Modelling Residential Energy Demand for Rural India: Enabling Renewable Energy Access

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A thesis presented in fulfilment of the requirements for the degree of Doctor of Philosophy

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Sheffield, United Kingdom
Year 2023

Abstract

Recently launched, the Global Energy Alliance for People and Planet (GEAPP) has set an ambitious goal to provide one billion people with clean, affordable, and reliable energy access by 2030. The vast majority of these populations live in rural and remote areas of Sub-Saharan Africa and South Asia. There is a dual imperative; we must identify appropriate pathways for large-scale electrification to ensure clean, affordable, and reliable energy access for all while transitioning to net-zero futures. In this thesis, we aim to develop a comprehensive understanding of the rural electrification pathways adopted in India, emphasising the potential for off-grid solutions, particularly solar mini-grids. Through our analysis, we identify research gaps concerning the social and economic complexities considered in mini-grid planning. Moreover, when examining existing electricity demand estimation models for mini-grids, we observe a lack of research data that may impede the scalability of these models and delay the clean energy transition in rural India.

In this thesis, we address these research gaps in two parts: In the first part, we highlight the importance of estimating electricity demand growth in rural communities through case studies of three hamlets in the state of Maharashtra, India. These were each recently electrified with decentralised solar mini-grids and battery storage. We conducted 70 household energy use surveys and collected data on appliance ownership and its usage over time to estimate long-term electricity demand growth in the community. The growth in appliance ownership is modelled by considering the rate of diffusion of each appliance. Based on this, we investigated three demand growth scenarios and their impact on the mini-grid sizing approaches. Our results show the cost-effectiveness of utilising a multi-stage approach to size mini-grids, i.e. capacity expansion to accommodate increasing demand. Through sensitivity analysis of multiple variables associated with the mini-grid model, we also found that total system costs are most sensitive to fluctuations in demand growth rates and a decline in the costs of solar PV and batteries. This part is summarised by highlighting the relevance of electricity demand in rural electricity planning and the need for better methodologies to forecast long-term electricity demand to inform the techno-economic sizing of off-grid energy systems.

The second part of the thesis has the objective of developing an innovative framework to more rigorously characterise long-term energy demand and its potential for integration with rural electrification planning tools. In this framework, the electricity demand curve is described as consisting of two components: a longitudinal component, which captures growth trends over a certain period of time (e.g. over several years), and a transverse component, which represents daily demand curves (24 hours cycle). To estimate the daily electricity demand of rural households, a model was constructed utilising a nationwide socioeconomic time use survey dataset to discern activities that exhibit significant electricity consumption. These activities were then correlated to find probabilities of relevant appliances in use. The model computes appliance switch-on times based on the relevant coincident activities and appliance usage times based on the duration of these activities to construct load profiles. To demonstrate the significance of this demand model, we analysed time-use activities performed in rural households of four different states in India and compared their load profile characteristics. For the multiannual demand, we have developed a conceptual system dynamics model to forecast the longitudinal growth in demand, estimated based available secondary data sources. We discuss how this more exploratory model could be integrated with the transverse daily load model to build an integrated energy demand model.

Lastly, we conclude the thesis by discussing how the present contribution could be usefully complemented and reinforced through future research work, with the aim of developing a generalised energy demand model involving social and economic complexities in designing renewable energy systems for rural electrification in the global south.

Dedicated to my dearest mother Bharati.........

Acknowledgements

This PhD thesis is the culmination of the efforts and contributions of many individuals. First, with the highest regard and appreciation, I extend my gratitude to Prof Darren Robinson, whose consistent guidance on this remarkable journey of learning, unlearning, and relearning has fundamentally changed my worldview. Thank you for offering me this incredible opportunity and for fostering my growth by teaching me the invaluable skill of critical thinking.

I am truly grateful to the Grantham Centre for their generous funding and support throughout my PhD journey. Dr Deborah Beck, your commitment to equity and inclusivity in practice has been both inspiring and a heartwarming example to follow – my sincere thanks for your influence. Prof Tony Ryan, your insightful discussions have enhanced my academic experience, and to Jana, Eva, Steffi, and Claire, thank you for your continuous support and encouragement.

Prof Sonal Choudhary, your invaluable support during the early stages of my PhD journey and your unwavering belief in me has profoundly inspired me. Thank you, Dr Milijan Odavic, for your critical feedback in early years. I am also immensely grateful to Dr Jim Uttley and Prof Robin Purshouse for reviewing my confirmation reports and offering constructive feedback on my research proposal. I would also like to extend my special appreciation to Dr Ana Sancho Tomas for her incredible support and positive influence throughout thesis work and beyond. Dr. Parag Wate and Dr. Ben Purvis, your impressive work has always made me feel like standing on the shoulders of giants. Thank you for inspiring me with your expertise and knowledge.

I would also like to extend my heartfelt appreciation to the group at Imperial College London, with whom I collaborated on a part of my thesis work. Prof Jenny Nelson, your passion and dedication have inspired me in many ways. Thank you, Dr. Ajay Gambhir, for your meticulousness and keen eye for detail regarding the subject matter. Heartiest thank you to Dr. Phil Sandwell for his kindest support and sharing his knowledge of mini-grid modelling and to Paloma Arriaga Ortega for sharing research interests and working with me you guys made the lockdown working bearable – Thank you!

I am immensely grateful to all my peers at the Grantham Centre for sharing their knowledge and passion for sustainability through engaging journal clubs and interactive training modules, helping me build new perspectives. A special thank you to seniors Florentine, Roberta, and Jonathan for insightful discussions, but my warmest thanks go to Suma and Mary - Thank you both for being my strongest support system in Sheffield.

I would like to express my gratitude to my fellow floor 9 colleagues, whose company and conversations have expanded my intellectual horizons and kept me grounded. Thank you, Aliyu, Aya, Victoria, Esti, Choo Yoon, Tha'er, Jakleen, Omar, Niveen, and Sergio, for our food fuddles, and coffee breaks. Humeyra Bash, our forest sessions compelled me to write this thesis, and I could not have done it without you! Thank you from the bottom of my heart, and a big hug!

I extend a special thanks to my Indian friends in the UK who have always shown care and shared love through their mouth-watering delicacies. Charu, Shalabh, Sayantan, Priyanka Choubey, Karan, Meera, and Shaunak, your presence has made my time in the UK memorable. Thank you.

During my PhD, I worked from home for the most part, which gave me the opportunity to turn my friends into online colleagues from various parts of the world and different time zones. Thank you, Priyanka Singh, for our productive pomodoro sessions, Nivedita Sairam, for your wonderful and enthusiastic discussions, Divya, for your comforting and guiding talks, and Vishwa, for always cheering me up.

Thank you to all my friends from undergrad who have always been just a call away, patiently listening to my endless ramblings. Adithya, Roshni, Kalpana, Priyanka Borse, Harsh and Bhavya – If I had long enough arms to extend and give a group hug to all of you!

To my dearest Mummy and Papa, I am eternally grateful for your immeasurable efforts in providing me with an education and guiding me along this journey. This accomplishment is not solely mine but truly belongs to both of you. Thank you Aai papa for your love, care and constant encouragement. Thank you to my siblings, Anuradha, Sachin, Pranali and Rohit for all the fun chats. The warmest appreciation to my true pillar of strength, Hetal, Niju and Ajay - thank you for being my guiding torch. To Rahul, I am so grateful to you beyond the words can convey, thank you for being my constant in chaos!

Last but not the least, I sincerely appreciate UK weather for helping me discover the strength within me to endure discomfort of darkness and gain wisdom from the wounds. Living here has been a journey of self-discovery, teaching me more about myself than anyone or anything else in the world ever could.

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1 Introduction

1.1 Renewable energy access in the Global South

Energy is considered to be one of the essential human needs; thus it is central to every challenge and opportunity the world faces today. Globally, nearly 759 million people are expected to receive electricity access for the first time in this decade, and more than 2 billion people will need access to clean and reliable energy sources for cooking at the same time (SE4all, n.d.). Majority of these people reside in rural areas of various Global South countries, so focused efforts will be made towards achieving transformative economic growth in these areas through electrification projects(IEA, 2021). It is projected that around 84% of the global energy demand growth in this decade will come from the Global South (Wolfram, Shelef, & Gertler, 2012). On the other side, production of energy, which is the main source of greenhouse gas emissions, presents a dual challenge: providing clean and affordable energy to meet the rising demand while simultaneously working to reduce emissions. The conventional approach to electrifying rural communities has traditionally been to expand the national grid, with a heavy reliance on a fossil fuel energy mix which has detrimental impact on the environment. However renewable energy technologies can help promote a balanced approach to economic development considering investments in human capital, environmental degradation, and depletion of natural resources. (Kamoun, Abdelkafi, & Ghorbel, 2019). Electrification plays a pivotal role in fostering economic growth and studies have consistently shown a strong correlation between electricity access and economic development. In the recent past , with the decline in renewable technology prices, decentralised a.k.a. off-grid energy production is also gaining traction(IRENA, 2021). Another research study highlights that, particularly in remote villages with low electricity needs, biomass gasifiers or solar emerge as more cost-effective alternatives than extending the main power grid(Mahapatra & Dasappa, 2012).

Figure 1.1 depicts the intricate and interconnected relationship between economic growth, energy access, and achieving net-zero targets. Of all countries, India finds itself in a particularly unique position. Whilst it is the country with fourth largest emissions contributing nearly 6.65% of the world's total carbon emissions, it grapples

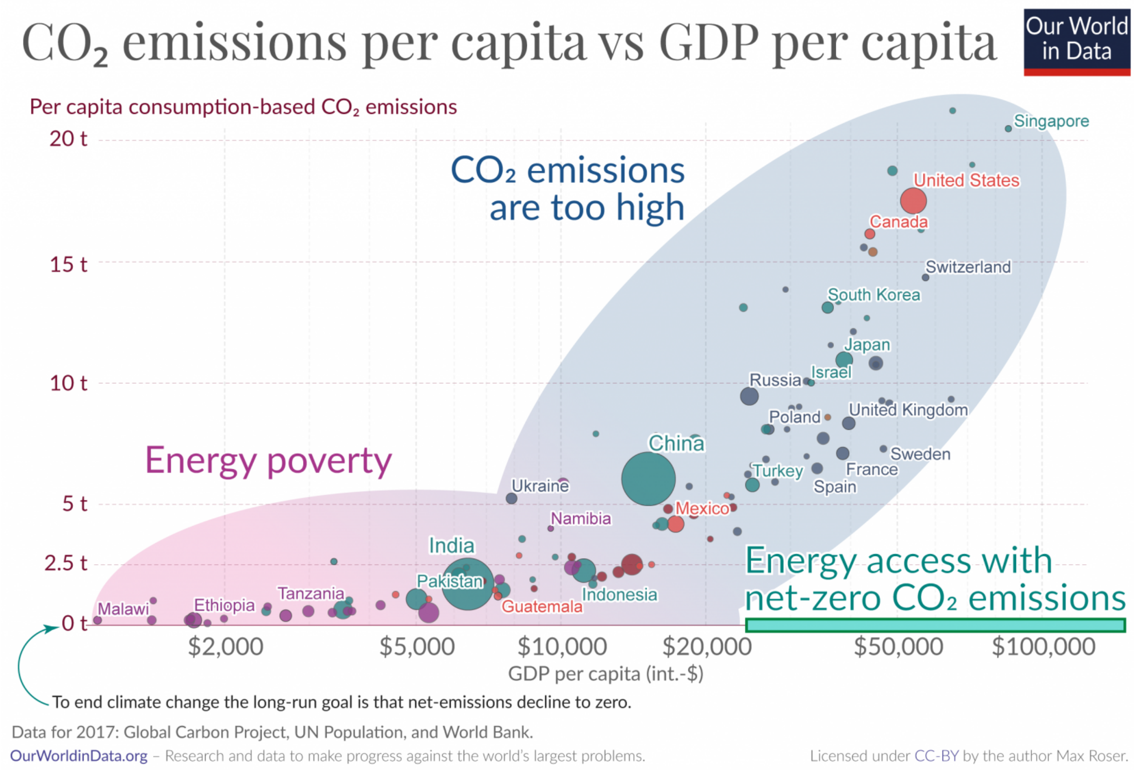


Figure 1.1: *Our world in data, Data source - World Bank (Ritchie et al., 2019)*

with poor energy access for significant segment of its population. According to the World Energy Council's 2016 forecast (World Energy Council & Institute, 2016), global electricity demand is anticipated to peak in 2030. As one of the largest consumers of coal worldwide, India heavily relies on costly imports of fossil fuels. Presently, approximately 74% of the country's energy demand is met by coal and oil, necessitating an urgent exploration of alternative electricity generation sources. In line with this, India has set an ambitious Nationally Determined Contribution (NDC) to achieve 50% cumulative electric power installed capacity from non-fossil fuel-based energy resources by 2030 (Contribution, 2022).

As per the Load Generation and Balance Report of the Central Electricity Authority of India, it was projected that the demand for electrical energy in 2021-2022 will be minimum 1915 terawatt hours (TWh), with the peak electric demand expected to reach 298 GW(Central Electricity Authority, 2022). India has made significant progress in providing electricity to rural areas over the past ten years by expanding the central grid and utilising off-grid renewable energy sources (India energy outlook report (IEA), 2021). As rural electrification progress, it is likely economic activities also expand and as household incomes increase, acquisition of energy-consuming appliances is anticipated to rise, resulting in a surge in residential energy consumption(Wolfram et al., 2012). The increased demand for electrical appliances in the residential sector can be attributed to the rise in income levels. Moreover, the demand for electricity has also been driven by the need for materials in the construction, transportation, capital goods, and infrastructure industries. Additionally, the transition to electric vehicles and induction cook stoves is also expected to further contribute to the growth in electricity demand in residential sectors.

1.2 Rural residential energy demand

Residential energy use is the largest share of total energy supplied in India, accounting for 31.76%, a 7.15% increase from the previous year (Central Electricity Authority, 2022)and likely to continue rising further. To gain a deeper insight into the residential energy demand from rural households, it is essential to look at electrification as a non binary approach. Figure 1.2 provides a multi-tier framework (Bhatia & Angelou, 2015) that delineates different levels of energy access and illustrates the potential progression of electricity usage. For instance, it is evident that solar home systems can cater up to tier 1 and tier 2 electricity requirements, whereas for higher tiers, solutions such as mini-grids or interconnected mini-grids / grid-connected mini-grids systems would be more suitable. However, many barriers still prevent reliable and sustainable energy access in rural communities. Whilst decentralised energy access through renewable sources is found cost-effective, the most significant obstacle is the cost of off-grid renewable energy generation, which is not affordable for many rural communities (Palit & Kumar, 2022). According to the research study by (Urban, Benders, & Moll, 2009), if primarily renewable energy-based end-uses were adopted for rural electrification in India, it could lead to a reduction of up to 99% in total CO_2 emissions and a decrease of 35% in primary energy use by 2030 compared to the business-as-usual scenario. This highlights the need for a better understanding of residential energy demand in the context of renewable energy planning in India(Khosla, 2018).

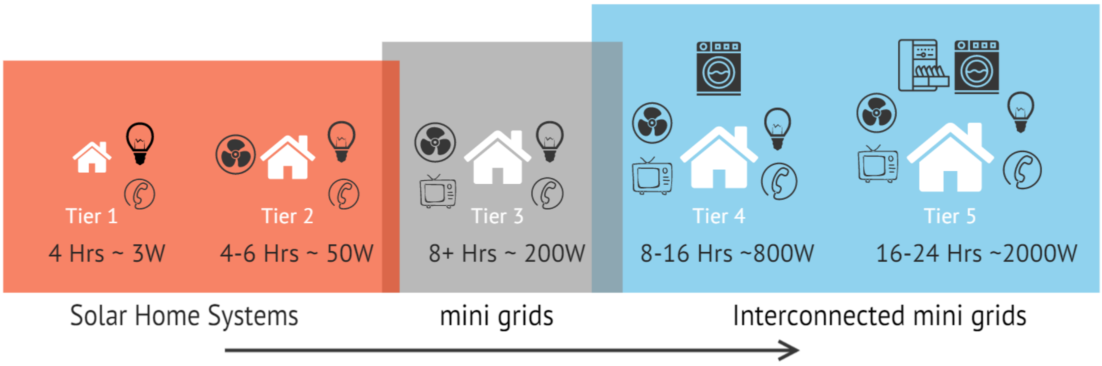


Figure 1.2: *Simplified Schematic of Multi-tier Framework adapted from (Bhatia et al. 2015) The wattage presented here is reflective of conservative allowance defined in the framework. The supply sources mentioned here are just indicative of possible off-grid options for each tier of access.*

1.3 Research Motivation

Taking into account the literature, it became evident that decentralised solar mini-grids could have the potential to provide a holistic and sustainable solution for rural household electrification in India. However, their widespread expansion encountered several challenges. These obstacles included the absence of a regulatory framework, the need for designs ensuring effective and autonomous operations, insufficient financing and business models, and the more pressing issue of inaccurate demand assessment.[1]. Research suggest that these challenges can be overcome by optimising design and planning (Akbas, Kocaman, Nock, & Trotter, 2022), implementing appropriate policies and regulations that are tailored to the local rural context (Bhattacharyya & Palit, 2016), offering multichannel financing options (Malhotra, Schmidt, Haelg, & Waissbein, 2017), and acquiring reliable data sources (Lorenzoni et al., 2020). We endeavored to tackle the challenge of demand assessment, especially in understanding the growth of electricity demand in communities served by solar mini-grids, and how this growth impacts both system design and performance over the system's lifetime.

As we expand our research scope, it was evident that understanding the rising demand for electricity when planning decentralised renewable systems is of utmost

[1] Here, demand assessment comprises of estimating present and future demand for long-term planning

importance. However, whether we consider decentralised or grid-connected systems, understanding residential energy demand is a pivotal factor in shaping India's future clean energy transition, wherein the need for storage becomes a primary consideration. Whilst research studies on urban household energy use from India are available, lack of literature and scarcity of data from rural household energy use pertains. Accurately assessing energy demand in rural contexts is fraught with uncertainties, particularly when households have no prior experience with electricity usage(Riva, Tognollo, Gardumi, & Colombo, 2018). These uncertainties surrounding load profiles can result in additional costs, as exemplified in a case study in Malawi, where costs rose as high as US $.92 to US $6.02 per watt-hour(Louie & Dauenhauer, 2016).This challenge is exacerbated in communities with no prior access to electricity, where traditional energy sources provide the only means of estimating an electric load profile(Gambino et al., 2019). These uncertainties affect both short and long-term renewable energy planning.

Historically, residential energy demand has been modelled based on various factors, including demographics, socioeconomic conditions within the local context (Ziramba, 2008), and the available supply sources (Pachauri, 2004). In recent times, there has been an increased utilisation of Geographic Information System (GIS) for projecting long-term energy demand.(Blechinger, Cader, & Bertheau, 2019) (Ciller et al., 2019) (Mentis et al., 2017). Despite the advancements in tools and techniques, estimating realistic household demand in rural areas remains error-prone with a high margin of error.(Hartvigsson & Ahlgren, 2018). However, a notable research gap exists in the literature concerning energy demand models that can predict future energy demand growth. It is crucial to take into account several factors, such as the number of household appliances owned by individuals and the time-sensitive nature of their usage, including peak and off-peak usage times. In this thesis, our aim is to address the existing gaps in the current knowledge base on energy demand modelling and to develop a framework that can effectively model energy demand from households across multiple time horizons, incorporating socioeconomic information. The model is calibrated using rural household data from India, with the approach designed to be scalable and generalisable.

1.4 Aim and Objectives

In this thesis, our primary aim is to better understand rural residential energy demand, assess its implications on decentralised renewable systems, and introduce a multi-scale framework to integrate time-sensitive energy consumption patterns. The research objectives are outlined as follows.

1.4.1 Research Objectives

Objective 1: Estimate electricity demand growth in rural communities in India gaining energy access through renewable mini-grid systems, specially solar-based.

- We visited five hamlets in the Shahapur district of Maharashtra receiving electricity via decentralised solar mini-grids and conducted household energy use surveys.
- Estimated bottom-up community scale load profiles representative of each appliance following S-shaped diffusion in the ten years of system lifetime.

Objective 2: Examine the impact of electricity demand growth on the required mini-grid system size and the potential need for adaptive capacity expansion.

- Three scenarios of demand growth were designed, including baseline, S-shaped adaptive growth, and target.
- The sizing optimisation tool CLOVER (Continuous Lifecycle Over Variable Energy Resource) was used to investigate the impact of these demand growth scenarios on system costs and reliability levels.
- A sensitivity analysis was carried out for size variables, and the impact of these variables on two different sizing approaches was presented. These approaches included a one-off installation versus capacity expansion in two steps at every five years.

Objective 3: Develop a multi-scale framework to model energy demand with a focus on capturing the time-sensitive nature of energy use in rural households.

- The residential energy demand was decomposed into three sub-components: longitudinal (long-term), seasonal (medium-term), and transverse (daily).

- To capture the transverse energy demand, which relates to the diurnal variations in energy consumption, we proposed an energy demand model. This model was calibrated based on Time Use Survey data on residential activities.

- Using this model, we generated appliance-wise daily load profiles, which were representative of the energy use patterns in rural households.

Objective 4: Conceptualising long-term electricity demand growth based on longitudinal appliance adoption in rural households.

- We conceptualised a system dynamics model to estimate longitudinal growth in household appliance ownership.

- To test the model, we demonstrated preliminary results of the trend of appliance adoption in a hypothetical rural community. This was based on primary assumptions drawn from data obtained from the National Family Health Survey.

1.5 Thesis contribution

This thesis makes knowledge contributions in three key areas. To begin with, it effectively identifies the research gaps in understanding energy demand from rural India, with a specific emphasis on how demand grows after acquiring energy access. This is particularly intriguing due to India's extensive rural electrification over the past decade, yet there is a noticeable absence of models or research studies that sufficiently underscore rural residential energy use and its contribution to daily peak electricity demand. This becomes more crucial in the context of achieving net zero targets, as India will undergo a large-scale clean energy transition, necessitating a thorough estimation of peak demand, which will inevitably impact storage management costs. Additionally, the thesis delves into the implications of energy demand growth on decentralised renewable systems such as solar mini-grids in rural India. It also undertakes an analysis to determine whether incremental or modular system design would prove beneficial and make mini-grids sustainable in the long run. The third primary contribution lies in the methodological aspect. Addressing the consensus in the research community about the lack of a socioeconomic dimension in the technical design of renewable energy systems, specifically decentralised systems, this thesis introduces the concept of multi-scale demand estimation methods. These methods incorporate social practices based on time-dependent activities and cursorily pinpoint how to incorporate expert opinions or on-ground observations into technical designs based on system dynamics modelling. By combining these approaches, the aim is to make techno-social systems more inclusive and tailored to community needs.

1.6 Organisation of thesis

The thesis is structured into several chapters, each aimed at achieving specific objectives. Chapter 2 outlines the history of rural electrification in India. Chapter 3 addresses objective 1, the estimation of bottom-up load profiles for three different demand growth scenarios in a community of households based on surveys and appliance diffusion and objective 2, which involves a comparison and analysis of fifteen mini-grid modelling tools and implementation the CLOVER optimisation tool to investigate two mini-grid sizing approaches to assess the impact of capacity expansion of mini-grids adapting to growing electricity demand. Objectives 3 is achieved in Chapters 4 and 5. The need for modelling the time-sensitive nature of energy demand is demonstrated based on residential activity data recorded in a national-scale time use survey. Chapter 6 conceptualises a system dynamics model for identifying trends of appliance adoption in rural households, thereby achieving objective 4. Finally, Chapter 7 concludes the research and lists some future research directions.

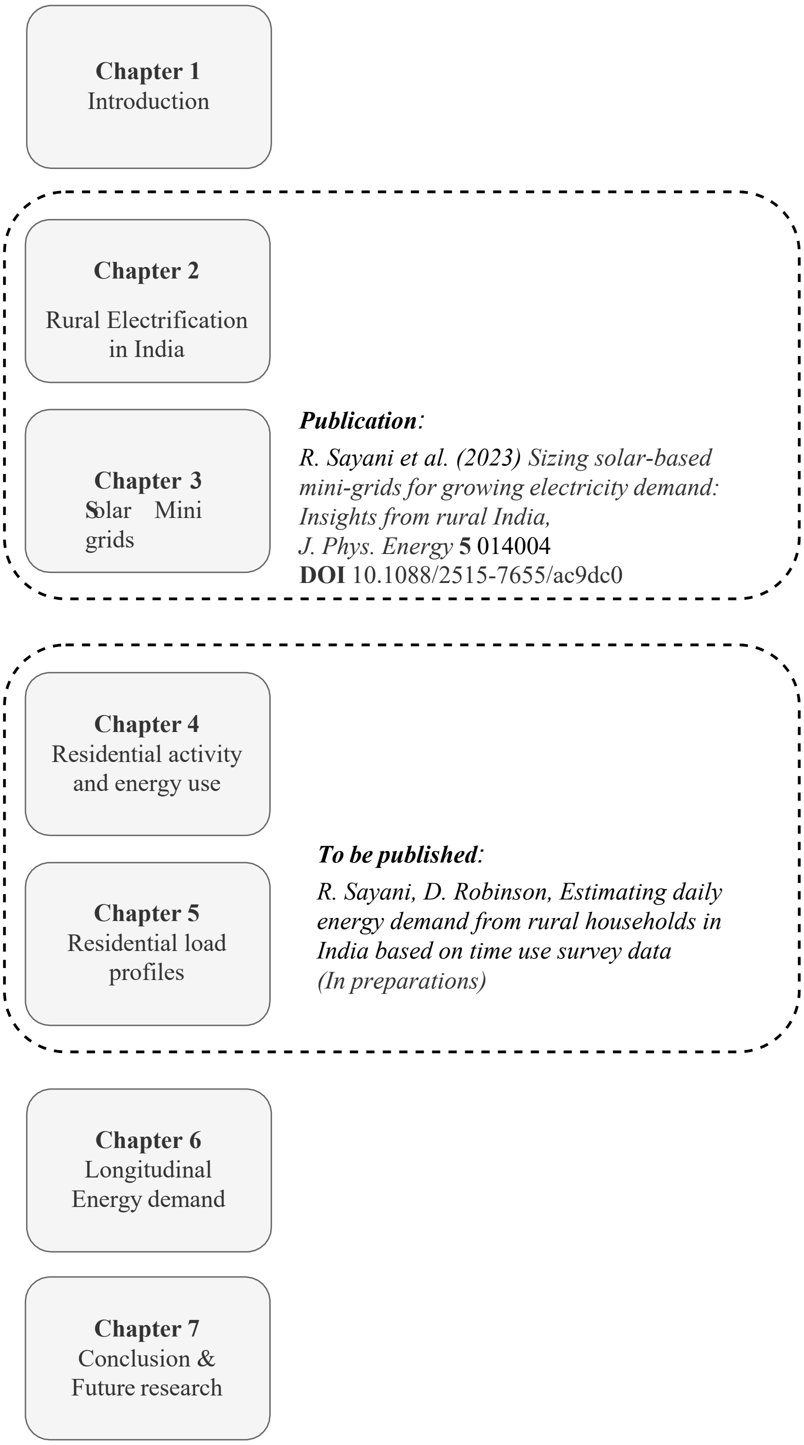


Figure 1.3: *Thesis Structure*

Chapter 2

Rural electrification in India

As for the future, your task is not to foresee but to enable it.

—-*Antoine de Saint-Exupèry The Wisdom of the Sands (1948)*

2 Rural electrification in India

This chapter outlines the history of rural electrification in India. It briefly describes energy policies introduced and the outcomes or obstacles faced in achieving electrification. We then provide critical insights into the energy transition challenges in rural India and describe the role of extending central grid, standalone solar and hybrid mini-grids in achieving universal electrification. We identify mini-grids as one of the ways India could achieve clean energy access and describe three different mini-grid business models currently in operation. Further we emphasise on how mini-grids can contribute towards the decarbonisation of rural India in the long-run.

2.1 Rural electrification in India

Clean, affordable and reliable access to energy is crucial in harmonising sustainable economic growth and a low-carbon future within our planetary boundaries. As we discussed in the previous chapter India is in a unique position, facing this dual challenge which mandates a rapid transformation of its energy sector(India energy outlook report (IEA), 2021). [2]. Approximately 70 % of the population lives in rural areas in India, which inherently links its economic growth predominantly to rural development(GNESD, 2014). Since the time of India's independence in 1947, rural electrification has been on the agenda of every major government. Indeed, the government has implemented a range of measures to improve India's infrastructure for rural electrification, including setting up new transmission and distribution lines extended from the national grid, upgrading existing infrastructure, and incorporating decentralised renewable energy sources to provide electricity to last-mile households [3]. Following concerted efforts spanning more than five decades to bring rural electrification plans to fruition, in March 2019, the current Government claimed that nearly 99.99% of households in India are electrified (India energy outlook report (IEA), 2021) (Palit & Kumar, 2022). The new initiatives are now expected to improve the reliability and quality of electricity supply in rural areas. However, several challenges remain in addressing the environmental consequences of electricity generation, such as rising greenhouse gas emissions and air pollution (India energy outlook report (IEA), 2021).

The Government of India has laid out various schemes and initiatives to facilitate

[2] Energy access can be decomposed into two forms, one is electric power (electricity) that is used for running a variety of electrical or electronic devices, and the other can be energy used for cooking, such as biomass; we have focused on the electricity in the current study

[3] http://www.saubhagya.gov.in/dashboard

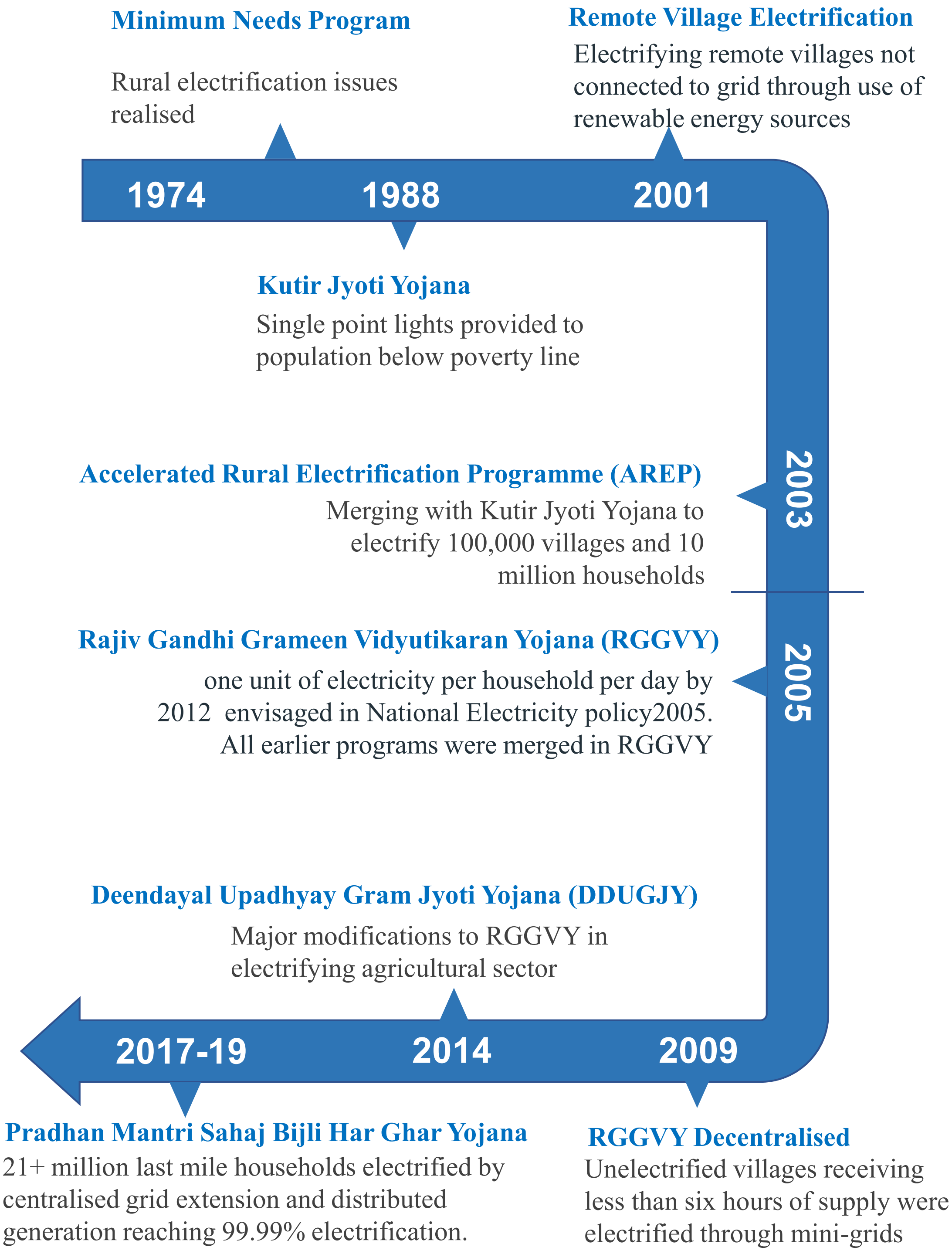


Figure 2.1: *Electricity access in rural India*

electricity provision in rural and remote villages through grid extension and distributed renewable sources. Figure 1 outlines the time frame of the critical policies and targets that contributed to achieving near-universal electricity access in India. Early efforts were primarily focused on the electrification of irrigation systems to increase farm yields across rural villages in the context of economic development(Palit & Bandyopadhyay, 2017). However, a lack of electricity in households still had a direct and negative impact on the quality of life for the rural population. First-of-its-kind rural household electrification started with the Minimum Needs Program proposed in the fifth five-year plan in 1974 [4] aiming to provide essential services to the rural population. Following this, in the late 1980s, Kutir Jyoti Yojana [5] was launched to make single-point access to electricity available to people living Below the Poverty Line (BPL) - those whose annual income was less than 11000 Indian rupees (US$135) [6]. These programs were grant-funded by the Central Government and implemented by the state governments, with beneficiaries receiving a single-point connection, a light bulb and a meter at no cost. The energy bills were paid by the beneficiaries every month as per the distribution company's norms. Despite its noble aims, these early programs achieved only marginal success for various reasons, including a lack of resources and incompatible infrastructure for grid expansion to operate cost-effectively in rural areas (Upadhyay & Badoni, 2014) (Palit & Bandyopadhyay, 2017). Persisting in their efforts, the Government initiated the Remote Village Electrification program in 2001. This program implemented distributed renewable energy sources, such as small hydro, solar power and biogas plants based on local availability, to bring electricity to un-electrified villages and hamlets where national grid extension was infeasible and economically non-viable. The aim was to provide a minimum of 1 kWh per household per day. Unfortunately, state governments concluded that it was not achievable cost-effectively through renewable technologies due to prohibitively high costs. Nevertheless, this program helped in providing limited access to essential services like solar home lighting to some 10,318 remote villages and has helped reduce the use of polluting fuels like kerosene, which had previously been used for lighting in many of these villages [7]. However, halfway through the execution of the program, as per the Rural Electrification Policy 2006, villages/hamlets using isolated lighting technologies were not to be designated as "electrified" (Ministry of New and Renewable Energy, 2013). Despite considerable efforts made to uplift rural economies through electrification programs, many obstacles remained in unlocking their full potential.

In 2005, the Government of India merged all previous schemes and launched an ambitious integrated scheme *Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY)*, with

[4] http://planningcommission.nic.in/plans/planrel/fiveyr/5th/welcome.html
[5] Parliament of India, Lok Sabha Library archive - Kutir Jyoti Yojana
[6] 1 USD = 81.81 Indian rupees as of December 2022
[7] Remote Village Electrification - Ministry of New and Renewable Energy

the aim of providing electricity to the entire population in India, with a special focus on eliminating poverty through energy access. The scheme was implemented by the Ministry of Power and funded through a combination of central and state government resources and loans from the World Bank. Under the scheme, the Government allotted financial assistance to electricity distribution authorities in states and union territories through grants to meet the capital expenditure required for electricity infrastructure development. It also targeted local stakeholders' capacity building, bringing holistic development of rural habitations. Through RGGVY, the Government adopted a multi-pronged approach of providing electricity access to households through extending grid connectivity, off-grid solutions and decentralised mini-grid systems based on renewable energy sources for the first time. Under this *Yojana* 312,000 villages were electrified, and more than 22 million households falling below the poverty line received connections free of charge. Despite this remarkable stride in increasing electricity access, the *RGGVY* scheme fell short of its target of 100% household electrification in the stipulated time and achieved very limited socioeconomic impact, leaving last-mile households in darkness ("Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY)", 2015) (Burlig & Preonas, 2021). There were mixed outcomes of RGGVY reported; land acquisition disputes delayed RGGVY in most states. In other states it was delayed due to regulatory process which added to the slow progress. Additionally, poor identification of BPL households led to exclusion from the beneficiary list, further impacted implementation (Government of India, 2014).

The remaining electrification goals then were accommodated in *Deen Dayal Upadhyaya Gram Jyoti Yojana* in 2015. The key aim of this scheme was to address specific issues related to the transmission and distribution of agricultural and non-agricultural end-uses of electricity; to manage peak loads more effectively. By 2017, the electrification rate in India rose to more than 80 % (Outlook, 2018). With this momentum, the *DDUGJY* scheme also aimed to improve the duration of electricity access in electrified households in rural areas and give access to electricity to community spaces such as schools and clinics, enabling holistic rural development. However, nearly 14,700 last-mile villages were yet to gain access to electricity.

Finally, the *Saubhagya* scheme was launched in 2017 under the umbrella of *Pradhan Mantri Har Ghar Bijli Yojana*, with the goal of providing energy access to last-mile households, using a combination of rapid grid extensions, solar home systems and distributed generation where grid extension was not feasible. Approximately 40 million households received access to electricity under this scheme, and in March 2019, the Government announced 99.99 % of nationwide electricity access on the Saubhagya dashboard. India has achieved an exceptionally high electrification rate, with roughly 400 million households having received electricity access in the last decade alone(Palit & Kumar, 2022).

India is a vast country and is politically divided into 36 entities: thirty states and six union territories. Hence the experiences and impacts of the national-scale electrification plan differed considerably from state to state. Challenging the assertion of the Government's claim, a few independent studies have assessed the status of electrification in villages across various states in India and reported their observations. Firstly, Agrawal *et al.* (Agrawal, Mani, Jain, & Ganesan, 2020) surveyed more than 10,000 households in six different states and observed that 2.43 % households were still not electrified. Secondly, a village was considered 'electrified' even if just 10% of the households and public places received connections, according to the definition of 'electrified' village carried forward from the previous schemes, raising many questions regarding the accuracy in accounting for connections (GoI, 2015), and thirdly and quite importantly, end-users reported that they would not be able to pay energy bills, even if the connections were provided free of charge and tariffs were subsidised so that the Government did not give connections to those households who were unwilling or unable to pay(Urpelainen, 2019). Burgess *et al.* (Burgess, Greenstone, Ryan, & Sudarshan, 2020)further investigated causal relationship and inferred that there is a difference of perception at both ends, utility and consumers in rural India. . This lack of reconciliation can lead to somewhat vicious cycle, i.e. distribution companies may bear massive losses, and consequentilly may reduce supply of electricity to rural areas, feeding back a negative impact on service satisfaction, as experienced by rural customers. Similarly, Swain *et al.* (Ashwini K Swain, 2019) questioned the adequacy of electricity access and emphasised the importance of reliability and quality of supply in rural areas as a way forward. However, as awareness of the benefits of electricity has grown, off-grid energy solutions have become increasingly attractive to consumers, including solar lanterns, solar home systems (SHS) and decentralised renewable energy (DRE). Although according to a survey conducted by the Council of Energy, Environment, and Water (CEEW), only 0.33 % households have access to off-grid renewable energy sources (S. Agarwal, Mani, Jain, & Ganesan, 2020).

Providing reliable, affordable and sustainable access to electricity requires appropriate technologies, multi-channel financing, social adaptation, regulatory frameworks and, more importantly, strategies for electrification pathways that can minimise the negative environmental impact. Based on historical efforts towards rural electrification in India, three viable pathways have emerged:

- Extension of the centralised national grid.
- Solar lanterns and home systems (SHS), designed for individual households.
- Mini-grids, community-scale electricity network (solar, small hydro, biogas, wind or diesel generator).

Each of these pathways has its advantages and drawbacks. A range of factors determines the viability and impact of each pathway, including quality of supply, reliability of operation and maintenance, consistent financing and, in particular, whether it can meet the needs and desires of its specific end users in the long term.

- **Grid extension**: Central grid extension has proven advantages, allowing access to reliable and high-capacity electricity. It can serve a variety of electricity needs at the household level as well as for commercial and community services with higher power demands. Centralised networks are also resilient against uncertain demand and seasonal changes, making it a robust pathway for electrification in a country like India with a high variance in demand and varied climate zones (Candelise et al., 2022). Additionally, India is an agrarian economy; since the 1970s, the government has provided free or heavily subsidised electricity to rural farmers. Hence from an end-user perspective, this made the grid extension pathway the cheapest option. These advantages do, however, come at a very high cost in terms of building infrastructure for extending the grid to provide new connections to rural areas, particularly when the end-user market volume is low and nascent. Typically, for every 1$ invested in generation on average, the state utilities make 0.4 $ in revenue, making grid extension economically non-viable in the long run(Burgess et al., 2020). This leads to frequent load-shedding in rural areas and reduces the reliability of power supply, in turn forcing the rural population to use alternate solutions like polluting substitutes such as diesel and biomass(Harish, Morgan, & Subrahmanian, 2014). On the other hand, the overall energy mix in the grid electricity supply is dominated by fossil fuels such as coal and lignite (*Power sector at a glance, Ministry of Power, Government of India*, 2022). Over half of carbon dioxide emissions in India arise from electricity generation, 60% of which is a result of the combustion of coal(Raghuvanshi, Chandra, & Raghav, 2006). Considering future prospects, electrification by extending the central grid could be financially non-viable and environmentally unsustainable, especially in the rapidly growing economy of India.

- **Solar home systems**: As the cost of solar technologies continues to decline, off-grid solar appliances like solar lanterns, solar torches and especially solar home systems (SHS) gained traction. SHS is comprised of solar panels, batteries, LED lights and often a phone charging port. These systems are seen as a viable option to meet basic electricity demands in last-mile households and remote areas. Generally, the access is limited to Tier 1 of the Multi-tier Framework (less than 50W of power available for less than four hours per day) (Bhatia & Angelou, 2015). Nearly 3,000 villages received standalone solar systems under the Government's *Saubhagya* scheme in 2018 [8]. In the same year, the CLEAN network reported that approximately 10 million solar lanterns and solar lamps were sold in India (CLEAN, 2017). While SHS and off-grid solar lighting solutions are stepping stones towards energy access goals, they offer limited power capacity and lack long-term reliability. Moreover, these systems are usually found in domestic end-use, which are rarely scaled up to enable income-generating productive energy services. However, solar home systems have recently been integrated virtually to form a mini-grid network that enables productive use and higher power capacities, but these are still in their infancy.

- **Mini-grids**: Mini-grids are small-scale electricity grids that are designed to provide power to small villages and hamlets. The majority of mini-grids are solar-based, usually comprising solar panels and batteries as storage systems or diesel generators. A small percentage of them employ small hydro plants or wind turbines. Mini-grids are increasingly seen as an alternate and ideal solution for remote locations where central grid extension is difficult and, in contrast to SHS, are better equipped to provide reliable, clean energy to households, businesses, and a wide variety of other end-users. Currently, slightly less than 1 % of total solar capacity in India is contributed by solar mini-grids. Various technical and socioeconomic barriers have hampered wide-scale mini-grid deployment in India. A lack of private capital is one of the major reasons (Comello, Reichelstein, & Sahoo, 2017), (Dr Shashi Buluswar, Dr Hasna Khan , Tia Hansen, n.d.). Mini-grid development in India is discussed in more detail in section 2.2.

From the supply side, grid extension is a 'top-down' approach, organised and delivered hierarchically, whereas off-grid access via SHS or mini-grids is a 'bottom-up' approach, fragmented and delivered to meet small community scale energy needs. From the demand side, mixed opinions were received on energy use and demand growth from a small segment

[8] http://www.saubhagya.gov.in/dashboard

of the population surveyed to assess the impact of each electrification pathway(SPI and ISEP, 2019). Regardless of whether we consider rural electricity access from a supply-side or a demand-side perspective, none of the above-discussed pathways and distribution models can be considered a complete solution in a standalone manner(Palit & Bandyopadhyay, 2016). Instead, the future of rural electricity dispatch may combine multiple sources, depending on the quality of supply and reliability, finances, i.e. cost of generation and end-user affordability as well as environmental sustainability.

2.1.1 Environmental impact - sustainability

India has set a goal to reach net-zero emissions by 2070. This is a challenging target given that India has to reduce emissions from its existing electricity infrastructure, which represents the greatest source of emissions currently, whilst ensuring that new developments have a low carbon footprint. This challenge is more pronounced than in developed economies because much of India's future emissions will come from power infrastructure that is yet to be built or acquired (India energy outlook report (IEA), 2021). Therefore, energy planning today must prioritise environmental considerations to meet future electricity demand from rural areas. Decentralised renewable energy alternatives, such as solar PV, can greatly reduce emissions compared to traditional coal-fired power stations. The emissions from solar PV systems can range from 50-130 gCO2eq/kWh over their lifetime, including the need for local infrastructure such as battery storage and distribution networks(Ortega-Arriaga, Babacan, Nelson, & Gambhir, 2021). In contrast, extending the central grid with coal-fired power plants can result in emissions of 675-1,689 gCO2eq/kWh. India's rural electrification program, such as *Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY)* and *Saubhagya* scheme, aims to provide 8-20 hours of electricity access per day to villages through the expansion of the central grid infrastructure and, in areas where this was not financially feasible or possible, through solar home systems (SHS) and mini-grids. However, these systems do not have to be mutually exclusive and can be used in combination. If mini-grids are designed with the potential for future connection to the central grid, in the long term, they will support the decarbonisation of the central electricity network (Comello et al., 2017) (Palit & Kumar, 2022).

2.1.2 Quality of supply - reliability

Quality and reliability of supply can be evaluated through two metrics: hours of supply and the capacity of supply (single-phase or three-phase). The capacity of grid supply is typically high. However, the number of hours of supply can vary greatly in rural areas, ranging from 8 to 20 hours (Agrawal, Mani, et al., 2020). Grid electrification can bring many positive benefits, but numerous barriers exist, which can impede reliable and consistent power supply. These include losses in transmission due to long distances, low demand and consumption resulting in insufficient revenue, inconsistent payment of connection fees, financial limitations to households' ability to procure electrical appliances, and poor operation and maintenance of local infrastructures (e.g. poles and wiring), leading to frequent damage and increased repair costs. All of these factors act as impediments to the reliable power supply in the grid extension scenario(Alstone, Gershenson, & Kammen, 2015). Alternatively, locally installed large-scale grid-tied solar projects also have potential advantages due to economies of scale, resulting in lower costs of energy per unit and more efficient operations, thus reducing system losses compared to traditional distribution networks. Likewise, solar mini-grids could offer a reliable power supply at a local level without having to rely on long-distance transmission lines that suffer from high losses (Bhattacharyya, Palit, Sarangi, Srivastava, & Sharma, 2019). Another research study highlighted the lack of reliable power supply in grid-connected rural areas and deficit-related losses incurred by consumers. The study also emphasised that augmentation of grid supply with local biomass or diesel-based backups can be a way forward(Harish et al., 2014). In terms of standalone off-grid systems, such as decentralised solar mini-grids, communities can choose the minimum level of reliability they want or define what are critical and non-critical loads in order to obtain the best balance between costs, reliability and performance. This way, customers connected to mini-grids can achieve reliable access at an affordable price (Ciller et al., 2019).

2.1.3 Economics of electrification - affordability

Comparing the costs of generation under different electrification options, grid extension versus off-grid solutions, is an arduous process due to the topography of areas involved, variable fuel costs and the different metrics used in planning estimates over the years. Examples of such metrics include the cost of electricity transmission and distribution, type of fuel utilised and level of demand, and in the case of off-grid, storage system designs. In the context of demographic and geographic constraints, grid extension is usually more economical in densely populated villages, while off-grid systems are often cheaper in sparsely populated regions that are far away from an existing power grid. In a generalised review of studies, it is found that delivery costs of off-grid solutions can range between \$0.2 - \$1.4 per kWh compared to costs below \$0.1/kWh up to over \$8/kWh for extending the current electrical infrastructure to rural areas (Ortega-Arriaga et al., 2021). In the case of India, Amutha *et al.* (Amutha & Rajini, 2016) found that a combination of solar, wind and hydro off-grid energy is relatively cheaper than grid extension if the village is farther than 75 km from the existing grid (which is generally the case for the majority of un-electrified or recently electrified villages). On a similar note, an earlier study found that the total delivery cost of grid-based electricity (levelised unit cost of electricity and costs associated with transmitting/distributing) in remote areas located in the distance range of 5-25 km varies from \$ 0.03/kWh to \$ 2.82/kWh [9], depending on peak electrical loads of up to 100 kW and the load factor [10](Nouni, Mullick, & Kandpal, 2009). In contrast, Narula *et al.* (Narula, Nagai, & Pachauri, 2012) found that decentralised distributed generation, e.g. off-grid solutions like SHS and mini-grids, are emerging as cost-effective options that are independent of distance from the grid but do depend on the level of demand. For example, off-grid solutions can meet the lighting and mobile charging needs of rural populations. However, to meet an evolving demand for high-power appliances in households, higher investments may be required than for grid extension and infrastructure. Overall, some of these estimates may have focused on the short-term costs rather than the long-term investments altogether, complicating the process of comparing the costs of electrification pathways.

From the end-user perspective, i.e. energy costs to households, Government subsidies play a major role and are one of the primary determining factors influencing whether a household will gain connection to an electricity network (Urpelainen, 2019). The Indian Government has heavily subsidised grid electricity tariffs for the majority of rural households, with minimal connection and administrative fees. For the population living below the poverty line, grid electricity is provided completely free of charge (GoI, 2016). Whereas off-grid projects in certain rural regions of India are either privately owned or partially funded by grants, they often charge higher tariffs per unit of electricity to recover their investments. This makes off-grid electricity more costly than grid-connected options for the majority of rural households(GNESD, 2014) (Daniel Schnitzer, Deepa Shinde Lounsbury, Juan Pablo Carvallo et al., 2014). However, a faster-than-anticipated decline in the cost of renewable sources (Luderer et al., 2022), especially solar and battery technologies, can render decentralised mini-grids a more financially attractive option to both suppliers and

[9] 1 USD = 81.81 Indian rupees as of December 2022

[10] The load factor is the ratio of an average load to the peak load over a given period of time. The higher the load factor, the lower the cost of electricity

end-users in the long-run (Dr Shashi Buluswar, Dr Hasna Khan , Tia Hansen, n.d.). Despite the promising outlook, mini-grids have not attracted significant private investments in India (Singh, 2016), although this scenario is beginning to change. The Rockefeller Foundation, for example, and its Smart Power India[11] programme, in collaboration with Tata Power, is implementing 10,000 mini-grids throughout rural India to serve nearly 5 million homes by 2026 (Dr Shashi Buluswar, Dr Hasna Khan , Tia Hansen, n.d.).

2.2 Mini-grid models in India

Currently, there are three business models in practice in India, private, partly subsidised and fully subsidised.

- **Private mini-grids**: This type of mini-grid follows a standard business model. The developers build, own and operate mini-grids and generate revenue for profit. Husk Power Systems (HPS) and Mera Gaon Power (MGP) are examples of privately owned mini-grids. HPS has provided electricity to over 200,000 people in some 300 villages and hamlets since 2007 in the state of Bihar. MGP has also set up solar-powered mini-grids in Uttar Pradesh, connecting 15,000 households across 500 hamlets. The composition of mini-grids is mainly based on biomass (rice husk) and solar PV. Typical tariffs are higher for users connected to private mini-grids compared to heavily subsidised grid power [12]. Therefore, the quick expansion of the grid infrastructure poses a significant risk to the sustainability of privately owned mini-grids, particularly due to the absence of incentives for private investors (Schmidt, Hawkes, Gambhir, & Staffell, 2017) (Subramony, Doolla, & Chandorkar, 2017) (Candelise et al., 2022) (Daniel Schnitzer, Deepa Shinde Lounsbury, Juan Pablo Carvallo et al., 2014).

- **Partly subsidised**: In this category of mini-grid, developers procure large subsidies or grants for capital costs of the system from either international donors or corporate social responsibility funds. They generate a small revenue to cover the costs of operation and maintenance, including battery replacements. Gram Oorja Pvt ltd, Oorja Solutions Pvt ltd, Mlinda foundation and Naturetech Infra are examples of developers across various states in India which follow this partly subsidised model. The unit cost to users in this model is moderate, yet households connected to partly

[11] https://smartpowerindia.org/

[12] HPS & MGP tariff for baseline usage = $\$2 - 3$ per month

subsidised mini-grids spend a higher proportion of their family income on their electricity bill (See section 3.5 for more details on Gram Oorja's business model).

- **Fully subsidised**: Fully subsidised mini-grids are generally funded by the Government or third-party donations. Two government agencies in India, WBREDA[13] and CREDA[14], have implemented grant-funded mini-grids. WBREDA has set up over 20 solar power plants with a total capacity of 1 MWp, providing electricity to 10,000 households in the state of West Bengal. CREDA has electrified 35,000 households across 1400 villages and hamlets in Chattisgarh with 1-6kWp solar mini-grids. The goal of these projects is to quickly increase the rate of electrification, resulting in the installation of small-scale mini-grids to meet the baseline demands of remote hamlets. However, as cost recovery is not a concern for these mini-grids, the quality of service is often low and cannot keep up with increasing demand. Village Electricity Committees(VEC) are responsible for managing and operating these mini-grids, and almost none or minimal charges are borne by households receiving electricity through these grids.

India has been implementing solar mini-grids since the 1980s, facilitated by national and state policies like the Saubhagya Scheme. Approximately more than 4000 pico-grids and mini-grids were established in regions like Uttar Pradesh, Chhatisgarh and Jharkhand in the northern side, addressing the need for reliable electricity access. Despite their potential, challenges have arisen, including issues with financial planning and understanding community needs. The Rockefeller Foundation and other organisations are now driving new investments and promoting mini-grids as a solution for rural and remote communities. However, scaling up faces hurdles, particularly concerning high initial investment costs and revenue collection challenges. Government grants and international funding could alleviate financial burdens, while policy improvements might enhance developer access to finance. Addressing revenue collection concerns may involve implementing stricter policies, such as discontinuing supply for non-payment. Additionally, the coexistence of mini-grids with the national grid poses a challenge, emphasising the necessity of a clear regulatory framework to define integration conditions. Despite these challenges, mini-grids have the potential to serve as a hybrid grid component, supporting utilities and providing reliable, environmentally friendly energy. They offer quicker connections and the potential for community development by powering various applications.

[13] West Bengal Renewable Energy Development Agency

[14] Chhattisgarh state Renewable Energy Development Agency

Ensuring a reliable and consistent electricity supply from mini-grids is essential to making them a viable business model. If the performance standards are not up to par, fewer people will be willing to pay for the service, resulting in decreased revenue for their developers. Additionally, this will lead to increased operational costs due to the need for more maintenance. Therefore, providing a high-quality service is essential to achieving sustainable and viable business models for mini-grids in the long term. Social enterprises operating mini-grid systems face significant challenges in balancing the technical and social aspects of the system to ensure customer affordability and business viability. This requires careful management of the socio-technical complexities inherent in mini-grid processes, such as balancing the cost of energy production with the need to meet energy demands from the community and their ability to pay for energy services. The sustainability of a business model in this context depends on how well these socio-technical aspects are integrated and managed in the design, operation, and maintenance of the mini-grid system (Bandi, Sahrakorpi, Paatero, & Lahdelma, 2022). In this sense, the success of a mini-grid model is heavily influenced by key design factors such as the choice of renewable energy source, estimating electricity demand for the sizing of system components, and the lifespan of those components. The selection of these parameters can greatly impact the financial feasibility of the mini-grid and the cost of the energy necessary to make the system profitable. In the next chapter, our focus will be on comprehending significant obstacles, such as the accuracy of demand assessment and the long-term utilisation of mini-grids. We aim to introduce various metrics for sizing optimisation and examine whether increasing capacity will enhance the financing for mini-grids.

Chapter 3

Solar mini-grids

3 Solar mini-grids

In this chapter, a comprehensive overview of mini-grids in the context of the global south is presented. This is followed by an in-depth discussion of existing literature regarding mini-grid planning and sizing tools, highlighting research gaps in the field. These gaps include the need for accurate estimation of demand growth, analysis of mini-grid sizing approaches that can adapt to increasing demand and utilisation, and the consideration of resource efficiency throughout the lifetime of the mini-grid system. To address these gaps, a pilot study involving a field survey was conducted in a community that recently gained access to electricity through a decentralised solar mini-grid. The outcomes of the survey were used to estimate the bottom-up electricity demand of the community and generate plausible demand growth scenarios for the next ten years. Subsequently, the importance of determining optimal component sizes in solar mini-grids is evaluated. This was achieved by utilising the Continuous Life-cycle Of Variable Energy Resources (CLOVER) model to study two different sizing approaches in relation to demand growth scenarios. Furthermore, a sensitivity analysis was performed on seven different parameters to evaluate their impact on optimal system size and associated costs of mini-grid systems. Overall, this chapter provides insights into the various factors that should be considered for long-term sustainability of mini-grid systems in the global south.

3.1 Overview of mini-grids

To achieve universal access by 2030, it is necessary to implement a combinatorial approach to electrification by extending the main grid, mini-grids, and off-grid solar or wind, as discussed in previous chapters. The World Bank Group's Energy Sector Management Assistance Program (ESMAP) released the most comprehensive report on mini-grids in 2019(ESMAP, 2019). The report provides an in-depth analysis, stating that approximately half a billion people can be supplied with electricity cost-effectively through mini-grids (ESMAP, 2019). This is due to multiple factors, including steeply decreasing costs of solar and wind technologies, a dramatic increase in the quality of service, technological innovation and micro-financing models. In combination, these have made modern mini-grids a scalable option to supplement grid extension and solar home systems. The ESMAP report also estimated that globally at least 19,000 mini-grids had been installed and are currently being operated in 134 countries, representing a total investment of around 28 billion USD and providing electricity to approximately 47 million people. Of these 19,000 mini-grids, Asia has the highest number to date, while the African continent holds the highest potential for future mini-grid deployment and is forecasted to outrank Asia by 2030. It is estimated that some 210,000 mini-grids will be required to serve the target populations of half a billion globally and that approximately 220 billion USD will be required in public and private investments in total(ESMAP, 2019). Planning such large-scale capital investments for mini-grids requires a multidisciplinary undertaking.

Given the scale, it is important to have techniques in place to guide the planning and management of large capital investments to address the challenges in mini-grid deployment. These can be categorised as i) **Technological**: such as identifying the appropriate site location for the mini-grid, the optimum size of system components, and composition of resources for mini-grids to ensure that these are cost-competitive and can yield reliable energy dispatch with ease of maintenance ii) **Economic**: such as lowering generation costs, effective tariff plans, and planning for substantive revenue streams to recover investments and the costs of future component replacement iii) **Social and Political**: including estimating accurate electricity demand from the community, temporal energy growth and energy policies that catalyse clean energy transitions iv) **Environmental**: to avoid rising emissions, adopting a diverse composition of mini-grids, based on renewable energy as a primary source for electricity generation. In order to make mini-grids sustainable in the long term, all these categories need to be considered at the design stage. Holistic modelling tools can aid the process of deploying mini-grids at a larger scale. Moreover, mini-grid planners can escalate the process of finding cost-optimised configurations of energy generation infrastructure and optimising energy dispatch with the help of such tools.

3.2 Mini-grid modelling

The literature on modelling renewable energy systems, whether they are standalone or connected to the central grid and incorporate storage, is extensive. These models aim to optimise system costs by identifying the most efficient resource combination. Various factors, including system reliability, emissions, socioeconomic considerations, and community affordability, are taken into account. Before delving into mini-grid modelling, Figure 3.1 provides a schematic representation of a solar mini-grid with a photovoltaic array and battery storage. The electricity generated is distributed to domestic, public, and commercial buildings, supporting the power needs of income-generating appliances like flour mills or irrigation water pumps. In this study we specifically focus on domestic end-use and

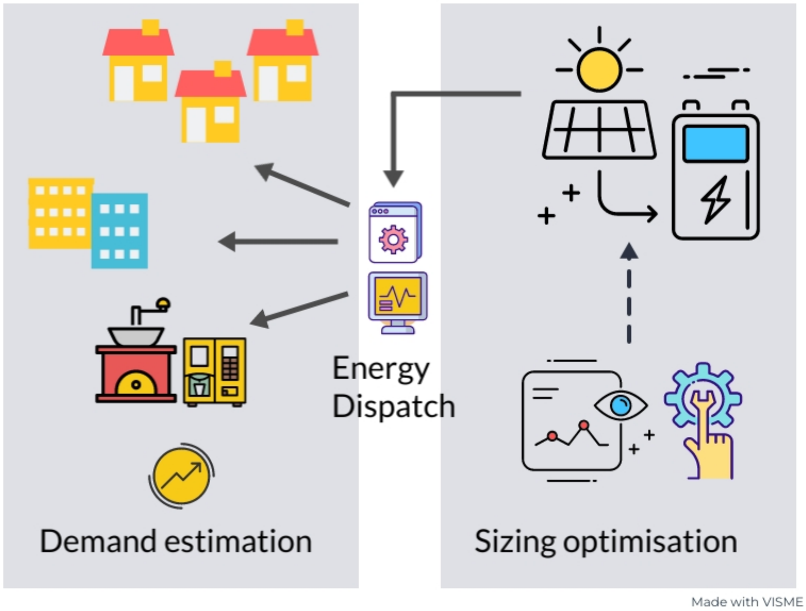


Figure 3.1: Schematic of mini-grid system

renewable energy access via decentralised solar mini-grids.

Mini-grid models are designed to enhance the operational efficiency of systems by considering variables such as resource availability, weather patterns, energy demand and more. These models serve as invaluable decision-making tools in the strategic planning and execution of mini-grid projects, offering the capability to assess diverse scenarios and anticipate their implications. These modelling tools keep evolving and refining as new data and technologies are made available and hence it is crucial to understand foundational methodologies and assumptions upon which they are constructed. Within the existing literature, mini-grid modelling tools can be categorised into two distinct types: planning tools and sizing tools. Planning tools primarily serve the purpose of identifying optimal locations where mini-grids represent the most cost-effective electrification option. Conversely, sizing tools are implemented to ascertain the optimal dimensions and configuration of a mini-grid system to ensure efficient operation. In this section, an in-depth analysis and comparison of the functionalities of these two categories of tools is presented. This analysis will cover the core methodologies of each tool and outline their respective strengths and limitations, along with systematic evaluation of how the three key features of the models are addressed within each tool's core methods. These key features are

- **Site Selection**: Identifying the optimum location for the installation of a mini-grid is essential, as it not only determines the distribution and transmission path but also influences the economic situation, which in turn informs decision-making regarding the financial viability of off-grid services. We compare the data and methodology used in existing models, as well as the scale at which the model is implemented in the case studies that are referred.

- **Demand Assessment**: Estimating short-term (daily load), medium-term (seasonal) and long-term demand (over a system's lifetime) is a critical step in mini-grid planning, as discussed in Chapter 2. Various methods are explored in the literature, including top-down econometric methods and bottom-up stochastic methods. We surveyed existing literature to understand whether or not the model can capture evolving electricity demand and what methods are used for demand projection.

- **Optimisation for Sizing**: Configuring the correct size of each component is a determining factor in whether or not mini-grids will be viable in the long run. We compare the methods used for this optimisation, the objectives of the model, and whether the model is tested for capacity expansion in the future, i.e. incremental sizing to meet growing demand, in the case studies considered here.

Considering the importance of these three key features, we're looking at five planning tools in Table 1 and ten sizing tools in Table 2.

Table 1: Mini-grid planning tools

Model Name	**Scale**	**Site selection**	**Demand Assessment**	**Sizing optimisation**	**Case study and Ref.**
OnSSET	District State National Continent	GIS + Techno Economic	Bottom-up (Static demand)	LCOE (One-off)	Sub-Saharan Africa [a], Nigeria [b]
Network Planner	Urban Peri-urban Rural National	GIS + Techno- Economic Demographics	Econometric (Arbitrary demand growth)	LCOE (One-off)	Ghana [c], Liberia [d], Nigeria [e]
GeoSIM	Urban Peri-urban Rural	GIS+ Power network+ Topographic	Bottom-up (Demand growth over Planning Period)	Capital Costs	Tanzania [f]

Table 1 continued from previous page

Model Name	Scale	Site selection	Demand Assessment	Sizing optimisation	Case study and Ref.
REM	Rural National	GIS+ Power network+ Technical+ Socioeconomic	Bottom-up (Repetitive over a year)	LCOE System Reliability (One-off)	Africa [g] and South Asia
micrOgridS (RLI)	National District	GIS+ Topographic+ Techno Economic	Bottom-up Latent Demand (Repetitive over lifetime)	LCOE (One-off)	Nigeria [h]

[a] (Mentis et al., 2017)
[b] (Isihak, Akpan, & Ohiare, 2020)
[c] (Kemausuor, Adkins, Adu-Poku, Brew-Hammond, & Modi, 2014)
[d] (Modi, Adkins, Carbajal, & Sherpa, 2013)
[e] (Akpan, 2015)
[f] (Analyst, n.d.)
[g] (Ciller et al., 2019)
[h] (Blechinger et al., 2019)

3.2.1 Mini-grids models

OnSSET: OnSSET, an open-source spatial electrification tool, was developed to allow decision-makers to identify the most effective electrification plans at various scales, from the village level up to the continental scale. OnSSET uses a range of data sources, such as GIS databases (mainly sourced from Open Street Maps), night light data for existing central grid networks, topology, potential resource availability data (such as solar or wind), and economic data. It is unique in its consideration of small-hydro mini-grids, which are enabled by including topology databases. OnSSET uses a Multi-tier Framework to estimate initial energy demand scenarios and to project growth based on transitions between tiers, considering household income level and demographic data. The model focuses on a single objective of minimising LCOE, and operational strategies are chosen according to the minimised investment required. As energy demand increases, diesel generation is selected as the primary complement for mini-grids because the model does not consider environmental factors (Mentis et al., 2017).

Network Planner: The Network Planner is an innovative web-based tool for designing electricity networks for a wide range of scales. It is possible to build scenarios and conduct sensitivity analyses of certain parameters using this model, which can provide insights into the effects of individual factors on total investments required for electrification with grid extension or off-grid solutions. Energy demand is estimated using a top-down approach, with household type characterised based on urban, peri-urban or rural and population density using GIS and census data. To optimise the cost of electrification, the energy network is represented using MV lines for grid extension and LV lines for mini-grids. The tool utilises a heuristic method known as minimum spanning trees (or minimum weight spanning trees) to calculate the cost of extending the central grid network to some area, comparing electrifying that area with either SHS or Diesel generation. This approach is unique in that it assigns different weights to each connection of the network, resulting in minimum-weight pathways of electrification. The model considers socioeconomic factors such as income and population density; however, it does not account for grid reliability, which is a critical factor in designing off-grid or grid-based electrification projects. Furthermore, the electrification scenario outcomes are exceptionally sensitive to changes in household electricity consumption. For example, increasing the household demand from 100 kWh to 150 kWh results in a nearly 20% decrease in un-electrified communities being electrified by off-grid solutions compared to grid extension; this shows that consideration of electricity demand at the designing stage is a key factor in determining the potential of off-grid energy.

GeoSIM: GeoSIM (Geospatial Rural Electrification Planning) is a commercial power network planning tool that applies state-of-the-art GIS technology to identify generation sites based on LV/MV networks at local and national levels. It is built based on the Huff model, a spatial interaction tool that calculates probabilities based on two types of distances: traditional Euclidean (straight-line) distance and travel time along a street network. In the context of electrification, this model is applied to delineate probability-based energy markets, taking into account social and economic parameters to identify the least-cost site locations for hybrid mini-grids or related off-grid solutions. It uses bottom-up energy demand assessment to accurately forecast high or low-energy consumption areas and to reliably and extend these inputs to strategic energy planning for mini-grid projects. It also enables post-implementation performance monitoring. Being a commercialised tool, GeoSIM's methods are not published in the literature. Thus far, its use has been limited to small-scale projects in developing countries.

REM: the Reference Electrification Model (REM) is designed as a platform for large-scale rural electrification planning, primarily in developing countries. REM uses a clustering technique to determine the least-cost option for electrification. This involves a combination of heuristics and algorithm-based cost optimisation by employing a modified version of the Hooke-Jeeves algorithm, otherwise known as 'pattern search', to find the clusters of consumption points. This algorithm performs a three-dimensional search space comprised of the diesel generator capacity, the total capacity of the solar panels and the battery capacity. It uses this information to calculate the objective function, which is the total cost of mini-grid investments for a large number of options, eventually moving in the direction of the lowest cost. REM accounts for the reliability of the system by incorporating a non-monetary cost of unmet load, i.e. social cost, in its static planning simulation, which makes the model flexible in terms of setting a cost versus reliability trade-off, i.e. the model can be customised to prioritise critical and non-critical loads and choose the level of desired reliability. However, initial energy demand is assessed empirically, and demand evolution isn't considered. REM implies a simple load-following strategy and fixed pricing mechanisms. REM will be commercialised in collaboration with a startup called Waya energy ltd. to provide enhanced customer support. Currently, it is a 'work in progress' and has been verified with only a few case studies.

RLI model Developed by the Reiner-Lemoine-Institut GmbH, this is sometimes referred to as "micrOgridS", an open-access tool designed to simulate and optimise electrification through grid-tied or off-grid energy systems. It uses a load projection tool to create an initial energy assessment based on targeted demographic and socioeconomic data, such as night light GIS data, household income levels and national GDP per capita. This data is used to estimate three levels of energy use and to generate a daily demand curve based on household clusters. Seasonality and various single-phase end-use (generally domestic) and three-phase end-use (productive use / income generating large appliances) are also considered to offset the consumption patterns throughout the day. Precisely, the model considers five different data sets - economic raster data, land use, road network, grid pathways, power network and protected areas to find the least-cost electrification option. These data sets are weighted and input into a Minimum Spanning Tree Algorithm to identify the best pathway. The load projection tool is the primary strength of the model. However, the accuracy of initial load estimations relies heavily on the availability of large datasets. Unfortunately, many developing countries may not have the necessary data available. Even when this data is available, it can be a challenge to achieve the desired level of accuracy due to the quality and types of data structures. The model's spatial resolution is at the level of 0.5 square kilometres; Clustering of population density at this scale can potentially result in large errors, which can directly affect the electrification pathway chosen. Like the earlier described tool, Network Planner, RLI may potentially underestimate the suitability of off-grid energy planning strategies.

The use of planning tools has become imperative in identifying the feasibility of mini-grids in various geographic locations. These tools employ metrics like the levelised cost of generation and the net present cost of electrification pathway to determine the viability of mini-grid implementation. However, the accuracy of demand assessment is crucial to the success of mini-grid planning and deployment. Currently, demand assessment is mostly based on satellite mapping or econometric methods, and is sensitive to parameters such as the distance granularity used in GIS planning. Therefore, there is a need for more precise mini-grid planning methods in order to successfully scale up the adoption of mini-grids. As a result, this study also considers and evaluates other sizing tools, assessing them for their effectiveness in terms of the aforementioned key features. Table 2 outlines the sizing tools and their limitations and strengths respectively.

Table 2: Mini-grid sizing tools

Model Name	**Scale**	**Site selection**	**Demand Assessment**	**Sizing optimisation**	**Case study and Ref.**
HOMER	Rural Urban	Techno Economic+ Meteorological	Feasible Load (Arbitrary/ repetitive)	Net Present Cost (Flexible)	Bangladesh [i], Pakistan[j], India[k], Honduras[l], Ethiopia[m], A review[n]
iHOGA	Rural Urban	Techno Economic+ Social	Static present day load	Net Present Cost / LCOE (one-off)	Colombia[o] India [p]

Table 2 continued from previous page

Model Name	Scale	Site selection	Demand Assessment	Sizing optimisation	Case study and Ref.
PoliNRG	Rural	Techno Economic Social Demographic	Bottom-up (Present day/ repetitive over lifetime)	Net Present Cost Loss of Load (one-off)	Tanzania[q] Uganda[r]
AVEREMS	Rural	Techno Economic Demographic	End-use specific (Present-day Demand)	Capital Costs (One-off)	Peru[s] Nicaragua[t]
DER-CAM	Rural	Techno Economic Social	Bottom-up (Appliance growth over lifetime)	Capital Costs (Capacity Expansion)	Tanzania [u]
PSO	Rural Urban	Techno Economic	Bottom-up (Static and constant growth)	Net Present Cost + (Capacity Expansion)	Lesotho [v] Kenya [w]
ESCoBox	Rural	Techno Economic Social Meteorological	Bottom-up (Present day/ Possibility of Growth)	Decision Support Tool	Kenya[x]
OSeMOSYS	Rural	Techno Economic Social Meteorological	Bottom-up (Demand/ Growth (Historical)	Net Present Cost	India[y]

Table 2 continued from previous page

Model Name	Scale	Site selection	Demand Assessment	Sizing optimisation	Case study and Ref.
CLOVER	Rural	Techno Economic Social Meteorological Environmental	Bottom-up (Utilisation+ Appliance Growth)	Levelised Cost of Used Energy (Capacity Expansion)	India[z],

[i] (Shoeb & Shafiullah, 2018)

[j] (Waqar et al., 2017)

[k] (Phurailatpam, Rajpurohit, & Wang, 2018)

[l] (Del-Citto, R., Micangeli, 2018)

[m] (Brenna, Foiadelli, Longo, & Abegaz, 2016)

[n] (Sen & Bhattacharyya, 2014a)

[o] (Lujano-Rojas, Monteiro, Dufo-López, & Bernal-Agustín, 2012)

[p] (Saiprasad, Kalam, & Zayegh, 2019)

[q] (Mandelli, Brivio, Colombo, & Merlo, 2016)

[r] (Brivio, Moncecchi, Mandelli, & Merlo, 2017)

[s] (Ferrer-Martí, Domenech, García-Villoria, & Pastor, 2013)

[t] (Ranaboldo, García-Villoria, Ferrer-Martí, & Pastor Moreno, 2015)

[u] (Hartvigsson & Ahlgren, 2018)

[v] (Ghaem Sigarchian, Orosz, Hemond, & Malmquist, 2016)

[w] (Fioriti, Frangioni, & Poli, 2021)

[x] (Gammon, Boait, & Advani, 2016)

[y] (Riva, Colombo, & Piccardi, 2019)

[z] (Beath et al., 2021)

HOMER: (Hybrid Optimisation Model for Electric Renewable) is a widely used commercial software for mini-grid energy planning in developing countries. Its optimisation includes a variety of stand-alone renewable energy sources, including wind, hydropower, biomass, photovoltaic (PV) arrays, hydrogen and flywheel storage, to determine the most effective size and combination of components for mini-grids. The model considers all possible combinations of system components and applies power balance constraints to find the combination of resources with the least Net Present Cost. Although the model is highly sensitive to certain parameters such as wind speed, solar radiation, fuel prices and component costs, it uses a repetitive hourly energy demand profile throughout the year, which can potentially result in under or over-sizing of mini-grids. The operational strategies it uses for load following and charging cycles are also limited in scope. Nevertheless, HOMER has an advantage over other tools in its capacity to assess a variety of renewable energy sources and the corresponding reduction in GHG emissions. It also has a user-friendly graphical interface.

iHOGA : iHOGA (Improved Hybrid Optimisation by Genetic Algorithms) is a software tool developed to simulate and optimise renewable energy-based hybrid grids in both stand-alone and grid-tied modes. The model is built on genetic algorithms, which is an effective method for the optimisation of energy systems with a large number of parameters. It has two loops, the primary and secondary, to optimise cost and determine the optimum size of renewable generation and storage. The primary loop optimises the Net Present Cost of the system, taking into account component size, energy demand and other technical details. The secondary loop evaluates various control strategies for energy dispatch, such as charging cycles of a storage system, source priority and reliability of supply. iHOGA also considers multiple objectives such as reduction of emissions, limiting unmet demand and improving the human development index in the optimisation of system sizing, which is the unique advantage of this model. Temperature effects on equipment efficiency, maintenance and lifetime cost predictions are also taken into account in the planning simulation. Furthermore, iHOGA enables AC grid connection, and grid planners can use Net metering for feed-in-tariffs when required. However, the model has only been tested for a few use cases and is at a nascent stage. It is currently only available commercially.

PoliNRG: PoliNRG, an abbreviation for Politecnico di Milano -Network Robust Design, employs four categories of model: bottom-up stochastic energy demand assessment from the community, renewable generation, optimisation for least cost configuration of the system and an operations and dispatch strategy. To estimate energy demand from the community, PoliNRG applies LoadProGen, a bottom-up stochastic method based on survey data and field observations, but this can be difficult to scale up. An iterative heuristic optimisation process is applied to find the least-cost option of electrification while taking into account the cost and reliability of the system through the calculation of loss of load probability. An Imperialist Competitive Algorithm (ICA) is used to find the optimum solution from a two-dimensional search space consisting of PV and battery sizes, which is then tested for robustness in order to find the cost-minimised configuration of the mini-grid.

AVEREMS: (Autonomous Village Electrification through Renewable Energy and Microgrid Systems) is divided into three phases: construction, generation and distribution. To identify the optimal site for the mini-grid, a Greedy Randomised Adaptive Search algorithm (GRASP) is applied in the construction phase. Initially, all of the consumption points are considered as individual distributed generation points, which results in the highest cost solution before the algorithm runs to find the least cost configuration of a hybrid grid, such as solar-wind-battery, based on the distance between the generation and consumption points. Primary constraints applied in the optimisation are that 100% of the demand should be met, days of autonomy are kept to a minimum, and batteries kept at maximum discharge capacity, as well as all the consumption points being consistently connected to the mini-grid for the duration of the simulation. GRASP consists of two phases: the first generates a set of solutions based on a randomised greedy approach, and the second performs a local search to find the minimised cost configuration. The simulation takes into account load growth in the sizing of the system based on field observations, but this can limit its scalability. In terms of operation, the priority of energy dispatch and tariff design is checked in Peru and Nicaragua, while component-wise maintenance is considered in the planning simulation, making the predictions of operation and maintenance costs more realistic.

DER-CAM+VenSIM: DER-CAM, an abbreviation for the Distributed Energy Resources- Customer Adaption Model, has been developed for the cost optimisation of mini-grids. This model combines three ways to optimise the initial system and also estimate the effects of capacity expansion strategies. These methods include a MATLAB-based bottom-up energy demand model, and system dynamics approach using VenSIM for testing capacity expansion and cost optimisation on investments based on DER-CAM. The system dynamics models are advantageous in terms of improving system sizing accuracy as mini-grid models have a large parameter space. Despite their utility, they are sensitive to fast and small variations in daily load. Therefore, a separate bottom-up energy demand model based on micro-scale data has been created to complement these limitations. The two methods are then combined with DER-CAM for cost optimisation based on Mixed-integer Linear Programming. The conceptual framework and functionalities of this model are powerful, but it is also correspondingly less user-friendly and uses the proprietary software products MATLAB and VenSIM.

PSO: Particle swarm optimisation (PSO) is a straightforward and computationally inexpensive meta-heuristic optimisation method. A case study from Iran (Borhanazad, Mekhilef, Gounder Ganapathy, Modiri-Delshad, & Mirtaheri, 2014) includes multiple objectives in sizing simulation, which are equally weighted, Cost of energy (CoE) and Loss of power supply probability. These two objectives are linearly scaled and taken as constraints in single-objective optimisation, making it converge faster. PSO finds global optima and works efficiently on continuous functions, a key strength. Another case study in Kenya (Fioriti et al., 2021) *et al.* take into consideration the uncertainties associated with electricity demand growth and component degradation over multiple years. To further account for these uncertainties, a predefined scenario tree structure is utilised, allowing for different capacity expansion strategies for each scenario to more accurately assess the potential risk associated with demand growth and sizing.

ESCoBOx: ESCoBox is a decision support tool designed to assist rural mini-grid planners, particularly those in low-income countries. It is composed of two sub-parts: a disaggregated demand assessment tool and a battery modelling tool. Monte Carlo simulations are applied to calculate disaggregated demand from individual appliances, tested and validated through field experiments in Gambia. Smart metering was used to introduce demand-side management plans to reduce peak demand. System sizing simulations primarily rely on peak demand from the community. However, given that rural communities are generally smaller in terms of the number of households, the uncertainty in peak demand is heightened. Here, demand-side flexibility can be advantageous in optimising battery size and, ultimately, total system costs. EScoBox's storage modelling tool incorporates the Wöhler curve for battery lifetime prediction, which calculates the battery life cycle based on the depth of discharge. It is claimed to be more accurate than the linear model of HOMER.

OSeMOSYS: (Open Source energy MOdelling SYStem) is a linear programming model which can be used to analyse the development of the energy system of a country or region over a multi-year time horizon by identifying the least-cost energy system that meets a set of constraints and goals. The objective function of finding the optimum size of components is based on minimising the total investments required to support decision-making on renewable financing. In the context of mini-grid sizing, OSeMOSYS was implemented by Riva *et al.* (Riva, Colombo, & Piccardi, 2019) in India, which included the present and future demand for electricity, the cost of different technologies and the available renewable energy resources in the area. The strength of this model comes from the consideration of demand evolution based on a Gompertz curve for incorporating technology diffusion. However, it does not consider the additional positive environmental impact of using renewable mini-grids.

CLOVER: CLOVER (Continuous Lifetime Optimisation of Variable Energy Resources) is a model developed to aid decision-making in the sizing of renewable energy systems. It primarily has two objective functions, one minimising the Levelised Cost of Used Energy (LCUE) (Discussed in detail in section 3.6) and the other reducing GHG emissions. It uses hourly energy demand from individual appliances to create a yearly demand profile with seasonal variations and growth in appliance ownership to create a load profile over the system's lifetime. For finding the optimum size of the system components, CLOVER implements criteria for reliability in terms of blackouts. In other words, it ensures the desired level of energy demand is met over the system lifetime while finding the least-cost configuration for the mini-grid. CLOVER also considers grid supply and mini-grids functioning in conjunction or stand-alone, accounting for both grid supply and mini-grid for the frequency blackouts to optimise supply reliability. More details on the methodology of CLOVER are discussed in section 3.6.

It is evident that planning tools have the benefit of being scalable and can assist in identifying areas for electrification on a large scale, they may not accurately calculate the optimal size of mini-grids. On the other hand, sizing tools offer a higher level of accuracy when determining the appropriate size and composition of a mini-grid, but they are often complex and challenging to scale for widespread use. Thus, both planning and sizing tools play crucial roles in mini-grid modelling, with planning tools being more suited for broader electrification plans and sizing tools being better suited for individual case studies. Despite the availability of these tools, there are still research gaps that need to be addressed in order to further enhance the widespread implementation of mini-grids to close the global energy access gap. Based on this, we identify that the constant evolution of demand must be taken into account during system design, with a greater emphasis on precision. Failure to accurately consider this aspect could have significant consequences in terms of mini-grid size and cumulative system costs. Furthermore, it is also crucial to consider incorporating capacity expansion into system sizing in order to meet the evolving demand. Additionally, resource efficiency plays a crucial role in the longevity of the system and should not be overlooked during the design and planning process. Therefore, it is imperative that sizing tools are readily available as open access resources, and are easily scalable to assess wider geographic ranges. This would greatly speed up the process of mini-grid planning, while also ensuring accuracy and resource efficiency .

3.3 Demand estimation in mini-grid modelling

Electricity demand exhibits fluctuations that vary by season and time of day (Rallapalli & Ghosh, 2012). Accurate forecasting of electricity demand is crucial for mini-grid developers and operators. The main distinction in their needs is the forecast horizon. Developers need to prioritise the long-term horizon while operators focus on medium to short-term forecasts. Electricity demand forecasting can be classified into three categories: long-term, medium-term, and short-term. Long-term forecasts are utilised for policy-making, system planning and resource allocation. Medium-term forecasts aid in the planning of yearly maintenance activities, storage management and energy demand management. Short-term forecasts assist in the daily operation of mini-grids and electrical networks to efficiently manage daily loads. In this chapter, we focus on demand estimations for the long term, considering mini-grid energy at the early planning stage.

Accurately estimating the electricity demand of rural communities is a major challenge in the design and sizing of mini-grid systems due to various factors, including data scarcity, uncertainty and the intricate socioeconomic dynamics of rural communities (Riva et al., 2018) (Van Ruijven et al., 2011). The scarcity of data makes it hard to know the patterns of electricity consumption and total energy needs that helps in finding the optimal size of components needed for a mini-grid. These complexities add an extra layer of difficulty to the already challenging task of accurately estimating electricity demand in rural communities, making it essential to carefully weigh the various factors before determining an estimate. A review by Bhattacharyya *et al.* (Bhattacharyya & Timilsina, 2010) distinguished two main approaches for demand estimation in developing economies - top-down and bottom-up. A top-down approach, such as econometric methods, makes use of aggregated data at a national and/or regional level, which is generally available for open access by Government agencies. These methods do not capture the complexities of the local contexts, such as the prevalent urban-rural divide, the rate of technology adoption, and energy transitions from traditional fuels (e.g. biomass). On the other hand, bottom-up methods, for example, based on comprehensive household energy use surveys, allow for a more granular and realistic representation of local demand, but they require substantial data availability to capture the contextual situations in different regions. Therefore, it is important to consider the pros and cons of each approach when estimating electricity demand from a rural community, as both approaches have their own strengths and limitations.

Both researchers and mini-grid developers survey early adopters in a target community to forecast long-term demand because household energy surveys closely represent the energy needs in the rural community (Blodgett, Dauenhauer, Louie, & Kickham, 2017) (GIZ, 2016). Moreover, surveying early adopters allows for the gathering of additional information, such as the choice of appliances bought, the ability to pay for energy services and expectations for energy access. Previous research has revealed a lack of consistency between survey data and actual measurements or other data-based proxy methods used to calculate energy access demand (Louie & Dauenhauer, 2016)(Hartvigsson & Ahlgren, 2018). Hartvigsson *et al.* (Hartvigsson & Ahlgren, 2018) compared interview-based load estimations with actual monitored appliance-based load profiles in Tanzania and found that the interview-based estimations resulted in overestimations of 48-117%. Blodgett *et al.* (Blodgett et al., 2017) analysed energy-use survey data from 176 households in Kenya and found that an evaluation of its suitability rarely accompanies technical design data after installation. Although the use of surveys and interviews can be beneficial in gaining a basic understanding of energy access, it is not always accurate in estimating long-term energy demand growth (Blodgett et al., 2017) (Stevanato et al., 2020). Therefore, survey data needs to be combined with other methods, such as assuming a certain level of growth in energy demand over a given period for medium-term or long-term energy demand forecasts. This could be based on growth patterns observed in the past, national plans, or global energy access targets, allowing for a more accurate and comprehensive assessment of long-term energy demand. Applying these trends and scenarios of demand growth can help reduce forecast uncertainty, but this typically necessitates the utilisation of complex mathematical optimisation techniques (Riva et al., 2018). To understand energy access and demand growth comprehensively, a combination of both survey data and other methods should be employed. More details on energy demand modelling are discussed in chapter 4, section 4.2.

3.4 Mini-grid sizing

To ensure reliable and affordable energy access via mini-grids, it is crucial to size the components of the system optimally because it has a direct impact on the total cost of the system and the investments required, which in turn determines not only the price of the electricity produced but also the quality of service over its lifetime(GIZ, 2016)(Fioriti et al., 2018)(Akbas et al., 2022). Over-sizing or under-sizing a mini-grid system can have negative consequences as well. If the mini-grid is oversized, it can result in increased investment and higher operational costs, as well as lower efficiency (Riva, Colombo, & Piccardi, 2019) (GIZ, 2016). While under-sizing mini-grids may lead to unreliable supply, blackouts, and reduced service quality, which can lead to customer dissatisfaction (Aklin, Cheng, Urpelainen, Ganesan, & Jain, 2016) and higher operation and maintenance costs (GIZ, 2016). Thus, the sizing of mini-grid systems implies a cost-reliability trade-off, which might be influenced by estimated demand and/or the desired reliability of the system. For example, Louie *et al.* (Louie & Dauenhauer, 2016) explored the incremental cost of improving system reliability from 99% to nearly 100% for off-grid photovoltaic (PV) systems in Malawi and found that this increases the cost by an average of 46%. Hence, it is important to size the individual components of mini-grids optimally, and this can be achieved by incorporating technological and socioeconomic complexities into mini-grid planning (Bandi et al., 2022). In this chapter, we focus on solar mini-grids exclusively; however, the modelling tool can, in principle, be generalised to include other sources.

Each tool discussed in table 2 exhibits a unique set of advantages over the others that can be potentially distinguished by its consideration of the energy demand model and optimisation objectives. The focus of our research has centred around two specific aspects: the ability to account for the dynamic nature of demand in community-oriented mini-grids and a sizing optimisation which can consider a capacity expansion approach. The majority of the modelling tools discussed for mini-grid sizing involve static or repetitive demand, with only a few accounting for the likelihood of electricity demand growth over time. Van Ruijven et al.(Van Ruijven et al., 2011) considered demand growth by creating a bottom-up demand model that requires historical information, while Riva *et al.*(Riva, Gardumi, Tognollo, & Colombo, 2019) employed endogenous factors such as household income to *soft-link* energy demand growth and constructed multi-year load profiles. The usage of these static profiles or elementary growth models may lead to a holistic assessment of the energy needs of a community. CLOVER, however, enables the accounting for demand evolution over granular periods and allows for tuning the rate of individual appliance diffusion, potentially representing realistic scenarios of demand growth and thereby enabling the accurate sizing of mini-grids. CLOVER has a few useful features and advantages over other tools. For instance, we can choose between two different optimisation objective functions: reducing costs and/or GHG emissions of mini-grids over their entire lifetime. Within CLOVER, we can design future electricity demand growth scenarios and test capacity expansion in sizing optimisation to adapt to the growing demand, which is explored in depth in this study. It also enables the assessment of system performance over a granular period (Sandwell, 2017) (Sandwell, Wheeler, & Nelson, 2017)[15].

Moreover, the existing literature on mini-grid design has primarily relied on static forecasting of generation and storage capacity. There has been limited research on the sizing of systems to accommodate future capacity expansion. According to Allee *et al.* (Allee, Williams, Davis, & Jaramillo, 2021a), static forecasting involves one-off system sizing of individual components of mini-grids and calculates one-time investment on mini-grids; in other words, single investments for one-off installation. To overcome this limitation, the authors recommended that future research should explore the techno-economic feasibility of the modular mini-grid design. Stevanato *et al.*(Stevanato et al., 2020) have similarly emphasised the importance of considering planned expansions over two years*. Their study resulted in modularly designed mini-grids that performed better economically than relying on a single investment decision step. Hartvigsson *et al.*(Hartvigsson, Stadler, & Cardoso, 2020) explored the use of system dynamics in conjunction with the DER-CAM model to incorporate capacity expansion in mini-grids in Tanzania. The authors demonstrated the cost-effectiveness and efficiency of capacity expansion in mini-grids. To this end, we implemented CLOVER simulations to optimise the size of solar mini-grids and investigate two different sizing approaches, one-off installation of mini-grid versus a two-stage approach with re-sizing of PV and storage after five years.

In addition to considering the demand growth and sizing optimisation to assess the possibility of capacity expansion, CLOVER allows investigation into system performance over its lifetime. This is rarely examined thoroughly at the planning stage using the models discussed above. To this end, in this chapter, we aim to address the following research questions:

- What is the initial electricity demand of a typical un-electrified rural community (100 households) in India and how could this grow over time?

- How should mini-grid components be optimally sized to adapt to the growing electricity demands of rural communities in India?

- What are the benefits of two sizing approaches, i.e., one-off sizing versus capacity expansion after 5 years?

[15] We also had advice available from the developers of the code during the analysis as this research work was a collaborative approach

- What are the system performance and quality of supply characteristics of cost-optimised mini-grids over their lifetime?

In this chapter, we explore the electricity demand growth in recently electrified rural communities in India and its impact on sizing solar mini-grids. Using Shahapur as a case study, we determine cost-optimal mini-grid sizing to meet projected demand growth by 2030. The study offers valuable insights for designing and deploying solar PV mini-grids in rural India, investigating the effectiveness of incremental sizing for economically sustainable energy solutions. The rest of this chapter is organised as follows: section 3.5 describes a pilot study conducted in rural India where solar mini-grid is installed recently. The methodology implemented in CLOVER is explained in section 3.6. This is followed by the Results, showing how demand growth scenarios and other parameters impact mini-grid system sizing, as described in section 3.7. Then, we explain the efficacy of this strategy to size mini-grid systems in Discussion section 3.8. We close the chapter by reiterating our main findings in the Conclusion, in section 3.9, with a summary of future research directions and suggestions on sizing strategies for mini-grid developers, practitioners and researchers.

3.5 Rural household energy survey: a pilot study

In May-June 2019, we conducted a pilot study of five solar mini-grids in the state of Maharashtra India. This case study examines the demographic and energy access patterns in remote hamlets inhabited by marginalised communities[16] living below the poverty Line. These remote settlements typically comprise 30-50 households in each hamlet, and agriculture is the primary source of income, supplemented by labour work and natural resources. For this pilot study, we partnered with the organisation Gram Oorja [17]. Gram Oorja has built and installed more than 100 mini-grids in various rural and remote locations across India. Gram Oorja follows a partly funded business model for solar mini-grid installations, where the upfront capital costs are covered by Corporate Social Responsibility (CSR) grants and donations, while the recurrent operations and maintenance costs are met through regular billing arising from each household's electricity consumption. Bills are collected on a monthly basis, and revenues are deposited into a village bank account and managed by a democratically chosen village energy committee. A combination of a

[16] The population in three of the hamlets in Shahapur district had to migrate and settle here when the Vaitarna and Tansa dams were being built in the late 1950s

[17] https://gramoorja.in/

fixed fee and a per-unit tariff is charged to households with solar mini-grid connections. A one-off connection fee is also collected at the beginning from each household to ensure users' longer-term commitment. The cost of public lighting is included in the fixed monthly fee, and villagers also make in-kind contributions in the form of labour for construction, materials for installation, or land for the plant and control room. Gram Oorja works with local NGOs and trusts to implement energy access projects and promote the holistic, sustainable development of these communities.

We conducted 70 energy use surveys (Questionnaire available. see Appendix A.3.1) at five different locations, including Darewadi, Vanvasipada, Talwada, Vadpada, and Shiswadi, in May-June 2019[18]. Darewadi is located in the Junnar district and has been utilising a mini-grid system since 2012. This is the first mini-grid Gram Oorja installed, while the mini-grid in Vanvasipada was installed in May 2016. A cluster of three hamlets, Talwada, Vadpada and Shishwali, in the Shahapur district was provided electricity access through solar mini-grids in March 2018. These five mini-grids were powered by monocrystalline silicon photovoltaic panels, with total capacities ranging from 2.8-14.4 kWp, and were equipped with lead-acid batteries for energy storage. The mini-grids operated in alternating current mode. Brief technical specifications for each mini-grid are provided in Table 3. Each hamlet had a unique configuration that was tailored to meet the specific needs and given the availability of the space. The systems were designed to ensure a reliable power supply, and regular tariff collection generated a stable and constant stream of revenue that could support the relatively high maintenance costs of the mini-grids.

Name of Place	Households (Surveyed)	PV Capacity (kWp)	Battery capacity
Darewadi	38 (5)	9.4	48V, 750Ah
Talwada	58 (16)	14.4	48V, 1020Ah
Shiswali	41 (25)	9.9	48V, 750Ah
Vadpada	12 (9)	2.8	48V, 300Ah
Vanvasipada	41 (10)	8.8	48V, 750Ah

Table 3: Technical specifications of five hamlets with solar mini-grids

The primary objective of the survey questionnaire was to evaluate energy demand after one year of access and to gain insight into the energy needs of the community connected to the solar mini-grid. We gathered information on demographics, appliance

[18]The ethics application and approval letter for this pilot study are given in Appendix A.3.2

Figure 3.2: Electricity access in rural India

ownership and time of use of appliances from 70 randomly sampled households in the five communities. For ease of comparison, we normalised the total number of households in each community to 100 for the estimation of long-term load profiles. For further analysis, we focused on survey responses (n=50) from three hamlets located in the Shahapur district (Talwada, Vadapad, and Shiswali), as these hamlets had received energy access in the same month (March 2018), 15 months prior to the surveys conducted. The survey responses revealed growth in average appliance ownership, usage hours for each appliance and nominal power rating, as shown in Table 4. Some participants responded to open-ended questions saying refrigerators were their aspiring energy need. Inconsistencies were observed in the ownership and usage of other types of appliances, such as irons or mixer grinders [19]. Due to the difficulty in accurately calibrating the usage hours of these appliances, only the appliances listed in Table 4 were considered for further calculations.

Figure 3.3 presents meter data from Talwada. It captures the effect of the three seasons in India - summer, winter, and monsoon - on the hamlet's energy use. Typically, consumption peaks in the summer months of April and May and is low in the winter months of December and January. The low consumption in March is due to it being the first month of energy access. By January and February 2019, a growth in appliances was

[19] Only two households responded with iron and mixer grinder ownership

Appliance Type	Avg. Ownership (2018)	Avg. Ownership (2019)	Nominal Power (W)	Usage hours (Summer)	Usage hours (Winter)
LED bulb	3	3.68	6	4.6	5
Television	0	0.3	20	4	4
Mobile phone	1	1.36	5	4	4
Fan	0	0.36	40	6	0-1
Radio	0	0.04	5	4	4
Refrigerator	0	0	220	2	1.8

Table 4: Appliance details

observed. Figure 3.4 shows the increment in median usage of electricity[20] from 2018 to 2019 to be 33% in Talwada. Guided by this meter and billing data, we attempted to design three electricity growth scenarios in a prospective (or hypothetical) hamlet that gains access to electricity via a solar mini-grid.

3.5.1 Electricity Demand growth scenarios

Three scenarios for electricity demand were analysed to assess their effects on the sizing, performance, and costs of mini-grid systems in rural India.

- **Baseline scenario**: The baseline demand is considered as the minimum electricity consumption level in a household upon receiving access to a mini-grid for the first time. Gram Oorja provided a demand stimulus package to all customers, including 4 LED bulbs and one plug point to charge mobile phones, along with the connection to the mini-grid. With this, lighting and mobile charging defined the baseline electricity demand for a prospective hamlet. This Baseline scenario aligns with the definition of Tier 1 electricity access, as defined by the International Energy Agency (IEA) (IEA, 2020) and the World Bank's Multi-Tier Framework (MTF) (Bhatia & Angelou, 2015), which is 76 Wh per household per day. The usage profiles were derived from the time of use information of each appliance in the survey responses. An average usage time per appliance was used to create a representative profile for the

[20] Note to self - Median is a better metric than mean in identifying patterns or trends in electricity usage that captures the central tendencies in the data distributions

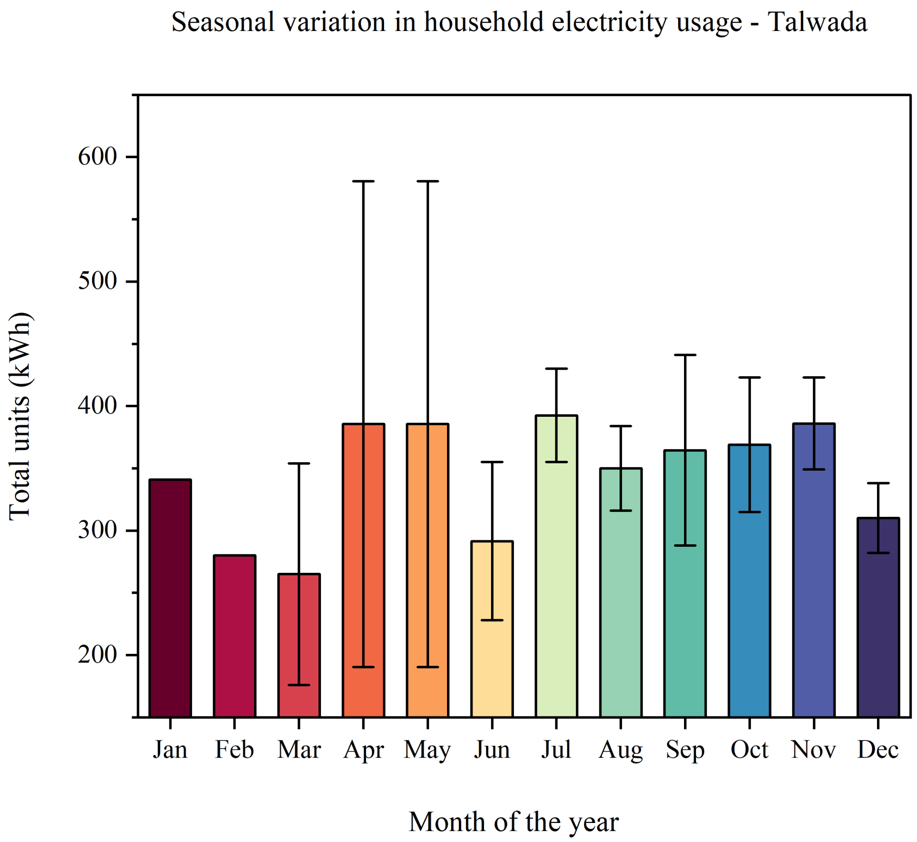


Figure 3.3: *Seasonality observed in monthly billing data from Talwada between 2018 and 2019*

community[21].

- **Adaptive growth scenario**: To estimate growing electricity demand, we employed the Bass model (Bass, 1969) for innovation diffusion as described in Equation 1, to define demand growth as a function of appliance growth. This model enabled us to create adoption profiles of each appliance in each community over the ten-year period of mini-grid access analysed.

$$F(t) = \frac{1 - \exp\left(-(p+q)t\right.}{1 + (\frac{q}{p})\exp\left(-(p+q)t\right.} \tag{1}$$

Equation 1 calculates the rate of appliance purchase, F(t), based on the number of early adopters, p, and buyers who imitate their peers, q. We made an informed guess of the values of p and q for individual appliances based on field observations on households' purchase decisions and appliance ownership inputs from surveys. We also use different growth rates for each appliance, as the adoption of large appliances

[21]Household sample size, n=50

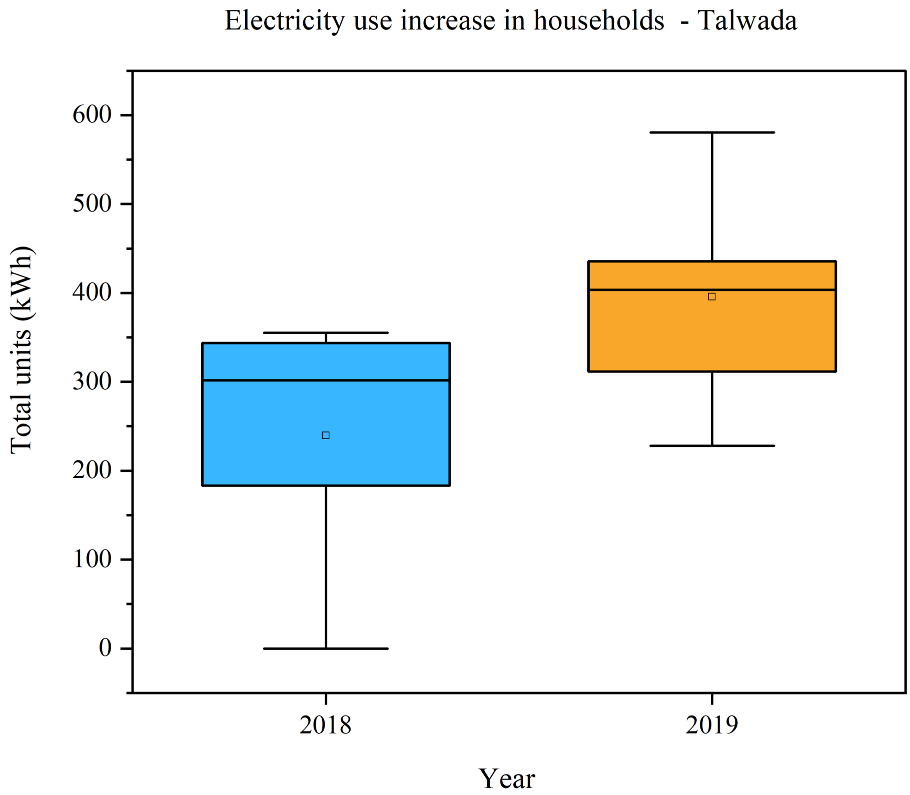


Figure 3.4: *Total growth in electricity usage calculated based on monthly bills between March 2018 and December 2019*

such as refrigerators is slower than that of appliances like TVs or fans. More details on the coefficient values are given in Appendix A.3.3.

- **Target Scenario**: Following IEA guidance on energy access and the SDG 7 target by 2030(SE4all, n.d.), we constructed a scenario for generalised residential electricity consumption in rural households for the ten-year period, hypothesising that the demand is immediately high and static throughout this period. This scenario reflects a conservative level of demand designed to meet electricity needs in rural Indian communities by 2030. The demand in this scenario (779 Wh per household per day) is equivalent to the upper end of Tier 2 of the World Bank's Multi-tier framework (Bhatia & Angelou, 2015). In other words, if households living below the poverty line receive energy access to tier 1, the Target scenario hypothesises that all households should transition to tier 2 (upper) within 10 years or by 2030.

Following these criteria for growth, we generated stochastic load profiles for a prospective community of 100 households at an hourly resolution for a ten-year period [22]. The Baseline load and Target load set a lower and upper bound of consumption levels, respectively, whereas the adaptive scenario load profile attempts to express a more realistic representation of latent demand from an unelectrified or recently electrified community. Evidently, the rate of growth can differ greatly among communities; as such, we performed a sensitivity analysis by varying the appliance adoption coefficients for each appliance and calculated the estimated 10-year load profiles for different rates of adoption, including slow, medium and fast. A community scale load profile was generated using a bottom-up method, as discussed in the next section. This method incorporated daily utilisation profiles obtained from time-use data and supplemented with growth trends derived from appliance ownership data.

3.5.2 Stochastic load profiles

We calculated load profiles by analysing survey data according to the following steps.

1. Consider the number of appliances in the community, and the times of usage, from surveys.
2. Produce a utilisation profile for each appliance.
3. Stochastically generate a profile of the number of appliances that are in use at any given time.
4. Calculate the load profile for each appliance.
5. Calculate the total load for all appliances in the community.

The number of each appliance of a given type in use at a given time in the community is represented by $N_{\mathrm{i}}(t)$. This can be derived from the average ownership found from the surveys and the community size and can incorporate growth in ownership rates. The utilisation profile of an appliance is defined to be the probability that it is in use and is given by $U_{\mathrm{i}} \, \epsilon \, [0, 1]$. The utilisation profile represents the typical average usage of each appliance of a given type across the community, assuming each device is used independently and can vary between days and months of the year. The number of appliances of each type used by the community is given by ${N_{\mathrm{i}}}^{\mathrm{T}}(t)$. This is generated stochastically for each time-step of the simulation period, from values drawn at random from a binomial distribution given by

[22] 10-year period was chosen for the target scenario being capped at 2030

$B_{\mathrm{i}}(t)(N_{\mathrm{i}}(t), U_{\mathrm{i}}(t))$. From the number of appliances in use at a given time and the nominal power of each appliance type $W_{\mathrm{i}}(t)$), the total load $E_{\mathrm{i}}(t)$) resultant from each appliance type is given by:

$$E_{\mathrm{i}}(t) = W_{\mathrm{i}}(t) * N_{\mathrm{i}}{}^{\mathrm{T}}(t) \tag{2}$$

Thus, the total load of the community across all appliance types, $E^{\mathrm{T}}(t)$, is given by:

$$E^{\mathrm{T}}(t) = \sum_{i} E_{\mathrm{i}}(t) \tag{3}$$

Tables 15, 16 and 16 in Appendix A.3.3 show the inputs for each demand growth scenario to calculate $N_{\mathrm{i}}(t)$. The rate of diffusion of each appliance plays a major role in determining the number of appliances owned by the community and, consequently, the total community load profile. The values of the coefficients innovation (p) and imitation (q), as stated in Equation 1, ultimately influence the rate at which the community adopts each appliance. This rate can be influenced by a variety of factors, such as the cost of appliances (Richmond, Agrawal, & Urpelainen, 2020) and the level of education as well as gender roles(Dhanaraj, Mahambare, & Munjal, 2018). In practical terms, these values represent households' appliance purchase decisions over time, which is hard to predict. For the baseline load profile, we considered appliances that were part of the demand stimulus package provided by Gram Oorja and growth in appliance adoption was kept at zero. In the adaptive and target scenarios, a refrigerator was included as an additional appliance that households may acquire in the future. The usage profile of refrigerators was taken into account based on guidance from the literature (UK Aid, 2019) and smart meter data recorded for the refrigerator use by Prayas group (Prayas, 2021). We also considered seasonality by varying the hours of usage of lights and cooling devices between the summer and winter months, as summarised in Table 4[23]. Our current study only focuses on domestic load evolution by considering load growth as a function of the growth in appliance ownership within households rather than an increase in the number of households connected to the mini-grid, an additional number of households driven by population growth/migration or appliances used for income generation. In the following section, the resultant stochastic load profiles for the community scale are presented and discussed in detail.

[23]Some assumptions on this are made based field observations and based on conversations with community - the season at the time of survey was peak summer

Demand growth scenarios will allow developers and practitioners to account for realistic growth rates comprehensively by considering the S-curve adoption trend of appliances and incorporating these into optimisation tools to improve system sizing. Additionally, to increase the accuracy of future demand estimates, it is also preferential to consider specific factors such as population growth, economic development (for example, the ownership of productive appliances and the revenue derived from their use) or changes in energy policies that could affect adoption rates of energy services. Furthermore, data from previously electrified villages can be used to inform grounded assumptions about future demand growth. Ultimately, this will reduce uncertainties surrounding system sizing and the costs associated with off-grid electrification projects.

3.6 CLOVER optimisation for sizing mini-grid

In this section, we describe the methodology used to size a mini-grid using CLOVER optimisation. The diagrammatic representation presented in Figure 3.5 consists of three interconnected modules: a load profile (demand growth), an optimisation for sizing, and system simulations. The load profile focuses on expected loads derived from survey data and projected for a ten-year period. These load profiles are then linked with the Optimisation module for sizing, which requires boundary conditions in terms of the desired level of reliability and techno-economic data for generation and storage. The third module is composed of two levels: one considering technical inputs for storage system specifications and the other extracting real-time meteorological data required for renewable generation, such as solar, to extract system performance. These modules take two distinct sets of inputs: (a) inputs specified by the users (represented by solid arrows) and (b) inputs derived from energy system simulations (dashed arrows). The user-specified inputs encompass a range of parameters, including the financial and technical characteristics of the system. Full aggregated and anonymised data and modelling techniques used in this study are openly accessible at (https://github.com/rjsayani/Clover-analysis).

3.6.1 Demand growth scenarios for sizing approach

We implemented CLOVER simulations to investigate a community load profile of a total of 100 households connected to a mini-grid for three different demand growth scenarios, as discussed in chapter 2. To characterise current and future electricity demand, baseline and target demand scenarios set the lower and upper bound of the mini-grid size. Demand is considered static in nature in both these scenarios and thus this approach is modelled as a

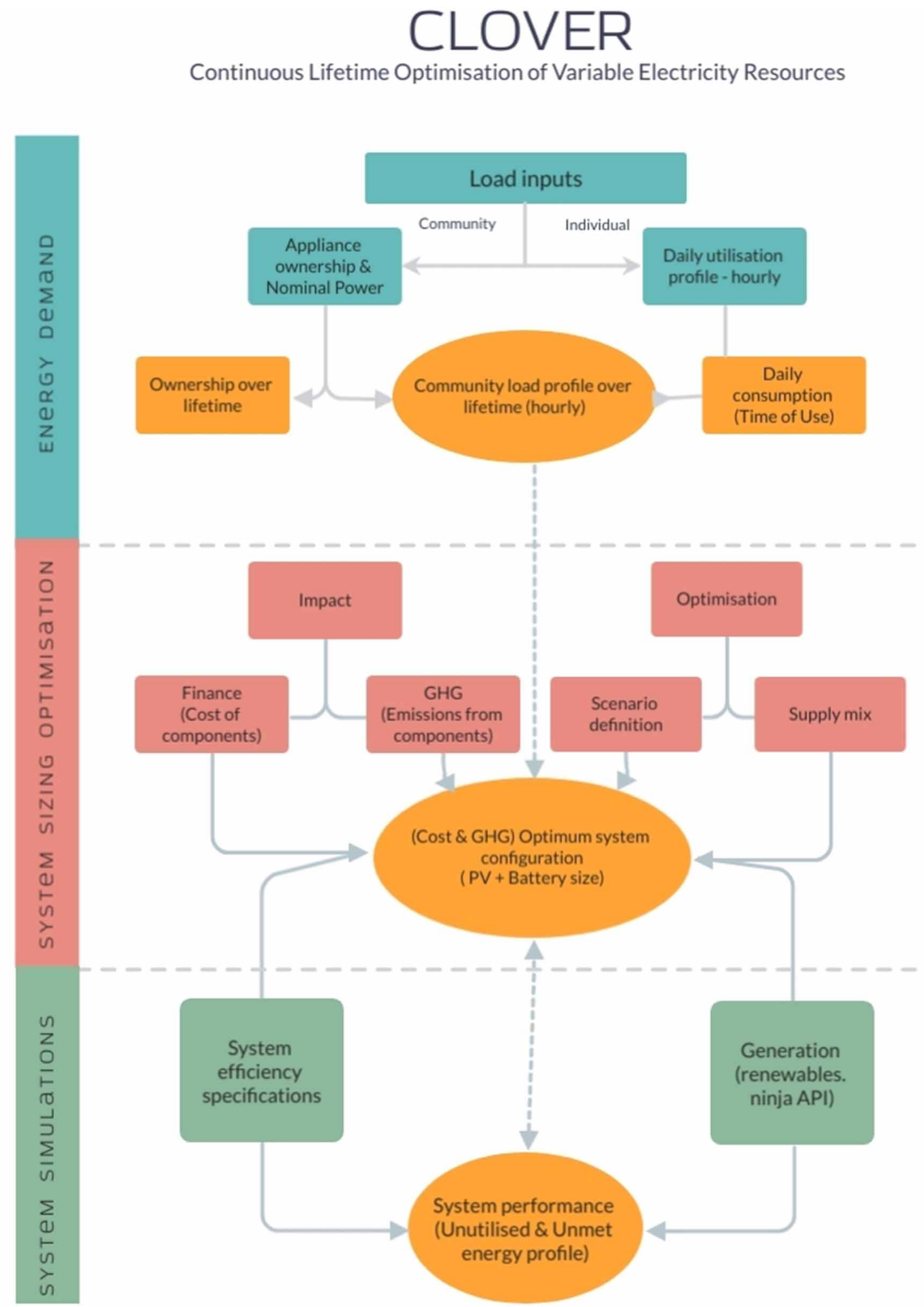


Figure 3.5: *Overview of CLOVER model adapted from (Sandwell* et al *2017a). CLOVER modules are divided into blocks: (a) energy demand (b) system sizing optimisation, and (c) system simulation.*

one-off installation (referred as one-step sizing in this chapter), while the adaptive scenario involves resizing the system after five-years, allowing for a capacity expansion (referred as multi-step sizing) based on logistic demand growth. One-step sizing optimisation finds the cost-optimum system prior to mini-grid installation, considering a system to be 'sufficient' to meet the electricity demand over its entire ten-year lifetime. Conversely, multi-step optimisation is an incremental sizing approach which allows for the implementation of the 'sufficiency' criteria after five years of mini-grid operation, to resize the system to meet an increased demand. To assess the implications of each demand growth scenario on total system costs and performance we tested them for respective sizing approaches as shown in Table 5.

Scenario name	**Location**	**Sizing approach**	**Demand growth**	**Iteration period (years)**
BS-SH	Shahapur	One-step	Static	10
Adapt-SH-mstep	Shahapur	Multi-step	S curve	5
Adapt-SH-onestep	Shahapur	One-step	S curve	10
Target	Generic	One-step	Static	10

Table 5: Scenario specifications

3.6.2 Optimisation for sizing

Clover utilises a heuristic search algorithm and sufficiency criteria to identify the least cost systems. The algorithm works by following single-line optimisation in a two-dimensional search space consisting of PV and battery sizes to find the minimum size of a system that is required to meet the estimated demand. This process is illustrated in figure 3. Once the minimum size is found, a sufficiency criterion is employed to define the permissible threshold for supply reliability. This is then optimised to locate the least-cost system available. (Sandwell, 2017)(Sandwell, Ekins-Daukes, & Nelson, 2017). The permissible threshold for blackouts can be defined as a proportion of the time in a day that a blackout is allowed, i.e. when 95 % is required, 1.2 hours of blackouts in a 24-hour period is the permissible threshold. The optimum system size is that which must meet this sufficiency criterion i.e. the minimum reliability specified and for which the Levelised Cost of Use Electricity(LCUE) is the lowest. These two metrics are described in detail in the next section.

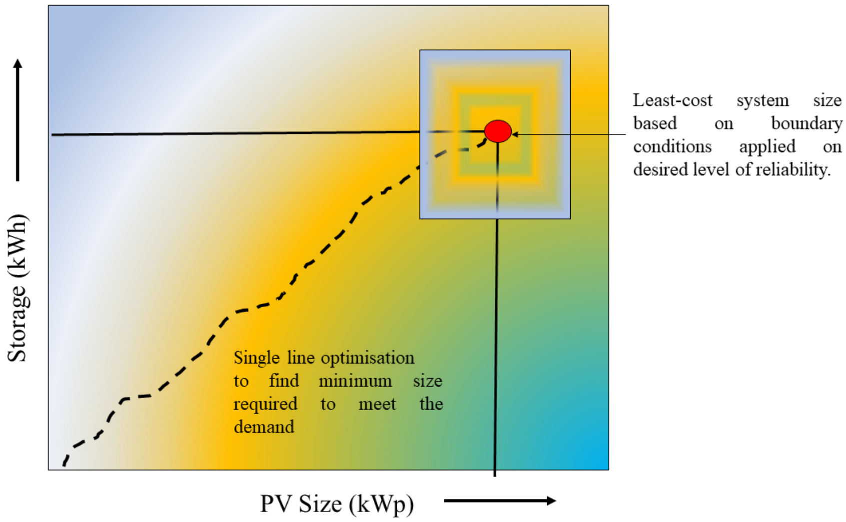


Figure 3.6: *Illustration of heuristic search optimisation for finding cost-optimal system size*

To find optimum system components, several techno-economic inputs are needed, which are system specific. This includes technical inputs such as battery C-rate and conversion efficiency as well as finance inputs, including equipment costs, operation and maintenance (O&M) costs, discount rates and cost reductions of PV and battery over time. GHG inputs are composed of embedded emissions from various components of the system and those offset from substituting fuels such as kerosene. We generated inputs on demand and energy supply balance from energy system simulations in CLOVER. Further details of the optimisation method can be found in (Sandwell, Ekins-Daukes, & Nelson, 2017). All system-related techno-economic inputs considered in this study are listed in table 5.

3.6.3 Metrics to assess mini-grids

In order to perform a comprehensive analysis of costs, we incorporated two financial indicators computed from the CLOVER optimisation. The first metric, cumulative system costs ($), includes both the equipment costs and operational and maintenance (O&M) costs over the system's lifetime. The second metric, LCUE ($ per kWh), differs from the conventional levelised cost of electricity (LCOE) in that it explicitly takes into account the levelised cost per unit of electricity consumed by the community, rather than the electricity generated by the system as a whole. This distinction is particularly important when evaluating systems that allow for consideration of different reliability levels. As presented in Sandwell *et al.*(Sandwell, Ekins-Daukes, & Nelson, 2017), the LCUE is given by:

$$LCUE = \frac{\sum_{n=1}^{N} \frac{I_n + M_n + F_n}{(1+r)^n}}{\sum_{n=1}^{N} \frac{E_n}{(1+r)^n}} \tag{4}$$

LCUE is the discounted sum of all capital investment I_n, O&M costs M_n, and fuel costs F_n (which is zero in this case) over each year, divided by the sum of the discounted energy E_n that is used (demand that is met) in each year. r_n is the discount rate for each year and N is 10 in this study.

In addition to LCUE, the reliability of the system was taken into account when finding a cost-optimal mini-grid size. A threshold for blackouts (95 % reliability) was set, which denotes the level of electricity demand that must be met per day. This reliability threshold can have a considerable influence on the total size of the mini-grid, particularly on storage units. Further information regarding the optimisation process in CLOVER can be found in Baranda Alphonso *et al.*(Baranda, Sandwell, & Nelson, 2021). After the cost-optimal system size is obtained for each scenario, we assessed the system performance at an hourly resolution over the system's lifetime using energy system simulations, as described in the next section.

3.6.4 Energy system simulations

Energy system simulation calculates an energy balance E_B in mini-grids on an hourly basis. In this simulation, first, the solar power generation profile is derived for the ten-year period based on historical solar irradiance data taken from MERRA2 using the renewables.ninja API (Pfenninger & Staffell, 2016). Then, the energy balance E_B is calculated by subtracting total energy demand E_D (see Equation 2.6) from the solar energy generated for a specified system defined by E_G.

$$E_B(t) = E_G(t) - E_D(t) \tag{5}$$

The energy balance also considers the storage profile, which is calculated based on:

$$\begin{cases} E_s(t) = S(C_{in}) & \text{for } E_B(t) > S(C_{out}) \\ E_s(t) = (-S(C_{in}) & \text{for } E_B(t) < -S(C_{out}) \end{cases} \tag{6}$$

In this equation, the storage energy flow E_s is calculated based on the storage capacity S and the C rates of lead-acid batteries, which is denoted as Cin and Cout. The first case represents the situation where the energy in the battery E_B is greater than the storage capacity minus the C_{out} rate, while the second case represents the opposite scenario where the energy in the battery is less than the negative of the storage capacity multiplied by the C_{in} rate [24]. Correspondingly, the simulation ensures storage energy flow for a set bound of capacity for a given threshold of reliability in the energy balance; any surplus energy is then considered as unutilised. This unutilised energy, as well as the unmet energy calculated from the energy balance, is then evaluated to assess the performance of the system in both one-step and multi-step adaptive scenarios. Energy simulation uses technical specifications of the system, such as C-rates of lead-acid batteries, state of charge, depth of charge, conversion efficiency, battery life cycles etc. The inputs considered in the calculations are given in Table 6 with related references.

Table 6: Technical inputs considered in CLOVER optimisation

Technical parameters	**Value**	**Units**	**Notes**
PV azimuth	180	Degrees	From north
PV tilt angle	29		From horizontal
Battery depth of discharge	40	%	Observation
Battery C-rate PV lifetime	0.33 20	— Years	Agarwal et al (2013)(N. Agarwal, Kumar, & Varun, 2013) IRENA (2020, 2021) (IRENA, 2021)
Battery lifetime	1000	Cycles	Institute for Transformative Technologies (2017)(Institute for Transformative Technologies, 2017)
Battery conversion efficiency	95	%	Sen and Bhattacharyya (2014)(Sen & Bhattacharyya, 2014b)
Financial parameters	**Value**	**Units**	**Notes**
PV module	372	\$ per kW	Loom Solar (2022)[25]
PV module O&M	7.45	\$ per kW	2 % capital costs (Chambon et al 2020)(Chambon, Karia, Sandwell, & Hallett, 2020)
PV cost decrease	10	%	IRENA (2020, 2021)(IRENA, 2021)
Battery storage (Lead-acid)	150	\$ per kWh	Institute for Transformative Technologies (2017)(Institute for Transformative Technologies, 2017)
Battery storage O&M	1.50	\$ kWh per annum	1% of capital costs; own assumption
Storage cost decrease	4	%	Schmidt et al (2017) (Schmidt et al., 2017)
Connection cost	30	\$/Household	Field observations
Misc Cost	100	\$ per kW	Includes logistics, installation and maintenance costs not covered above. Values are based on assumptions.
Discount rate	4.25	% p.a.	As of October 2021 (FRED 2021)(FRED, 2021)

[24]further description of the storage energy calculations available in Beath *et al.*(Beath et al., 2021)

Parameters	Low value	Central value	High value
Demand growth rate	Slow growth rate (S-curve)	Medium growth rate (S-curve)	Fast growth rate (S-curve)
Logistics cost	Misc. costs: 50 $ per kW	Misc. costs: 100 $ per kW	Misc. costs: 200 $ per kW
Iteration period	5 steps, 2 years (Short iteration period)	2 steps, 5 years (multi-step)	1 step, 10 years (one-step) (Longer iteration period)
Blackouts	99% (Less blackouts)	95% blackouts	90% (More blackouts)
PV - battery cost (rate per year)	PV cost decrease: 20% Battery cost decrease: 8% (Lower cost)	PV cost decrease: 10% Battery cost decrease: 4%	PV cost decrease: 5% Battery cost decrease: 2% (Higher cost)
PV - battery degradation (lifetime)	PV lifetime: 10 years Battery lifecycles: 1000 Battery lifetime loss = 40% (Lower system lifetime, more degradation)	PV lifetime: 20 years Battery lifecycles: 1000 Battery lifetime loss = 20%	PV lifetime: 30 years Battery cycle lifetime (cycles): 1000 Battery lifetime loss = 10% (Higher system lifetime, less degradation)
Discount Rate	Discount rate lower 3.35%	Discount rate current 4.25% (Oct 2021)	Discount rate higher 5.15%

Table 7: Description of sensitivity analysis parameter variations

3.6.5 Sensitivity analysis

Lastly, we conducted a sensitivity analysis to understand the impact of seven parameters on system costs in each sizing approach. These parameters are demand growth rate, logistics costs, iteration period (or system re-sizing frequency), the probability of blackouts, solar PV and battery cost, and degradation,and discount rate (as presented in Table 7). The ratio of system cost in the multi-step approach to system costs in the one-step approach indicates the cost-saving potential of modular sizing with corresponding parametric values. We then examined unutilised and unmet energy in depth for one-step and multi-step adaptive scenarios to reassess the resource efficiency of multi-step sizing.

3.7 Results

In this section, we present four different temporal variations of load profile generated for a community of 100 households. These include: i) the daily average load curve for each scenario, ii) the monthly average load profiles to demonstrate seasonality, iii) the S-shaped growth curve over a ten-year period to examine adaptive growth, and iv) the impact of growth rates on the monthly average load, through sensitivity analysis. As seen in Figure 3.7, the peak load occurs during the evening hours in all scenarios. This peak is primarily caused by the increased use of lights and TVs, as well as the use of ceiling fans and refrigerators during the summer months. The load curves for both the baseline and target scenarios remain static throughout the ten years, as these scenarios depict the lowest and highest levels of demand taken into consideration in the study.

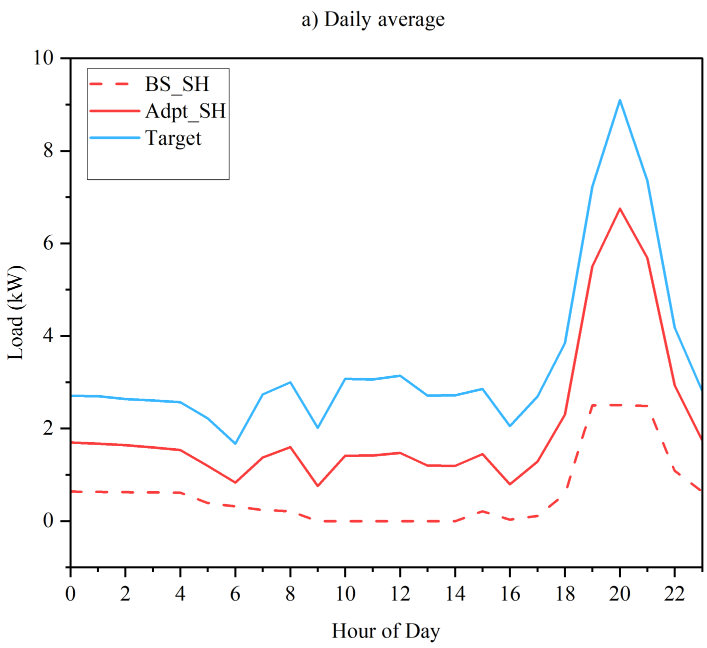


Figure 3.7: *Daily load profiles in three scenarios*

In constructing the stochastic load profile, the effect of seasonality on appliance usages, such as refrigerators and fans, which are influenced by ambient temperature, was taken into account. As seen in Figure 3.8, where the seasonal variation in the load is evident by comparing the winter (November-January) and summer months (April-June), in which refrigerators and fans account for more than half of the total demand. While seasonal variations were also considered in the baseline and target loads, the variations are more visible in the target load than the baseline due to ownership of the refrigerator. Similarly, usage of high-power consuming appliances such as refrigerators, fans, and TVs increases over time, and the consumption level of the adaptive scenario is similar to the target, shown by the S-curve yearly growth in Figure 3.9. These load curves indicate that the total load varies significantly with changes in appliance ownership.

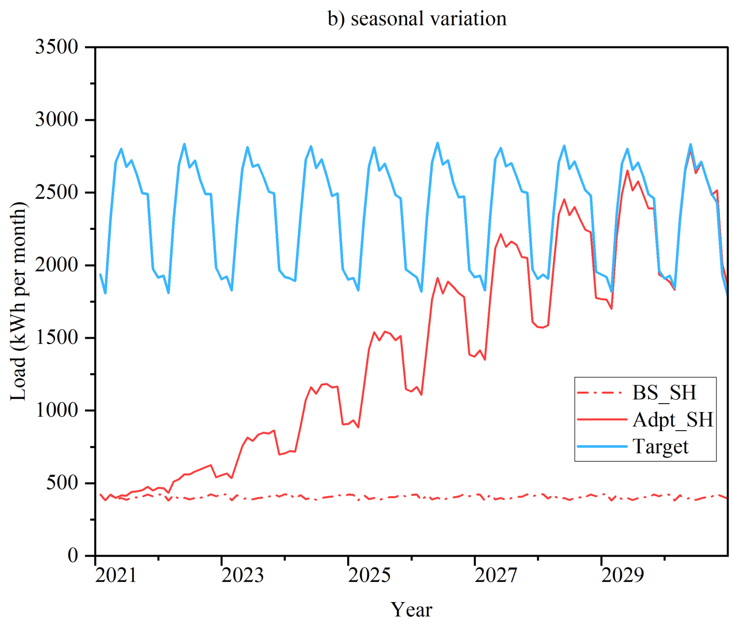


Figure 3.8: *Seasonality in three scenarios*

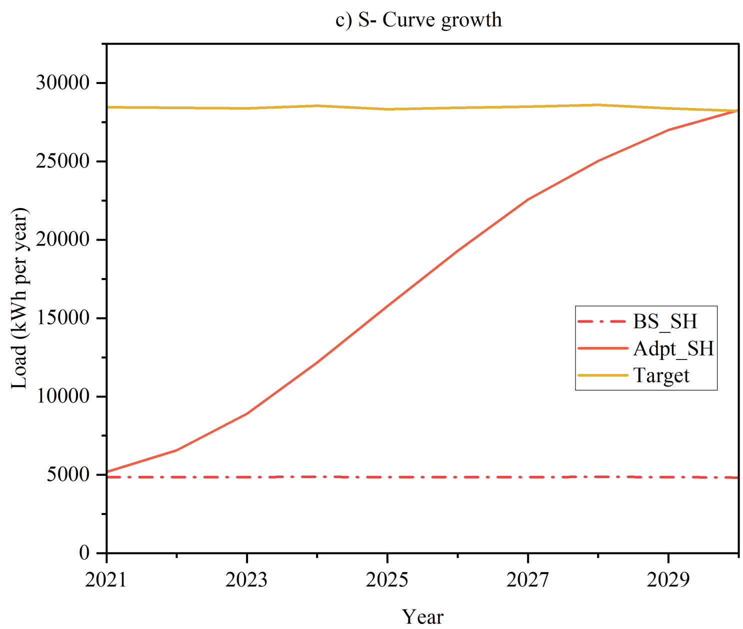


Figure 3.9: *S-shape growth over lifecycle*

Figure 3.10 illustrates the load evolution over a ten-year period at slow, medium and fast rates of appliance adoption. As per our demand characterisation, large cooling appliances such as refrigerators are bought less frequently than others in rural India, due primarily to their cost, whereas mobile phones and lights are adopted immediately upon

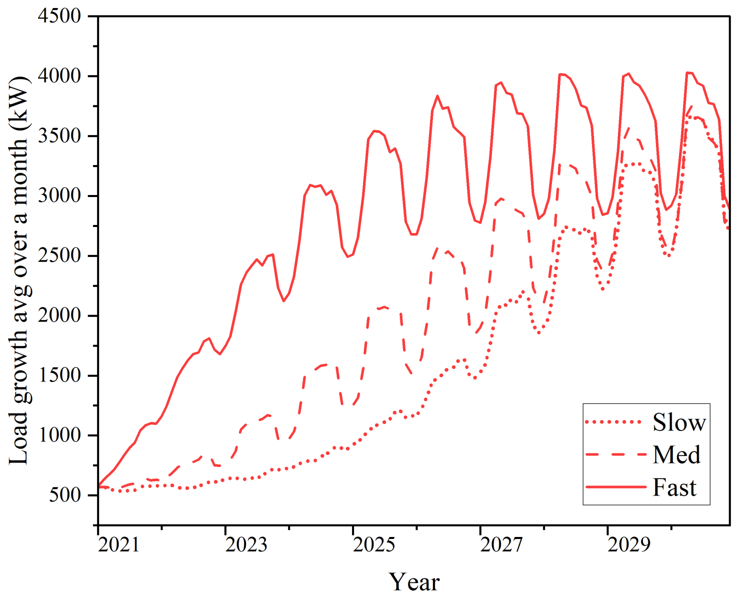


Figure 3.10: *Three different growth rates in the adaptive growth scenario*

a household receiving access to electricity. The community load profile at each growth rate also exhibits seasonal variation, which is dominated by the use of refrigerators and ceiling fans. Based on the analysis of meter and billing data and median electricity consumption from Talwada (See figure 4), we found that the medium growth curve is more representative. This growth rate was found to be consistent with previous studies on understanding factors that drive domestic appliance ownership in rural India (Aklin et al., 2016)(Richmond et al., 2020). Hence the medium growth scenario was considered for further analysis of sizing mechanisms.

3.7.1 System size

The outcome of the cost-optimised mini-grid size for each load scenario is shown in Figure 3.11. To ensure the system's reliability, the blackout frequency was set to 5%, and the resolution for PV at 1 kWp PV and battery at 5 kWh during the optimisation process. In terms of practicality, the resolution indicates that as the load evolved, the PV and battery were topped up by a unit of 1kWp of PV panel and 5kWh of batteries. This approach allows us to choose a cost-effective solution for a permissible level of blackouts.

The size of the actual mini-grid installed in Shahapur ranged from 2.88-14.4 kWp PV and 14.4–48.96 kWh battery. However, these systems were designed for a different number of households, as specified in table 3. These results are normalised for a community of

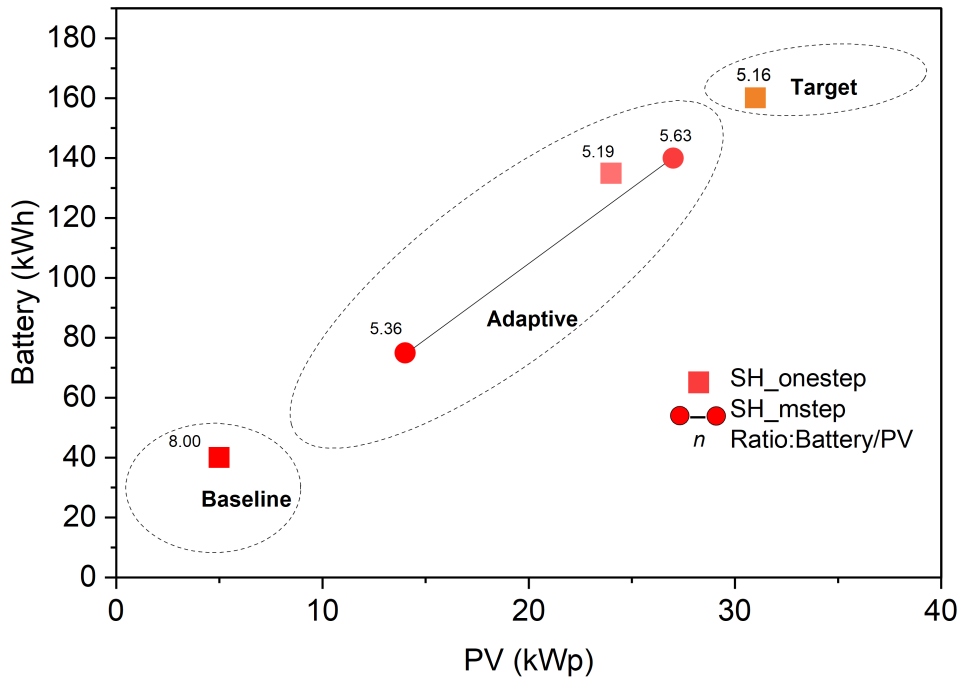


Figure 3.11: *System size, for both solar PV (kWp) and battery (kWh), for each scenario at the beginning of the period. The number beside each square/bubble represents the ratio of battery to PV, indicating the balance between daytime and night-time load. The reliability of the system is 95% in all scenarios.*

100 households. The baseline demand remains constant and minimum during the entire simulation period. Hence, the requisite capacity of the system to meet this demand is the lowest among all scenarios. For this scenario, the optimal configuration comprises a 5 kWp PV and a 40 kWh battery system. Conversely, the target demand exhibits the highest value and requires the largest capacity system, 31 kWp PV and 160 kWh battery, to satisfy this demand. As shown in figure 3.11, squares represent the one-step sizing approach, and connected circles depict the multi-step sizing approach for the adaptive growth scenario. The multi-step approach divides the optimisation into two periods of five years each and adjusts the system capacity at the midpoint to meet the growing demand. The one-step and multi-step sizing approaches result in similar sizes at the end of the investigated period. However, it is the size of storage at the beginning of the first 5-year period in multi-step, which is 75 kWh, is significantly smaller than in the 10-year period, which is 140 kWh. In simple words, the large storage energy may not be fully utilised until the demand matures.

3.7.2 System cost

The optimisation results gave insights into the impact of system size on overall costs and capital required to provide electricity access through solar mini-grids. These costs include costs of individual components as well as their O& M over the system life cycle. Figure 3.12 shows the total system costs and LCUE ($ per kWh) of the optimised system size for each scenario. The findings demonstrate that adopting a two-step mini-grid sizing strategy can yield cost savings of up to 12% in total system costs. This is evidenced by figure 3.12, which indicates that the LCUE at the end of the assessment period is lower for the multi-step sizing approach in comparison to the one-step method. For example, the LCUE is 0.34 USD per kWh in the multi-step sizing versus 0.37 USD per kWh in the one-step sizing approach. This finding suggests that when considering the whole system's lifetime, capacity expansion is more affordable than one-off installation. Interestingly, the LCUE of the largest system (target scenario) is the lowest. This is primarily due to the underlying assumption that demand is consistent from the beginning of the simulation period. Thus, the design of the system is well matched to the demand throughout the system's lifetime, resulting in consistently high utilisation and, therefore, a lower LCUE.

To increase affirmation of the apparent cost-saving potential, a sensitivity analysis of seven different parameters on total system costs in each sizing approach is shown in figure 3.13. The values of these parameters can be found in table 7. We analysed the low, central, and high values of these parameters for the adaptive demand growth scenario in Shahapur. The results present the cost ratio of multi-step sizing to one-step step sizing for demand growth rate, logistics cost, iteration period, reliability (or frequency of blackouts), PV and battery cost and PV and battery degradation and discount rate.

This analysis reveals that multi-step sizing offers potential cost savings in comparison to one-step sizing for all parameters examined. Variations in demand growth rates and cost reductions in solar PV and storage have a significant impact on total system costs, as demonstrated in Figure 3.13. Conversely, changes in logistics costs show less sensitivity. By increasing the iteration period from a single ten-year step to five two-year steps, we discovered a cost-saving potential of 9%. Total system costs are higher with fewer blackouts, which corresponds to greater reliability. The cost-saving potential of multi-step sizing is greater still as the target reliability approaches 99%. Higher values of solar PV and battery lifetime, which result in less degradation, show less cost sensitivity than lower values. The length of the investigation period, which is 10 years [26], may explain this finding, as

[26] The PV system is expected to last 20 years. We analysed the mini-grid utilisation for 10

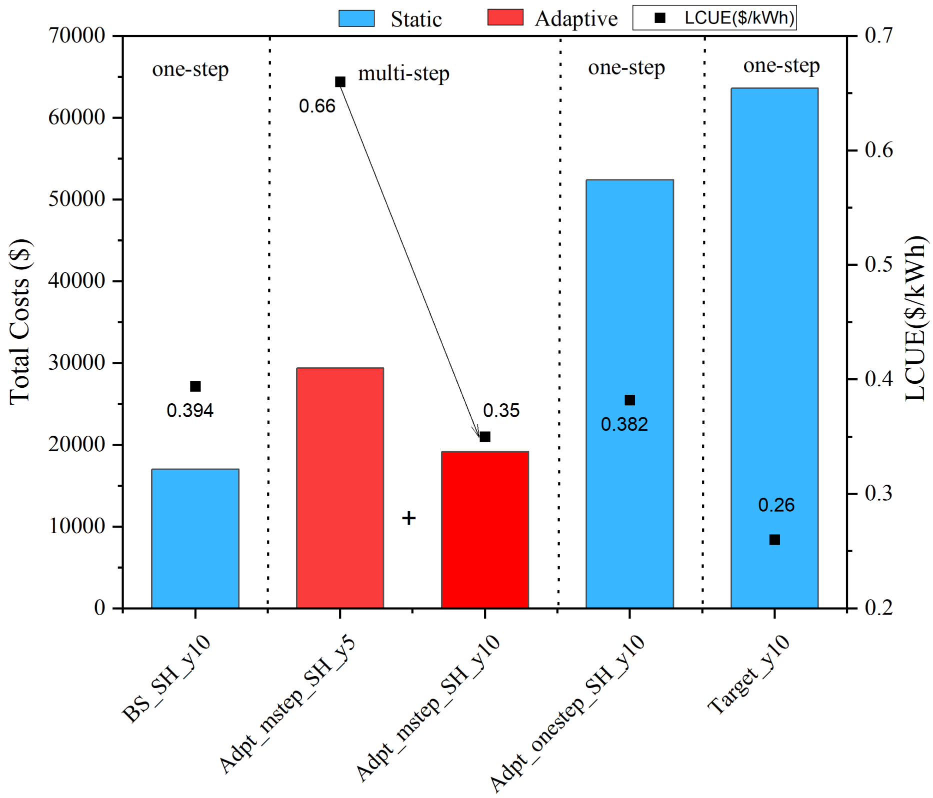


Figure 3.12: *The total costs and LCUE for each scenario. The bars on the primary vertical axis (left) represent the cumulative costs of the resultant optimum system for each scenario, whilst the secondary vertical axis (right) shows the LCUE ($ per kWh). Multi-step costs are divided in two columns corresponding to the first and last five years of the ten year period. The sum of these columns represents the total cumulative costs for multi-step scenarios.*

it is shorter than the expected solar PV lifetime of 20 years. Nonetheless, the analysis revealed a close interdependence between cost sensitivity and degradation.Similarly, when considering higher discount rate (5.15%) compared to the central scenario (4.25%) the cost-saving potential of the multi-sizing approach is approximately 9%.On the other hand, if the discount rate decreases to 3.35 % the savings can be around 6%. These results confirm the relationship between cost-saving potential, system performance and reliability levels. Consequently, we conducted a further investigation into the implications of different sizing approaches on system performance, as presented in Figures 3.14 and 3.15.

years with the assumption that demand growth would stabilise after this period or that a specific demand target would be reached by 2030.

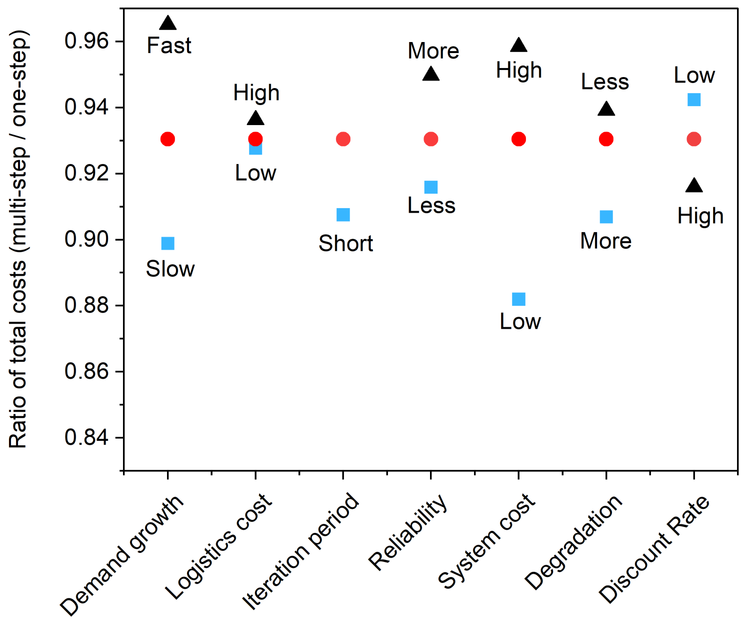
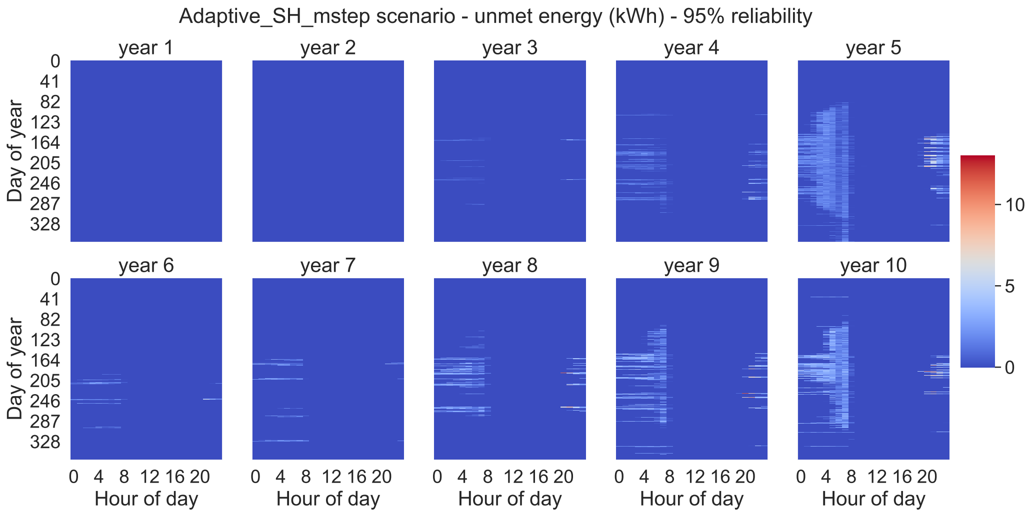


Figure 3.13: *Sensitivity analysis of seven parameters, the red dot represents the central scenario for the mini-grid in Shahapur (table 8)*

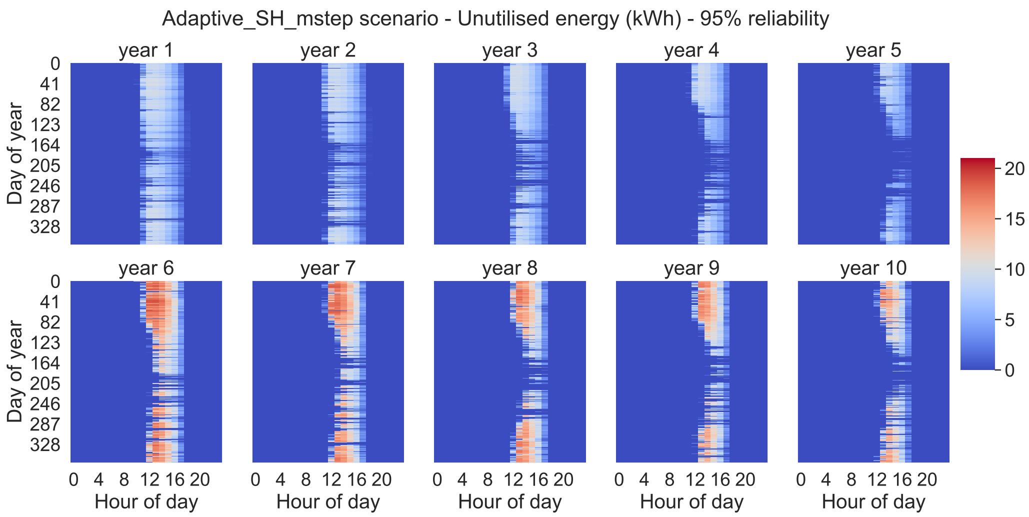
3.7.3 System performance

The performance of the system over a 10-year period is shown in Figure 3.14, including the hourly details of unmet energy (Fig. 3.14(a)) and un-utilised energy (Fig. 3.14(b)) throughout the simulation period for the multi-step Shahapur scenario. As indicated by Figure 3.14(b), unutilised energy is relatively high during the initial two years of each step (Years 1-2 and 6-7) as demand rises and battery capacity deteriorates over time. Additionally, intermittent occurrences of supply shortages are depicted in Figure 3.14(a), with fewer instances observed during the initial three years of the simulation but an increase in the final years of each step due to demand growth. Notably, brownouts or blackouts are most often observed between 2 am and 7 am, after midnight, and to a lesser extent during peak demand periods in the evenings. While during the summer months these brownouts could cause thermal discomfort if the community is not able to use cooling appliance like ceiling fans, whereas in winter months these brownouts or blackout might be acceptable. Furthermore, the unmet energy profile (Figure 3.14(a)) demonstrates a visible inverse correlation with seasonal load variations, with higher supply shortages experienced during the summer months when electricity demand is greater.

Figure 3.15 demonstrates a comparison of system performance regarding one-step mini-grid sizing. Notably, no instances of brownouts or blackouts occurred until Year 5. This



(a) a



(b) b

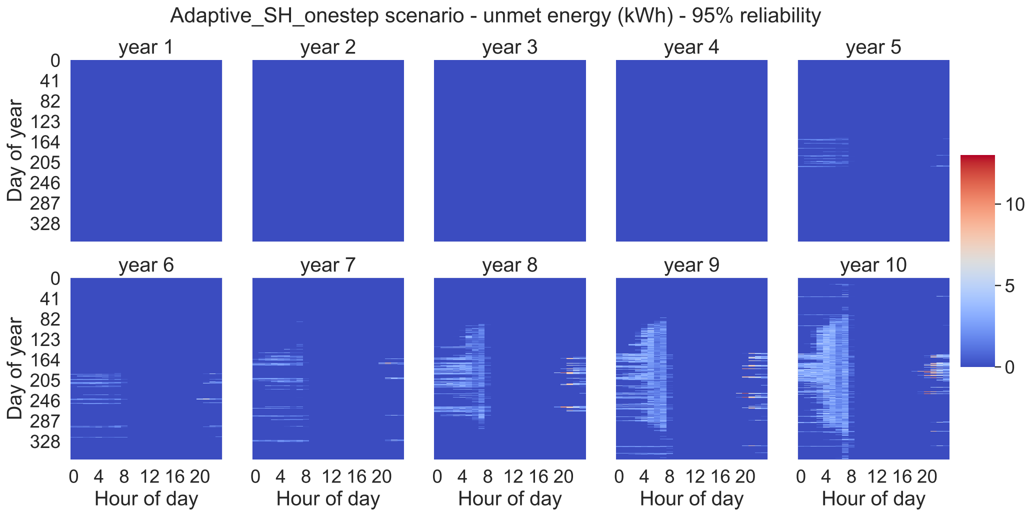
Figure 3.14: *System performance of multi-step sizing for the adaptive growing demand in Shahapur, at an hourly scale per year over a ten-year period, with 95% reliability. (a) unmet energy in kWh and (b) Unutilised energy in kWh for a central scenario.*

can primarily be attributed to the excessive storage capacity and minimal electricity demand at the initial stages of the period, as illustrated in Figure 3.15(a). However, as the batteries degrade over time and demand increases, the unmet load rises, particularly during the summer months of Years 9 and 10, which is clearly evident in Figure 3.15(b). The equivalent profile of the state of charge of storage over the system lifetime is demonstrated in Figure 7.6 in Appendix A.3.4. It is essential to consider that battery lifecycles typically span around 1000 cycles. The influence of this cycle count becomes apparent in the storage dynamics heatmap (refer to Figure 7.6 in Appendix A.3.4), where unmet demand begins to rise during peak hours in year 3. However, it's crucial to note that this value isn't fixed at 1000 cycles, as it heavily depends on the state of charge and depth of discharge—meaning that not all cycles fully discharge the batteries. Additionally, we have demonstrated the effect of battery degradation by altering the cycle count in the sensitivity analysis. This alteration indeed impacts system costs, but notably less so than the impact of demand growth.

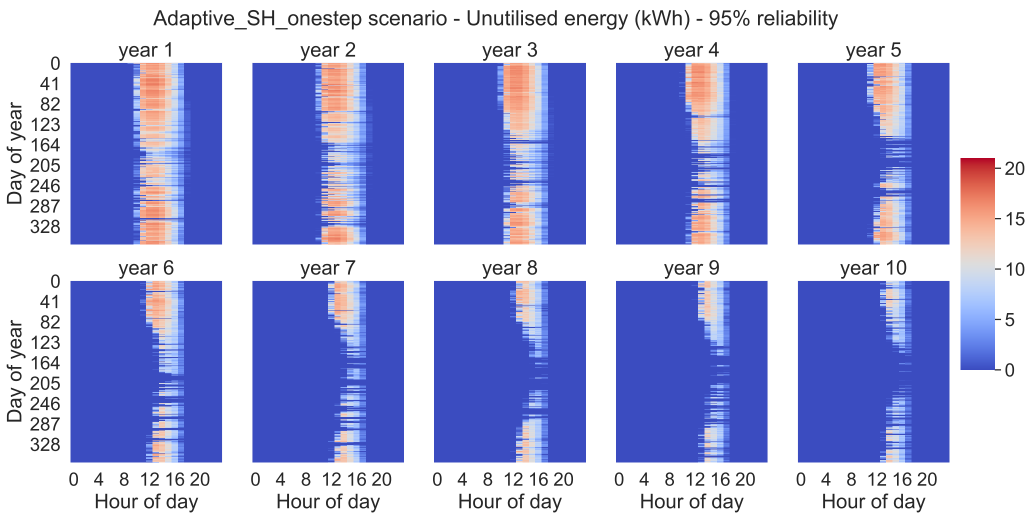
Another crucial aspect is the consideration of resource efficiency concerning the energy balance between unmet energy and un-utilised energy. The energy balance acts as a crucial indicator of potential brownouts and blackouts during the system lifetime. The investigation reveals that the one-step sizing approach results in 32% more un-utilised energy over the entire period in comparison to multi-step sizing, as shown in Figure 3.16. The energy balance in mini-grids draws attention to the resource efficiency contrast between both sizing approaches. Intriguingly, the one-step approach demonstrates an increase in unmet energy and a decrease in un-utilised energy, while multi-step sizing the mini-grid adapts to the growing demand, thereby achieving an energy balance. These findings provide useful insights into the system performance of cost-optimal mini-grids while highlighting the implications of future growing demand, as shown in figure 3.16.

3.8 Discussion

The implementation of a modular or multi-stage sizing has the potential to achieve cost savings, in comparison to a one-step sizing approach, in terms of total system costs and LCUE during the simulated period, as demonstrated in the results section. This observation is consistent with earlier studies by Stevenato *et al.*(Stevanato et al., 2020), which revealed that the utilisation of a multi-year formulation and capacity expansion strategies enabled the optimisation process to arrive at a more cost-effective solution. Similarly, Fioriti *et al.*(Fioriti et al., 2021) advised the adoption of multi-year approaches over single-

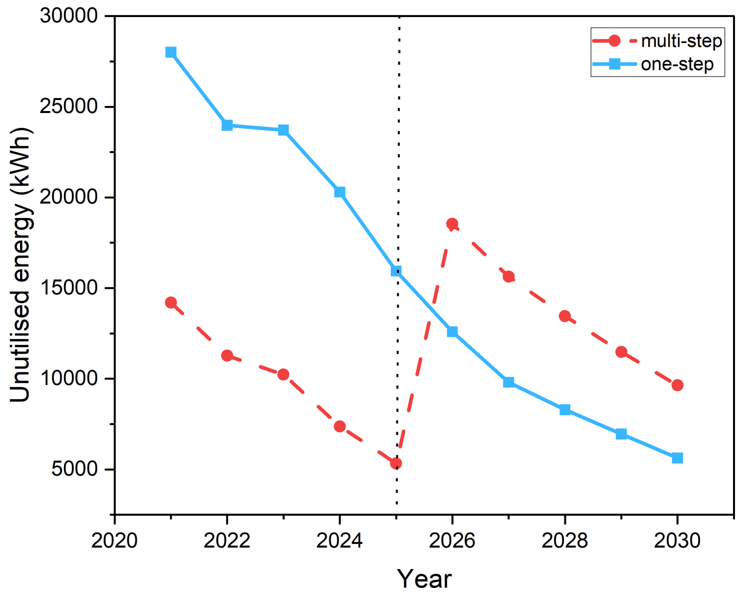


(a) a

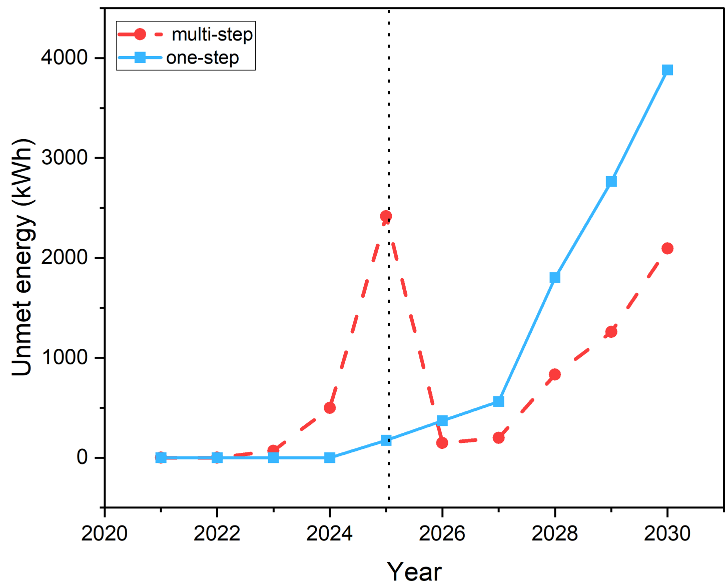


(b) b

Figure 3.15: *System performance of one-step sizing for the adaptive growing demand in Shahapur, at an hourly scale per year over a ten-year period, with 95% reliability. (a) Unutilised energy in kWh and (b) unmet energy in kWh for central scenario.*



(a) Un-utilised energy



(b) Unmet energy

Figure 3.16: *(a) Un-utilised energy and (b) unmet energy summed over a year in Shahapur mini-grid with different sizing approaches for the central scenario. The vertical dashed line represents the capacity expansion undertaken mid-point in year 5 for multi-step sizing. Total unutilised energy over the system lifetime in one step is 155,204 kWh compared to 117,152 kWh in multi-step. Total unmet energy in multi-step is 7511 kWh compared to 9555 kWh in one-step.*

year formulations, as they can cover a broader range of design factors. Our investigation suggests that the main cost savings are linked to equipment expenses, as O&M costs, as shown in Appendix A.3.5. Figure 7.5. Thus, one of the advantages of the multi-step sizing strategy is its ability to reduce expenses on depreciating assets. Although a one-step sizing approach may present advantages such as lower unit costs via bulk purchasing and reduced field visits for capacity expansion in later years, careful consideration of O&M costs is required in future modelling attempts, as accurately predicting transport costs is challenging because they are influenced by exogenous factors such as road networks and fuel costs. However, our results have revealed that the trade-off between cost and reliability becomes increasingly steep when reliability exceeds 99%, as previously noted by Lee *et al.* (Lee, Soto, & Modi, 2014), Sandwell *et al.* (Sandwell, Wheeler, & Nelson, 2017), and Chambon (Chambon et al., 2020)

Results showed that the multi-step sizing approach performed better than the one-step approach in terms of energy generation and usage. Specifically when facing increasing demand in later years. The one-step approach leads to more unmet and unused energy compared to multi-step sizing. The contrasting results on system performance, particularly on energy balance, as illustrated in figures 3.14 and 3.15, demonstrate the implications of adopting different sizing approaches in mini-grid design. The technology chosen for solar PV and battery in our study could potentially explain the observed system performance. Notably, most brownouts or blackouts occurred during the night (between 12am and 7am) and occasionally in the evenings of summer months when batteries were discharged, similar to the findings reported by Lee *et al.* (Lee et al., 2014) in a solar mini-grid in Mali. Nevertheless, the impact of blackouts on customer satisfaction may be less significant if they occur during the middle of the night in the winter months. However, the unavailability of services to meet peak demand in summer evenings may have a more significant effect on customer satisfaction, particularly for cooling needs, based on the use of ceiling fans in this region. Further research should consider additional parameters, such as days of autonomy, which were excluded from our analysis. Future studies might also usefully examine the demand for potential applications of electricity for clean cooking, such as electric cookers. We recommend designing mini-grids with higher reliability levels to accommodate clean cooking loads, which are a crucial everyday demand in mini-grids that have not yet been connected.

Mini-grid developers and donors have the opportunity to realise cost savings through the use of multi-step or modular sizing techniques, but such an approach may have financial implications that should be carefully considered. Specifically, in order to accommodate future capacity expansion, it would be necessary to reserve resources or raise new funds. Failure to do so could result in limited access to electricity in the community from Years 5-10 if the second planned installation is not completed. In order to optimise modular sizing, it is recommended that demand be measured over time to ensure that developers can adjust their mini-grids accordingly, should demand to grow faster than anticipated. Conversely, the decision to oversize the mini-grid at the outset of a project to meet a target demand carries the risk of misspending investment if demand fails to meet expectations.

When designing mini-grids, careful attention should be paid to demand growth rates and the cost decline associated with solar PV and storage*[27], as the sizing approach chosen (over-sizing or modular) can have a significant impact on costs. It is also recommended that a life cycle perspective be employed when designing future mini-grids, as this perspective is critical not only for considering the financial implications of different sizing approaches but also for assessing the environmental impacts of various electricity sources. For instance, research has shown that solar PV and battery systems in India can have a carbon intensity that is ten times lower than diesel-only systems (Beath et al., 2021). Similar methodologies have been applied to investigate the cost and emissions intensity implications of mini-grid design in India (Few et al., 2022).

3.9 Conclusion

3.9.1 Summary and Conclusion

Estimating future electricity demand in the off-grid sector is fraught with uncertainty. Here, we implemented the Bass diffusion model, which is a practical approach that can make realistic demand growth projections when market potential information, such as the number of appliance adopters, is known or estimable. While these values are difficult to predict accurately, especially in recently electrified rural communities, multi-stakeholder engagement with the target community and developers' previous experience in recently electrified villages could improve its estimation. Such engagement should involve local stakeholders and experts on electrification and energy access. Through such engagement, it is possible to identify the needs and preferences of the local community and their willingness to pay for different energy services. Additionally, understanding the area's socioeconomic dynamics can help inform projections about future electricity demand.

[27]*We have considered lead-acid batteries in this study, but some of the battery technologies such as lithium-ion, costs are not declining further since last year

In this study, we examined various demand growth scenarios, two sizing methods, and the cost-sensitivity of seven parameters for mini-grid design for representative Indian rural communities of Shahapur. Our analysis revealed that demand growth estimates were a more significant driver of system size and had a higher impact on costs compared to the baseline initial demand. Furthermore, a modular approach to mini-grid design, which involves adjusting installed capacity according to demand growth rather than initial over-sizing, showed potential for cost savings and improved resource efficiency from a techno-economic perspective. These cost-saving opportunities increased significantly as mini-grids were designed for higher reliability levels. Our results indicated that using a modular approach to size mini-grids could lead to potential cost savings of up to 12%, compared to a static optimisation approach. Moreover, modular sizing could help accelerate electrification efforts by providing basic access in more villages initially and adjusting capacity expansion in subsequent years instead of installing oversized systems in fewer villages. However, practical considerations, such as funding availability and related business models, may influence the sizing approach. It is crucial to have a detailed understanding of the available appliances and their diffusion prospects in the target community to enhance demand growth projections. Our methodology is relevant to solar PV and battery technologies, locations, and demand profiles, but it can be generalised to other renewable technologies implemented in energy access contexts.

Lastly, this study also confirms that more granular approaches to modelling energy demand can enhance the evaluation of technical and economic aspects of energy systems. Estimating energy demand, however, is a complex undertaking that requires a multi-disciplinary approach. In the next chapters, we will develop a novel framework for energy demand modelling for rural households that incorporates the technical, economic and social aspects of energy access, as well as recommend scenarios of long-term demand growth projections.

Chapter 4

Residential activities and energy use

4 Residential activities and energy use

This chapter begins with an overview of the literature on long-term energy demand modelling and draws attention to the significance of time dependency when estimating residential daily energy demand. The importance of accurately calculating peak demand for energy storage sizing is also highlighted. With this in mind, we utilised a nationwide time use survey to understand the social practices reflected in daily activities that influence electricity use. We describe the survey sampling methods, inclusion of weights and demographic details of sub-sampled rural households and individuals from four different states in India. We then discuss the outcomes of empirical analysis carried out to understand daily activities performed by individuals in each state and compare their social practices.

4.1 Electricity Demand Assessment in rural areas

Energy demand assessment is pivotal for decentralised energy planning, not only for providing initial energy access but also for decarbonising existing energy infrastructure. An in-depth understanding of electricity requirements at various times and locations enables energy providers to effectively plan and invest in renewable energy sources, storage technologies, and energy-efficient measures. This proactive approach helps to prevent overcapacity or undercapacity, resulting in a more efficient and optimised electricity grid, thereby facilitating the transition toward a low-carbon or net-zero energy system.

In the preceding chapters, the primary focus of energy assessment revolved around mini-grid planning, relying on surveys that proved to be inaccurate and unfeasible considering the magnitude of the energy transition. India is confronted with a twofold challenge: while it strives to decarbonise its urban energy infrastructure, a substantial rural population is gaining access to electricity for the first time. This complexity makes the energy transition in India both intricate and constantly evolving. Understanding the growth of energy demand in rural India is crucial for proactively planning energy access and facilitating a transition to cleaner energy sources, especially considering that the energy demand in rural India is still not thoroughly understood. As inferred from prior chapters, it is evident that detailed load profiles enhance energy planning. Hence, the development of energy demand profiles for rural households can prove to be beneficial for long-term planning.

The development of granular load profiles plays a significant role in crafting efficient energy systems suited for standalone, interconnected, or grid-connected configurations.

Understanding the precise timing and quantity of energy demand in these areas enables the creation of tailored systems that optimise energy usage, ultimately enhancing the reliability and sustainability of rural power supplies. Given the intermittency of renewable power supply such as solar or wind, storage solutions are mandatory requirements to meet basic electricity demand. The primary sources of value for energy storage in India, both in the immediate and long run, lie in energy time-shifting and capacity services. The capability of energy storage to facilitate diurnal energy time-shifting significantly influences the deployment of storage technologies. These technologies enable the transfer of energy from periods of lower value to high-value periods, such as shifting solar energy abundance from midday to high-demand periods during early morning or late evening. This approach aids in mitigating startup expenses for traditional generators while also decreasing the curtailment of renewable energy (NREL (National Renewable Energy Agency), 2021).

4.2 Residential energy demand

4.2.1 Residential energy demand theories

As we discussed in Chapter 3, estimating long-term electricity demand is an essential part of renewable energy planning owing to its significant impact on both systems costs and resource efficiency. It may also influence energy policies necessary for facilitating the transition to clean energy and mitigating the impact of climate change more broadly(Gupta, 2014) (Grover & Chandra, 2006). The task of modelling future residential[28] electricity demand is challenging, as it involves a multitude of variables and complex socioeconomic dynamics. Early theories involved conceptualising household energy use based on traditional fuel choices such as the *"energy ladder"* (Hosier & Dowd, 1987) theory. It postulates that, as household income increases, it will lead to a transition from traditional fuels to more sophisticated and modern energy carriers. Then as households make economic progress, this relationship was believed to follow a linear trend. Later in the early 2000s, Masera *et al.*(Masera, Saatkamp, & Kammen, 2000) presented a critique of the *"energy ladder"* model and proposed an alternative theory known as *"energy stacking"* to facilitate the adoption of efficient and modern fuels, which may follow nonlinear trends. It posits that households often use multiple energy sources simultaneously rather than completely transitioning from one energy source to another linearly. The theory acknowledged that household energy consumption is complex and dynamic in nature as it potentially in-

[28]Residential and household are used interchangeably in this chapter

volves many factors driving the change in consumption, such as affordability, accessibility, reliability and cultural preferences.

In more recent literature, the factors determining electricity consumption in households are classified into two major categories: endogenous and exogenous factors. The endogenous factors are intrinsic household features including but not limited to household size, income levels, ownership of land or property and education. In contrast, exogenous factors involve external variables such as geographical location, climate conditions, energy policies, subsidies, and accessibility to reliable power supply (Kowsari & Zerriffi, 2011)(Riva, Gardumi, et al., 2019). In order to improve the estimated level of energy demand and project future demand realistically, it is essential to consider a multitude of variables in the energy demand model.

A vast literature on forecasting residential energy consumption is based on exogenous factors, which are generally techno-economic features. Energy demand characterisation performed based on topography, agricultural commodities or forest accessibility (Rijal, Bansal, & Grover, 1990), climate conditions (Ghisi, Gosch, & Lamberts, 2007) (Blechinger et al., 2019) gross domestic product growth (Ziramba, 2008) or income and price elasticity variations over seasons (Filippini & Pachauri, 2004) are examples of studies which include exogenous factors. Endogenous factors, on the other hand, are typically socioeconomic in nature, for example, analysing technology adoption (Riva, Gardumi, et al., 2019) (Van Ruijven et al., 2011), or per capita expenditure (Rahut, Behera, & Ali, 2016). Bhattacharyya *et al.* (Bhattacharyya & Timilsina, 2009) suggests that a fundamental understanding of energy consumption in a household based on economic context follows the maximum utility principle; i.e. a household will opt for an energy service which gives the maximum benefit for the price/effort that consumers are willing to pay. Whilst Walker(Walker, 2014) has argued that energy demand can be seen as a result of how social practices rely on various forms of energy service and that the temporalities involved within these practices can generate the underlying dynamics of energy demand on long-term, seasonal, and weekly and daily timescales. Kowsari *et al.* (Kowsari & Zerriffi, 2011) proposed a three-dimensional framework which focuses on household-level qualitative and quantitative data to capture micro-trends and identify the inter-relationships between different variables. It takes into account human behaviours and social context to reduce the emphasis on income as the major determinant of energy consumption. This framework can be used as a basis for building new theoretical and empirical models for assessing rural household energy use in the developing world, which can potentially aid in decentralised renewable energy planning.

4.2.2 Residential energy demand modelling

Since the 1970 energy crisis, a large amount of literature has been devoted to forecasting household energy demand and discussing technological, socioeconomic and environmental factors influencing current and future energy demand. A seminal review of models by Swan *et al.*(Swan & Ugursal, 2009) distinguished these models into two broad categories: top-down and bottom-up models. The top-down approach treats the residential sector as an energy sink. In contrast, the bottom-up approach extrapolates the estimated energy consumption of a representative set of individual houses to wider geographical scales. Within top-down models, there are two groups: econometric and technological. Econometric models are based primarily on price and income, whereas technological models attribute energy consumption to macro characteristics of the entire housing stocks or appliance ownership trends. These models have tended to be used by the energy sector, to anticipate future aggregated demands for energy. Bottom-up models anticipate end-use consumption by applying a variety of physical and statistical modelling methods, including regression analysis, discrete choice methods or conditional demand analysis to construct long-term load profiles and to test the impacts of strategies, at varying degrees of dis-aggregation, to alter these profiles. Despite their general applicability, these models have been found lacking in their ability to capture the context of developing countries(Bhattacharyya & Timilsina, 2009).

A review by Bhattacharya *et al.*(Bhattacharyya & Timilsina, 2009) highlighted challenges in forecasting energy demand in specifically focusing on developing countries context. The study differentiated between simple approaches, such as employing a single variable like economic growth rate (GDP) or household income elasticity to project future demand, and sophisticated approaches like top-down econometric models with multiple variables or demand estimations using bottom-up end-use analysis considering multiple factors such as appliances stock, population demographics, or affordability levels. This review study further identified gaps in the literature regarding the translation of existing models to developing countries. These models often are limited in accurately reflecting informal energy use, the mix of modern and traditional fuel choices, and the socioeconomic context associated with the urban-rural divide. Both of these comprehensive review studies (Swan & Ugursal, 2009) and (Bhattacharyya & Timilsina, 2009) covered multi-sector energy demand, as well as the evaluation of a diverse mix of supply sources, thereby providing a holistic perspective on energy systems and their interactions.

A recent review by Riva *et al.* (Riva, Colombo, & Piccardi, 2019) explicitly focused on rural energy demand assessment in long-term renewable energy planning in the context of rural electrification. Its emphasises on the upcoming projects of energy access in rural areas should consider socioeconomic changes caused by new technologies and model residential energy demand based on end-use functions and appliance diffusion. The authors also reiterated observations from Swan *et al.* that bottom-up approaches are suitable for contexts with rapid technological development in developing countries. Based on the existing literature, a few categories of methods commonly used for energy demand models have emerged. The next section covers a brief description of these models, relevant case studies in developing countries, and their strengths and limitations in terms of their suitability for assessing household energy demand in rural contexts in developing countries.

- **Econometrics:** Econometric models are statistical models widely implemented by economists and social scientists to analyse data and make predictions or inferences about specific phenomena relevant to energy use and their dependency on socioeconomic parameters. To project future household energy use trends, such models typically rely on historical and/or macro-level aggregated data on many variables like household size, income, expenses, fuel prices, GDP growth rates etc. Econometric estimations span from elementary single equations featuring one dependent and independent variable or reduced-form analyses to more complex simultaneous equations involving multiple independent variables. Numerous studies have utilised these models, with examples particularly relevant to developing countries, such as investigations into household energy demand in Nepal and Bhutan. Pokharel *et al.*(Pokharel, 2007) utilised the log-linear Cobb-Douglas model; emphasising energy balance in fuel transition for household energy use to achieve economic objectives in Nepal. Rahut *et al.*(Rahut et al., 2016) implemented multivariate probit and Tobit models calibrated using *Living Standard Survey data* in Bhutan. Although econometric models offer simplicity and interpretability, they may be constrained by data availability and quality. Moreover, these models rarely capture endogeneity at the household level. Econometric models are unable to estimate the temporality involved with energy use, which is highly important in renewable system designs.

- **Regression**: Regression methods encompass a vast range of techniques and are commonly applied to estimate household energy demand. Conditional demand analysis (CDA) is one example of a regression method that is used to predict demand based on the conditional relationship between energy consumption and various socioeconomic factors such as income, household size, and climate conditions(Aydinalp-Koksal & Ugursal, 2008). Aklin *et al.*(Richmond et al., 2020) have applied linear regression to appliance usage based on the source of energy available to different households in order to estimate parameters influencing household energy demand in rural India. Similarly, Allee *et al.*(Allee, Williams, Davis, & Jaramillo, 2021b) compared machine learning techniques and found Lasso regression outperformed other models while finding uncertainties in energy demand from rural households in Tanzania. Regression techniques can enhance the accuracy of energy demand modelling by analysing the relationships between various factors. However, their effectiveness depends on the availability of high-quality micro-data, which may be limited or inaccessible in many developing countries.

- **Scenario-based models**: LEAP (Long-range Energy Alternative Planning), developed by the Stockholm Environment Institute (SEI), is a widely used tool for energy demand analysis, particularly in rural electrification projects throughout the Global South. It uses economic, demographic and energy-use information to create scenarios that show how energy consumption will change over time. The most commonly designed scenarios are 'Business-as-usual' or 'Government-policy-roll-out' to examine the costs and environmental impacts of each scenario. LEAP provides flexibility in how the demand data is structured, ranging from highly disaggregated to highly aggregated. There are also different methodologies available for energy demand analysis, such as Activity Level Analysis and Stock Analysis. Activity Level Analysis looks at the final energy demand or useful energy demand, while Stock Analysis looks at the current and projected stocks of energy-using devices. Perwez *et al.*(Perwez, Sohail, Hassan, & Zia, 2015) also utilised the LEAP model to forecast Pakistan's energy scenarios till 2030 to guide energy policies required to meet emissions criteria. Likewise, in Colombia, Nieves *et al.*(Nieves, Aristizábal, Dyner, Báez, & Ospina, 2019) designed two scenarios of energy demand growth up to 2050, considering parameters such as population and household size in order to comprehensively estimate aggregate residential demand. The majority of scenario-based models are designed to facilitate decision-making on energy policies. Although these models prove effective in achieving their intended objectives, it is important to note that they exhibit a high degree of sensitivity to numerous variables. However, sensitivity analyses of these variables are rarely presented as they tend to be computationally intensive.

- **End-use models**: MAED (Model-based Analysis of Energy Demand) and REMG (Residential Energy Model Global) are built using the bottom-up approach, considering the end-use of energy. The MAED model is a stochastic model that simulates household energy demand by considering the energy use of individual appliances and activities. It uses a combination of survey data and statistical analysis to estimate the energy demand for different activities such as cooking, heating, cooling, and lighting. The MAED model has been used in various studies to estimate the impact of energy efficiency policies and programs on household energy demand in OECD countries but is readily extendable to incorporate developing country contexts, for instance, in Syria(Hainoun, 2009). REMG, as described in (Van Ruijven et al., 2011) and (Daioglou, van Ruijven, & van Vuuren, 2012), was developed to better understand the underlying trends of energy use in developing countries (India, China*, South Africa, South East Asia, Brazil). The model is able to reproduce many of the dynamics that determine future residential energy demand, providing insights into the energy transition, energy supply functions, fuel switching, inequality, urbanisation, and the use of solid fuels for cooking. Both these models heavily rely on high-quality structured data, and interpretation of some calibration factors may be improvised in the case of REMG.

- **Housing Stock Energy Models**: Housing stock energy modelling is a framework used to analyse the energy use and sustainability of housing units in a given geographic location. It looks at factors like construction materials, heating and cooling systems, and energy efficiency to assess overall energy performance and find ways to improve sustainability. In a recent policy brief for Welsh Government (Robinson, Tilley, Price, & Lloyd, 2023) analysed two categories of housing energy models - traditional and dynamic, and how they are used to study energy use in houses. The authors also highlight the impact of external factors like climate and infrastructure on energy use. Traditional models focus on short-term interventions and building physics, while dynamic models look at long-term impacts, including the effects of climate change and the shift to low carbon energy sources like heat pumps. (Mastrucci, van Ruijven, Byers, Poblete-Cazenave, & Pachauri, 2021) described a study that used different global scenarios and modelling techniques to assess the impact of residential buildings on energy demand and CO_2 emissions for heating and cooling. The study considered factors such as geographical context, socio-economics, and building characteristics. It also utilised climatic data and a classification system to define different climate zones. The study covered macro-regions in Europe, North America, Central Asia, South asia and countries in the Global South.

4.2.3 Residential energy demand in India

About a quarter of India's total electricity consumption comes from the residential sector, and it is expected to rise five to six times by 2030(The World Bank, 2008)(Chunekar, Varshney, & Shantanu, 2016). Various studies have been conducted in order to project India's future residential demand using econometric models, bottom-up end-use estimations or hybrid methods. The 2008 World Bank report (The World Bank, 2008) presented the most comprehensive study on residential electricity consumption in India. It projected annual energy consumption from 2005-06 to 2031-32 using nonlinear regression based on factors such as household size, appliance ownership, per capita expenditure, GDP growth, and geographic location. The study surveyed 600 households across 12 cities and 5 climatic zones. Two scenarios were designed to measure efficiency, with a significant difference in electricity consumption between them. The rebound effect[29] may lessen potential savings. In Scenario 1, while GDP grows at an annual average rate of 7.8%, household electricity usage grows by 5.8% per annum, indicating lower income elasticity for households as consuming units. Urban et al.(Urban et al., 2009) evaluated the need for government policies in rural electrification in India using a scenario-based approach. They assessed energy demand in four electrification pathways: central grid-based, decentralised diesel-based, decentralised renewable energy-based using electric appliances, and decentralised renewable energy-based using primarily renewable energy appliances. Results showed that rural electrification with renewable energy could reduce CO2 emissions by up to 99% compared to grid and diesel systems, and correspondingly decrease primary energy use. Poblete Cazenave *et al.*(Poblete-Cazenave & Pachauri, 2021) extended an econometric model that is applied to micro-data from surveys in four countries in the Global South, including India. The model is used to test scenarios exploring differences in future income, population size and distribution, and electricity access, and the authors found that in scenarios with higher income growth and urbanisation, electricity demand is higher than in scenarios with lower income growth and urbanisation, even though population growth is higher in

[29] In conservation and energy economics, the rebound effect (or take-back effect) is the reduction in expected gains from new technologies that increase the efficiency of resource use, because of behavioural or other systemic responses.

those scenarios. The adoption of electrical appliances considerably differed across countries, appliance types, and income levels. In recent years, Agrawal *et al.*(Agrawal, Harish, Mahajan, Thomas, & Urpelainen, 2020) conducted a large-scale survey in size different states of India and checked multiple factors affecting household electricity consumption and quality of supply and found every 1 hour of supply increase, entails a 1.25 % consumption increased. Another model for bottom-up residential electricity consumption called RUMI[30] has been recently developed by the Prayas group with the aim of analysing government policies to improve energy efficiency measures. The aforementioned studies tested electricity demand from the bottom-up at the appliance level, but lack crucial information on the time-sensitive nature of electricity consumption and peak load growth in long-term electricity planning.

4.2.4 Need for time-sensitive energy assessment

In the context of renewable energy planning, it is important to consider three distinct forecasting horizons for energy demand: multi-yearly, seasonal, and daily. This is partly due to the intermittency inherent in renewable energy sources, which necessitates planning at a multi-time scale, but also because of the demand dynamics mentioned above. Econometric models, typically applied at the macro scale, often fail to capture the intricacies of social dynamics and the time-sensitive nature of energy consumption. On the other hand, end-use and regression models that take social dynamics into account are generally case-specific, limiting their scalability. Furthermore, these models may not adequately capture temporal granularities in energy demand patterns, presenting an additional challenge for effective storage management.

Residential energy demand curves are often referred to as rigid in terms of time of use and the timing of peak loads. Understanding time-dependent activities and incorporating the social dimension can be instrumental in capturing intra-day variations in energy consumption patterns (Torriti, 2014). As a result, comprehensively examining energy demand across various time horizons and from a techno-social-economic perspective can offer crucial insights for more effective renewable energy planning and implementation.

Energy consumption models that incorporate time-dependent activity data have been employed in various countries in the Global North, including the UK(Lőrincz, Ramírez-Mendiola, & Torriti, 2021) and France(Wilke, 2013). These models consider the impact of daily activities, occupancy patterns, appliance-level end-use, and demographic character-

[30] https://github.com/prayas-energy/Rumi

istics on residential energy consumption. The Centre for Time Use Research curates the *Multinational Time Use Studies*[31], an extensive database of time-use surveys from around the world, covering over 25 countries and spanning more than five decades. The database enables researchers to study time-use patterns, such as work, leisure, and household activities, across different cultures and time periods. These types of comprehensive survey provide a standardised dataset which offers valuable insights into human behaviour and can inform consequential use of electricity in daily activities. These surveys involve individuals recording their activities, the duration of these activities and the timing of each activity over a 24-hour period in a diary at specific intervals of 10-30 minutes. The data collected from time use surveys can provide valuable insights into how individuals allocate their time across different activities and how this varies by demographic characteristics such as age, gender, and socioeconomic status. Numerous studies have investigated energy consumption patterns based on time-use surveys in OECD countries, yet such research is scarce in the Global South.

4.2.5 Importance of Time-use energy modelling

Time Use surveys can offer unique insights into the energy consumption patterns of households and are highly relevant in identifying peak time of energy demand. First, they can capture social practices that are distinctly different in urban and rural areas, thus highlighting the urban-rural divide that presents a challenge(Bhattacharyya & Timilsina, 2010). Secondly, the granularity provided by time-use data is also critical in the calibration of peak energy demand, which is vital in designing batteries for storage in solar mini-grids as we discussed in previous chapter. Thirdly it can support the creation of scenarios for energy transitions, especially in terms of cooking where a mix of traditional fuels such as firewood and LPG are used; electric stoves have only recently begun to gain traction in the Global South (Pachauri, Poblete-Cazenave, Aktas, & Gidden, 2021). Additionally, a report by National Renewable Energy Laboratory monitored 36 micro-grids (with 4,660 meters) currently operating in Africa and summarises classifying household time-sensitive consumption patterns can help with tariff design, allowing for the implementation of time-of-use rates or reduced tariffs to incentivise desired load profiles . Whilst this approach gives insights into existing energy usage patterns, it can also inform understanding of the energy usage of appliances in the future (Li et al., 2020). This is especially beneficial in rural households, where there has historically been a lack of appliance ownership, but

[31] https://www.timeuse.org/

also where significant growth in this ownership is expected in the near future(Chunekar et al., 2016). Identifying the future electricity demand from home appliances is also highly relevant because of their respective power ratings, which significantly affect the daily load curve. Energy demand projections based on Time Use can also give insights into designing cross-subsidies between productive use and residential use for Demand Side Management (DSM) because of the ability to predict the evening peak more accurately. Adeoye et al.(Adeoye & Spataru, 2019) developed a model for household energy projections in Nigeria; however, it was calibrated using synthetic time-use data. In this thesis, we introduce a multi-scale framework to estimate household energy demand in rural India, accounting for time granularities at various scales and incorporating the local socioeconomic context. This approach aids in informing the technical design of future renewable energy systems.

4.3 A Multi-scale framework for residential energy demand

Although the terms "electricity demand" and "load profile" are sometimes used interchangeably in this thesis, they have distinct meanings. In this context, we interpret electricity demand as the sum of existing load and aspiring energy needs. In contrast, the load profile is more explanatory of the demand that is met or should be met. This distinction is important when considering energy planning, as the electricity demand denotes a descriptive or explanatory phenomenon, whereas the load profile is characterised as actionable or prescriptive. The research and data gaps in existing literature regarding the rural household energy demand models in developing countries provide a foundation for the new framework that can offer a holistic view of future residential load profiles. In this regard, we decompose the temporality of the long-term electricity load profile into three components: Longitudinal, seasonal and transverse. This framework can serve as a basis for the new data-backed empirical model of rural household energy demand. Figure 4.1 illustrate these three components. Longitudinal demand considers changes that occur over several years, while seasonal variations refer to the effects of seasons on electricity demand within a given year. Transverse, which refers to a wave propagating perpendicular to the direction of propagation in physics, is a term we use to define electricity demand reflecting a consumption pattern over a 24-hour period that extends along the axis of time.

- **Longitudinal**: This part of the load profile accounts for the changes in energy demand that occur over several years, typically driven by factors such as population growth, economic development, changes in energy efficiency, and shifts in the

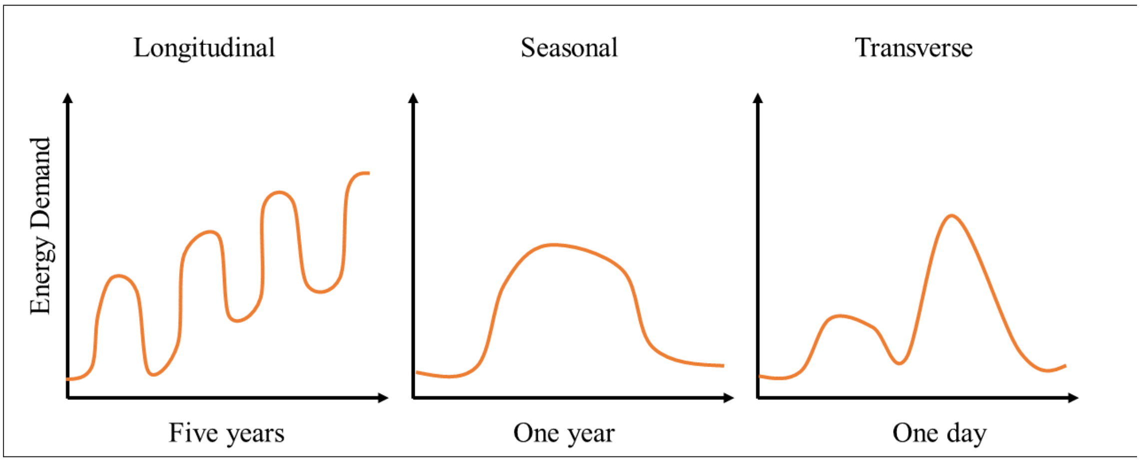


Figure 4.1: *The decomposition of long-term energy demand growth into three components: longitudinal energy demand, seasonal variations, and transverse energy demand. These graphs are provided solely for illustrative purposes and are representative of the shape of actual load profiles.*

energy mix. In this context, longitudinal demand represents the long-term trends in energy consumption, which can be influenced by appliance diffusion and policies on energy efficiency. Chalal *et al.*(Chalal et al., 2017) gathered longitudinal data on consumption in the UK which helped explain the socioeconomic factors influencing the household's energy demand evolution and subsequently predicted possible future transition patterns for a period of 10 years. In the context of renewable energy planning, the longitudinal load profile primarily informs decision-making on the future size of the system and aids in designing policies to improve energy efficiency. More about this is discussed in Chapter 6.

- **Seasonal**: This component captures the impact of seasonal factors on energy demand within a given year. Seasonal variations in energy demand often result from changes in weather patterns, such as temperature fluctuations or variations in daylight hours, that affect heating, cooling, and lighting needs. While obtaining information on weather-influenced parameters such as temperature, relative humidity, and heating/cooling degree days is relatively straightforward with the help of bioclimatic design toolkits like PyClim(Robinson, 2020), it is important to consider the other side of the equation as well. Cooling appliance usage is not solely determined by these weather-related factors; thermal comfort plays a significant role in driving energy demand for cooling systems (Rawal et al., 2022). In this context, understanding and modelling thermal comfort becomes crucial for accurately predicting energy consumption related to cooling appliances. This framework can be readily extended to take into account both weather-influenced parameters and thermal comfort, to developed a correspondingly more comprehensive and accurate energy demand model.

- **Transverse (diurnal variations)**: Transverse demand represents the daily pattern of energy use over a 24-hour period, reflecting how consumption changes throughout the day; noting that there may in principle be multiples of these days, e.g. to distinguish between weekdays and weekends. Transverse demand is influenced by factors such as daily routines, working hours, and the timing of various energy-intensive activities (e.g., cooking, laundry, or industrial processes). In this context, the term "transverse" signifies that the demand pattern extends along the time axis, covering the full range of daily activities. To model transverse demand, we analyse hourly or sub-hourly data on time-dependent activities to identify typical daily patterns to estimate the intra-day variations in energy consumption.

To understand energy use in rural households in India comprehensively, our goal is to develop an energy demand model that encompasses all three forecasting horizons and integrates the techno-socioeconomic features of the local context. Our primary objective is to investigate the diurnal variation of energy use in rural households that are representative of social practices. We will utilise the recently conducted national-scale time use survey in India. Although this survey design is quite similar to the Multinational Time Use Survey (MTUS), there are some notable differences. For instance, the MTUS diary data is recorded at 10-15 minute intervals, while the Indian data is documented at 30-minute intervals. Additionally, some variations exist in the demographic information collected. In order to accomplish this objective, we undertake an empirical analysis of the Indian time use survey data, assessing its suitability for modelling energy demand across varying spatio-temporal scales, covering individual households up to the district or state level within the rural Indian context.

In this chapter, our primary focus will be on gaining a deeper understanding of time-dependent energy use. This will serve as the foundation for developing an energy demand modelling framework tailored to rural Indian households. Residential energy demand modelling based on time-dependent activities will be discussed in Chapter 5, and the longitudinal and seasonal components of energy consumption will be discussed in greater detail in Chapter 6. Section 4.4 delves into time use surveys in India, providing an overview of the sampling strategies employed and the methods used to process the collected data. In Section 4.5, we will shed light on the demographic and socioeconomic characteristics of the time use data, which play a crucial role in shaping energy consumption patterns. This chapter concludes with a presentation of the results, showcasing activity profiles from four distinct states in India. An assessment of the suitability of this information for energy demand modelling will then be summarised.

4.4 Time Use Survey India

Since 1950, the Government of India has been collecting an extensive range of socioeconomic data through National Sample Surveys (NSS). The NSS is handled by the National Sample Survey Organisation (NSSO), which is formed as a part of the Ministry of Statistics and Programme Implementation (MOSPI). The working groups of statisticians and economists assigned by the MOPSI are responsible for organising the surveys, developing survey designs, setting up questionnaires, supplying field staff with instructions, and overseeing data collection and analysis. These groups gather unit-level data (households and individuals) from all parts of India. Thus, NSSO survey data provides a vast source of information for research and policy-making in the country. The surveys are carefully planned to ensure equal representation of all demographics, with samples divided into rural and urban sectors.

Between 2019-2020, NSSO conducted the Time Use Survey (TUS), with the aim of understanding how Indians spend their time across different activities throughout the day, such as paid work, unpaid care-giving and household work, leisure and self-care. The survey also collects data on how people's time use differs by age, gender, education, location and other socioeconomic factors. This data has been used to inform policies and programs related to employment, education, social welfare and gender equity. As noted earlier, it can also help energy system modellers to understand the time-sensitive nature of electricity consumption, particularly regarding when and where peak electricity demand occurs. This can help identify opportunities for energy efficiency measures and storage management strategies in renewable energy planning. Furthermore, the survey can provide insights into patterns of occupancy in households, particularly in the rural sector, where there's serious data paucity. Thus the availability of a rich time use survey dataset from rural India can be utilised for energy demand modelling, which can inform the design and implementation of the clean energy transition and improve access to reliable electricity in rural areas.

4.4.1 Sampling TUS India

The survey has been conducted in urban and rural sectors, with all inhabited villages within each NSS State region[32] constituting a rural stratum. A stratified two-stage survey design has been adopted for the TUS. The first-stage is to identify the first stage units (FSU), which are villages in rural areas or Urban first sub-units (UFS blocks) in urban areas or sub-units (SUs) in some special cases. The second stage is the selection of households which are also called Ultimate Stage Units (USU), and the surveying of 2 to 3 individuals in each household. FSUs are divided into rural and special strata. Rural strata are all inhabited villages in each NSS State region. Special strata are villages in areas with a sparse population where the village-level population is less than 600 people. The survey period has been divided into four sub-rounds of three months' duration each in order to ensure a uniform distribution of samples throughout the duration [33]. A total of 14 households are selected from each FSU and surveyed uniformly across all 7 days of the week. 2 households are canvassed on each day of the week. The selection of households is done based on Simple Random Sampling Without Replacement (SRSWOR). Figure 4.1 summarises the sampling method used in TUS India.

Table 8: Sampled number of households and individuals in four states and selection criteria

State	**Total Population *Census 2011**	**Households Surveyed (Rural)**	**Individuals Surveyed (Rural)**	**GDP 2019-2020 (GoI2019, n.d.) USD (Bn)**	**Climatic Conditions (Rawal et al., 2022)**	**Region**
Uttar Pradesh (UP)	199,812,341	11153	39654	230	Composite	Northen
Maharashtra (MH)	112,374,333	6245	19497	350	Hot-dry+ Composite	Western
Tamilnadu (TN)	72,147,030	4159	10939	210	Warm-Humid	Southern
Nagaland (NG)	1,978,502	672	1900	3.7	Composite +Cold	North-eastern

[32] List of NSS regions can be found here NSS regions

[33] In some parts of India, some places aren't uniformly surveyed in all four sub-rounds because of the arduous field conditions, these include Andaman and Nicobar Islands, Lakshadweep, Ladakh region (Leh and Kargil districts) of Jammu & Kashmir and rural areas of Arunachal Pradesh and Nagaland

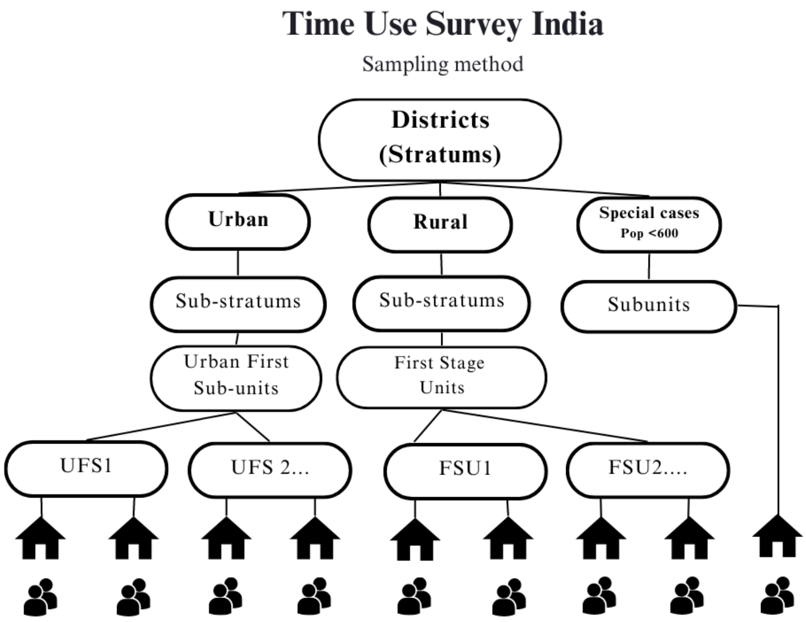


Figure 4.2: *Time Use Survey Sampling*

The survey is conducted through face-to-face interactions with the sampled households and individuals aged 6 years or above in all thirty states and six union territories of India. In this chapter, we consider sub-samples of rural households from four states: Uttar Pradesh, Maharashtra, Tamil Nadu and Nagaland, to provide insights into the variability of time use patterns across different geographic regions and socio-demographic compositions within India. India has diverse climatic conditions and varied economic circumstances that can potentially impact the time-use. To represent this diversity, we have selected these four states based on population size, climatic conditions and economic situation. Details on the number of surveys conducted, total population and climatic conditions in each state are given in table 7 (see Appendix A.4.1 to compare rural households sampled compared to a number of urban households). When the data needs to be used at an aggregated level, the consideration of weights is crucial to ensure the representativeness of the population and de-risk biases in the data. These weights are given by multipliers in the NSSO unit-level data. More about the weights is discussed in section 4.4.2.

The survey data is divided into five levels: levels 1 and 3 relate to household unit data, and levels 2, 4, and 5 to individual records. The questionnaire of the survey is available for open access on the NSSO website. As for reference, it can also be found on this GitHub repository [34] In the household level data, the demographic section covers information on

[34]TUS analysis GitHub repository https://github.com/rjsayani/TUS_india and NSSO TUS

monthly expenses, energy service usage, dwelling structure and types of fuel employed for cooking; while individual records encompass information pertaining to age, education, and marital status. Table 8 gives a list of variables and their descriptions in the household data. Time use activity related variables and their descriptions are given in Table 9.

Table 9: Household unit data variables and descriptions

Variables	**Description**	**Level**
Date of Survey	Gives time the survey was taken and information on sub-round	HH1
Sector and HHID	Sector and number of households	HH1
HH Size	Total number of members living in a household Numeric value	HH3
Land Ownership	Ownership of land in hectares coded (1-12 for incremental ownership) 99 for no ownership	HH3
Monthly Expenses (A)	Numeric value (up to 10 digits)	HH3
Monthly imputed goods for own consumption (B)	Numeric value (up to 10 digits)	HH3
Monthly wages received in kind (C)	Numeric value (up to 10 digits)	HH3
Amount spent on durable goods (D)	Numerical value (up to 10 digits)	HH3
Overall monthly expenses (A+B+C+D/12)	Numeric value (up to 10 digits)	HH3

2019–2020, https://mospi.gov.in/time-use-survey.

Table 9 continued from previous page

Variables	Description	Level
Energy use (cooking)	Coded for 10 different categories 1- Firewood, 2-LPG, 3-Natural Gas, 4-Dung, 5- Kerosene, 6-coal,7-Gober gas, 8-biogas, 10-charcoal, 11-electricity, 12-no cooking, 19-other	HH3
Energy use (Lighting)	The primary source of energy for lighting, 1-electricity, 2-kerosene, 3-oil, 4-gas, 5-candle, 6-no lights, 9-others	HH3
Washing clothes	Codes 1- Mechanised (this can be with electricity or without) 2- Manual by a member of household 3- Outsourced (either commercial or through house-help)	HH3
Cleaning floor	Codes 1- Mechanised (this can be with electricity or without) 2- Manual by a member of household 3- Outsourced (either commercial or through house-help)	HH3
Dwelling structure	Codes - 1 kutcha, 2- semi-pucca, 3-pucca, 9- no dwelling	HH3

Table 10: Individual unit data related to Time use variables and description

Variables	Description	Level
Common sector, HHID and Person ID	Common id with sector, state, district and household id and associated individual id	TUS2
Type of enterprise	Location of work/occupation of individuals	TUS2
Day of the week	Day of the week when survey is conducted (1-7, Monday to Sunday)	TUS2
Gender	Codes - 1- Male, 2- Female, 3- Transgender	TUS4
Age	Numeric value (up to 3 digits)	TUS4
Marital Status	Codes 1- never married 2-married 3- widowed 4- divorced	TUS2

Table 10 continued from previous page

Variables	Description	Level
Highest level of Education	Codes 1- Not literate, 2- Below primary, 3- primary, 4-middle primary, 5-secondary, 6- higher secondary, 7-diploma, 8- Certificate course, 10-Graduation diploma, 11-Graduate, 12-post graduate and above	TUS2
Activities	Activities are recorded based on 3-digit codes at 30 mins intervals. These codes are adapted from ICATUS 2016	TUS5
Major Activity	If there is more than one activity recorded at the same time interval, if the primary activity is major -1, if not 2.	TUS5
Simultaneous Activity	If there is more than one activity recorded at the same time interval and simultaneously occurred, 1-yes, 2-no	TUS5
Multiple Activity	If there is more than one activity occurs within the same time interval, 1- yes, 2-no	TUS5
Where	Location of the activity being performed. 1- home 2- outside home 3-not fixed	TUS5

4.4.2 Weights in Time Use Survey

Weighting serves as a crucial step in survey data analysis. Each unit record within a selected sample is assigned an estimation weight, which facilitates aggregation of causal or descriptive statistics of relevant population parameters, such as a specific population's average income. Unit weight also signifies the number of individuals in the population the sample unit represents. For instance, in a random sample of 25 individuals drawn from a population of 100 members, each sampled individual effectively represents four members of a population. Survey weights are generally critical for mitigating bias when estimating population means or proportions of variables in the context of a descriptive analysis(Bollen, Biemer, Karr, Tueller, & Berzofsky, 2016). It is essential to consider weights when analysing complex surveys, such as stratified time-use surveys based on SRSWOR(Lavallee & Beaumont, 2015).

In TUS India unit data, the weights are given in terms of a *Multiplier*, and the value of the multiplier (MLT) for households is calculated based on:

$$MLT = \frac{H}{h_{st}} \tag{7}$$

Where H is the total number of households in the FSU being surveyed, and $h_(st)$ is sampled households in that FSU. s and t represent the stratum and substratum, respectively. The multiplier for individual unit data in TUS levels 2,4 and 5 is calculated based on:

$$MLT = \frac{N}{n_{st}} * \frac{H}{h_{st}} \tag{8}$$

$N$is the total number of FSUs in the sub-stratum, and $n_(st)$ represents the sampled FSUs from that sub-stratum. Information on estimating parameters based on NSS data notes that a weight w for each unit is $MLT/100$. The calculation of descriptive parameters for the population Pop can be estimated through the utilisation of the variable of interest y, as measured for each unit within the sample s. An estimation weight w_k is assigned to every sample unit (individual or a household) k and subsequently employed to derive estimates of the parameters of interest. For example, the estimator of the population total $Y = \sum_{k \epsilon U} y_k$ is given by:

$$Y = \sum_{k \epsilon s} w_k * y_k \tag{9}$$

The estimation of more complex population parameters, for example, the probability of an activity i being performed by person k at time t, can be done similarly by assigning weight w_k to each person [35],

$$P_{ik} = \frac{\sum_k w_k * I_{ik}}{\sum_k w_k} \tag{10}$$

Where I_{ik} is 1 if an individual k is engaged in an activity i on the reference day and 0 otherwise. Likewise, the average time T spent by an individual k on activity i with consideration of weight can be calculated thus:

$$T = \frac{\sum_k w_k * T_{ik}}{\sum_k w_k} \tag{11}$$

Here T_{ik} indicates the amount of time spent on an activity i by respondent k, and w_k is the weight assigned to person k. To mitigate bias in our analysis, we have considered the weightage calculated described above.

[35]The equation is followed from American Time Use Survey weightage consideration - ATUS manual

4.4.3 Treating outliers

Many factors can induce bias in the statistical analysis of survey data, and one of these relates to the presence of outliers. These are values that are significantly different from the other observations and can be either caused by human errors (enumeration error by field surveyors in this case), or they can be genuine extreme cases. Outliers can have a significant impact on numeric data such as income and expenses. If left untreated, they can strongly influence statistical inferences drawn from the analysis and induce a bias in the conclusions drawn. Therefore, it is important to identify and remove or replace these outliers using appropriate methods. The TUS India level 3 household data, as presented in Table 8, represents survey response variables such as overall expenses, household size, and monthly consumption as numerical values. The overall monthly expenditure is calculated based on 4 variables: Usual monthly expenses, Amount spent on purchasing durable goods in the last year, amount imputed by homegrown goods, and money received in kindness (gifts). It is important to note that these variables may contain extreme or unusual values that could potentially be classified as outliers, although it is challenging to identify outliers in such data. For instance, *durable goods* are quite an ambiguous variable. It can be an electric appliance or a piece of expensive jewellery. This then further complicates the task of finding which observations among the data are either genuine and extreme points or results from erroneous estimation or data entry.

(Osborne & Overbay, 2004) demonstrated the impact of outliers on statistical inferences in two ways: by checking accuracy levels and their correlation with the rest of the population and by comparing error rates. It is imperative to choose whether outliers need to be removed or replaced. Various methods have been implemented by statisticians to treat outliers depending on the type of data, sample size and the assumed causes of errors behind outlier observations. To summarise, a few commonly used methods that are relevant to income and expense data are:

- **Winsorisation**: This method involves replacing extreme values with the nearest values within a specified range of data. For example, the upper 5% of income/expense values can be replaced with the value at the 95th percentile.

- **Trimming**: Trimming is a widely used method which is removing a fixed percentage of observations from both the upper and lower ends of the distribution. For example, the top and bottom 5% of values are removed from the data, considering this to result from erroneous entry.

- **Z-score method**: The Z-score and robust Z-score methods are based on calculating the z-score of each observation and removing those that fall outside of a defined threshold. A typical z-score is the number of standard deviations away from the mean that the observation falls. A widely used threshold applied for z-scores is greater than 3 or less than -3.

- **Interquartile range (IQR) method**: IQR is similar to trimming, but it involves identifying outliers as observations that fall outside a specified range based on the IQR. For example, outliers can be identified as observations that fall outside 1.5 times the IQR below the first quartile or above the third quartile.

In this chapter, we have investigated the effectiveness of two methods for handling outliers in TUS household data; the IQR method, which removes certain data points falling outside specified quartiles, and the Winsorisation method, which is a non-parametric technique for replacing outliers with nearby values. The details of the outcomes of the outlier treatment are presented and discussed in the forthcoming section.

4.4.4 Household activities

The central aim of this chapter is to determine time-dependent activities performed by individuals that have an impact on electricity consumption. In the TUS level 5, the start time and end time of each activity performed by an individual is recorded at a time interval of 30 minutes for a 24-hour period from 04:00 am to 04:00 am the next day (see table 9). All activities are encoded based on the International Classification of Activities for Time-Use Statistics (ICATUS) 2016. Table 10 lists all major divisions and sub-divisions of activities categorised in ICATUS, and we identified sub-groups of ten activities that may potentially influence energy use based on guidance from the work on energy demand modelling based on time-use data of Wilke *et al.* (Wilke, Haldi, Scartezzini, & Robinson, 2013),(Wilke, 2013) and Torriti *et al.*(Torriti, 2017). These ten activities in our analysis which can either have a direct energy use associated with it, such as the use of television and radio, or a passive use of electricity, such as studying and learning at home or eating meals, which may require lights. Furthermore, personal hygiene and in-house employment activities may be difficult to predict in terms of electricity use in the absence of concrete information on corresponding device ownership, but are integral parts of daily routine and thus provide significant insights into occupancy levels in the household. Sleeping and related activities have a strong influence on occupancy levels, as well as the usage of ventilating, cooling or heating appliances during different seasons of the year, based on thermal comfort considerations. In this regard, we further emphasise sleeping and related activities as they may also have an influence on storage management in the case of renewable electricity access in rural households.

Three variables are defined in relation to activities recorded in TUS level 5: major activity, multiple activity and simultaneous activity (see table 9). A major activity occurs if a respondent is performing more than one activity at the same time in 30 mins interval (simultaneously or consecutively), one of which is the primary (or major) one. For example, if someone is watching TV while eating a meal, eating may be identified as primary and watching TV as a somewhat passive secondary activity. *Multiple activity* indicates if a person is engaged in more than one activity that happened within a span of 30 minutes. For example, personal hygiene and eating breakfast can be noted within the same time interval, though not in the order in which they occurred. Respondents can note up to three such activities that occurs in span of 30 mins, but the major activity is identified as one of the two or three multiple activities recorded. Simultaneous activities refer to cases when more than two activities occur at the same time, with the input being a boolean. This is consistent with the other two variables.

In summary, the methods employed in analysing activity groups guide the characterisation of the load profiles for rural households. A step-by-step flowchart illustrating the process can be found in Figure 4.3. This method is subsequently applied to the time-use data analysis of rural households across four states in India, enabling a comparison of activity charts and an assessment of the similarities and differences in social practices that actively or passively influence household energy consumption in each state.

4.5 Results

4.5.1 Demographics of TUS data

This section presents the demographic characteristics of the surveys conducted, including information on age, education, and gender balance in the sampling. The age distribution is representative of the overall national age distribution in each state, except in Uttar Pradesh, where around 42% young persons between the ages 6-20 are surveyed. There are nearly even populations sampled between male and female respondents in each state. However, the number of transgender respondents surveyed is less than 0.05% in most states and nil in Nagaland. Notably, the respondents are not equally distributed in terms of education level, with the vast majority of participants having completed schooling. Literacy level among participants in Uttar Pradesh is severely low, whereas the other

Table 11: Activity codes and groups based on ICATUS 2016

Activity Major division (ICATUS) 2016	**Sub-division of Activities (ICATUS) 2016**	**Activity code**	**Activity groups defined**
Employment and related activities	Employment within household (producing goods for sale)	12	1
Unpaid domestic services for household members	Food and meals management and preparation	31	2
Unpaid domestic services for household members	Cleaning and maintaining of own dwelling and surroundings	32	3
Unpaid domestic services for household members	Care and maintenance of textiles and footwear	34	4
Learning	Homework, being tutored, course review, research and activities related to formal education	62	5
Culture, leisure, mass-media and sports practices	Mass media use for entertainment (TV)	842	6
Culture, leisure, mass-media and sports practices	Mass media use for entertainment (Radio)	843	7
Self-care and maintenance	Eating and drinking	92	8
Self-care and maintenance	Personal hygiene and care	93	9
Self-care and maintenance	Sleep and related activities	91	10

three states are quite similar. The survey was conducted uniformly across different days of the week, as highlighted in Figure 4.4, which shows a balance between all seven days. However, the date of the month varied across states. To capture the effect of seasonality on time use, the survey was taken evenly in all sub-rounds, except in Nagaland, where field conditions might be arduous during winter months due to the cold climate. The temporal balance in the survey design is a crucial factor that ensures the representativeness of the sample and increases the overall generalizability in modelling energy use based on TUS. Taking into account the distribution of demographic factors can help in our understanding of the different perspectives that influence the survey responses.

4.5.2 Energy use recorded in TUS data

TUS Level 3 data on household energy service provides insight into the current and potential use of electricity for everyday tasks such as cleaning, cooking, lighting and washing clothes. This information is essential in understanding the complexities of technology diffusion in rural areas. It is unsurprising that a mix of different fuels is used for cooking across different states, including firewood, LPG, charcoal and electricity. Numerous socioeconomic factors influence the fuel transition in rural areas, with affordability and access to clean cooking being two of the most important drivers. Figure 4.6 shows that, with Maharashtra and Tamilnadu being economically advantageous states compared to the other two, their cooking energy is dominated by LPG, whereas in the populous state of Uttar Pradesh, nearly half of the population still relies on firewood. A transition to clean cooking remains a major challenge in rural India, where electric cooking stoves hold the most potential. This will be discussed further in Chapter 6.

Energy use in activities such as cleaning and washing clothes is typically divided into three categories: mechanical, manual, and outsourced. In most states, this being done manually by a member of the household remains the most prevalent. However, in economically progressing states, technological solutions are adopted to automatise these tasks, and it is likely that many of these activities will be mechanised in the future. In Maharashtra, a relatively higher number of households are using mechanical ways for washing clothes, which suggests that there is a potential market for appliances such as washing machines. This shift will not only influence the amount of electricity being used by these machines but will also be crucial in determining the timing of these tasks and hence the time of use of these machines.

Lighting is a key component of energy consumption, and this is reflected in the responses given by households in all four Indian states. The majority of households reported using electric lights, indicating at least Tier-1 access to electricity being available for most. However, a noteworthy proportion of households in Uttar Pradesh reported relying on kerosene lamps for lighting, which suggests that there are still some areas in this state where access to electricity might be limited or less reliable. Kerosene lamps have a detrimental impact on the environment and the health of those exposed to them.

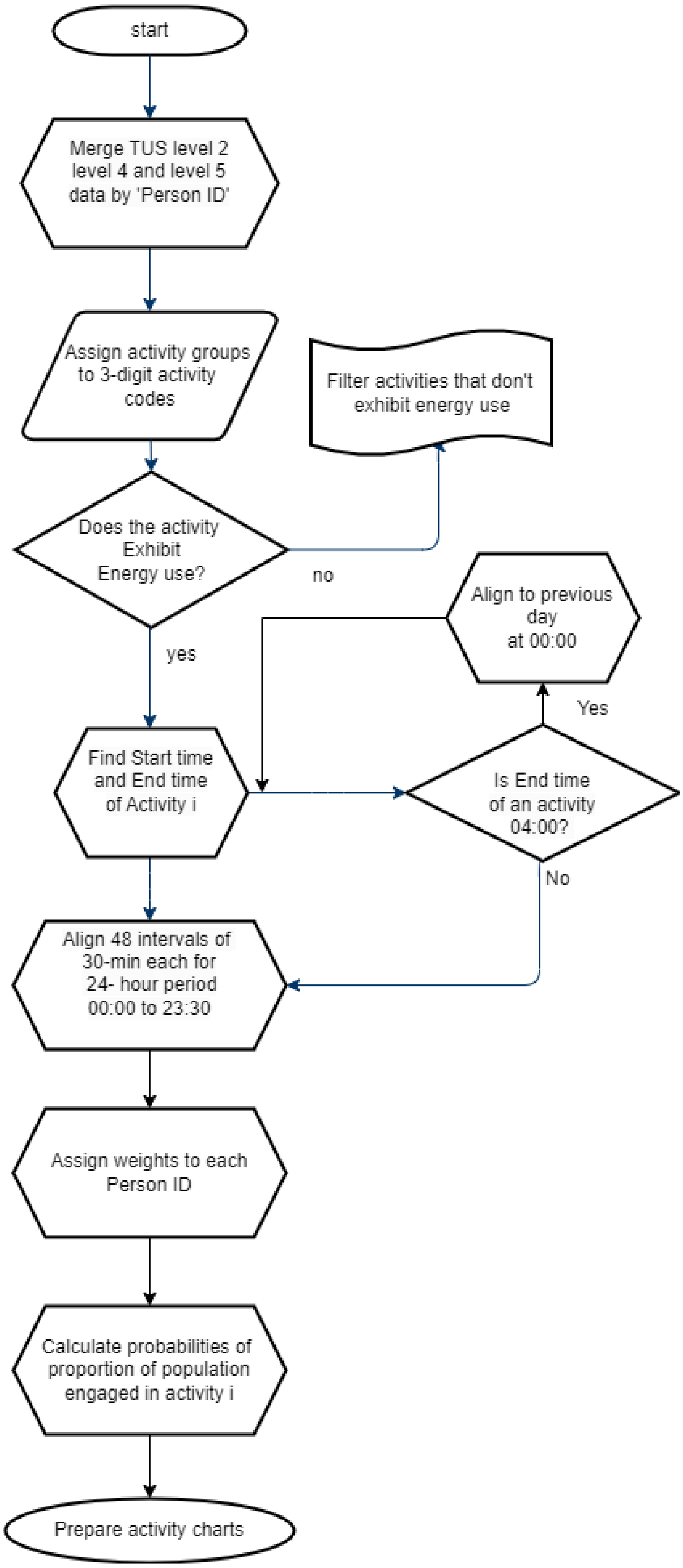


Figure 4.3: *Flowchart for analysing time-dependent activities*

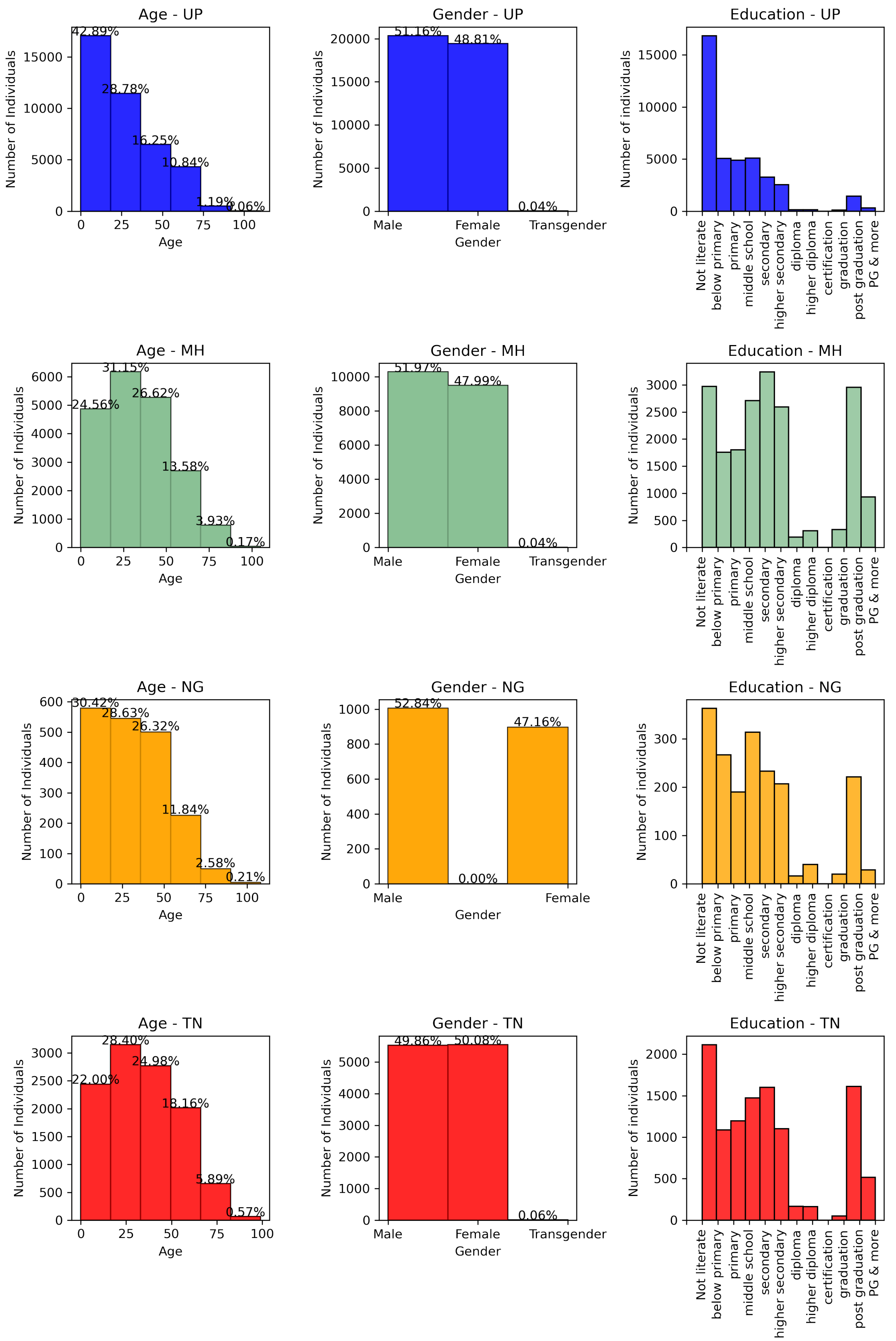
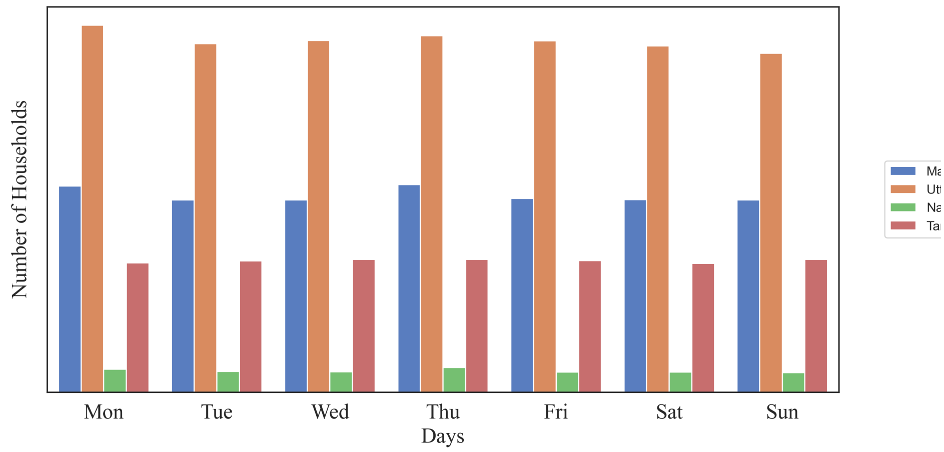
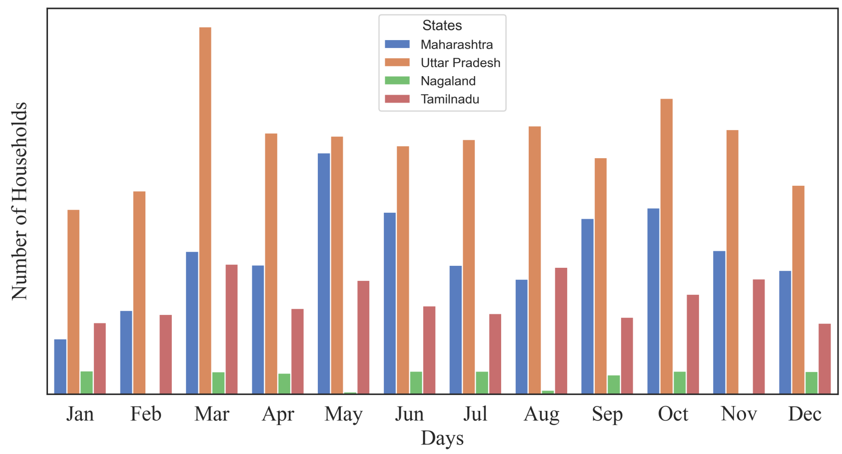


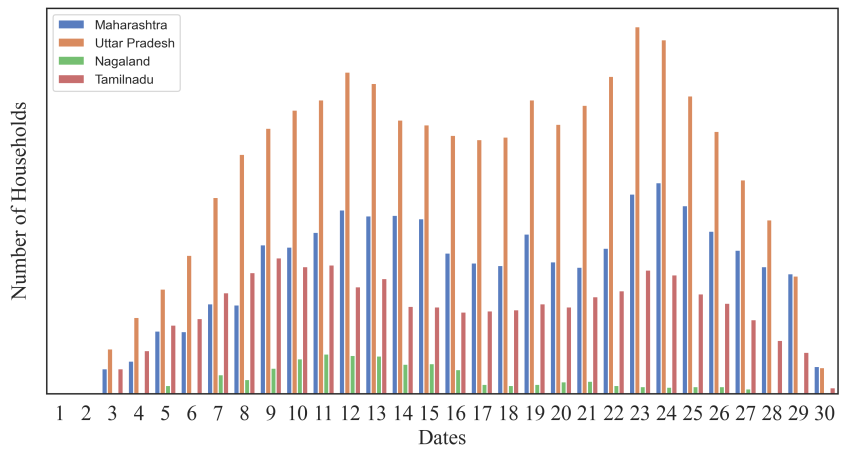
Figure 4.4: *Distributions of Age, Gender and Education in survey respondents, here UP = Uttar Pradesh, MH = Maharashtra, NG= Nagaland, TN = Tamilnadu*



(a)



(b)



(c)

Figure 4.5: *(a) describes the days of the week the survey is taken and (b) represents days of the month the survey is taken, and (c) captures all the months of the year*

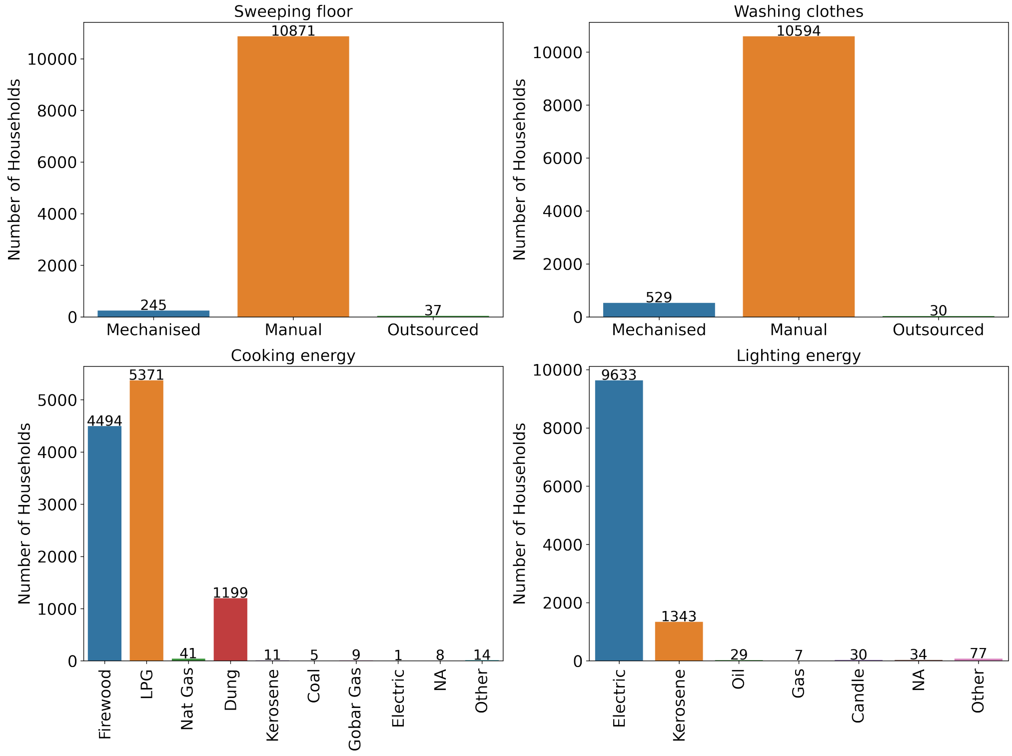


Figure 4.6: *Energy use in Uttar Pradesh*

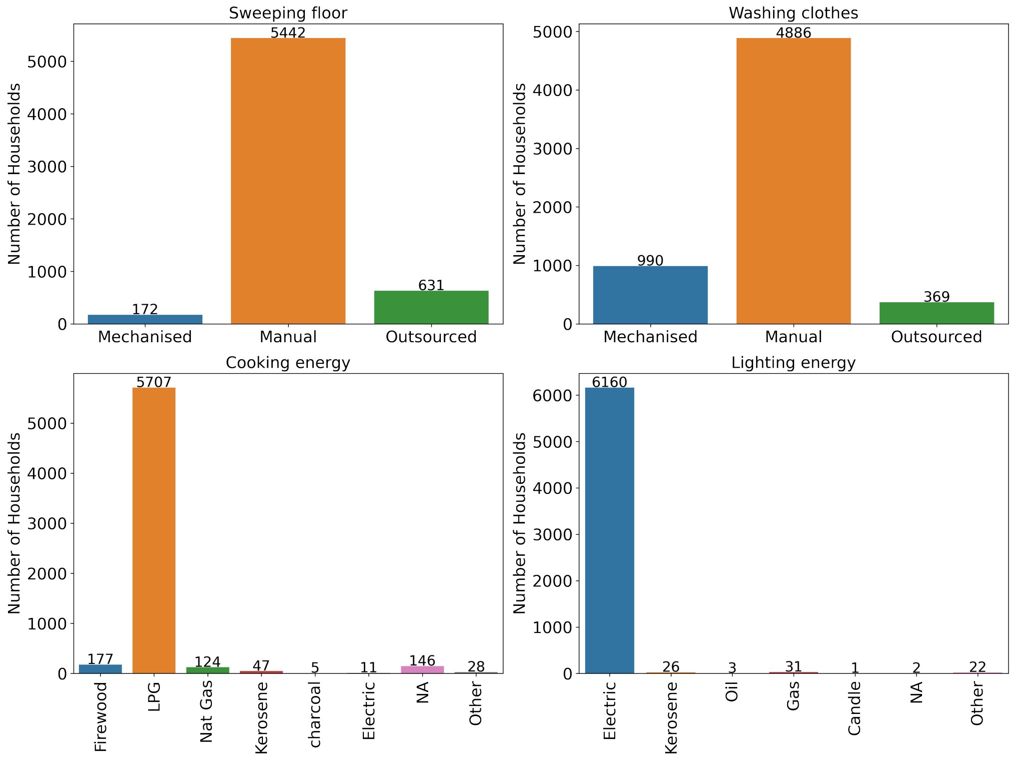


Figure 4.7: *Energy use in Maharashtra*

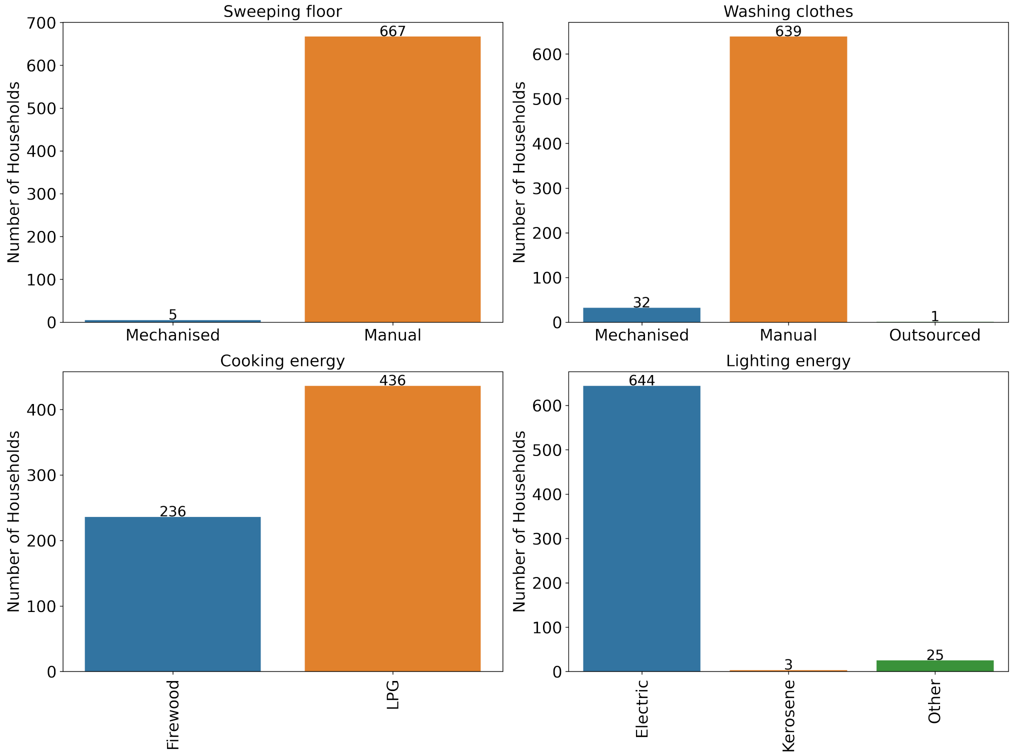


Figure 4.8: *Energy use in Nagaland*

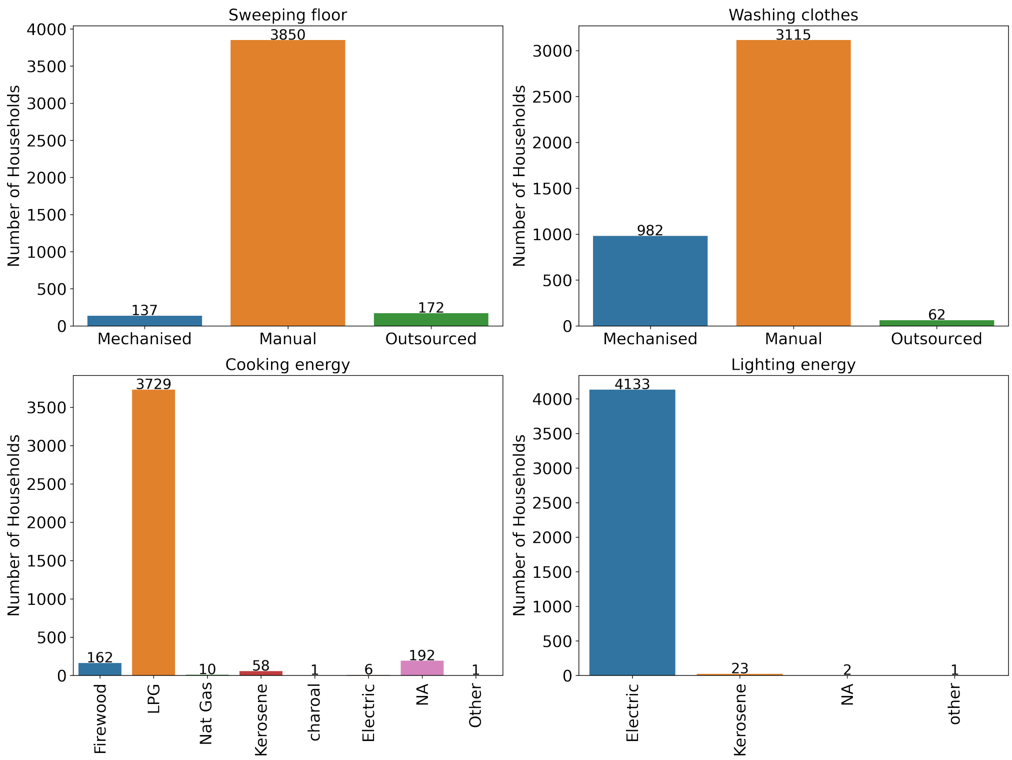


Figure 4.9: *Energy use in Tamilnadu*

4.5.3 Economic characteristics of TUS data

Figure 4.8 and Figure 4.9 show the effect of outlier treatments on two univariates, household size and overall monthly expenses. We compared all variables with numeric data entries in household level 3 and found a pair-wise correlation of each variable. As a result, household size and overall monthly expenses showed a correlation (see Appendix A.4.2), but the presence of outliers strongly influenced the descriptive statistics of these variables. As noted earlier, we tested two methods to handle these values. Figure 4.8(a) shows the original data on overall monthly expenses; the Median value of expenses in rural Maharashtra is higher than that of the other three states, as it is an economically progressing state. Meanwhile, Nagaland and Tamilnadu exhibit nearly similar median expenses, with Uttar Pradesh having the lowest among the rest. There is a strong presence of extreme values on the upper end, the highest being in Maharashtra, slightly less than $4000 USD[36]. Although this value at the upper extreme may be a genuine observation, it does not concur with the average annual high-income estimated at a national scale. A survey conducted by People Research on India's Consumer Economy (PRICE), an independent not-for-profit organisation in 2020 (*People Research on India ' s Consumer Economy*, 2021) covered 200,000 households, with 80,000 of them being in rural areas in 100 districts across India. Their report on micro-economic data reveals that 10% of the high-income population in India accounts for 29% of the total income, with an average annual household income of $9170 USD, while the low-income 10% population accounts for only 3% of the total income, with an average annual household income of $1710 USD. Keeping this range as a guide, we implemented two methods for treating the values that are at far extremes: IQR+1.5 and Winsorisation.

Figure 4.10(b) provides a visual representation of the impact of the IQR outlier treatment on the overall monthly expense data. The IQR outlier treatment involved the removal of observations that fell outside the range defined by 1.5 times the first quartile and 1.5 times the third quartile. In Maharashtra, 5980 out of 6245 households, or approximately 95.8%, were included within this range, resulting in the removal of 265 households that exhibited extreme values. As a result of this outlier treatment, the mean, maximum, and minimum values were significantly altered. Prior to the IQR treatment, the minimum monthly expense was $6, whereas the maximum expense reported was $3871. In contrast, following the IQR treatment, these values shifted to $22 and $433, respectively. Notably,

[36] All the values are originally recorded in rupees, taken in US dollars here for the simplicity and comparison, the rate of a currency is taken at USD 1 = 81.81 Indian rupees as of December 2022

the mean overall expense also shifted considerably, decreasing by \$21 from \$181 before the treatment to \$160 after. A similar shift in descriptive statistics of the rest of the three states is also observed and enlisted in Table 11 for reference.

In addition to IQR, another approach, Winsorization, is shown in Figure 4.10(c). In this method, for instance, extreme values are replaced with the values corresponding to the 1st and 99th percentile, thereby bounding the range of the data. In the case of the state of Maharashtra, this approach resulted in a minimum expense of \$22 and a maximum expense of \$667, leading to an approximate decrease of \$4 in the mean expenses. Notably, these values align more with the average high-income households' statistics on a national scale, though it has been debated over the years whether matching national averages with survey data perpetuates misconception (Deaton & Kozel, 2005). Nevertheless, Winsorization can be an effective method for handling extreme values in the upper bound, minimising the deviation of the mean value from its original value.

Figure 4.11(a) shows original data on household size in each state. The original data from rural households in Uttar Pradesh contained an extreme value for the maximum number of members in a household of 21. It can be either an outlier which needs to be removed or handled with a reasonable assumption of the upper limit. However, this value might be legitimate from a cultural perspective where *joint families* are common in Indian societies. Therefore, treating this value as an outlier and dropping it might not be appropriate. Both of the outlier treatment methods, IQR and Winsorization, might not be sufficient for handling outliers while dealing with household size data. They might result in an improper estimation of household size. In addition, it's worth noting that household size may not always have a linear correlation with monthly expenses, but it may have a nonlinear relationship that needs further analysis. Table 11 also highlighted all the minimum, maximum and mean values of household size in all four states for reference.

The IQR method for outlier detection assumes that the data follows a normal distribution, which is not the case in all scenarios of TUS household data. Non-normal distributions may result in the misidentification of outliers or the failure to detect true outliers, thus impacting the accuracy and reliability of the analysis. Therefore, we also tested Winsorization, which may be more suitable for non-normal data. However, Winsorization may also have its limitations and may lead to misrepresentation of data in certain cases. For instance, Winsorization may result in slightly higher reported expenses for the bottom of the pyramid populations, as it replaces the extreme values in the lower bound with less extreme ones and increase the value of the average expenses. This could

Table 12: Outliers' impact on descriptive statistics of household level 3 variables: Household size and overall monthly expenses

States	Values	Overall Monthly Expenses Original $	Overall Monthly Expenses IQR $	Overall Monthly Expenses Winsorisation $	Household Size Original	Household Size IQR	Household Size Winsorisation
MH	Min	6.1 (n=6245)	6.1 (n=5980)	22.0 (n=6245)	1 (n=6245)	1(n=6135)	1(n=6245)
	Max	3681.7	433.9	667.1	18	7	8
	Mean	181.5	160.6	177.4	3.5	3.4	3.5
UP	Min	3.6 (n=11153)	3.6(n=10615)	18.9(n=11153)	1(n=11153)	1(n=10864)	1(n=11153)
	Max	1102.9	181.4	274.0	21	8	10
	Mean	88.3	80.3	87.42	4.3	4.2	4.4
NG	Min	11.4 (n=672)	11.4 (n=648)	24.7(n=672)	1(n=672)	1(n=668)	1(n=672)
	Max	611.1	249.5	336.1	9	7	7
	Mean	120.5	113.1	119.8	3.3	3.2	3.3
TN	Min	5.2(n=4159)	5.2(n=4005)	18.6(n=4159)	1(n=4159)	1(n=4151)	1(n=4159)
	Max	977.8	285.2	366.7	10	7	6
	Mean	125.8	116.1	124.4	2.9	2.9	2.9

potentially exclude equal representation of all income levels in the analysis and induce bias in estimations. Therefore, careful consideration of the specific data characteristics and the potential impact of different outlier detection methods is necessary to ensure the accuracy levels in analysis. Economic attributions of various households can have a significant influence on activities performed in households and the energy use behaviours of members occupying the house.

4.5.4 Time dependent residential activity profiles

This section provides insights into the social practices of rural households as a function of time-dependent activities. We will refer to these as activity profiles henceforth. Figure 4.12 displays the probabilities of the proportion of populations engaging in activity profiles of rural households across all four states, taking into consideration ten domestic activities occurring over a 24-hour period with potential implications for residential energy consumption. Time use data is recorded based on a 24-hour cycle starting at 04:00 am to the next day at 04:00 am; survey participants have responded to activities they engage in within discrete intervals of 30 minutes.

In the activity profiles of all four states in India, there are certain similarities in daily

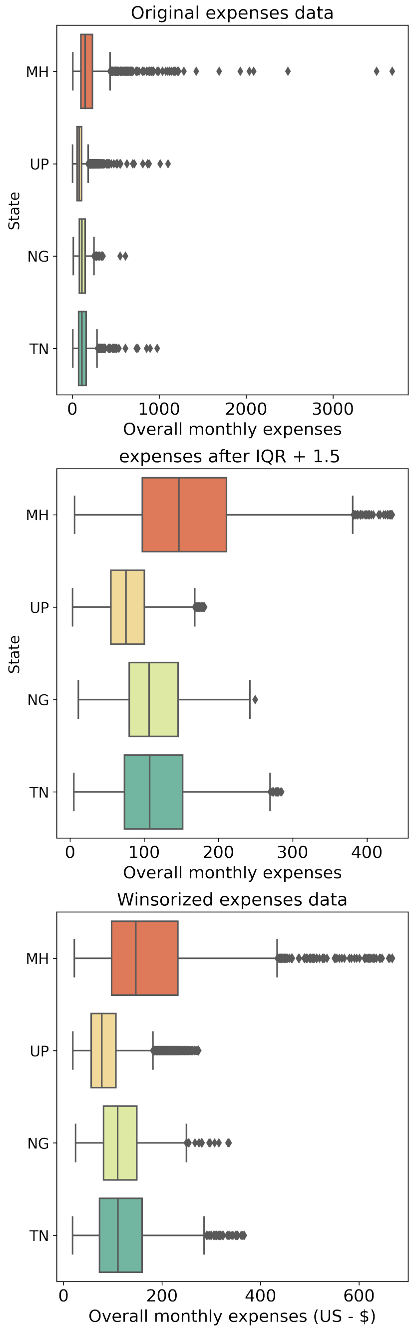


Figure 4.10: *Monthly expenses with original data, IQR and Winsorisation*

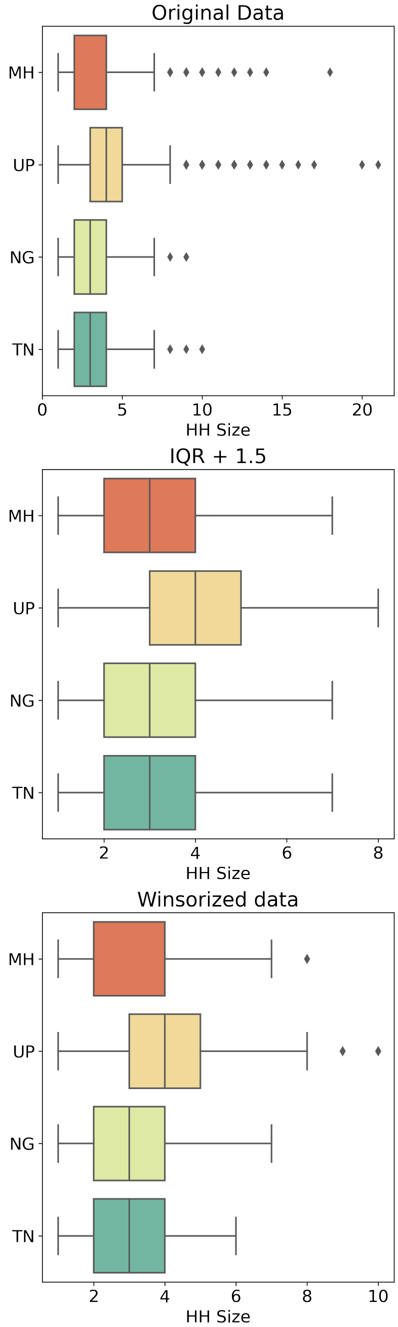


Figure 4.11: *Household size with original data, IQR and Winsorisation*

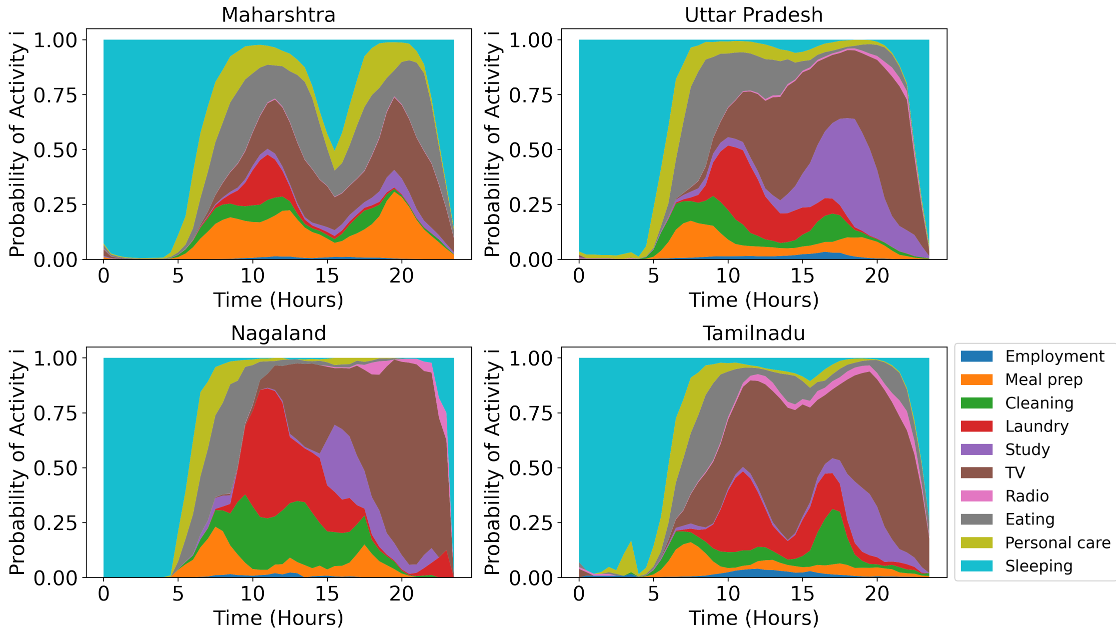


Figure 4.12: *Residential activity profiles of four states without consideration of weights of individual respondents*

routines but also notable differences in the time of their occurrences. For example, long-duration activity, such as sleeping in Maharashtra, is seen in two different time periods - night and afternoon. However, in Nagaland, people do not appear to take afternoon naps. Similarly, the timing of laundry activities also varies between the states. While in Maharashtra, only a segment of the population undertakes the activity only for a short duration in the morning (perhaps reflecting the increased use of mechanised washing); in Nagaland, it is carried out in the afternoons until the early evening. These activities are indicative of the time of use of appliances such as ceiling fans and washing machines, respectively, which majorly contribute to residential peak energy demand. Other activities, such as meal preparations, are comparatively more elaborate in Maharashtra, with a major part of the population preparing meals for lunch during the late mornings and for dinner during the evening. Whereas, in Nagaland, the probability of people preparing meals is less during the evening when there is a high probability of people watching a TV, which might occur simultaneously with eating meals.

In this analysis, we also incorporated weights assigned to individual respondents, as elaborated in section 4.4.2. The activity profiles, which include the weighted probabilities of populations, are shown in Figure 4.13. Upon comparison with non-weighted survey activity profiles in Figure 4.12, these weighted activity profiles appear remarkably similar. The discrepancies between the two profiles range from $10^{-}2$ to $10^{-}4$, as illustrated

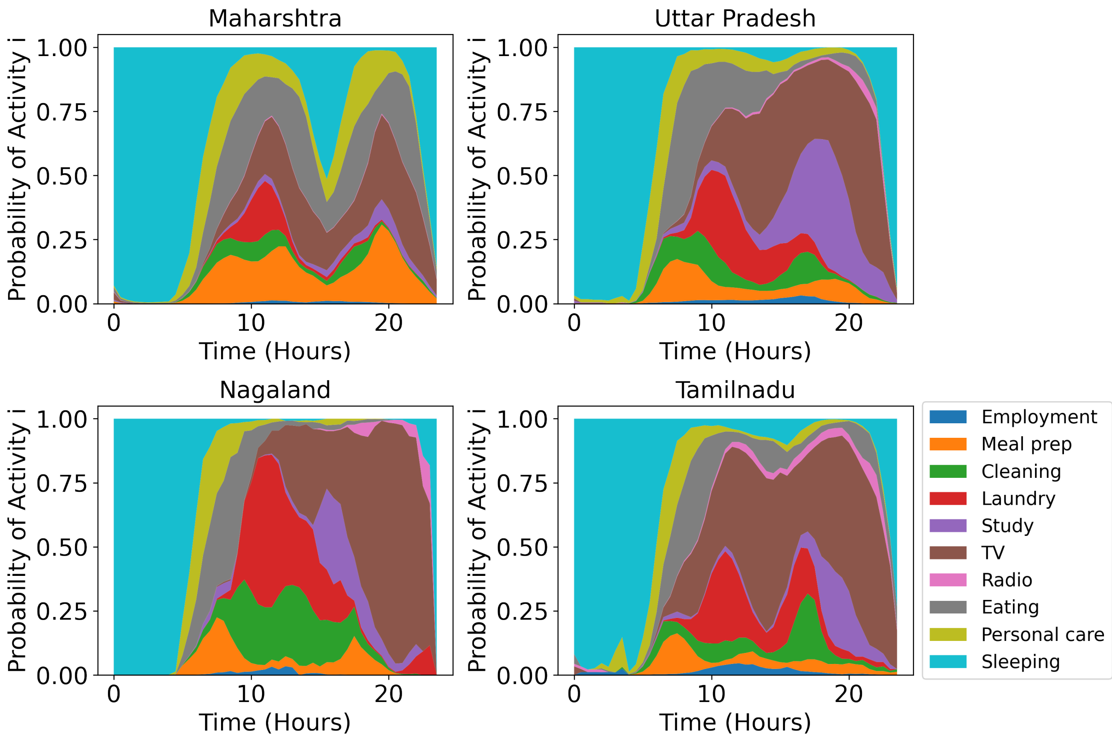


Figure 4.13: *Residential activity profiles of four states without consideration of weights of individual respondents*

in Figure 4.16. This observation suggests that the sampling of the time-use survey is representative of its sub-populations. In conclusion, we have verified the suitability of the Indian time-use survey data for the calibration of activity modelling, which will be discussed in further detail in Chapter 5.

4.6 Summary

This chapter began with an overview of energy demand models, emphasising the importance of accounting for the time-sensitive nature of energy use. We then introduced a multi-scale framework for energy demand modelling. We discussed its applicability to Global South countries, with a focus on model calibration with time use survey data. The Indian Time Use Survey dataset from 2019-2020 was then presented, along with identification of categories of activity with significant energy use implications. A thorough data assessment examining demographic characteristics, energy use variables, and economic parameters show that Indian TUS data has the necessary attributes to support high quality disaggregated energy demand modelling based on residential activities. In support of this, we presented activity profiles for four different states, confirming the representativeness

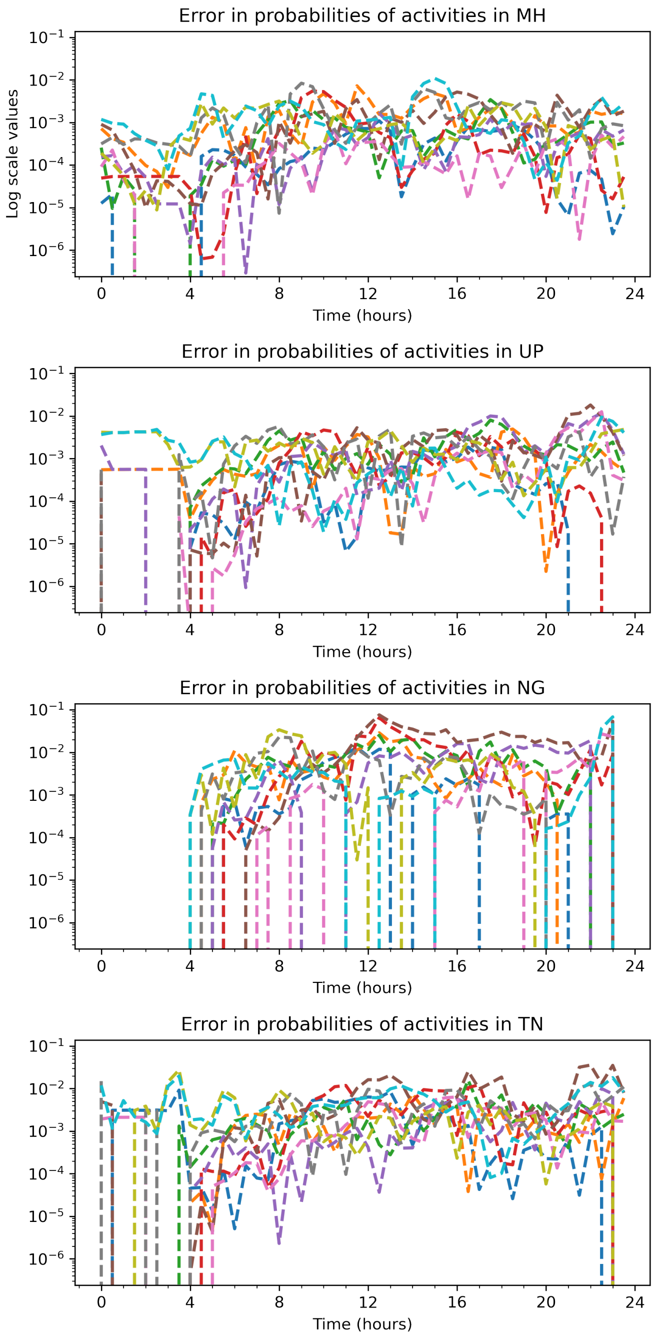


Figure 4.14: *Difference in probabilities with and without consideration of weights in TUS data of four states*

of the datasets for sub-populations by considering the weights of individual respondents. In the following chapter, we will calibrate models for residential activities to construct a load profile underpinning the time-sensitive nature of energy demand.

Chapter 5

Residential energy demand model

5 Residential load profiles

In this chapter, we introduce a model designed to create bottom-up load profiles at the household level, with the goal of scaling up to the community or village level. The model is calibrated using residential activity data derived from Time Use surveys in India (in this, two states are considered: Uttar Pradesh and Nagaland). Specifically, we address three key tasks: i) calculating starting probabilities for activities, which inform the start time of correlated appliances; ii) the duration of activities once initiated, which influences the duration of appliance use; and iii) Generating representative load profiles of televisions in use in rural communities of Uttar Pradesh and Nagaland. Additionally, we compare Gaussian and Weibull distributions for duration modelling, providing error statistics for both. The chapter concludes with a summary and outlines future work needed to further refine the model, as it is currently a work in progress.

5.1 Overview of residential activity modelling

Expanding upon the groundwork done in the previous chapter, the focus of this chapter shifts toward building a model of residential activities in order to construct load profiles using a bottom-up approach. The task of characterising residential load profiles is challenging as it involves multiple social and behavioural aspects of energy use with a high degree of stochasticity. An early model accounting for this stochastic nature of residential energy use is found in (Capasso, Lamedica, Prudenzi, & Grattieri, 1994); the model used two-level aggregation of behavioural and engineering probability functions and a Monte Carlo process to construct a load profile highlighting the shape of the daily residential demand curve and its significance.

Other more granular models have been recently developed to generate demand patterns from residential activity sequences. One such model, introduced by (Widén & Wäckelgård, 2010), was validated against measured demand based on key features such as end-use composition, diurnal and annual variations. Similarly, (Richardson, Thomson, Infield, & Clifford, 2010) presented a model that mapped occupant activity onto the appliance use and stochastically created synthetic demand data with a one-minute time resolution. This model was constructed using individual appliance power consumption data and nationwide ownership statistics and was validated using high-resolution measured data from 22 local dwellings in the UK. The effectiveness of the model lies in its ability to represent the time-coincidence/diversity of demand due to the inclusion of after-diversity demand and power factors. Wilke *et al.*(Wilke, 2013) have developed a stochastic bottom-up energy use model capable of predicting load profiles based on occupancy levels, appliance stocks and residential activities. The model was calibrated with French Time Use Survey data (TUS) validated against measured data. Torriti (Torriti, 2017) has reviewed several models built to estimate residential energy demand based on time use studies. The author evaluated these models based on what type of data has been used, what statistical methods are implemented and identified their limitations, and in conclusion, highlighted the importance of the quality of data.

Time use survey data is a valuable resource for researchers and academics as it is unique in nature, translating qualitative narratives of people's day-to-day activities into quantitative information in discrete time steps (Gershuny, Margarita, & Lamote, 2020). However, the quality of the data collected can have a significant impact on the accuracy of models developed based on time-use studies. In the previous chapter, we extensively discussed the robust nature of Indian Time Use Survey (TUS) data and its suitability for building time-use energy demand models. In the present chapter, our primary aim is to discern the patterns of daily electricity consumption and the corresponding appliance usage in rural households, taking into account the influence of time-dependent activities performed in rural households in India. To this end, we present a preliminary bottom-up stochastic model which addresses the following questions:

- What proportion of the population initiates activities that result in energy consumption by the related appliance?
- Once initiated, what is the average duration of the activity and, in turn, the corresponding appliance usage period?
- What are the anticipated energy consumption patterns exhibited by the appliances while in use?

To address these questions, Section 5.2 presents a methodology of the bottom-up approach. Each subsection of the methodology elucidates the model structure and analysis, along with corresponding results from two states in India: Uttar Pradesh and Nagaland[37]. Section 5.3 focuses on the application of Monte Carlo methods to generate appliance-level

[37] Uttar Pradesh because it has the highest population in India with low electrification rate and Nagaland because it has small population size with low electrification rates. The government claimed that all the villages in both states are electrified 100 %, however there are no independent studies found affirming the claim

load profiles, illustrating the efficacy of the residential activity model. The key findings and discussions are followed in Section 5.4, as well as an outline of future research directions. Finally, Section 5.5 provides a conclusion to the chapter.

5.2 Methodology for residential energy demand model

As the primary objective of the model is to understand the time-sensitive nature of daily energy use in households, key parameters of interest include the start times and usage duration of appliances. Hence the methodology associated with the energy model based on residential activities comprises four steps:

1. Estimating the starting time probabilities of each activity. (Section 5.2.1)
2. Calculating the probabilities of activity duration once initiated. (Section 5.2.2)
3. Duration modelling - fitting Gaussian and Weibull distributions to each activity duration. (Section 5.2.3)[38]
4. Constructing appliance load profiles based on the corresponding activity data for a prospective hypothetical village. (Section 5.2.4)

Figure 5.1 illustrates the schematic representation of the steps undertaken in the methodology, and the following subsections describe the model structure in detail.

5.2.1 Probability of starting an activity

First, we initialise the residential activity records [39] and calculate the probability $P_i(t)$ of individuals starting an activity i at any given time t. Given that our data is recorded in discrete 30-minute intervals, we applied a 1D Gaussian filter to reduce fluctuations. The Gaussian function is used as a mask to overlap the original data, resulting in a smoothed output.

The one-dimensional Gaussian filter $f(x)$ is described as :

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \tag{12}$$

Where x is the observed value, and σ is the standard deviation. The convolution process involves calculating the sum of element-wise products at each time step, yielding a

[38] In 2nd step we calculate probabilities and in 3rd we calculated probability density function

[39] for more details on activity types considered, see Table 10 in Chapter 4

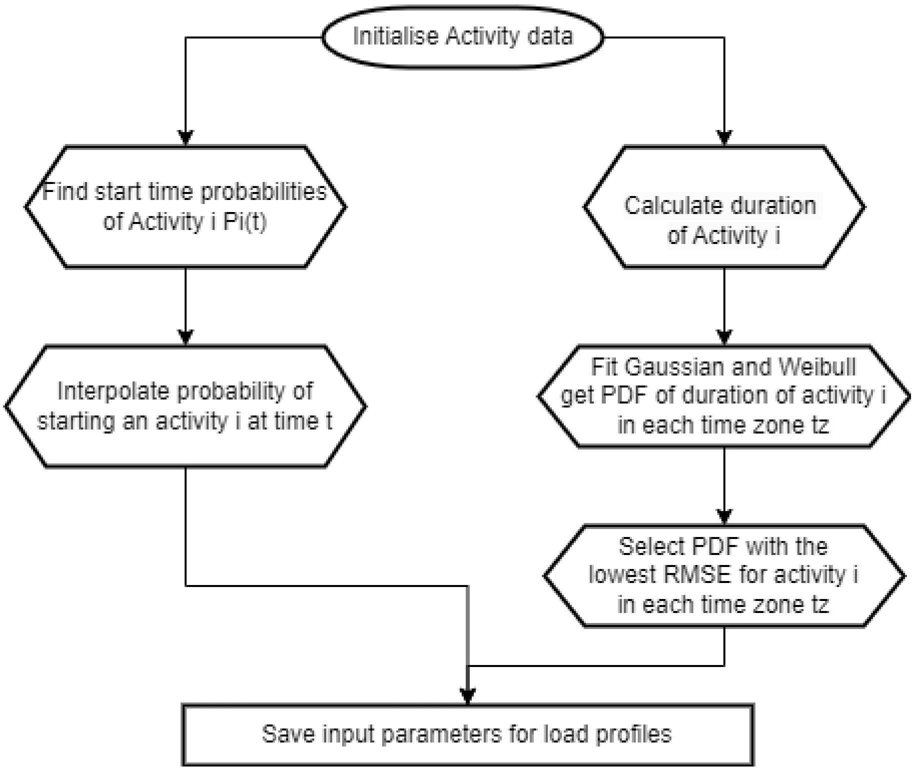


Figure 5.1: Schematic of activity modelling steps

smoothed output. Subsequently, the smoothed output is interpolated using a cubic function. Figures 5.2 and 5.3 display the resulting probabilities of initiating ten activities in rural households of Uttar Pradesh and Nagaland, respectively. Distinct characteristics are evident in both states, particularly with activities such as watching TV and sleeping. In Uttar Pradesh, a considerable proportion of the population seems to engage in afternoon naps, while in Nagaland, a relatively higher percentage of people watch TV in the evening.

It is important to note that within the first activity group, *employment*, we only considered activities performed inside the house for profit, commonly known as 'working from home' in recent times. However, since the survey data was collected prior to the pandemic and agriculture serves as the primary source of livelihood in rural India, this activity is not initiated by a significant number of individuals. However, with the rise of working from home culture and strong encouragement towards women's empowerment in villages (referring to *griha udhyog*) these activities are likely to increase in the future with corresponding increases in the utilisation of appliances such as electric sewing machines.

5.2.2 Probabilities of the duration of activities

Once these residential activities are initiated, we are interested in calculating how long these activities will last for. The probability $P_i(\Delta t)$ of the duration of each activity i is

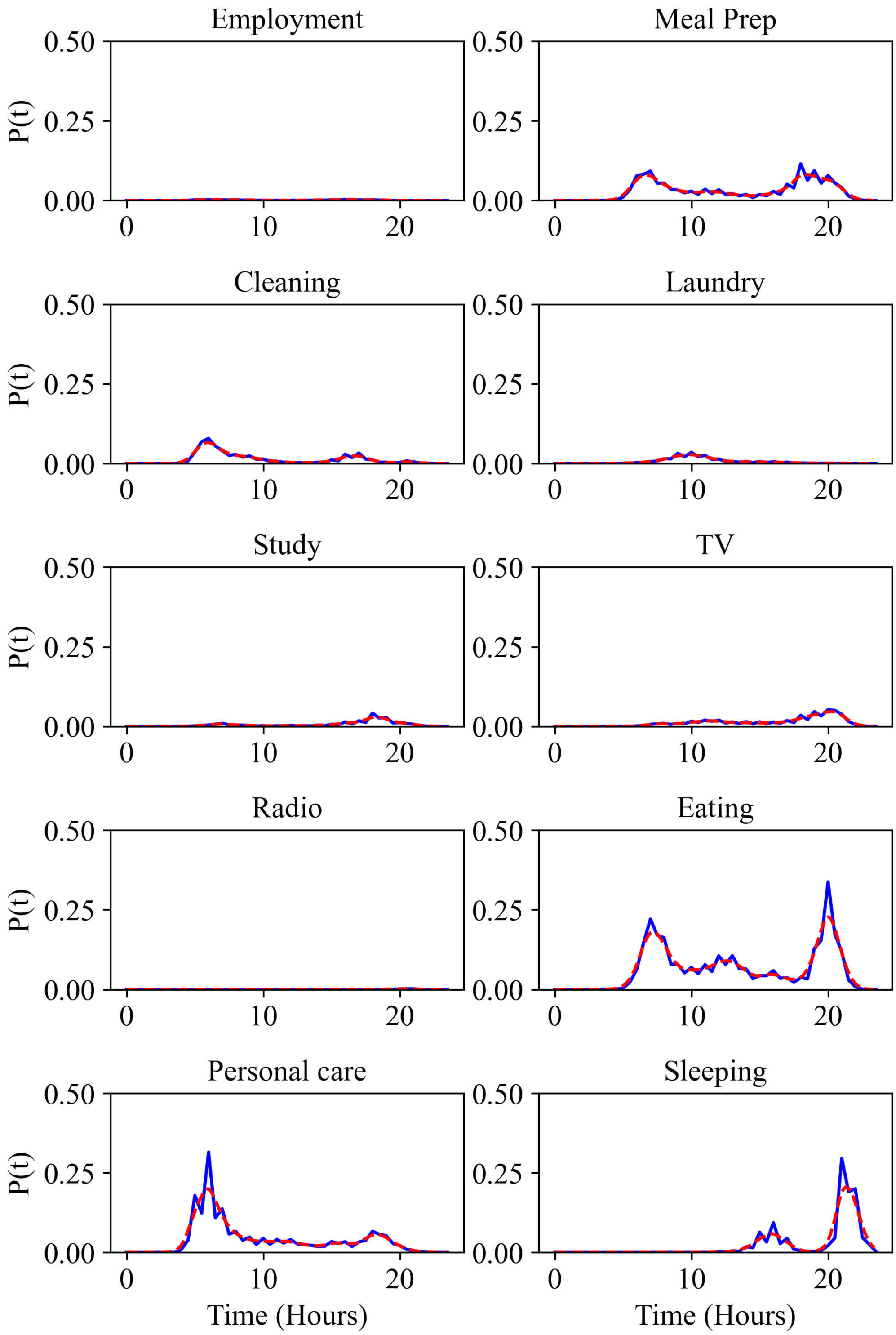


Figure 5.2: Probabilities of the starting ten activities in rural Uttar Pradesh (n=39654)

. *The solid blue line denotes the original data, and the red dashed line is smoothed data with a Gaussian filter.*

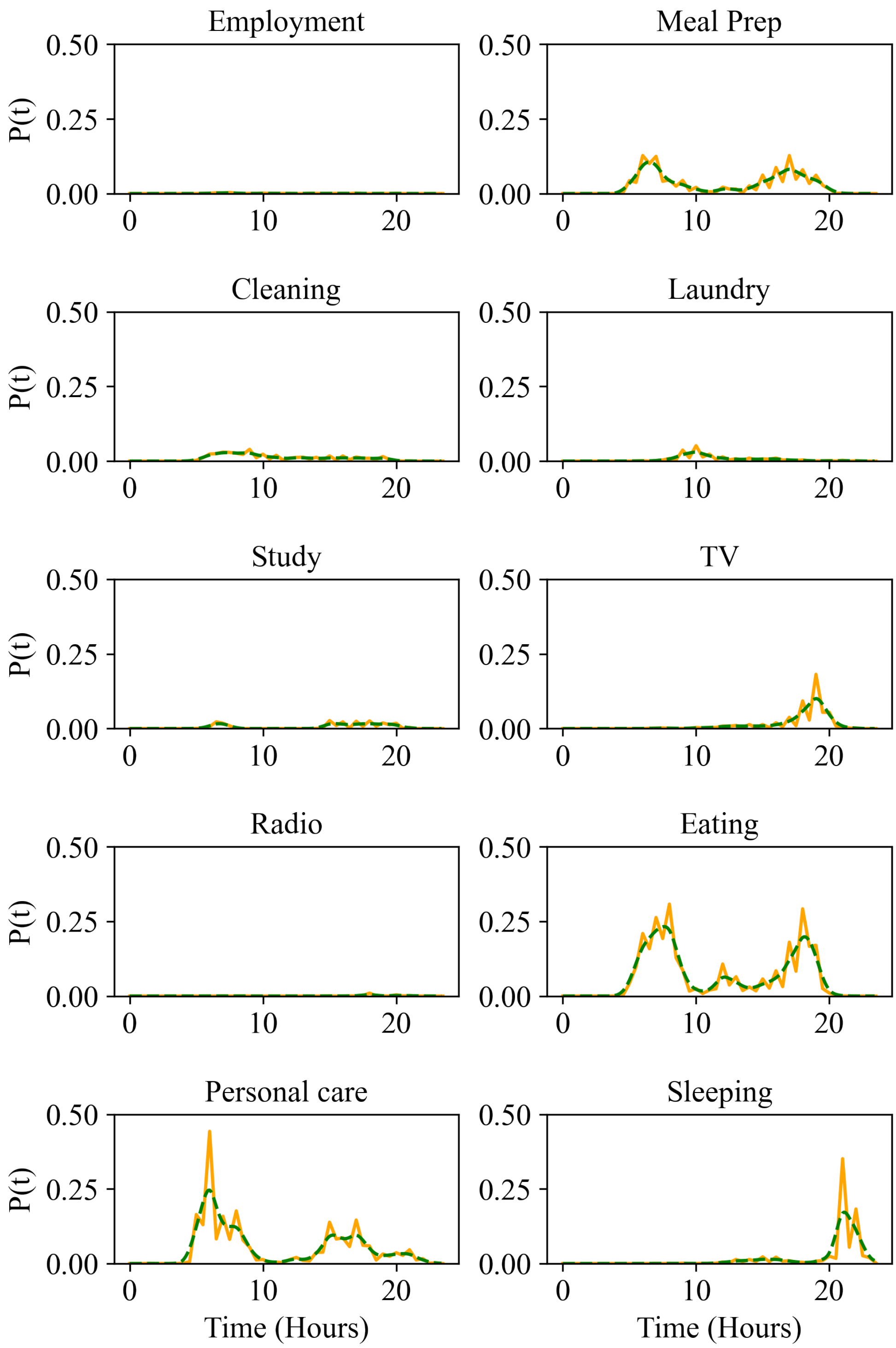


Figure 5.3: *Probabilities of the starting ten activities in rural Nagaland (n=1900). The solid orange line denotes original data, and the green dashed line represents smoothed data with a Gaussian filter*

calculated based on

$$P_i(\Delta t) = \frac{n_i(\Delta t)}{N} \tag{13}$$

$P_i(\Delta t)$ denotes the probability of x people performing the activity for a duration of Δt. $x(\Delta t)$ represents the number of people performing the activity for a duration of Δt. N is the total number of people. Each bar in the chart represents a 30-minute time interval. For instance, in Uttar Pradesh, once individuals begin watching TV, approximately 45% of the population continues to watch for 1 hour, while fewer than 20% watch for more than 1.5 hours. In contrast, the duration of TV watching in Nagaland is comparatively evenly distributed, with nearly 30% of the population watching for 1 hour and an equal percentage watching for 2 hours.

This observation may be attributed to the fact that the intervals are discrete, while people in developing countries, particularly rural areas, tend to perceive time as a continuum rather than discrete units, as noted by Hirway (Hirway, 1999). In simpler terms, instead of reporting the precise duration of an activity, individuals often provide rough estimates and round off the hours spent on a particular activity.

Another crucial distinction to consider regarding activity durations is the distribution of sleeping activity, which is markedly different from other activities due to its significantly longer duration when occurring at night. However, it is also essential to recognise that sleeping occurs during two distinct time zones, especially in Uttar Pradesh, where a considerable portion of the population takes shorter afternoon naps. This observation necessitates dividing time into four zones—morning, afternoon, evening, and night—to gain deeper insights into activity duration and how they are influenced by these time zones. We employ this approach with respect to all ten activities in each zone. The wide-scale utilisation of ceiling fans during the summer season at night while sleeping also highlights the energy consumption implications of this activity. Moreover, as previously discussed in Chapter 3, from the supply-side perspective, the nighttime use of ceiling fans significantly impacts the storage size requirements for renewable mini-grid systems.

5.2.3 Duration model fitting

As a next step in the process of building the electricity demand model, we fitted the Gaussian distribution (also known as the normal distribution) and Weibull distribution to the duration of each activity. First, we divided activity records into four time zones, 4 am to 10 am as the morning, 10 am to 16 pm as the afternoon, 16 pm to 8 pm as the evening and 8 pm to 4 am the next day as nighttime. Following this classification, we fitted the

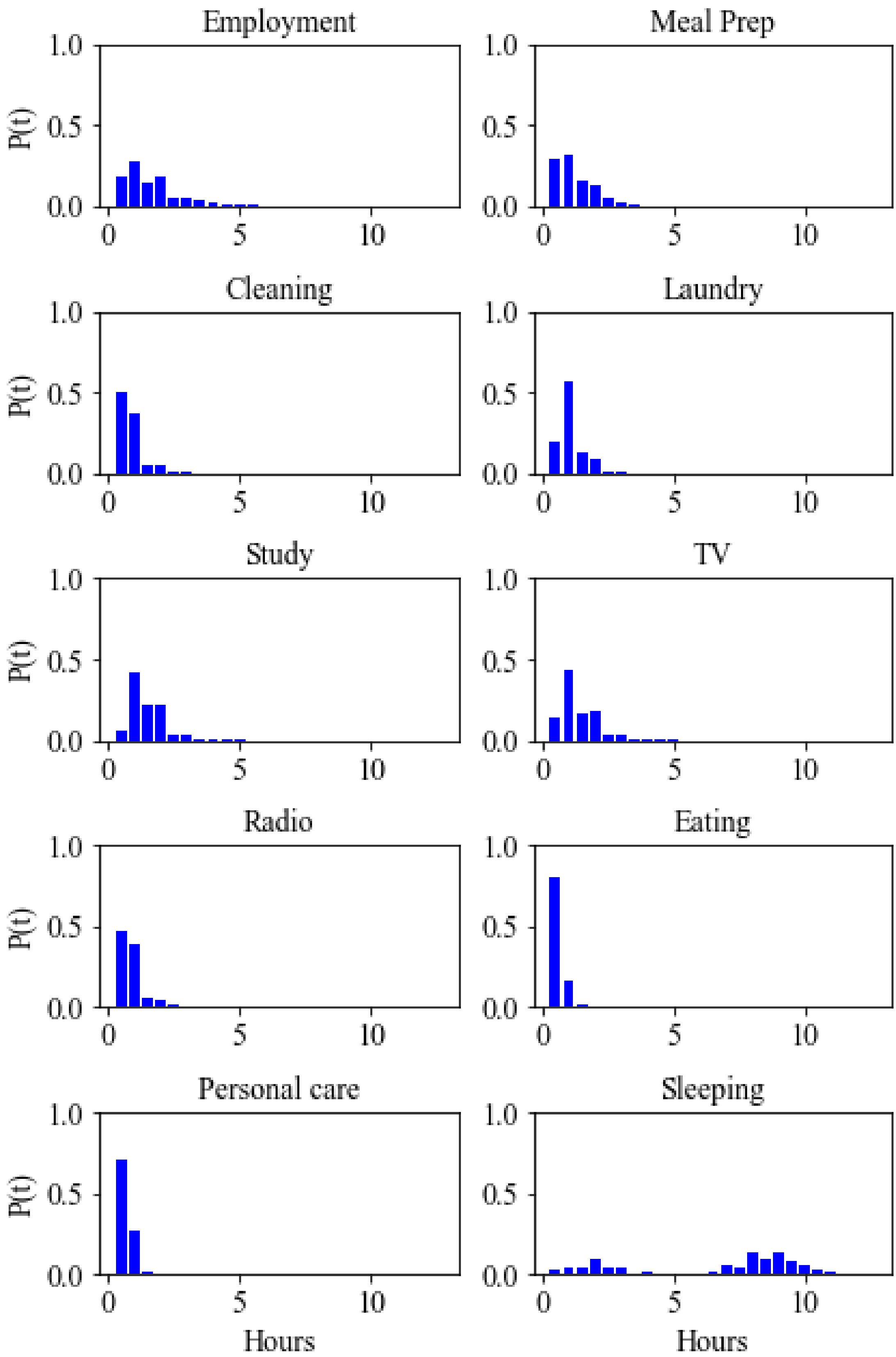


Figure 5.4: *Probabilities of the duration of activities Uttar Pradesh (n=39654)*

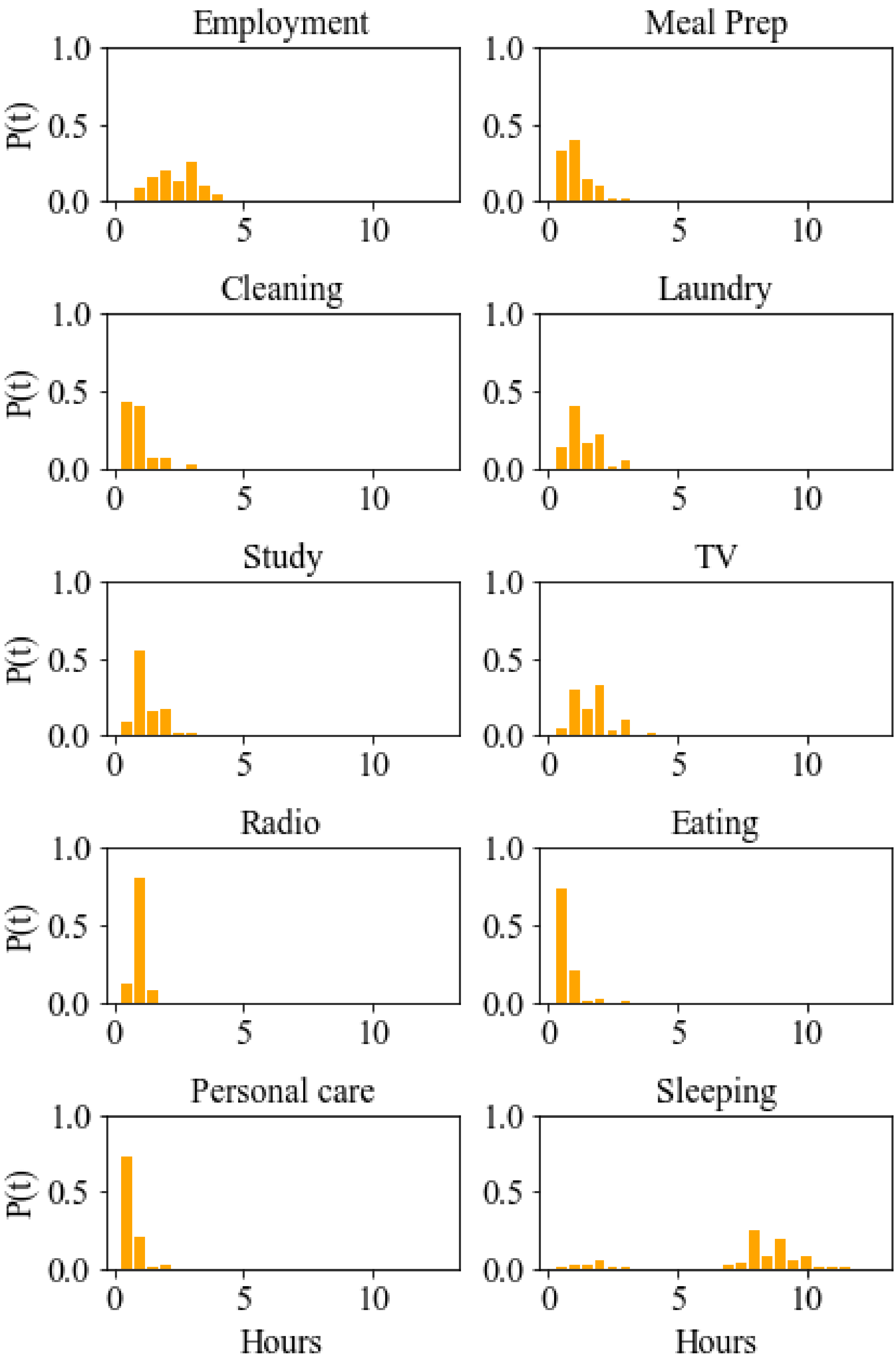


Figure 5.5: *Probabilities of the duration of activities Nagaland (n=1900)*

respective distributions to the original data.

The Gaussian distribution (interchangeably written as the normal distribution) is a continuous probability distribution that is often used to model random variables that are distributed symmetrically around a mean value. The Probability Density Function (PDF) of a Gaussian distribution with mean μ and standard deviation σ is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{14}$$

Where x is the random variable, μ is the mean, and σ is the standard deviation. The Weibull-min distribution is a continuous probability distribution. The probability density function (PDF) of a Weibull-min distribution with shape parameter k and scale parameter λ is:

$$f(x) = \left\{ \tfrac{k}{\lambda}\left(\tfrac{x}{\lambda}\right)^{k-1} \exp\left(-\left(\tfrac{x}{\lambda}\right)^{k}\right) \&x \geq 0 \ \&x < 0 \right. \tag{15}$$

Where x is the random variable, k is the shape parameter, and λ is the scale parameter.

The PDF describes the relative likelihood of observing different values of the random variable. To compare the goodness of fit, the Root Mean Squared Error (RMSE) is calculated for each activity in each time zone. RMSE is a measure of the differences between the predicted values and the actual values.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{16}$$

where n is the number of data points, x_i is the actual value of the and $\hat{x_i}$ is the predicted value of the point.

We identified three activities that have a direct association with electricity usage, including watching TV, laundry (potential use of washing machines as ownership increases), and sleeping, as discussed in the previous section. The observed data and fitted distributions for these three activities are presented in Figures 5.6 and 5.7 for Uttar Pradesh and Nagaland, respectively. For each of these activities recorded in the four time zones, both Gaussian and Weibull distributions are displayed, along with their respective RMSE values. Weibull distribution tends to fit better than the Gaussian distribution for activities that are short in duration but have a high probability density function (PDF).

The primary focus of model fitting is on activities such as laundry in the morning and sleeping at night, where both distributions exhibit a good fit. For example, in Nagaland (Figure 5.7), the RMSE for laundry in the morning is 0.08 for the Weibull fit and 0.09

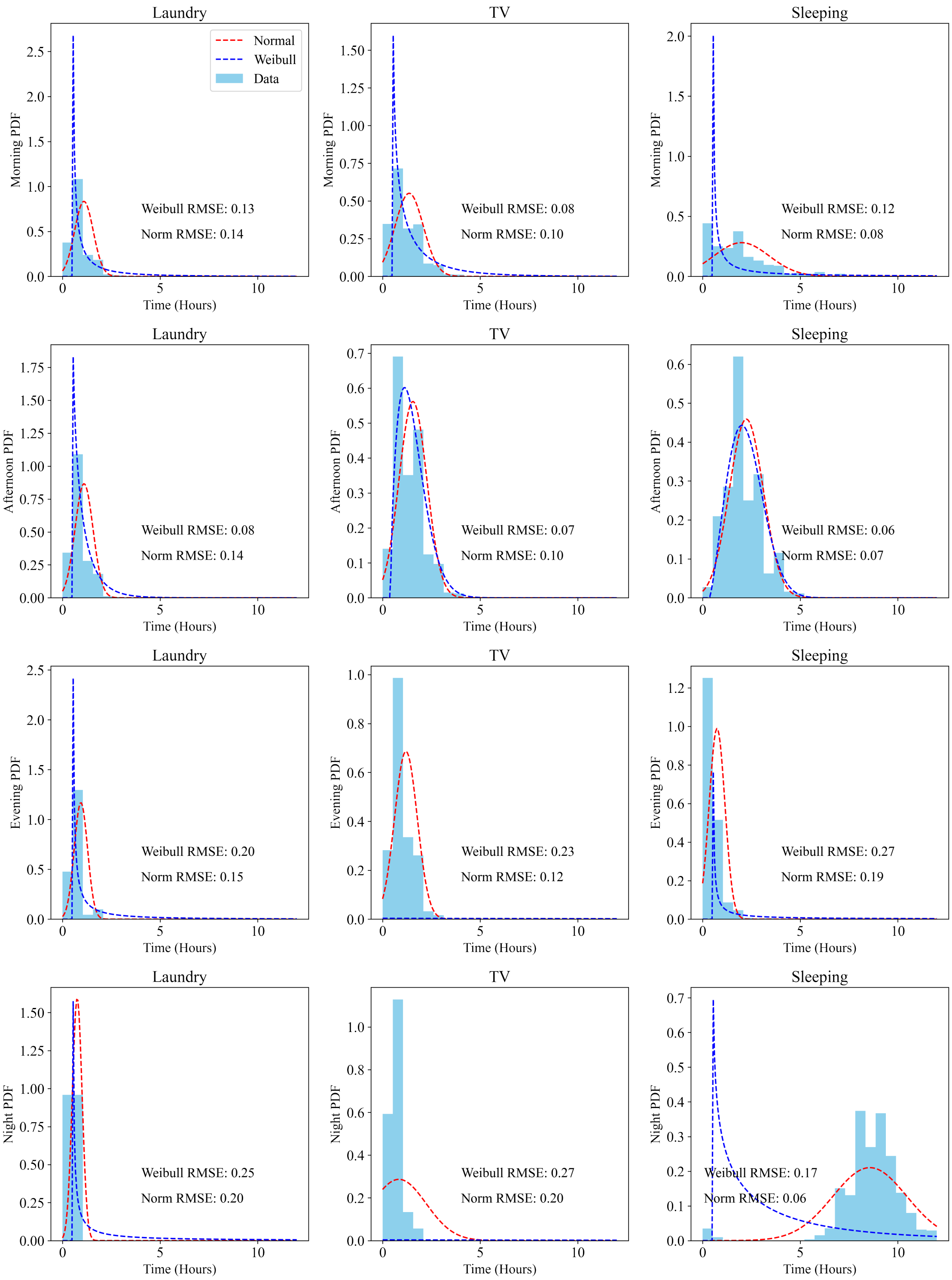


Figure 5.6: *Duration modelling of activities in Uttar Pradesh, the histogram represents original data, the red dashed line shows a Normal fit, and the blue dashed line shows a Weibull fit.*

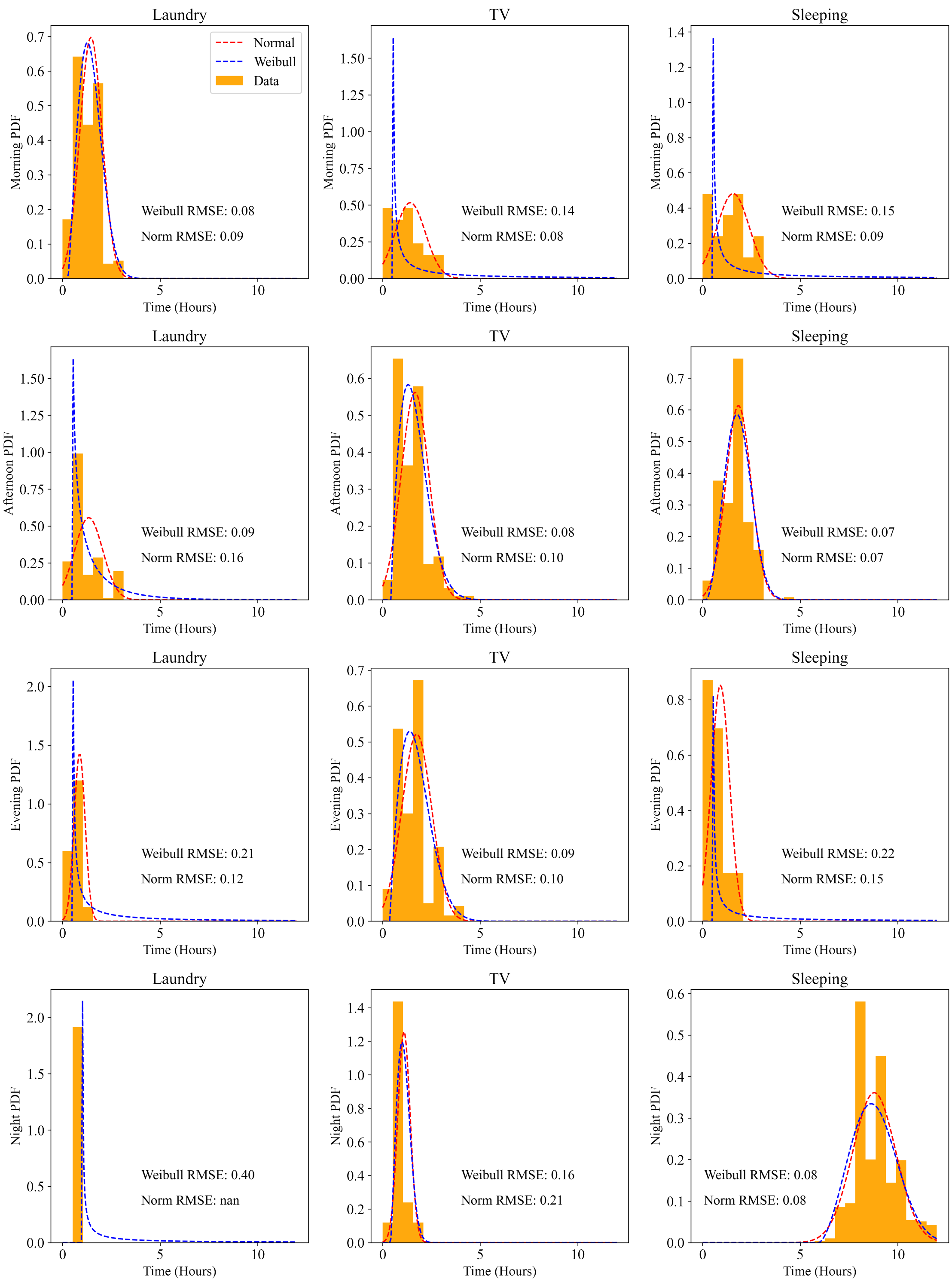


Figure 5.7: *Duration modelling of activities in Nagaland, the histogram represents original data, the red dashed line shows a Normal fit, and the blue dashed line shows a Weibull fit.*

for the normal fit. However, laundry at night is highly unlikely, and similarly, sleeping in the evening is less likely to occur. Neither of these activities shows a good fit due to the inherent nature of the data. In Nagaland, afternoon naps also demonstrate a good fit. The activity of watching TV fits well in three time zones, with RMSE values less than 0.1 in all three, except for the morning. For further load profile calculations, we will consider the duration probability density function (PDF) of each activity in each time zone with the lowest RMSE.

In Uttar Pradesh, the Weibull distribution, in contrast, does not show a good fit for key activities and tends to overfit the peak. This observation might be due to discrepancies in the data. For example, nighttime sleeping has a small number of people recording sleep for only 30 minutes because of the way data is recorded from 4 am to 4 am. Nighttime sleeping is recorded in two separate time slots: individuals reported sleeping at 10 pm and ending the activity at 4 am, then continuing the same activity from 4 am to 6 am. We have combined these recordings into a single entry; however, for a small number of observations, this could be erroneous or genuine. Similarly, all other activities show a good fit, except for TV watching in the evening and night, which exhibit slightly higher RMSE values. We utilise these duration PDFs with the lowest RMSE values to generate load profiles for the corresponding appliances, aiming to identify electricity consumption patterns. The methodology for this process is discussed in detail in the following section.

5.3 Load profiles

The generation of load profiles based on time-dependent activities, fundamentally it is built upon the assumption that the switching on times and duration of appliances are derived by human interactions with electrical devices. These interactions can be categorised into four types: 1) appliances that autonomously switch on and off (e.g., fridge), 2) appliances that are user-initiated but switch off automatically (e.g., washing machine), 3) appliances that are user-initiated and usage varies throughout the day (e.g., television and cooker), and 4) a subgroup of appliances that adhere to scheduled switching on and off (e.g., air conditioning). For the purpose of illustration, we have chosen to derive load profiles only for appliances falling under type 3. However, for a more comprehensive representation of energy usage, a deeper understanding of factors like seasonality and thermal comfort becomes imperative.

Our primary objective is to establish stochastic load profiles corresponding to individual appliances based on their respective activity profiles, encompassing both starting times and duration. As illustrated in Figure 5.8, the process involves sequential steps, hinging on two critical inputs: the interpolation function (as discussed in Section 5.2.2) and the duration Probability Density Function (PDF) of each activity across different time zones, detailed in Section 5.2.3. Following the initiation of the process, utilising binomial probability, we determine the initiation status of an activity at each time step over the 24-hour period. If the appliance is switched 'ON', we sample a random duration from the duration PDF. This procedure is iterated at each time step throughout the 24-hour duration to determine the appliance's ON/OFF profiles.

5.3.1 Monte Carlo Simulation / random sampling

Every randomly sampled profile is described as the path. In this process, we are sampling 10,000 such paths and finding a mean path that represents the time of an appliance usage. When n is the number of paths, T is the total number of time steps, $P_{\text{start}}(t)$ is the start probability at time step t and $f_{\text{duration}}(t)$ is the duration PDF for each time zone, the mean path $\bar{X}$ is defined as:

$$\bar{X} = \begin{bmatrix} 0 & 0 \cdots & 0 \end{bmatrix}_{T\times 1} \tag{17}$$

For each path $i \in 1, 2, \ldots, n$, we repeated the following:

$$X_i = \begin{bmatrix} 0 & 0 \cdots & 0 \end{bmatrix}_{T\times 1} \tag{18}$$

When $t < T$, the start probability $P_{\text{start}}(t)$ (which is similar to $P_i(t)$ using the interpolation function described in section 5.2.2. A random number $r \sim \mathcal{U}(0, 1)$ is generated. If $r < P_{\text{start}}(t)$ in each time zone, duration $d \sim f_{\text{duration}}(t)$ is sampled from the duration PDF $f_{\text{duration}}(t)$. The path X_i is updated for the duration d, and the process is repeated with every t incremented by d

$$X_i[t : t + d] = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}_{1\times d} \tag{19}$$

The mean path $\bar{X}'/$ is updated based on equation (20)

$$\bar{X}' = \bar{X} + X_i \tag{20}$$

and the final mean path is given by:

$$\bar{X} = \frac{1}{n}\bar{X}' \tag{21}$$

In the following section, we will illustrate the load profiles of individual appliance, focusing on the time-dependent usage of televisions which has straight forward consequence of

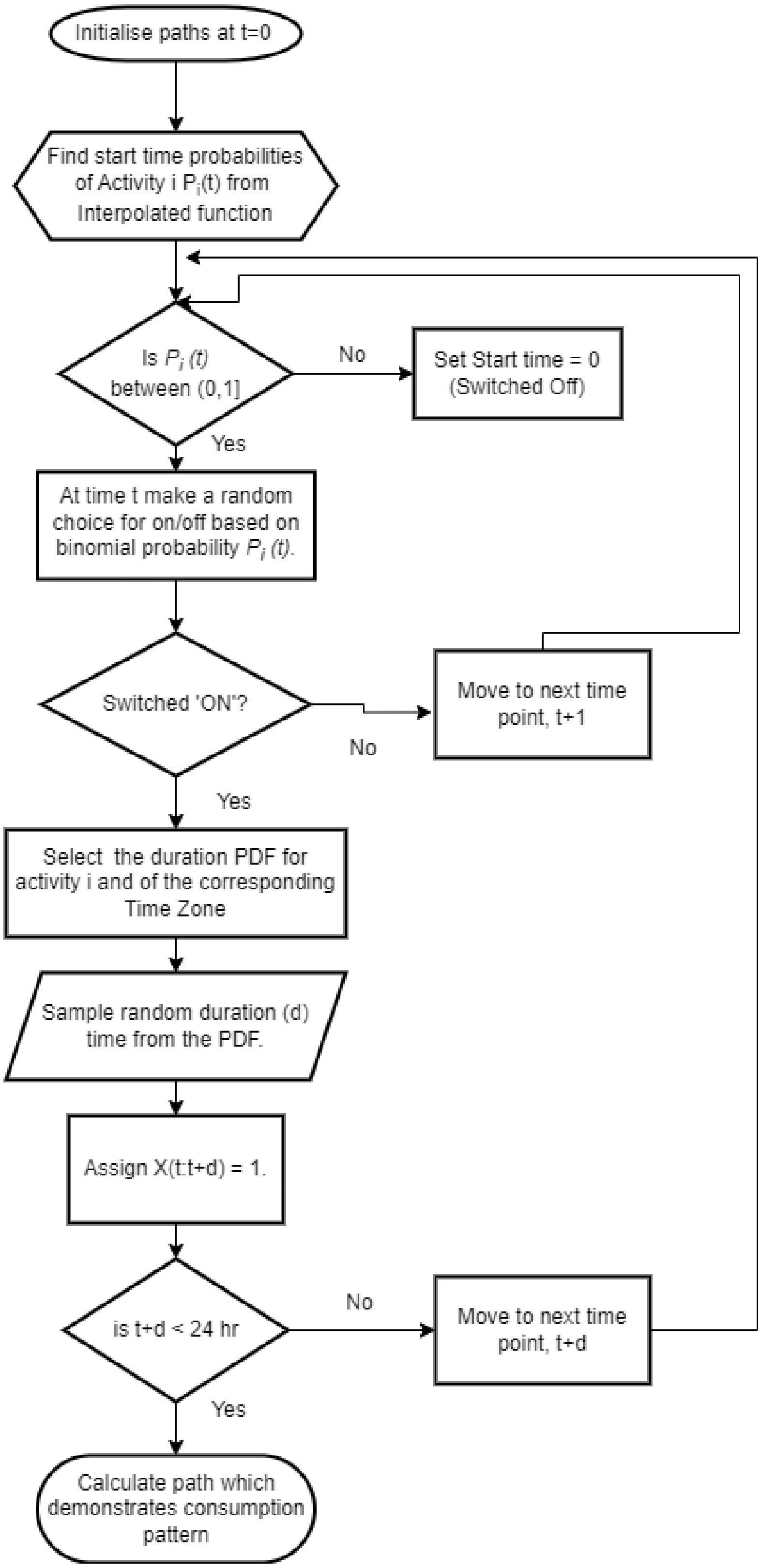


Figure 5.8: *Flow chart for generating load profile of relevant appliance*

electricity usage . These profiles are based on activity data gathered from rural households in the states of Uttar Pradesh and Nagaland, showcasing how appliance usage pattern is influenced by the respective activities.

5.3.2 Appliance wise load profiles

The objective of this simulation is to showcase the conceptual model to generate a stochastic load profile of individual appliances. This model is calibrated based on corresponding activity data recorded by rural households in Uttar Pradesh and Nagaland. To demonstrate its functionality, we can implement it in two ways within a hypothetical scenario:

i) In a target community or village consisting of 100 households, the aim is to generate individual appliance level load profiles and aggregate them to household or community level, for example, finding the daily usage patterns of televisions. Due to the limited availability of information on appliance ownership in TUS, our initial assumption is that each household owns one television; then we ask, what will the average usage pattern of television within this population be? By applying the random sampling technique discussed in the previous section, we determine the time-dependent activity profile (a.k.a. path); in this context, this activity of *watching TV* can be directly correlated with the television's load profile[40]. The resulting load profile represents the aggregate television energy consumption within the community, as well as the average usage times over a 24-hour period. Importantly, in this model, we can simulate usage patterns at different time scales with smaller intervals which can be instrumental in understanding the dynamics of energy consumption.

ii) Alternatively, the model can be used to simulate a sequence of daily usage profiles, say for 30 days with a time interval of 10 minutes (or less). In this case, the mean path (activity profile) provides the average load profile of a single appliance, a television say, over a month. The primary objective of this model is to identify diurnal variations in appliance usage, which we have termed the 'transverse' component of the load profile.

Figures 5.9 display the daily load profiles for televisions, in a hypothetical community of 100 households in Uttar Pradesh. These profiles are shown at 10-minute intervals for a single day, illustrating the first approach. Figures 5.11 show similar load profile for Nagaland, further emphasising the utility of this approach. The majority of TVs are switched on during the evening time in both states contributing to the peak loads. This insight

[40]Considering that the nominal power consumption of a 32-inch television varies between 65-80W, an average power consumption of 70W was assumed for the calculations

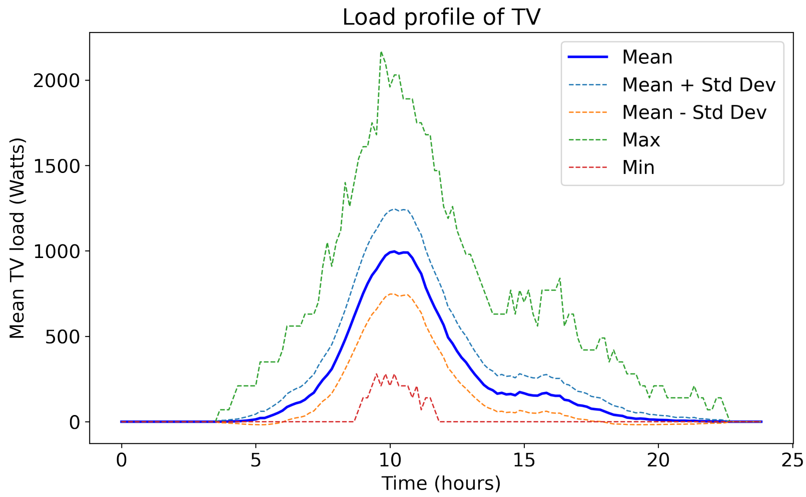


Figure 5.9: *TV load profile in Uttar Pradesh community (n=100)*

underscores the importance of considering the timing of activities that significantly contribute to peak loads when predicting appliance usage patterns. As previously mentioned, for simplicity, we have assumed a 100% ownership for the appliances in this hypothetical community. In real-world situations, comprehending appliance ownership involves navigating the intricate interplay between social and technological systems. A detailed discussion of appliance ownership is given in Chapter 6, as this aspect falls within the scope of the longitudinal component of the load profile. By distinguishing between the transverse and longitudinal components, this research aims to provide a comprehensive understanding of the factors influencing residential load profiles, thereby enabling us to develop a multiscale energy demand model.

5.4 Discussion

5.4.1 Model validation and future tasks

The study described in this thesis has faced a consistent challenge of data paucity. In an ideal world, we would empirically validate load profile modelling workflow described above with the use of disaggregated real time monitored data, similar to model validation performed by (Wilke, 2013). For example, utilising smart meter-monitored data of residential electricity use. However, the scarcity of comparable datasets from rural India presents a challenge for model validation. One potential data source is the eMARC household energy dataset, monitored by the Prayas Group [41]. Nevertheless, this dataset is aggregated, and

[41] http://emarc.watchyourpower.org/

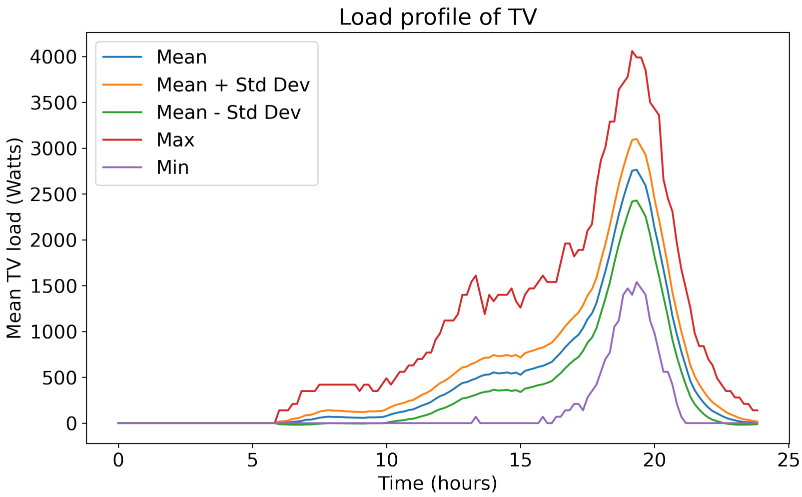


Figure 5.10: *TV load profile in Nagaland community (n=100)*

appliance-level consumption is not specifically monitored. Furthermore, the sample size of rural households is quite small, limiting the applicability of this data source for our model validation purposes.

However, the load profile modelling workflow is conceptually simple. For each appliance and its dependent activity, we wish to know when that activity will start and the duration for which it will survive. These we have shown are well captured by the model. We, of course, assume that appliance power demand is constant and well-estimated in our workflow, and this may not be the case. Nevertheless, we suggest that, for the present purposes and given the data available, this pragmatic approach of testing the key component of time dependency is a reasonable one. Clearly, it would in the future be desirable to empirically validate the combined model when high-granularity appliance-level smart meter data from rural households does become available.

5.4.2 Strengths of transverse energy model

The proposed model effectively captures diurnal variations in energy consumption at the individual appliance level, offering valuable insights into daily usage patterns. Additionally, the model is readily scalable and generalisable, allowing for adaptation across different local contexts. Furthermore, by incorporating social practices and the nuances of daily life, a wide range of scenarios can be accommodated by the model for estimating future energy demand. Thus increasing the scope of load profile characterisation for various socioeconomic groups or demographics, ensuring a holistic understanding of energy consumption patterns and facilitating the effective renewable energy transition in rural areas.

5.4.3 Limitations of transverse energy model

Whilst the strengths of the proposed model are promising, it has certain limitations that must be acknowledged. Firstly, the model primarily provides only average estimates, and causal relationships between activities are difficult to incorporate. Secondly, to fully realise the potential of the time use model, it is crucial to combine it with high-quality appliance ownership data. This is due to the complex relationship between household size and ownership, which complicates the task of linking the number of appliances in use with the number of people utilising them.

Furthermore, the model depends on national-scale time use surveys, which are often unavailable in many Global South countries. When available, these surveys are typically conducted infrequently, with long gaps between iterations. For instance, India's last survey before the current one (in 2019-2020) was conducted in 1999. Lastly, it is important to recognise that residential activity-based energy models can primarily predict energy use resulting from active interactions with appliances, such as when an occupant initiates energy consumption. However, non-interactive energy use or externally stimulated energy use, as observed in appliances like refrigerators or ceiling fans, is more difficult to predict using time use data alone. To account for these types of energy use, a more comprehensive understanding of factors such as seasonality and thermal comfort is required.
Furthermore, the model depends on national-scale time use surveys, which are often unavailable in many Global South countries. When available, these surveys are typically conducted infrequently, with long gaps between iterations. For instance, India's last survey before the current one (in 2019-2020) was conducted in 1999. Lastly, it is important to recognise that residential activity-based energy models can primarily predict energy use resulting from active interactions with appliances, such as when an occupant initiates energy consumption. However, non-interactive energy use or externally stimulated energy use, as observed in appliances like refrigerators or ceiling fans, is more difficult to predict using time use data alone.

5.5 Summary

In this chapter, we have presented the transverse demand component of the proposed multiscale model, which constructs appliance-level bottom-up load profiles based on residential activity data obtained from the Time Use Survey in India. Our approach involved calculating the starting time probabilities of various activities, as well as the duration for which these activities persisted once initiated. We derived Gaussian and Weibull probability density functions for the duration of these activities and evaluated the goodness of fit for each distribution.

Utilising these parameters, we implemented Monte Carlo simulations to construct load profiles for the corresponding appliances in use. The conceptual functioning of the model is demonstrated through average load profile for televisions in two states: Uttar Pradesh, which has the highest sample size in the Time Use Survey, and Nagaland, which has the lowest. We subsequently discussed the challenges associated with model validation, the strengths and limitations of the time use energy model, and the necessity of linking it to appliance ownership data.

1. Considering the level of occupancy, we can model the usage times of lighting and generate stochastic load profiles. The use of lights notably contributes to the evening peak period (given the data of daylight availability). This aspect becomes particularly crucial when devising plans for decentralised energy systems as the evening peak demand significantly influences the storage requirements.

2. By integrating occupancy and activity data with the seasonal dimension of the framework, we can also project the usage patterns of ceiling fans, a widely owned appliance with substantial nominal power ratings. Given the escalating temperatures and prolonged heatwaves in India, the operation of fans plays a critical role in shifting peak demands. Ceiling fans could notably contribute to afternoon peak demands during summers in rural India; this would also benefit from a mechanism for assessing occupants' thermal discomfort, which would act as a trigger for switching on the fans.

3. Looking ahead, as we transition towards clean cooking practices, the adoption of electric cook stoves may further intensify the evening peak demand or possibly create new peak periods. A comprehensive time-use survey capturing meal preparation and cooking times will be instrumental in understanding the future demand for cooking activities. Presently, clean cooking practices in rural India are at an early stage; however, for achieving net-zero pathways, focusing on clean cooking is essential, demanding further research initiatives.

While our present illustration focuses solely on activity modelling for televisions, it's crucial to note that this model is adaptable to a broader spectrum of appliances, presenting a versatile framework for future applications and extensions. In the following chapter, we will discuss the details of appliance ownership and explore how it can be integrated into the model to develop long-term energy demand estimates for rural villages.

6 Longitudinal energy

In this chapter, we present a conceptual framework for a system dynamics model to estimate long-term longitudinal growth in appliance ownership and its electricity usage within rural households in India. We begin by highlighting the necessity of this model and provide a brief literature review to contextualise our approach. Next, we outline our research objectives and explore the methodology of system dynamics, explaining the preliminary building blocks of the proposed model. Finally, we discuss the challenges associated with developing such models due to data scarcity and suggest potential future directions for research in this area.

6.1 Overview of Appliance Ownership

India's future grid size lacks a definitive forecast, with estimates ranging from 650 to 1000 gigawatts (Dubash, Khosla, Rao, & Bhardwaj, 2017). This wide range could lead to varying supply needs and risks, including energy security concerns and stranded assets due to inaccurate demand predictions (Khosla, 2018). All over India, residential energy use is the largest share with 31.76% of the total energy supplied, showing an increase from 29.34% in 2019-20. This represents a 7.15% growth in the domestic sector compared to the previous year. (Central Electricity Authority, 2022). As we have seen in previous chapters, estimating this growth in electricity consumption can have multi-fold impacts on sustainable energy planning. Understanding this longitudinal component of demand is thus of paramount of importance. Longitudinal growth in appliance ownership refers to evaluating the increase in the number of appliances owned by households over specific intervals of time. This means understanding how and why the number of appliances, like refrigerators, washing machines, or televisions, increases in households as time goes by. This growth is influenced by various factors such as household income, access to electricity and changing lifestyles. It is therefore necessary to understand individual decisions that are "constructed" by interactions between social and technological systems and these decisions are determined by services such as comfort and convenience provided by the home appliances that are purchased(Wilson & Dowlatabadi, 2007). We must also consider the positive feedbacks arising from energy efficiency measures and changes in societal aspirations for energy services and comfort. For example, Wilson *et al.* highlighted that the ownership of air conditioners in American homes increased from 12% in 1962 to 75% in 2001, now accounting for 50% of U.S. household energy use. Likewise, a recent report by the *International Energy Agency* on the Indian energy sector (India energy outlook report (IEA), 2021) projected electricity consumption to increase six-fold by 2040, primarily due to rising air conditioner ownership. Efficiency measures are expected to have the potential to reduce the associated energy use by as mush as a quarter in targeted policy scenarios.

The rapid electrification of rural India has led to a significant increase in household appliance ownership, which, in turn, has intensified energy consumption in the last decade. The dynamics of growth and electrification are a complex web of underlying forces and feedback mechanisms. Rural electrification, in particular, is expected to have a positive impact on the availability of new economic and educational opportunities. This, in turn, could make electricity and associated appliances more affordable, which could then increase local electricity demand(Khandker, Barnes, & Samad, 2012). Walia *et al.*(Walia, Tathagat, Dhingra, & Varma, 2019) conducted a nationwide study in India to understand the ownership patterns and associated electricity consumption of appliances. The study found that appliances such as cell-phone chargers, TV sets, set-top boxes, cooktops/stoves, refrigerators and ceiling fans have penetrated 80% or more of the market. The study also found that energy consumption is higher in summer than in winter across socio-economic strata, dwelling type, and climatic zones except for cold climates. Space and water heating appliances are major contributors to winter peak demand, while summer peak demand is attributed to space cooling devices. This study was conducted only in urban households, no similar studies exist for rural areas, whilst other studies confirmed significant ownership differences between urban and rural regions in India (Kulkarni, Sahasrabudhe, Chunekar, & Dukkipati, 2022). *National Electricity End-use Monitoring (NEEM)* by Bureau of Energy Efficiency in India (NEEM, 2007) [42]NEEM by BEE conducted a pan-India study of over 5,000 urban households in 2017, appliance ownership and usage were examined alongside socio-economic indicators and climate zones. The data indicates that appliance ownership and usage are on the rise significantly, with households shifting towards family nuclearisation. Per capita energy use is also increasing. The results also provide good insights on variations in energy consumption across climatic zones, demographic parameters, and socio-economic strata for the major appliances. Factoring in ownership, air-conditioners, refrigerators and ceiling fans have the largest urban household footprints, highlighting India's increasing demand for cooling appliances. The survey covered more high and middle income households than low income households. The growth dynamics in low income rural households may not be reflective in this study.

[42]*

In order to accurately estimate the longitudinal growth of appliance ownership in rural India, researchers require data collected over long periods of time. The Consumer Pyramids Household Survey (CPHS)[43] is one such survey. It has been conducted three times a year since 2014 and includes information collected from more than 200,000 Indian households. The CPHS data is representative of national, state, and urban-rural levels and has been used to examine various aspects of the living standards in India such as income equality, access to finance, unemployment and other issues. While the CPHS data provides an invaluable source of information, there are some concerns surrounding its sampling methodology and survey process, which is biased towards high income households. The CPHS dataset has also been compared with the National Family Health Survey (NFHS) 5[44] conducted by The International Institute for Population Sciences, Mumbai for the Ministry of Health and Family Welfare (MoHFW) and confirmed the biasness in CPHS data(Kulkarni et al., 2022).. This survey covers data on appliance ownership for 636,000 households across both rural and urban regions. Despite its extensive coverage, the NFHS data has limitations, as it is administered relatively infrequently. Of the five survey rounds in the last 50 years, only three are open access. This is insufficient for analysing long-term patterns. Despite the inherent constraints in both datasets, they provide valuable information for the framework to model longitudinal energy demand patterns in rural India.

6.2 System dynamics for appliance ownership growth

Appliance ownership growth in the context of rural electrification and sustainable energy planning involves not only technical factors but also social, economic, and environmental factors, with interconnected influences. As discussed previously, the growth in household energy demand is driven by various factors, including perceived improvements in quality of life and social status, cost considerations, availability of local resources, and access to relevant technology. This can be understood as a complex system, a concept central to systems theory as defined by Flood and Jackson (1991). Complexity in systems can be characterised as organised simplicity, disorganised complexity, or organised complexity.

1. Organised Simplicity: This could refer to systems that are relatively straightforward with clear and easily understandable structures and relationships. In such systems, the components interact in a more linear and predictable manner.

[43] CPHS survey
[44] NFHS-5

2. Organised Complexity: This likely relates to systems that are intricate and have numerous interconnected elements. Despite the complexity, there might be some level of order and organisation within the system, and understanding the relationships between components can result in improvised systems.

3. Disorganised Complexity: These type of systems refer to challenges with many more independent variables that require sophisticated statistical analysis to understand.

In rural electrification energy planning, many models are heavily focused on technical aspects and often lack the capacity to accommodate qualitative inputs, such as the impact of specific policies, preferences of local communities, or on-ground observations of energy use behaviours. These purely technical models, based on predefined assumptions and input parameters, are often referred to as black box models (e.g., HOMER), particularly when dealing with a wide array of parameters. Recognising rural electrification as "Organised complexity" highlights its similarity with socio-technical systems. This concept denotes a system with numerous interconnected elements, resisting effective analysis through traditional statistical methods. Such systems often manifest as wicked problems, shaped by individuals' responses to new information or their decision-making processes, with the potential for reduced complexity with increased understanding. Within this framework, understanding appliance ownership in the context of rural electrification fits within the organised complexity paradigm, where system dynamics emerges as an apt technique for study. This approach can be categorised as a 'white' or 'grey' model, depending on input parameters derived from expert opinion or aggregated data. It effectively captures interconnections and feedback mechanisms, offering a more comprehensive understanding of underlying factors and facilitating more informed decision-making processes.

System dynamics, first developed by Prof. J.W. Forrester at MIT in the 1950s, is a modelling and simulation method for analysing complex behaviours in the social sciences, through computer simulations(Forrester, 2009). Dyner *et al.*(Dyner et al., 1995) pioneered the application of System Dynamics in the energy sector by developing a methodology that informed energy policy formulation, using the Medellin Metropolitan Area in Colombia as a case study. Their model considered the complex interconnections among various economic sectors, energy demand, and alternative energy sources, while accounting for macroeconomic financial constraints and energy supply and demand in each sub sector. This comprehensive model assessed the consumption of energy from gas and alternative sources, the impact of energy efficiency and conservation programs, and the influence of electricity tariff changes on consumption, offering valuable insights for energy policy.

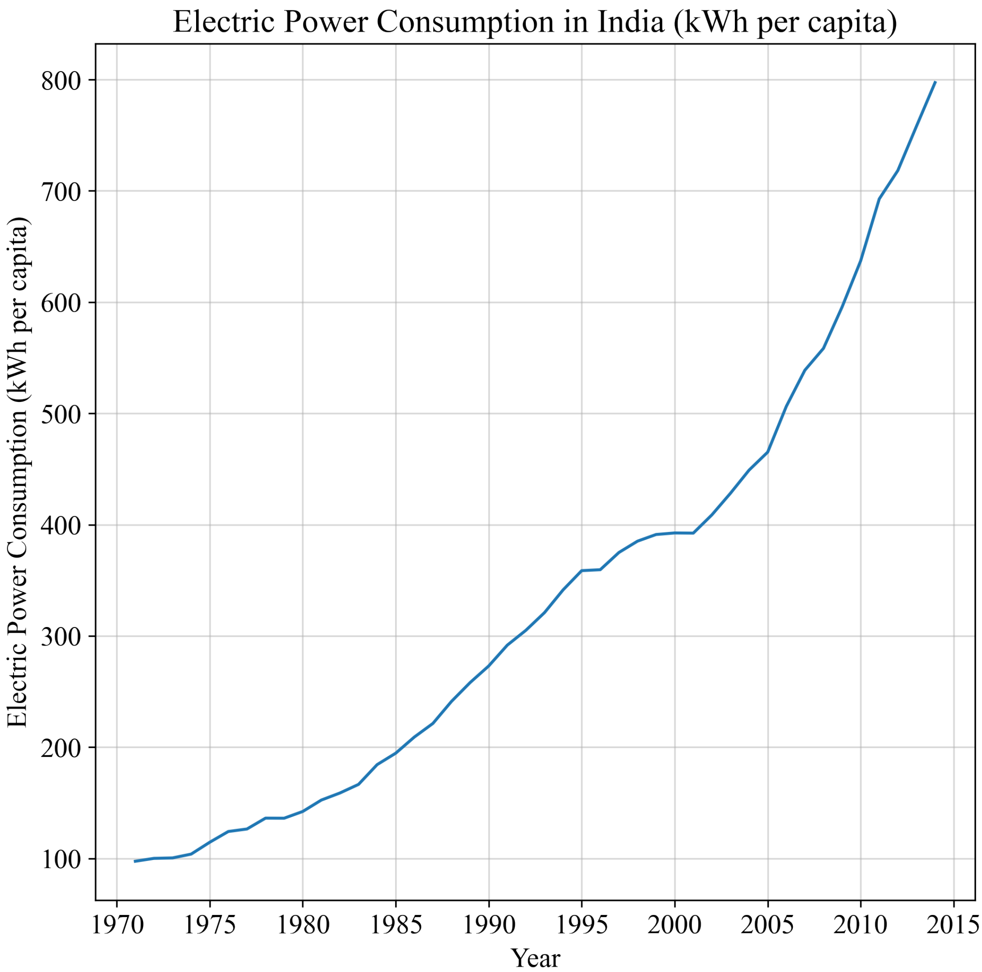
Tonini *et al.* (Tonini, Sanvito, Colombelli, & Colombo, 2022) and Hartvigsson *et al.* (Hartvigsson et al., 2020) suggested the use of System Dynamics models to understand the long-term, bottom-up electricity demand in rural electrification in Kenya and Tanzania, respectively. Tonini *et al.* (Tonini et al., 2022) incorporated the impact of external factors, such as local economic growth through income generating appliances and micro-credits, on overall residential energy demand increase in their analysis. On the other hand, Hartvigsson *et al.* (Hartvigsson et al., 2020) examined the potential for capacity expansion in mini-grids within their study.

In this chapter, our overarching research aim is to investigate the growth trajectory of per capita residential electricity consumption in rural India. Our objectives are to develop a bottom-up understanding of appliance growth trends and assess the potential positive impact of energy efficiency measures on consumption patterns. We hypothesise that as rural electrification progresses, per capita energy consumption will initially grow exponentially, as illustrated in Figure 6.1[45], but will ultimately plateau as the system nears saturation in appliance adoption, following the S-shaped curve discussed in Chapter 2.

To effectively analyse our dynamic hypothesis, we propose a system dynamics model with feedback mechanisms that captures some of the key relationships between exogenous factors such as energy efficiency measure and endogenous factors such as affordability, which influence residential electricity consumption. By comprehensively understanding these interconnected components, we can project realistic long-term demand growth from rural households.

To demonstrate the conceptual workings of this model, we draw guidance from the CPHS dataset and construct a basic model to generate long-term projections for individual appliances - washing machines in the for instance - within the rural context. To this end, Section 6.3 describes the building blocks of the system dynamics model and presents preliminary results for this single appliance type. Section 6.4 introduces a model incorporating additional parameters to account for energy efficiency measures and discusses the challenges posed by data scarcity. Finally, Section 6.5 outlines future research directions for integrating longitudinal and transverse components within the model.

[45]The data shown in this figure does not differentiate between rural and urban sector, neither it captures sub sectors of energy use i.e. residential or industry



Source IEA Statistics 2014 iea.org/stats/index.asp

6.3 System Dynamics

System Dynamics modelling underpins causal relationship between variables in the form of feedback loops, stocks, flows, and time delays to simulate and predict the behaviour of interconnected components within a system over time. We hypothesise that a community or village, consisting of nearly 1,000 households, represents a complex system in which numerous parameters influence electricity usage. To examine this system, we formally define variables using the building blocks of stock, flows and feedbacks. By capturing the underlying structure and dynamic relationships between parameters, the model allows for the identification of leverage points with which to test a variety of scenarios and potentially to estimation variable sensitivity and its impact on system behaviour, i.e. factors influencing electricity demand growth trends.

6.3.1 Building blocks

In system dynamics models, stocks and flows are two fundamental concepts used to represent and analyse the behaviour of complex systems. Additionally, feedback loops are an essential aspect of these models, as they help to capture the dynamic interplay between stocks and flows within a system.

1. **Stocks**: Stocks, also known as state variables or levels, represent the accumulations of resources, information, or any other measurable quantity within a system. They can be thought of as the "memory" of the system, as they capture the system's current state at any given time. As shown in figure 6.2, in our basic appliance diffusion model, we defined two stocks, potential household ownership of appliance and existing appliance ownership.

2. **Flows**: Flows, also referred to as rates or transitions, are the variables that control the movement or transfer of resources, information or other quantities between different stocks within a system. They represent the processes that cause the stocks to change over time. In the basic appliance diffusion model, the adoption or purchase of appliances by households is defined as a flow or transition.

3. **Auxiliary variables**: These variables can represent constants, parameters or mathematical functions that are used to capture the complex interactions and dependencies of stocks and their intermediary interactions with other variables. These are the key parameters through which we can embed multiple factors influencing the system i.e., a community of households owning certain appliances. In our basic model, we

include *Awareness* related parameters that strongly influence the adoption of any appliance. More on the key parameters is discussed in the next section.

4. **Feedback loops**: Feedback loops are fundamental components of system dynamics models, as they capture the interconnections and causal relationships within a system. There are two categories of these loops. 1) A reinforcing loop also known as positive feedback loop expresses the cycle of cause and effect that leads to an exponential growth or decline in the system's behaviour. When an action or change in a variable leads to an effect that further amplifies the initial action, a reinforcing loop is formed. For example, in our basic model, we create a 'word of mouth' or 'awareness' reinforcement which increases growth in appliance ownership. 2) A balancing loop also known as negative feedback loops is a cycle of cause and effect that helps to maintain stability or equilibrium within a system. In a balancing loop, a change in a variable triggers a response that counteracts or opposes the initial change, eventually bringing the system back to a state of balance. We will incorporate this feedback loop in our proposed model.

Using the building blocks of system dynamics modelling, a conceptual basic appliance diffusion model has been developed and simulated using the Vensim software, a popular tool created by Ventana Systems. The model focuses on the spread and adoption of a particular appliance over time. The structure of the model, as illustrated in Figure 6.2, includes stocks, flows, and auxiliary variables, which together represent the key elements of the system.

The model is designed with a single reinforcing loop, which demonstrates the growth of appliance diffusion. In simple terms, this means that as more people adopt the appliance, this in turn leads to an increasing rate of adoption by others (a phenomenon referred to in the UK as 'keeping up with the Jones's'). This can be driven by factors such as word-of-mouth or increasing awareness of the appliance. Equations defined for the variability of each parameter are defined in Table 12 with descriptions and units. The time step is kept to 3 months and the method of integration is Euler.

Using the NFHS-5 dataset as a reference for appliance ownership in rural India, we found that the average ownership of washing machines in rural Indian villages is currently at 9% (see appendix A.6.1). This value has been used as a starting point for the baseline adoption of washing machines in our model. We have simulated and presented preliminary results, showcasing a sigmoidal growth over the next ten years, spanning from 2023 to 2033. Figure 6.3 illustrates the growth trends for washing machine ownership.

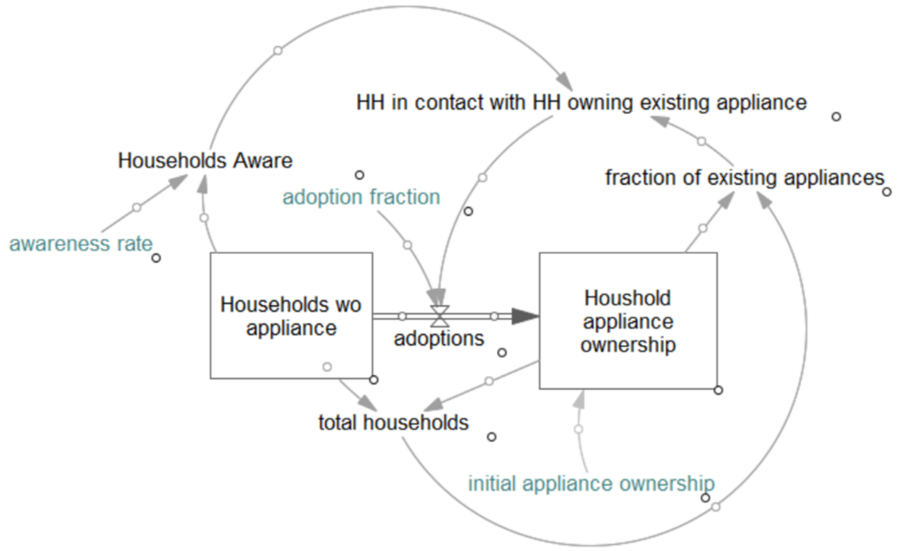


Figure 6.1: *Basic appliance diffusion model*

Table 13: Auxiliary parameters and description of basic diffusion model

Key Parameter	Equation	Description	Unit
Household Aware	Household w/o appliances*awareness rate	How many numbers of households get aware of appliances	HH/Year
Awareness Rate	Constant	Number of HH getting aware of appliances per year (Reflective of imitation - word of mouth)	Number/year
Adoption Fraction	Constant	Percentage of new appliances penetrated the potential market (reflective of innovation coefficient)	Dimensionless
Fraction of existing appliances	HH Appliance Ownership / total households	Percentage of household already owns the appliance	Dimensionless
HH in contact with HH owning existing appliance	Households Aware * fraction of existing appliances	Number of unaware household interacting with household owning an appliance	HH/Year

Table 14: Input parameters for basic diffusion model

Scenario	Initial Ownership	Final Ownership	Awareness Rate (app/year)	Adoption Fraction
Baseline	90	867	90	0.009
Midline	150	930	150	0.01
Optimum	250	1028	250	0.003

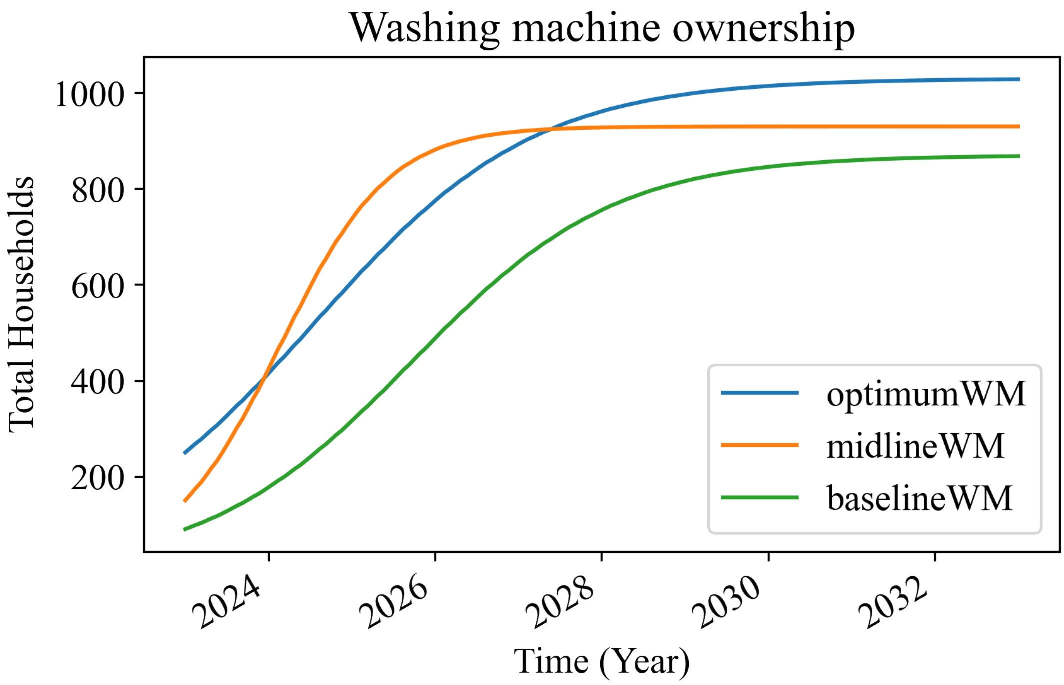


Figure 6.2: *Diffusion of washing machines in a hypothetical rural communities with assumptions on baseline, midline and optimum growth in ownership*

We have incorporated assumed awareness rates and adoption fractions for both optimum and midline growth scenarios to emphasise how these variables can influence the growth patterns. By comparing these scenarios, we can better understand the sensitivity of the model to changes in awareness and adoption rates. The presented model is conceptually straightforward; however, it may not fully capture the realistic adoption of appliances. As mentioned earlier, appliance ownership can be influenced by numerous factors, and understanding the dynamics of the causal relationships between these parameters is crucial. To create a more accurate representation of real-world adoption, it is important to account for the complex interplay amongst the most significant of these influencing factors within the model.

6.4 Longitudinal Appliance ownership

We have expanded our model to account for more key parameters that influence appliance ownership, such as affordability, marketing campaigns and other factors. Details of the rationale underlying the choice of these parameters is given as follows:

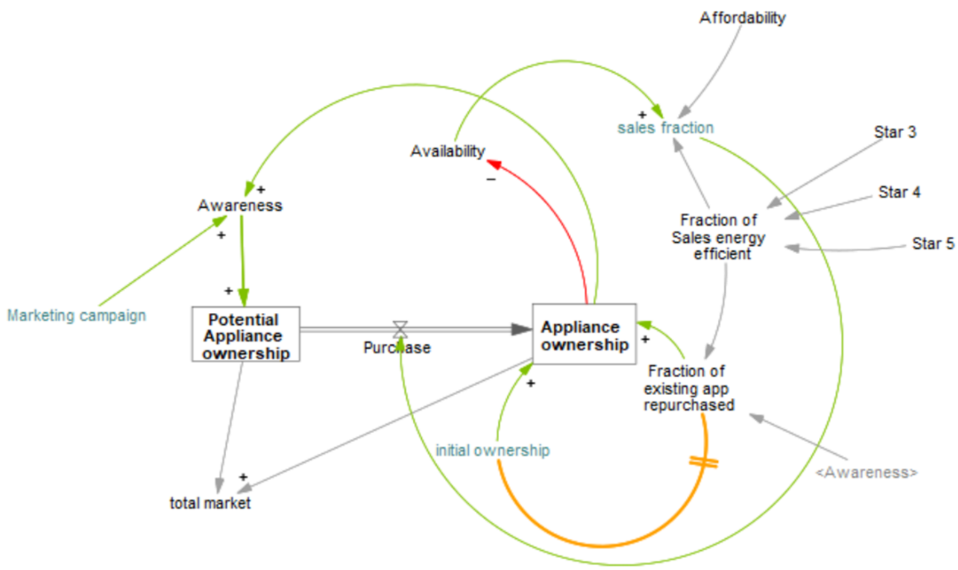


Figure 6.3: *Proposed model with multiple factors*

6.4.1 Key Parameters

- **Awareness**: One key influencer of energy consumption is the awareness of the energy-efficient of appliances. Adoption decisions are also influenced by marketing campaigns. Our basic model considered the effects of such awareness on the overall adoption of appliances. The proposed model will extend it to cover the impact of marketing campaigns as well. For example, Chunekar *et al.* (Chunekar, Aditya, 2023) found a lack of awareness regarding five-star rated ceiling fans in India, as the Star Labelling program had only recently been launched. However, promoting awareness about energy-efficient fans could have a massive impact on overall residential electricity consumption. With 30-40 million new ceiling fans sold annually, adding to the nearly 400 million existing fans in use, these appliances contribute 40% of total residential electricity consumption. Enhancing awareness of energy-efficient options could therefore significantly reduce both adoption and subsequent energy usage.

- **Availability**: The availability of specific types of appliances in the nearest market hub to a village can significantly impact overall appliance ownership, as this factor creates a balancing feedback to the total stock. This is particularly pronounced in remote areas, where distribution systems are intricately linked with road networks and local transport systems, making appliance accessibility more challenging. With the rise of online sales for home appliances, the impact of availability on overall stock can be highly sensitive. Online sales can potentially overcome some of the distribution challenges faced in remote areas, making appliances more accessible and influencing the overall ownership rate.

- **Affordability**: Affordability is a highly influential factor when projecting appliance ownership, especially for rural households. As Agrawal *et al.* (Agrawal, Harish, et al., 2020) found in their study, affordability is even more sensitive in rural settings due to the dual challenge of having both the purchasing power to acquire appliances and the ability to afford the ongoing costs of powering them. However, affordability is also a notoriously difficult parameter to determine because it is affected by factors including varying income levels, economic conditions, fluctuating appliance prices, availability of financing options and the cost and reliability of electricity.

- **Repurchase rate**: A strength of system dynamics modelling lies in its ability to incorporate delays and the nonlinear nature of certain parameters that affect system behaviour. In the context of appliance ownership, repurchase rates can involve such delays, as shown in orange in the proposed model. Delays come into play when households decide to repurchase broken appliances or buy an additional unit of the same kind. Incorporating delays helps account for the time lag associated with these decision-making processes. Considering delays in the model also raises the question of whether newly purchased appliances are more energy-efficient than the ones they replace. This aspect is crucial, as it influences the overall energy consumption patterns and the potential environmental impact of increased appliance ownership.

- **Star labelled appliances**: The Bureau of Energy Efficiency (BEE) in India has initiated star labelling campaigns to raise awareness about energy-efficient appliances. These campaigns can significantly impact overall energy consumption by promoting the use of energy-saving devices. However, they may also negatively affect affordability levels, as energy-efficient appliances tend to be more expensive. For now, the proposed model only includes the energy efficiency rating in a cursory manner. In future iterations, it would be beneficial to incorporate energy efficiency as part of a balancing loop. This would allow for a more comprehensive understanding of the trade-offs between energy efficiency and affordability, ultimately resulting in a more realistic representation of appliance adoption dynamics and the corresponding impact on energy consumption.

Each parameter in the model requires initial input data. For example, awareness can be derived from marketing and sales data of individual appliances, while availability depends on distribution and sales information in the local context. Affordability can be calculated using macroeconomic data, such as the ratio between income and expenses for various sub-populations. The Time Use Survey provides partial information on people's ability to spend on durable goods, but it does not offer a complete picture because this input can be quite ambiguous, as the definition of durable goods in the TUS includes both purchasing (new and used) and repairing household durables. Durable goods also cover a wide range of items, making it challenging to accurately estimate affordability for specific appliances. On the other hand, there is a significant lack of data on repurchase rates and energy efficiency, which limits the impact and accuracy of the model. Addressing these data gaps is essential to create a more comprehensive understanding of appliance adoption dynamics and their consequences for long term energy consumption estimation.

6.5 Conclusion and Future research

Future research efforts should emphasise the inclusion of the additional aforementioned features to establish a more robust foundation for modelling longitudinal growth in appliance adoption. By refining the model and incorporating more comprehensive data, there is potential to gain a cohesive understanding of the dynamics of appliance ownership, including the potential impacts of policy and energy efficiency measures on this ownership and corresponding energy consumption. It is our belief that the ultimate aim should be to merge this longitudinal modelling with daily appliance usage, derived from residential activity modelling, to enable the projection of long-term load profiles. Such an integration stands to aid modellers in developing realistic scenarios of energy demand growth in the rural domestic sector, contributing significantly to renewable energy planning and the clean energy transition in rural India.

However, it should be recognised that the current integration of such systems is complex due to the distinct functionalities of the tools used. The system dynamics model is developed in VenSIM, while the transverse aspect of the model is created in Python. Although tools like PySD[46] offer the ability to convert VenSIM model files into Python modules, allowing for modification, simulation, and observation of these converted models, on the other side, the development of a System Analysis and Design Methodology (SADM) in Ventity software could potentially support future integration. However, this remains

[46]https://pysd.readthedocs.io/en/master/structure/vensim$_t$*ranslation.html*

a direction for future research and was not feasible within the scope of this thesis due to time constraints.

7 Conclusion and Future research

In this thesis, we endeavoured to extend our understanding of residential energy demand within the context of rural electrification via renewable energy sources, primarily solar mini-grids. To reach this goal, we first estimated electricity demand growth scenarios for rural communities through the energy use surveys and appliance diffusion. We then analysed the impact of these demand growth scenarios on two different sizing mechanisms of solar mini-grids, thereby highlighting the importance of accurately assessing the demand growth. In the second part, we proposed a multi-scale framework for estimating longitudinal (long-term) and transverse (daily) demand based on appliance ownership and its usage times. Conceptual model functionalities were demonstrated with preliminary results showing diurnal variations in energy use as well as longitudinal trends in appliance adoption. The main objective of this thesis was to improve the accuracy of energy demand models used in renewable energy planning by embedding the local socioeconomic context which was fraught with high error margins in existing body of literature.

7.1 Objective 1

Estimate electricity demand growth in rural communities gaining energy access through solar-mini grids.

To achieve our objective of improving load estimations for solar mini-grid planning, we conducted household energy surveys in five hamlets of Shahapur district in the state of Maharashtra. Of these hamlets, three had recently received access to electricity for the first time, 15 months prior to the surveys. To simulate long term (ten years) of stochastic load profiles, we considered the growth in demand as a function of household appliance ownership in the community. We used two types of information to derive these load profiles - appliance adoption coefficients guided by appliance ownership after one year of electricity access and appliance usage times based on surveys conducted. We hypothesised three different demand growth scenarios - baseline, adaptive, and target. The baseline and target scenarios set the lower and upper bounds of load profiles, respectively, while the adaptive profiles followed an S-shape growth based on the evolution in appliance adoption. This mixed-method approach of combining survey data with appliance diffusion allowed us to better understand and characterise the demand for electricity in these hamlets.

7.2 Objective 2

Examine the impact of electricity demand growth on the required mini-grid system size and the potential need for adaptive capacity expansion.

In this objective, we conducted a comprehensive literature review of fifteen mini-grid modelling tools to evaluate whether they considered evolution of electricity demand for sizing mini-grids. We then investigated the impact of three demand growth scenarios on two different mini-grid sizing approaches: a one-off installation and capacity expansion to accommodate growing demand. Analysis of the results showed that estimating demand growth is a critical factor in determining the mini-grid size and cost. Additionally, our findings suggest that a modular approach to mini-grid design, which involves adjustment of capacity based on demand growth rather than a one-off installation, can lead to cost savings and improved efficiency. Our research indicates that the use of modular sizing can result in cost savings of up to 12%, and that system costs are the most sensitive to variations in demand growth rates and cost decreases in solar PV and batteries. The analysis from this study highlights the important financial and operational implications of demand growth scenarios and choice of mini-grid sizing approaches when designing systems for rural electrification.

7.3 Objective 3

Develop a multi-scale framework to model energy demand with a focus on capturing the time-sensitive nature of energy use in rural households

The objective of our study was to develop a comprehensive multi-scale framework to model energy demand from rural households. The framework encompasses three different scales: longitudinal, seasonal, and transverse. The longitudinal scale considers the energy demand of rural households over a period of years. The seasonal scale takes into account the variations in energy demand caused by weather changes within a year, while the transverse scale focuses on the daily demand fluctuations or diurnal variation.

Our study highlights the lack of existing models that can capture the time-dependent use of energy, as well as the potential impact of residential activity on energy demand. To better understand this relationship, we implemented residential activity modelling based on national scale Time Use Surveys conducted in India. These surveys provide valuable insights into the timing and frequency of corresponding energy use related to household activities (social practices), which we demonstrated through the activity profiles of rural households in four different states. The main objective here is to develop in-depth understanding of the transverse component of a multi-scale model, which constructs appliance-level bottom-up load profiles based on the residential activity data obtained. To achieve this, we calculated the starting time probabilities and duration of these activities, which were used to create Gaussian and Weibull probability density functions. This information was then utilised to construct load profiles based on Monte Carlo simulations for the corresponding appliances. As an illustration, we presented the average load profiles for televisions and washing machines use in rural households of Uttar Pradesh and Nagaland, demonstrating the conceptual functioning of the model. Finally, we discussed the challenges associated with model validation, the strengths and limitations of the time use energy model, and the necessity of linking it to appliance ownership data.

7.4 Objective 4

Conceptualising long-term electricity demand growth based on longitudinal appliance adoption in rural households.

We developed a system dynamics model to better understand the longitudinal nature of energy demand, specifically in terms of appliance ownership and individual decision-making. Our goal was to create a proof-of-concept model that could accurately capture the dynamics of appliance ownership and purchase power, assuming certain rates of adoption and awareness of energy-efficient appliances. To illustrate the potential impact of our model, we simulated the ten-year growth trend of washing machine ownership in a hypothetical rural community of approximately 1000 households. However, we must acknowledge that our model is limited by a severe lack of data regarding the longitudinal nature of energy demand growth. Nonetheless, it is a crucial step forward in understanding demand growth and also effectively design energy efficiency interventions.

7.5 Future research

- The immediate next step would be to incorporate seasonal variations and thermal comfort as additional component to proposed multi-scale residential energy demand model. This will enable a more accurate representation of energy demand patterns at different scales, from individual appliances to households and communities. In addition, load factor[47] and diversity factor [48] should be taken into account while aggregating individual appliance load profiles to households and community scale, allowing for a more precise estimation of energy demand.

- The next step in this research will be to design various scenarios of residential demand based on demographic characteristics of rural households and tailor the model to the local context, specifically for the community that mini-grids are planned for. This will involve testing the residential energy demand model for each scenario and evaluating its effectiveness in predicting energy demand.

- The modelled load profiles can be reintegrated in CLOVER as a replacement for the need of survey input to assess the impact of survey-based or model-based load profiles on mini-grid sizing. The impact of these load profiles on mini-grid sizing can be evaluated to determine the feasibility of using model-based load profiles for mini-grid sizing.

- In the long term, the aim is to scale up and generalise the model to make it ready for integration with large-scale electrification tools like OnSSET. This will allow for a more comprehensive analysis of energy demand and the design of electrification strategies that are tailored to the specific needs of communities.

[47] Load factor is the ratio of average power demand to maximum demand, it represents how much of the available capacity is being used

[48] diversity factor is the ratio of the sum of individual maximum demands to the maximum demand of the group, and it represents the variation of demand across a group of consumers.

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Appendices

Appendix A.3.1 - Questionnaire Questionnaire is attached to the GitHub repository https://github.com/rjsayani/Clover-analysis Appendix A.3.2 - Ethics approval

The University Of Sheffield.

Application 025937

Section A: Applicant details

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Programme name:
Postgraduate Research - School of Architecture

Module name:
ARC76731
Last updated:
16/05/2019

Department:
School of Architecture

Applying as:
Postgraduate research

Research project title:
Sustainable management of energy to improve quality of life in developing countires

Has your research project undergone academic review, in accordance with the appropriate process?
Yes

Similar applications:
- not entered -

Section B: Basic information

Supervisor

Name	Email
Darren Robinson	d.robinson1@sheffield.ac.uk

Proposed project duration

Start date (of data collection):
Thu 23 May 2019

Anticipated end date (of project)
Sat 15 June 2019

3: Project code (where applicable)

Project externally funded?
N/A

Figure 7.1: *Ethics application page 1*

Project code
Grantham Centre for Sustainable Futures

Suitability

Takes place outside UK?
Yes

Involves NHS?
No

Health and/or social care human-interventional study?
No

ESRC funded?
No

Likely to lead to publication in a peer-reviewed journal?
Yes

Led by another UK institution?
No

Involves human tissue?
No

Clinical trial or a medical device study?
No

Involves social care services provided by a local authority?
No

Involves adults who lack the capacity to consent?
No

Involves research on groups that are on the Home Office list of 'Proscribed terrorist groups or organisations?
No

Indicators of risk

Involves potentially vulnerable participants?
No
Involves potentially highly sensitive topics?
No

Section C: Summary of research

1. Aims & Objectives

The aim of this study is to accurately assess the household energy needs of off grid communities. We are interested in establishing optimised energy allocation that would improve energy service quality in rural households. This could bring benefits such as clean energy at affordable rates to consumers, smooth operation at grid level and broadly, better understanding of consumer's energy using behaviours.

2. Methodology

1. I will take interviews of participants by asking questions mentioned in a Survey questionnaire and gather the data.
2. I will also make inventories of appliance ownership and a list of shared appliances (and their characteristics) in the community.
3. From obtained answers about the activities people perform over a routine day, I will extract the activities that involve energy consumption.
4. Then I will calculate daily load profiles of energy usage by statistical methods using python, and perform time series analysis.

3. Personal Safety

Have you completed your departmental risk assessment procedures, if appropriate?

Figure 7.2: *Ethics application page 2*

In progress

Raises personal safety issues?

Yes

I am planning to take data from the villagers in rural areas of India. Namely hamlets of Darewadi and Dahigaon in the Maharashtra state of India. These places are 30-100kms from metropolitan cities like Mumbai and Pune. For this work, we are collaborating with an organisation called 'Gram Oorja' which has headquarter located in Pune. Mr. Anshuman Lath, in-charge of business operations at Gram Oorja and Mr. Kiran Auti, senior engineer at Gram Oorja have agreed to guide me and accompany me in the village area for the entire period of data collection.

For all field work days, I plan to stay in Pune and travel in a group from Pune to nearby villages via hired car. In case of emergency, I have two family friends living in the same city. I will share their contact details with my supervisors as well as Gram Oorja staff.

Also, I can read, write and speak the local language spoken in these villages, hence I can anytime communicate with local people for help if required.

Section D: About the participants

1. Potential Participants

I have collaborated with an organisation named 'Gram Oorja'. This organisation has deployed several micro grids in villages near by Pune district in Maharashtra, India where the access of electricity was not available or scarce.
My participants are the people of these villages who are using energy services provided by Gram Oorja.

2. Recruiting Potential Participants

I am planning to contact participants in person by arranging a group meeting at first. In this meeting, I will explain them about my work and how it will help them to receive improved energy services in future. I will ask for feedback after the meeting and to decide whether they are willing to participate.

2.1. Advertising methods

Will the study be advertised using the volunteer lists for staff or students maintained by IT Services? No

- not entered -

3. Consent

Will informed consent be obtained from the participants? (i.e. the proposed process) Yes

I will inform all the participants about the research work prior to the interview and I will obtain their consent on paper before the I start the interview.

All documents will be made available in both English and the local language.

4. Payment

Will financial/in kind payments be offered to participants? No

5. Potential Harm to Participants

What is the potential for physical and/or psychological harm/distress to the participants?

In this work, participants are only expected to answer a few questions regarding their electricity usage. This will just demand around 15 minutes of their time. We do not envisage any adverse health risks arising from this study.

How will this be managed to ensure appropriate protection and well-being of the participants?

I will ask participant's preferred time and will contact them only at that given time slot. I will ask for their consent as well before starting the interview. I will also provide them freedom to terminate the interview any time if they wish to and to choose not to answer any question if they don't wish too.

Section E: About the data

1. Data Processing

Figure 7.3: *Ethics application page 3*

Will you be processing (i.e. collecting, recording, storing, or otherwise using) personal data as part of this project? (Personal data is any information relating to an identified or identifiable living person).
No

Please outline how your data will be managed and stored securely, in line with good practice and relevant funder requirements

All the data taken by survey will be entered in a computationally readable format as a CSV file. Then I plan to use my university service of 'research group data storage' to store these data files. These files will be only accessible to me and my supervisors. I will ensure that these file are never shared or stored in any public accessible domain.

Section F: Supporting documentation

Information & Consent

Participant information sheets relevant to project?
Yes

Document 1060187 (Version 1) All versions
Participation information sheet which describes the details of my research work which I will explain to the participants before collecting the data

Consent forms relevant to project?
Yes

Document 1060188 (Version 1) All versions
Consent form to get signed by participants before the interview

Additional Documentation

Document 1060483 (Version 1) All versions
Questionnaire for the interview

Document 1060482 (Version 1) All versions
field trip risk assessement

External Documentation

- not entered -

Section G: Declaration

Signed by:
Reena Jayantilal Sayani
Date signed:
Thu 25 April 2019 at 01:13

Offical notes

- not entered -

Figure 7.4: *Ethics application page 4*

The University Of Sheffield.

Downloaded: 07/12/2023
Approved: 16/05/2019

Reena Sayani
Registration number: 180124736
School of Architecture
Programme: Postgraduate Research - School of Architecture

Dear Reena

PROJECT TITLE: Sustainable management of energy to improve quality of life in developing countires
APPLICATION: Reference Number 025937

On behalf of the University ethics reviewers who reviewed your project, I am pleased to inform you that on 16/05/2019 the above-named project was **approved** on ethics grounds, on the basis that you will adhere to the following documentation that you submitted for ethics review:

- University research ethics application form 025937 (form submission date: 25/04/2019); (expected project end date: 15/06/2019).
- Participant information sheet 1060187 version 1 (17/04/2019).
- Participant consent form 1060188 version 1 (17/04/2019).

The following optional amendments were suggested:

(1) Would be useful to briefly describe the type of company Gram Oorja are, to confirm there are no ethical conflicts in working with them. (2) Could you also clarify what time of day you will be working in the villages, presumably daytime working will be less risky than if you were there at night? (3) Could you confirm age criteria for participants, I assume you will not be interviewing children but clarifying this is useful. (4) It sounds like you will be collecting personally identifiable data and therefore response to section E should be changed, with brief details given of how you will maintain anonymity as appropriate. Shouldn't the answer to processing personal data be yes? The consent form will require a signature, which would identify the participant. In small village communities, it may also be possible to identify a participant from their descriptions of activities and the appliances they own. This is not a problem, you just need to be clear on how you would protect their identity, e.g. using arbitrary ID code for participants in data file and keeping consent form separate, not identifying individual behaviours and data when reporting results, etc. (5) Will the information sheet and consent form be translated into the local language? Will all participants be literate/able to understand written information? (6) If you have a mobile phone and it can work in the field data collection areas, please keep it with you all the time. You should maintain daily contact with your supervisors and family members throughout the data collection period. You should also let them know what they should do if they do not hear from from after a certain period. This is to safeguard your personal safety and well-being while undertaking the field work.

If during the course of the project you need to deviate significantly from the above-approved documentation please inform me since written approval will be required.

Your responsibilities in delivering this research project are set out at the end of this letter.

Yours sincerely

Chengzhi Peng
Ethics Administrator
School of Architecture

Please note the following responsibilities of the researcher in delivering the research project:

- The project must abide by the University's Research Ethics Policy: https://www.sheffield.ac.uk/research-services/ethics-integrity/policy
- The project must abide by the University's Good Research & Innovation Practices Policy: https://www.sheffield.ac.uk/polopoly_fs/1.671066!/file/GRIPPolicy.pdf
- The researcher must inform their supervisor (in the case of a student) or Ethics Administrator (in the case of a member of staff) of any significant changes to the project or the approved documentation.
- The researcher must comply with the requirements of the law and relevant guidelines relating to security and confidentiality of personal data.
- The researcher is responsible for effectively managing the data collected both during and after the end of the project in line with best practice, and any relevant legislative, regulatory or contractual requirements.

Figure 7.5: *Ethics Approval letter*

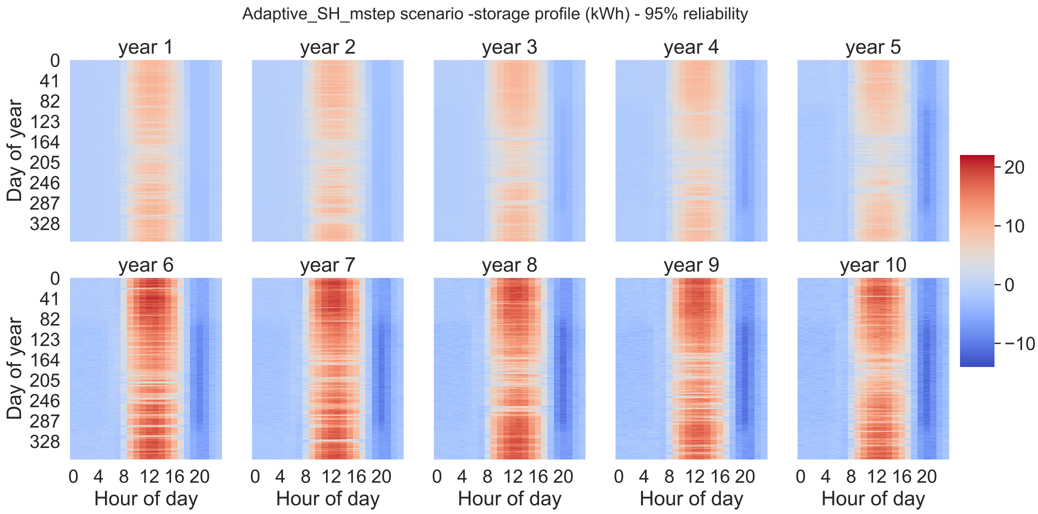
Appendix A.3.3 - Appliance diffusion inputs

Appendix A.3.4 - storage system performance

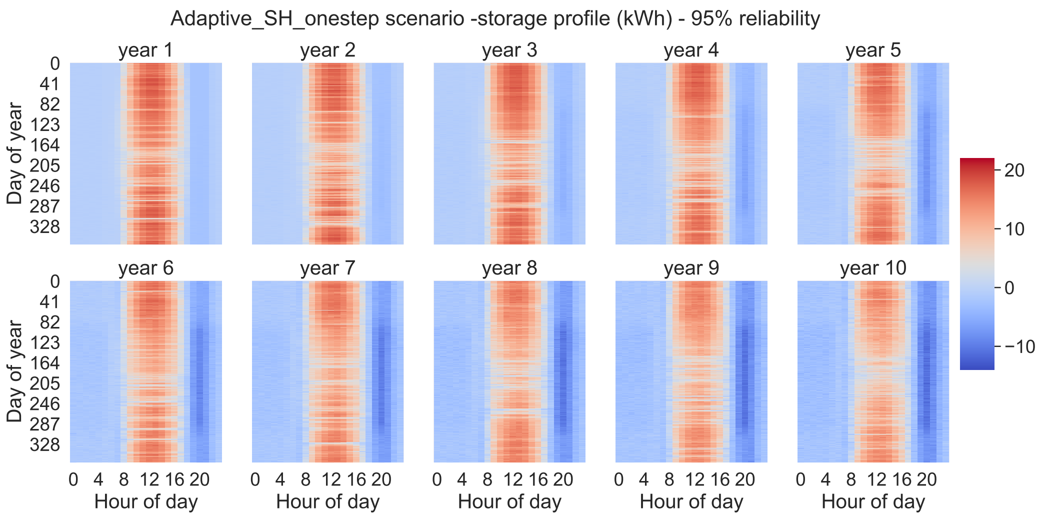
Appendix A.3.5 - cost breakdown

Appendix A.4.1 Sampling of households in four states of India in TUS.

Appendix A.4.2 -Correlation between two variables and effect of outlier treatment IQR.



(a) a



(b) b

Figure 7.6: *System performance for adaptive growing demand in Shahapur, at an hourly scale per year over a ten-year period, with 95% reliability. Storage state of charge in kWh of (a) one-step sizing and (b) multi-step sizing.*

Baseline	Average		Diffusion	
	Ownership		coefficients	
Appliances	Initial	Final	innovation (p)	Imitation (q)
Lights	3	3	0	0
Mobile phone	1	1	0	0
Security Light	1	1	0	0
TV	0	0	0	0
Fan	0	0	0	0
Refrigerator	0	0	0	0

Table 15: Appliance diffusion coefficients

Adaptive	Average		Diffusion	
	Ownership		coefficients	
Appliances	Initial	Final	innovation (p)	Imitation (q)
Lights	3	5	0.01	0.9
Mobile phone	1	1	0.01	0.9
Security Light	1	1	0	0
TV	0	1	0.05	0.9
Fan	0	1	0.05	0.8
Refrigerator	0	1	0.02	0.5

Table 16: Appliance diffusion coefficients

Target	Average		Diffusion	
	Ownership		coefficients	
Appliances	Initial	Final	innovation (p)	Imitation (q)
Lights	3	5	0	0
Mobile phone	1	2	0	0
Security Light	1	1	0	0
TV	0	0	0	0
Fan	0	0	0	0
Refrigerator	0	0	0	0

Table 17: Appliance diffusion coefficients

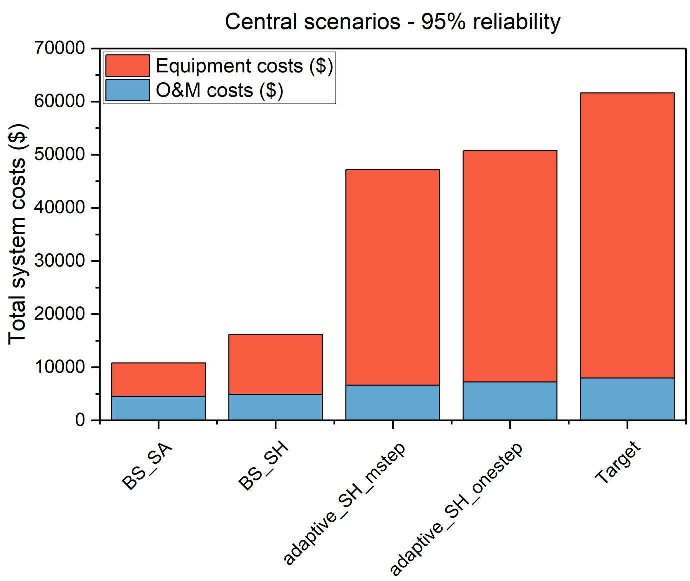


Figure 7.7: *Costs breakdown (equipment and O&M costs) per scenario considering 95% reliability.*

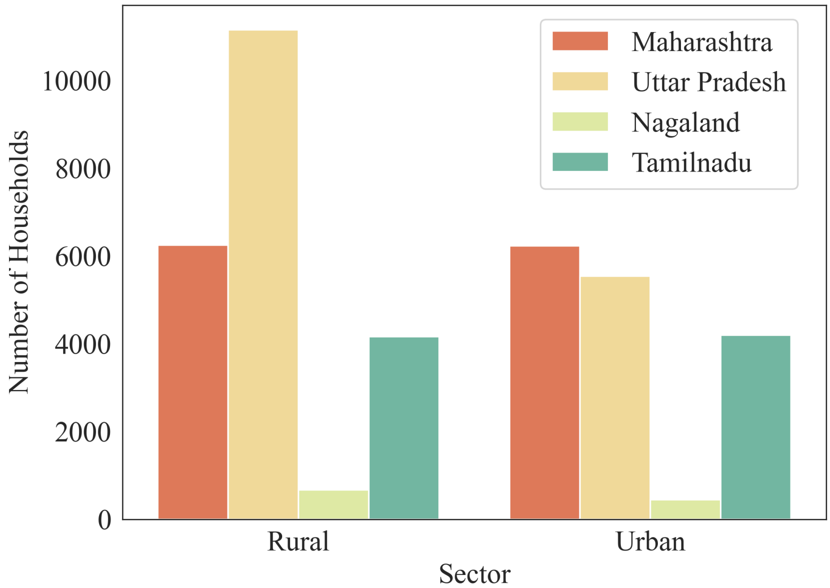


Figure 7.8: *Sampling of rural households compared to urban households*

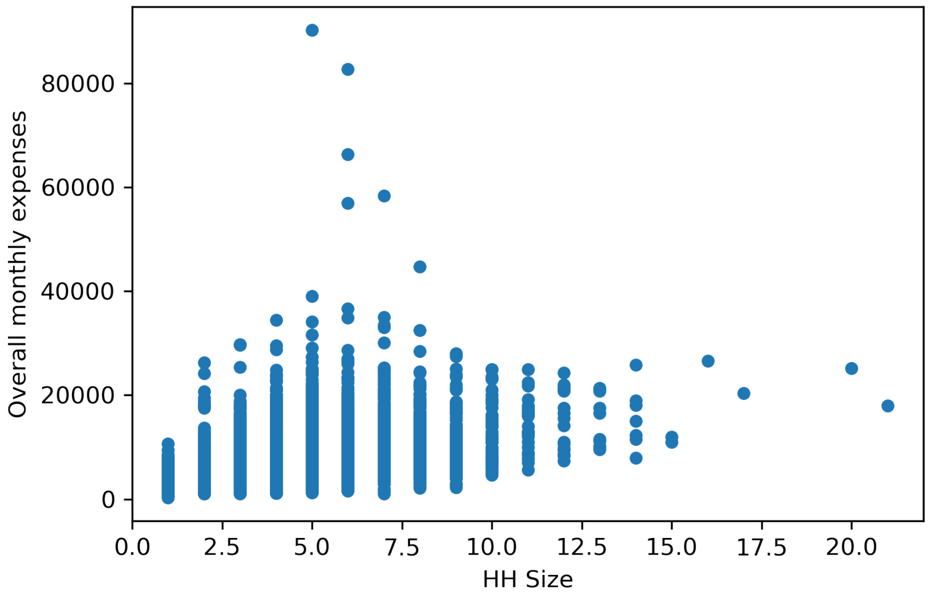


Figure 7.9: *Before outliers with IQR UP*

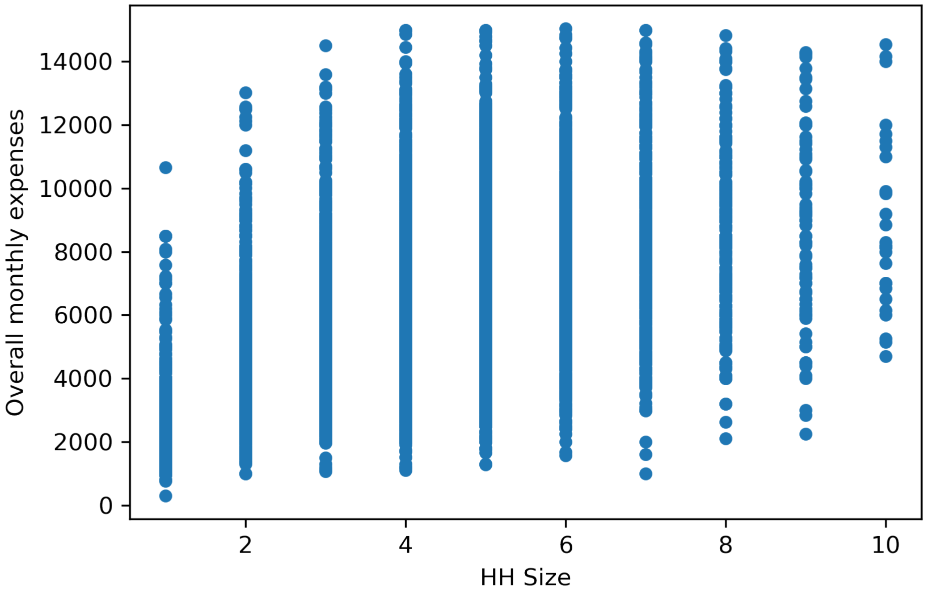


Figure 7.10: *After removing outliers with IQR UP*

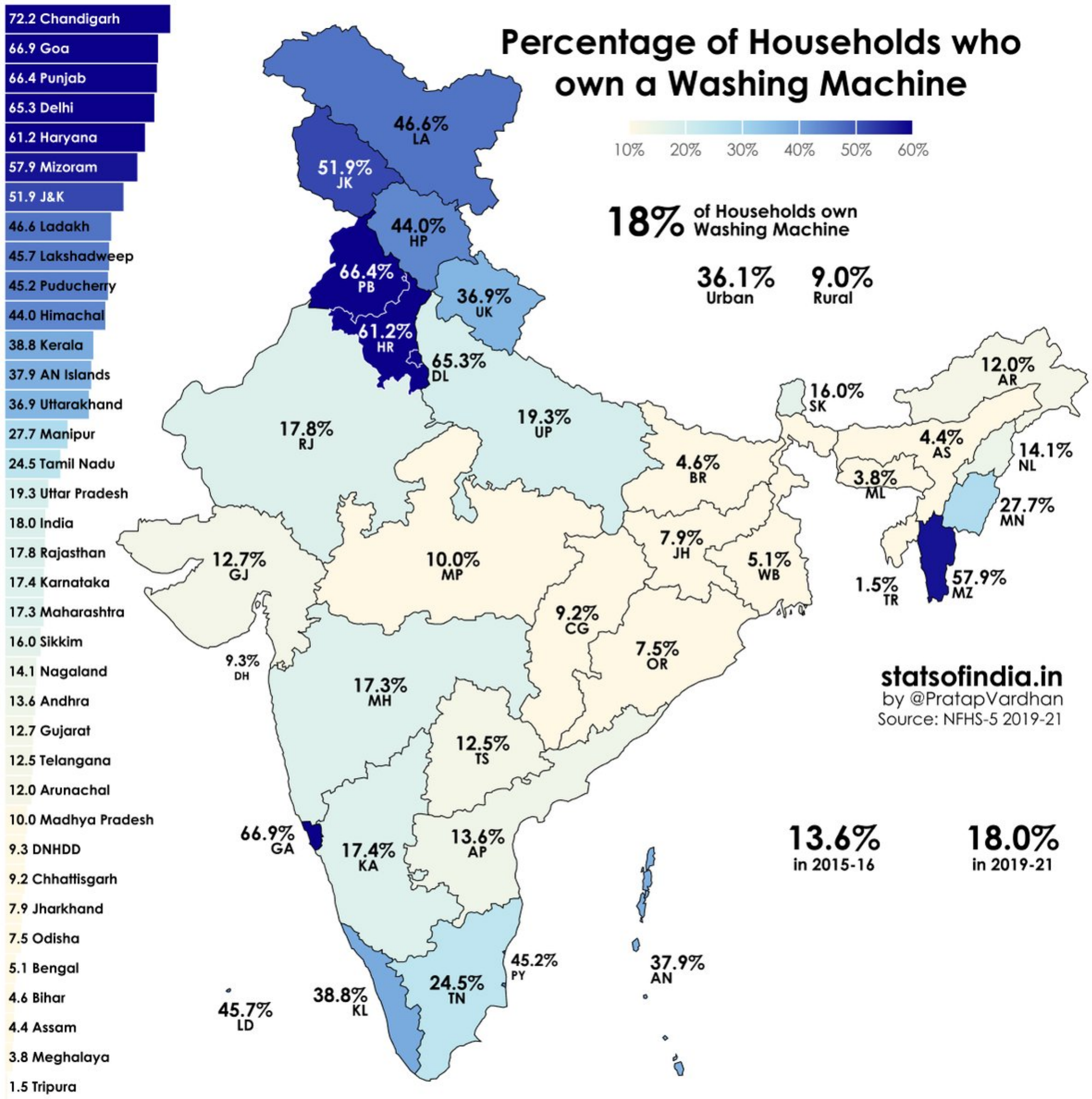


Figure 7.11: *Washing machine ownership statistics based on NFHS round 5, source: Statsindia group*

Appendix A.6.1

Guidance on initial ownership of washing machine taken from this data