What Smart Meters Can Tell Us

Insights on Electricity Supply and Use in Mathura and Bareilly Households

Shalu Agrawal, Sunil Mani, Karthik Ganesan, and Abhishek Jain

Report | February 2020

India's power sector is undergoing a rapid transformation with rising demand and changing energy mix.

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ceew.in

Suggested citation: Agrawal, Shalu, Sunil Mani,karthik Ganesan, and Abhishek Jain. 2020. *What Smart Meters Can Tell Us Insights on Electricity Supply and Use in Mathura and Bareilly Households.* New Delhi: Council on Energy, Environment and Water.

Cover image: Milan Jacob/CEEW.

Peer reviewers: A. K. Bohra, ex-MD, Jaipur Vidyut Vitran Nigam Limited (JVVNL), Rahul Tongia, Fellow, Brookings India, Anil Mehta, Principal-Public Policy, Secure Meters Ltd, Neeraj Kuldeep, Programme Lead, CEEW, and Prateek Aggarwal, Programme Associate, CEEW.

Publication team: Alina Sen (CEEW), Mihir Shah (CEEW), Venkatesh Krishnamoorthy, Priyanka Adhikari, and Friends Digital.

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Acknowledgments

First of all, the authors thank all the sampled households for their voluntary participation and allowing us to capture their electricity consumption patterns. We thank the field resource personnel, Devendra Singh and Vivek Tiwari from Morsel Research and Development Private Ltd., for their tireless effort in the household selection, smart meter installation, data collection, and customer engagement. We thank Sumeru (India), Private Ltd., for providing the smart meters that aided our data acquisition process.

We owe a debt of gratitude to several people for helping us during the smart meter installation process and apprising us of the ground realities: the officials of Uttar Pradesh Power Corporation Ltd (UPPCL), Madhyanchal Vidyut Vitaran Nigam Ltd. (MVVNL), Dakshinanchal Vidyut Vitran Nigam Ltd (DVVNL), Shri Brahm Pal (Director, UPPCL, Lucknow), Smt. Varalika Dubey (CE, UPPCL, Lucknow), Shri V. K. Gangwar (CE, DVVNL, Mathura), Shri Ajay Garg (SE, DVVNL, Mathura), Shri N. K. Mishra (CE, MVVNL, Bareilly), Shri S. K. Saxena (SE, MVVNL, Bareilly) and other divisional, sub-divisional, and local level staff.

We express our sincere gratitude to Nipun Batra and Kavita Vaishnaw from IIT Gandhinagar for their valuable contribution during data analysis. Our deepest gratitude goes to the reviewers—A. K. Bohra, ex-MD, JVVNL; Rahul Tongia, Fellow, Brookings India; Anil Mehta, Principal—Public Policy, Secure Meters Ltd.; Neeraj Kuldeep, Programme Lead, CEEW; and Prateek Aggarwal, Programme Associate, CEEW—for their critical feedback and comments that have helped us in refining this report. We thank the entire power sector team at The Council, especially Kanika Balani, for providing valuable assistance during the entire study.

Finally, we thank our outreach team, particularly Alina Sen, Communications Specialist, for her guidance and support at the publication stage and her efforts to ensure that the report meets CEEW's quality standards.

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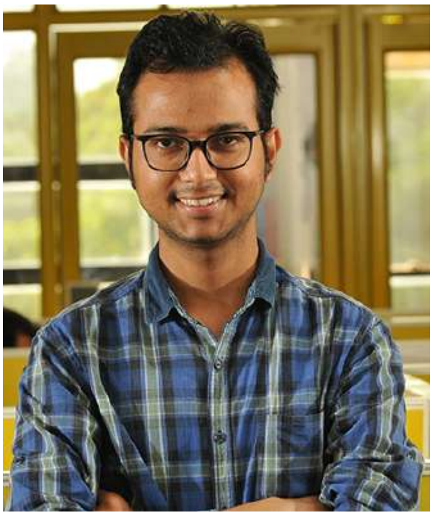
"Discoms can use smart meters for better service delivery, load management and to enable low carbon transition in India. For this, it is crucial that this intricate technology is deployed in a systematic manner."



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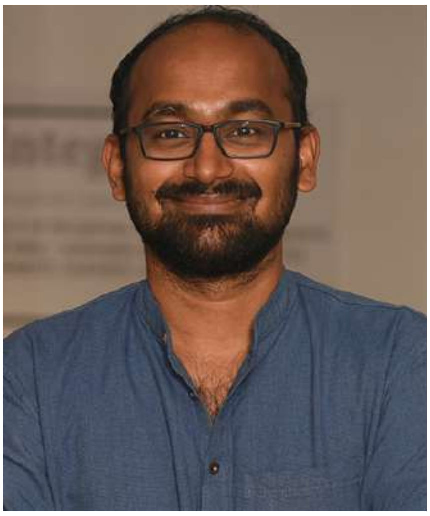
"Ensuring 24x7 power for all would require an understanding of micro-level household consumption patterns. Even though smart meters can provide such information on real time basis, it needs to be constantly validated from the field, so that it generates robust policy insights."



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An engineer by training, Karthik leads The Council's work on the power sector. His research has focused on the operational reform of discoms in India and the competitiveness of various power generation sources. He has also led a first-of-its-kind evaluation of the impact of industrial policies on the renewable energy sector in India. Karthik holds a master's degree in Public Policy from the Lee Kuan Yew School of Public Policy at the National University of Singapore. He also holds an undergraduate degree in Civil Engineering and an MTech in Infrastructure Engineering from the Indian Institute of Technology, Madras.

"A smart meter is only as smart as the person or system, looking at the data it sends out. What we change based on the insight will determine the efficacy of the smart meter revolution."

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"The government of India has massive ambitions to deploy smart prepaid meters across the country. Here we make an attempt to understand their on-ground practicalities, and how can the utilities leverage smart meters to transform themselves from passive energy suppliers to active energy service providers."

Contents

Image: Milan Jacob/CEEW


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Abbreviations

ACs	air conditioners
AMI	advanced metering infrastructure
CAR	compressor activity rate
CBA	cost–benefit analysis
CEA	Central Electricity Authority
DT	distribution transformer
EESL	Energy Efficiency Services Limited
GHG	greenhouse gas
GPRS	general packet radio service
ISGF	India Smart Grid Forum
kWh	kilowatt-hour
MBC	metering, billing, and collection
NSGM	National Smart Grid Mission
NTA	notified town areas
PFC	Power Finance Corporation
POSOCO	Power System Operation Corporation Limited
RES	renewable energy sources
ToU	time of use
UDAY	*Ujwal Discom Assurance Yojana*
UPERC	Uttar Pradesh Electricity Regulatory Commission

Power utilities in India face the daunting task of meeting the rising electricity demand by offering reliable electricity services.

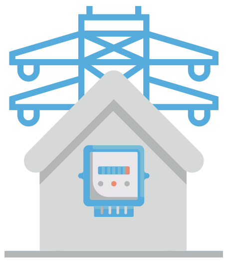
Image: iStock

Executive summary

Power utilities or discoms in India face the daunting task of meeting the rising electricity demand by offering reliable electricity services, at the same time, engaging in efforts to recover the costs of operation and continually allocating resources to invest in upgrading the power infrastructure. The continually surging residential demand, which makes up one-fourth of the country's power consumption, adds up to the challenges of discoms. However, discoms lack an adequate understanding of electricity usage patterns at the household level and its variation with time and season. The limited information about electricity use from conventional meters at a low frequency (once a month) does not render it suitable for demand analysis.

India is an attractive smart-meter market in the world, which remains largely untapped, boasting of 215 million domestic connections nationwide. Nearly 2 million smart meters have been installed across the country so far. The adoption of smart meter technology in India provides an opportunity for the power distribution companies (discoms) to gather real-time information on residential electricity demand and make better decisions to manage it.

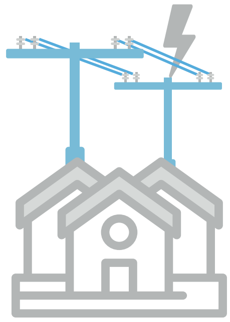
We provide insights into the household consumption pattern by collecting high-frequency data from 93 smart meters that we installed in urban households in Mathura and Bareilly districts of Uttar Pradesh. We also investigate the gaps in the quality of supply and discuss how power distribution companies can utilise the smart meter data for effective service delivery and demand management. Households were sampled in a purposive manner from multiple residential areas and within a substation jurisdiction to capture diversity in the quality and duration of supply and consumption behaviour. We started collecting smart-meter data from May 2019. This study presents preliminary insights based on the data collected between May-October, 2019.



Smart meters provide an opportunity for the power distribution companies to gather real-time information on residential electricity demand and make better decisions to manage it

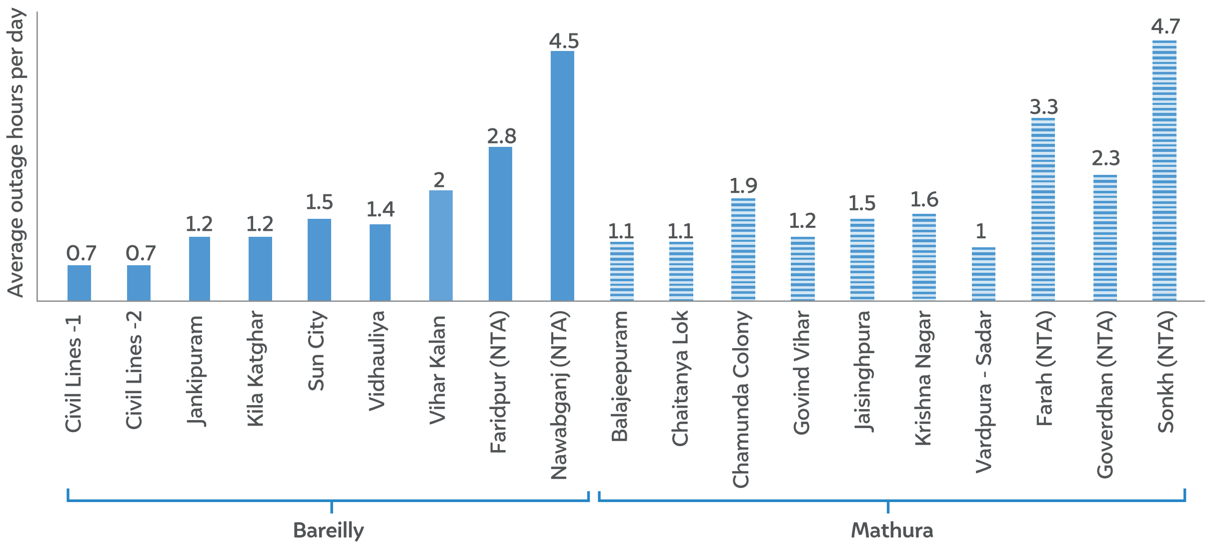
Findings on the quality of electricity supply

- Urban households in the residential areas that we covered in the study received electricity supply for 22 hours on average. However, there was a variation in the duration and quality of electricity supply across urban areas.
- Households in the notified town areas (NTAs) receive poorer supply as compared to those residing in the district headquarters (Figure ES 1). While households in NTAs endured power outages of around 3.5 hours a day, with an average of 6 interruptions per day, households in district headquarters witnessed shorter (1.3 hours a day) and fewer interruptions (3.5 times a day). Discoms need to focus more on the supply situation in NTAs.
- Interviews with field-officials indicate that most outages can be attributed to two factors: tripping/faults and unscheduled load-shedding/shutdowns due to repair work or infrastructure upgrades. NTAs in Bareilly also experienced power cuts due to scheduled load-shedding.
- Besides the duration of supply, it is also important to consider the quality of supply. Variation in voltage is a major concern. A few residential areas suffered from low voltage issues, mainly due to inadequate capacity, with voltages dropping by 25–30 percent during the peak load.
- Outages recorded at the household level differ significantly from the outage duration reported by the discoms at the feeder-level (11 kV), underscoring the need to monitor supply quality at the end-user level.



Most residential areas received electricity supply with higher than prescribed voltage levels for a significant fraction of time

ES 1: Households in NTAs face more power outages than those in district headquarters



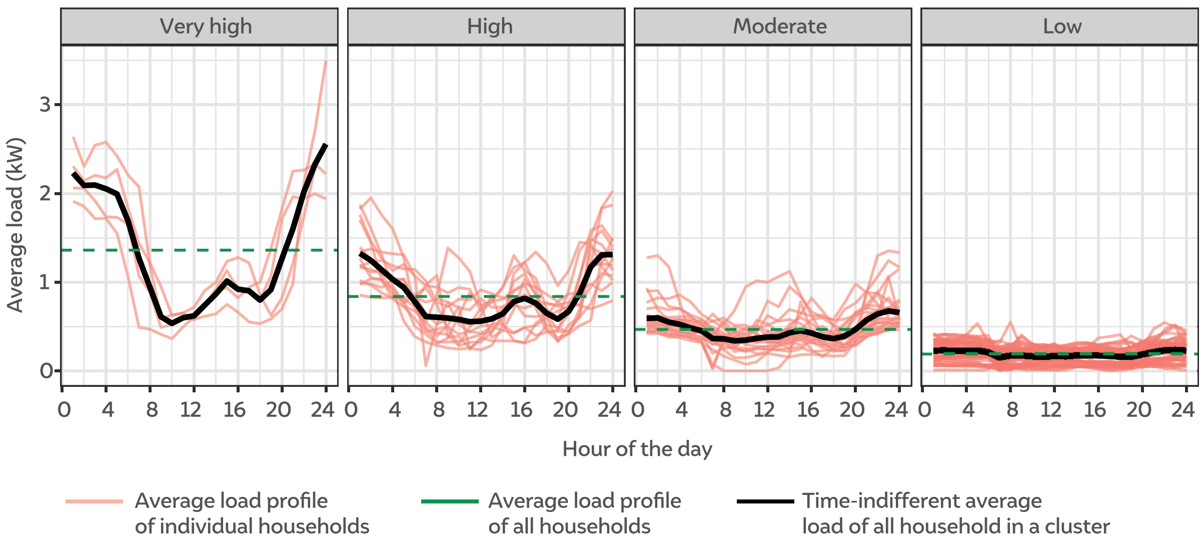
Source: Authors' analysis

Findings on electricity use in households

- Between May and October 2019, the sampled households consumed 280 units of electricity per month, on average. While households using only fans for space cooling spend up to 200 units per month between May and October, those with coolers and air conditioners guzzled more power, in the range of 200–1000 units a month.
- Customer segmentation using k-means clustering suggests that households having air conditioners and/or coolers comprise high and very-high demand clusters, and are the key contributors to peak demand (Figure ES 2).
- The economic status of the household, measured by reported monthly expenses, is a key predictor of the ownership of advanced cooling appliances. Residential electricity use, as well as peak demand, tends to rise with an increase in household income levels.
- An analysis of the usage pattern of air conditioners, with the help of the current signature, reveals that sample households switched on the air conditioner for an average of 5.5 hours a day. The household's economic status dictates the use of air conditioners, as evident by the moderate use of the appliance in many households.
- There is a significant difference in the appliance usage perceived by the households and the actual observed usage gathered from the smart meter data. Most households tend to over-estimate or under-estimate their AC usage, suggesting that people have limited information to optimise their energy usage.

Most households tend to over-estimate or under-estimate their AC usage, suggesting that people have limited information to optimise their energy usage

ES2: Households can be classified into four clusters based on demand, from low to very high levels of consumption



Source: Authors' analysis

Key recommendations for discoms to utilise smart meter data

Improving billing efficiency and reducing commercial losses seem to be the primary objective of discoms for deploying smart meters in India. We argue that discoms can go further in utilising the smart metering infrastructure to provide reliable, cost-effective, and sustainable electricity services to the consumers. Based on our insights on the electricity supply situation and demand patterns, we propose three key recommendations.

- **Monitor network health and ensure quality power supply**

  Any problem in the distribution network affects its overall health, which can result in the end consumers receiving low supply hours compared to the supply at the feeder level. In order to achieve the policy target of uninterrupted power supply, discoms can effectively make use of the smart meter infrastructure to monitor tail-end supply parameters, such as power outages, voltage profile, and power factor, and ensure better network health through predictive maintenance and infrastructure upgrades.

- **Track electricity demand and identify customers driving the peak demand**

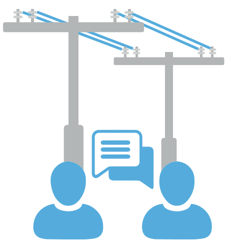
  Smart meter data proves useful to gain a clear understanding of the household load profile, peak demand, and its drivers, which can be used by discoms to profile different customer segments. This data, in turn, could be used to forecast demand, assess the capacity of the distribution network to handle the load at all times, and further plan for infrastructure expansion. Discoms could also explore alternative strategies to augment supply, such as peaking power, demand shifting, and distributed storage.

- **Engage with consumers for demand-side management**

  Apart from making supply-side interventions within their span of control as the electricity service provider. We propose three potential avenues:

  a. *Providing periodic feedback to consumers on self-consumption and that of others to promote conservative energy use.* We find that most people tend to estimate their energy consumption wrongly and have inadequate information to optimise their usage or purchase decisions. Discoms, by providing feedback on energy usage in general, and AC use, in particular, could help households keep a better check on their overall energy consumption, which would also increase consumers' trust in the electricity bills. Discoms could consider indicating the hours of AC use in the electricity bill.

  b. *Implementing demand response mechanisms in a targeted manner.* The increase in the use of air conditioners and coolers by households would make load management further challenging for discoms. Discoms should design and test new mechanisms, such as time of use (ToU) pricing targeted towards residential consumers who contribute to peak demand. By resorting to this measure, discoms would be able to achieve load shifting/reduction and also manage their procurement costs associated with rising peak demand. Discoms could also incentivise peak consumers to adopt distributed generation and/or storage to reduce withdrawals from the grid during peak hours and achieve load shaving.



Discoms should find ways to engage directly with the residential consumers for managing demand and also push them towards exhibiting efficient consumption behaviour

India's power sector is undergoing a rapid transformation, as we are witnessing changes in power generation, regulatory measures, as well as consumption patterns. This environment provides an opportunity for discoms to transform from being just an electricity supplier to an energy service provider by engaging with the consumers to help them save electricity and improving the overall consumer experience.

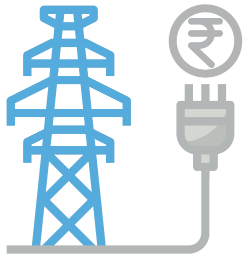
Smart metering initiatives in the country are well-timed to enable this transition. However, the smart-meter deployment should be carried out in realistic timelines taking into account technology advancements and various implementation challenges. A systematic approach and treating smart-meters as an integral part of grid-modernisation efforts would be crucial to tap into the multiple opportunities that the technology offers.

With increased electrification, more people are using electric appliances. A study participant in Bareilly watching TV.

Image: Milan Jacob/CEEW

1. Motivation for the study

Following the implementation of the *Saubhagya* scheme, nearly all Indian households are electrified. The government's next policy target is to provide a 24x7 power supply to all the consumers. Despite some improvements in the duration of power supply, the uninterrupted supply remains an uphill task on account of multiple factors. A limited understanding of electricity consumption pattern in the residential sector, mainly due to the paucity of relevant data (Chunekar, Varshney, and Dixit 2016), is a key barrier. To manage the loads, utilities in the past have resorted to load-shedding (blackouts or brownouts) or procured expensive power. Utilities now are tasked with a policy-driven imperative of providing uninterrupted power, in addition to improving their financial health. To achieve both, a better understanding of demand would be crucial for effective load management.



To achieve 24x7 power supply and improve their financial health, a better understanding of electiricy demand would be crucial for discoms to manage loads effectively

Residential consumption, which now makes up one-fourth of the country's total electricity use, is projected to increase significantly over the next decade (Khosla 2018). Improved supply, higher electrification rates, use of more appliances, and lifestyle changes have all contributed to the rising demand, which is likely to increase exponentially in future. The following questions arise for an understanding of residential consumption patterns: How does the household electricity use vary on an hourly, daily, and seasonal basis? Which appliances contribute the most to electricity use in houses, and to what extent? Which appliances and consumers would drive the changing demand pattern going forward?

Answers to these questions can help in effective planning of electricity supply systems and designing interventions to manage the rising demand. The information about consumption that is currently retrieved from conventional meters and the frequency of data collection is not sufficient for getting a clear picture of the variations in household consumption. Smart meters, which have been deployed by several utilities, enable continuous two-way communication between the utility and the consumer, facilitating the acquisition of consumption data at a higher frequency in real-time.

We look at the following questions to suggest effective ways to utilities so that they provide a reliable supply and manage the load efficiently:

1. What can the smart meter data tell us about electricity supply and its use in households?
2. How can the smart meter data be used for managing household electricity demand?

We do so with the help of supply and consumption data of 93 urban households from two districts in Uttar Pradesh. The data was collected with the help of smart meters that we installed at the selected households as submeters, between May and August 2019. We begin by discussing the developments in smart metering technology and how Indian power utilities are tapping into the opportunities offered by this technology in Chapter 2. We explain our study design in Chapter 3. In Chapters 4 and 5, we provide insights on the quality of supply and household consumption patterns. In the concluding Chapter 6, we discuss the policy implications of our insights and key recommendations. The report presents preliminary findings based on the smart meter data collected between May and October 2019.

2. Mapping the smart metering landscape

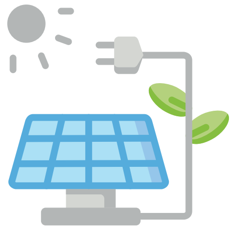
Electricians installing a smart meter at the main supply of a household in Mathura.

In this chapter, we briefly introduce the concept of advanced metering infrastructure (AMI) and the opportunities that smart meters present to the power utilities. We also provide a snapshot of trends in the smart meter market and policy drivers across various countries. Finally, we delve on the developments in India so far and the key issues that need policy attention.

2.1 AMI and smart meters

AMI is an integrated system of smart meters, communication networks, and data management systems, which facilitates two-way communication between the utilities and consumers. Smart meters form the core of an AMI. They measure energy flow like conventional electronic meters. The 'smart' component arises from their ability to collect and transmit the consumption and supply-related data at specified time intervals, on a real-time basis. The data can be communicated through various channels and is stored in a centralised server, from where it can be extracted and analysed to generate useful insights.

The AMI aids in the seamless operation of power utilities by facilitating higher billing efficiency through remote and accurate bill generation, enabling better network health through real-time monitoring of critical parameters, and improving service delivery through outage management system (CEA 2016). Utilities can also use the high-frequency consumption data for demand forecasting, predictive modelling, and to study peak demand patterns, which can assist them in infrastructure planning and cost-effective power procurements.



A smart grid would enable higher penetration of distributed energy in the grid than would otherwise be possible

Smart meters form the basis of a smarter grid, which in turn offers a significantly high level of control and responsiveness to varying grid conditions. A smart grid would also enable higher penetration of distributed energy in the grid than would otherwise be possible. Even the customers could rely on smart meters for monitoring and managing their electricity demand and expenses. In short, besides facilitating efficiency in the meter-to-cash cycle, AMI offers multiple avenues for utilities for improved operations, planning, and facilitating the clean energy transition (Wood Mackenzie 2019).

2.2 Global trends and drivers

Globally, many countries have embraced the AMI technology for upgrading their utility infrastructure for electricity, gas, and water supplies. The global smart meters market is growing rapidly and is expected to double from USD 665 million in 2017 to USD 1.2 billion by 2024 (Wood Mackenzie 2019). Until recently, countries in Western Europe, the United States, and China accounted for the majority of smart meter installations (Research and Markets 2019). A few countries, including China, Japan, Spain, and France, are close to full deployment of smart meters. Going forward, emerging economies in Asia-Pacific are expected to lead the market growth of smart meters.

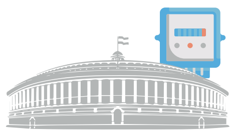
Across countries, the transition to smart meters is mainly driven by government policies, even though the policy motivations differ. In EU, the smart meter push is driven by the '20–20–20' objective, which aims to achieve 20 per cent of total EU's energy consumption from renewable energy sources (RES), 20 per cent increase in energy efficiency, and 20 per cent reduction in greenhouse gas (GHG) emissions compared with the 1990 levels by the year 2020 (Exl Utilities Academy 2016). Initiatives in the United States and Japan are primarily focused on creating a responsive and robust smart grid capable of moderating critical system failures. In the United Kingdom, the roll-outs aim to enable customers to use energy efficiently and save on the bills. Italy, on the other hand, has rolled out smart meters to detect and prevent electricity theft, a critical issue ailing its power sector (Álvarez, Ghanbari, and Markendahl 2014). In China, the provision of reliable and cheap electricity to support the country's economic growth has been the primary driver (Banga 2019). In short, AMI implementation across countries is driven by diverse objectives, ranging from loss reduction and creation of a responsive smart grid to supporting the clean energy transition through energy efficiency at the end-user level and higher penetration of renewable resources in the energy mix.

2.3 The smart meter discourse in India

Taking hints from the global developments, India has also joined the ranks of fast-growing smart meter markets. Several smart grid pilot projects have been implemented across India, through which more than 140,000 smart meters have been installed (see NSGM (2019) for details). However, the aggressive policy push for smart meters came only recently.

In 2015, the *Ujwal Discom Assurance Yojana* (UDAY) scheme, aimed at financial turnaround of ailing distribution companies (discoms) in India, mandated a complete switch to smart meters for all households consuming more than 500 kWh per month by December 2017 and those consuming higher than 200 kWh per month by December 2019 (Ministry of Power 2018a). This directive was later changed to follow a feeder-wise deployment, instead of a customer-wise deployment, to ensure that the last-mile communication network can be established and maintained in a cost-effective manner (ISGF 2017). Under the UDAY scheme, ~1.4 million smart meters have been deployed so far, as per UDAY dashboard. The government also announced a separate plan for installing 4.1 million smart meters in urban areas, as part of the ongoing *Integrated Power Development Scheme*. However, the progress under these schemes has been extremely slow, primarily due to high investment costs (Powerline 2019).

In 2017, Energy Efficiency Services Ltd. (EESL), a five-way joint venture of public sector corporations under the Ministry of Power, entered the AMI landscape to bring down the smart meter costs through demand aggregation and bulk procurement (The Hindu Business Line 2019). In July 2017, EESL floated its first mega tender for 5 million smart meters on behalf of the states of Haryana and Uttar Pradesh. As of October 2019, EESL has succeeded in deploying 0.625 million smart meters in India. EESL financing the smart meter deployment through a deemed savings model, wherein the company makes the entire upfront investment and manages the infrastructure for the next eight years. It plans to recover its investment from deemed savings accruing to the discoms on account of their enhanced billing accuracy, elimination of meter-reading costs, and other efficiencies through the installation of smart meters.



In 2019, India's Union Minister of Power announced the government's plan to convert all the domestic meters into smart pre-paid meters by 2022. Two million smart meters have been deployed so far

In early 2019, the Union Minister of Power announced the government's plan to convert all the domestic meters into smart pre-paid meters by 2022. EESL is the nodal agency to implement the *Smart Meter National Programme*, aimed at the universal roll-out of smart meters. The primary objective of the government for switching to smart meters through policy intervention is the financial turnaround of ailing discoms in the country by reducing their technical and commercial losses (Ministry of Power 2019). Replacing conventional meters with smart meters would minimise human intervention in the process of metering, billing, and collection (MBC), enable remote billing and provide a remote control for connection and disconnection to discoms. The remote control of discom operations is expected to reduce their losses that usually happen through electricity theft, non-payments, defective meters, and erroneous bills due to collusion between consumers and meter readers/billing agents (Ganesan, Bharadwaj, and Balani 2019). Along with the metering of feeders and distribution transformers, smart meters would also assist the discoms in carrying out robust energy audits and plug the leakages through appropriate diagnosis.

2.4 Need for a holistic approach

India has 215 million domestic connections nationwide (Ministry of Power 2018b), making it the largest untapped smart meter market in the world. It is, therefore, relevant to look at the deployment of smart meters not as a mere use of a sophisticated product but as a comprehensive solution for achieving the government's goal of 24×7 power for all Indians (Banga, 2019). So far, 800,000 smart meters have been deployed in the country, but a rethink on the policy drivers, deployment strategy, and implementation timelines is still necessary, drawing from the experiences of smart meter roll-out in India and elsewhere.

Reviewing the policy vision driving the smart metering initiatives

Smart meters are capable of achieving much more than improving the financial health of discoms by cutting their losses and increasing their billing efficiency. They form an integral part of AMI and grid modernisation efforts. The smart meters provide critical data that can help discoms assess the gaps in power supply due to local faults, poor voltage profile, and capacity inadequacy, so that they can modify their distribution network to work more efficiently. The high-frequency consumption data (collected at a 15-minute interval as compared to once a month) is more granular and can be effectively used to assess demand patterns, forecast future demand, and develop new tariff plans. In short, smart metering infrastructure can transform the way the discoms procure power and plan infrastructure management and expansion. Borrowing from the EU's '20-20-20' objectives, utilities in India must also leverage AMI to enable the low-carbon transition in India, through higher penetration of distributed solar systems and engaging customers to make energy-efficient choices and lower their consumption.

Setting realistic timelines given the system building requirements

A systematic approach to smart-meter roll-out would be crucial to tap into the multiple opportunities that the technology offers. The current government policy target of achieving universal roll out within a short timeframe of three to five years, appears to ignore the various implementation challenges that are likely to be encountered during smart meter deployment in India as well as time taken by other countries. Implementation of AMI in the United States and Europe began in 2009 and is projected to reach 82 and 74 per cent, respectively, by 2024. Germany, Brazil, Mexico, and other countries have just begun to roll out smart meters.

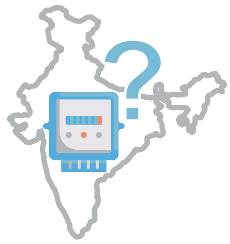
AMI implementation is an intricate exercise, which requires systems building, integration of multiple interfaces, and organisation-wide capacity building. Moreover, the smart meter technology landscape is changing fast with the advent of second-generation smart meters and the planned phase-out of the 3G communication network. Pursuing full deployment within a very short timeframe may push the discoms into the trap of technology lock-in, with

1. Conversion rate used: 1 USD = INR 70.

significant financial implications. It is, therefore, essential that smart meter deployment is carried out in realistic timelines taking into account technology advancements and revising the strategy in line with implementation challenges.

Vetting deployment plans with robust cost-benefit-analysis

A comprehensive cost-benefit analysis (CBA) should guide the decision concerning the utility of smart meter roll-out. Installation of smart meters entails a high upfront cost, because of which only a few utilities in India have adopted the capital investment route for AMI roll-out. Most others have contracted EESL, which is deploying smart meters under the leasing model. Under this model, EESL charges the discoms a fee of ~INR 86 per month per customer (UP-ERC 2018). When extrapolated to the total domestic customer base (215 million households), these costs imply that discoms would have to incur a recurring annual expenditure of USD 3.17 billion (INR 22,190 crore). Even if the costs were to further reduce due to economies of scale, it seems unclear whether Indian utilities have a robust CBA-based rationale for deploying smart meters at scale. Current decisions appear to be based on deemed savings estimates, even though EESL has no liability in case the energy savings are not commensurate with its expectations. Thus, there are concerns about the financial sustainability of smart meter roll out, as many discoms in India are struggling to meet their financial and loss reduction targets set under the UDAY scheme, with their losses mounting to USD 4 billion (INR 28,369 crore) as reported during the fiscal year 2019 (Chatterjee 2019). To deploy smart meters at scale, under a savings-linked model, it will be crucial to create a detailed, high-accuracy baseline through independent third parties and spell out a governance mechanism to resolve conflicts (USAID, 2018)are struggling to meet their financial and loss reduction targets set under the UDAY scheme, with their losses mounting to USD 4 billion (INR 28,369 crore) as reported during the fiscal year 2019 (Chatterjee 2019). To deploy smart meters at scale, under a savings-linked model, it will be crucial to create a detailed, high-accuracy baseline through independent third parties and spell out a governance mechanism to resolve conflicts (USAID, 2018)



The current target of achieving universal roll within three years appears to ignore the various implementation challenges likely to be encountered during their deployment across the country

Sunil Mani (extreme right) and Shalu Agrawal discussing the smart meter pilot with DVVNL officials in Mathura. Shalu Agrawal (below) meeting household respondents during the survey.

Images: CEEW

3. Research design

A high-frequency data provides finer details of the household's electricity consumption patterns and its variation with time and season. As such, consumption data is not easily available; we installed single-phase smart meters in 93 urban households in Mathura and Bareilly districts in the state of Uttar Pradesh (UP). We explain the sampling strategy, meter installation, and data collection process in this chapter. We conclude the chapter with insights and experiences we gathered from the field.

3.1 Sampling strategy

Our objective was to capture the maximum variation in household consumption. We designed a suitable sampling strategy with an initial sample size of 100 households, which is large enough to capture variations across the households and yet small enough to manage the field-related challenges.

Geographic distribution of the sample

We chose two districts—Mathura and Bareilly—in a purposive manner. These districts have tier 2 or tier 3 towns, which are likely to experience rapid growth in demand for power in the near future. Further, the urban areas in these districts receive power supply for at least 20 hours, as per anecdotal evidence. It is essential for capturing household consumption well, as long hours of power cut would have limited the understanding of actual (uncurtailed) demand. Finally, the research team has some amount of familiarity with the local community, which was crucial for managing exigencies during meter installation and data collection.

We sampled households in residential areas from both the district headquarters and a few notified town areas

In most districts in India, the district headquarters is invariably the largest urban area, which is administered by a municipal council or a municipal corporation, while the smaller urban areas are classified as notified town areas (NTAs). Families living in district headquarters are likely to be more urbanised compared to those living in the NTAs. For this study, we sampled households in residential areas from both the district headquarters and a few NTAs. We also sampled households from residential areas receiving power supply from different substations, in order to capture the variation in supply. Table 1 provides details about the geographic distribution of the sample.

Criteria for household selection

We sampled households in a purposive manner based on the two key criteria: number of rooms and appliance inventory. Past studies confirm that these variables are strongly associated with the household's electricity demand and its consumption pattern (Filippini and Pachauri 2004; Singh, Mantha, and Phalle 2018). Further, these can be used as a proxy for understanding the household's socio-economic status. During the fieldwork, we made attempts to sample households with different combinations of the number of rooms and appliance inventory in both the districts.

However, we sampled households having a single-phase electricity connection only, which account for the majority of the residential consumers. Households with three-phase connections are not considered in this study. We also excluded households that did not meet any of the following criteria:

- Living in the house for at least one year and having no plans to move out over the next one year.
- Carrying out no significant commercial activity from within the residential premises.
- Receiving electricity bills on a regular basis.
- Having no plans for construction or renovation activities over the next one year.

Table 1
Geographic distribution of the households covered in this study

Source: Authors' analysis

District	Types of urban area	Substation	Residential Area	Household sample
Bareilly	Muncipal Corporation (District headquarter)	CB Ganj	Vidhauliya	5
			Weston Colony	1
		Civil lines	Civil lines -1	5
			Civil lines -2	3
		Jankipuram	Jankipuram	4
		Kila Katghar	Kila katghar	5
		Mahanagar	Sun city	6
			Vihar Kalan	4
	Notified Town Area	Faridpur	Faridpur	8
		Nawabganj	Nawabganj	8
Mathura	Muncipal Corporation (District headquarter)	Birla Mandir	Jaisinghpura	3
		Jai Gurudev	Chaitanya Lok	4
			Balajeepuram	3
		Krishna Nagar	Krishna nagar	3
		Masani	Chamunda Colony	3
			Govind Vihar	5
		Mathura Cantt	Kotwali	1
			Mohalla Adat - Sadar	1
			Vardpura - Sadar	3
		Farah	Farah	4
	Notified Town Area	Goverdhan	Goverdhan	8
		Sonkh	Sonkh	6

Based on our sampling strategy, we could gain a nuanced understanding of the supply quality in different types of urban areas and consumption pattern and choices of urban households in the focus districts. However, due to small sample size and exclusion of households with three-phase connections, the insights cannot be generalised to the entire urban population in the focus districts.

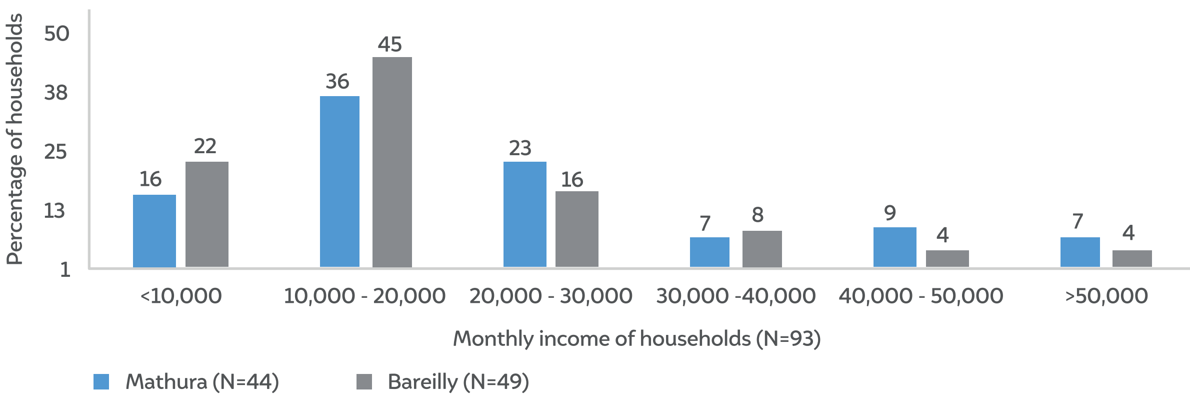
3.2 Sample characteristics

With the help of in-person surveys, we captured the socio-economic characteristics and appliance ownership pattern of the sampled households. Our sampling strategy ensured that the sampled households are quite diverse in terms of demographic and economic characteristics. See Annexure 1 for details on the demographics. Here we discuss the economic profile and appliance ownership pattern of households studied.

Economic characteristics

The combined income of a majority of the sampled households (60 per cent) was less than INR 20,000 per month (Figure 1). The share of households having a larger income is higher in Mathura when compared to Bareilly. So, we infer that households in the Mathura sample are socio-economically better than those in the Bareilly sample. However, in terms of monthly household expenditure, the two samples are quite comparable, with median values of INR 10,000 and INR 10,500 in Bareilly and Mathura, respectively.

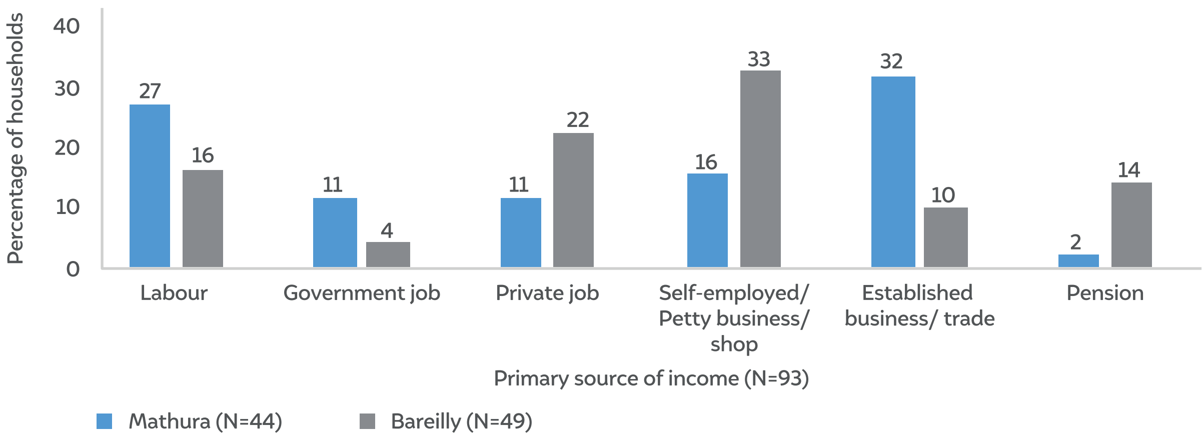
Figure 1: Sample households in the Mathura district are economically better off than those in Bareilly district



Source: Authors' analysis

The samples are also diverse in terms of the primary source of income of the household (Figure 2). One-fourth of the households rely on salaried jobs (government/private) for their monthly income, while another fourth derive income from running a petty business (such as retail shops) or one or more members of the household are self-employed. Further, a member of the household in one-fifth of the sample has an established private business. In another one-fifth of the sampled households, one or more members engage in labour activities, implying an uncertain source of income for the household. These trends may have significant implications on consumption trends noticed across households sampled from these two towns.

Figure 2: Sample households have diverse sources of income



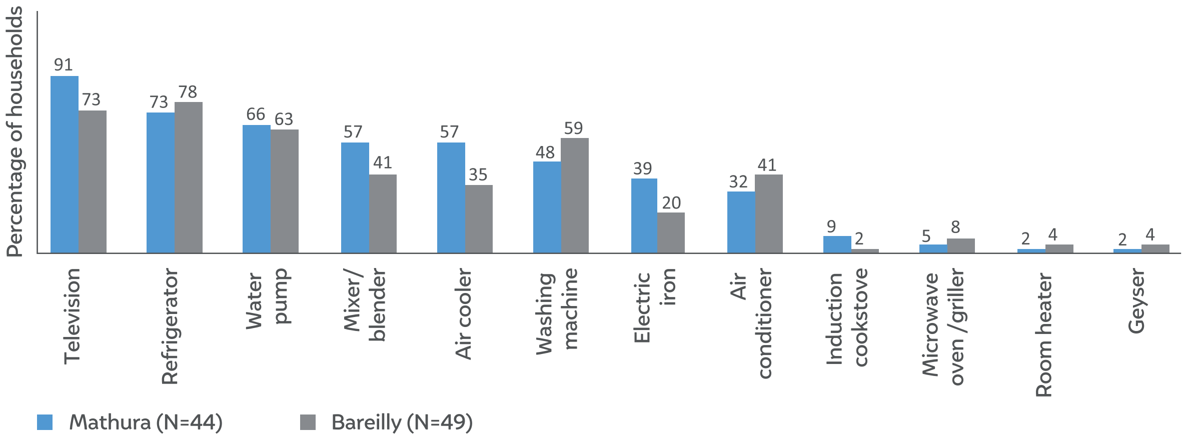
Source: Authors' analysis

Appliance ownership

All the sampled households have grid electricity connections as per the study requirement. All the households have lights and fans, but the ownership of medium to high-power appliances is not uniform. More than three-fourths of the sampled households have a television and a refrigerator, but coolers and air conditioners (ACs) are present in 45 and 37 per cent of the households, respectively. Around 16 per cent households have both coolers and ACs. Ownership of water pumps, mixers, and washing machines is also quite high. But very few households have in their possession other high-power appliances, such as geysers, room heaters, induction cook stoves, or ovens.

Figure 3 compares the penetration of different appliances among the households sampled from the two districts. Though the use of appliances such as the refrigerator and water pumps is quite similar, there are differences in ownership of other moderate and high-power appliances.

Figure 3: Appliance penetration among the sample households varies across the two districts



Source: Authors' analysis

3.3 Meter installation and data acquisition

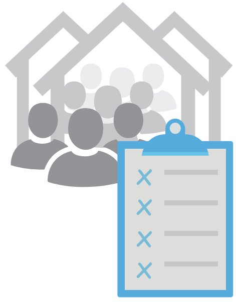
We procured single-phase smart meters manufactured by Sumeru Verde Private Limited. The meters were programmed to capture consumption and supply variables at every 3-minute interval, so a total of 480 measurements were recorded for each day. Annexure 2 illustrates the parameters that were captured from a sample household. The data is communicated over cellular network (Vodafone GPRS network).

We hired and trained two resource persons with the help of a market research company. They were responsible for getting consent from the household, installing the smart meter with the help of electricians, and resolving any issues related to data communication or customer engagement. The first smart meter in our sample household was installed on 23 April 2019 and the last on 6 September 2019. Our initial target was to install 100 meters, but we had to remove a few due to several reasons discussed in the next section. As of 1 November 2018, we had 93 smart meters installed and communicating. Smart meters were installed at the mains supply to the household similar to submeters. The households did not bear any financial liability or derive any utility from the installation. We recorded aggregate consumption parameters only and did not monitor usage pattern at the appliance level.

We also conducted a 20-minute structured survey with the sampled households to capture information related to households' socio-economic background, electric appliances in use, their key characteristics (age, capacity, BEE star rating), and perceived usage patterns. Chapter 4 provides details on the profile of the samples.

3.4 Implementation challenges and gaps in data

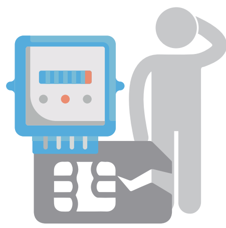
High-frequency consumption data can be collected from smart meters using which useful insights can be gathered for various purposes. However, management of such a high-end technology itself can pose multiple challenges. Here, we briefly discuss three key challenges encountered during meter installation and data acquisition.



Many households declined to participate in the study for fear of inflated bills, partly fueled by rumours on social media

Getting the consent from the household for installing smart meters on their mains supply was the first challenge. We initially adopted a snowball sampling technique to identify households willing to participate in this study. However, we soon found out the limitations of this approach, as majority of the households were unwilling to let a non-governmental entity install a monitoring device in their house, particularly one that may interfere with their electricity connection. So, we sought help from the district-level officials of the electricity department, who helped us by sending the local linemen with our field team to obtain consent from the household. Even though the linemen enjoy consumer trust in matters concerning electricity, we faced the issue of high non-response. Many households refused to participate and cited reasons such as risk of increased bills, no personal benefit, or simply 'not in my backyard'.

Our team still managed to get adequate consents, after which the challenge of retaining their participation emerged. A few households in Mathura requested us to remove the smart meters, stating, without evidence, that the smart meters led to higher bills. These fears were partly fuelled by related rumours spread on social media. The timing of our installations, i.e., onset of summer, was the main factor behind such concerns, as it coincided with a spurt in the household electricity use. We managed to assuage participants' concerns in most places, but we had to remove meters from three locations.

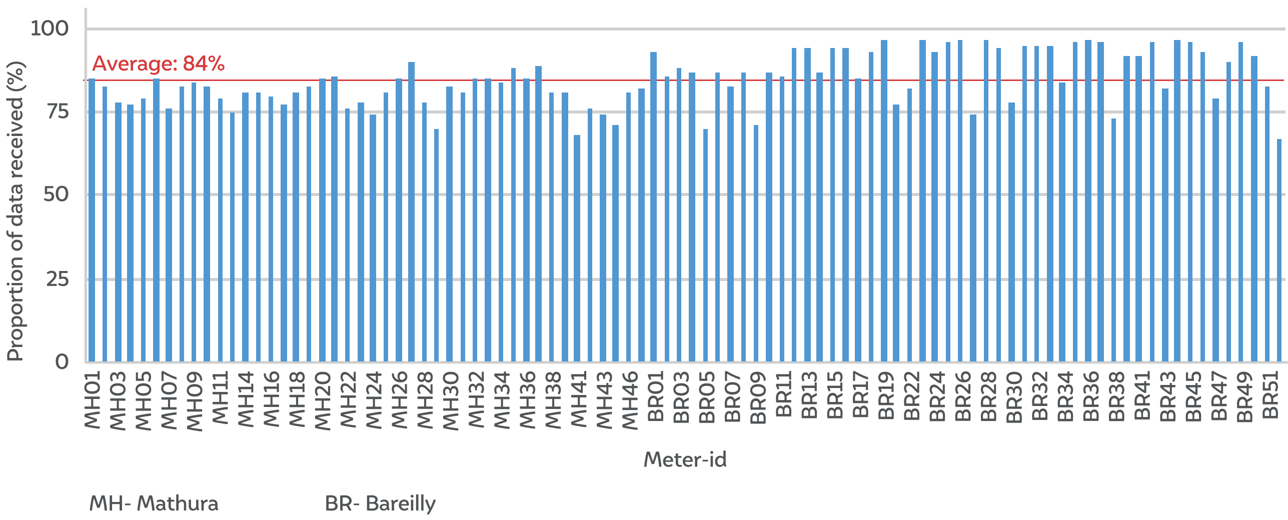


We lost ~15% data due to network issues, software bugs, data pack shortage, and even hardware damage

Finally, ensuring a seamless communication between smart meters and the server was the third and most difficult challenge. We had to periodically monitor whether meters were transmitting all the data packets. In many instances, we found large packets of data missing due to low network strength. To overcome this issue, provisions were made to retrieve data multiple times a day. In some cases, we replaced the SIM cards and used the SIM cards of a different service provider. We also lost a few days of data from many meters, as the data consumption was higher than that was expected and the SIM cards stopped working once the data pack was exhausted. It took us 7–15 days to replace those SIM cards, due to which data for many days was completely lost. Some amount of data was lost due to gaps in programming, such as swapping of data across multiple columns. Finally, in a few cases, our meters stopped communicating due to issues in communication module or hardware damage due to power surge. Whenever such problems were diagnosed, the smart meter was repaired or replaced. Due to reasons cited above, we lost ~15 per cent of data on average, over a period of around 6 months. Figure 4 shows that some amount of data is missing from the almost all the meters, ranging from 3 to 33 per cent.

2. Our meters can store data for up to 3 days, after which the new data overwrites the old data. For instance, if there was no communication for four consecutive days, day 1 data gets overwritten by day 4 data.

Figure 4: Across 93 smart meters, 3–33 per cent of data is missing



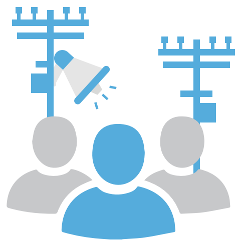
Source: Authors' analysis

Our experience clearly shows that diverse factors that may hinder seamless data acquisition from smart meters, which in turn may adversely affect discoms' ability to bill for electricity use in an accurate manner. We received a few complaints of inflated bills from households in Mathura whose conventional meters have been replaced by smart meters, potentially due to software-related errors. Inflated or inaccurate billing may result in consumer distrust in the smart meter technology, especially because several rumours were spread on social media to this effect.

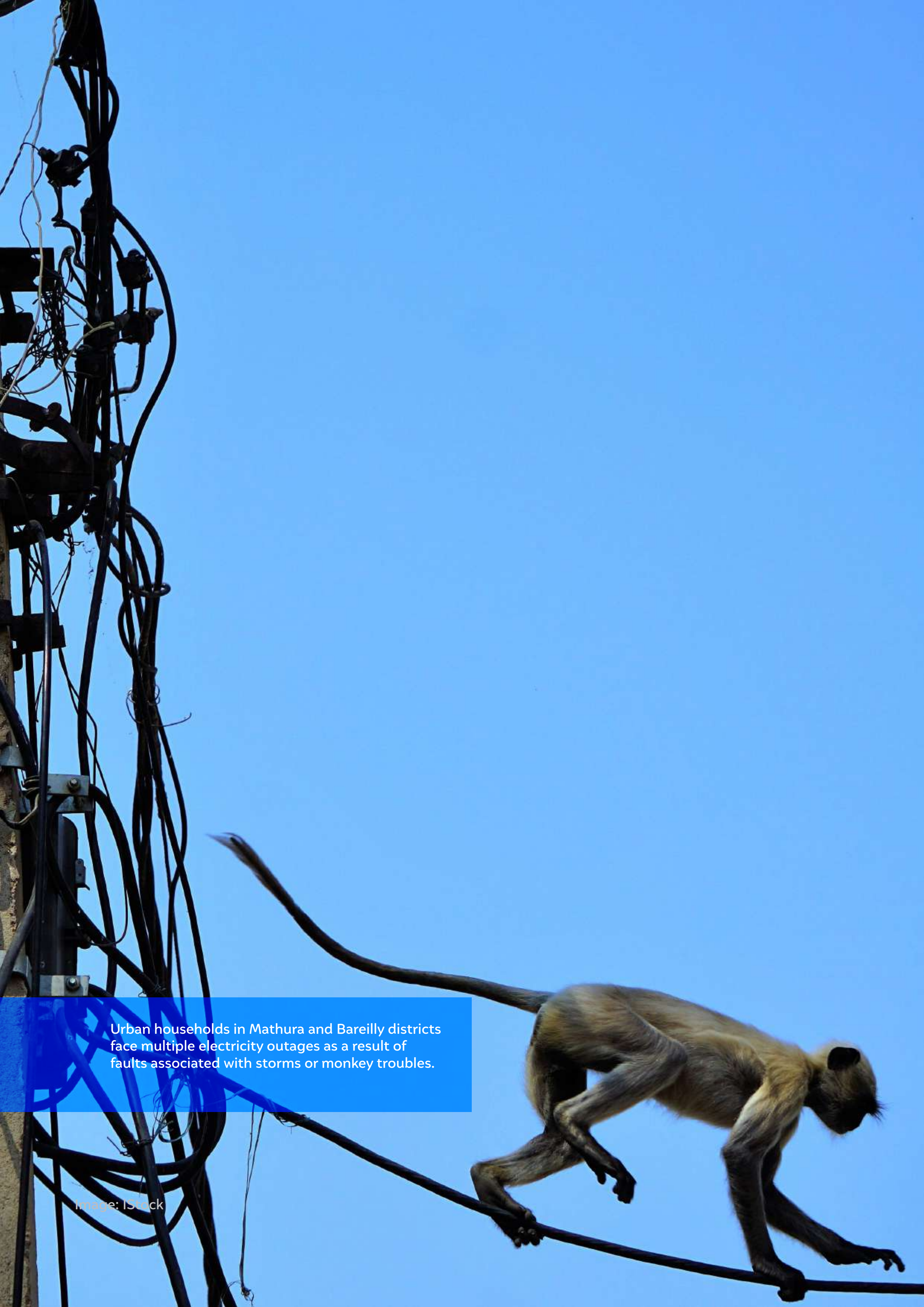
It is, therefore, imperative that discoms actively monitor the quality of data collected from the smart meters and cross-check to verify if the consumption recorded at the consumer end correlates with that measured at the distribution transformer (DT) and the feeder level. Putting out relevant statistics in the public domain would inspire confidence among consumers and facilitate rigorous assessment of the benefits and implications of smart metering initiative in general. Outreach and awareness programmes should also be undertaken to erase the trust deficit between discoms and customer, which prevails at present.

3.5 Data reliability

The credibility of any data-based study depends on the reliability of the data record itself. We compared the household consumption recorded by some of our smart meters (18 meters installed in Mathura) with that of the discom meters with the help of manual inspections. For each household, we recorded the cumulative consumption from both discom and our meters on the same date. The first and second readings were observed at an interval of 30–45 days. For 18 out of 34 meters installed in Mathura, which were monitored for 30–45 days, consumption as per the smart meter reading was within ±7 per cent error range of the discom meter reading. On average, our smart meters under-recorded data by 1 per cent, indicating fairly accurate readings. See Annexure 3 for further details.



Discoms need to undertake awareness programmes to enhance consumer trust in smart meter technology



Urban households in Mathura and Bareilly districts face multiple electricity outages as a result of faults associated with storms or monkey troubles.

Image: iStock

4. Quality of electricity supply in households

In this chapter, our discussion focuses on the duration and quality of power supply received by the households in our study, with the objective of understanding the role that smart meters can play in assisting the discoms to provide better services. All our analysis in this study is based on the data collected between May and October 2019.

4.1 Supply duration

Between May and October 2019, the sample households in which smart meters were installed received 22 hours of power supply on average, which means an average power outage of 2 hours per day. The average duration of outages ranges from 30 minutes to 5 hours across households, indicating that all urban households within a district show variations in the duration of supply. So, we analysed the outages faced by households in different residential areas.

Figure 5 shows that households in Faridpur and Nawabganj in Bareilly district and Farah, Goverdhan, and Sonkh in Mathura district suffered from long hours of power cuts (3.5 hours/day) as compared to the rest of the households in the district headquarters (1.3 hours/day). Besides longer outages, households in NTAs also faced more frequent outages (6 times a day on average) as compared to households in district headquarters (3.5 times a day) (Figure 6).

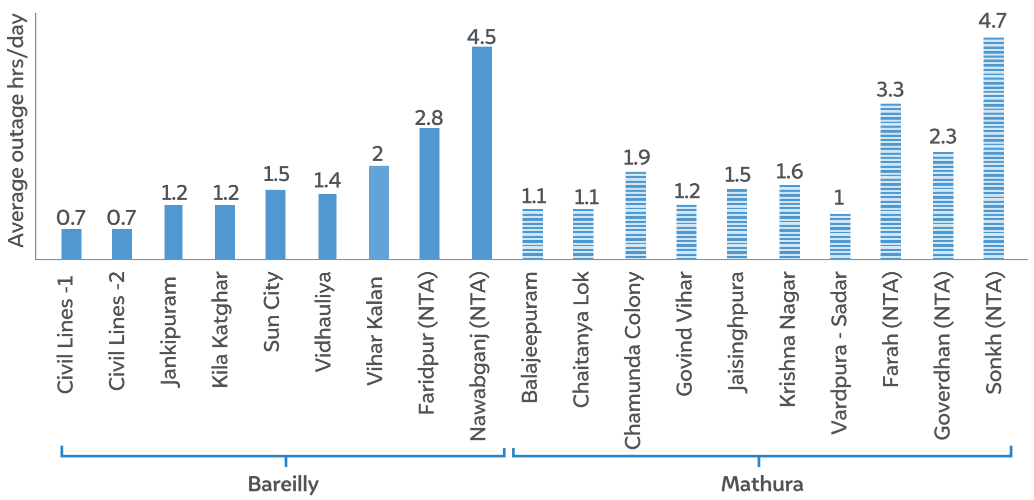
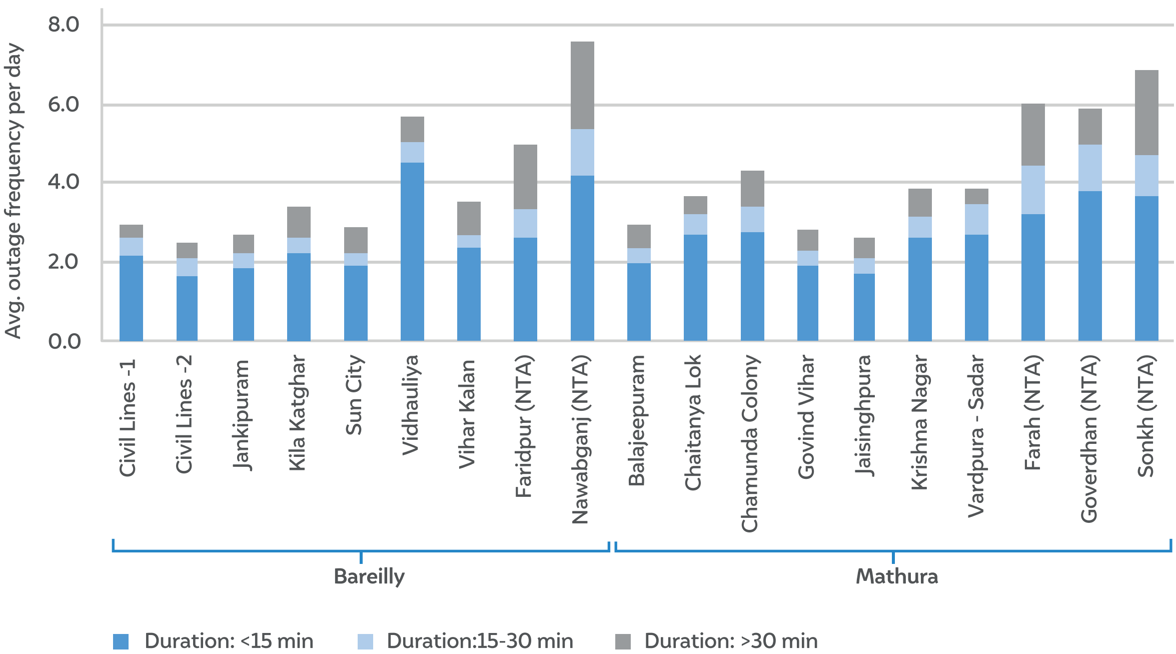


Figure 5
Households in NTAs face more power outages than those in the district headquarters

Source: Authors' analysis

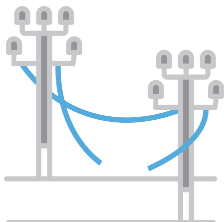
Figure 6: Households in NTAs endure frequent power cuts, though most are of short duration



Source: Authors' analysis

To better understand the pattern of outages, we analysed the outage frequency and its duration. Figure 6 shows the share of short (less than 15 minutes), medium (15–30 minutes) and long (more than 30 minutes) duration outages in the daily outage frequency. It can be seen that across all residential areas most power interruptions last for a short duration, though NTAs also suffer from a few long-duration power cuts.

Our conversation with utility officials and staff suggest that most outages can be attributed to two factors: tripping/faults and unscheduled load-shedding/shutdowns due to repair work or infrastructure upgrades. A major share of faults and even shutdowns during the monsoon months in North India are due to storms. Other reasons behind faults include blowing of fuse in houses, or loose connections due to monkeys dangling on electrical wires. The latter is a major concern in Mathura.



Most outages are of short duration and can be attributed to faults and unscheduled load shedding

When we spoke to officials and linemen regarding the higher outages in NTAs of Mathura, they informed us that they happen mainly due to unscheduled load-shedding, which is undertaken to facilitate the infrastructure expansion or upgrades, such as replacement of old cables and electricity poles, and laying of underground lines under the IPDS programme. In Sonkh, scheduled load-shedding for 30–60 minutes is undertaken during the morning hours to prevent the use of water motors, so that the drinking water supply can reach all homes.

In contrast, officials in Bareilly NTAs state that higher outages in NTAs are partly due to scheduled load-shedding, as district authorities have been directed to supply electricity for around 20 hours a day in NTAs. This is evident from a higher share of medium and long duration (>30 minutes) outages in both Faridpur and Nawabganj.

An assessment of the timing of outages reveals that majority interruptions happened during daytime (Figure 7). This is encouraging as fewer interruptions happened during the night hours of peak electricity consumption when residential consumers need electricity the most.

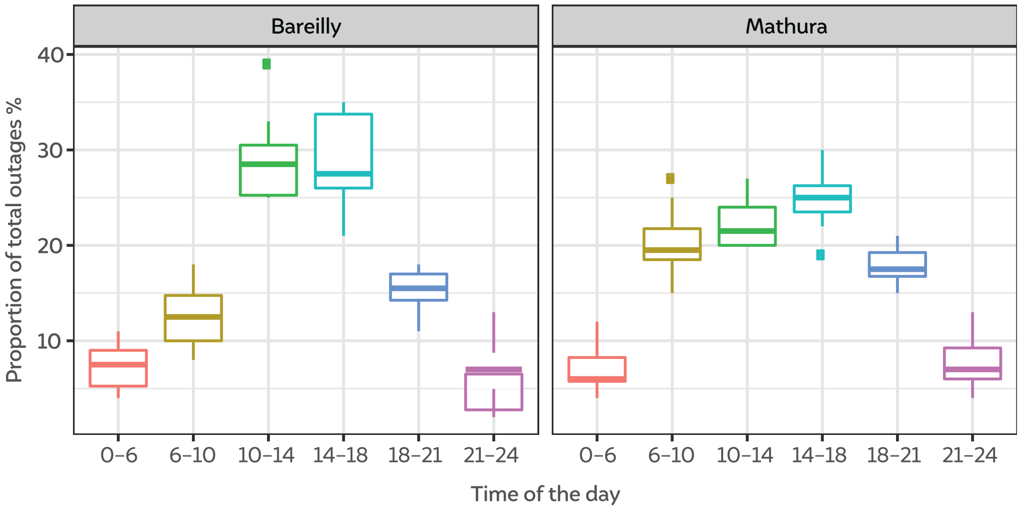


Figure 7
Across all residential areas, most power cuts happen during the daylight hours

The boxplots show the variation in values across all residential areas covered in each district.

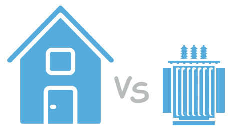
Source: Authors' analysis

We observe that the duration is quite good in many urban areas, but gaps in supply are visible in smaller town areas. Our findings on power outages differ significantly from the outage duration at 11 kV feeders reported by the discoms. As per the Urja portal, Bareilly and Mathura faced total power outage of 3.5 and 4.8 hours in July 2019 at 11 kV feeder level (Ministry of Power 2020), which is quite low as compared to what our data suggests. This difference highlights that the gaps in capacity and health of the distribution network can translate into low supply hours to the final consumers than what is claimed or supplied at the feeder level. To achieve the policy target of uninterrupted power supply, it would be crucial to monitor supply quality at the end-user level and address the issues efficiently.

4.2 Voltage profile

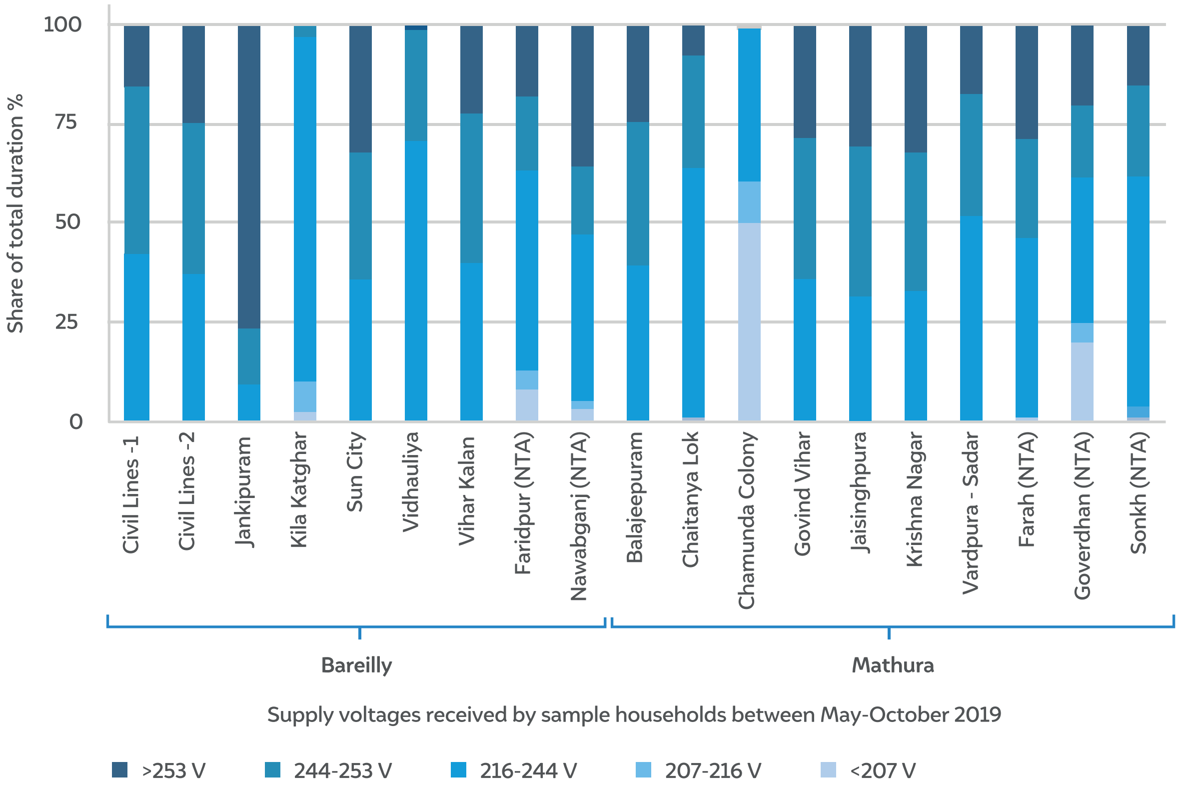
We analysed the supply voltages received by the sampled households located in different residential areas. We use the average voltage value for every 3-minute timestamp and estimate the proportion for which voltage values remain within the prescribed ±6 per cent range of 230 V (UPERC 2005). Figure 8 shows the distribution of supply voltages received by sample households in each residential area between May and October 2019.

Of the residential areas covered in this study, 70 per cent received voltages falling outside the prescribed 230 V ± 6 per cent range (216–244 V) for more than 50 per cent of the total duration. Looking at the 230V ± 10 per cent range, every second household received voltage outside this range for at least 25 per cent of the observed duration. Significantly high-voltage supply was observed across most urban areas and a few areas in the districts covered received a low-voltage supply for a significant duration.



Outages observed at the household level (2 hours/ day) are much higher than those reported at the feeder level (3.5-4.8 hours/month)

Figure 8: Almost all residential areas face high-voltage issues



Source: Authors' analysis

The issue of high voltage was observed across all, except two, residential areas. This problem is particularly daunting in the Jankipuram area of Bareilly where supply voltages remain higher than the prescribed limits for the majority of the time. We also observe several instances when the maximum voltage recorded in a timestamp exceeds 350 V. Such issues occurred mainly in NTAs in Mathura and Bareilly districts. One of our sample households lost a few appliances to power surge; in another instance, one of our smart meters got damaged. Even a few instances of such high voltage supply pose serious risks to consumer and appliance safety, particularly because many households rely on appliances manufactured locally, which are often not compliant with BIS safety regulations. It is therefore important that utilities actively investigate the reasons for such deviations and implement appropriate mechanisms to regulate the supply voltage.

The issue of low-voltage supply (below 207 V) was noted only in a few residential areas, particularly Chamunda Colony, where households received very low voltages for the major duration of supply. Field verification suggests that this issue arises mainly due to inadequate transformer capacity and also partly due to the prevalence of electricity theft and high-use of motor equipment in this area. We also observed low voltages in a few households in two NTAs: Goverdhan in Mathura and Faridpur in Bareilly.

Figure 9 shows the average monthly voltage profile of households sampled in three areas. Most sample households in these areas receive very low-voltage supply for most of the observed months. The profile improves somewhat during September and October, potentially due to reduced electricity demand. A few households in Faridpur and Goverdhan area have desirable voltage profile, and these are connected to different feeders than the households receiving poor supply.

Low voltage levels during the non-peak hours can be attributed to power demand in these areas exceeding the planned distribution capacity. We also notice that voltage drops are particularly high (25–30 per cent drop) during the peak hours. Such high levels of voltage drop when residential demand is at its peak (see Chapter 5) imply increased current withdrawals and higher energy losses in the distribution line. Thus, there is an urgent need for load assessment and capacity expansion in these residential areas.

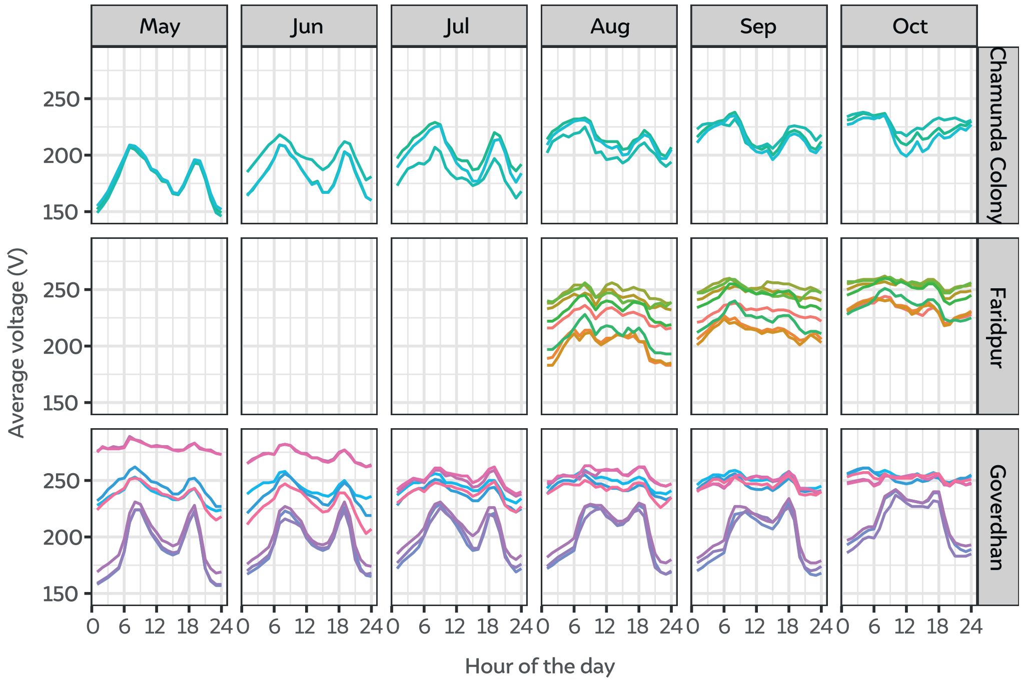


Figure 9
Households in a few residential areas faced very high voltage drops during peak hours

Coloured lines represent hourly voltage profile of individual households. In some parts of Bareilly, our data collection started from August 2019.

Source: Authors' analysis

4.3 Sanctioned versus maximum demand

The gaps in supply duration and spike or drop in voltages can be partly understood by comparing consumers' maximum demand with their sanctioned load. Domestic consumers are assigned electricity connections with a sanctioned or contracted load based on typical appliances owned by them. Discoms use this information for network planning and demand assessment. However, over time, consumers buy new appliances, which spikes up their maximum demand and increases the net load that a distribution network has to bear. At present, discoms rely on a manual process to ascertain the maximum demand of consumers through meter readings, and even this exercise is not undertaken regularly. In the event of several households exceeding their sanctioned load during the peak demand period, which may force the discoms to undertake load-shedding.

While our sample is not representative of the consumers served by any distribution transformer, we compared the sanctioned load and maximum demand of our sampled households to understand the gravity of the matter. We used the 30-minute average load (kW) of households for each month to analyse whether or not they exceed their sanctioned load. Figure 10 shows that nearly 30 per cent of the sampled households exceed the contracted load at least once. Half of these households frequently breached the sanctioned limits for three or more consecutive months, while the rest did so just once or twice in a month or two. While the latter cases are not a major concern, households in the former category, which are situated largely in Mathura, need upgrading of their sanctioned load as per the utility norms.

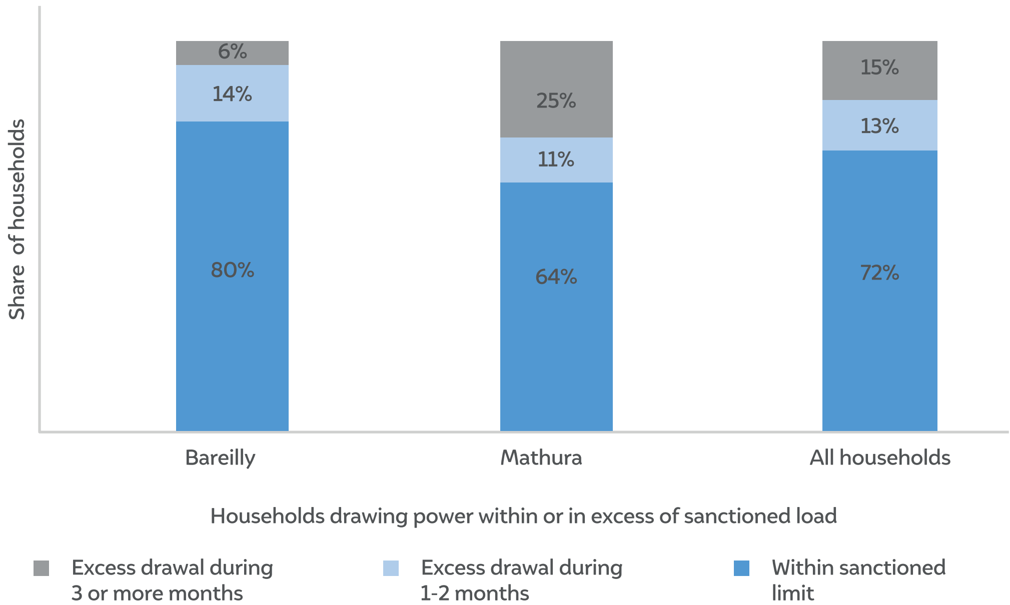


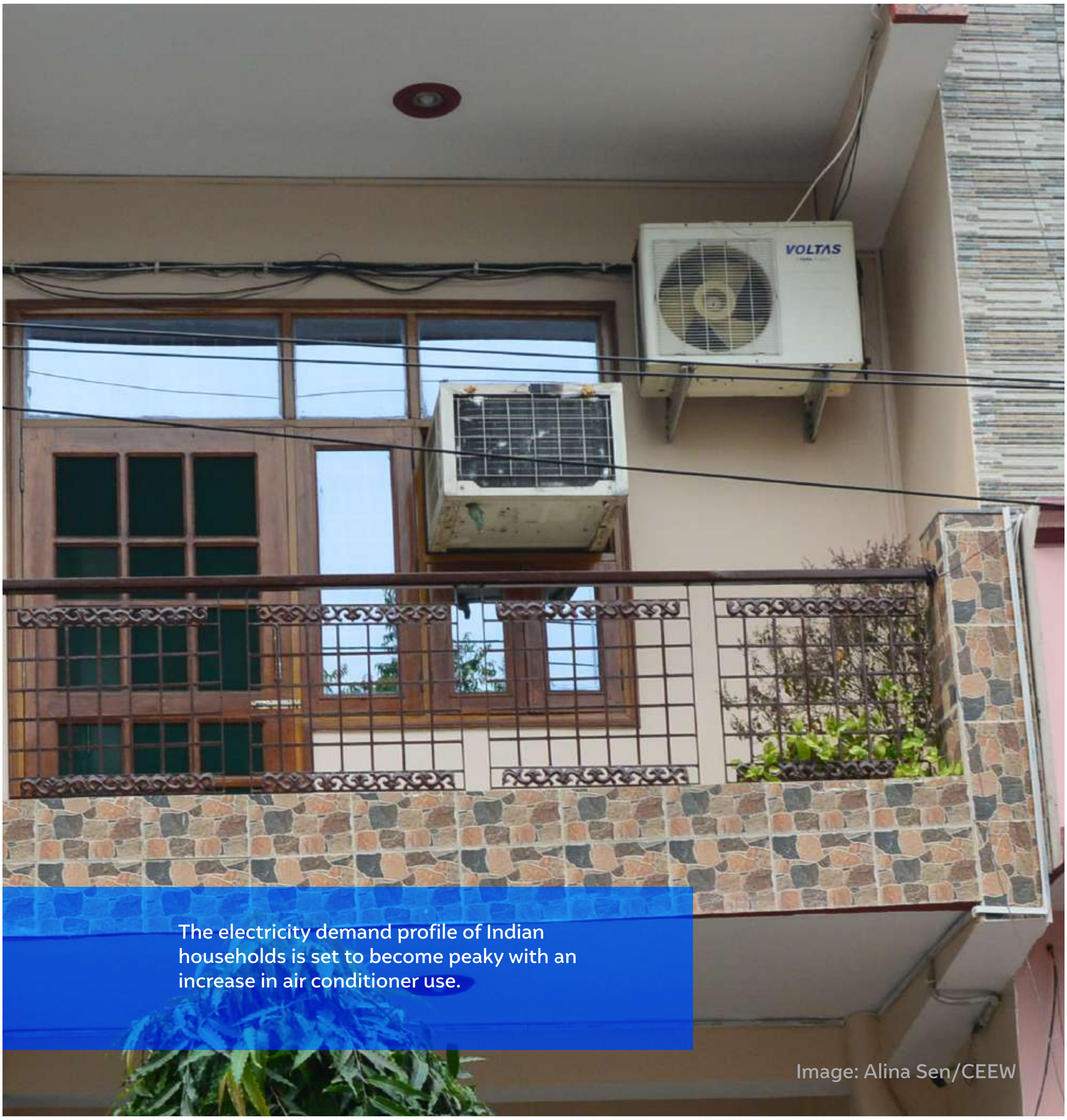
Figure 10
One-sixth of sample households exceed their sanctioned load frequently during three or more consecutive months

Source: Authors' analysis

All the households drawing excess power for three or more months use ACs, but most have a sanctioned load of 1–2 kW. Most of them started using the AC only recently (less than five years), even though they have been using electricity for decades. Thus, with rapid uptake of ACs, discoms will need to assess maximum demand and adequacy of distribution capacity on a more frequent basis. Smart meters can facilitate this process immensely by auto-flagging the consumers exceeding their sanctioned load for a pre-defined period. Discoms could then easily identify the feeders/DTs with more violations and take suitable measures.

3. The sanctioned load is the maximum electrical load in kW or kVA agreed to be supplied by the discom. The maximum demand is the average load in kW or kVA recorded during a 30-minute period of maximum use in the billing period.

5. Electricity use in the households



The electricity demand profile of Indian households is set to become peaky with an increase in air conditioner use.

Image: Alina Sen/CEEW

In this chapter, we discuss the electricity consumption patterns of the sampled households, and also look at what causes variation in demand and its drivers. We also explain how the utilities can use the smart meter data to identify the customer segments and appliances contributing the most to the peak demand and make use of innovative measures for demand management.

5.1 Variation in consumption pattern

As per the data from smart meters, between May and October 2019, sampled households consumed 280 units of electricity per month. However, consumption varies significantly across households, from as low as low 15 units a month to 970 units a month. In total, 20 per cent of the sampled households spent less than 100 units per month, while 15 per cent used more 500 units per month. This demonstrates that our sample comprises a wide spectrum of electricity consumers, confirming the utility of our sampling strategy of selecting households by their appliance ownership and house size (number of rooms).

Figure 11 shows the variation in households' electricity demand across months. Power consumption in Mathura is highest in June, the hottest month of the year. The consumption declines marginally during the monsoon months of July–September, potentially due to reduced loads due to drop in temperature, and reduces significantly during October when most households tend not to use their cooling appliances or use them very minimally.

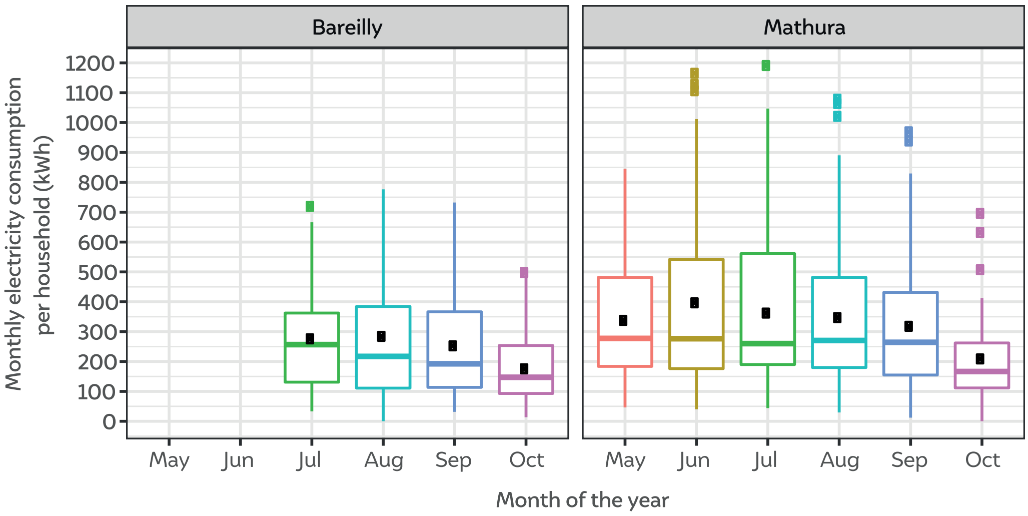


Figure 11
Household electricity consumption in Mathura sample peaks during June

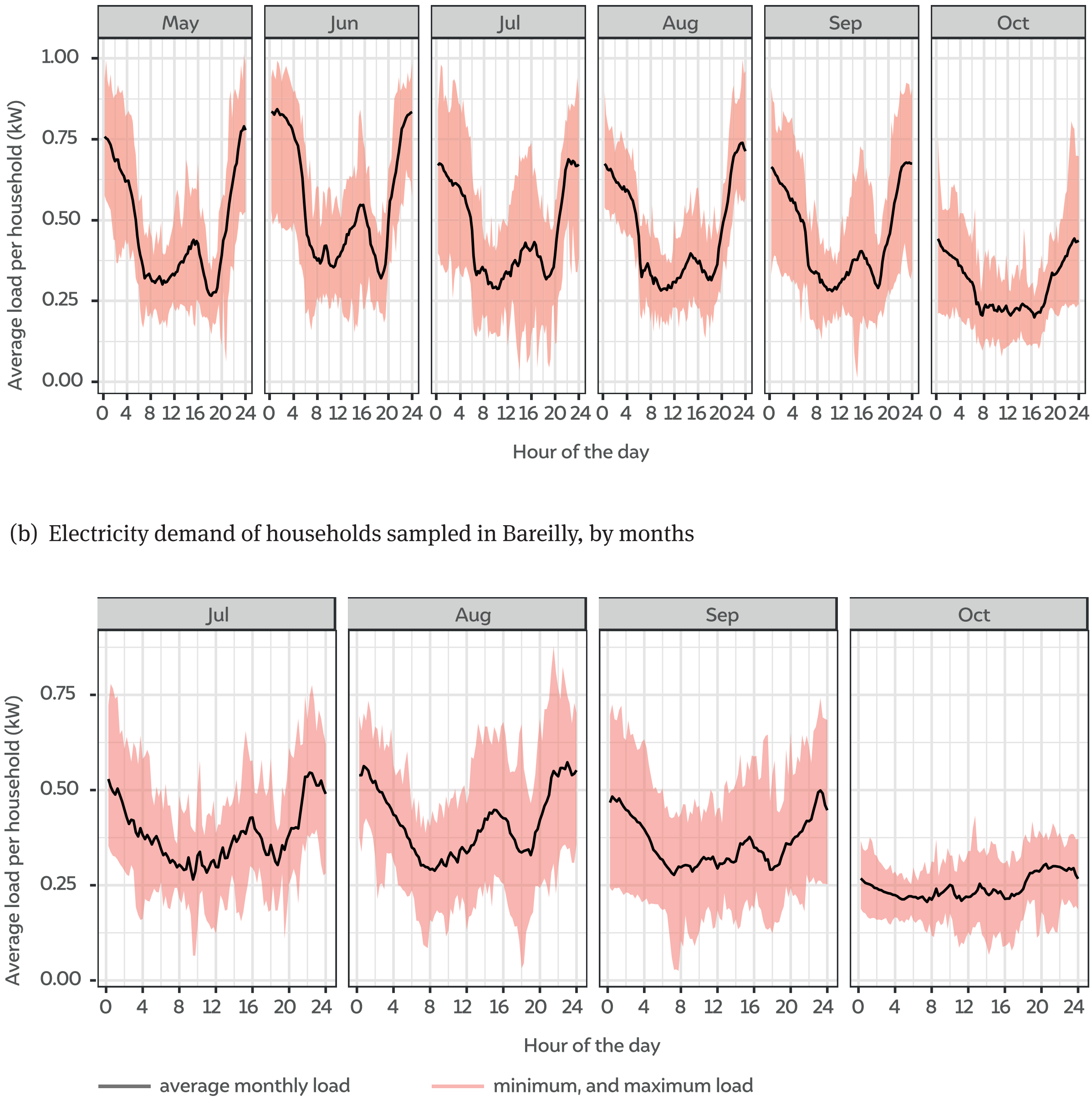
The black dots correspond to the average monthly consumption for a given month. The data collection in Bareilly started in July 2019, so we do not have data for May–June.

Source: Authors' analysis

Figure 12 shows the daily variation in the electricity demand of sample households in Bareilly and Mathura. The average demand of households in Mathura sample peaks around midnight and is highest between late evening and early morning (8 p.m. to 5 a.m.). This consumption pattern clearly shows that the residential users consume most electricity during late evening and night when most household members are at home, and a majority of the cooling appliances are switched on. This kind of usage has significant implications in the state of Uttar Pradesh, where the residential sector accounts for 42 per cent of total power sales (PFC 2017), and electricity demand typically peaks during the night hours during summer and monsoon (POSOCO 2016). Annexure 4 shows the typical demand pattern for UP. As the temperatures are highest at around 3 p.m., we witness a secondary peak during the afternoon. This can be due to the presence of fewer household members are at home during the daytime. Overall, the load curve flattens significantly going from September to October.

Figure 12: Household electricity use peaks during the night

(a) Electricity demand of households sampled in Mathura, by months



Source: Authors' analysis

We observe similar trends for households sampled in Bareilly (Figure 12(b)). However, the average peak demand, as well as typical load levels, are much lower than those observed in Mathura households, across different months. We infer that the differences can be attributed to appliance ownership pattern. However, a higher share of households in the Bareilly sample (41 per cent) have ACs as compared to samples in Mathura (32 per cent), and both districts have a comparable temperature profile (see Annexure 5). This suggests that household electricity use is a function of various factors. We discuss the contributing factors in more detail in subsequent sections.

5.2 Key drivers of electricity demand

In order to understand the variation in electricity demand, it is important to understand its key drivers. We conducted a linear regression analysis keeping the average monthly electricity demand of households between May and October as the independent variable (results in Annexure 6).

As per our data, household expenditure emerges as the most important determinant of demand. This is likely because households that indulge in higher expenses have more appliances and a higher propensity for their usage. Other factors are not statistically significant, mainly due to the high standard error associated with the small sample size.

We explore the relationship between household expenditure and electricity demand with the help of a cooling appliance index, a measure of the types and number of cooling appliances in a household. See Box 1 for details on index construction. We find that the index has a strong positive correlation with the monthly household expenditure, as reported during the surveys (Figure 13). It becomes clear that with an increase in income levels of the household, their ownership of cooling appliances would increase and with it, the household electricity demand during the summer and monsoon seasons.

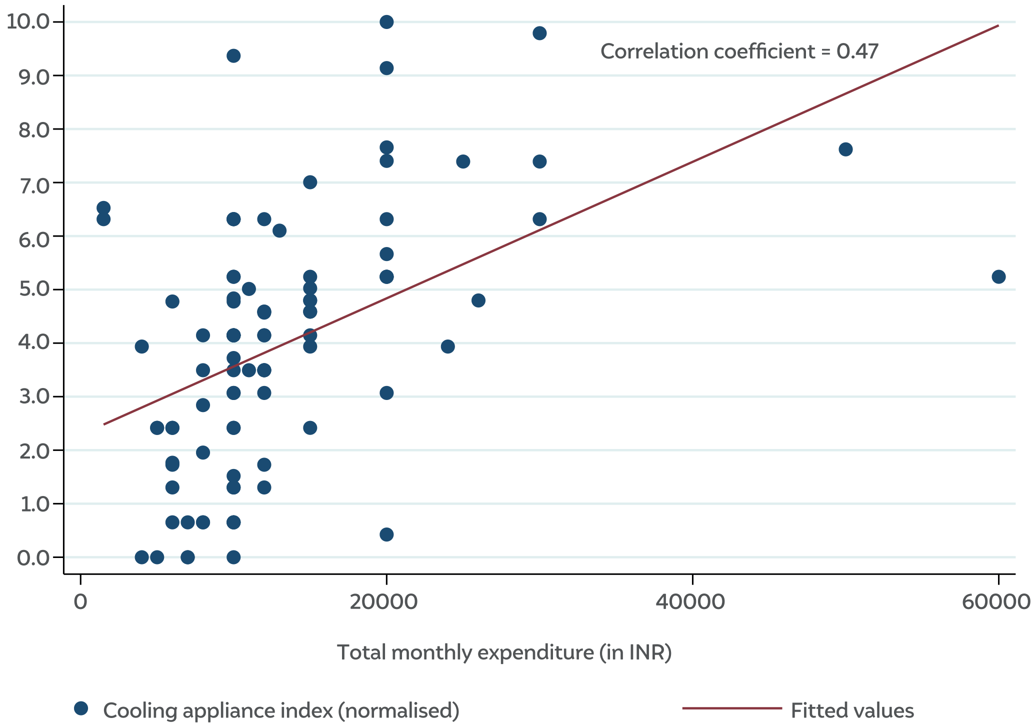


Figure 13
Economically better off households own a higher number of cooling appliances

Source: Authors' analysis

4. To obtain the average electricity load, we first down-sampled the 3-minute data by taking the average for each household to 15-minute interval for each day. Then, we averaged the data of all households for each block for each day in a month. Days when less than 10 meters communicated were dropped.

Cooling appliance index

We use the approach proposed by Filmer and Pritchett (2001) to construct a cooling appliance index based on the number of typical cooling appliances used in households: fans, refrigerators, coolers, and ACs. We first obtained weights for each variable (number of fans, coolers, refrigerators, and ACs) using the principal component analysis and applied those weights on the normalised values of each variable. This gave us the cooling appliance index, which shows negative values for around 50 per cent of the sample households. For ease of interpretation, we rescaled this index such that the final index values range between 0 and 10. For this purpose, we used feature scaling (or min–max scaling) formula: Xnorm (or (IVx))=(X – Xmin)/(Xmax – Xmin), where IVx is the normalised index value, Xmin is the initial minimum value (–2.31) and Xmax was the initial maximum value (3.52) of the cooling appliance index.

The index takes values between 0 and 10 and is a monotonically increasing function of cooling appliance ownership, i.e., a higher value for ownership of higher-order cooling appliances. Table 2 shows the index values for households grouped by appliances owned.

One can see that households owning just fans have the lowest mean score, and it keeps on increasing with the ownership of more and more appliances. For instance, households with fans and refrigerator have a higher mean score (2.97) when compared with households owning only fans (0.69). As the index value depends on the number and type of appliances owned, we observe some overlaps in the minimum and the maximum values across categories. However, the robustness of the index can be established by the fact that it automatically assigns a higher score to households that possess a higher-order appliance (measured by the rarity of the appliance). For instance, households with fans, refrigerator and AC have a higher score compared to households with fans, refrigerator, and cooler, despite both of them having three appliances.

Table 2
Cooling appliance index increases with the ownership of advanced cooling appliances

Cooling appliances index increases with the ownership of advanced cooling appliances

Appliances	Sample Size	Mean	Min.	Max.
Only fans	17	0.69	0	1.96
Only fans and refrigerator	15	2.97	1.77	5.02
Only fan, refrigerator and cooler	24	4.56	2.84	9.37
Only fan, refrigerator and air conditioner	16	5.09	3.94	7.66
All four appliances	15	7.08	5.01	10
Any of the four cooling appliances	93	3.96	0	10

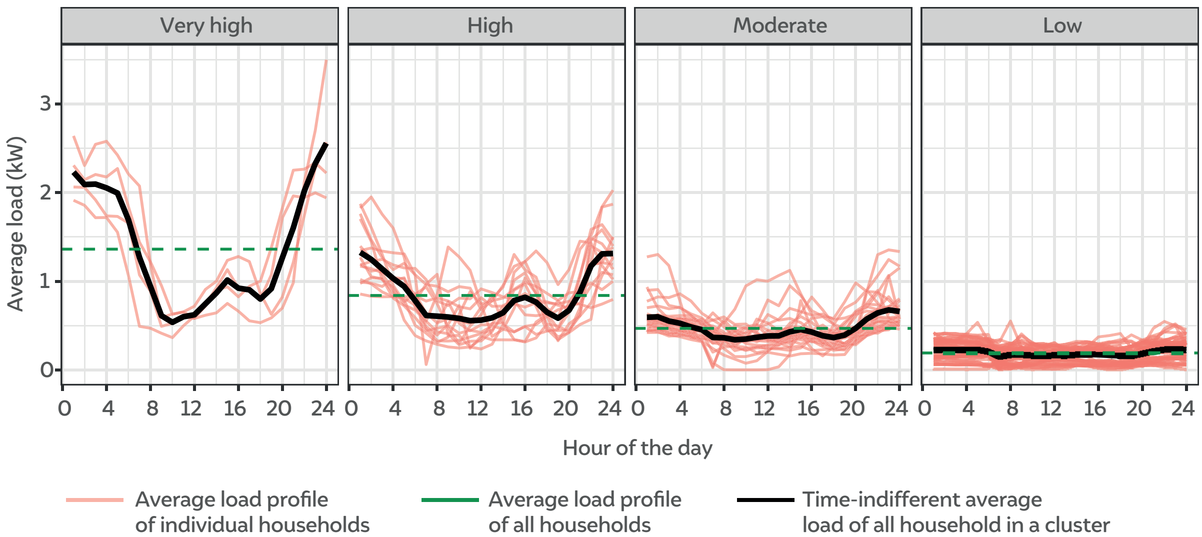
Source: Authors' analysis

5.3 Profiling customers driving peak demand

Utilities can classify households as low- or high-consumption consumers based on their monthly consumption data, but such classification does not necessarily reflect their contribution to peak load. In order to identify consumers and appliances contributing the most to peak load, we employ k-means clustering and segment households into four clusters based on their load profile in August. We have classified these as low, moderate, high, and very-high demand clusters.

Figure 14 shows that the high and very-high demand clusters comprise households driving the night-time peak demand. The moderate demand cluster also displays a slightly higher demand during night, while low-demand cluster has a nearly flat load profile. Figure 15 shows the variation in load parameters and the load factor of the three segments. As expected, the load factor of high and very-high demand clusters is lower than the desirable limit of 60 per cent.

Figure 14: **The sampled households can be classified into four clusters based on load profile, from low to very high levels of demand**

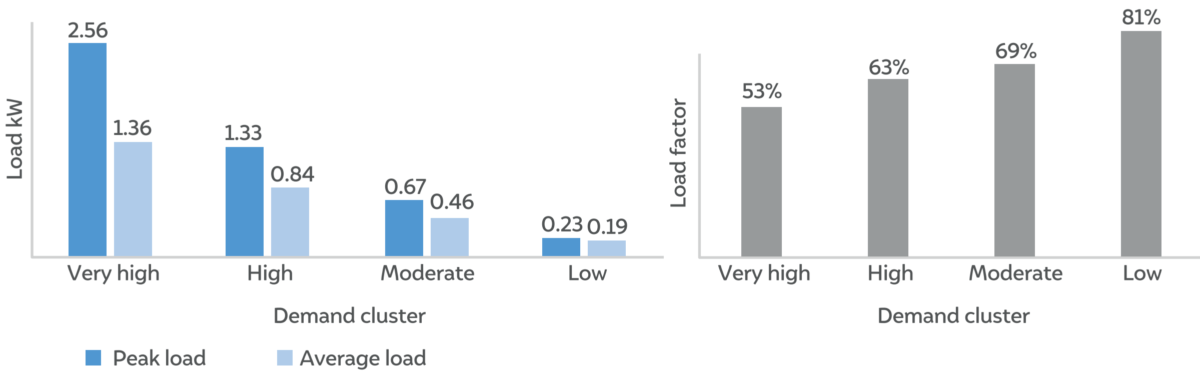


Source: Authors' analysis

5. As we do not have data for May–July for many households in the Bareilly sample, we have done this analysis for the month of August. Annexure 7 provides the detailed methodology employed for the clustering process.

6. Load factor is the ratio of the total number of units consumed during a given period to the total number of units that would have been consumed had the maximum load been maintained throughout the same period.

Figure 15: The load factor of households in very high demand clusters is less than 60 per cent



Source: Authors' analysis

We analysed the appliance ownership and household expenses of the households within these four clusters to understand the customer profile. Figure 16(a) shows that the appliance ownership is indeed a key differentiating factor. Low-demand households, with nearly flat load profiles, primarily rely on fans for air circulation during summer. Moderate demand households predominantly use coolers, with a few using ACs. A few AC users may fall in this category, potentially due to their conservative use of ACs. High-demand households are predominantly AC users, with a few having large coolers. Very-high demand households, which are a few in our sample, typically have an AC and a cooler, or sometimes two ACs, due to which they have highly skewed load curve, with very high peak demand during the night-time. We also notice that these segments also differ in terms of their economic profile, as average monthly expenditure of the households in these segments increases with demand level (Figure 16 (b)).

(a) Ownership of cooling appliances

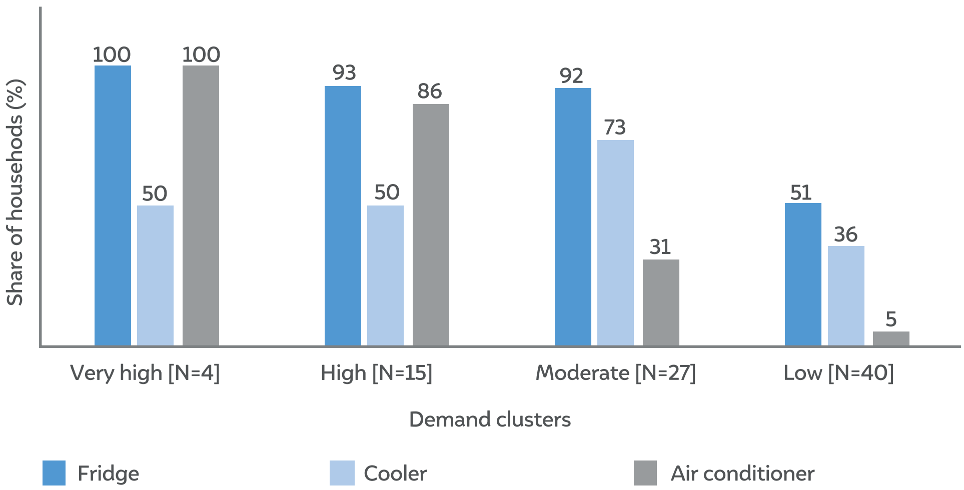
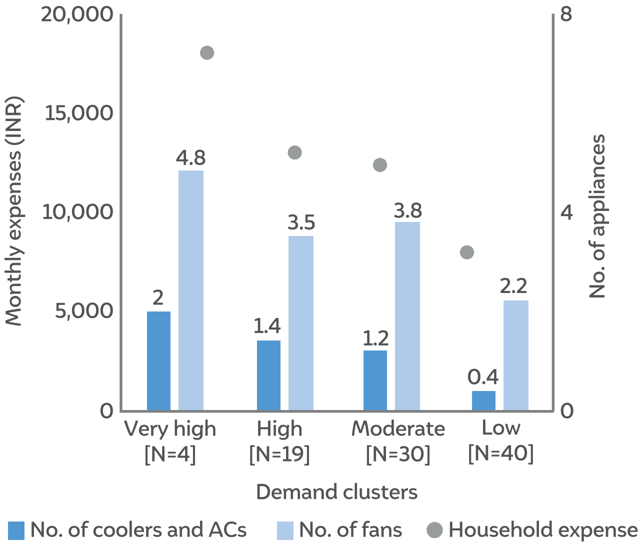


Figure 16
Demand clusters have varied appliance inventory and expenditure levels

Source: Authors' analysis

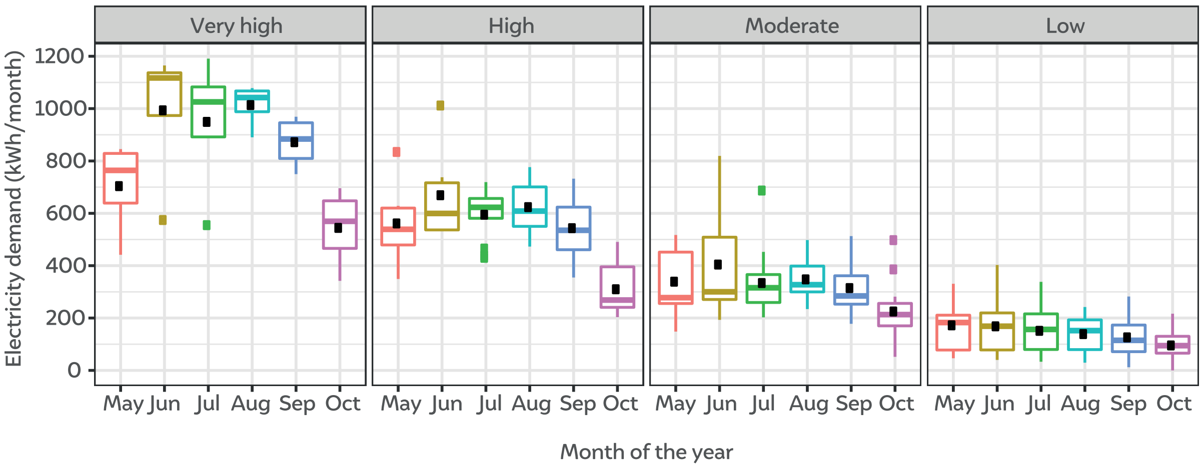
(b) Household expenses and no. of cooling appliances



As this segmentation is based on data for August, we assess the reliability of this clustering methodology for other months by analysing the monthly variation in electricity demand from all the clusters. Figure 17 shows that there is a significant inter-cluster variation in household demand across months. Similarly, the intra-cluster variation in demand tends to be small, particularly for low and moderate demand clusters. However, there are some exceptions, suggesting that segmentation using data from different months would have yielded slightly different results. For greater accuracy of customer segmentation, the demand patterns in a larger sample of households need to be assessed.

It can also be seen that low-demand households have nearly the same consumption profile across all the months, which indicates their limited capacity to change appliance use behaviour. In contrast, the electricity demand of households in the very-high and high-demand clusters varies widely across months and is highest between June and August. Thus, the high overall demand, as well as the high peak demand, emanates from households with advanced cooling appliances.

Figure 17: Electricity use in high-demand clusters varies significantly across months



Source: Authors' analysis

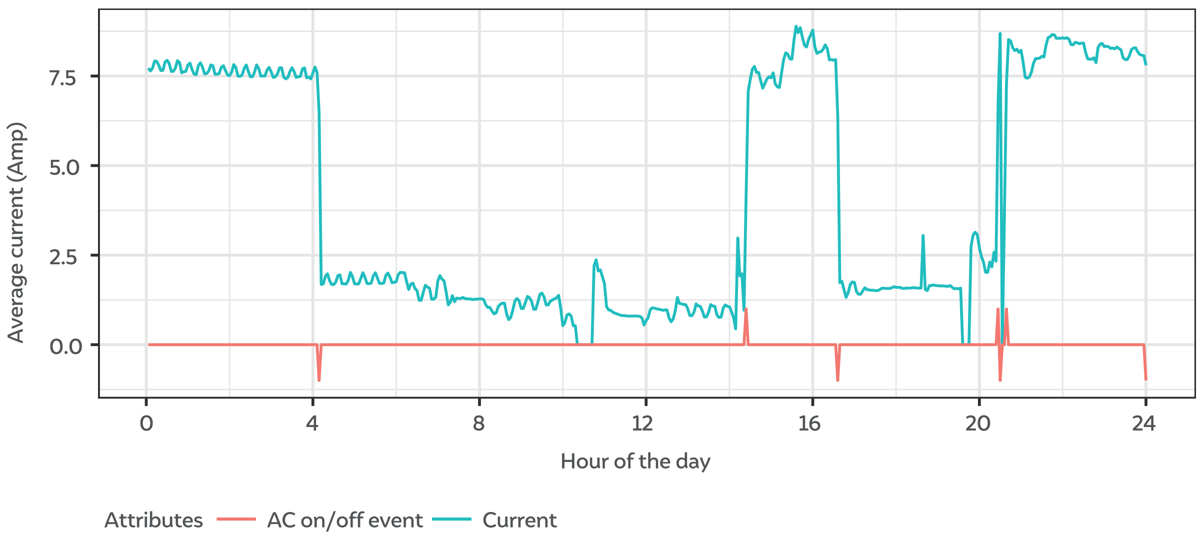
5.4 Air conditioner usage pattern

The ownership and use of air conditioner (AC) is a key factor determining the household's electricity demand and its load profile. The usage pattern of ACs by households, therefore, assume importance. Out of the 93 sampled households, 34 of them own an AC. Of these, all except two have a single AC. To understand AC usage pattern, we analysed the current signature of households having one AC with the help of 3-minute interval data. We identified the compressor on/off events by locating the events in the current time series of nearly equal magnitude and opposite sign.

Figure 18 shows the current profile of two households that possess non-inverter window AC of 1.5-ton capacity but having different ratings, age, and usage pattern. The compressor in Figure 18(a) remains 'on' for nearly all hours of AC use, indicating a very high compressor activity rate (97 per cent). This potentially reflects the use of an undersized AC or a preference for low-temperature setpoint due to which the compressor has to work for a longer duration. In contrast, the AC compressor in Figure 18(b) cycles on/off with high frequency during the night hours (every 3 minutes) but moderately (within 15 minutes) during the day. As per our conversations with the AC manufacturers, such high cycling rates during night-time may be due to high humidity but low ambient temperature levels (due to rainy season). See Box 2 for details on the working of AC compressors.

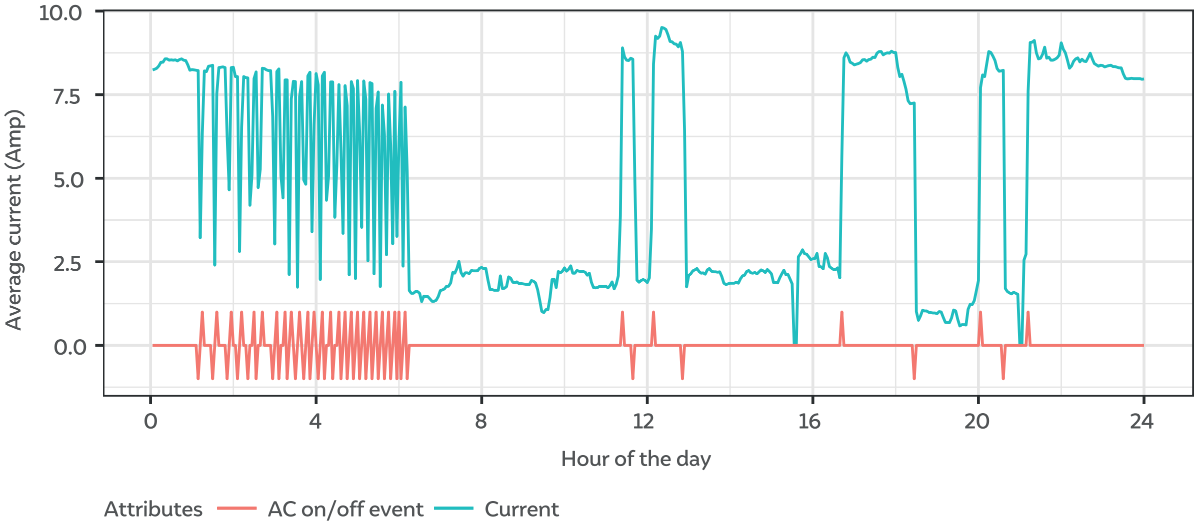
Figure 18: Current profile and AC 'on/off' event detection for two sample households

(a) A household with 1.5 ton new 3-star window AC [date: 01-08-2019]



Source: Authors' analysis

(b) A household with 1.5 ton 4-year-old 5-star window AC [date: 03-08-2019]



Source: Authors' analysis

Compressor operation in fixed-speed and inverter air conditioners

A working air-conditioning unit accomplishes two functions: reducing temperature and humidity levels. This is achieved with the help of a compressor that compresses the refrigerant gas in the AC to cool it, which in turn cools the incoming air from the room in the evaporator unit.

In fixed-speed ACs, the compressors work as long as the ambient temperature is higher than the set temperature or the humidity levels are higher than the optimal levels. Thus, the compressor turns 'on' and 'off' depending upon the requirement. Moreover, each time the compressor turns 'on', it draws a high starting current and operates at a fixed speed thereafter. The size of the room also determines the compressor cycling rate. Thus, the fixed-speed AC compressor is 'on' for a longer duration, if

- the AC is under-sized, i.e., of lower than required capacity based on the room size,
- the ambient temperature levels are very high, implying a higher need for cooling, and
- the relative humidity levels are high, such as during monsoon months, implying a higher need for moisture reduction.

In contrast, inverter ACs have variable speed compressors, which can operate at different speeds (25–100 per cent). Here, the compressor is always 'on', though the compressor speed and hence the current drawn is higher when the AC starts and is adjusted to keep the temperature and humidity at the desired levels. When ambient temperatures or humidity levels are not very high, inverter ACs can operate at a lower load. This is why inverter ACs draw less power and energy on an average than non-inverter ACs and are more energy-efficient as well. Consumers shifting to inverter ACs stand to benefit as energy consumption becomes lower (depending upon usage hours). It would also be beneficial for the utilities as these ACs tend to have a softer start (absence of starting current spike) and lower power requirement (Goyal 2014)

Daily hours of AC use

With the help of compressor 'on/off' events, we estimated the daily hours of AC use, which includes compressor 'on' time and compressor 'off' time (when the time between two consecutive compressor 'on' and 'off' event is less than 20 minutes). We find that the sample households used the AC for an average of 5.5 hours a day between May and October. AC usage varies across households and with seasonal changes. Figure 19 shows that AC usage is higher between June and September and reduces significantly in October when the average temperature drops below 28 degrees Celsius.

Figure 19: Average hours of AC usage varies with seasonal changes

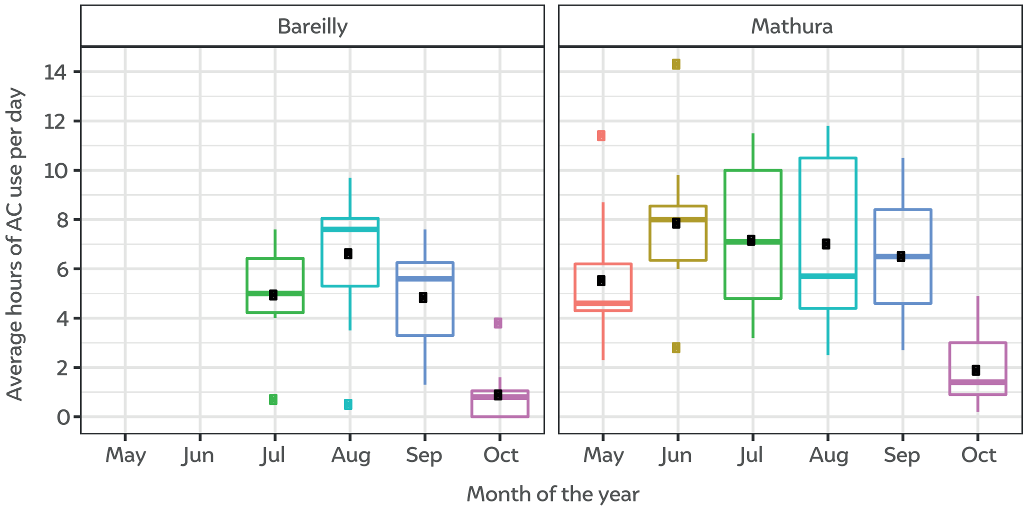


Figure 19
Average hours of AC usage varies with seasonal changes

The black dots correspond to the average values. The data collection in Bareilly started in July 2019, so we do not have data for May–June.

Source: Authors' analysis

We also observe that many AC users in Mathura district use the AC for a longer duration than those in Bareilly district. This variation in usage pattern could be partly linked to the household's economic profile, as the income of households in the Mathura sample is slightly higher than those in the Bareilly sample. Figure 20 also shows that hours of AC use has a positive correlation (coefficient = 0.31) with the household's monthly expenditure (a proxy for income levels). This suggests that even though many sample households use ACs conservatively at present, their usage is likely to go up with an increase in income levels. The wide variation in AC usage patterns underscores the importance of identifying the factors that drive higher usage.

7. We only consider households for which at least an entire week's data for one of the key summer months (May–August) is available. Overall, eight households were excluded and all these are from the Bareilly sample.

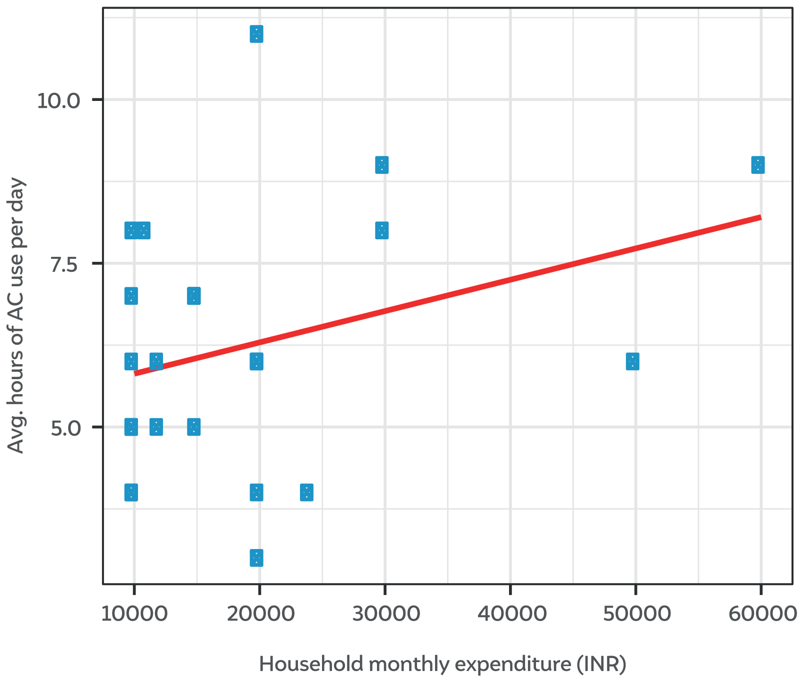


Figure 20
Better off households tend to use AC for longer hours.

Source: Authors' analysis

Compressor activity rate for AC

We also analysed the compressor activity rate (CAR) for ACs in our sample and estimated it as the ratio between compressor 'on' time and hours of AC use. We find that the average CAR for AC users in our sample is 80 per cent, and it varies between 40 and 100 per cent. In nearly 50 per cent of the cases, the compressor was 'on' for 80–100 per cent duration, which is relatively higher than a typical assumption of 60 per cent. Basic correlation analysis confirms that the CAR is strongly and negatively correlated (coefficient =-0.42) with the temperature setpoint, as reported by the air-conditioner-using households during the surveys (Figure 21). Households using the AC at lower set points tend to have a higher CAR, as the compressor has to run for a longer duration to achieve the set point.

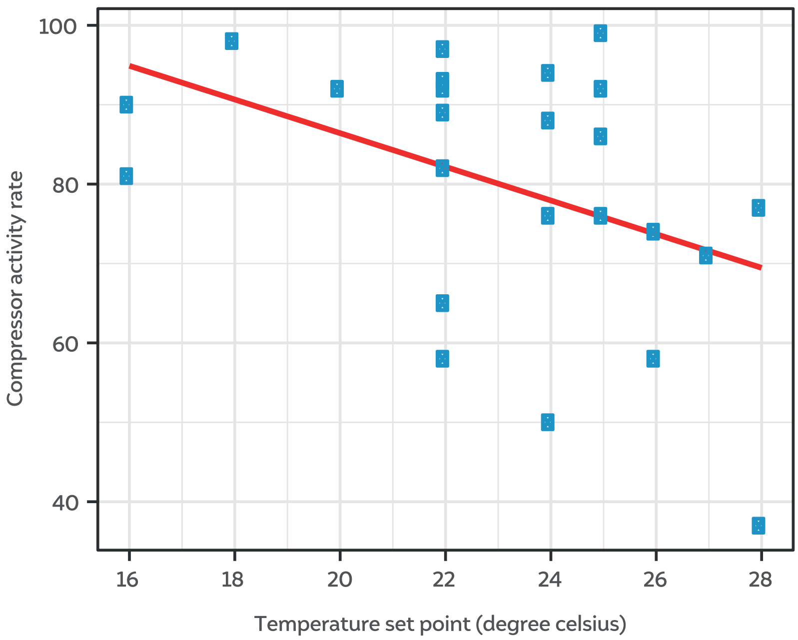


Figure 21
AC compressor activity rate is typically higher for low-temperature set points

Source: Authors' analysis

As per the Bureau of Energy Efficiency (BEE), the ideal room temperature is 24-25°C. However, 60 per cent users typically run their air-conditioners at 16-22 degrees, which is associated with higher CAR and, thus, higher energy consumption. To encourage the use of ACs efficiently, BEE has recently mandated that all ACs should have a default temperature setting of 24 degrees (ANI 2020). A sustained campaign to educate consumers about the benefits of using AC at a higher setpoint would also help households save on energy bills associated with AC use. However, households using AC at high-temperature setpoint may also have high CAR, as shown in Figure 21. This may be due to the use of under-sized AC or high thermal leakage from the building. Smart-meter enabled diagnosis of AC compressor activity could help the users to identify appropriate strategies to optimise their AC energy consumption.

Role of usage pattern in the economics of energy-efficient ACs

We also analysed the annual hours of AC usage for 11 households in our sample, for which data for all six months is available. We find that the sample households use AC for an average of 1020 hours/year, and the usage varies across households from 400 to 1800 hours/year, assuming that households start using the AC from May onwards.[8] For these households, electricity use for AC constitutes 20-50 per cent of total monthly demand between May and October, which is a significant contribution (Figure 22). Moreover, the share of AC in total demand increases with higher AC use.

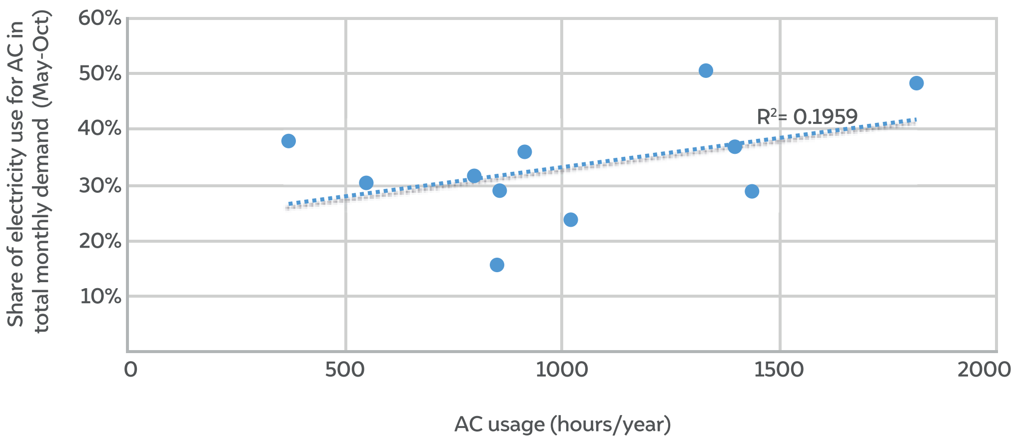


Figure 22
Contribution of ACs in household electricity demand increases with usage hours

Source: Authors' analysis

The use of more efficient ACs, identified by BEE star labels, could help the consumers reduce their energy consumption and electricity bills. However, more efficient AC units are also more expensive. The number of hours for which a consumer uses AC has significant implications for the potential energy and cost savings associated with the adoption of higher efficiency models.

8. All air conditioner using households in our survey reported that they use the air conditioner for 2–4 months in a year. So, we assume that the air conditioner use during April is zero due to lack of data for that month.

Taking the AC usage pattern of the sample households as a reference, we estimated the payback time if the users were to choose higher star-labelled AC over a 2-star non-inverter AC. We did this analysis for 1.5-ton split AC for both non-inverter and inverter technology. Table 3 shows the cost and energy specifications of the AC models considered for this analysis. See Annexure 8 for detailed calculations on energy consumption and cost savings when consumers with different usage patterns were to make a choice between different star-labelled ACs. For this analysis, we assume that households use AC under standard test conditions. We assumed the power tariff of INR 6.5 /unit, which is the rate applicable for consumption slab of 300-500 unit/month, as per the latest tariff in UP.

AC star rating and type	Capital cost (INR)	ISEER	Reported energy consumption of AC (units/year) under std. conditions and 1600hrs/year
2 star non-inverter	32,500	3.45	1,167
3 star non-inverter	34,000	3.65	1,103
3 star inverter	37,000	3.7	1,045
2 star inverter	46,000	5.33	767

Table 3
Capital cost and energy consumption values for 1.5-ton split AC

Source: Authors' compilation for AC models available on online retail portals

* ISEER (Indian Seasonal Energy Efficiency Ratio) is the ratio of the total amount of heat energy removed from the indoor air in a year to the total amount of power consumed annually

Table 4 shows that households that use AC for more than 1800 hours, i.e., 12 hours a day for five months in a year, would be able to recover the additional expenditure on a 3-star non-inverter AC within 3 years and that on 5-star inverter AC in less than 5 years. For such households, it would be cost-effective to choose an inverter or higher star-labelled AC over a 2-star non-inverter AC.

However, for consumers who use the AC conservatively, i.e., for a shorter duration, the payback period for extra investment on a 3- or 5-star inverter AC could range from 5-25 years, when the designated life of an AC is just 5-6 years. Households with less than 1000 hours of annual AC use may not find even a 3-star non-inverter AC attractive at the current price and tariff rates.

AC use pattern	Annual hours of AC use	Payback time for extra investment on a higher star AC over a 2-star non-inverter AC		
		3-star non-inverter AC	3-star inverter AC	5-star inverter AC
6 months, 12 hours/day	2,160	2.7	4.2	3.8
6 months, 10 hours/day	1,800	3.2	5.0	4.6
6 months, 8 hours/day	1,440	4.0	6.3	5.8
6 months, 5.3 hours/day	960	6.0	9.5	8.7
6 months, 2 hours/day	360	16.0	25.2	23.1

Table 4
Payback time for extra investment on higher star-labelled ACs depend on the usage hours

Source: Authors' analysis

Such high payback periods for households displaying conservative AC usage raises questions regarding the assumptions used for designing star labels. BEE assumes AC usage of 1600 hours for estimating the energy consumption of AC listed on the star labels, which is much higher than the annual usage displayed by most consumers sampled in this study. While our sample is not representative of all AC users in the country, star labels must reflect energy consumption values based on representative usage.

More importantly, we notice that the energy consumption values on BEE star labels are quite low as compared to the actual consumption witnessed by consumers. As per our estimates using smart meter data, a sample household using a new 1.5-ton non-inverter 3-star split AC for 360 hours/year consumes 645 units for running the AC, which is 2.6 times the consumption one would expect as per the values listed on BEE star label (see Annexure 8). This is mainly due to the difference between the test and the use conditions of AC. BEE tests the energy efficiency of the ACs based on their ability to cool a space to 27˚C at 50 per cent relative humidity and an ambient temperature of 35˚C (Somvanshi 2019). However, most households use ACs at higher set points, and even the prescribed setpoint is 24˚C. As ACs consume more energy at lower temperature set-points, consumers using AC at setting lower than 27˚C are bound to use more energy than that printed on the star label. Further, the ACs are tested for a standard ambient condition whereas the ACs are used under varied climatic conditions in the country. Our analysis suggests that the consumption values listed on the star labels are not representative of the real-world performance of ACs.

In this regard, smart-meters can help generate empirical evidence about household preferences concerning AC use as well as actual energy consumption by ACs under various ambient conditions. Such evidence could be used for designing more realistic star-labels, such that consumers can make informed decisions concerning AC purchase and use.

Smart meter data-enabled decision making

Discoms could help the consumers to make the right decision by providing insights about their AC usage pattern with the help of smart meter data. We observe that there is a significant difference in the appliance usage perceived by the households and the actual observed usage gathered from the smart meter data. While 60 per cent of the AC users under-estimated their usage of the AC by an average of 4 hours a day, the rest over-estimated the usage typically by 3 hours a day. This clearly shows how people tend to wrongly estimate their energy consumption and have inadequate information to optimise their usage or purchase decisions.

Sharing of feedback on the household's energy usage in general, and AC use in particular, could help the households keep a better check on their AC use. This measure would lead to people trusting their electricity bills. During the surveys, many households complained that the electricity bills were too high despite their electricity use being limited. Discoms could consider indicating estimates for hours of AC use in the electricity bill. For consumers already having an AC, this information would help them make an informed decision for buying a second AC. For others, discoms could first identify aspiring consumers (based on their monthly consumption during summers) and give advisories based on observations from existing AC users. For instance, discoms could create typical usage profile of AC consumers at a substation/feeder level, and use it to generate customised advisories.

Insights from smart meter data can help the households keep a better check on their overall energy consumption

Image: Alina Sen/CEEW

Image: Alina Sen/CEEW

6. Discussion and recommendations

Power utilities or discoms in India face the daunting task of meeting the rising electricity demand by offering reliable electricity services, at the same time engaging in efforts to recover the costs of operation and continually allocating resources to invest in upgrading the power infrastructure. The continually surging residential demand, which makes up one-fourth of the country's power consumption, adds up to the challenges of discoms. A clear understanding of the electricity usage patterns at the household level and its variation with time and season, and household preferences, would help discoms draw an efficient plan for load management and infrastructure strategies. The limited information from conventional meters at low frequency of data collection does not render it suitable for demand analysis. The smart meter technology offers an opportunity for power utilities to gain a clear picture of household usage patterns and suitably manage the rising electricity demand.

We explored the ways in which smart meters can help discoms track and effectively manage the residential electricity demand and assist in the design, planning, and operation of the distribution network in an efficient manner. To accomplish our objective, we collected data from smart meters installed at 93 urban households in two districts—Mathura and Bareilly—in the state of Uttar Pradesh. As our sample is small and not statistically representative of the focus population, we ensured diversity in our sample by choosing households having a varied appliance inventory and living in residential areas falling under the jurisdiction of different substations. Our findings are only indicative of the variation in supply situation and demand patterns. We believe that a similar assessment could be done at scale with the help of smart meters deployed by the discoms.

Monitoring and managing network health and supply quality

As discussed in this report, we found variations in the duration and quality of electricity supply in both districts. The monitored households received an average supply of 22 hours a day in our study period between May and October 2019. The duration of supply varied even across urban areas of the same district. Households in NTAs, which are small urban areas, endured longer and more frequent outages as compared to those in district headquarters. Most interruptions were shorter in duration, which indicates the prevalence of faults or unscheduled load-shedding. While a few residential areas in the NTAs received consistently low voltages, with voltage drops reaching 25–30 per cent during peak load, in contrast, most others faced the challenge of high-voltage supply endangering life and equipment.

Discoms must use smart meter data for monitoring supply quality, predictive maintenance and infrastructure planning

Our findings highlight the need for the discoms to actively monitor the supply situation at the end-consumer level to locate areas with poor voltage profile, potentially indicating capacity gaps, unforeseen increase in demand or electricity theft. Accordingly, discoms can take appropriate measures for voltage regulation and capacity upgradation. Using smart meter data, discoms get tail-end visibility, which can be effectively utilised for predictive maintenance and infrastructure upgrades.

We also noticed that nearly one-third of the sampled households drew power in excess of their respective sanctioned load, though one-sixth of the surveyed consumers did so for three or more consecutive months, which is a serious concern. At present, discoms rely on a manual process to ascertain the maximum demand of consumers through meter readings, and even this exercise is not undertaken regularly. This partly explains why voltage drops and transformer burnouts are not uncommon. Smart meters can give discoms a greater understanding of consumer demand in real time, which they could use to identify consumers exceeding their sanctioned load for a sustained period of time. Discoms, in addition to planning for infrastructure expansion to meet the rise in peak demand, which lasts for a small fraction of total time blocks in a year, should also explore alternative supply augmentation strategies, demand shifting, distributed generation, and storage (Parray and Tongia 2019).

Planning for the rise in overall and peak demand for electricity

Smart meter data can help discoms provide energy feedback to consumers and implement time of use tariffs for better load management

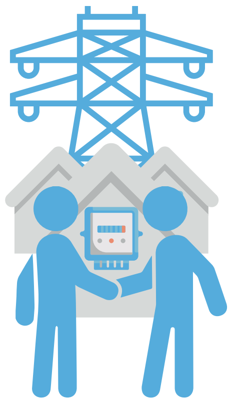
As discussed earlier, we observed that electricity use in households is commensurate with their economic status. Increased income of the household means it can afford to have advanced cooling appliances. In our sample, households using only fans consumed less than 250 units a month, but those with coolers and ACs display a wide variation in electricity usage, exhausting anywhere between 200 and 1000 units a month, during our study period between May and October 2019. With increase in income levels as well as the rise in temperatures due to climate change, more households are likely to install coolers and ACs at home for space cooling. This would definitely lead to a surge in demand.

Although increase in demand would convert into higher revenue for discoms, load management challenges await them in terms of higher use of ACs, as they are the major contributors to peak demand during night-time. Between May and October, the monitored households used the AC for an average 5.5 hours a day, with majority of the use concentrated around midnight. In order to meet such sudden spike in demand, discoms need to procure fast-ramping peaking power, which is more expensive. Thus, it would become crucial for the discoms to track and anticipate the uptake of these appliances and employ diverse strategies for demand-side management.

Devising innovative strategies for demand management

Granular insights on household electricity use can help the utilities assess and design suitable mechanisms to manage the rising demand at the consumer end. As discussed earlier, households often have inadequate information about their electricity use, as many of them tend to over-estimate or under-estimate their appliance use. By providing information about energy use on a daily or weekly basis, discoms could push the consumers towards using electricity in a conservative manner as well as help them take optimal decisions concerning appliance purchase. For instance, discoms could provide customised advisory to households indulging in high AC use and potential savings from switching to a more efficient AC. A periodic feedback to consumers on self-consumption and that of others on their electricity bills or through mobile communication could also help in lowering consumption.

Discoms must also design and test mechanisms for demand response, such as time of use (ToU) pricing, which is applied for commercial and industrial customers in India. However, if this tool has to be extended to domestic consumers in India, it would be essential to identify the target audience, such that the ToU scheme is both effective (yields the desired demand reduction) and equitable (doesn't burden less affluent consumers). As our analysis suggests, it is the households using ACs and/or coolers that contribute to the peak demand and they could be targeted for demand response. Smart meter data can help discoms identify consumers who drive the peak demand as they tend to have a markedly different load profile. Price-sensitive consumers could realise savings by avoiding consumption at peak hours, especially of the AC as it accounts for a significant share of the overall consumption. Further research is needed to explore potential tariff designs and their effectiveness in generating adequate response from the consumers.



Smart metering infrastructure can help discoms to transform from being just an electricity supplier to an energy service provider

Another demand management strategy that discoms must explore is incentivising consumers who exhibit peak consumption to adopt distributed solar generation and/or battery storage. This way consumers can reduce their withdrawals from the grid during peak hours and discoms could achieve load shaving. Data from smart meters at the consumer and distribution level could be used to identify strategic pockets for such interventions, helping discoms reduce investments required for infrastructure upgrades as well as avoid the purchase of expensive power during peak hours. This would also help the discoms achieve their renewable energy targets.

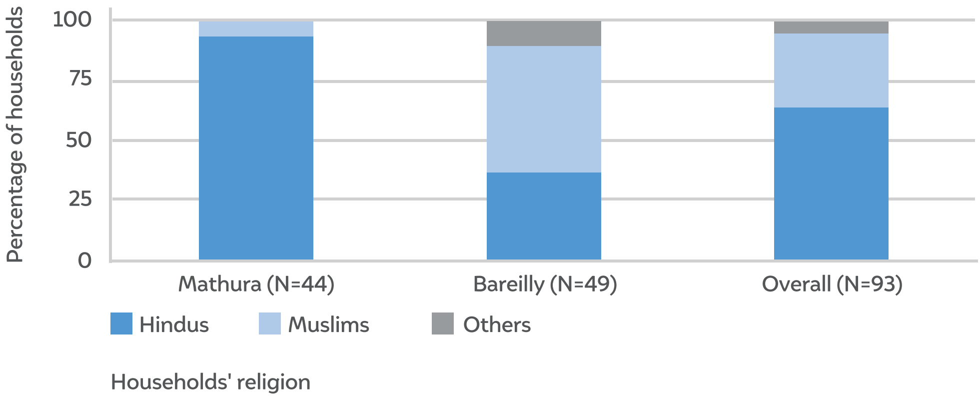
India's power sector is undergoing a rapid transformation, as we are witnessing changes in power generation, regulatory measures, as well as consumption patterns. This environment provides an opportunity for discoms have to transform from being just an electricity supplier to an energy service provider by optimising costs, engaging with the consumers to help them save electricity, and improving the overall consumer experience. Smart metering initiatives in the country are well timed to enable this transition. Discoms should maximise the utility of investments towards smart meters by looking beyond metering, billing, and collection efficiencies.

Annexures

Annexure 1: Demographic characteristics of the sampled households

We analysed the key demographic characteristics of the sampled households in Mathura and Bareilly districts. Comparing the samples in both these districts, we find that the primary decision-makers in the sampled households have similar levels of education and the family size doesn't vary much (Figure A.1).

However, the sample households differ in terms of religion and caste. A majority of sampled households in Mathura district follow the Hindu religion, where less than 10 per cent are Muslims; in the Bareilly district, the share of Muslims is relatively higher at 53 per cent. This reflects the variation in social composition of the two districts; the share of Muslims in Mathura and Bareilly district is 8.5 per cent and 39 per cent, respectively (Census, 2011).



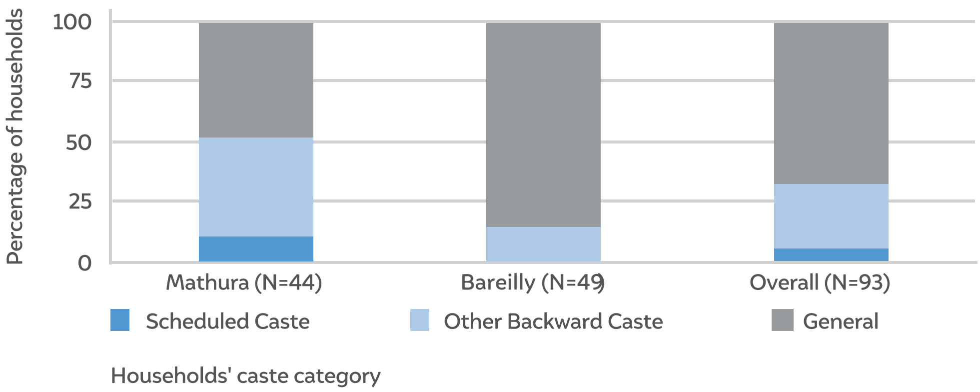
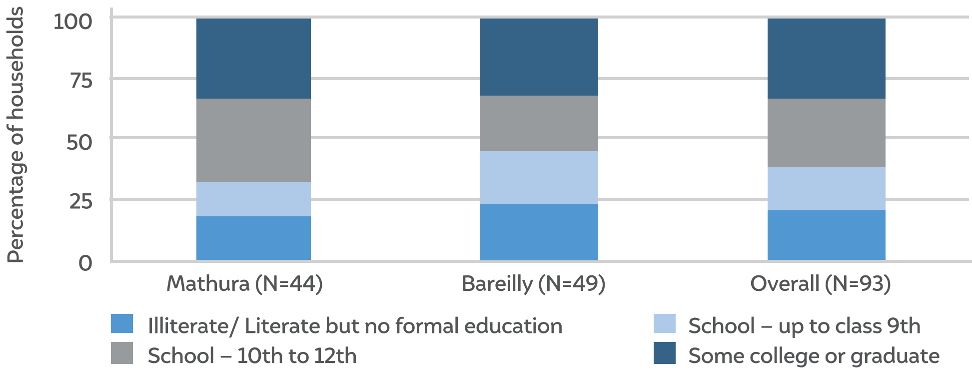
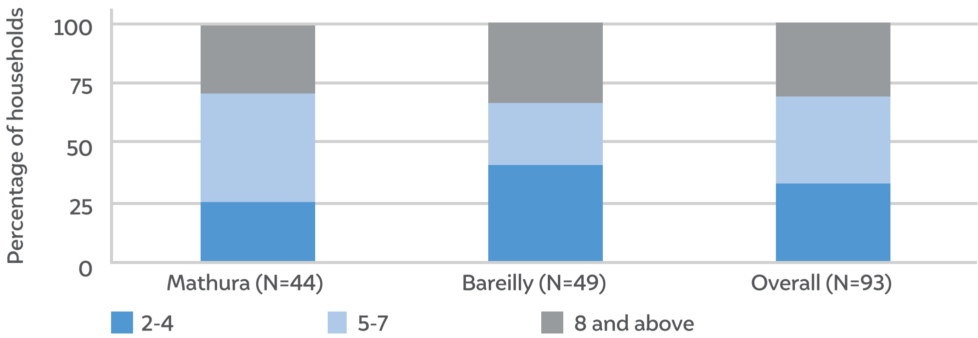


Figure A.1
Sampled households have diverse demographic characteristics

Source: Authors' analysis



Level of education of the primary decision maker



Family size

Annexure 2: Supply and consumption parameters captured using smart meters

We captured 10 parameters for each household with the help of smart meters, including energy consumption (kWh and kVAh) and minimum, maximum, and average values for voltage and current. We estimate power (kW) values using the kWh values. Table A.1 illustrates the format in which data was obtained

Table A.1: Snapshot of data collected for a sample household (MH23, 15 May 2019)

Meter_id	x_Timestamp	t_kWh	t_kVAh	z_Avg.Voltage..Volt.	z_Max.Voltage..Volt.	z_Min.Voltage..Volt.	z_Avg.Current..Amp.	z_Max.Current.Amp	z_Min.Current..Amp.	y_Freq..Hz.
MH23	5/15/19 0:00	0.021	0.022	231.49	232.26	230.85	2.17	2.39	1.99	50.04
MH23	5/15/19 0:03	0.09	0.09	231.93	232.19	231.72	7.9	7.91	7.85	49.98
MH23	5/15/19 0:06	0.089	0.09	231.8	232.05	231.47	7.88	7.92	7.8	49.9
MH23	5/15/19 0:09	0.09	0.09	231.77	232.23	231.4	7.86	7.88	7.81	49.98
MH23	5/15/19 0:12	0.09	0.09	231.99	232.37	231.72	7.85	7.91	7.84	50.02
MH23	5/15/19 0:15	0.09	0.09	232.65	233.24	231.83	7.88	7.91	7.8	50.01
MH23	5/15/19 0:18	0.089	0.089	232.69	233.09	232.33	7.79	7.82	7.76	49.96
MH23	5/15/19 0:21	0.089	0.089	232.68	233.09	232.15	7.78	7.8	7.75	49.97
MH23	5/15/19 0:24	0.089	0.089	235.78	239.09	232.19	7.68	7.79	7.52	49.98
MH23	5/15/19 0:27	0.088	0.089	239.18	239.41	238.83	7.53	7.57	7.5	50.04
MH23	5/15/19 0:30	0.09	0.089	239.38	239.84	239.05	7.56	7.62	7.55	50.04
MH23	5/15/19 0:33	0.089	0.09	239.6	240.13	239.09	7.57	7.61	7.51	49.98
MH23	5/15/19 0:36	0.088	0.088	239.95	240.49	239.45	7.52	7.56	7.46	49.98
MH23	5/15/19 0:39	0.089	0.089	240.77	241.22	240.2	7.48	7.5	7.44	50.04
MH23	5/15/19 0:42	0.088	0.088	240.9	241.47	240.2	7.45	7.46	7.42	50.02
MH23	5/15/19 0:45	0.089	0.089	241.28	241.76	240.78	7.45	7.52	7.42	50.02
MH23	5/15/19 0:48	0.088	0.089	241.37	241.72	240.89	7.5	7.51	7.43	49.98
MH23	5/15/19 0:51	0.089	0.088	241.86	242.48	241.32	7.42	7.44	7.39	50.02
MH23	5/15/19 0:54	0.088	0.089	242.19	242.62	241.25	7.41	7.48	7.39	50.04
MH23	5/15/19 0:57	0.088	0.088	242.29	242.59	241.87	7.41	7.45	7.38	50.04
MH23	5/15/19 1:00	0.089	0.089	242.76	243.02	242.33	7.4	7.41	7.36	50.04

Figure A.2 illustrates the variation of the obtained values over a day for a particular household. Figure A.2(a) shows that the voltage varies between 220 and 260 V, except when it drops to zero. The temporary drop around 8 a.m. seems like a fault, while the extended drop for around an hour at 2 p.m. appears to be a case of load-shedding. Figure A.2(b) shows the variation in electricity use by the household with the help of current and load (kW) values. The sustained current spikes of around 5 A between 12 a.m. and 8 a.m. indicate the current drawn by the AC, while the short-lived spike around 5 p.m. appear to be current drawn by an electric motor load, such as food processor or water pump use.

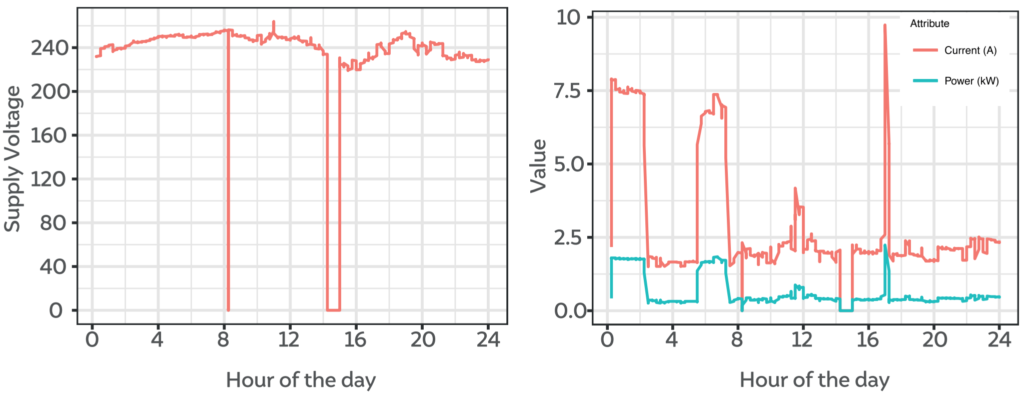


Figure A.2
Variation in supply and consumption parameters over a day (MH23, 15 May 2019)

Source: Authors' analysis

Annexure 3: Accuracy of smart meter data vis-à-vis data from discom meters

We compared the household consumption data recorded by our smart meters with that of the discom meters. We conducted manual inspections of 35 households in Mathura district; the first and second readings were observed at an interval of 30–45 days. For more than one-third of these households (13/35), we couldn't record the discom meter readings, as they were not clearly visible due to marks on the meter casings. For another four households, there were gaps in data (data missing for 4 days). So we excluded these households from the present analysis. For the remaining 18 meters, consumption as per smart meter reading was within ±7 per cent error range of the discom meter reading (Figure A.3)

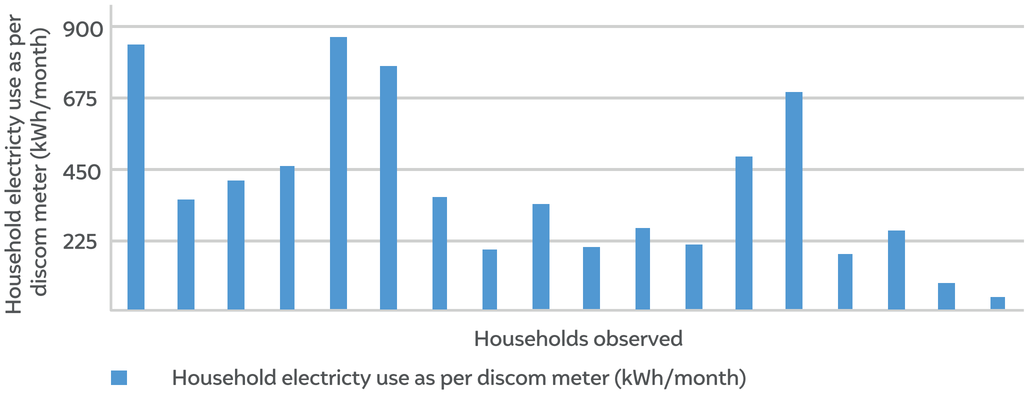


Figure A.3
Smart meter data reading compare well with that from discom meters)

Source: Authors' analysis

Observation from the field

Many households find it difficult to monitor their consumption from electricity meters, as the meter casings lose visibility due to weather conditions. In cases where meter readers rely on visual inspection for bill generation, this situation raises concerns about the accuracy of bills received by the households. Discoms have begun using hand-held devices to overcome this challenge. Use of smart meters would also help overcome this challenge and allow households to actively monitor their consumption with the help of feedback from discoms.

Annexure 4: Electricity demand pattern in Uttar Pradesh

Figure A.4 shows the total electricity demand pattern across various months in the state of Uttar Pradesh. During the months of May-October, the overall state-level demand is highest during the night hours.

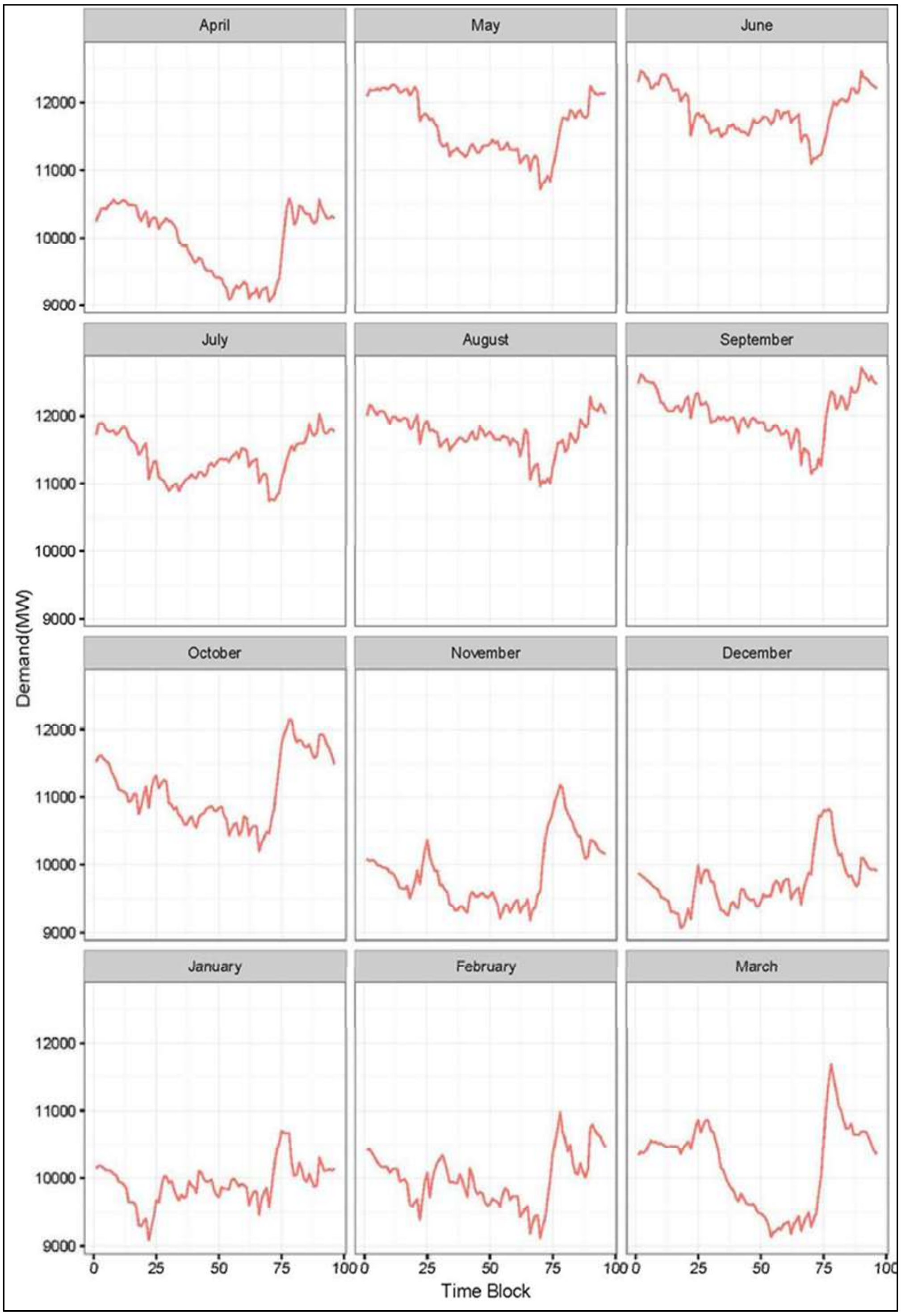


Figure A.4
Typical monthly demand pattern in Uttar Pradesh

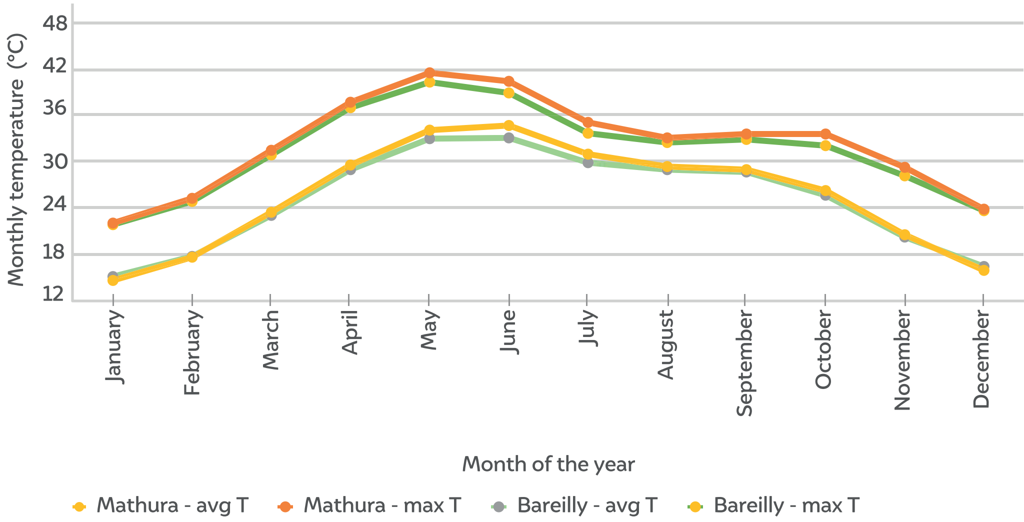
Source: (POSOCO 2016)

Source: (POSOCO 2016))

Annexure 5: Temperature profile of the districts covered in the study

The figure A.5 shows the average and maximum temperatures in Mathura and Bareilly in different months. It can be seen that both the districts have comparable temperature profile.

Figure A.5: Monthly average and maximum temperature in Mathura and Bareilly districts



Source: Climate data (2019)

Annexure 6: Regression results for drivers of household electricity demand

We assumed the natural log of average monthly consumption (kWh) obtained from the smart meter data as the dependent variable. We included average monthly expenditure (natural log) of the households as a key explanatory variable, as past studies have found the household's economic status as a major driver of electricity demand. We also included all important covariates expected to be associated with electricity consumption in line with the past studies. These include demographic factors such as the highest education of primary decision-maker, household caste, religion, and household size. We also controlled for the average hours of power supply received by the households (supply_hrs) and quality of voltage supply measured by the proportion of total duration when the households received to low-voltage supply (low_vol_dur). Finally, we also included district-level fixed effects to account for the variation in unspecified district-level factors that could affect household consumption of grid electricity.

Table A.2 presents the regression results. The model can explain around half of the total variation in monthly electricity consumption. However, due to the small sample size (leading to high variance in the residuals), most variables do not assume the required significance level.

Table A.2
Factors explaining monthly electricity consumption of sampled households

Source: Authors' analysis

	Coef.	St.Err.	p-value	95% Confidence interval		Sig
edu_school_upto9	-0.040	0.236	0.867	-0.509	0.430	
edu_school_upto12	0.336	0.261	0.203	-0.184	0.855	
edu_collegegrad	0.068	0.269	0.801	-0.467	0.603	
caste_general	0.055	0.183	0.764	-0.309	0.419	
religion_hindu	0.156	0.216	0.473	-0.274	0.586	
lnhhsize	-0.052	0.212	0.808	-0.473	0.370	
occu_salaried	0.444	0.287	0.126	-0.127	1.015	
occu_business	0.824	0.237	0.001	0.352	1.295	***
lnmonthexp	0.438	0.126	0.001	0.186	0.689	***
low_vol_dur	-0.006	0.004	0.155	-0.013	0.002	
supply_hrs	0.060	0.060	0.321	-0.060	0.181	
districtfe	-0.305	0.192	0.117	-0.687	0.078	
Constant	-0.506	1.865	0.787	-4.219	3.206	

Mean dependent var	5.342	SD dependent var	0.841
R-squared	0.463	Number of observations	93.000
F-test	5.745	Prob > F	0.000
Akaike crit. (AIC)	198.900	Bayesian crit. (BIC)	231.824

**** p<.01, ** p<.05, * p<.1*

9. We only consider households for which at least an entire week's data for one of the key summer months (May–August) is available. Overall, eight households were excluded and all these are from the Bareilly sample.

10. Caste is included as a dummy variable with value 1 for general category households (n=63) and 0 for other categories representing lower social status (n=30).

11. Religion is included as a dummy variable, with value 0 for Hindu households (n=59) and 1 for other religions (primarily Muslim households) (n=34).

12. District is included as a dummy variable, with value 1 for Bareilly, and 0 for Mathura.

Annexure 7: Methodology for clustering households by their load profile

For the clustering process, we first down-sampled the data to hourly level (24 points per day) for all the households for each month. Figure A.6 illustrates the hourly load profile for a household in Mathura (MH10) for all the days during which data was recorded. Figure A.7 shows the typical load profiles for all households for all the months under observation.

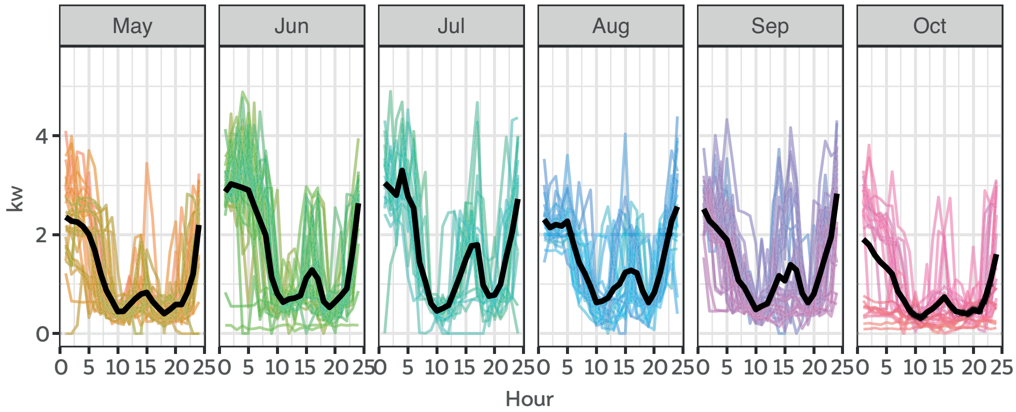


Figure A.6
Daily and typical load profile of a sample household across months

The black line shows the average load profile obtained by averaging load for each hour.

Source: Authors' analysis

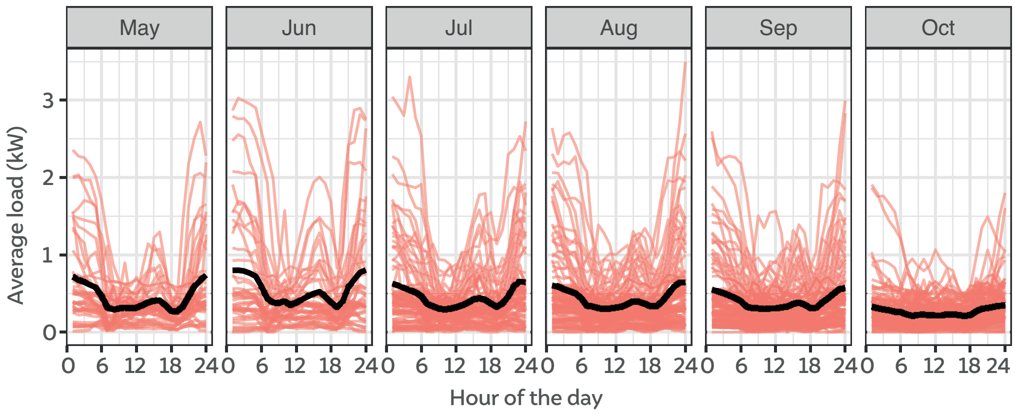


Figure A.7
Typical load profile of all households across months

The black line shows the typical load profile for all households considered together.

Source: Authors' analysis

Thereafter, we then clustered the data (<home, day> pair) using k-means function of cluster package in R into different clusters. We did the clustering with the load profiles for the month of August, when all 86 households (92 per cent) were communicating and using their typical summer loads. To do so, we first found the optimal number of clusters using the Ward's method for hierarchical clustering. Figure A.8 shows the dendogram for the sampled households, with households having closest load profile connected with the shortest branch. As the figure illustrates, four clusters can be clearly identified (households clubbed within red boxes). Accordingly, we segment our sample into four clusters using k-means cluster analysis. See Figure A.9 for the cluster plot.

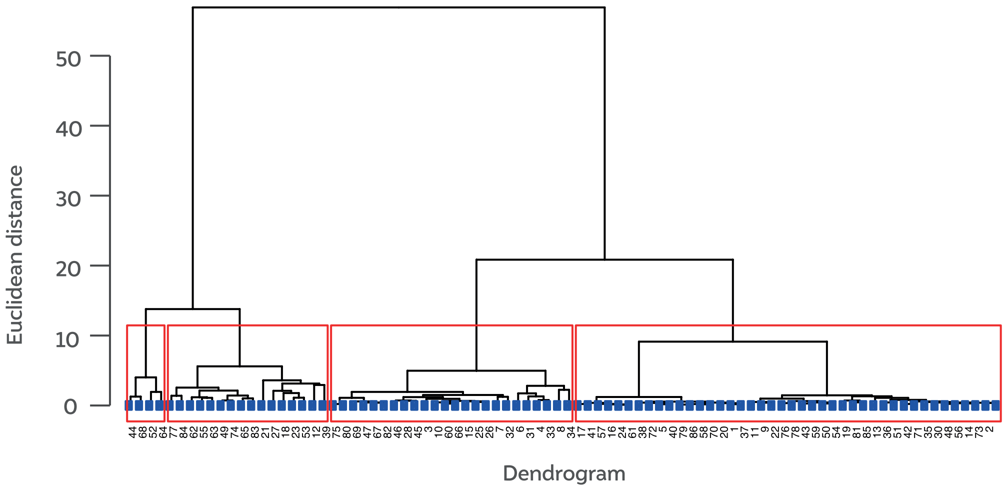


Figure A.8
Household cluster hierarchy dendogram (Ward's method)

There are four prominent clusters as shown by the red boxes

Source: Authors' analysis

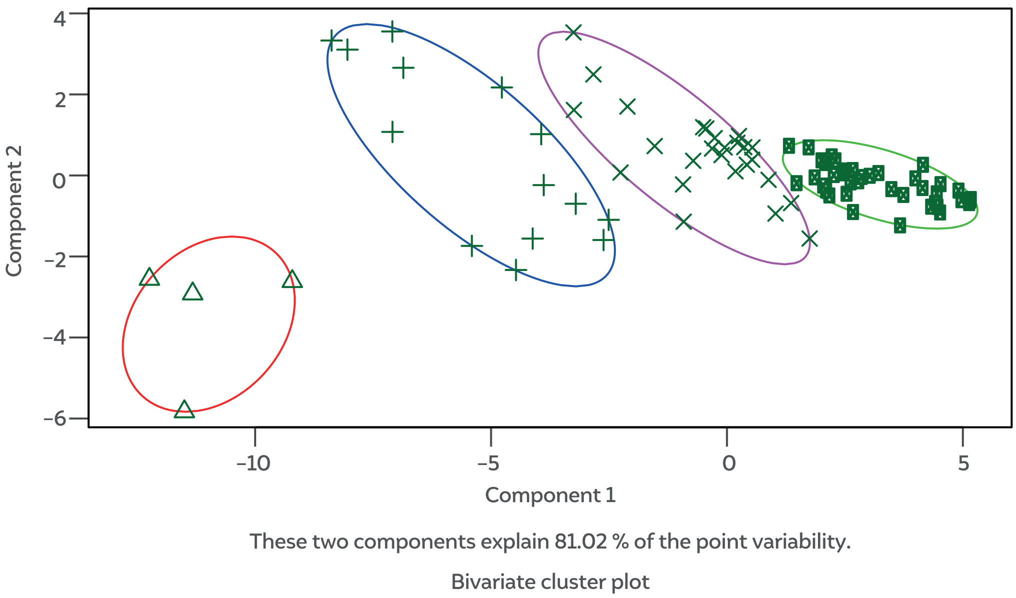


Figure A.9
Cluster plot against first two principal components for the household load profile for the month of September

Source: Authors' analysis

Annexure 8: Calculations for estimating payback time for AC purchase

In order to calculate the payback time for the extra investments towards a higher star-labelled AC, we first calculated the electricity that ACs of different ratings would consume when used for various hours of usage (Table A.3). This is estimated by extrapolating the energy consumption values mentioned on the star-labels of respective AC models (see Table 3). We assume that the ACs will be used under the test conditions. Using the energy consumption values, we estimate the energy savings and cost savings that consumers would incur if they were to choose a higher star-labelled AC over a 2-star one. These estimations are shown in Table A.4 and A.5, respectively. We use the estimates of cost savings and additional expenditure for a higher rated AC to calculate the payback time, which is shown in Table 4.

AC star rating and type	AC energy consumption (units/year)				
	AC usage: 2160 hrs/yr	AC usage: 1800 hrs/yr	AC usage: 1440 hrs/yr	AC usage: 960 hrs/yr	AC usage: 360 hrs/yr
2-star non-inverter	1,575	1,313	1,050	700	253
3-star non-inverter	1,489	1,241	993	662	248
3-star inverter	1,411	1,176	941	627	235
5-star inverter	1,035	863	690	460	173

Table A.3
Energy consumption of various star-labelled ACs for varied usage pattern

Source: Authors' analysis

AC star rating and type	Energy savings (units/year)				
	AC usage: 2160 hrs/yr	AC usage: 1800 hrs/yr	AC usage: 1440 hrs/yr	AC usage: 960 hrs/yr	AC usage: 360 hrs/yr
3-star non-inverter	86	72	58	38	14
3-star inverter	165	137	110	73	27
5-star inverter	540	450	360	240	90

Table A.4
Energy savings upon switching from 2-star non-inverter AC to higher star-labelled ACs at varied usage pattern

Source: Authors' analysis

AC star rating and type	Cost savings (INR/year) at a tariff of INR 6.5/unit				
	AC usage: 2160 hrs/yr	AC usage: 1800 hrs/yr	AC usage: 1440 hrs/yr	AC usage: 960 hrs/yr	AC usage: 360 hrs/yr
3-star non-inverter	562	468	374	250	94
3-star inverter	1,071	892	714	476	178
5-star inverter	3,510	2,925	2,340	1,560	585

Table A.5
Cost savings upon switching from 2-star non-inverter AC to higher star-labelled ACs at varied usage pattern

Source: Authors' analysis

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The 'smart' meters allow two-way communication between the utility and the consumer.

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