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# Sizing solar-based mini-grids for growing electricity demand: Insights from rural India

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Supplementary material for this article is available [online](#)

## Abstract

Mini-grids are a critical way to meet electricity access goals according to current and projected electricity demand of communities and so appropriately sizing them is essential to ensure their financial viability. However, estimation of demand for communities awaiting electricity access is uncertain and growth in demand along with the associated cost implications is rarely considered during estimation of mini-grid sizing. Using a case study of two rural communities in India, we assess the implications of demand growth on financial costs and performance of a mini-grid system consisting of solar photovoltaic (PV) panels and battery storage using two different system sizing approaches. We show a cost-saving potential of up to 12% when mini-grids are sized using a multi-stage approach where mini-grids gradually expand in several stages, rather than a single-stage optimisation approach. We perform a sensitivity analysis of the cost of the two sizing approaches by varying six key parameters: demand growth rate, logistics cost, system re-sizing frequency, likelihood of blackouts, solar PV and battery cost, and degradation rate. Of these, we find that system costs are most sensitive to variations in demand growth rates and cost decreases in solar PV and batteries. Our study shows that demand growth scenarios and choice of mini-grid sizing approaches have important financial and operational implications for the design of systems for rural electrification.

## 1. Introduction

Access to clean and affordable energy is at the intersection of sustainable development, social welfare, and environmental stewardship. About 733 million people currently lack electricity access worldwide, most of whom are located in rural locations (Akbas *et al* 2022, IEA *et al* 2022). Decentralised electrification will play an important role in providing electricity access to underserved communities where the grid cannot be extended given their remoteness (Cozzi *et al* 2020, IEA *et al* 2021) and off-grid systems options, such as mini-grids powered by renewable sources, are expected to provide and enhance access to the current un-electrified population (Cozzi *et al* 2020, IEA *et al* 2021). These systems are a relatively sustainable alternative with a lower carbon footprint compared to fossil-fuel powered systems. The Global Energy Alliance for People and Planet (GEAPP) was launched at the most recent United Nations Climate Change Conference of the Parties (COP26), with the purpose of providing reliable renewable electricity to 1 billion people and avoiding 4 billion tonnes of greenhouse gas (GHG) emissions by 2030. One of the main pillars of GEAPP to achieve its commitment is through the scaling up of renewable mini-grids (Alliance 2022). In this

context, strategic planning of rural electrification via mini-grids is essential in achieving electricity access, especially in remote rural locations.

Despite the promising potential of renewable mini-grids, several gaps remain in the literature on how to correctly size these systems throughout their lifetime to serve communities currently lacking energy access. Notably, realistic electricity demand assumptions are uncertain (Ortega-Arriaga *et al* 2021) and there is a lack of measured data on the utilisation of mini-grids and how this changes and grows over time (Blodgett *et al* 2017, Prevedello and Werth 2021). Thus, it is challenging to forecast the current and future demand of unelectrified communities, which in turn affects mini-grid design and financial feasibility (Louie and Dauenhauer 2016, Blodgett *et al* 2017). Moreover, most studies consider static mini-grid designs which do not account for capacity expansion in the future (Allee *et al* 2021). There is a lack of mini-grid sizing tools considering demand evolution over time (Stevanato *et al* 2020). Additionally, the financial, technical, and operational sustainability of mini-grids remain to be demonstrated (Stritzke and Jain 2021, Bandi *et al* 2022). To this end, this study investigates the initial electricity demand of two rural communities in India and models mini-grid sizing to meet their current and projected (by 2030) electricity needs in a cost-optimal manner. We use a new modelling tool which is able to account for demand growth by including future capacity expansion. Additionally, we analyse the implications of varying model parameters on the system size and cost.

### 1.1. Electricity demand in rural communities

Demand estimation of electricity is an important driver for the design and sizing of off-grid systems. However, it is difficult to accurately estimate the electricity demand of rural communities due to data scarcity, uncertainty, and socio-economic intricacies (Van Ruijven *et al* 2011, Louie and Dauenhauer 2016, Riva *et al* 2018). A review identified top-down and bottom-up approaches as the main forecasting methods of energy demand in developing countries (Bhattacharyya and Timilsina 2010). Riva *et al* (2018) also identified the strengths and weaknesses of each method. On the one hand, top-down methods rely on aggregated data, at a national and regional level, which is relatively easy to obtain, but these data do not capture the complexities of the local context such as technical progress, innovation diffusion and behavioural changes. On the other hand, bottom-up methods allow for local demand representation and more realistic demand projections, but with the drawback of requiring substantial data availability to capture contextual situations in different regions (Swan and Ugursal 2009, Bhattacharyya and Timilsina 2010, Riva *et al* 2018).

A common approach to forecast demand used by both researchers and mini-grid developers is to carry out surveys in the target community with a focus on early adopters (GIZ 2016, Blodgett *et al* 2017). However, previous studies reported prediction errors when comparing surveys with actual measured values (Louie and Dauenhauer 2016, Hartvigsson and Ahlgren 2018) or with alternative data-driven proxy methods (Blodgett *et al* 2017). Another common method applied to forecast demand in the energy access literature is to use arbitrary trends, whereby demand is assumed to evolve continuously over a period according to growth trends, national plans, or energy access goals. The use of arbitrary trends coupled with multiple scenarios of demand growth help refine forecast uncertainties, but this often requires the adoption of complex mathematical optimisation methods (Riva *et al* 2018). Errors (or inaccuracy) in estimating energy demand can magnify at the design stage and could have significant impact on mini-grid size and capital costs.

### 1.2. Mini-grid sizing

There are three main obstacles in current mini-grid sizing practice. Firstly, errors in demand forecasts result in inappropriate sizing of the systems, consequently causing supply shortages, reliability issues and customer dissatisfaction if the system is undersized, or higher costs if it is oversized (Akin *et al* 2016, Louie and Dauenhauer 2016, Peters *et al* 2019, Riva *et al* 2019). Thus, the sizing of mini-grid systems implies a cost versus reliability trade-off which is directly impacted by demand projections and/or the desired reliability levels of the system. Louie and Dauenhauer (2016) for example explored the incremental cost of improving system reliability from 99% to near 100% for off-grid photovoltaic (PV) systems in Malawi, and found that this increases the cost by an average of 46%.

Secondly, most of the modelling tools available to size mini-grids do not consider demand evolution and growth over the duration of the modelling period. Thus, constant and repetitive load profiles are commonly used which do not reflect the potential growth in electricity demand as a community develops over many years (Riva *et al* 2018). Furthermore, few studies explore sizing for system capacity expansion in the future (Riva *et al* 2019, Stevanato *et al* 2020, Allee *et al* 2021).

Thirdly, most mini-grid designs are based on static forecasts of generation and storage capacity throughout the system's lifetime (Allee *et al* 2021). Static forecasts refer to single-time forecasts of generation and storage capacity covering the complete period of system lifetime. Allee *et al* (2021) suggested future research should focus on the techno-economic feasibility of modular mini-grid design. Stevanato *et al* (2020)

found that planned model expansions presented better economic performance instead of considering only a single investment decision step.

Achieving electricity access for all by 2030 is a great challenge that requires investigating different sizing approaches for design of mini-grids in communities with lack of reliable supply. To overcome these three key issues it is necessary to apply a modelling approach which accommodates several potential demand scenarios, which can develop and grow over time, and using analysis of mini-grid systems which can expand their capacities over time in a modular fashion.

### 1.3. Electricity access and mini-grids in India

India is one of the 20 most access-deficient countries worldwide (IEA *et al* 2021). In recent years, India has made considerable progress in providing access to its underserved population, especially through off-grid renewable systems. In 2019, India was one of the three countries with the greatest number of people connected to mini-grids; solar PV is the main mini-grid technology in India (IEA *et al* 2021). Nevertheless, lack of electricity access is still an issue for 2.4% of Indian households (Agrawal *et al* 2020). In rural areas, power distribution companies face the challenge of providing even the minimum lifeline supply of one unit (1 kWh) per day for each household (India 2015). The Government of India recognises the key potential renewable sources have in bridging India's energy access gap cost-effectively. It also states that the deployment of renewable mini-grids should be a main component in India's energy transition (India 2015).

Solar PV mini-grids coupled with battery storage have been found to be economically viable for rural electrification compared to equivalent non-renewable options in India (Comello *et al* 2017). Government support, notably in the form of incentives to lower generation costs and clear policies, as well as community involvement in the decision-making process, have enabled progress on mini-grid deployment in India, especially in the state of Uttar Pradesh (Come Zebra *et al* 2021). However, some of the main barriers hindering solar mini-grid adoption are lack of awareness and limited mini-grid coverage (SPI and ISEP 2019). A survey found that 75% of the rural population in 50 villages in India were aware of solar mini-grids (SPI and ISEP 2019), although adoption was low given that usually mini-grids are located closer to commercial hubs to foster the use of economically productive appliances. The survey also found that rural mini-grid customers were satisfied with the continuity and quality of power supplied by these systems. Moreover, mini-grid customers were satisfied with the services even though most of them faced affordability challenges. This finding suggested that a better service experience, by offering better reliability and quality of supply, can be more important than pricing for customer satisfaction (SPI and ISEP 2019). Customers value reliable power supply and are willing to pay more for mini-grid services which can provide this reliability (Graber *et al* 2018, Sharma *et al* 2020).

### 1.4. Research questions and paper overview

In view of the potential solar mini-grids have to close the electricity access gap in rural communities in India, this paper addresses the following research questions:

- What is the initial electricity demand of a typical un-electrified rural community (100 households) in India and how could this grow over time?
- How should off-grid systems be sized, to optimise their financial viability, in the context of increasing electricity demand in rural Indian communities?
- What are the system performance and quality of supply characteristics of cost-optimised mini-grids over their lifetime?

To address these questions, we investigate the initial electricity demand in two rural communities in India. We also determine the least-cost mini-grid sizing strategy to provide a projected level of demand growth by 2030. We do so by using a modelling software (Winchester *et al* 2022) capable of considering load evolution scenarios and providing technical details on systems performance and capacity expansion. The contributions to knowledge of this research are to provide developers and governments comprehensive evidence to aid decision-making while designing and deploying solar PV mini-grids for rural electrification. Similarly, we aim to determine whether oversizing or incremental sizing of systems is a better strategy to meet a growing energy demand in India in a financially sustainable way.

The rest of this paper is presented as follows: After introducing the two different rural Indian communities, the demand growth scenarios and the tool used to model mini-grid sizing are presented in the Methodology (section 2). In the Results section (section 3), we show how demand growth scenarios and other parameters impact mini-grids' system sizing. Then, we describe the optimum strategy to size mini-grid systems in the Discussion (section 4). We close the paper by reiterating our main findings in the Conclusion (section 5), suggesting how practitioners should plan to accommodate demand growth in future mini-grids.

**Table 1.** Technical specifications of mini-grids installed in Shahapur and Sarvantara.

Community	Hamlet	PV	Battery	Number of households
Shahapur	Talwada	14.4 kWp (45 panels of 320 Wp)	48.96 kWh	58
Shahapur	Shishwali	9.6 kWp (30 panels of 320 Wp)	36 kWh	41
Shahapur	Vadpada	2.88 kWp (9 panels of 320 Wp)	14.4 kWh	12
Sarvantara	—	4.6 kWp	12.5 kWh	35

## 2. Methodology

This study investigates the impact of electricity demand growth on mini-grid sizing.

The methodology adopted for this research is divided into four sections: case studies, primary data collection through energy use surveys, scenario definition, and energy system modelling using a mini-grid sizing tool.

### 2.1. Case studies

The two different communities investigated are Sarvantara, a small rural village located in northern India, and a cluster of three hamlets at Shahapur tehsil (a unit of administrative division) in western India (figure 11 in appendix B).

Sarvantara is in the district of Bahraich of the state of Uttar Pradesh (Government of Uttar Pradesh 2022). Sarvantara has around 100 households, of which 35 households received electricity access for the first time. A solar PV mini-grid was installed in June 2017 by Oorja Development Solutions Ltd, which is comprised of 4.6 kiloWatt-peak (kWp) polycrystalline Si-PV panels and a total storage size of 12.5 kiloWatt-hours (kWh), with one 8.4 kWh lead-acid and one 4.6 kWh Li-ion battery. The mini-grid system operates on a direct current (DC) distribution network (Hauser 2018).

Shahapur is a tehsil in the district of Thane in the western state of Maharashtra in India. In 2018, three hamlets in Shahapur received electricity access for the first time via solar PV mini-grids. The mini-grids were installed by Gram Oorja Solutions at Talwada and Shishwali in February 2018, and at Vadpada in March 2018. The installed mini-grids operate in alternating current (AC) mode; with an energy mix of monocrystalline silicon PV and lead-acid batteries for storage. Brief technical specifications of each mini-grid are given in table 1.

### 2.2. Energy use surveys

Surveys were conducted to understand the energy demands of rural communities in India, which received electricity access for the first time via their respective mini-grid systems. The questionnaires used to carry out the surveys gathered information relating to demographics, appliance ownership, and time of use of appliances. Details of the questionnaire are provided in appendix A. A baseline survey was carried out at the end of May 2017 in Sarvantara, before the village had access to either a mini-grid or the national grid. In total 55 households were surveyed. In June 2019, a total of 50 randomly sampled households were surveyed in the three hamlets of Shahapur (table 1). The responses from households surveyed in Sarvantara ( $n = 55$ ) and Shahapur ( $n = 50$ ), were considered for analysing energy demand in each location. We calculated the initial demand, which is further referred to as baseline demand, as a starting point for the different growth scenarios considered in this study. Following this, we normalised the total number of households in each community to 100, for ease of comparability. Further details on survey analysis and modelling are explained in sections 2.3 and 2.4.

### 2.3. Scenario definition

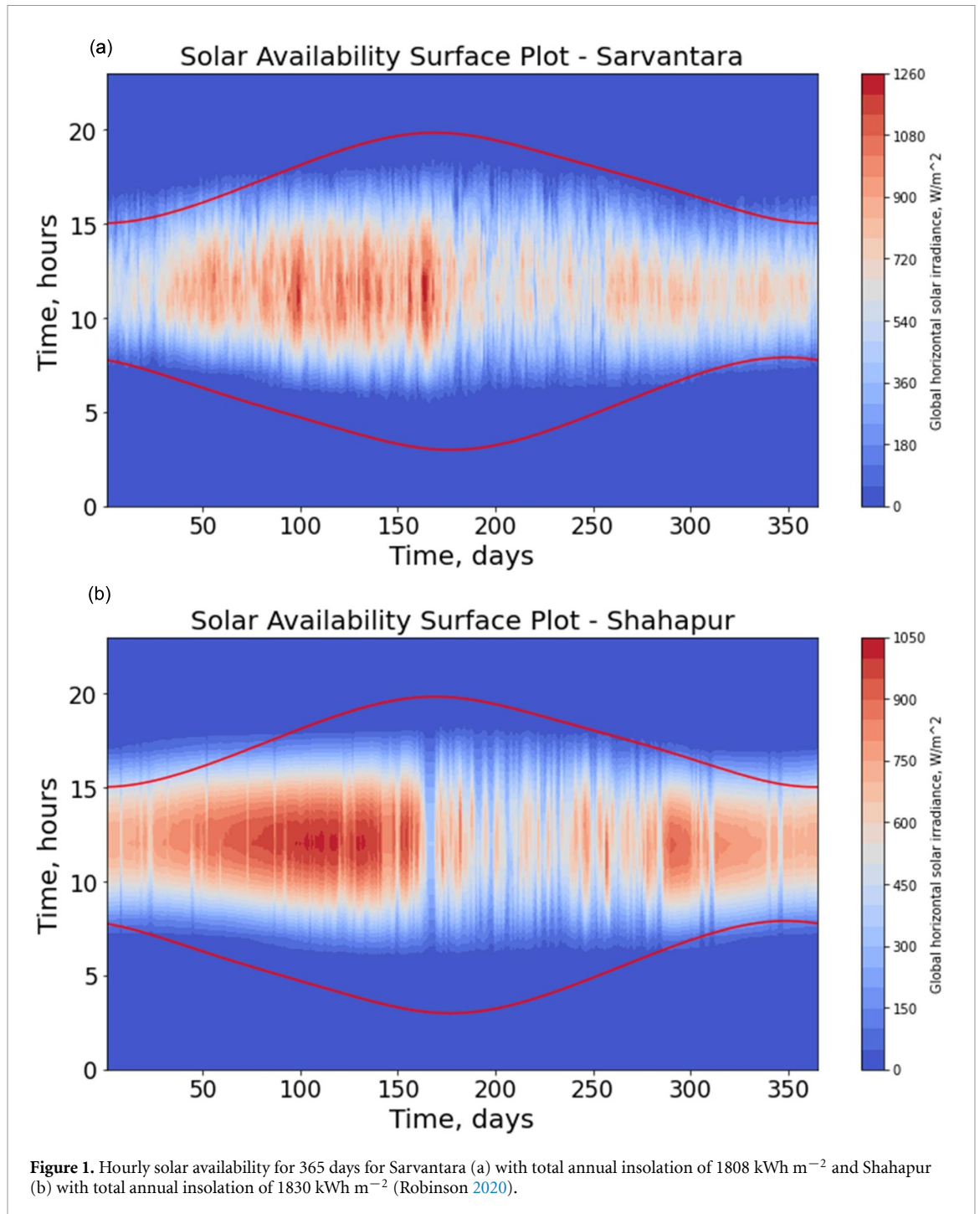
#### 2.3.1. Energy supply mix

High solar availability at Sarvantara and Shahapur makes PV an ideal choice for primary generation. Figure 1 shows solar profiles for each location at an hourly scale over a one year period. The weather analysis charts were extracted from PyClim, an open access climate analysis toolkit (Robinson 2020). Initially, the mini-grids installed in both communities had a mix of solar PV and storage. However, Sarvantara also received access to the national grid in March 2018. For simplicity, only mini-grid access was considered in this study. To be compatible with the Indian main grid and allow for future interconnection with the grid network, AC-based mini-grids (Nathan *et al* 2022) were chosen for this analysis.

#### 2.3.2. Demand growth scenarios

We considered three electricity demand scenarios to evaluate their impact on mini-grid system sizing, performance and costs in rural India.





### 2.3.2.1. Baseline scenario

Baseline demand was defined as the electricity consumption level communities had when they received mini-grid access for the first time. This scenario was designed to test the lower bound of the size of the system, i.e. the minimum generation capacity required to meet the baseline electricity demand in each location. In the case of Sarvantara, the developer assessed the initial electricity demand based on interviews prior to mini-grid access. For Sarvantara, we calculated the average ownership of devices based on survey responses to create the load profile of a representative household in the community. Whereas in Shahapur, the developer provided four light emitting diode (LED) bulbs and one phone charger, as a demand stimulus package, to all customers along with the mini-grid connection. For Shahapur baseline demand, we considered the devices provided by the developer as the initial household ownership.

In each location the Baseline scenario aligns with the definition of Tier 1 electricity access, both in terms of the services provided under the International Energy Agency (IEA) stratification of energy access (IEA 2020) and the definition of the World Bank's Multi-Tier Framework of 76 Wh per household per day (Bhatia

and Angelou 2015). The daily utilisation profiles of appliances for the baseline demand were calculated by analysing the usage times of each appliance captured in the survey responses. We considered the average usage times per device to create a representative profile in each location. Further details on load assumptions and calculations are provided in section 2.4.1.

### 2.3.2.2. Adaptive growth scenario

To anticipate future electricity demand, demand growth was defined as a function of appliance growth using the Bass model for innovation diffusion (Bass 1969), as described in equation (1). We used this model to create adoption profiles of each appliance in each community during the ten year period of mini-grid access analysed,

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \left(\frac{q}{p}\right) e^{-(p+q)t}}. \quad (1)$$

In equation (1)  $F(t)$  is the rate of appliance purchase,  $p$  denotes the number of early buyers and  $q$  denotes buyers who imitate their peers. Values of  $p$  and  $q$  vary for individual appliances as it is based on households' decisions to prioritise which appliance to buy while making a purchase decision (Radpour *et al* 2021). These values were estimated based on field observations and appliance ownership inputs from the surveys. Adoption of large appliances such as refrigerators is slower than the adoption of appliances like TVs or fans and hence we use different growth rates for each appliance. Further details are presented in section 2.4.1.

### 2.3.2.3. Target scenario

This scenario was constructed following guidance on what constitutes electricity access, as defined by the IEA and the SDG 7 target by 2030 (IEA 2020). The demand in this scenario (779 Wh per household per day) is equivalent to the upper end of Tier 2 of the World Bank's Multi-tier framework (Bhatia and Angelou 2015). In particular, we hypothesised generalised residential electricity consumption in rural households for the ten year period, considering that the demand is immediately high and static throughout this period. Since the target demand is the same for both locations and the insolation levels are also similar, for simplicity, we only considered Shahapur for the Target scenario.

The scenarios were designed to meet electricity needs in rural Indian communities by 2030, thus results are reflective of a conservative level of demand.

## 2.4. Energy system modelling using CLOVER

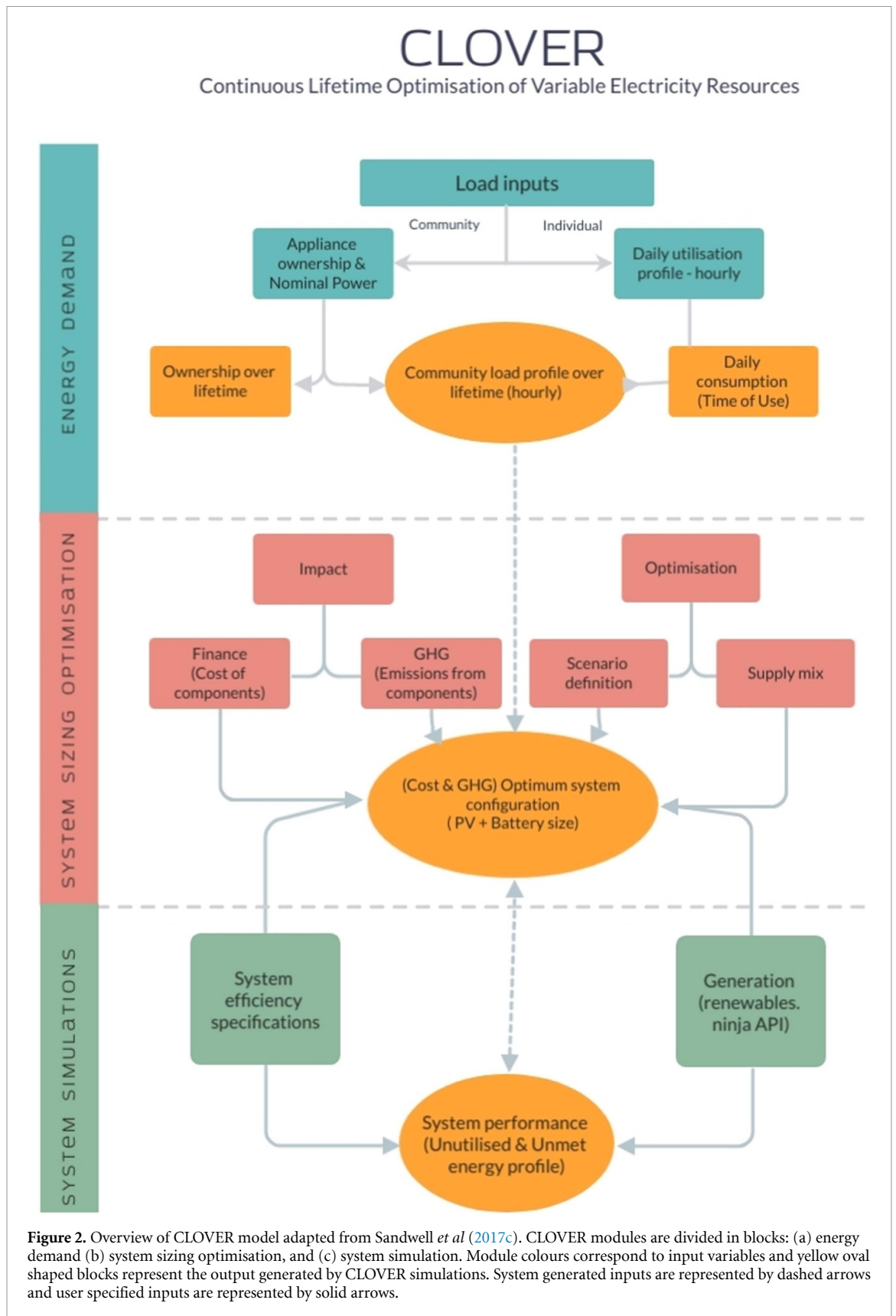
In this study, we used the CLOVER (Continuous Lifetime Optimisation of Variable Electricity Resources) energy system modelling tool to make an informed decision on sizing mini-grids in rural India over the system's lifetime. CLOVER has several different functionalities and advantages over other tools. For example, the user can opt-in between two different optimisation objective functions: reducing costs and/or GHG emissions of mini-grids over their entire lifetime. CLOVER enables assessment of system performance over a granular period (Sandwell 2017a, Sandwell *et al* 2017c). Moreover, it also allows the user to design future electricity demand growth scenarios, which is explored in depth in this study. Figure 2 presents an overview of the CLOVER model. Full aggregated and anonymised data and modelling techniques used in this study are open access and available at (<https://github.com/rjsayani/Clover-analysis>) (Sayani and Ortega-Arriaga 2022).

### 2.4.1. Load and demand growth

Input data for the load calculations were derived from responses to the surveys that are discussed in section 2.2. CLOVER considers two types of inputs to determine the load profile: (a) data on each appliance type such as average ownership in the community, nominal power, and adoption coefficients (given in equation (1)), and (b) the time of use profile of each appliance. As an output, load profiles are stochastically generated for each appliance based on its time of use profile, at an hourly resolution, for the duration of a given system lifetime. We used a process similar to that described in Sandwell *et al* (2016) and Chambon *et al* (2020), which can be summarised as:

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





The number of each appliance of type  $i$  at time  $t$  in the community is given by  $N_i(t)$ . This can be derived from the average ownership found from the surveys and the community size, and can incorporate growth in ownership rates described in section 2.3.2.

The utilisation profile of an appliance is defined to be the probability that it is in use and is given by  $U_i(t) \in [0, 1]$ . The utilisation profile represents the typical average usage of each appliance of a given type

**Table 2.** Load inputs of appliances considered. Assumed nominal power values were taken from (Bhatia and Angelou 2015, Sandwell *et al* 2016, UK Aid 2019). Hours of usage were based on survey responses (table 7 in appendix) and on previous studies (Sandwell *et al* 2016, Chambon *et al* 2020).

Appliance type	Nominal power (W)	Hours of usage (summer)	Hours of usage (winter)
LED bulbs	6	4.6	5
Television (TV)	20	4	4
Mobile Phone	5	4	4
Fan	40	6	0–1
Radio	5	4	4
Refrigerator	220	2	1.8

across the community, assuming each individual device is used independently, and can vary between days and months of the year.

The number of appliances of each type in use by the community is given by  $N_i^T(t)$ . This is generated stochastically for each timestep of the simulation period from values drawn at random from a binomial distribution given by  $B_i(N_i(t), U_i(t))$ .

From the number of appliances in use at a given time and the nominal power of each appliance type,  $W_i(t)$ , the total load  $E_i(t)$  resultant from each appliance type is given by

$$E_i(t) = W_i * N_i^T(t). \quad (2)$$

And hence the total load of the community across all appliance types,  $E^T(t)$ , is given by

$$E^T(t) = \sum_i E_i(t). \quad (3)$$

Table 4 in appendix B shows the inputs used for each demand growth scenario to calculate  $N_i(t)$ . In this study load growth was taken as a function of growth in appliance ownership in households only, rather than an increase in the number of households or ownership of appliances for productive uses, limiting this analysis to only domestic load evolution.

Load profiles for each device and the communities overall were constructed for the three different scenarios defined in section 2.3.2. This was done using the process described above for the ten year period for each scenario in each location. For the baseline load profile we considered appliances observed in the surveys, while in the adaptive and target scenarios, a refrigerator was included as an additional appliance that households may buy in the future. Guidance on usage profile of refrigerator was taken from (UK Aid 2019, Prayas 2021). We varied the hours of usage of lights and cooling devices between summer and winter months to consider seasonality, summarised in table 2.

The rate of diffusion of each appliance has a significant influence on the temporal evolution of the number of devices owned by the community and hence the load profile, as shown in figure 3. This rate varies because of different factors such as cost of appliances (Richmond *et al* 2020) and level of education (Dhanaraj *et al* 2018). The rate of diffusion of each appliance is moderated by values of innovation and imitation as defined in equation (1) in section 2.3.2. In practical terms, these values and  $N_i(t)$  overall represent households' appliance purchase decisions over time, which will be influenced by many factors. Thus, to understand the significance of the rate of adoption, we constructed three different community load profiles by varying appliance adoption rates (figure 3) to represent a range of possible future adoption scenarios.

#### 2.4.2. Energy system simulation and performance

As shown in figure 2, simulations take inputs on system efficiency specifications such as storage efficiency, conversion efficiency, battery charging cycles and minimum state of charge. In addition to these, the energy available from solar power generation profile  $E_G(t)$  was derived for the ten year period based on historical irradiance data from the renewables.ninja API (Pfenninger and Staffell 2016). We calculated the energy balance  $E_B(t)$ , the difference between energy from generation and the community energy demand  $E_D(t)$ , using

$$E_B(t) = E_G(t) - E_D(t) \quad (4)$$

in which the terms accommodate conversion and transmission efficiencies in the CLOVER calculations, but these terms are not shown here for brevity. The energy balance is used to assess the usage of the storage based on the net demand for electricity, the state of charge of batteries, and the battery discharge current (C-rate), with further description of the storage energy calculations available in Beath *et al* (2021). Following this,

**Table 3.** Scenario specifications.

Scenario name	Location	Sizing approach	Demand growth	Iteration period (years)
BS_SA	Sarvantara	One-step	Static	10
BS_SH	Shahapur	One-step	Static	10
Adapt_SA_mstep	Sarvantara	Multi-step	S curve	5
Adapt_SH_mstep	Shahapur	Multi-step	S curve	5
Adapt_SA_onestep	Sarvantara	One-step	S curve	10
Adapt_SH_onestep	Shahapur	One-step	S curve	10
Target	Generic	One-step	Static	10

system performance metrics, such as total used energy, unmet demand and unutilised energy, were generated over the entire investigation period.

#### 2.4.3. Optimisation and system sizing

We used CLOVER to optimise the mini-grid size so as to minimise total costs from the system over its lifetime. CLOVER follows a heuristic search algorithm and sufficiency criteria to find the least cost system. In other words, it evaluates the search space with possible combinations of system sizes (for instance PV and battery) and performs simulations incrementally over a range of possible system capacities to find the mini-grid size which is sufficient to meet the defined load at the lowest cost (Sandwell 2017a, Sandwell *et al* 2017c). Here we defined sufficiency criteria based on system reliability, i.e. permissible threshold for blackouts measured as a proportion of time. The optimum system is that which exceeds a minimum threshold of reliability at the lowest cost of electricity (Levelised Cost of Used Electricity or LCUE), as defined in section 2.4.4.

As shown in figure 2, two different sets of inputs were taken for optimisation calculations: (a) user specified (represented by solid arrows) and (b) inputs generated by energy system simulations (dashed arrows). User specified inputs include finance, GHG and technical parameters of the system being investigated. Battery C-rate and conversion efficiency are some of the technical variables considered. Finance inputs include equipment costs, operation and maintenance (O&M) costs, discount rates, and cost reductions of PV and battery over time. GHG inputs are composed of embedded emissions from various components of the system and those offset from substituting fuels such as kerosene. We generated inputs on demand and energy supply balance from energy system simulations in CLOVER. Further details of the optimisation method can be found in (Sandwell 2017a). All the inputs considered in this study are given in table 5 in appendix B.

The demand growth scenarios described in section 2.3.2 were modelled to investigate mini-grid size over ten years. Each scenario differs in sizing approach depending on the number of time periods (steps) chosen for the optimisation process. Two approaches were implemented: (a) one-off installation (one-step sizing), and (b) incremental or modular (multi-step sizing). The latter allows for capacity expansion within the ten year period, undertaken at the period mid-point in Year 5.

Among the scenarios designed to characterise current and future electricity demand, baseline and target demand scenarios set the lower and upper bound of the mini-grid size, whereby demand is considered static in nature, hence system sizing was performed using one-step optimisation. In contrast, the adaptive scenario captures demand growth following the S-curve, which was suitable for multi-step optimisation. In practice, one-step optimisation implies finding the cost-optimum system prior to mini-grid installation and considering the system which is 'sufficient' to meet the electricity demand over its entire ten year lifetime. Conversely, multi-step optimisation represents an incremental sizing approach which allows the intervention of the 'sufficiency' criteria after five years of mini-grid operation to resize the system to meet a growing demand. In total, we investigated seven scenarios with different sizing approaches and demand growth assumptions to assess the implications of each on total system costs and performance, shown in table 3.

#### 2.4.4. Metrics to assess mini-grid performance

For a detailed cost assessment, we included two financial metrics computed from CLOVER optimisation outputs: (a) cumulative system costs (\$) which comprises equipment costs and O&M costs over the systems' lifetime, and (b) LCUE ( $\$/\text{kWh}^{-1}$ ). LCUE differs from conventional levelised cost of electricity by explicitly considering the levelised cost per unit of electricity consumed by the community, instead of electricity generated by the system overall, which is important when considering systems which permit shortfalls in reliability. As presented in Sandwell *et al* (2017a), the LCUE is given by:

$$\text{LCUE} = \frac{\sum_{n=1}^N \frac{I_n + M_n + F_n}{(1+r)^n}}{\sum_{n=1}^N \frac{E_n}{(1+r)^n}}. \quad (5)$$

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

In addition to these, a criterion for reliability of the system was also considered whilst optimising mini-grid size. We set the threshold for blackouts in CLOVER system optimisation, which indicates the level of electricity demand that must be met. For example, when the system reliability is 95%, the cost-optimal system must meet electricity demand on average for 22.8 out of 24 h of the day; in this case, 1.2 h of blackouts or brownouts are permitted. Thus, the reliability threshold can have a significant impact on the total size of the mini-grid, especially on storage units. More information on the optimisation process in CLOVER can be found in Baranda Alonso *et al* (2021). We extended our analysis to understand how system cost varies with different sizing approaches by changing six parameters: demand growth rate, logistics cost, iteration period (or system re-sizing frequency), likelihood of blackouts, solar PV and battery cost, and degradation (as presented in table 6 in appendix B). After the load profiles were generated and a cost-optimal system size was found for each scenario, we then assessed the systems' long-term performance at an hourly scale for the ten year period. We analysed unutilised and unmet energy in depth for one-step and multi-step adaptive scenarios, these are discussed in detail in section 3.

### 3. Results

#### 3.1. Electricity demand growth

Figure 3 shows temporal load evolution of a community of 100 households in Shahapur over the ten year period at a slow, medium, and fast rate of appliance adoption. Under our demand characterisation, large cooling appliances like refrigerators are adopted slowly in rural India due to multiple factors (Dhanaraj *et al* 2018), whereas mobile chargers and lights are adopted as soon as a household receives access to electricity. The community load profile at each growth rate also indicates seasonal variation, which is mainly dominated by the use of refrigerators and fans. Based on field observations on appliance ownership growth in Shahapur and Sarvantara, the medium growth curve was considered as the central optimisation scenario. This rate of growth was found consistent with previous studies on drivers of domestic appliance ownership in rural India by (Aklin *et al* 2016, Richmond *et al* 2020).

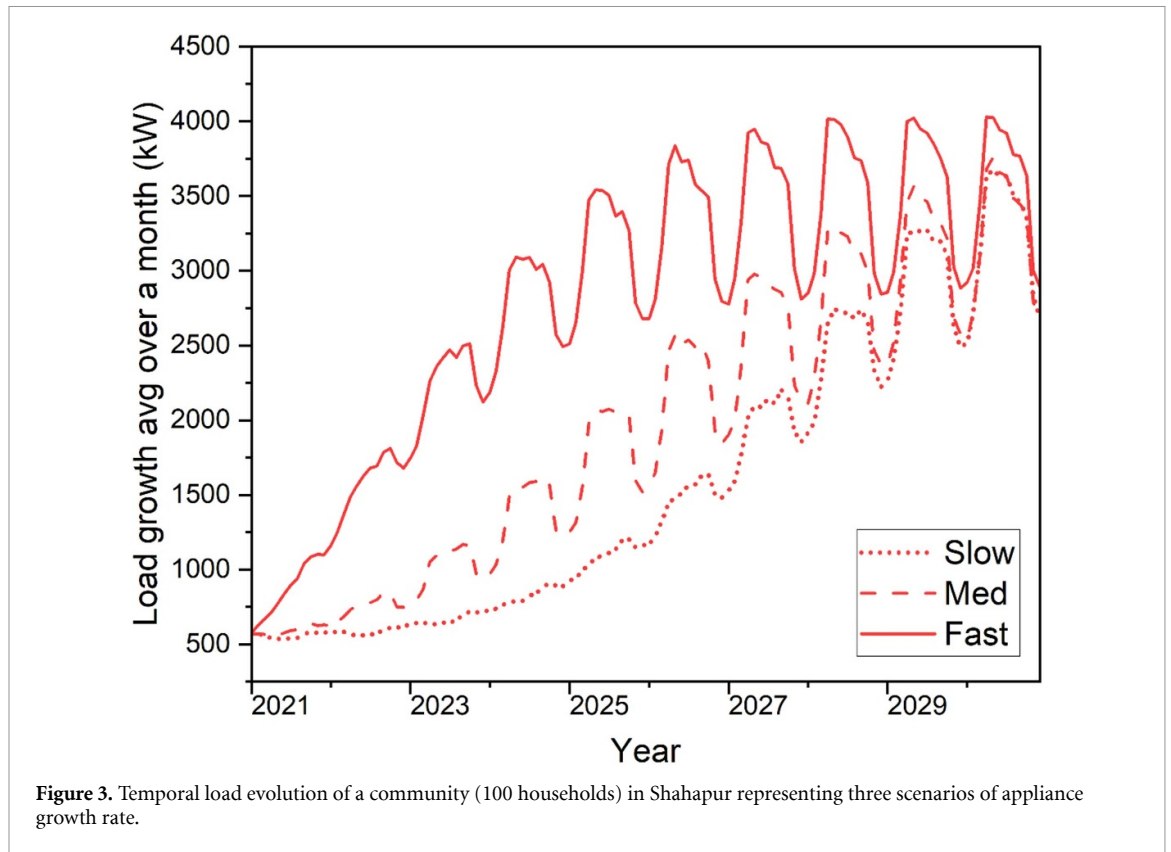
Figure 4 captures community load profiles, driven by growth in appliance ownership, in five different scenarios at different scales. As observed in figure 4(a), the peak load occurs during the evening in each scenario. This peak is mainly dominated by the increased use of lights and TVs, and by the use of ceiling fans and refrigerators during the summer months. In the baseline demand, there is a significant difference in the magnitude of the evening peak load between Sarvantara and Shahapur, arising from appliance ownership at the time of connection. Hamlets in Shahapur were provided with a demand stimulus package by the developer which included four LED bulbs and a phone charger along with the mini-grid connection.

Given that the use of some appliances, such as refrigerators and fans, is influenced by ambient temperature, seasonality was incorporated in constructing the stochastic load profile and this effect is visible in figure 4(b). In figure 4(b), seasonal variation in the load is clear when comparing the winter (November–January) and summer months (April–June), in which refrigerator and fan account for more than half of the total demand. While seasonal variations in the baseline and target loads were also considered, appliance ownership remained constant during the simulation period, serving as a reference for the lower and upper bound of the load. As ownership of refrigerator, fan, and TV increases over time, the demand of the adaptive scenario reaches the target at the end of the simulation period, shown in the S-curve yearly growth in figure 4(c). These growth rates suggest that the variation in load profiles can have substantial influence on the size of the mini-grid required.

#### 3.2. System size

The resultant size (in terms of solar PV and battery capacity) of the cost-optimised mini-grids for each load scenario is presented in figure 5. The system reliability was set to 95% (or blackouts occurring 5% of the time) in all scenarios, with a resolution during the optimisation of 1 kWp PV and 5 kWh battery.

The size of the actual mini-grid installed in Sarvantara is 4.6 kWp PV and 12.5 kWh battery and the systems installed in Shahapur ranged from 2.88–14.4 kWp PV and 14.4–48.96 kWh battery. However, these systems were designed for a different number of households as specified in table 1. In our results, baseline



demand is constant and it is the lowest throughout the simulated period. Therefore, the system required to meet this demand is the smallest in both locations compared to other scenarios. For Sarvantara, the optimum system size is 3 kWp PV and 20 kWh battery, and for Shahapur, this is 5 kWp PV and 40 kWh battery. Similarly, since target demand is the highest, the largest system (31 kWp PV and 160 kWh battery) is required to meet this demand.

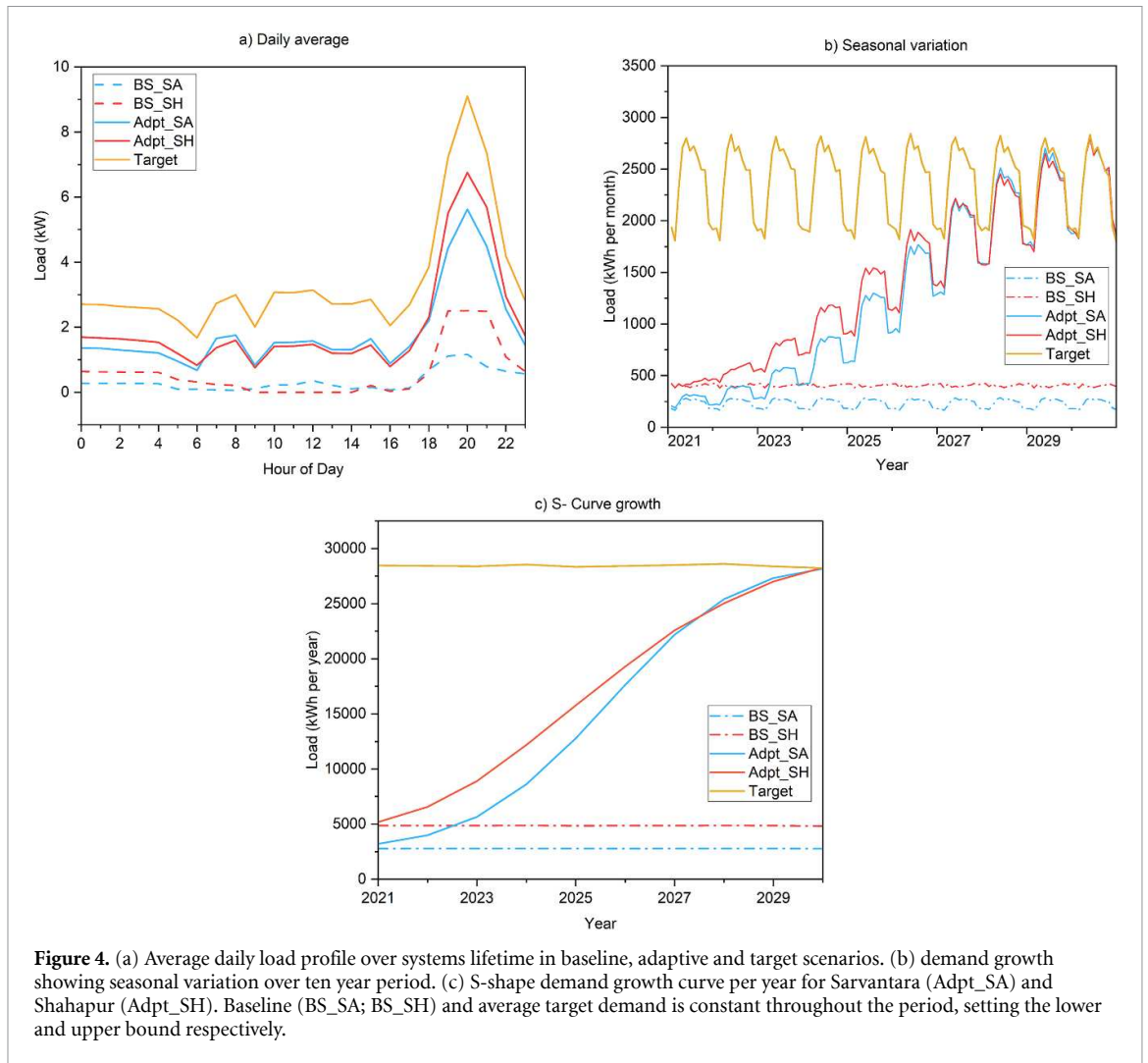
For the adaptive growth scenario, the two different sizing approaches are presented: the one-step sizing approach is represented by squares, and the multi-step sizing approach is depicted by connected circles. In the latter case, the optimisation is divided in two periods of five years each and the system capacity is adjusted at the midpoint to meet the growing demand. As observed in figure 5, the one-step and multi-step sizing approaches result in similar sizes at the end of the investigated period. However, the difference between system sizes at Years 5 and 10 in the multi-step approach is large enough to imply that this approach may be potentially preferable to oversizing from the beginning (one-step). For instance, in the case of Sarvantara the battery requirement for the initial five years is 55 kWh, whereas with the one-step sizing approach 125 kWh are initially required.

### 3.3. System cost

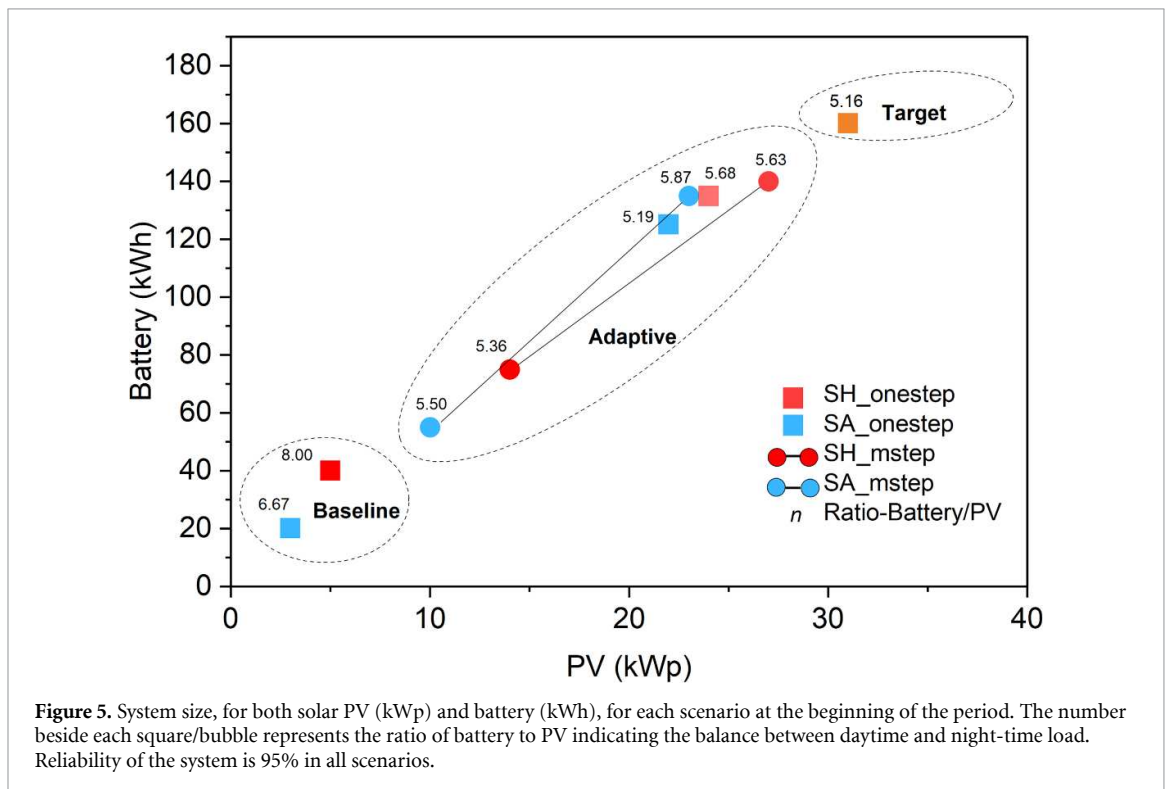
The optimisation results led to insights on how system size translates to overall costs and investment requirements for providing electricity access via mini-grids. These costs cover new equipment cost and O&M costs over the mini-grids life cycle. Figure 6 shows total system costs and LCUE ( $\text{\$ kWh}^{-1}$ ) of the resultant systems in each scenario. Results showed there is up to 12% saving potential in total system costs when mini-grids are sized in two steps rather than in one-step only. From figure 6 it can be observed that at the end of the period, the LCUE for the multi-step case is lower than one-step sizing in both locations. For example, the LCUE is  $0.34 \text{ USD kWh}^{-1}$  in the multi-step sizing versus  $0.37 \text{ USD kWh}^{-1}$  in the one-step sizing approach for Shahapur. This finding suggests that when considering the whole system's lifetime, capacity expansion is more affordable than one-off installation. Interestingly, the LCUE of the largest system (target scenario) is the lowest. This is primarily due to the underlying assumption that demand is consistent from the beginning of the simulation period and thus the design of the system is well matched to the demand throughout the system's lifetime, resulting in consistently high utilisation and therefore a lower LCUE.

To ensure consistency in inferences on the apparent cost advantage of multi-step sizing of mini-grids, we explored the sensitivity of six different parameters on total system costs in each sizing approach. The values of these parameters can be found in table 6 in appendix B. We analysed the low, central, and high values of



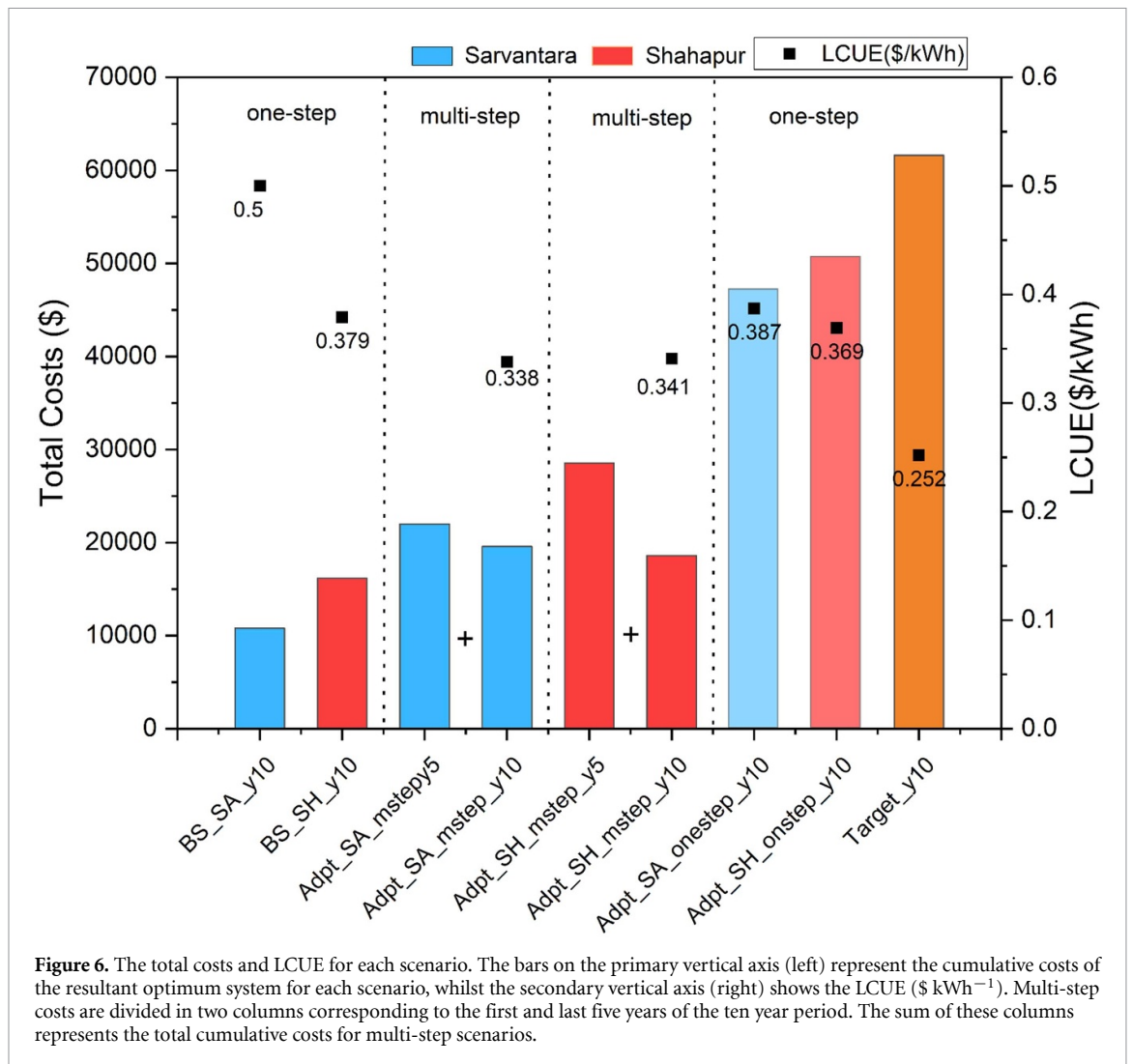


**Figure 4.** (a) Average daily load profile over systems lifetime in baseline, adaptive and target scenarios. (b) demand growth showing seasonal variation over ten year period. (c) S-shape demand growth curve per year for Sarvantara (Adpt\_SA) and Shahapur (Adpt\_SH). Baseline (BS\_SA; BS\_SH) and average target demand is constant throughout the period, setting the lower and upper bound respectively.



**Figure 5.** System size, for both solar PV (kWp) and battery (kWh), for each scenario at the beginning of the period. The number beside each square/bubble represents the ratio of battery to PV indicating the balance between daytime and night-time load. Reliability of the system is 95% in all scenarios.



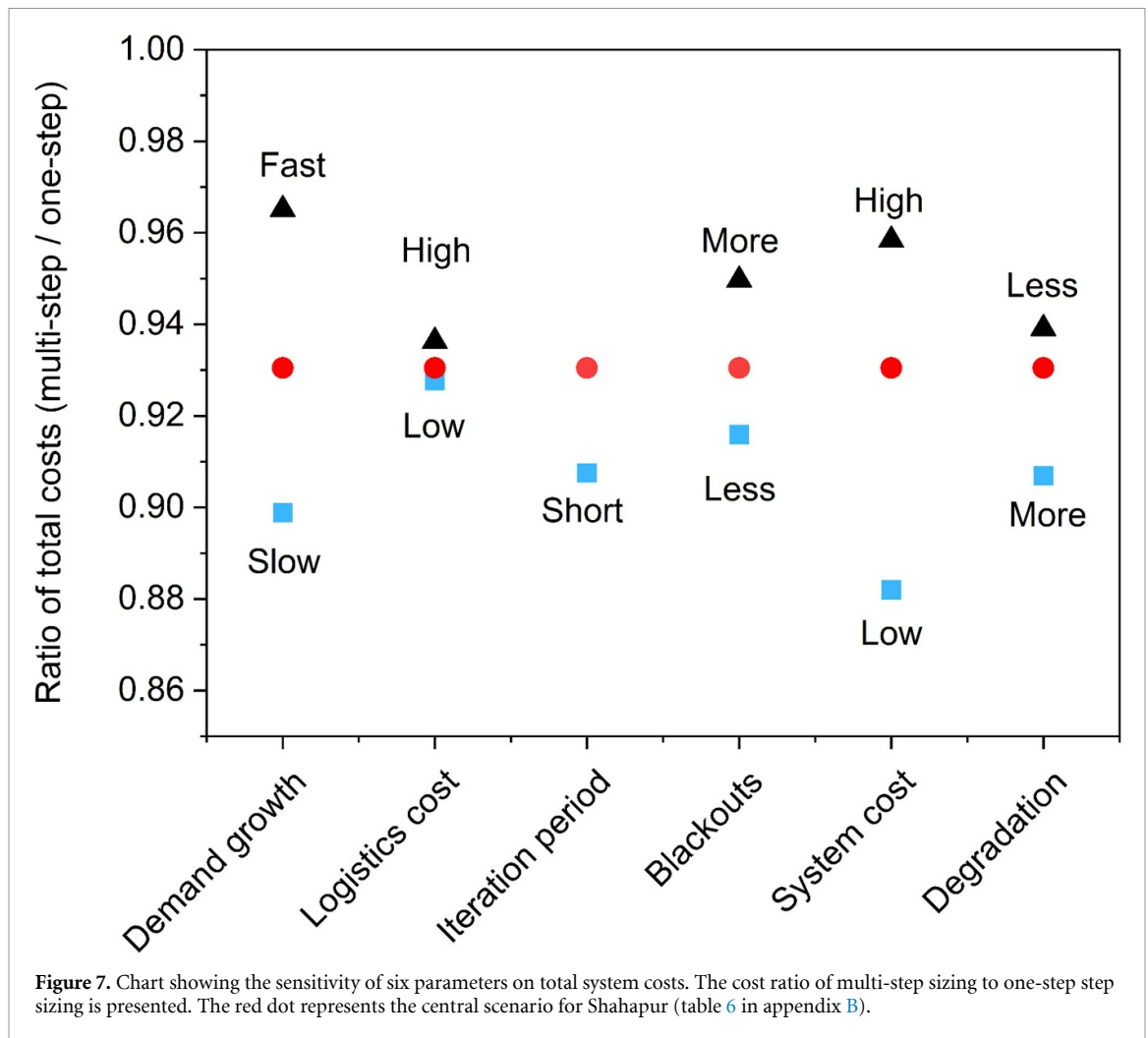


these parameters for the Adaptive demand growth scenario in Shahapur. Figure 7 presents the cost ratio of multi-step sizing to one-step step sizing for demand growth rate, logistics cost, iteration period, reliability (or frequency of blackouts), PV and battery cost and PV and battery degradation.

Results showed that for all parameters analysed, multi-step sizing had cost-saving potential compared to one-step sizing. Total system costs are especially sensitive to variations in demand growth rates (as shown in figure 3) and cost decreases in solar PV and storage. Less sensitivity was observed for changes in logistics costs. We found a cost-saving potential of 9% when increasing the iteration period from one-step of ten years to five steps of two years each. Fewer blackouts (or, equivalently, higher reliability) increased total system costs. There is a greater cost-saving potential with a multi-step sizing approach as reliability reaches 99% (fewer blackouts). Lower values of solar PV and battery lifetime (equivalently, greater degradation) are more cost-sensitive than higher values of solar PV and battery lifetime (less degradation). This may be because the length of the investigation period (10 years) is less than the expected solar PV lifetime (20 years). However, we found that cost sensitivity and degradation are tightly interdependent. These findings reaffirm that there is an association between cost-saving potential, reliability levels, and system performance. Thus, we investigated further the implications on system performance from different sizing approaches, as seen in figures 8 and 9.

### 3.4. System performance

Figure 8 shows system performance details, in terms of unutilised energy (figure 8(a)) and unmet energy (figure 8(b)) presented hourly over all days of each year in the Shahapur multi-step scenario. From figure 8(a), it can be observed that more energy is unutilised in the first two years of each step (Years 1–2 and 6–7) compared to the following three years, as demand grows and battery capacity degrades over time. Figure 8(b) represents intermittent occurrences of supply shortage regarding unmet energy, which is visibly less during the first three years of the simulation but it increases in the final years of each step due to demand growth. The noteworthy aspect of these analyses is the time of brownouts or blackouts occurrence. These are



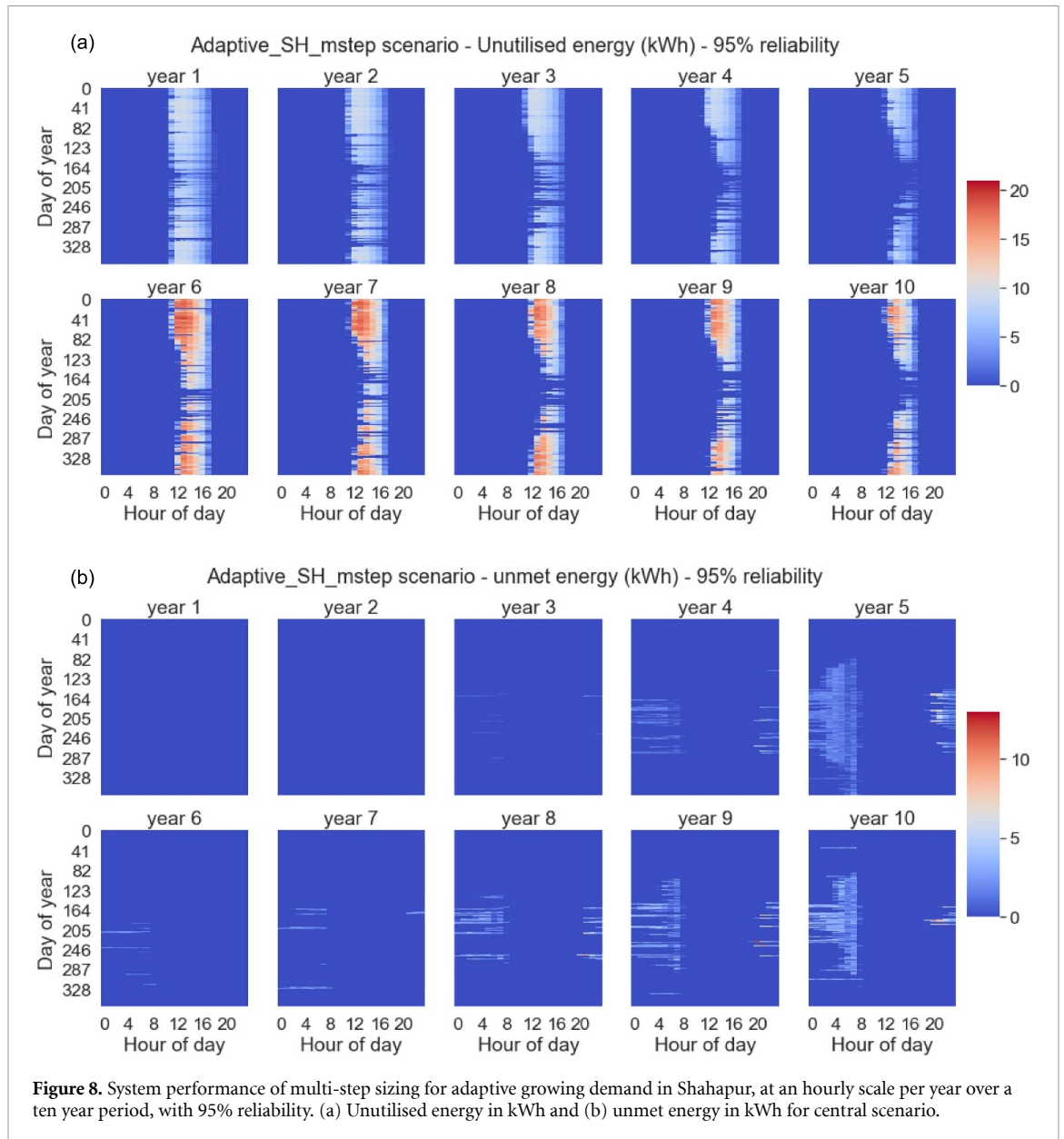
generally observed past midnight, between 2am and 7am, and very occasionally but to a higher degree during the evenings when demand is at its peak. Additionally, seasonal variation in the load is inversely visible in the unmet energy profile (figure 8(b)); more shortage of supply is experienced during the summer months when electricity demand is higher.

In contrast, as shown in figure 9, when system performance is compared with one-step mini-grid sizing, no brownout or blackout occurred until Year 5. This is primarily due to oversized storage capacity and low electricity demand at the beginning of the period (figure 9(a)). However, as batteries degrade over time whilst demand increases, more load remains unmet especially during the summer months of Years 9 and 10 (figure 9(b)).

Similarly, as presented in figure 10, the total amount of energy unutilised during the whole period is 32% higher in one-step sizing than in multi-step sizing for Shahapur. Another important factor to evaluate here is resource efficiency by looking at the energy balance between unmet energy and unutilised energy. This energy balance can be a valuable indicator of brownouts and blackouts that may occur during the investigation period. Figure 10 summarises this energy balance in Shahapur and highlights a contrast in terms of resource efficiency in both sizing approaches. Interestingly, unmet energy gradually increases and the unutilised energy gradually decreases over time in one-step approach, while in multi-step energy balance is achieved by adapting mini-grid size to the growing demand. Overall, these results provide important insights into system performance of cost-optimal mini-grids including implications of future growing demand (figure 13 in appendix B).

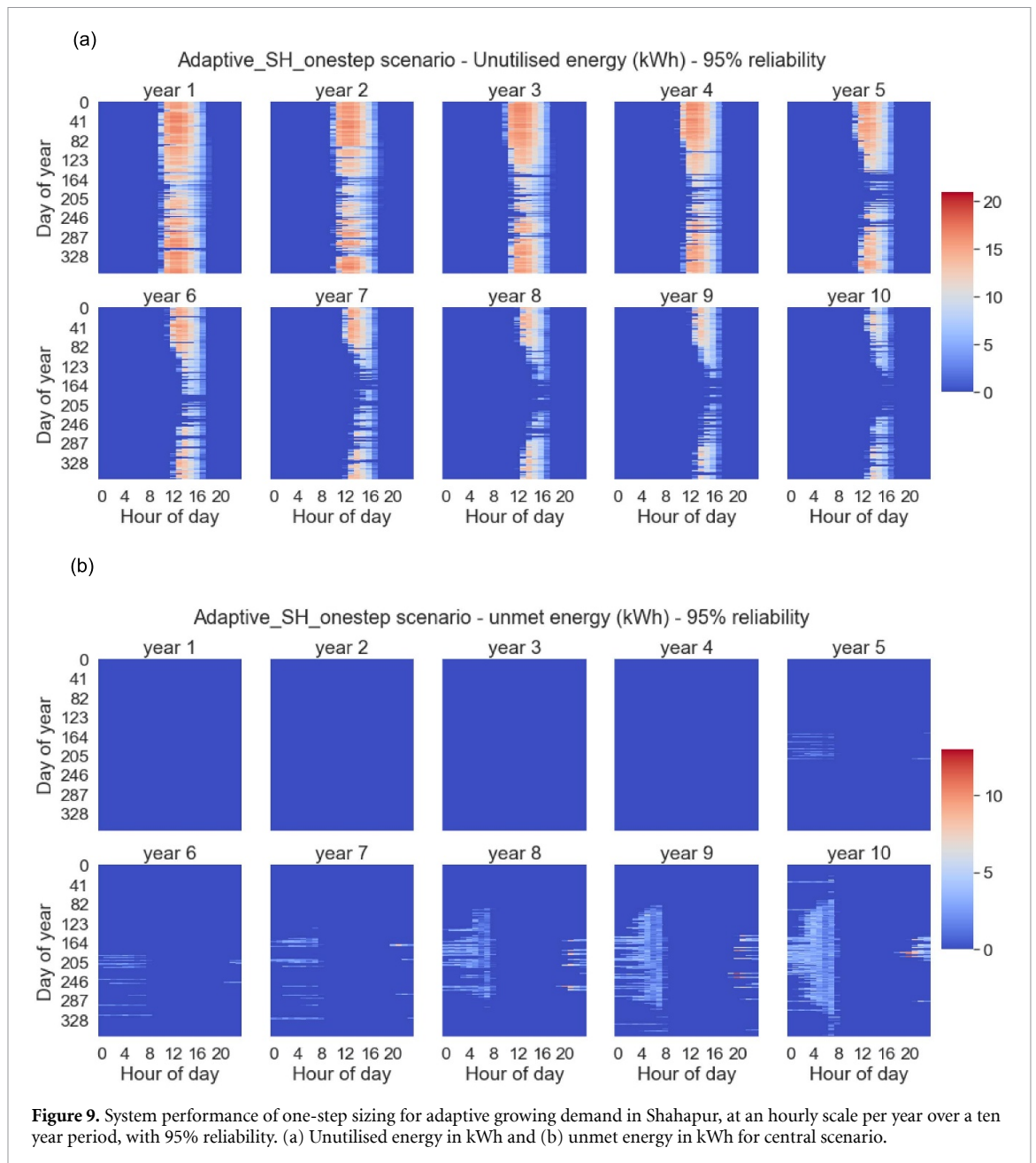
#### 4. Discussion

In this work, we found that future electricity demand growth assumptions from off-grid communities are a stronger driver of system size and costs than baseline demand. However, estimating future electricity demand in the off-grid sector is fraught with uncertainty (Mandelli et al 2016, Few et al 2022). Here, we implemented



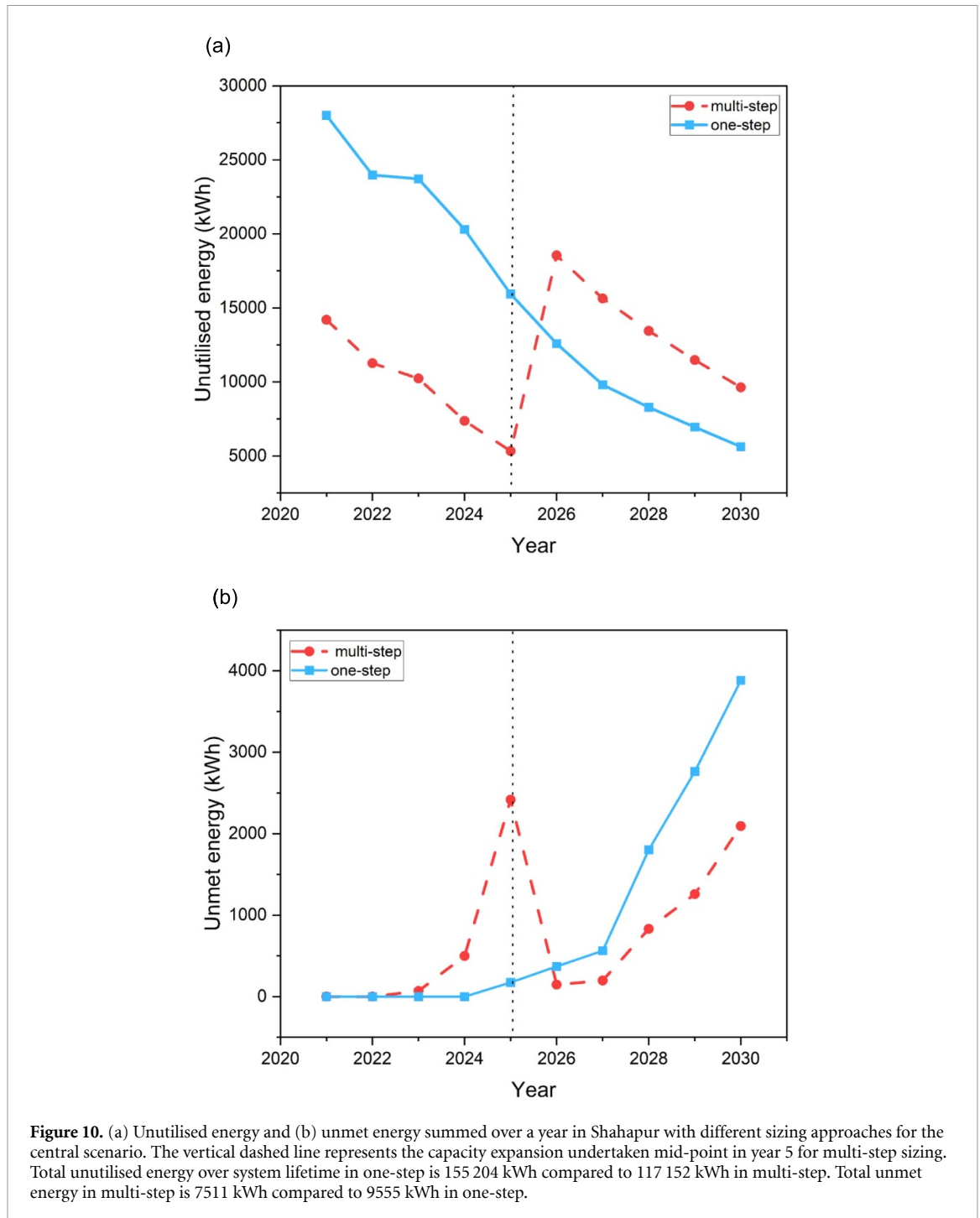
the Bass diffusion model which is a practical approach that can make realistic demand growth projections when market potential information such as number of appliance adopters is known or estimable. While these values are difficult to predict accurately (Radpour *et al* 2021), especially in recently electrified rural communities (Bhattacharyya and Timilsina 2010), multistakeholder engagement with the target community and developers' previous experience in recently electrified villages could improve its estimation. This would allow developers and practitioners to account for demand growth scenarios comprehensively by considering S-curve growth of appliances and incorporating these in optimisation tools to improve system sizing.

Multi-step sizing or modular design has cost-saving potential compared to one-step sizing, both in terms of total system costs and LCUE at the end of the simulated period, as shown in figure 6. This is in line with previous research by (Stevanato *et al* 2020), which found that the combination of multi-year formulation and capacity expansion approaches allowed the optimisation process to reach a more cost-effective solution. Similarly, (Fioriti *et al* 2021) recommended using multi-year approaches over single-year formulations as they are able to capture more design aspects. We found that most of the cost-savings potential is related to equipment costs, as O&M costs were comparable in all scenarios (figure 12 in appendix B). Thus, one of the advantages of the multi-step sizing approach is that it helps curb costs on depreciating assets. Although system oversizing (one-step) appears to be less cost-effective than multi-step sizing, the former has other possible advantages such as bulk purchasing at lower unit costs and fewer field visits to upgrade capacity expansion in further years. However, a detailed consideration of O&M costs is needed in future modelling efforts, given that it is challenging to accurately consider transport costs as they depend on exogenous factors



such as road networks and fuel costs. Nevertheless, our findings have shown that the cost versus reliability trade-off increases steeply as reliability reaches 99%, as noted previously by (Lee *et al* 2014, Sandwell *et al* 2017b, Chambon *et al* 2020).

We also found that the multi-step sizing approach is more efficient in terms of energy generation and usage than one-step. For example, larger amounts of energy are unmet and unutilised when applying a one-step approach (instead of multi-step sizing) in the case of growing demand in Shahapur. As shown in figures 8 and 9, results on system performance, especially on energy balance, are contrasting, demonstrating the implications of using different sizing approaches for mini-grid design. The possible explanation for the observed system performance could be the chosen technology of solar PV and battery used in this study. Typically, the majority of brownouts or blackouts occurred during the night (between 12am and 7am), and occasionally in the summer months evenings when batteries are discharged. Similar findings were reported by (Lee *et al* 2014) for a solar mini-grid in Mali. However, this system performance impact may be specific to solar PV-battery mini-grids, and thus it will vary depending on other back-up supplies analysed. In either case, the impact of blackouts on customer satisfaction will be less if these occurred in the middle of the night. However, service unavailability to meet peak demand in the summer months evenings may have a greater impact on customer satisfaction, especially for cooling needs. Further research should consider other parameters such as days of autonomy, as this was excluded in our analysis. Future studies should also include



demand for potential applications of electricity for clean cooking, for example via electric cookstoves. We suggest designing mini-grids with higher reliability levels to be able to accommodate for clean cooking loads, as an essential demand every day, in mini-grids yet to be installed.

Mini-grid developers and donors could take advantage of multi-step (or modular) sizing to save costs, but this may have other financial implications. For example, they would need to reserve resources or raise new funds to upgrade future capacity expansion. A potential risk could be limited electricity access from Years 5–10 onwards if the second planned installation is not implemented in the community. To improve modular sizing, we suggest verifying the demand with measurements over time. If demand grows faster than expected, developers could resize their mini-grids sooner than originally planned. In contrast, by installing the mini-grid that will meet the target demand at the start of the project (oversizing), developers risk mispending their investment if demand does not grow as expected. When designing mini-grids, developers



should pay careful attention to demand growth rates and cost decreases of solar PV and storage as these parameters are more cost-sensitive to the sizing approach chosen (oversizing or modular). Another recommendation is to employ a life cycle perspective when designing future mini-grids. This perspective is also key when considering the environmental impacts of different electricity sources. For example, solar PV and battery systems can have ten times lower carbon intensity compared to diesel-only systems in India (Beath *et al* 2021). Similar methodologies have been applied to investigate the costs and emissions intensity implications for mini-grid design in India (Few *et al* 2022).

## 5. Conclusion

We investigated different demand scenarios, sizing approaches and the cost-sensitivity of six parameters for mini-grid design in two rural Indian communities. We analysed the initial electricity demand of Sarvantara and Shahapur using a bottom-up stochastic method to characterise this demand in our baseline scenarios. A scenario of growing demand, to achieve a minimum level of electricity access by 2030, was modelled considering two sizing approaches: static (one-step) and modular (multi-step). As noted in this analysis, demand growth estimations are stronger drivers of system size and therefore costs compared to the baseline demand. Additionally, results showed that, from a techno-economic perspective, there are potential cost saving opportunities and improved resource efficiency when mini-grids are designed in a modular approach, whereby installed capacity is adjusted according to demand growth, as opposed to initial oversizing. These cost saving opportunities increase considerably as mini-grids are designed to ensure higher reliability levels. We show a cost-saving potential of up to 12% when mini-grids are sized using a modular approach, rather than a static optimisation approach. Moreover, modular sizing could potentially support strategic planning to accelerate electrification efforts by providing basic access in more villages in the first few years and adjust capacity expansion accordingly in the following years, instead of installing oversized systems in fewer villages. However, from a practical perspective, some developers might prefer to oversize their systems at the beginning to capitalise on economies of scale through bulk purchasing or to minimise field visits to mini-grid sites. Thus, ultimately the sizing approach will depend on the funding available and business model of the project. Despite this, it is important to have a detailed knowledge of the type of appliances available and their diffusion prospect in the target community to enhance demand growth projections. More granular approaches to model electrical appliance diffusion and usage may be merited here. Our methodology is also applicable to other solar PV and battery technologies, other locations and demand profiles, as well as other renewable technologies implemented in an energy access context.

## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

## Acknowledgments

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## Appendix A. Supplementary data

[Survey questionnaire](#) (in a separate file).



## Appendix B

### B1. Case studies locations



Figure 11. Map of India showing the case studies locations.

### B2. Input data details

Table 4. Scenarios load input data.

BS_SA	Average Ownership		Diffusion	
	Initial	Final	Innovation	Imitation
Appliances				
Lights	0.8	0.8	0	0
Mobile Phone	1.8	1.8	0	0
Radio	0.1	0.1	0	0
TV	0.05	0.05	0	0
Fan	0.15	0.15	0	0
Refrigerator	0	0	0	0
Adpt_SA	Average Ownership		Diffusion	
Appliances	Initial	Final	Innovation	Imitation
Lights	0.8	4	0.01	0.9
Mobile Phone	1.8	1.8	0.01	0.9
Radio	0.1	0.1	0.01	0.2
TV	0.05	1	0.03	0.9
Fan	0.15	1	0.03	0.9
Refrigerator	0	1	0.006	0.85
BS_SH	Average Ownership		Diffusion	
Appliances	Initial	Final	Innovation	Imitation
Lights	3	3	0	0
Mobile Phone	1	1	0	0
Security light	1	1	0	0
TV	0	0	0	0
Fan	0	0	0	0
Refrigerator	0	0	0	0

(Continued.)

Table 4. (Continued.)

BS_SA	Average Ownership		Diffusion	
	Initial	Final	Innovation	Imitation
Appliances				
Adpt_SH	Average Ownership		Diffusion	
	Initial	Final	Innovation	Imitation
Appliances				
Lights	3	5	0.01	0.9
Mobile Phone	1	2	0.01	0.9
Security light	1	1	0	0
TV	0	1	0.05	0.9
Fan	0	1	0.05	0.8
Refrigerator	0	1	0.02	0.5
Target	Average Ownership		Diffusion	
	Initial	Final	Innovation	Imitation
Appliances				
Lights	3	5	0	0
Mobile Phone	1	2	0	0
TV	1	1	0	0
Fan	1	1	0	0
Refrigerator	1	1	0	0

Table 5. Model input data.

Technical parameters	Value	Units	Notes
PV azimuth	180	Degrees	From north
PV tilt angle	29		From horizontal
Battery depth of discharge	40	%	Observation
Battery C-rate	0.33	—	Agarwal <i>et al</i> (2013)
PV lifetime	20	Years	IRENA (2020, 2021)
Battery lifetime	1000	Cycles	Institute for Transformative Technologies (2017)
Battery conversion efficiency	95	%	Sen and Bhattacharyya (2014)
Financial parameters	Value	Units	Notes
PV module	372	\$ kWp <sup>-1</sup>	Loom Solar (2022)
PV module O&M	7.45	\$ kWp <sup>-1</sup>	2% capital costs (Chambon <i>et al</i> 2020)
PV cost decrease	10	%	IRENA (2020, 2021)
Battery storage (Lead-acid)	150	\$ kWh <sup>-1</sup>	Institute for Transformative Technologies (2017)
Battery storage O&M	1.50	\$ kWh <sup>-1</sup> per annum	1% of capital costs; own assumption
Storage cost decrease	4	%	Schmidt <i>et al</i> (2017)
Connection cost	30	\$/Household	Field observations
Misc Cost	100	\$ kW <sup>-1</sup>	Includes logistics, installation and maintenance costs not covered above. Values based on assumptions.
Discount rate	9.5	% p.a.	As of October 2021 (FRED 2021)

**Table 6.** Additional scenarios with varying model parameters values (low and high) for sensitivity analysis.

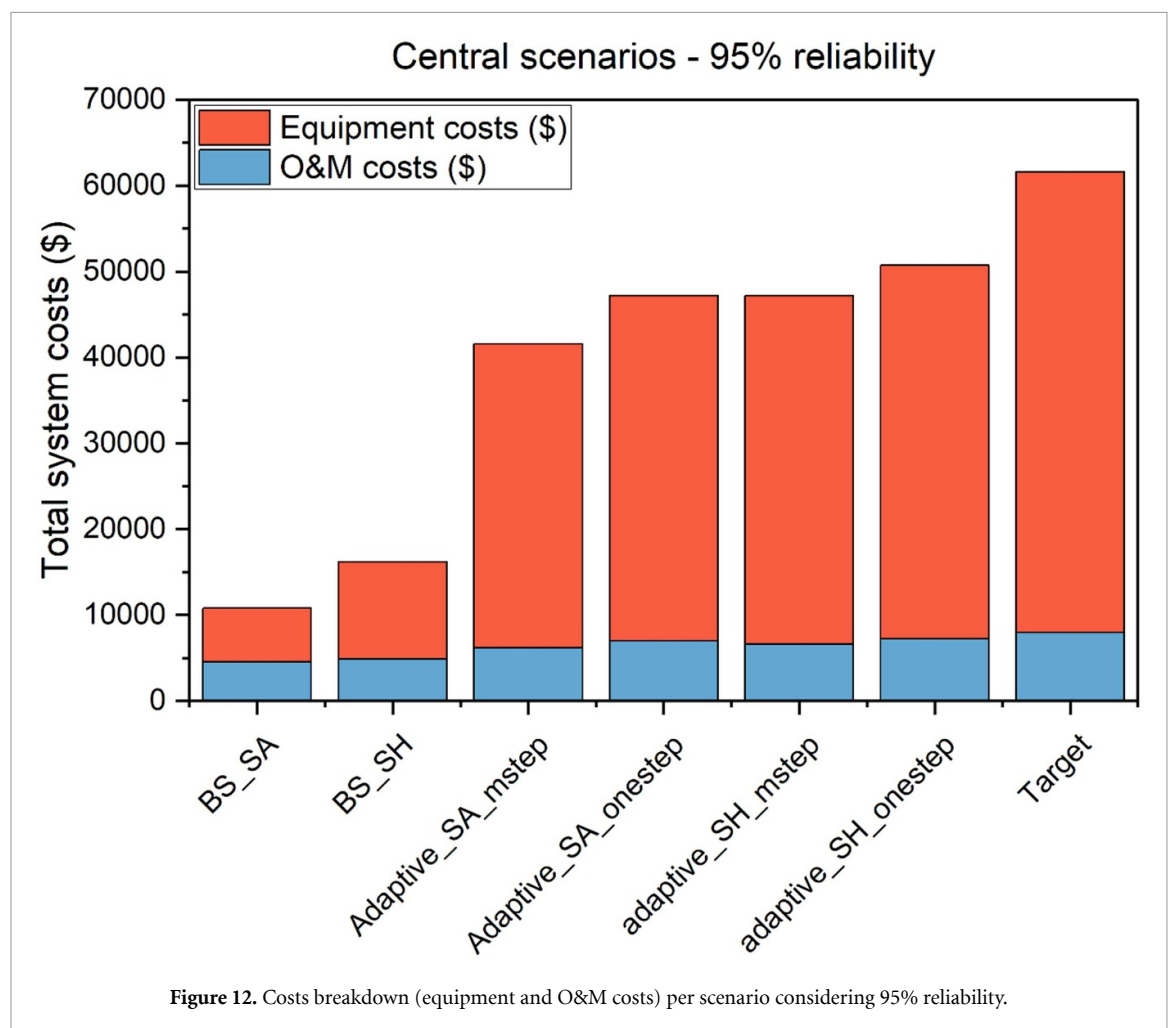
Additional scenarios	Parameters	Low value	Central value	High value	Location
1	Demand growth rate	Slow growth rate (S-curve)	Medium growth rate (S-curve)	Fast growth rate (S-curve)	Shahapur
2	Logistics cost	Misc. costs: 50 \$ kW <sup>-1</sup>	Misc. costs: 100 \$ kW <sup>-1</sup>	Misc. costs: 200 \$ kW <sup>-1</sup>	Shahapur
3	Iteration period	5 steps, 2 years (Smaller iteration period)	2 steps, 5 years (multi-step)	1 step, 10 years (one-step) (Longer iteration period)	Shahapur
4	Blackouts	99% (Less blackouts)	95%	90% (More blackouts)	Shahapur
5	PV & battery cost (rate per year)	PV cost decrease: 20% Battery cost decrease: 8% (Lower cost)	PV cost decrease: 10% Battery cost decrease: 4%	PV cost decrease: 5% Battery cost decrease: 2% (Higher cost)	Shahapur
6	PV & battery degradation (lifetime)	PV lifetime: 10 years Battery cycle lifetime (cycles): 1000 Battery lifetime loss = 40% (Lower system lifetime, more degradation)	PV lifetime: 20 years Battery cycle lifetime (cycles): 1000 Battery lifetime loss = 20%	PV lifetime: 30 years Battery cycle lifetime (cycles): 1000 Battery lifetime loss = 10% (Higher system lifetime, less degradation)	Shahapur

### B3. Sensitivity analysis

In all scenarios modelled, the resolution during the optimisation for solar PV and battery storage capacity step (system size increase) was 1 kWp and 5 kWh, respectively. The sufficiency criterion chosen was blackouts (or system reliability) with values of 0.1, 0.05, 0.01, depending on the scenario. LCUE was the optimisation criterion chosen to find the system size that will meet the specified system reliability at the lowest cost.

**Table 7.** Hours of usage of different appliances based on the survey responses in Sarvantara ( $n = 55$ ) and Shahapur ( $n = 50$ ). The number of users of an appliance is less than the sample size  $n$ , and this number is shown in the appropriate column for each appliance.

Appliance Type	Sarvantara (May 2017)					Shahapur (June 2019)				
	Average	Minimum	Maximum	Standard deviation	Number of users	Average	Minimum	Maximum	Standard deviation	Number of users
Fixed light	7	2	15	4	16	4	3	5	0.6	49
TV	4	3	4	1	3	3	3	6	1	14
Mobile phone	2	1	7	2	23	2	1	9	1.8	49
Fan	6	3	10	3	4	7	2	12	4.4	10
Radio	2	1	5	2	5	3	1	5	2.1	4
Security light	—	—	—	—	—	13	3	14	1.5	49



#### B4. Results

Despite being located in different regions of India, the hours of usage in Sarvantara and Shahapur have similar values. Fixed light usage seems to be higher in Sarvantara. However, during the field work in Shahapur it was found that households had an additional security light that they left on at night.

Figure 14(b) shows that between year 1 and 5 of multi-step sizing, storage size is small and sufficient to meet the initial load which is starting to grow from the baseline demand. While in the second step, the increased storage capacity in year 6 results in a higher level of charging during the day and of discharging during the evenings to meet the peak demand. In contrast, one-step sizing (figure 14(a)) shows higher levels of charging during the first years due to oversized storage capacity installed at the beginning of the period.

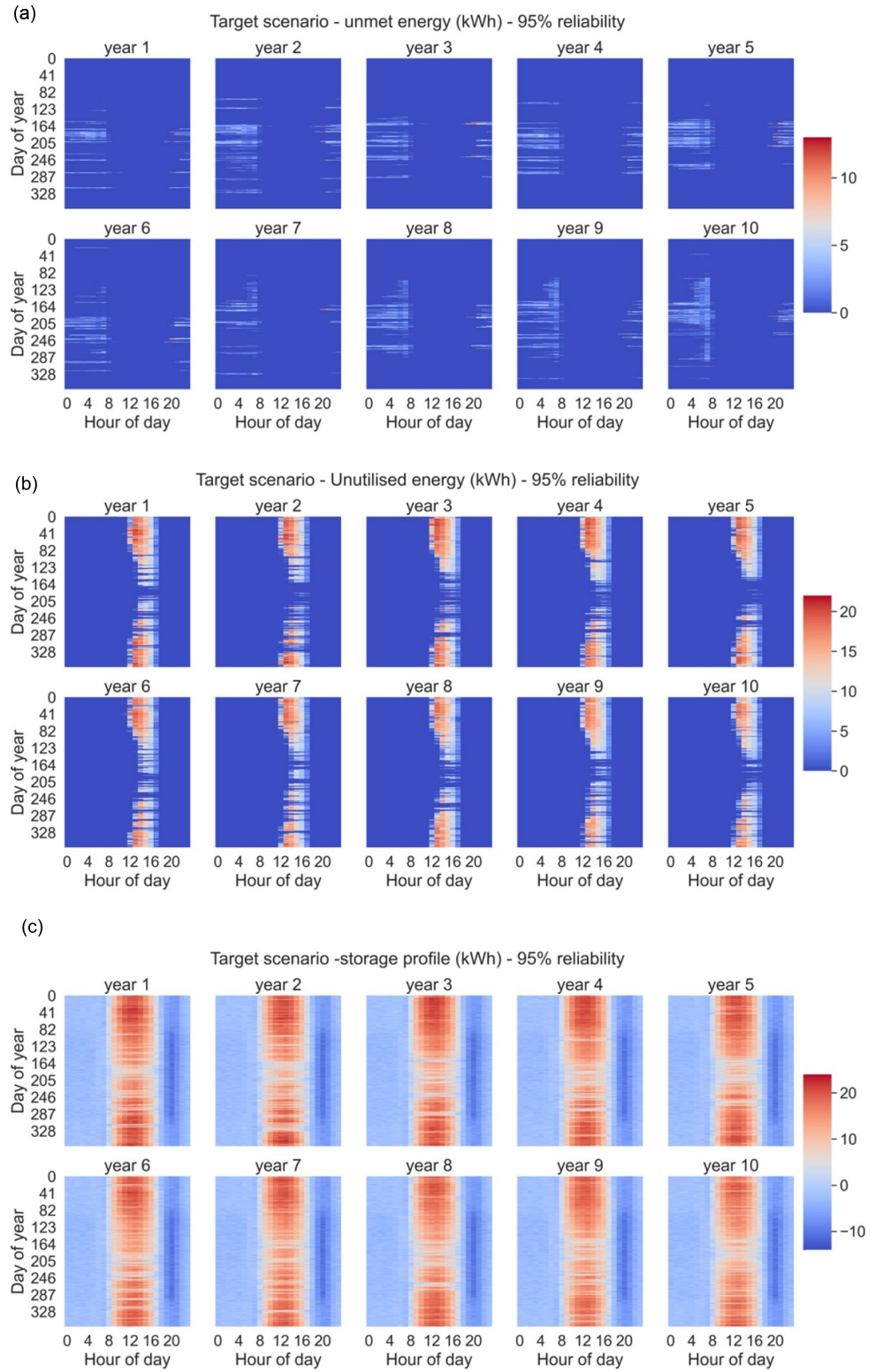
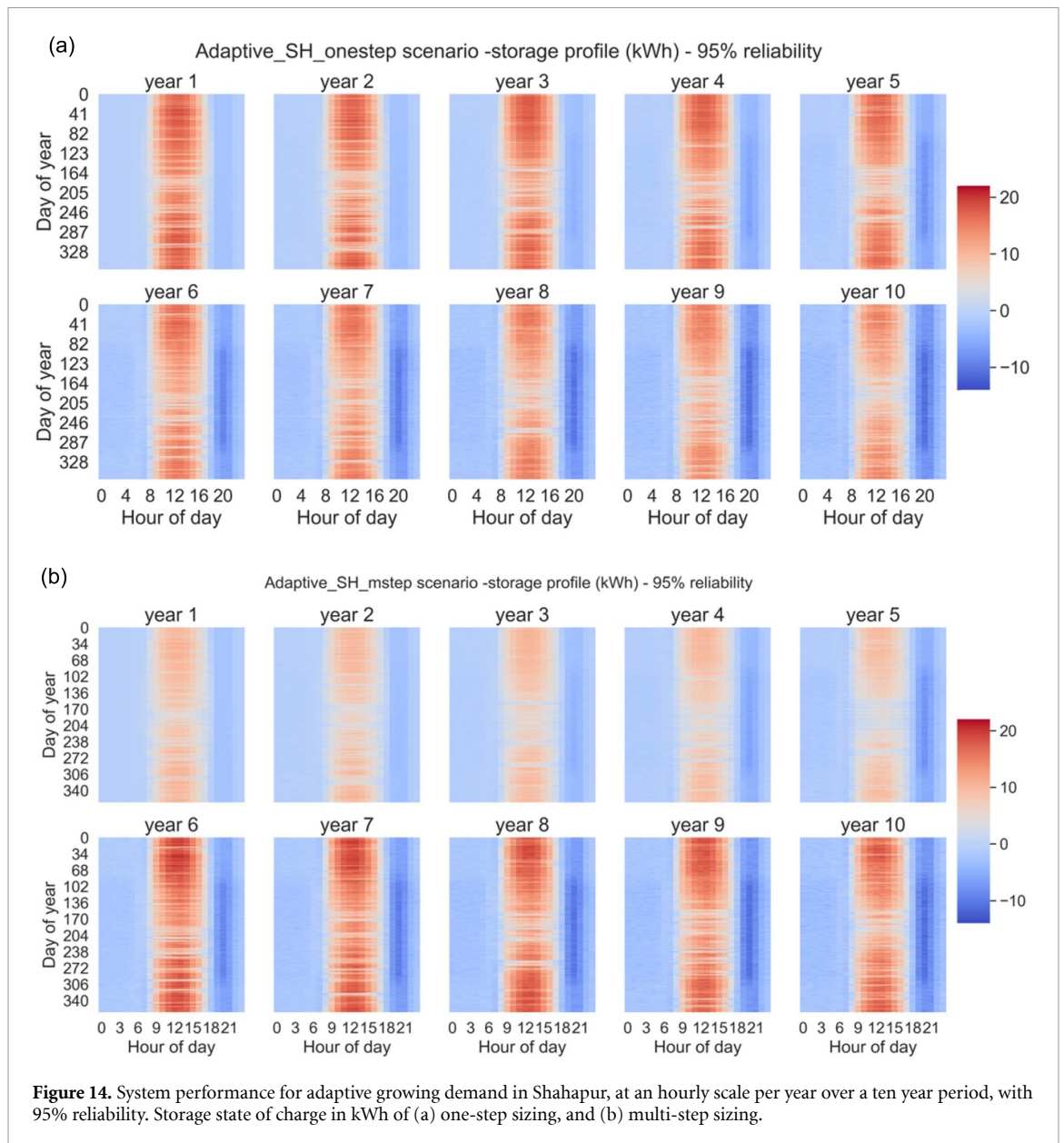


Figure 13. System performance of static demand in target scenario at an hourly scale per year over a ten year period, with 95% reliability. (a) Unmet energy in kWh, (b) unutilised energy in kWh and (c) storage profile in kWh.



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