**Article:**

Few, S. orcid.org/0000-0002-0876-158X, Barton, J., Sandwell, P. et al. (5 more authors) (2022) Electricity demand in populations gaining access: Impact of rurality and climatic conditions, and implications for microgrid design. Energy for Sustainable Development, 66. pp. 151-164. ISSN: 0973-0826

https://doi.org/10.1016/j.esd.2021.11.008

# Electricity demand in populations gaining access: impact of rurality and climatic conditions, and implications for microgrid design

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## Abstract

Almost 800 million people currently lack access to reliable electricity, for many of whom solar microgrid systems are expected to be the most cost-effective solution. Quantifying current and future electricity demand is crucial for cost-effective design of reliable microgrids. However, electricity usage is connected to a wide range of social and economic factors alongside climatic conditions, making estimation of demand challenging. This paper presents a framework facilitating each stage of solar microgrid design from demand estimation through to cost-optimal sizing of the microgrid and its economic and environmental characterisation. Household demand is simulated based upon (1) climatic conditions, (2) appliance ratings and usage patterns, and (3) rates of growth in appliance ownership based upon the Multi-Tier Framework for measuring household electricity access. Microgrid demands are simulated based on the combination of these with (4) nondomestic demand based upon locally available data. The framework is demonstrated across four rates of domestic demand growth and two climatic conditions ('tropical savanna' and 'humid subtropical'), alongside nondomestic demand based upon two operational microgrids (one rural and one peri-urban). When growth rates are high, newly introduced appliances tend to dominate, with differing impacts on the demand profile depending on power and usage times. Cooling represents a modest contribution to demand in the tropical savanna climate. However, in the hotter and more seasonally varying humid subtropical climate, cooling becomes the dominant driver of demand, increasing seasonality and proportion of demand at night. Nondomestic demand in the rural microgrid is primarily agricultural, and exhibits more seasonality and better alignment with daylight hours than demand in the peri-urban setting, which is more service-based. Across cases, increased seasonality and proportion of demand at night lead to poorer alignment with PV generation, increasing cost and GHG emissions per unit of electricity used in a cost-optimised microgrid system.

Keywords: electricity demand, microgrid, rural electrification, cooling demand, climate, technoeconomic assessment

## Introduction

Universal access to "affordable, reliable, sustainable, and modern energy" by 2030 represents the seventh of the UN's seventeen sustainable development goals (SDGs) and underpins many of the other SDGs (Nerini et al., 2018; United Nations, 2015). However, an estimated 789 million people still lacked access to electricity in 2018, and current rates of increasing access are not sufficient to meet this goal (International Energy Agency et al., 2020).

Many of those lacking access to electricity live in remote regions where off-grid and microgrid solutions are expected to be more cost-effective than national grid connection (Blechinger et al., 2019; Ortega-Arriaga et al., 2021). As such, the International Energy Agency and the World Bank estimate that mini grids are the least-cost option for 40 percent of those who will need to gain electricity access by 2030(Energy Sector Management Assistance Programme (ESMAP), 2019; IEA, 2017). Almost 90% of these are expected to be powered by solar photovoltaics (PV), with batteries providing backup power. However, solar microgrids remain capital intensive, and many of those lacking access to electricity also lack access to capital. Therefore, increasing affordability associated with solar microgrids represents a key challenge to accelerate the achievement of SDG 7. In light of international agreements to limit global heating, these microgrids should also be deployed with a minimum of associated GHG emissions (United Nations Framework Convention on Climate Change, 2015).

An understanding of the magnitude and temporal distribution of electricity demand is an important prerequisite for the design of a cost-effective and low emissions solar microgrid system. The magnitude of demand determines the size of system that will be required to meet this demand, and the temporal distribution of demand determines the appropriate balance between generation (eg. solar PV, diesel generation) and storage (eg. lithium-ion or lead-acid batteries). The existence of sharp peaks in demand (and smoothing of times of these between multiple users) defines required power capacity of the system (Narayan et al., 2018). The combination of the above factors determines the cost and GHG emissions intensity associated with meeting needs with a given level of reliability (Treado, 2015). Overestimating demand can lead to an oversized system, increasing associated cost and GHG emissions without delivering commensurate benefits. Underestimating demand can lead to a system which is unable to provide a reliable supply of electricity, potentially undermining electricity users' trust in the system, and their propensity to invest in activities which rely upon it (Gibson and

Olivia, 2010; Riva et al., 2018). As such, developing a better understanding of electricity demand, and factors which may influence this across contexts, is important for governments and NGOs invested in achieving universal access to modern energy, and microgrid developers seeking to design systems to accommodate present and future requirements.

Electricity use is interconnected with a wide range of social and economic factors through a complex network of causal relations (Bisaga and Parikh, 2018; Dominguez et al., 2021; Riva et al., 2019, 2018), potentially dependent on capacity building activities developed in parallel with microgrid deployment, and estimating demand in communities newly gaining access to electricity is fraught with challenges. There is little measured demand data, and much of what does exist is confidential. Survey approaches are frequently used to inform a baseline level of electricity demand, but these frequently show substantial discrepancies with measured demand. These discrepancies have been attributed to differences in appliance ownership, appliance ratings, and times of use between survey results and measured data (Blodgett et al., 2017; Hartvigsson and Ahlgren, 2018).

Further, microgrid systems typically include components lasting many years, and may serve users' demand over a long period. Therefore, estimating future evolution in demand is also important for the appropriate design of a microgrid system. Subject to appropriate social and economic conditions, electricity usage may increase over time, as electricity users gain access to a more reliable electricity supply, acquire new household appliances and develop income generating activities which make use of electrical devices (Gustavsson, 2007; Hartvigsson et al., 2021). This has been encapsulated in the concept of an "energy ladder", which considers that household energy choices change with income, following a linear movement toward higher forms of energy (Bhatia and Angelou, 2015). This represents a simplifying assumption, and in practice energy use is more dynamic, with households sometimes not climbing the ladder as expected, or combining sources of electricity (Bisaga and Parikh, 2018; Riva et al., 2018). However, it can still provide useful benchmarks by which levels of electricity access can be compared.

Electricity demand can vary between more remote and sparsely populated rural areas, and more accessible and densely populated peri-urban areas (Riva et al., 2018). This can be partly attributed to differences in forms of nondomestic electricity use, with a higher prevalence of agricultural activities such as milling and water pumping in rural areas, and of service activities such as bars, restaurants, and tailors in urban areas. Agricultural demand can vary seasonally depending on rainfall and crop cycles (Mukherjee and Symington, 2018) whilst service demand typically remains more consistent throughout the year. Where communities have access to larger markets through roads and telecommunication, these can present opportunities to generate additional income, but also impact electricity demand characteristics by extending working hours into the evening (Neelsen and Peters, 2011; Riva et al., 2018). This dynamic has been demonstrated for shops, barbers, and restaurants (Kooijman-van Dijk, 2012; Kooijman-van Dijk and Clancy, 2010; Meadows et al., 2003).

Household electricity demand associated with cooling technologies responds to daily and seasonal cycles (Barton et al., 2020; Bhattacharyya, 2015; Filippini and Pachauri, 2004). Cooling demand may be expected to be higher in hotter climates (Barton et al., 2020), but little attention has been devoted to this dependence in the context of populations newly gaining access to reliable electricity. Globally, electric fans and air conditioning (AC) account for almost 20% of energy demand in buildings. This is projected to triple by 2050 in a baseline scenario (International Energy Agency, 2018). Until now, the majority of the AC stock has been installed in more affluent countries with well-established grid-based electricity systems. However, the majority of growth is expected to occur through households installing their first AC unit in emerging economies in hot climates. Given the substantial overlap of regions with low access to electricity and those with the greatest need for cooling (ibid), there is the potential for substantial growth in cooling demand in some off-grid systems.

Motivated by the lack of quantitative data on electricity demand, previous studies have developed bottom-up techniques for analysing and modelling electricity demand amongst populations newly gaining access. The commercial software package HOMER offers a tool to create synthetic demand profiles, but provides little publicly available information on the approach and underlying assumptions guiding this process (HOMER Energy LLC, 2021). (Narayan et al., 2018) develop a stochastic model for electricity demand associated with households at each level of the World Bank's Multi-Tier Framework for energy access, highlighting the important role new sources of demand could play in determining household electricity demand and appropriate sizing of solar home systems to meet this demand. (Stevanato et al., 2020) take a scenario-based approach to model demand growth and implications for microgrid design in a single location over twenty years, using a stochastic tool developed by (Lombardi et al., 2019) and (Mandelli et al., 2016). This tool is developed specifically to model demand in communities newly gaining access to reliable electricity, and simulates electricity use across user types (household, school, hospital, hostel). Its application highlights the importance of demand growth assumptions for overall microgrid system design. However, it does not explicitly account for implication of climatic conditions on demand profiles.

(Barton et al., 2020) highlight the importance that climatic conditions could have in determining electricity demand, adapting a stochastic tool developed for estimating electricity demand in UK households with temperature profiles and appliance inputs representative of Indian conditions, but have not applied this tool in a microgrid context. (Alonso et al., 2021; Hartvigsson et al., 2021; Stevanato et al., 2020) incorporate diverse forms of nondomestic demand associated with different activities in specific microgrids into demand profiles. These works highlight the importance of type of nondomestic activity, which will depend on economic and rurality context, on demand profiles and appropriate microgrid sizing.

There remains substantial work to be done in connecting bottom-up approaches to simulating time-dependent electricity demand with dynamics affecting electricity demand across social, economic, and climatic contexts. This paper contributes by addressing the following three questions:

- What are the sources, magnitudes, and temporal distribution of domestic and nondomestic demand amongst populations newly gaining access to electricity and how do these vary between a more remote rural and a peri-urban context with greater access to markets?
- How might growing appliance ownership affect domestic demand growth over time, how might this affect load profiles, and how does this depend upon the variation in lighting and cooling requirements across climatic conditions?
- What are the implications of these differences for total electricity demand, and cost and emissions intensity associated with a cost-optimal solar microgrid system to meet this?

An open source framework is used to answer these questions, combining newly developed and pre-existing tools to estimate household demand based upon appliance ownership and climatic conditions, measured and modelled nondomestic demand profiles from a rural and a peri-urban location, and a microgrid sizing tool informed by these demand data.

## Methodology

The methodology used in this study consists of five distinct stages as summarised in Figure 1. First, real data on current domestic and nondomestic demand from microgrids in a rural and a peri-urban context are analysed. Second, potential future demand at a household level is simulated using the CREST demand model. This simulation is based upon appliance characteristics and ownership across tiers as specified in the World Bank's Multi-Tier Framework, coupled with climatic conditions derived from the Renewables.ninja platform for the location of the two microgrids from which current demand data was derived. Third, current demand from these two microgrids, as well as simulated future domestic demand, are characterised according to new and established metrics. Fourth, ten-year scenarios are developed for domestic demand at a microgrid level based upon differing proportions of households achieving different tiers of access by year. These scenarios are distinguished by rate of domestic demand growth: None, Slow, Medium, Fast, and Faster. Fifth, microgrid systems are simulated, cost-optimised, and characterised using the CLOVER model based upon each combination of rurality, rate of domestic demand growth, and climatic condition. The implications of each of these factors for cost-optimal PV and storage sizing, associated cost, and GHG emissions are considered in turn.

Data and modelling techniques are freely available at https://github.com/sheridanfew/ElDemAcc, although data from households and businesses is available only in an aggregated form to maintain privacy (Few, 2021).

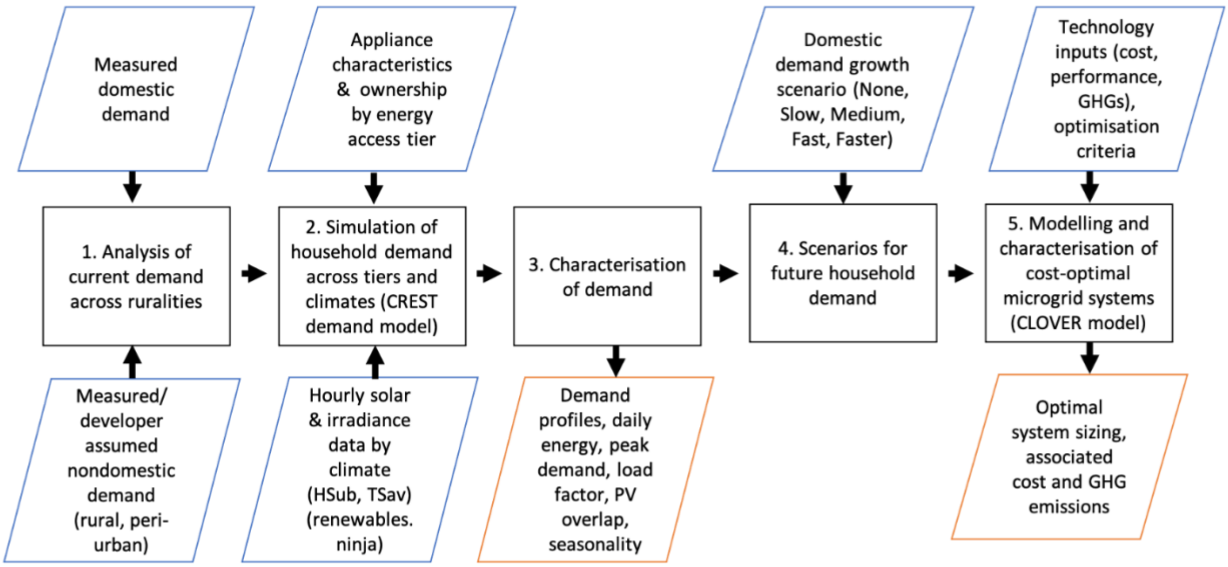



*Figure 1 Workflow associated with the methodology developed in this study*

### *Current demand across contexts*

Demand data is analysed for two operational microgrids, one in a peri-urban location (Gitaraga, Rwanda) relatively close to the capital city, and one in a rural location (Bhinjpur, Jharkand, India), which is substantially more remote and further from an urban centre. Services such as bars and hairdressers form a key part of nondomestic demand in the peri-urban context, alongside tailors and welding workshops. Agricultural activities, namely water pumping and rice polishing, are the sole sources of nondomestic demand in the rural context. The association of nondomestic demand with services in the peri-urban location and agricultural activities in the rural location is in line with previous studies examining sources of electricity demand in peri-urban (Neelsen and Peters, 2011; Riva et al., 2018) and rural contexts (Mukherjee and Symington, 2018). As such, whilst exact values will be specific to these locations, the assumed final end uses and nondomestic demand in rural and peri-urban contexts may be expected to be comparable to other similar locations , and could inform expectations in other locations gaining access to electricity.

For the peri-urban location, monitored demand data from 2019 is available from the microgrid developer on a sub-hourly basis across domestic and nondomestic end users. For the rural community, demand is not measured directly, but estimated by the microgrid developer based upon knowledge of daily and seasonal cycles in milling and irrigation, developed through an ongoing relationship with the community which the microgrid serves, in addition to knowledge of the characteristics of the equipment used. Whilst measured data is not available to verify this estimation, this still represents a useful starting point given the dearth of publicly available information on nondomestic load in an off-grid context. However, caution should be taken in overinterpreting these profiles. In previous studies, interview-based load profiles have overestimated energy demand for electric machines used by SMEs due to an incorrect assumption of constant high power demand during usage hours (Hartvigsson and Ahlgren, 2018), which could affect estimated profiles here too.

Domestic demand is assumed to be similar in the rural and peri-urban locations, since similar devices are present, although differences in routine are likely to have an impact on time of use of these devices in practice. As high-quality measured data is available for households in the Gitaraga site, this is used to represent domestic demand in both the rural and peri-urban contexts. These data are combined to build up comparable demand profiles across the year for the peri-urban, and a rural microgrid location, as shown in Table 1, where domestic demand is similar across the two locations, and nondomestic demand is based upon those observed in the case study locations. This nondomestic demand is scaled on a per capita basis in the peri-urban location, to make them comparable in size with the rural location. Further details of the communities from which data was gathered are included in an appendix.

*Table 1 Key details of microgrid-connected communities considered in this study*

| Community Details | Peri-urban | Rural |
|---|---|---|
| Number of households | 100 | 100 |
| Household appliances | Lights, USB charging | Lights, USB charging |

| | | |
|---|---|---|
| Nondomestic electricity users | 4 bars, 1 cinema, 2 hairdressers/barbers, 1 shop, 2 tailors, 1 welder/workshop, 1 mosque | 1 rice polisher, 1 irrigation pump |

*Simulation of future household demand by climate and energy access tier*

Future household demand is simulated based upon the World Bank's Multi-Tier Framework. This framework classifies electricity access across five tiers, based upon increasing availability of energy, power, associated energy services, and reliability (Bhatia and Angelou, 2015). Each of these tiers is also associated with the ability to power devices of increasing levels of power and energy consumption, ranging from those described as "very low power" (Tier 1) to "very high power" (Tier 5). Key parameters associated with household electricity demand across these tiers, alongside typical supply technologies as specified in (Bhatia and Angelou, 2015) are presented in Table 2. Whilst the energy access tiers cannot fully represent the complexity of changing practices around energy consumption, they still represent a useful set of benchmarks by which levels of energy access may be compared across studies.

There is no universal definition of "affordable, reliable, sustainable, and modern energy services" as described in SDG 7 (United Nations, 2015) or how this maps on to tiers in the Multi-Tier Framework. In calculating levels access to electricity, the International Energy Agency specify a minimum consumption of 250 kWh per year for rural households, and 500 kWh per year for urban households (IEA, 2020). These are equivalent to around 700 and 1400 Wh per day, respectively; the upper end of Tier 2 and lower end of Tier 3. The Energy for Growth Hub have described this level of access as an "extreme energy poverty line", consider 1000 kWh per household a requirement for the first stages of development in rural communities, and recommend 1000 kWh per person per year (5000 kWh per household) as a "modern energy minimum" (Moss et al., 2020). They stress that approximately 70% of this quota should be available for uses in the wider economy, with the remainder (around 4100 Wh per day) in the household, comfortably within Tier 4. As such, each of Tiers 1 – 4 are of interest in the context of provision of minimum levels of modern energy access, with Tier 5 representing a more ambitious goal above this minimum threshold.

*Table 2 – Multi-Tier Matrix for Measuring Access to Household Electricity Supply* (Bhatia and Angelou, 2015).

| Tier | Minimum Daily Energy Availability (Wh) | Minimum Available Power (W) | Example Electrical Appliances | Typical Supply Technologies |
|---|---|---|---|---|
| *1* | 12 | 3 | Task lighting, phone charging, radio | Solar lantern |
| *2* | 200 | 50 | Multipoint general lighting, television, computer, printer, fan | Rechargeable battery, solar home system (SHS) |
| *3* | 1000 | 200 | Air cooler (evaporative), refrigerator, freezer, food processor, water pump, rice cooker | Medium SHS, fossil fuel-based generator, mini-grid |
| *4* | 3400 | 800 | Washing machine, iron, hairdryer, toaster, microwave | Large SHS, fossil fuel-based generator, mini-grid, central grid |
| *5* | 8200 | 2000 | Air conditioner, space heater, vacuum cleaner, water heater, electric cooker | Large fossil fuel-based generator, central grid |

In simulating household demand, appliance ownership associated with households at each tier of the Multi-Tier Framework are defined based upon the deployment of a subset of devices from the examples specified in Table 2. The selection of this subset is somewhat arbitrary and motivated partly by those appliances for which data was available. This may be justified by the hypothetical nature of appliance ownerships at higher tiers, and the lack of data from deployed microgrids reaching these tiers of access. This selection leads to appliance ownership by tier as specified in Table 3, which are used as inputs in simulating household load. The deployment of high power appliances associated with Tier 5 represents an ambitious assumption, and is included in only one of our load growth scenarios.

Demand profiles associated with households using these sets of devices are stochastically simulated using the CREST demand model, described in (Barton et al., 2020; McKenna and Thomson, 2016). This model is chosen for its ability to simulate household demand across a range of appliances on a minute-by-minute basis, informed by measured data, in addition to its coupling with a thermal building model, allowing more accurate simulation of electricity demand associated with cooling technologies, and how this depends upon climatic conditions.

*Table 3 – Devices introduced for households at different energy access tiers in this study based upon* (Bhatia and Angelou, 2015)*. Each household at each Tier 1 - 5 operates appliances newly introduced at that tier, in addition to devices introduced at lower tiers.*

| Tier Intro-duced | Device | Category | Typical Usage (hrs/yr) | Operating Load (W/appliance) | Source |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 1 | Phone charger (×2) | *Appliance* | 667 | 3 | (Narayan et al., 2018) |
| | LED bulbs (×8) | *Lighting* | N/A | 3 | (Narayan et al., 2018) |
| 2 | Personal computer | *Appliance* | 1327 | 55 | (Barton et al., 2020) |
| | TV | *Appliance* | 1706 | 17 | (Verasol, 2020) |
| | Fan | *Space Cooling* | N/A | 20 | (Barton et al., 2020) |
| 3 | Fridge freezer | *Appliance* | 3185 | 65 | (Verasol, 2020) |
| | Air Cooler (evaporative) | *Space Cooling* | N/A | 100 | (Barton et al., 2020) |
| 4 | Iron | *Appliance* | 18 | 1000 | (McKenna and Thomson, 2016) |
| | Microwave | *Appliance* | 60 | 1080 | (Barton et al., 2020) |
| | Washing machine | *Appliance* | 830 | 403 | (McKenna and Thomson, 2016) |
| 5 | Vacuum Cleaner | *Appliance* | 37 | 2000 | (McKenna and Thomson, 2016) |
| | Electric Hob | *Appliance* | 115 | 2400 | (McKenna and Thomson, 2016) |
| | Air Conditioning | *Space Cooling* | N/A | 1250 | (Barton et al., 2020) |

Appliance characteristics are derived from a combination of sources. Where available, specifications for low power devices developed specifically for off-grid settings are used (Barton et al., 2020; Narayan et al., 2018; Verasol, 2020). These are typically those associated with lower tiers of access, such as phone chargers, LED bulbs, TVs, and fridge freezers. Data for higher power devices, which have so far been rarely deployed in an off-grid setting are taken from more generic sources (Barton et al., 2020; McKenna and Thomson, 2016). It should be noted that availability of efficient devices will differ between locations, and devices performing similar functions can vary substantially in their power usage and efficiency. Whilst not explored here, the use of inexpensive but inefficient devices has led to differences between estimated and measured demand in other contexts (Hartvigsson and Ahlgren, 2018).

For most appliances, demand is calculated based upon operating load of the appliance, typical hours of usage per year, times during which householders are present, and parameters determining typical device operating periods (McKenna and Thomson, 2016) (full data informing these available at https://github.com/sheridanfew/ElDemAcc). For cooling and lighting technologies, demand is modelled differently, as climatic conditions impact annual demand. Cooling demand is simulated through thermal building modules within the CREST model. Each household is stochastically assigned a demand temperature based upon survey results and measured data reported in (Huebner et al., 2013). Cooling technologies begin to operate in each household only when occupants are present and the internal building temperature reaches 2°C or more above the demand temperature. Cooling ceases once temperature falls 2°C below the demand temperature.

Two climatic conditions are explored based upon the two microgrid locations from which current demand data are taken: Gitaraga and Bhinjpur. These represent a tropical savanna (TSav) and humid subtropical (HSub) climate (Beck et al., 2018), respectively. Associated temperature, insolation derived from the Renewables.ninja platform for these locations (Pfenninger and Staffell, 2020, 2016), and rainfall profiles for the nearest cities (Kigali and Ranchi) (Climate Data, 2021) are shown Figure 2.

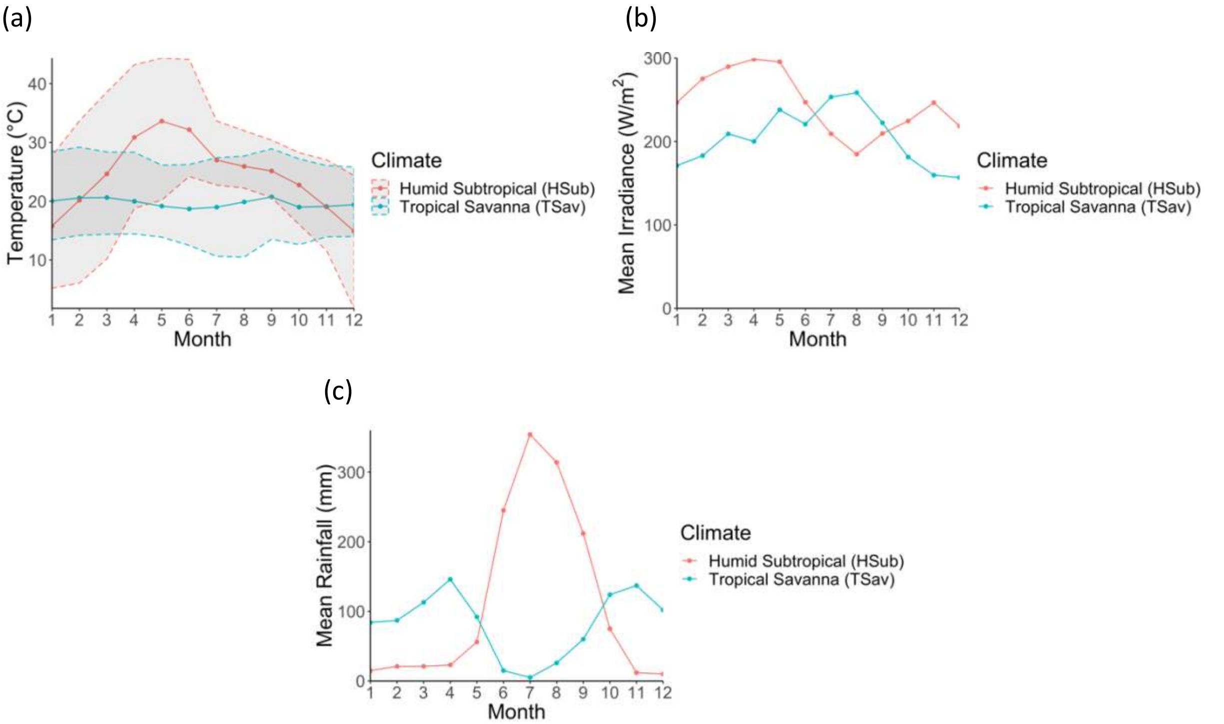



*Figure 2 Climatic conditions for considered tropical savanna and humid subtropical climates: (a) Mean, maximum, and minimum monthly temperature, (b) mean solar irradiance (direct and diffuse), and (c) mean monthly rainfall.*

The CREST demand model is used to generate 24 hours of minute-by-minute demand data across 25 households for a weekday and a weekend day of each month of the year, across energy access tiers and climatic conditions. These data are converted into hourly demand profiles, and concatenated to produce demand data for 365 consecutive days for each household across each energy access Tier 1 – 5, in each climatic condition, TSav and HSub. Average load profiles across households and days are shown in results sections, and a random selection of one of the 25 simulated households at the appropriate tier and climatic condition is made in developing load profiles for the whole microgrid system. It is chosen to simulate 25 households as this represents the approximate number of households at which variation in times of peak demand is sufficiently large that adding additional households has little impact on the shape of the overall demand profile (Love et al., 2017; McKenna and Thomson, 2016).

### *Characterisation of demand*

A number of metrics are used to characterise domestic and nondomestic demand profiles described above, in order to better understand the role that this demand plays in defining the demand in and specifications of the entire microgrid system. Following (Hartvigsson and Ahlgren, 2018; Lombardi et al., 2019; Narayan et al., 2018), demand is evaluated based upon the following four factors: (i) mean daily energy usage, quantifying the typical energy required, (ii) peak demand, quantifying the maximum power the system will need to supply, (iii) load factor, $f_{Load}$, quantifying the variability of demand:

$$f_{Load} = \frac{Average\ Demand}{Peak\ Demand}$$

And (iv) coincidence factor, $f_{Coincidence}$, quantifying the diversity in timings of demand between sources:

$$f_{Coincidence} = \frac{\sum_{i=1}^{n} Max(Aggregated\ Demand_i)}{\sum_{i=1}^{n} Individual\ Peak\ Demand_i}$$

(where $i$ represents a single source amongst a set of $n$ sources of demand). Two further factors are introduced: (v) the PV overlap factor quantifies the overlap between demand and PV resource:

$$f_{PV} = \sum_{h=1}^{24} \min\left(\widehat{PV}_h, \widehat{D_h}\right),$$

Where $\widehat{D}_h$ represents the mean demand from a source in hour $h$ of the day across the timeframe of available data, and $\widehat{PV}_h$ represents the mean electrical output from a PV panel in hour $h$ of the day at the same location, each normalised so as to sum to one over the day. Finally, (vi) the seasonality factor, $f_{Seasonality}$ quantifies the variability of demand across seasons, calculated by dividing the mean demand across the six months of the year with the lowest demand, by the mean demand across the six months of the year with the highest demand.

*Scenarios for future microgrid demand*

Four scenarios are developed with differing rates of growth in domestic demand. A timeframe of 2030 is selected as this is the target date by which the SDG 7 goal of universal energy access is due to be met (United Nations, 2015).

Growth in domestic electricity demand is calculated based upon the proportion of households reaching a given energy access tier per year. All households are assumed to be in Tier 1 in 2020. Growth in proportion of households reaching a higher energy access tier is based upon a logistic function (S curve), similar in form to the Bass function commonly used for the diffusion of new products based upon innovation and imitation (Mahaja et al., 1995). The proportion of households, $P_t(y)$ reaching tier $t$ in year $y$ is given by:

$$P_t(y) = \frac{1}{1 + e^{-(y - y_t)}}$$

Where $y_t$ represents the year in which 50% of households reach tier $t$, defined for each tier by scenario. Four scenarios of Slow, Medium, Fast, and Faster growth are developed based upon the majority of householders reaching Tiers 2, 3, 4, and 5 by 2030, respectively. These scenarios are based upon equal timings between years at which 50% of households achieve each tier, with 5, 3.3, 2.5, and 2 years between tiers in slow, medium, fast, and faster scenarios, respectively.

The proportion of households reaching (or exceeding) each tier by year in these scenarios are shown in Figure 3. The Slow scenario, in which households do not reach Tier 3, arguably would not constitute access to modern energy as set out in the SDGs (United Nations, 2015). Tier 5 electricity access is typically more associated with a central grid or large fossil-based generator than a microgrid system (Bhatia and Angelou, 2015), and the Faster scenario, in which the majority of households achieve Tier 5 (associated with vacuums, electric hobs, and air conditioning) is not expected to occur in large numbers of microgrid systems. However, this still represents a useful limiting case to examine what the implications of meeting such loads through a microgrid system would be, and potentially for more affluent communities seeking a higher level of electricity service. Whilst growth in load over time has been observed in some off-grid electricity systems (Gustavsson, 2007; Hartvigsson et al., 2021), this is far from universal (Bisaga and Parikh, 2018; Riva et al., 2018). As such, Figure 3 represents scenarios of what could happen, and in some cases needs to happen to meet SDG 7, rather than a prediction of what will happen.

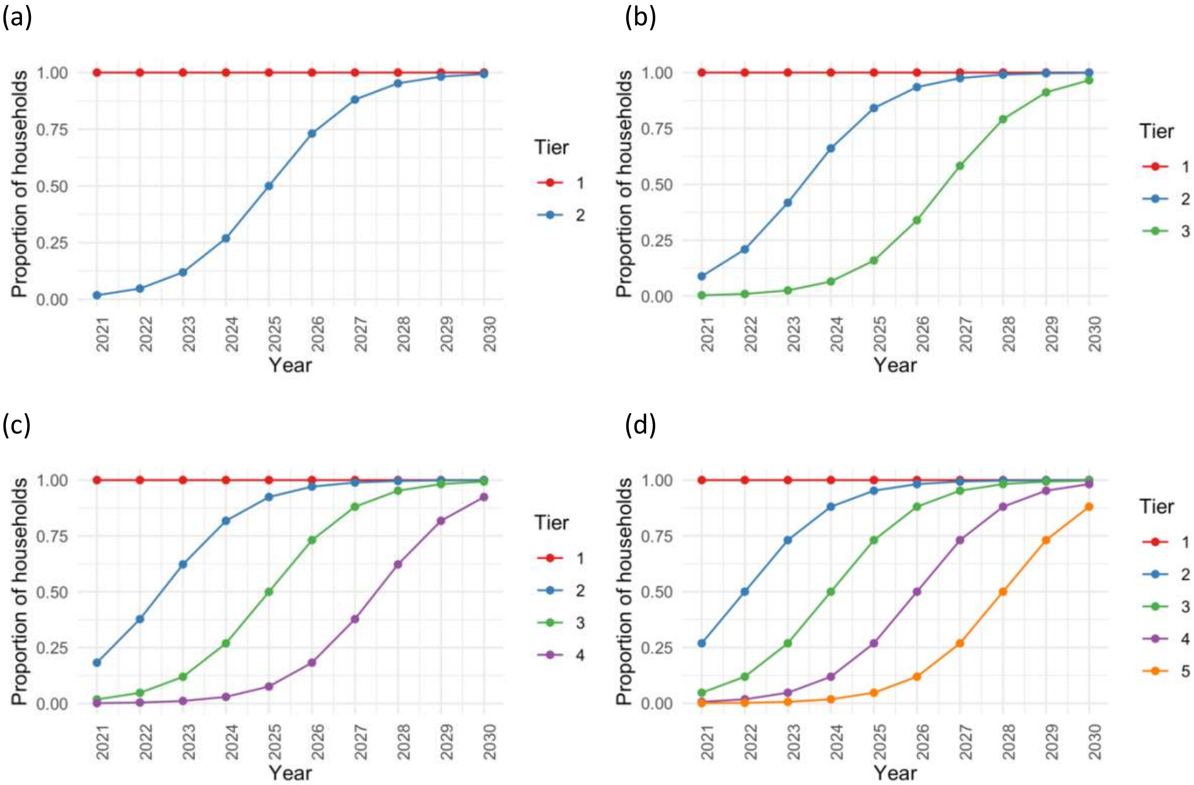



*Figure 3 Scenarios for proportion of households achieving higher tiers of electricity access up to 2030 in (a) Slow, (b), Medium, (c) Fast, and (d) Faster scenarios.*

These scenarios are considered across climatic conditions and alongside nondomestic demand associated with peri-urban and rural contexts, which, owing to a lack of sufficient data with which to build growth scenarios, are assumed to stay at 2019 levels throughout these scenarios. This represents a simplifying assumption, as in practice growth in household appliance ownership is likely to be related to growth in income generating activities and associated nondomestic electricity use.

### *Simulation and optimisation of microgrid system*

In order to quantitively assess the implications of the above demand profiles for microgrid system design, the open-source CLOVER (Continuous Lifetime Optimisation of Variable electricity Resources) microgrid simulation and optimisation tool is applied, using the above microgrid demand profiles as an input. An overview of this model and underlying assumptions is provided in supplementary materials, and it is described in detail in (Sandwell et al., 2017) and (Sandwell, 2017). This tool is used to calculate cost-optimal PV and storage sizing to meet electricity needs for 95% of hours in the ten-year operating period over which demand profiles are defined, and to determine the levelized cost of used electricity (LCUE) and lifecycle greenhouse gas (GHG) emissions intensity associated with electricity generated using this system. The microgrid systems under consideration do not produce any direct GHG emissions, so GHGs are assumed to be purely attributable to manufacture and transport of system components. This optimisation procedure is broken down into two five-year simulation periods, such that equipment may be added at the midpoint of the system operation to meet growing demand and replace capacity lost due to system degradation. This procedure is carried out for each combination of scenarios described in Table 4.

*Table 4 – Key variables explored in this study*

| **Variable** | Rurality *(determining nondomestic demand types)* | Climate *(determining use of cooling and heating technologies)* | Domestic demand growth *(determining appliances owned and operated used by householders)* |
|---|---|---|---|
| **Values Explored** | Peri-urban, rural | Tropical savanna, humid subtropical | None, slow, medium, fast, faster |

## Results

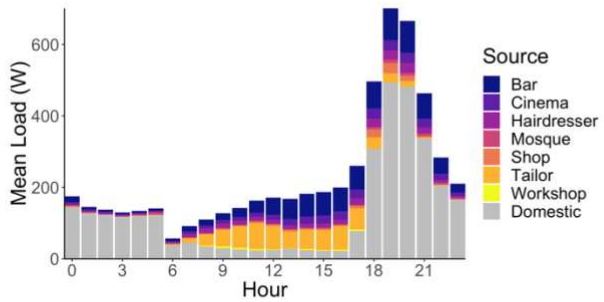
### *Characterisation of existing demand*

Figure 4 shows mean hourly demand profiles for a rural and a peri-urban community normalised to 100 occupants, with domestic demand assumed similar across the two locations, but differences in nondomestic electricity uses.

A number of features are notable here. Firstly, the peak magnitude of demand. This is substantially higher in the rural setting, dominated by the irrigation pump and rice mill, reaching levels around five times higher than total demand in the peri-urban setting. The microgrid operators have noted that the workshop uses a surprisingly small quantity of electricity (averaging 35Wh per day). Whilst a welding machine is installed here, it is rarely used, with the majority of work performed using manual and lower powered tools. This contrasts results reported for a set of microgrids in Tanzania, where electricity usage associated with a workshop and two millers were broadly similar, in the range of 14 – 37kWh per day (Hartvigsson et al., 2021).

Second, the temporal distribution of demand. In the rural setting, demand is primarily concentrated in the middle of the day, when solar resource is high. In the peri-urban setting, demand is more concentrated in the evening, with households and bars making the largest contributions. It is worth noting, however, that demand from some users in the peri-urban setting, the workshop and tailor in particular, are more concentrated in the middle of the day, but form a much smaller part of the overall system demand.

(a)




(b)

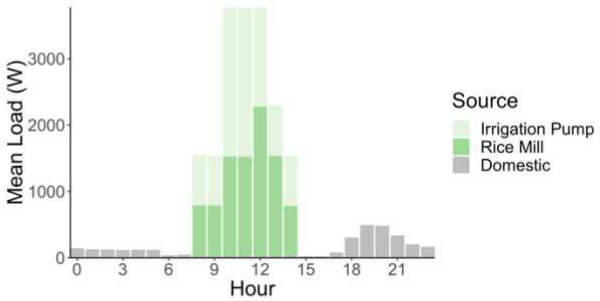
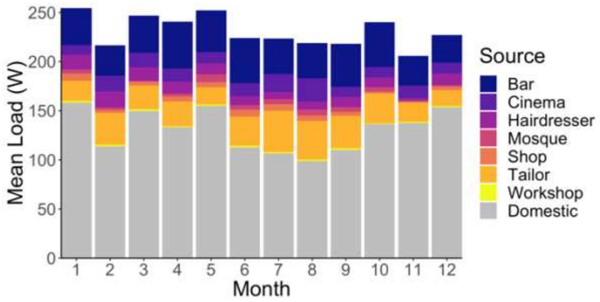



*Figure 4 Mean daily demand by source for a microgrid in (a) a peri-urban and (b) a rural location*

In considering the suitability of different systems to meet electricity needs, the distribution of demand both throughout the day and across seasons is important. Figure 5 shows mean demand by month from the same two microgrid systems. Overall demand is relatively consistent throughout the year in the peri-urban context, but is substantially higher between October and January in the rural context. This is primarily due to more intensive use of the rice mill during harvest seasons, and of the irrigation pump during dry seasons.

(a)




(b)

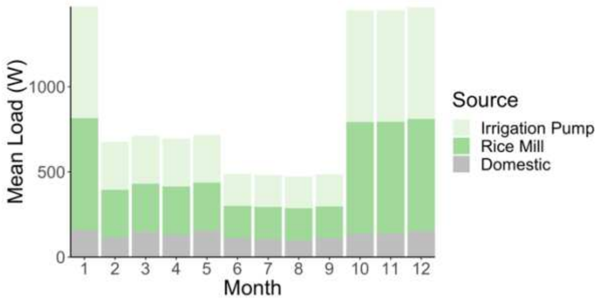



*Figure 5 Mean monthly demand by source for a microgrid in (a) a peri-urban and (b) a rural location*

Table 5 quantifies key metrics characterising demand associated with each of these sources, with standard deviation across days and across users included where data was available (although, as noted in the methodology, the sample size is relatively small). This further emphasises the substantially higher magnitude of nondomestic energy consumption and peak demand in the rural than the peri-urban setting. Referring back to minimum energy and power availabilities specified at different levels of the Multi-Tier Framework (Table 2), nondomestic users in the peri-urban setting have levels of daily energy consumption associated with Tiers 1 – 2, and peak power consumption associated with Tier 2 – 3, while both nondomestic uses in the rural setting would be classified as Tier 5. Substantial variation in these quantities between days and users may be observed for domestic and nondomestic users in the peri-urban setting for which measured data was available.

Load factor (mean demand divided by peak demand) varies substantially between users. This is lowest for the workshop, where a welding machine with exceptionally high associated demand is occasionally used, and higher for bars and households, where demand is more consistent. The higher load factors associated with nondomestic demand in the rural setting may be in part due to the use of synthetic rather than measured data from these sources. Since these were developed by the microgrid provider in order to assess overall energy needs of the system, they do not well capture sub-hourly variations, and associated short peaks in power usage, each of which would tend to reduce the load factor associated with this application.

Overlap with PV resource is high for sources of demand concentrated in the middle of the day, which includes the irrigation pump and rice mill in the rural context, and the tailor and workshop in the peri-urban context. PV overlap is substantially lower for nondomestic users with demand concentrated in the evening, such as the mosque, shop, cinema, and bars in the peri-urban context, and lowest of all in the domestic setting where demand is concentrated in the evening and overnight. Contrastingly, seasonal consistency is higher for domestic users than any nondomestic type. With the exception of the mosque, where the religious calendar will impact energy usage, demand from all the nondomestic users in the peri-urban context are more consistent across seasons than the more agricultural nondomestic demand in the rural context.

*Table 5 Key metrics associated with domestic and nondomestic demand in a peri-urban and a rural context*

| | | Daily Energy (Wh) | | | Peak Demand (W) | | Load Factor | | PV Overlap | | Seasonal Consistency | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | s.d. across days | s.d. across users | Mean | s.d. across users | Mean | s.d. across users | Mean | s.d. across users | Mean | s.d. across users |
| | **Domestic** | 30 | 6 | 36 | 10 | 15 | 0.12 | 0.03 | 0.12 | 0.11 | 0.81 | 0.31 |
| **Peri-urban** | **Bar** | 231 | 116 | 115 | 94 | 127 | 0.10 | 0.01 | 0.39 | 0.16 | 0.76 | 0.13 |
| | **Cinema** | 331 | 244 | - | 270 | - | 0.05 | - | 0.38 | - | 0.66 | - |
| | **Hairdresser** | 127 | 77 | 95 | 80 | 30 | 0.07 | 0.02 | 0.43 | 0.10 | 0.59 | 0.22 |
| | **Mosque** | 92 | 78 | - | 144 | - | 0.03 | - | 0.29 | - | 0.37 | - |
| | **Shop** | 108 | 91 | - | 192 | - | 0.02 | - | 0.30 | - | 0.46 | - |
| | **Tailor** | 330 | 312 | 379 | 231 | 157 | 0.06 | 0.03 | 0.67 | 0.05 | 0.59 | 0.09 |
| | **Workshop** | 35 | 66 | - | 236 | - | 0.01 | - | 0.71 | - | 0.68 | - |
| **Rural** | **Rice Mill** | 9031 | 4884 | - | 2250 | - | 0.17 | - | 0.72 | - | 0.41 | - |
| | **Irrigation Pump** | 9031 | 4884 | - | 2250 | - | 0.17 | - | 0.71 | - | 0.41 | - |

### *Simulation and characterisation of future household demand*

In order to consider implications of future growth in demand for microgrid design and operation, yearly profiles are simulated for households reaching energy access Tiers 1 – 5 in TSav and HSub climates (as described in the methodology). Mean daily demand by device across each of these tiers is shown in Figure 6a-e for the HSub climate, and mean monthly demand at Tier 5 in in Figure 6f. Similar plots are shown for the TSav climate in supplementary materials. Differences between climates are discussed subsequently and indicated in metrics presented in

Table 6.

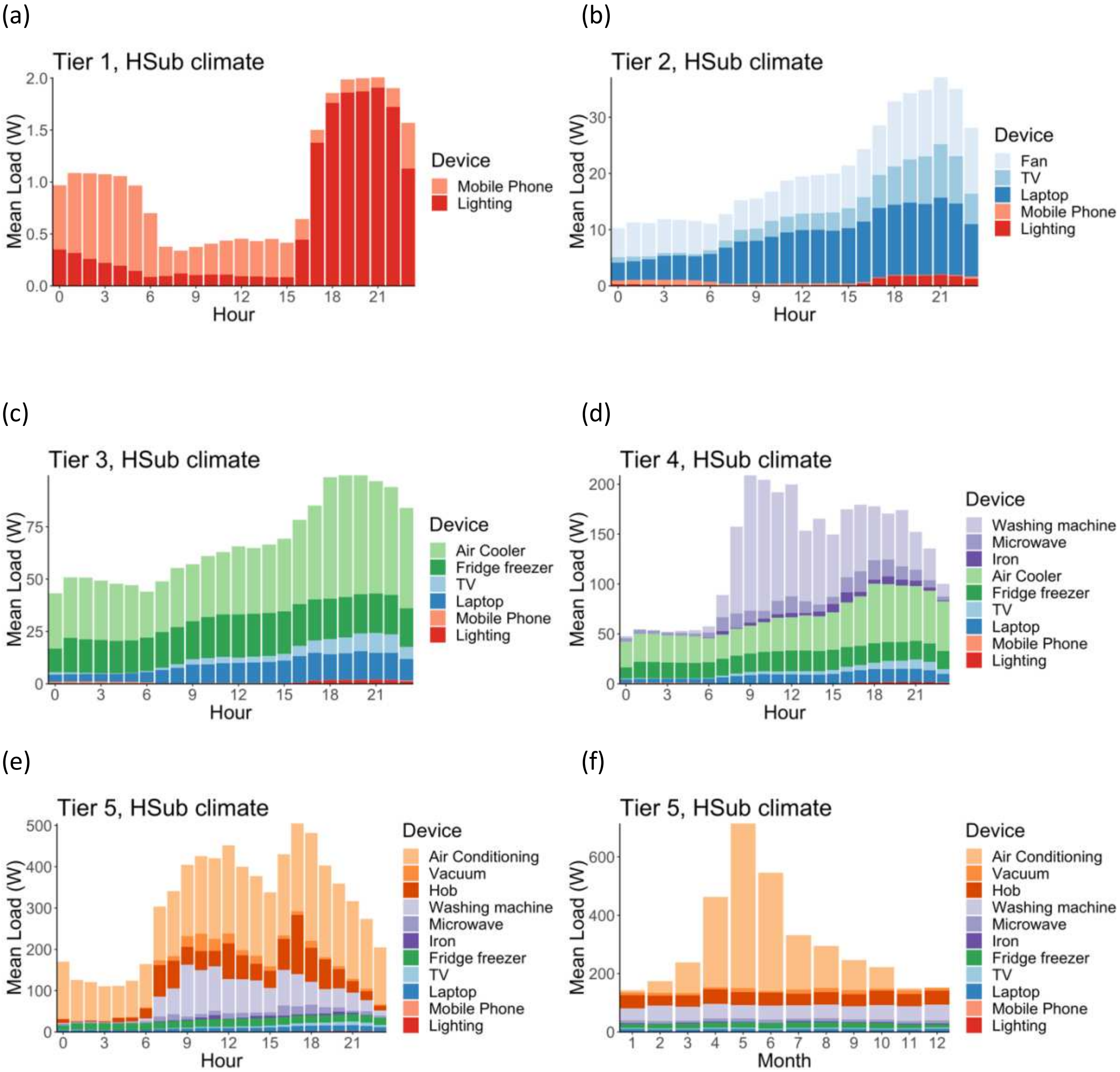



*Figure 6 (a-e) Mean daily demand by device for a simulated household in energy access tiers 1-5 in a humid subtropical climate, (f) mean monthly demand by device for a simulated household in energy access tier 5 in a humid subtropical climate.*

Figure 6 demonstrates the substantial growth in magnitude of electricity demand in moving from lower to higher tiers, with newly introduced loads dominating the demand profile in each case. Also notable is the shift in temporal distribution of demand associated with the change in appliance types dominating demand profiles in different tiers. There is a shift from maximum demand in the evening and overnight associated with mobile phone charging and lighting at Tier 1 (Figure 6a), to a less pronounced evening peak and higher daytime demand associated with a fan and a laptop in Tier 2 (Figure 6b), and a fridge and an air cooler in Tier 3 (Figure 6c). The introduction of a washing machine in Tier 4 substantially increases daytime demand, leading to a relatively flat profile throughout daytime and evening hours, which drops off during the night (Figure 6d). The introduction of air conditioning dominates demand in Tier 5, which is associated with highest demand in daytime and evening hours, but remains substantial throughout the night (Figure 6e). The introduction of a hob and a vacuum cleaner further increases daytime and evening demand at Tier 5.

Cooling technologies come to dominate demand in higher tiers, particularly Tiers 3 and 5, where the newly introduced air cooler and air conditioner represent more than half of the total demand. This change in daily demand profile might be expected to result in a better matching of PV resource to overall demand. However, cooling demand is highly seasonal, and drops off substantially during cooler months, meaning that ensuring sufficient PV is available to meet cooling demand during the hottest months requires an overcapacity of PV during cooler months. This is illustrated by the mean demand across months in Tier 5 shown in Figure 6f, dominated by air conditioning in the hotter months of April to September, and by other appliances in the cooler months of October to March.

Cooling represents a much smaller component of demand in the TSav than the HSub climate. Figure 7a shows the mean daily energy associated with cooling demand and other appliances across energy access tiers in each climatic condition. To illustrate the implications of these differences for overall demand profiles, Figure 7b and Figure 7c show mean demand across hours and months at Tier 5 in a TSav climate. In comparison to a HSub climate (Figure 6e and Figure 6f), load from the air conditioner is much lower, since the ambient temperature seldom reaches levels where cooling is required (Figure 2a). This leads to a lower overall demand which is more concentrated in the middle of the day and the evening (Figure 7b), and exhibits substantially less seasonal variation (Figure 7c). Trends between climatic contexts are similar across Tiers 2 – 5, although most pronounced in Tiers 3 and 5 where cooling represents the largest proportion of total demand in the Hsub climate.

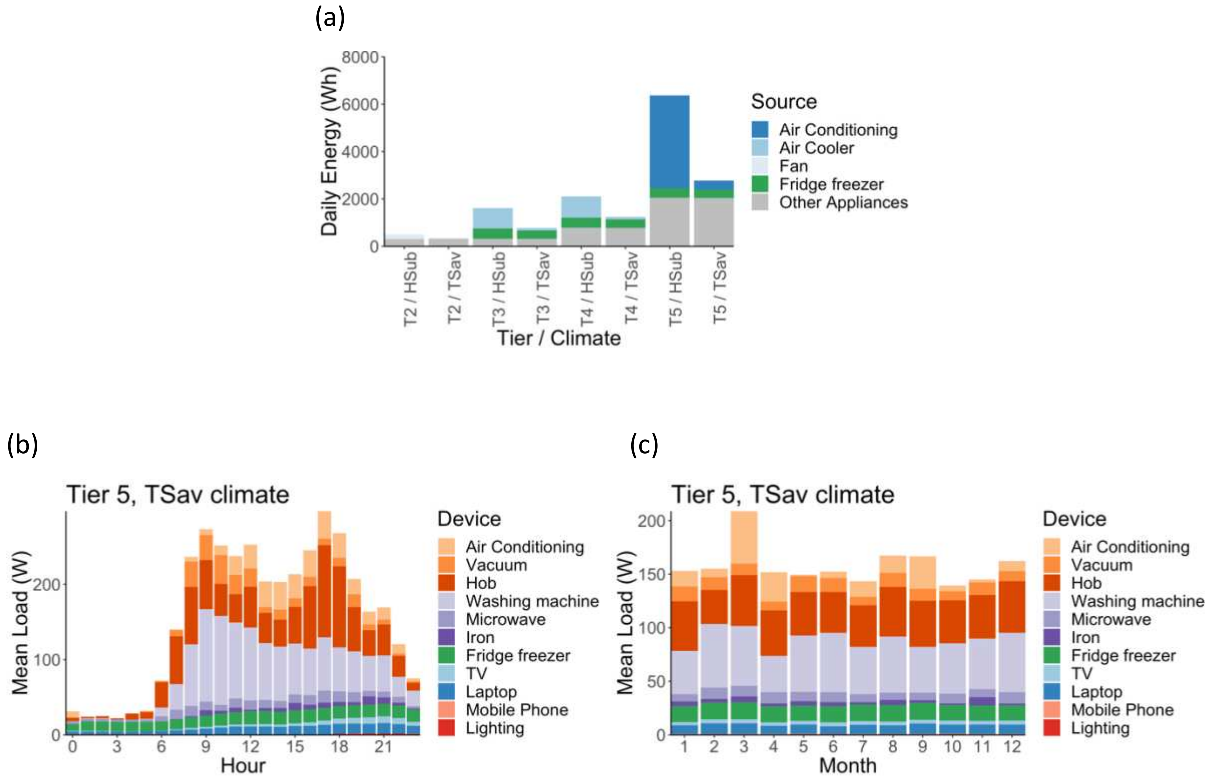



*Figure 7 (a) Differences in mean daily demand associated with cooling technologies for a simulated household in energy access Tier 2-5 in tropical savanna and humid subtropical climates, and (b) daily and (c) monthly mean demand by device for a simulated household in energy access Tier 5 in a tropical savanna climate.*

Key metrics associated with simulated demand profiles are presented in Table 6, with increases in daily energy and peak demand apparent in moving from lower to higher tiers and from a TSav to a HSub climate. Coincidence factors are also typically higher in higher tiers and HSub climates, where a greater proportion of demand is from cooling and operates at a near constant level throughout the day. Load factor (average demand over peak demand) are similarly higher in HSub than TSav climates from Tiers 2 and above where near constant cooling demand pushes up average demand more than peak demand. Load factor shows a more varied pattern, however, with increasing energy access tier, falling substantially, for example, between Tiers 3 and 4 where occasional high peak demands associated with use of the iron and microwave are introduced.

PV overlap factors increase with increasing energy access tier up to Tier 4, as demand shifts from evening and night towards the middle of the day, particularly in the TSav climate where overnight cooling demand is lower. PV overlap then falls slightly in going from Tier 4 to Tier 5, as overnight demand from the air conditioner is introduced. Seasonal consistency changes little between energy access tiers in the TSav climate, where seasonal cooling represents a relatively small proportion of demand, but varies substantially between tiers in a HSub climate, where seasonal cooling dominates the demand profile in Tiers 3 and 5.

*Table 6 – Key metrics associated with simulated household demand across energy access tiers and climates. Minimum daily energy and power availabilities associated with these tiers as specified in the Multi-Tier Framework are indicated in parentheses alongside daily energy and peak demand.*

| Energy access Tier | Climate | Daily energy (Wh) | Peak Demand (W) | Load Factor | Coincidence Factor | PV Overlap Factor | Seasonal Consistency |
|---|---|---|---|---|---|---|---|
| 1 | HSub | 24 (12) | 7 (3) | 0.15 | 0.42 | 0.19 | 0.74 |
| | TSav | 23 (12) | 6 (3) | 0.15 | 0.44 | 0.19 | 0.76 |
| 2 | HSub | 494 (200) | 103 (50) | 0.20 | 0.55 | 0.36 | 0.54 |
| | TSav | 349 (200) | 94 (50) | 0.16 | 0.43 | 0.37 | 0.51 |
| 3 | HSub | 1621 (1000) | 255 (200) | 0.27 | 0.69 | 0.38 | 0.39 |
| | TSav | 780 (1000) | 211 (200) | 0.15 | 0.42 | 0.41 | 0.64 |
| 4 | HSub | 3158 (3400) | 2903 (800) | 0.05 | 0.22 | 0.50 | 0.55 |
| | TSav | 2344 (3400) | 2878 (800) | 0.03 | 0.22 | 0.57 | 0.56 |
| 5 | HSub | 7367 (8200) | 5677 (2000) | 0.05 | 0.25 | 0.49 | 0.36 |
| | TSav | 3792 (8200) | 5316 (2000) | 0.03 | 0.18 | 0.56 | 0.57 |

Comparing daily energy and peak demand associated with simulated demand ( Table 6) to those specified for each tier in the Multi-Tier Framework (Table 2), it is apparent that peak demand is above the minimum threshold specified across tiers and climates, and is particularly high in Tiers 4 and 5 where high power appliances and air conditioning are introduced. Daily energy use is above the minimum availability specified for Tiers 1 and 2 across climates, but falls substantially below minimum availability in Tier 4 and 5 in the TSav climate. These results indicate the possibility of meeting services associated with higher energy access tiers with a smaller electricity system than might have been expected, but that this depends substantially on climatic context. It is also worth noting that values specified in Table 2 indicate minimum levels of available energy, and do not necessarily imply that all of this energy should be required.

### *Simulation and optimisation of microgrid system*

Characteristics of a cost optimised microgrid system to meet demand across ruralities, growth scenarios, and climatic conditions are compared in Figure 8. The size of the PV system required to meet demand in these scenarios from year 5 onwards is shown in Figure 8a, and the battery storage required per PV in Figure 8b. The levelised cost, and emissions intensity of used electricity associated with meeting this demand throughout ten years of microgrid operation are shown in Figure 8c and Figure 8d, respectively. These values are shown alongside initial PV and storage size, and capital cost in year 0, in

Table 7.

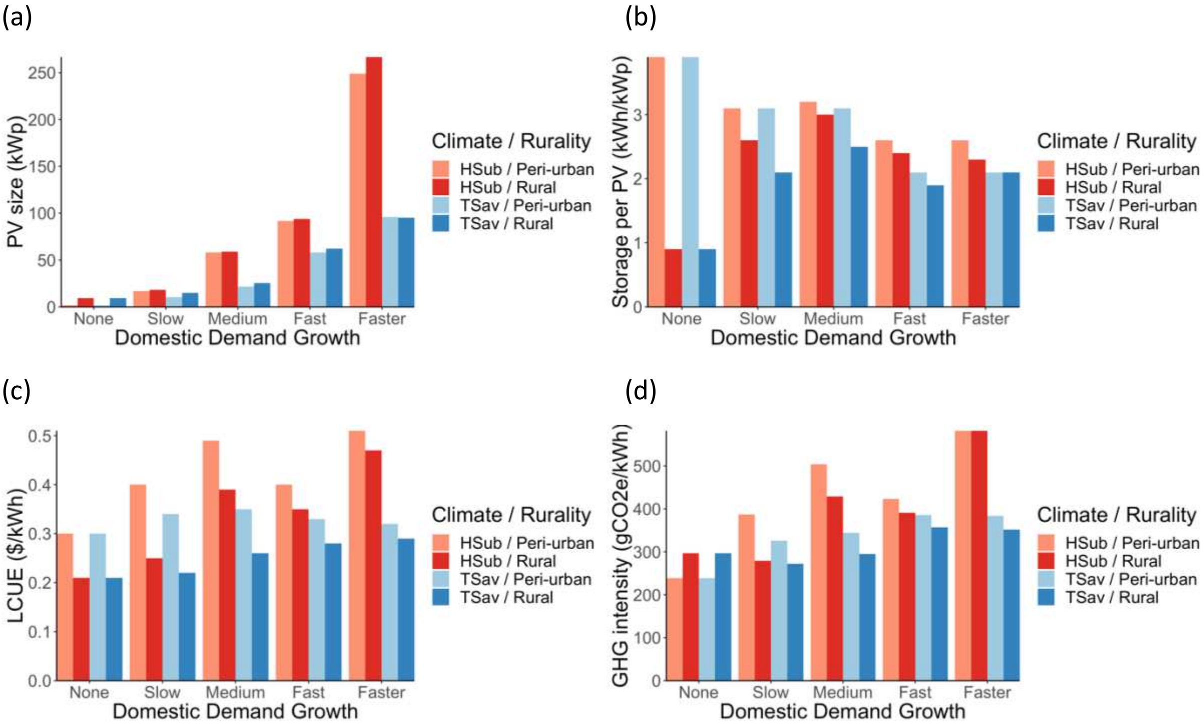



*Figure 8 Key metrics associated with an optimal microgrid system across tropical savanna and humid subtropical climates, peri-urban and a rural locations, and rates of domestic demand growth: (a) PV size in year 5, (b) storage per PV in year 5, (c) levelised cost of used electricity, and (d) greenhouse gas emissions intensity.*

Where demand is assumed to continue at current levels, differences in nondomestic demand associated with differences in rurality is a key factor in determining microgrid characteristics. The optimised PV system required to meet the substantial and seasonal daytime demand associated with milling and water pumping in the rural microgrid is four times larger than that required to meet the smaller loads associated with the peri-urban microgrid (Figure 8a). However, substantially more storage is required per PV capacity in the peri-urban than the rural context, where nondomestic demand associated with bars and hairdressers are more concentrated in the evening (Figure 8b). The combination of these factors lead to a slightly higher LCUE in the peri-urban context, and a slightly higher emissions intensity in the rural context (Figure 8c,d). However, this result is likely to be highly sensitive to assumptions surrounding cost and embedded emissions (**Error! Reference source not found.**), and in particular the balance of these between PV and storage.

Figure 8a also demonstrates the key role that the rate of domestic demand growth plays in determining the size of microgrid system required to meet demand. Required PV size is up to 40 times larger in the Faster domestic growth scenario than the No Growth scenario (with differences associated with different levels of nondomestic demand and climatic conditions across scenarios).

Differences in nondomestic demand become less important in determining microgrid characteristics in scenarios in which domestic demand grows quickly, whilst climate becomes more important. Additional cooling demand at higher tiers result in a much larger PV system being required in an HSub than a TSav climate in Medium, Fast, and Faster domestic demand growth scenarios (Figure 8a). Cooling is particularly dominant in the HSub climate in the Faster domestic demand growth scenario, necessitating a PV system with almost triple the capacity of that in the TSav climate.

Differences in required storage per PV are smaller in scenarios with faster growth in domestic demand (Figure 8b). This is because differences in demand across the day are more pronounced for nondomestic loads across considered rurality contexts (Figure 4) than for household loads across tiers and climates (Figure 6 and Figure 7). Higher nighttime cooling load in the HSub climate increases required storage relative to the TSav climate, but since a substantially larger PV system is also required, the storage per PV remains relatively similar.

Across growth scenarios, both LCUE and emissions intensity are substantially higher in HSub than TSav climates. This is primarily attributable to two factors. First, the higher degree of seasonality of cooling demand in the HSub climate, which necessitates a PV system which produces more electricity than is required for most of the year. Second, the higher nighttime cooling demand in the HSub climate, which necessitates a larger battery system.

*Table 7 – Characteristics of optimal microgrid systems across growth scenarios and climatic and rurality contexts*

| Growth Rate | Climate | Rurality | Total PV Size, Year 0 (kWp) | Total PV Size, Year 5 (kWp) | Storage per PV, Year 0 (kWh/kWp) | Storage per PV, Year 5 (kWh/kWp) | LCUE for ten year microgrid operation ($/kWh) | Initial Capital ($) | Emissions Intensity (gCO2e/kWh) |
|---|---|---|---|---|---|---|---|---|---|
| None | - | Peri-urban | 1.8 | 1.8 | 3.8 | 3.9 | 0.30 | 3,980 | 239 |
| | - | Rural | 8.6 | 9.3 | 1.1 | 0.9 | 0.21 | 9,636 | 297 |
| Slow | TSav | Peri-urban | 5.8 | 10.4 | 2.9 | 3.1 | 0.34 | 10,643 | 326 |
| | | Rural | 9.9 | 15.0 | 1.5 | 2.1 | 0.22 | 12,524 | 272 |
| | HSub | Peri-urban | 8.8 | 16.8 | 2.8 | 3.1 | 0.40 | 15,732 | 387 |
| | | Rural | 10.8 | 18.1 | 1.8 | 2.6 | 0.25 | 15,038 | 279 |
| Med | TSav | Peri-urban | 10.1 | 21.8 | 3.1 | 3.1 | 0.35 | 18,957 | 344 |
| | | Rural | 13.3 | 25.4 | 2.0 | 2.5 | 0.26 | 19,851 | 295 |
| | HSub | Peri-urban | 22.2 | 58.2 | 2.5 | 3.2 | 0.49 | 37,011 | 504 |
| | | Rural | 20.1 | 58.9 | 2.5 | 3.0 | 0.39 | 33,555 | 429 |
| Fast | TSav | Peri-urban | 18.0 | 58.1 | 2.7 | 2.1 | 0.33 | 31,345 | 386 |
| | | Rural | 19.8 | 62.2 | 2.1 | 1.9 | 0.28 | 30,260 | 357 |
| | HSub | Peri-urban | 42.5 | 91.7 | 2.4 | 2.6 | 0.40 | 68,738 | 423 |
| | | Rural | 41.2 | 93.8 | 2.2 | 2.4 | 0.35 | 64,232 | 391 |
| Faster | TSav | Peri-urban | 29.5 | 95.9 | 2.5 | 2.1 | 0.32 | 49,198 | 384 |
| | | Rural | 32.6 | 95.2 | 1.9 | 2.1 | 0.29 | 46,983 | 352 |
| | HSub | Peri-urban | 72.3 | 249.0 | 2.2 | 2.6 | 0.51 | 112,742 | 582 |
| | | Rural | 64.6 | 266.7 | 2.5 | 2.3 | 0.47 | 107,840 | 582 |

## Discussion and conclusions

This paper has presented an open-source framework facilitating all stages of microgrid system design and characterisation from demand estimation, through to cost-optimisation and characterisation of resulting system. This framework has been used to examine the impact of (1) rate of domestic demand growth, (2) climatic conditions, and (3) sources of nondomestic demand on household and microgrid demand profiles, sizing of cost-optimal microgrid systems to meet this demand, and cost and GHG emissions associated with these systems.

Nondomestic demand derives from agricultural processes (milling and water pumping) in the rural setting considered here, and primarily from services (shops, bars, hairdressers) in the peri-urban setting. The agricultural demand exhibits greater coincidence of periods of high demand with solar generation compared with service demand, which is more concentrated in the evening. This allows demand to be met directly by solar PV, reducing the need for storage in the rural setting, and decreasing cost and emissions per unit of electricity used. However, the seasonal nature of agricultural demand means that meeting demand with PV in peak months requires a system that is larger than is required for much of the year, increasing costs in the rural relative to the peri-urban setting. Whilst quantitative results will be specific to individual contexts, the higher level of seasonality in rural areas (Mukherjee and Symington, 2018) and higher levels of evening and night time load in peri-urban areas (Neelsen and Peters, 2011; Riva et al., 2018) are in line with previous studies. As such, implications of rurality for system design may be expected to be comparable to other similar locations, and results could inform expectations in other locations gaining access to electricity.

When domestic demand growth is fast, climatic conditions play a defining role in shaping microgrid demand profiles and characteristics of a cost-optimal microgrid to meet this demand, due to their impact on intensity of usage of cooling technologies. This is particularly important at higher levels of energy access and in hotter and more seasonally varying climates, where cooling technologies introduce higher levels of night-time demand and seasonal variability, increasing requirement for storage and necessitating the installation of a PV system which is larger than is required for much of the year, respectively. These factors both tend to increase cost and emissions per electricity delivered by a reliable microgrid system.

Whilst not quantitively explored in this study, the high degree of seasonal variation in some sources of demand may make it more cost-effective to meet this demand using a hybrid system, whereby a backup form of dispatchable generation is introduced in months of highest demand. Alternatively, new forms of demand could be introduced with a seasonality which is complementary to existing sources, or an interconnection made to a nearby source of complementary demand if one is available.

This work demonstrates the importance of a proper characterisation of demand for cost-effective microgrid sizing, and highlights the role that climatic conditions, different forms of productive use associated with different ruralities, and load growth can play in determining this. Whilst each location will have its own characteristics, these factors should each be considered carefully by developers when deploying a new microgrid system. The modular nature of microgrid systems based upon PV and batteries represents an advantage here, facilitating system expansion as demand evolves. This work also provides insight to governments and NGOs seeking to support the achievement of SDG 7, indicating the size of systems and levels of investment required if this goal is to be met, and how this may depend upon definition of modern energy and upon local context.

For tractability of this study, a number of simplifying assumptions were made which warrant attention in future work. Owing to lack of suitable data, no growth in nondomestic demand is assumed in scenarios considered here. In practice, this could vary substantially between contexts and become an important factor in defining demand profiles and microgrid characteristics. In order for a fair comparison of implications of the shape of demand profiles for microgrid costs, no costs and emissions associated with setting up the microgrid are included. In practice, these could form a large part of overall costs, especially in more remote settings and where overall system demand is lower. Rate of domestic demand growth, climatic condition, and rurality are treated as independent variables in this study. In practice, these could interact. For example, rurality could have a substantial impact on access to markets and appliances, which is likely to impact rate of growth in domestic and nondomestic demand.

A single form of building design was investigated across climatic conditions and energy access tiers. In practice, differences in built form will affect thermal characteristics of buildings and need for cooling, which could have substantial implications for electricity demand profiles. In some cases, cooling demand could be reduced by the development of more thermally efficient buildings. In others, changes from traditional to modern building design has reduced suitability for local climates, exacerbating needs for active cooling (Gupta, 2017; Mazzone, 2020). Future work could focus on the extent to which improved passive cooling could reduce electricity demand associated with heating and cooling, and on how this could change due to impacts of global heating. However, it should be noted that desire for cooling technologies can be driven by social desirability as well as thermal comfort (Mazzone, 2020), and reduction in demand associated with improved thermal efficiency of building could be limited.

Finally, this paper has focused on meeting of demand with microgrid systems. However, demand profiles presented here, and the methodology used to produce them, could also be used to assess the feasibility of other mechanisms of electricity provision, such as through standalone systems, interconnected microgrids, or connection to a larger regional or national grid system.

## Acknowledgements

The authors gratefully acknowledge the UK Engineering and Physical Sciences Research Council for funding through the "Resilient Electricity Networks for a productive Grid Architecture" (RENGA) (EP/R030235/1) and "Joint UK-India Clean Energy Centre (JUICE)" (EP/P003605/1) research projects. The projects funders were not directly involved in the writing of this article. The authors acknowledge Imperial College London's high performance computing service for its use in performing CLOVER calculations (Imperial College Research Computing Service, n.d.). The authors also acknowledge the kind support of MeshPower and Gram Oorja Solutions in making data available to the project and supporting in its interpretation, of the Electricity Access and ICEPT groups at Imperial College London in providing useful discussion and feedback, and particularly to Hamish Beath for providing useful feedback on an earlier draft of the manuscript.

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## Appendix: Further details of communities used in defining peri-urban and rural contexts

*Table 8 Key details of microgrid-connected communities considered in this study*

| Community | Gitaraga, Eastern Province, Rwanda (peri-urban) | Bhinjpur, Jharkhand, India (rural) |
|---|---|---|
| Location/Remoteness | Accessible<br>~20km from centre of capital city (Kigali)<br>~1km from major road | Remote<br>~100km from nearest city (Ranchi)<br>~19km from major road (a smaller dirt road reaches the community) |
| Number of Households | 180 | 93 |
| Global co-ordinates | -2.0760, 30.1207 | 22.7789, 84.4044 |
| Typical temperature range(Climate Data, 2021) | 14 – 27 °C | 9 – 38 °C |
| Household appliances | Lights, USB charging, few TVs. | Lights, USB charging, fans, few TVs. Two fridges, one cooling tower. |
| Nondomestic electricity uses | 8 bars, 1 cinema, 3 hairdressers/barbers, 1 shop, 3 tailors, 1 welder/workshop, 1 mosque, streetlighting<br>(NB. 3 of 8 bars, 1 of 3 hairdressers, and 1 of 3 barbers had insufficient measured data to inform contexts considered here) | 1 computer & printer, 1 rice polisher, water pumping, streetlighting |
| Demand data Availability | Monitored demand available for each electricity user at variable resolution (typically <2 mins). Available per appliance for domestic users. | Demand per appliance estimated based upon developer experience and site visit. |

| | | |
|---|---|---|
| Current system sizing | 6.5 kWp PV, 48 kWh PbA battery, backup diesel generator. | 18 kWp PV, 73 kWh PbA battery, no backup generation. |
| Commission date | 11/07/2018 | 24/02/2017 |
| Developer | MeshPower | Gram Oorja Solutions |