would likely require a dedicated dictionary for locations in and around Bangalore. Geolocating depends on the accuracy of Google Maps and the author’s judgement, again, prone to errors due to unfamiliarity. The quantity of unique points lost through geolocating may be a result of informal naming of locations by those producing the report; delayed updates of Google Maps in light of the rapid nature of the city’s development; or training the program to concentrate on Bangalore when BESCOM’s operational area covers a much wider area than the city itself. It is likely a combination of these factors, although the contribution from each is unknown.

Chapter 4

Conclusions

This study has examined the current electricity use in Bangalore by two methods. The first is a bottom-up engineering energy model, studied in chapter 2. Such a model is used widely in similar studies: those assessing spatial distribution, developing countries, or both. Results suggest a household electricity use of 1040kWh/a, 1767kWh/a and 2168kWh/a for low, medium and high income classes. However, variation in the available data, and no bounding of uncertainty in studies leads to a low confidence in the result of chapter 2, as well as the given uncertainty range: +70% or -42% of the average value for each income class. An indicative estimate of city electricity use is 3.54TWh, by use of household income distribution for the urban households of Karnataka state. An approximate supply of 3.08TWh was calculated for the BESCOM Bangalore Metropolitan Area Zone, which is 13% lower than the estimated city electricity use for a larger operational area. Due to the low result confidence, this study recommends that further data is collected for a bottom-up engineering model of Bangalore electricity use, particularly:

- Appliance ownership (including quantity per owning household).
- Appliance Unit Energy Consumption from metered and rated power information.
- Whole-dwelling electricity use, necessary to quantify ‘Other’ electricity use that is otherwise missed.
- Quantification of seasonal variation, by metering over a full year or seasonally representative weeks.

The recommendations follow from an analysis of literature and a long-term approach to continually assessing electricity distribution in buildings. Metering data can be correlated to appliance usage for future inferred load curve results.

Although the energy modelling approach was unsuccessful, an analysis of daily reports from the electricity provider Bangalore Electricity Supply Company Ltd. (BESCOM) in chapter 3 allowed the mapping of electricity supply interruption events within the city boundaries and the vicinity. This analysis provides the first steps towards understanding electricity use and infrastructural requirements with only one set of accessible, and continually updated data. Ward 49 is most affected by interruptions, in 263 of the 1260 events, while wards 24 and 7 are also affected in over 200 events. These three wards are in a similar location, to the north of BBMP, with wards 24 and 49 sharing a section of boundary. Peak interruption time occurs at maximum rate of change of electricity supply, 07:00 and 19:00, while baseload supply does not cause interruptions. Based on these results, plots of interruption events could be used as an alternative to supply load curves in an urban environment. When considering interruptions at the ward level, the building function distribution is alluded to by the time of day that peak interruptions occur as well as the days in the week that event frequency is high and low. The results suggest that ward 49 is more residential than ward 129, which experiences a much greater morning than evening interruption peak.

There exists evident disparity in infrastructural provision in Bangalore, particularly the recently expanded outer wards of the city. To fully analyse the potential for electricity supply options, a more robust method of estimating local demand based on a bottom-up model is needed. Analysis of interruption events has indicated a range of wards which are particularly prone to interruption events and would thus be most pertinent to consider for closer inspection. The use of interruption events is a seemingly novel and powerful approach to mapping city-scale spatial/temporal infrastructure. Further research is needed to validate the result of chapter 3, but they could indicate a long-term method for building sustainability into future electricity infrastructure design.

4.0.2 Future Research

Based on the results of chapters 2 and 3, the following points are recommended for future research in the context of understanding energy demand and designing supply in Bangalore:

- Metering and surveying of sample buildings. Sampling from different end-use sectors and income classes is recommended.
- Researching likely time of use of appliances for disaggregation of metering data and BESCOM load curve data.
- Comparing interruption data to a greater range of explanatory variables, such as income distribution, building end-use and building density.
- Creating a periodically updating map of interruptions in Bangalore, as a continual research aid as well as for visualisation by planners and government bodies.
- Assessing viable rooftop space and available land for the supply of electricity by sustainable, local sources. It is suggested to concentrate on those parts of the city most affected by interruption events, to obtain a manageable data set at the required spatial and temporal resolution.

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Appendix A

Acquisition and Cleaning of Data Pertaining to Chapter 3

The process summarised in section 3.1 is augmented in this appendix, in order to ensure repeatability. As BESCOM publish daily reports for both interruption and power supply, the primary sources of data in Chapter 3, there is scope to augment the results of this study over a greater timescale in future.

A.0.3 Data Acquisition

Daily interruption data was extracted from 31/12/2014 to 06/07/2015, due to the sporadic nature of report publishing prior to this date. Each report was downloaded and each interruption event corresponding to a 'load restriction due to overload' was extracted. This constituted 1288 of 4179 events, with the remainder including events such as tree trimming, faulty cables/feeders and supply failure. Load restriction events due to overload occurred more often than any other event in the reporting period.

Once extracted, the locations were assessed manually in order to clean the data (see section A.0.4 for further details), followed by grouping all unique locations and matching them to geographic locations (geolocation) using Google Maps Javascript v3 API (Google Inc., 2015). WikiMapia (http://wikimapia.org/) and OpenStreetMap (http://www.openstreetmap.org/) geolocation was also attempted, but the most matches were found by use of Google Maps. In some cases no match was found from a map API. where this occurred the location was searched in a database of districts within BBMP wards (http://bcity.in/wards), which successfully provided a result in a few cases. Locations with unique matches were placed in wards, while locations with multiple matches were compared to unique locations in the same event in order to attribute the most likely location. For instance, '80 feet road' is a location with matches in several districts of Bangalore. By locating the nearest '80 feet road' to the unique locations within the same event, a unique location is found for '80 feet road', which may change between events.

Daily load curves are also published by BESCOM. 248 reports were found for the 389 day period between 30/05/2014 and 23/06/2015. Using image recognition, a table is extracted from the published images (figure A.1). Image recognition does not correctly read the date titled on the image, so it is not possible to use the load curves to compare particular days of the year. The load curve data is reported for BMAZ, BRAZ and CTAZ operational areas, from which only the BMAZ data is applied to this study.

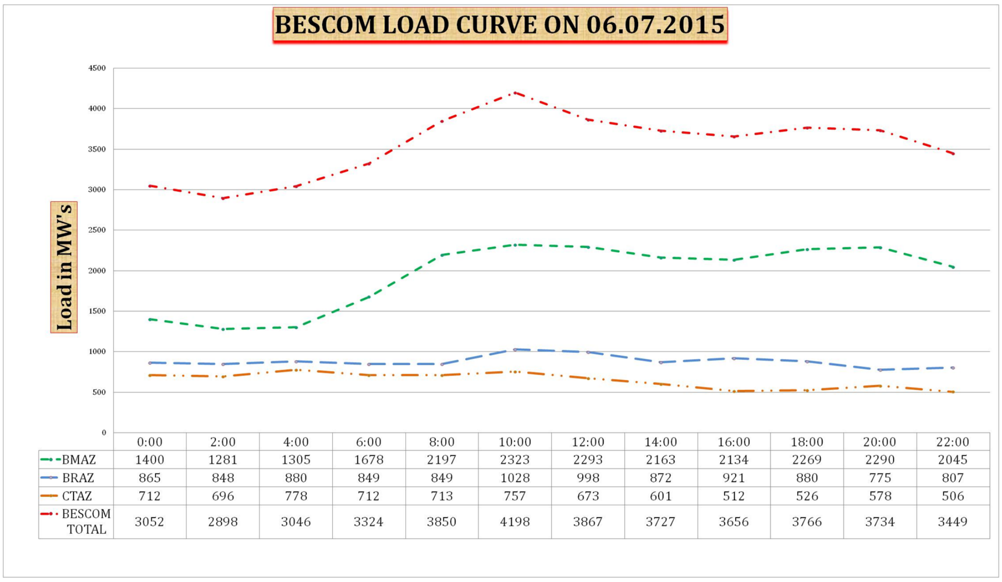

Figure A.1 Electrical supply load curve, as published daily by BESCOM in image format.

A.0.4 Data Cleaning[1]

Of the 188 days between 31/12/2014 and 06/07/2015, 171 days provided results and on 151 days there are load restriction events as a result of overloading. Lost days are a result of inconsistencies in the structure of the report excel files on the BESCOM website, from which the program is unable to extract data. Table A.1 shows the number of data points that exist at each stage of data cleaning. The first stage removed single characters, such as ‘A’ or ‘1’, or corrected misspellings, such as ‘Yelhanka’ where ‘Yelahanka’ is expected. Cleaning of misspellings could be undertaken programatically, by fuzzy matching a location to others, wherein spelling similarity is analysed, and editing all to match the most frequent spelling. However, Akshay nagar, Akshayanagar and Akshya nagar are all distinct locations that could be assimilated by fuzzy matching of data; there exists several examples of such similarities in the data. The inability of a program to distinguish between distinct locations and spelling errors led to the need to clean the data by hand. Similarly, when searching for locations on Google Maps, the incorrect geographic location was occasionally assigned. It is not simply possible to programatically compare that which was searched to that which was found as in some cases two different names refer to the same location; for instance, Pulikeshi Nagar and Frazer Town are synonymous. In this case, each ‘incorrect’ match was researched to ascertain the possibility for multiple names for the same location.

Following initial cleaning, the process of geolocating led to 481 unique locations being lost. Although 32% of unique locations are not geolocated, this represents only 15% of the total instances. Akashninar (92 occurrences) is the only location in the first 50% of most frequent events that is not

[1]This section refers only to cleaning of interruption data; load curve data did not require the same processing to provide the average load curve utilised in this study.

geolocated. 727 unique locations are subsequently uniquely geolocated. The remaining 287 unique locations are uniquely geolocated by comparison with unique geolocations in the same interruption event (as previously explained in section A.0.3).

Processing level	Events	Total locations	Unique locations
Raw data	1288	13515	2300
Post-cleaning	1288	13169	1495
Post-geolocating	1288	10952	1014
Final	1260	10792	351

Table A.1 Change in size of dataset through cleaning and processing of BESCOM interruption data.