Tailoring demand-reduction strategies for communities in India – a framework

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Abstract

This paper summarises the CEDRI method for quantifying baseline and future energy demand of a community – using a case-study community in Tamil-Nadu. The overall method includes modules relating to: i) dynamic building simulation for projecting future scenarios, ii) Hidden Markov Models for characterising and synthesising high resolution demand profiles, iii) Distributed Network modelling for performance issues in the local energy system, iv) results of co-production and householder engagement to help understand existing energy use, and identify likely future trends.

Although the method is designed to be technology-agnostic, future scenarios are proposed to demonstrate the working of the model, and the kind of outputs and metrics that are achievable – and, crucially, why these might be useful to different actors and sectors involved with reducing energy demand in buildings.

The work demonstrates that, for such diverse communities as can be found in India, replicability of method is more important than replicability of results. Rather than extrapolating the results of single case-study communities for much larger regions, CEDRI establishes a robust method that is agile enough to cope with different data limitations, building stocks, and behavioural approaches to comfort. The project also demonstrates the ability of dynamic building simulation to be used in conjunction with empirical energy data, network models, and qualitative information relating to cooling behaviour in specific populations.

Key Innovations

- Multi-disciplinary assessment of energy use in communities presented
- Incorporation of user-centred co-production methods and physical/technical modelling
- Tested out with real communities within a rapidly evolving part of the world

Practical Implications

The project shows the challenges in transferring methods of energy assessment to different environs. Although standard physical modelling has clear applications, variation due to household behaviour, culture, and external trends (climate, technology penetration etc) can be community- and geography-specific, requiring models to be adaptable to cope with different settings.

Introduction

When investigating built environment energy demand, there exist multiple end-use audiences who may require the results of any energy modelling tool. Building-specific modelling can speak to individual householders, whether through simple energy compliance calculations (e.g. Energy Performance Certificates (BPIE, 2014)) or more detailed building simulation. National-level modelling can be used to test scenarios at a much larger spatial scale, whether through genuine energy system modelling (such as MARKAL/TIMES (Taylor *et al.*, 2014)) or network modelling. Community-level energy modelling, defined here as being at multi-building (100s-1000s) scale, provides an interesting intersection between these two scales. There still exists the desire, and potential, to understand individual buildings (and occupants), but the modelling is at such scale to be useful to those actors working at network and energy system level, albeit at a local rather than national scale.

This scale of modelling can also, arguably, provide information to those most closely aligned to actionable areas of impact. When developing solutions for local energy systems, metrics relating to local peak demand and other characteristics are important for understanding widespread changes in energy provision and demand (e.g. change in technology expected to dominate a market, climate change, and the medium- to long-term changes these might create). Likewise, a local authority looking to understand the impact of a demand-reduction plan across a community (through metrics of carbon saving potential and technology selection) will require the tailoring that is possible through community-scale modelling, without the over-generalisations that are often produced from national/stock level modelling.

Regardless of geography, the challenge of producing workable, actionable demand reduction solutions across a community of buildings is multi-faceted. To ensure appropriate technology selection, it is necessary to consider the buildings themselves, the people using those buildings, and the local energy network serving them. Furthermore, the interactions between those different aspects require a deeper understanding of the issues that exist at model and disciplinary boundaries. When a specific country is identified for study, the challenge of capturing these variables, and how that might differ from other countries, becomes clear.

The Community Energy Demand Reduction in India (CEDRI) project (CEDRI, 2018) comprises multi-disciplinary research that uses behavioural science, building physics, data science and understanding of energy networks to provide a method that can holistically overview the impact, and consequences, of different demand-reduction scenarios in Indian communities. Being specifically focussed on India, the project is particularly centred on the impact of a rising cooling demand, and how this could be mitigated.

Modelling communities of buildings

As already noted, community energy modelling requires a balance between building-specific detail and a level of data capture and computational efficiency that allows for scalability. For modelling focussed on the built environment, there are approaches that relate to empirical (use of real energy data), semi-empirical (modelling informed or calibrated by real energy data), or purely theoretical/physical modelling (Jenkins *et al.*, 2020). The challenge with built environment energy modelling is not a lack of tools, but rather ascertaining the outputs required (and, often, the end-use audience), and then working backwards to an appropriate method that is robust and reliable for delivering those specific outputs. So, whilst a simple steady-state tool may be appropriate for a local authority wishing for a snapshot of energy ratings across a local housing stock, an investigation of current versus future peak demand across that community will not be served well by the same tools. Conversely, providing that same local authority with transient energy profiles from more computationally-intensive simulation models may also be inappropriate.

Even when selecting more detailed thermal simulation, capable of dynamic calculations that allow us to investigate energy as a function of time, it is often the case that, as we increase spatial scale of energy modelling (e.g. from singular to multiple buildings), there is a compromise to be made on some level of detail of the individual buildings. This may require a simplification of the input data (e.g. generalising building archetypes in some way (McCallum, Jenkins and Vatougiou, 2020)) and/or decreasing the temporal resolution (or other characteristic) of the model output.

This compromise can be evident in large-scale energy system models, such as MARKAL/TIMES, where optimisation can be carried out on multiple parameters across, ultimately, an entire country (e.g. for informing energy policy (Scottish Government, 2017)) but the temporal resolution of the energy calculations tend to be limited to profiles representing a finite number of design days. Even here, where transient demand profiles can be used, there is a reliance on the use of existing demand data to generate results. This makes the quantification of future scenario modelling difficult within such models, though is an area in constant development (Zeyringer *et al.*, 2014).

Although, traditionally, relying on largely theoretical assessments of energy use, dynamic simulation gives the temporal resolution required for more detailed, transient energy analysis. Furthermore, the use of such modelling for multi-building simulation is now relatively common due to improvements in efficiency of calculation and usability (Sousa *et al.*, 2017; Jenkins, 2018).

However, particularly when incorporating specific behaviours and attitudes within a community that may be different to assumed norms or averages, the use of real energy data is of great value (Murray, Stankovic and Stankovic, 2017). Although forms of empirical non-energy data can inform models, such as diary data (Suomalainen *et al.*, 2019), "energy behaviour" in theoretical models do not really go much further than simple activity schedules, often assumed to repeat in a very simplified way. As with theoretical modelling, there is still the need to bridge scale in empirical statistical modelling; that is, using the causation that is possible from individual buildings (from highly stochastic, low load factor profiles), whilst understanding that the aggregated form of that data (for multiple buildings, where load factor is higher due to diversity being accounted for) is generally of more value to many end-users, particularly those working with energy networks. Techniques for generating such diversity have been applied in the CEDRI project (Patidar *et al.*, 2018), and are noted later in this paper.

Energy demand in Indian buildings

Although an energy model may be designed with universality in mind, it is still important to understand the particulars of a given case-study area to be analysed. This is necessary to adequately account for the characteristics of that area (climate, housing stock, cultural factors etc) but also to understand the availability of the data describing those characteristics. An understanding of this may, ultimately, result in a model not being suitable for that area (as a key data input is unavailable) or assumptions might have to be updated to allow for modelling of a factor that is not described in a purely empirical way.

For a country as large and diverse as India, it is difficult to make assumptions of future demand at country-scale. Rather, geographies, buildings, behaviour towards energy, condition of the energy network, and climate all make more sense at a localised level. This potentially provides an argument for bottom-up modelling approaches that can be tailored on specific areas, with an understanding that limitations apply when upscaling such assessments (Yu *et al.*, 2017). Significant datasets now exist that attempt to describe building energy use at this localised level in India, albeit with some limitations on spatial and temporal resolution (GBPN, 2014).

For any scale of extrapolation to regional/national level, the lack of reliable building data to map this onto is a known problem in India. For example, previous census data (Ministry of Home Affairs, no date) describes 5% of India's 187 million homes as dilapidated, 58 million as "semi-permanent", and 35 million as "temporary". This will limit the data available to a community energy modeller in terms of quality (e.g. data for non-permanent homes not being recorded in a standardised way) and quantity (large proportions of homes not subject to regulatory processes that might involve capturing of data in the first place). However, the introduction of the Indian Energy Conservation Building Code (ECBC) (IMFR, 2015) demonstrates that energy efficiency is a growing concern and "green buildings" are becoming more established in the marketplace (reported as costing only 5% more than traditional buildings in India (Smith, 2015)).

For any modelling intending to understand future evolution of energy demand, India provides a further challenge; this is a country undergoing rapid change. Between 2000 and 2012, India's annual residential energy consumption rose from 80TWh to 186TWh (Shukla, Rawal and Shnapp, 2015). It is projected that there could be 40 billion m^2 of new buildings by 2050 (Yu *et al.*, 2017), with residential buildings already contributing an estimated 23% of electrical demand (Ministry of Statistics and Programme Implementation, 2016). Future energy modelling, of the type carried out by CEDRI, must therefore be highly contextualised with clear future energy scenarios.

Climate change, changes in purchasing power of a rising middle-class, and availability of technology is likely to mean that residential cooling plays a major part in this changing energy demand. This also means that, even if attempting demand reduction in a particular case-study (where, for example, appliance usage/penetration may have reached a higher level of maturity than elsewhere in the country), strategies for managing electricity demand across the whole country are likely to focus on reducing an inevitable rise in demand, rather than attempting a reduction in total demand from current levels.

Modelling approaches by discipline

Figure 1 illustrates the different sections of analysis that CEDRI has incorporated, and the intentions of these different disciplinary areas.

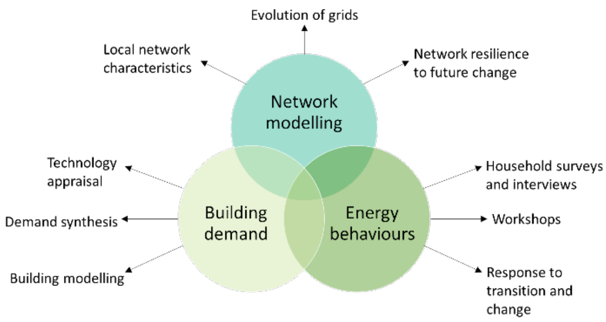


Figure 1: CEDRI project by discipline and activity

The detail of the modelling lends itself to community-scale case-study analysis, where data can be recorded at suitable resolution and, therefore, the assessment closely tailored to that case-study. CEDRI monitored weather and energy data from the chosen case-studies, were provided with some physical building information, and had access to householders themselves (during several site visits). The application of the method to a particular case-study is described later in the paper.

The project can therefore be described in terms of the analysis of three areas: i) Network modelling, ii) Building demand, and iii) Energy behaviours. Crucially, CEDRI attempts to bring these analyses together to describe a more complete picture of community energy use, with the additional intention of using this to provide guidance on demand reduction opportunities. These individual areas of analysis are summarised below.

Local energy networks

Distributed network models are well-established in industry for describing power flows at different locations of an electricity grid. Electricity network modelling usually aims to determine power flows and electrical characteristics such as voltage and current of the network, which result from local electricity demand and production. The methodology proposed within CEDRI is to use electricity grid modelling to assess the need for electric load reshaping due to technical constraints on the electric grid. Indeed, if local community consumption or production at specific times is beyond the acceptable limits of the electricity grid, it should be reduced accordingly depending on the technical and social acceptability of this reduction. To assess the compatibility of local electricity consumption with local grid characteristics, the CEDRI methodology considered distributed radial networks modelling, that corresponds best to local community infrastructures. Based on the physical characteristics of local networks, such as length and size of cables, materials, number of phases, electrical equipment (transformers), and location of the cables (underground or overhead), an electricity grid model computes the resulting impedances of each section of the electricity grid. Loads such as households are considered as ZIP loads, either with a constant power, impedance, or current consumption. Distributed production assets such as solar PV are also included in the model, and can be controlled to provide grid services such as voltage regulation (Couraud *et al.*, 2019). Using time-series inputs for household load profiles and distributed energy resources production, the electricity grid model is used to compute the resulting voltages and currents at each node of the network. Depending on these results, the network modelling activity can then highlight a need for demand reduction at specific nodes or phases or, on the contrary, a demand increase to prevent local over-voltage at specific times. These requirements are then sent to the other two CEDRI disciplines (building demand and energy behaviours) so they can assess the feasibility of the requested demand shift (Antonopoulos *et al.*, 2021). The resulting new load profiles from these two other disciplines are then reassessed by the network modelling activity to ensure they result in acceptable electrical voltage and currents. Following an iterative approach, the CEDRI method results in optimal demand profiles that meet end-users requirements as well as thermal and electrical specifications.

Modelling building energy demand

The built environment demand modelling of CEDRI is split between dynamic physical modelling (to help estimate the impact on specific building types from future scenarios) and statistical modelling of metered demand data (to understand diversity of current and future demand at a higher resolution).

Dynamic building modelling was conducted with EnergyPlus software, via DesignBuilder. This approach was selected due to the need to generate transient thermal building response and internal temperature profiles, as conducted in other residential studies (Yoon, Baldick and Novoselac, 2014; Huang and Wu, 2019). Although based on purely theoretical/physical modelling, this enabled the project to test specific retrofit approaches (e.g. building fabric) that may impact the temperature profiles in a positive sense, and therefore be demand-reducing measures that could be communicated and discussed with the householder.

In addition to the physical modelling, there was a need to upscale the measured energy demand data to represent a greater number of homes – and a desire to morph demand to account for changing external factors such as climate change. Therefore, a stochastic demand synthesising approach (specifically, STL-HMM-GP, described elsewhere (Patidar, Tanner, *et al.*, 2021)) was adopted that integrates a 'climate module'. The STL-HMM-GP algorithm facilitates detangling of complex demand profiles using a Seasonal Trend based on Loess (STL) decomposition approach (Cleveland *et al.*, 1990) and simulates the resulting stochastic component of high resolution demand using a Hidden-Markov Model Generalised Pareto (HMM-GP). The modelling approach can therefore be summarised in the following steps:

1. An STL decomposition algorithm is applied to decompose the electricity demand series into three components: i) Trend, ii) Seasonal and iii) Residual (stochastic) variations
2. The trend component of electricity demand is associated with the trend component of climate variables (temperature, relative humidity, solar radiation, wind direction, wind speed) through a partial least square regression (Guebel and Torres, 2013) to generate climate morphed trends
3. The residual component is fitted to a HMM model to simulate plausible profiles that match characteristics of the observed series
4. Electricity demands are synthesised by combining i) climate morphed trend of electricity demand (generated in step 2); ii) seasonal components (extracted from observed demand in step 1); and iii) simulated random components (generated using HMM in step 3).
5. Extreme values (>95th percentile) in the synthetic profiles are sampled from a GP distribution of extreme values of the observed profiles
6. A percentile-based bias correction is applied to account for logarithmic transformation of the original series

At the resolution desired (~minutely), Step 2 is crucial to accounting for diversity when aggregating multiple profiles together. This enables the tool to produce individual household profiles and, from these, aggregated profiles of multiple dwellings that could be linked to different future demand scenarios.

Household choices and behaviour

As well as focussing on the physical buildings and energy networks, it was essential for CEDRI to understand i) household actions that might explain the demand characteristics recorded and ii) how householders may change energy behaviour in the future, and respond to attempts to reduce and/or manage residential demand (with a particular focus on cooling).

Current energy practices were captured using both qualitative (observations, interviews) and quantitative approaches (Osunmuyiwa *et al.*, 2020). Twenty in-depth interviews were conducted with two different groups of householders. Group A had ten participants in monitored households. Group B had ten participants representing non-monitored households within Auroville. Interviewees exhibited diversity in appliance ownership, nationality, age, gender, building type, and household type (single or multigenerational). Interview questions converged around (i) local energy networks (grid challenges and adoption of solar PV); (ii) building type and its relations to cooling preferences; (iii) electricity use and cooling consumption behaviour in relation to individual and community values.

The interview data was used in designing the larger questionnaire. The questionnaire covered broader topics such as appliance ownership and usage, energy saving and pro-environmental behaviours, barriers to energy efficient behaviours, and preferences around Time of Use (ToU) demand response. The questionnaire was sent to 2000 people within Auroville, with 6% fully completed.

To generate scenarios for future energy practices, two types of co-production workshops were conducted (Osunmuyiwa *et al.*, 2021). The first co-production workshop was with households who had either participated in the interviews or questionnaire. Three types of exercise shaped the workshop:

- Extracted information from the questionnaire around ToU was presented alongside 30 year climate analysis of Auroville
- Participants were introduced to a demand management matrix with both technological and behavioural changes (minor, incremental, and disruptive shifts). They were asked to identify where they and the community were and discuss how energy practices will be altered based on this change
- A series of Demand Response (DR) cooling flexibility options were presented in lay terms and, through a scenario-based exercise, participants were tasked with creating a DR cooling policy for the community

A second co-production workshop was conducted with practitioners in Delhi. Twenty-five practitioners including academics, representatives of local utilities, policy think tanks, and regulatory actors were invited based on their knowledge of and experience with India's electricity networks and the built environment. Practitioners were asked to discuss current and future challenges around the implementation of DR strategies at the building and network level.

Integrating across model boundaries

It is not always possible, or desirable, to "hard-wire" different assessment techniques. For example, barriers between translating qualitative information (collected in co-production exercises) into input for a quantitative building model can make such direct integration tenuous. However, CEDRI allows the different techniques to influence each other by using common scenarios, responding to the same case-study, and allowing for direct communication where relevant and useful.

A diagrammatic representation of this integration is shown in Figure 2. Rather than describing a genuine, top-level energy system model, this structure allows for a different selection of tools to be used for different questions asked of community energy – and different points of integration between model boundaries can be seen for these different questions. For example, the network model can use synthesised demand data from the building modelling work, for both a baseline and future scenario, to understand the impact of projected demand changes on network performance. Cooling profiles extracted from demand data can be linked to the real activities (and cooling behaviours) reported in the householder study (e.g. reasons for operating A/C in a certain way). Choice of modelled demand reduction measures, within a dynamic simulation environment, can be tailored on feedback from a specific community to increase likelihood of those measures being accepted, and their projected savings realised. Broadly these questions can be categorised between those that might be posed by the network, and those posed by the householder – the latter requiring individual building assessment, the former some form of aggregation at scale.

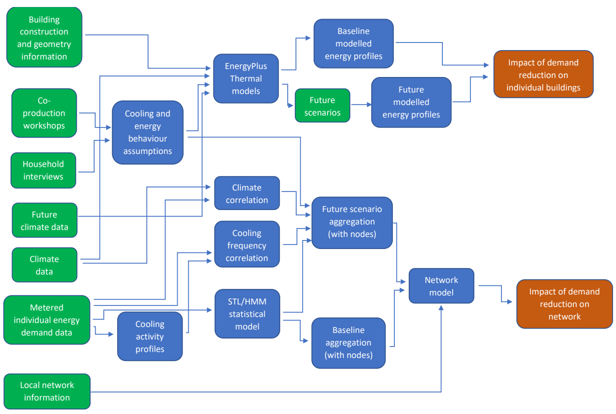


Figure 2: Integration of modelling activities in CEDRI

Application of method for Auroville case-study

Auroville is an intentional, and international, community in Tamil-Nadu with a population of 50,000. Two blocks of apartment buildings – "Citadines" and "Inspiration" – were monitored by CEDRI, containing 34 and 14 flats respectively (of which 21 and 9 units were chosen to be metered). Table 1 summarises these metered dwellings.

Other information was also recorded, such as type of lighting (noting a diverse mix of incandescent, CFL, LED and T5 with Electronic Ballast), use of electric fans and/or air conditioning (A/C), and other common household appliances (such as refrigerators). Unusually, cooking in Citadines was often via a community kitchen where most of the residents have their lunch. Cooking in other homes was often with a gas stove. This therefore had a clear impact on measured electricity demand, where cooking (in homes with individual electric stoves) can be a recognisable, and definable, period in the day.

The dwellings have single phase blink meters for monitoring electricity consumption, operating at a resolution of 16,000 blinks/kWh specification (0.06 Wh/blink) and three-phase meters with blink resolution of 800 blinks/kWh (1.25 Wh/blink). As the frequency of recording relies on the level of demand for blink meters, the monitored electricity consumption had irregular timestamps and data-cleaning methods were used to convert this to minutely resolution data, as further elaborated elsewhere (Debnath *et al.*, 2020). The household electricity consumption data was collected for November 2018-June 2019.

Table 1: Summary of Auroville metered properties

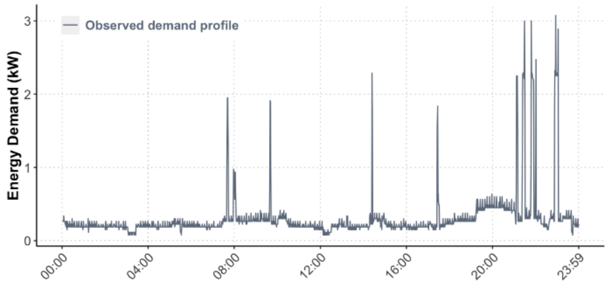
Flats	No. of dwellings	No. of occupants	Heating type	Cooling type
Citadines	21	23	None	Fans, A/C
Inspiration	9	10	Geyser	

The CEDRI method was used with this case-study to answer several research questions, a selection of which are noted below.

Synthesising electricity demand

Using the synthesis technique identified earlier, Figure 3 shows an example of a synthesised profile for a dwelling in Auroville, compared to an observed dataset. The technique demonstrates that semi-stochastic demand profiles can be synthesised from empirical datasets, and mimic the behaviour (in this case, particularly cooling behaviour) of real households in the original sample (Patidar, Jenkins, *et al.*, 2021). This then allows for multi-building aggregation that accounts for diversity and can be compared to substation-level demand profiles. Furthermore, with correlation identified between demand profile and other factors (e.g. external temperature, household occupancy, number of cooling devices), the aggregated demand profile can be morphed for a future scenario where such factors may be different (e.g. climate change, patterns of home-working, increase uptake in mechanical cooling).

(a)



(b)

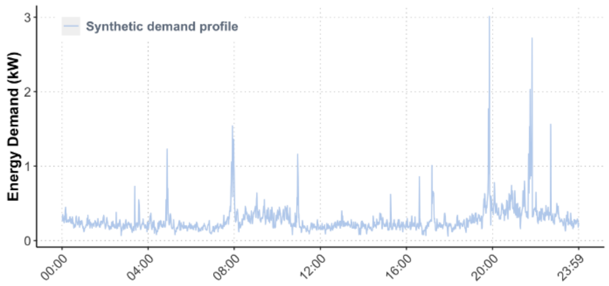


Figure 3: (a) Observed and (b) synthesised Auroville individual dwelling electricity demand profile

An example of this is shown in Figure 4, where synthesised, aggregated demand data for 610 dwellings has been altered to account for future, projected climate parameters (using the previously reference algorithms). Furthermore, this is still linked to a series of individual demand profiles (making up that aggregation) that can be used within the previously described networking modelling to ensure suitable local network performance.

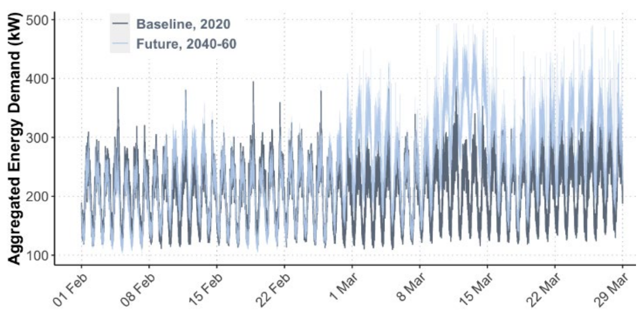


Figure 4: Example of future-morphed (2040-60) aggregated demand profile (N=610) compared to baseline (2020)

Building fabric futureproofing

CEDRI's dynamic building simulation approach (informed by the monitored data) shows the potential to reduce average daily indoor temperature and cooling electricity consumption during summer by retrofitting exterior walls and roof with insulating materials (Debnath and Jenkins, 2022). These materials should be implemented cautiously as the use of natural (and mechanical) ventilation instead of A/Cs in highly insulated buildings may increase the indoor temperature significantly. The size and nature of the simulation study was not intended for generalising community-scale conclusions for cooling demand across India. Instead, the study demonstrated a process where measured electricity consumption data combined with simulation, and contextual information of community households, can be used to enhance understanding of building insulation on indoor temperature and aggregated cooling energy demand. This was specifically considered for a residential community where A/C ownership was increasing, informed by the interactions, surveys, and co-production activities with the community itself.

Understanding local drivers of energy behaviour

Broad synthesis from CEDRI's behavioural analysis shows that current energy practices are driven by environmental identity, values, and emerging ecological realities (heat waves). While environmental values led to technological shifts such as the purchase of energy-efficient cooling appliances, subsequent patterns of use were profoundly shaped by situational factors (building, householders' health status, children etc.).

This analysis also helped explain the lack of diverse features in the measured demand profiles (such as in Figure 3). A relative homogeneity of non-cooling activity meant that the characteristics of electricity demand were highly correlated with approaches to cooling and summertime comfort.

Future scenario development

CEDRI's co-production approach shows that households have an appetite for radical technical innovations (e.g., demand response for cooling automation), especially if consulted and energy planners involve them in the design process. However, caution must be exercised as the observed appetite for technical innovation prevailed in areas with strong biospheric and altruistic values for the environment. Other forms of values, cultures and norms might be the prevailing factors in other local contexts. As such, negotiations around cooling practices must be considered – as automation will trigger new configurations of practices. Furthermore, India needs a blueprint of resources and toolkits on the range of ancillary services householders will offer. Efforts should be made to sensitise users on the requirements (capital and resources) of taking up such a role.

Additionally, the triggers for current cooling practices and appliance purchasing (and therefore the modelling of increased penetration of cooling devices across the wider building stock) was complex (Osunmuyiwa *et al.*, 2020). A "perception" of temperature, informed by wider discussions with (for example) medical practitioners, as well as the actually recorded temperature, played a part in i) a decision to purchase a cooling device and ii) how that device would be operated. Quantitative building models are not necessarily designed to translate such current and future actions into an aggregated cooling model of multiple homes.

Information required by practitioners

The second co-production workshop with practitioners, noted above, used Auroville as a case-study but brought in participants working more generally across India. The multidisciplinary nature of the project meant that technical issues relating to the future grid provision could be used to frame this qualitative exercise (Osunmuyiwa *et al.*, 2021). The intention was to understand the value of the tools and wider analysis being conducted by CEDRI. Specifically, practitioners:

1. Identified challenges around the implementation of energy demand flexibility policies for residential buildings in India
2. Unpacked core issues currently affecting India's local electricity networks and discussed potential changes in the next few decades, and how to address them
3. Suggested an increasing role for householders as prosumers and de-facto suppliers of ancillary services in India

This discussion demonstrated the difficult gap between future scenario mapping and actually delivering and designing a working energy system; the former allows a contributor to be speculative and discursive across multiple futures, whereas the latter requires definitive and actionable information. Within a rapidly changing landscape (as is observed in India), this places a great burden, and risk, on the assumptions used.

Further work

Inevitably, the work of CEDRI identified outstanding questions that could not be fully addressed by the project. The conversations had with practitioners noted an information gap for specific applications of demand response, and the communication of this to end-users.

Additionally, more tools/information are required to support policymakers and planners so that they can reflect values and norms when designing interventions to support a low-carbon energy transition. But these tools need to also be sensitive to behavioural and cultural values of the communities being studied – and quantitative tools are not always designed to do this. CEDRI adds to this toolkit, but in a relatively technology-agnostic way. Addressing the consequences of targeted technology adoption would be of great value.

Finally, more work is required on the technical (and/or statistical) limitations to extrapolating bottom-up modelling of the type described here. Likewise, there is value to further exploring potential bridging between this type of modelling and traditional, top-down energy system models. Doing so in a user-focussed way could provide more consistent recommendations that have a grounding in national energy policy, but are able to reflect specific issues facing discrete regions and communities.

Conclusion

A summary of findings from a multidisciplinary approach to community energy assessment in India has been presented. The work demonstrates the value of understanding buildings, energy networks, and the people using those buildings – but recognising, from a modelling perspective, where these different assessments can interact with each other to answer specific questions. The process of tailoring the models to a specific area of India demonstrates modelling functions that require development with local challenges in mind (e.g. available data, areas of energy use that are more important), whilst also noting techniques that have the potential for transferability to very different geographic areas of study.

The work of CEDRI notes in particular that:

- There is a need to match demand reduction strategies to specific communities with an understanding of future change in those communities
- Synthesising and upscaling demand profiles of buildings can help characterise these changes within nodal electricity network models and, therefore, the impact on local energy systems
- Purchasing and energy behaviours of households are crucial to the success of demand-reduction strategies – and care should be taken in over-generalising the extent of these behaviours to other communities
- Local behavioural and cultural aspects of energy use can (and should) be reflected in quantitative energy modelling, but this is difficult to achieve without direct engagement with those communities. Examples of this engagement have been demonstrated in this paper.

Acknowledgement

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