

Supplementary Material to “Electricity demand in populations gaining access: impact of rurality and climatic conditions, and implications for microgrid design”

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Additional detail on Microgrid Simulation and Optimisation tool (CLOVER)

In order to quantitatively assess the implications of demand profiles for microgrid system design, the open-source CLOVER microgrid simulation and optimisation tool is applied, using these profiles as an input. This model is freely available from (Sandwell, 2018), and is described in detail in (Sandwell et al., 2017) and (Sandwell, 2017). It is briefly described here to aid comprehension of results.

The CLOVER model has two primary functions: simulation and optimisation. In simulation mode, CLOVER begins with a profile of the microgrid load, L_h , defined over each hour h of the simulation period (typically several years), a PV array size, and a battery size. An hourly PV generation profile, PV_h , is defined over the same period based upon historical PV data from the MERRA-2 dataset obtained via the renewables.ninja platform associated with the microgrid’s location (Pfenninger and Staffell, 2020, 2016), PV panel size, and orientation.

A storage profile, SP_h , is defined based upon the difference between these quantities, representing the quantity of energy required from, or available to, the battery in each hour of the simulation.

$$SP_h = PV_h - L_h$$

For hours in which SP_h is positive, energy is stored in the battery up to the maximum allowable state of charge. For hours in which SP_h is negative, energy is supplied from the battery (at an efficiency cost) until it reaches the minimum allowable state of charge. The difference between energy supply (directly from PV and from the battery) and energy demand is recorded in a profile of unmet energy, U_h . A binary blackout profile, B_h , is defined with a value of 1 for hours in which U_h is nonzero, and a value of 0 at other times. Analysis of these parameters allows the definition of system appraisal outputs, such as the proportion of hours during which the system suffers a blackout:

$$Blackout\ Proportion = \sum_h^N \frac{B_h}{N}$$

Where N represents the total number of hours in the simulation period.

The CLOVER model also able to optimise PV and battery sizing for a microgrid system based upon successive simulations. In performing an optimisation, a number of additional input parameters are required: an iteration period, I , after which additional batteries and PV may be added to meet growing load or replace degraded components; a system operation period, P , over which the optimisation is performed; technoeconomic and embedded emissions data (such as PV and battery capital and maintenance costs, embedded emissions, discount rate); maximum and minimum allowed sizes for PV and battery capacity, PV_{max} , PV_{min} , S_{max} , S_{min} , and step sizes PV_{step} , S_{step} , to define the optimisation space; a sufficiency criterion to define when a system performs acceptably (less than 5% blackout proportion in this study), and an optimisation parameter to be minimised (levelized cost per unit of used electricity, LCUE, as defined in (Sandwell et al., 2016), in this study).

The optimisation procedure begins by conducting a simulation of a system with a PV array of size PV_{min} and a battery of size S_{min} over the iteration period, I . System appraisal outputs are calculated to determine (a) whether the system meets the sufficiency criterion, and (b) the value of the optimisation parameter for this system. If the system fails to meet the sufficiency criterion, a second simulation is carried out for a system with PV array size increased by PV_{step} . This procedure is repeated until a system is found which meets the sufficiency criterion, or PV_{max} is reached. A similar procedure is applied for each battery size between S_{min} and S_{max} with step sizes of S_{step} . All identified systems meeting the sufficiency criterion are identified as viable, and the system amongst these associated with the lowest value of the optimisation parameter is identified as optimal. This procedure is repeated over multiple iteration periods, I , between which load may grow, until the system operation, P , is reached. Remaining PV and battery capacity at the end of a given period are carried over to the next period, subject to degradation accrued over the first period. Once this procedure has been completed, an optimal system sizing over each period, I , is generated as an output, alongside system appraisal outputs associated with this optimal system, such as LCUE, emissions intensity over the entire operation period, P , and capital and O&M cost by iteration period, I .

Values of key technical and economic parameters used in these simulations are shown in Table 1. However, costs and impacts are calculated primarily for comparative purposes, and actual values will depend upon a broader range of social and economic factors than are considered here. For simplicity, the microgrid is assumed to run on direct current, and inverter costs are therefore not included. This

represents a reasonable assumption for relatively small microgrids, but in larger microgrids, higher losses will often make the use of alternating current more cost effective (Bhatia and Angelou, 2015). Flat set up costs associated with installation of the system are also excluded for ease of comparison between systems of different size. In practice, these would be expected to be important cost factors, particularly for smaller systems.

The discount rate is used in financial analysis to account for the time-varying value of investments, for example due to interest or loans, and to provide fair comparisons between options with different levels of capital and operating costs over their lifetime. The discount rate used here (10%) is consistent with other studies for minigrid projects in developing countries (e.g. 9.6% used in (Energy Sector Management Assistance Programme (ESMAP), 2019)) and for PV projects in India (e.g. 10.6% found by (Steffen, 2020)). The discount rate will be very context dependent. However, since the modelling of the microgrid system itself is conducted here primarily to give an indication of the impact of changing demand, rather than to provide absolute microgrid costs, we do not expect differences in discount rate to have a large impact on conclusions.

Table 1 – Values of key technical and economic parameters used in microgrid simulations

Quantity	Value	Source
PV cost	454 \$/kWp	Microgrid developer experience
PV lifecycle emissions	2066 kg CO ₂ e / kWp	(Das et al., 2018)
Lithium-ion battery cost	350 \$/kWh	(Few et al., 2019)
Lithium-ion battery emissions (g CO ₂ e / kWh)	157 kg CO ₂ e / kWh	(Hiremath et al., 2015)
Lithium-ion battery cycle life	3000 (at 80% DoD)	(Few et al., 2019)
Discount Rate	10%	(Energy Sector Management Assistance Programme (ESMAP), 2019; Sandwell, 2018; Steffen, 2020)

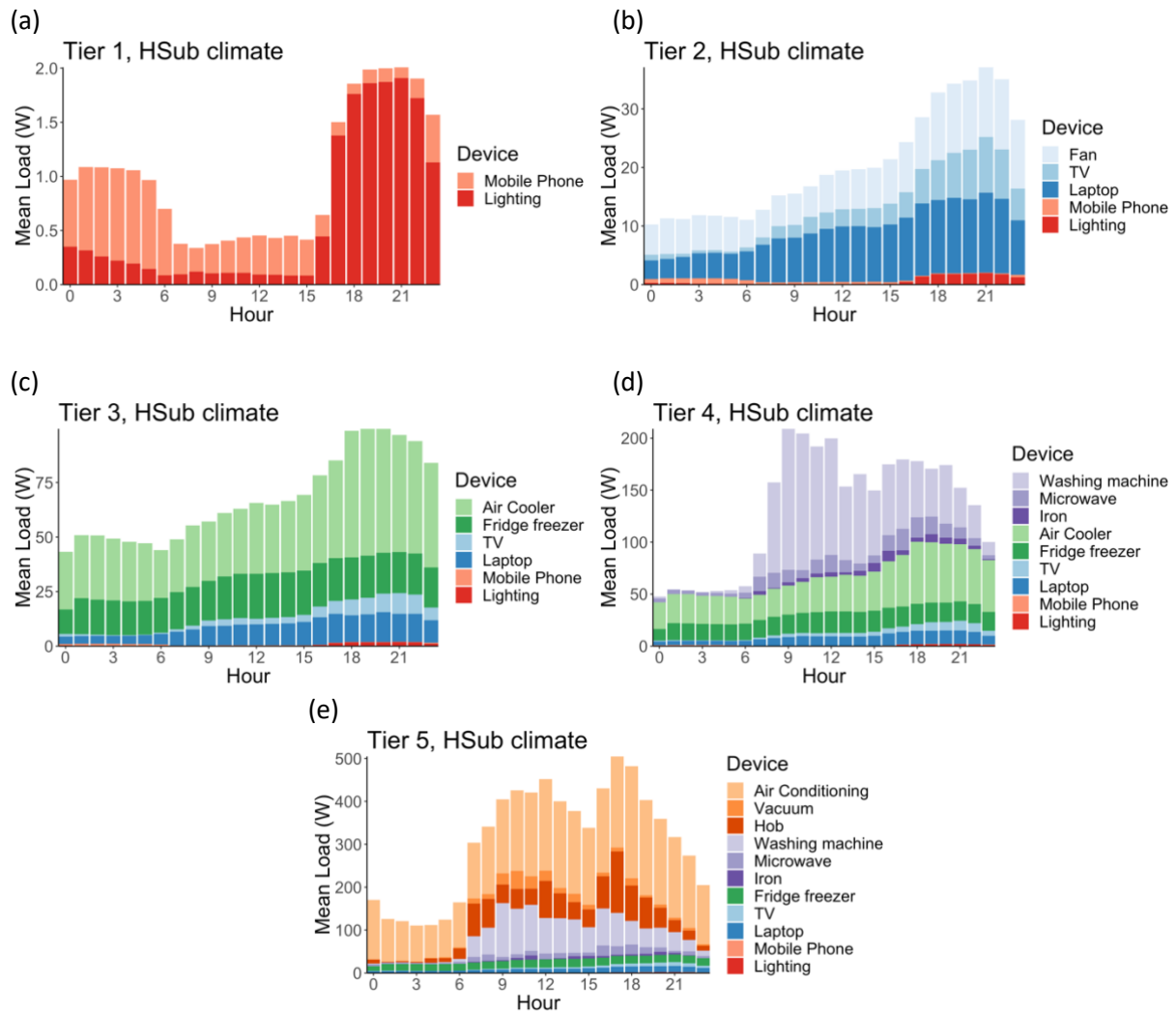


Figure 1 (a-e) Mean daily load for a simulated household in energy access tiers 1-5 in a humid subtropical climate

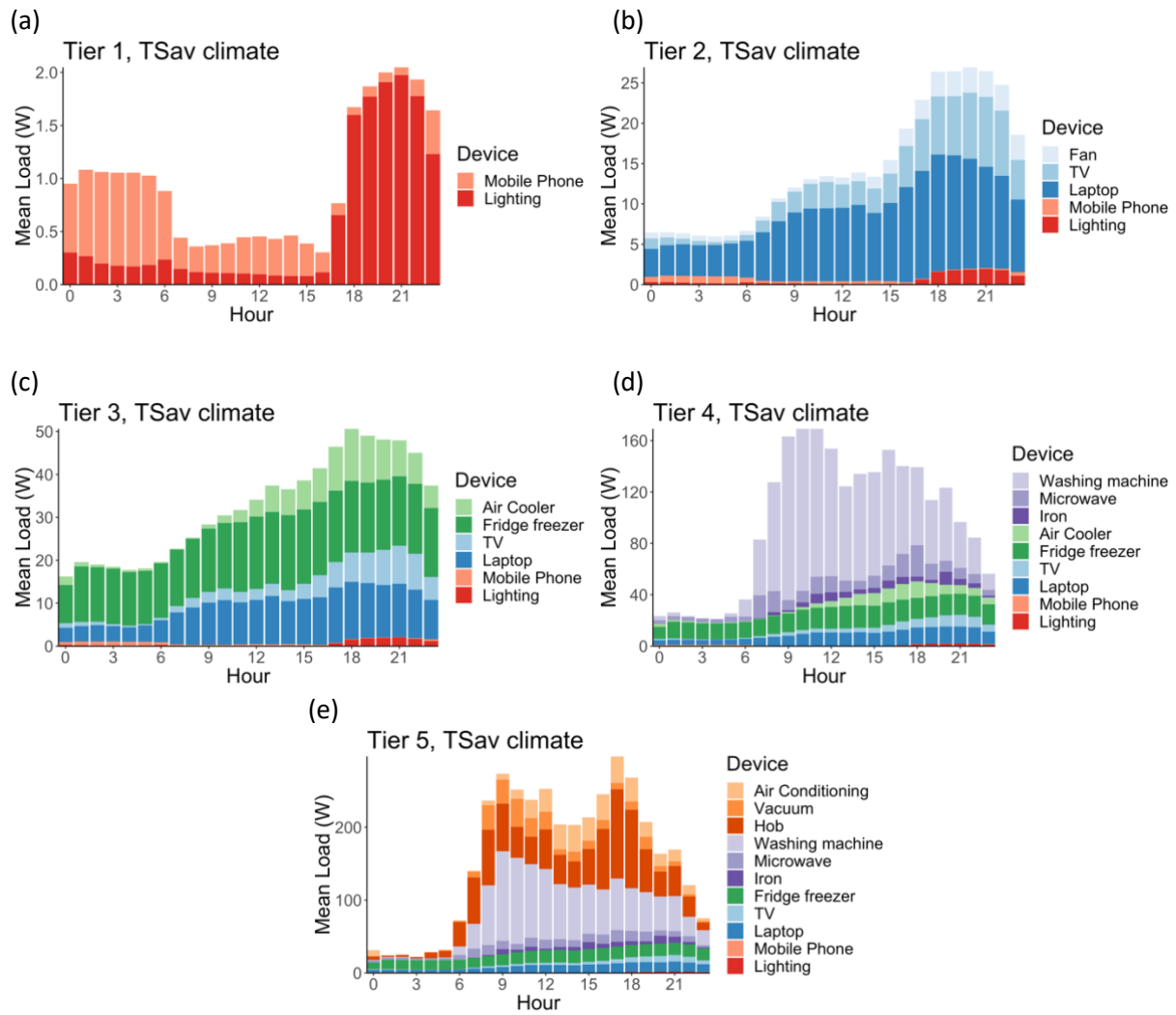


Figure 2 (a-e) Mean daily load for a simulated household in energy access tiers 1-5 in a tropical savanna climate

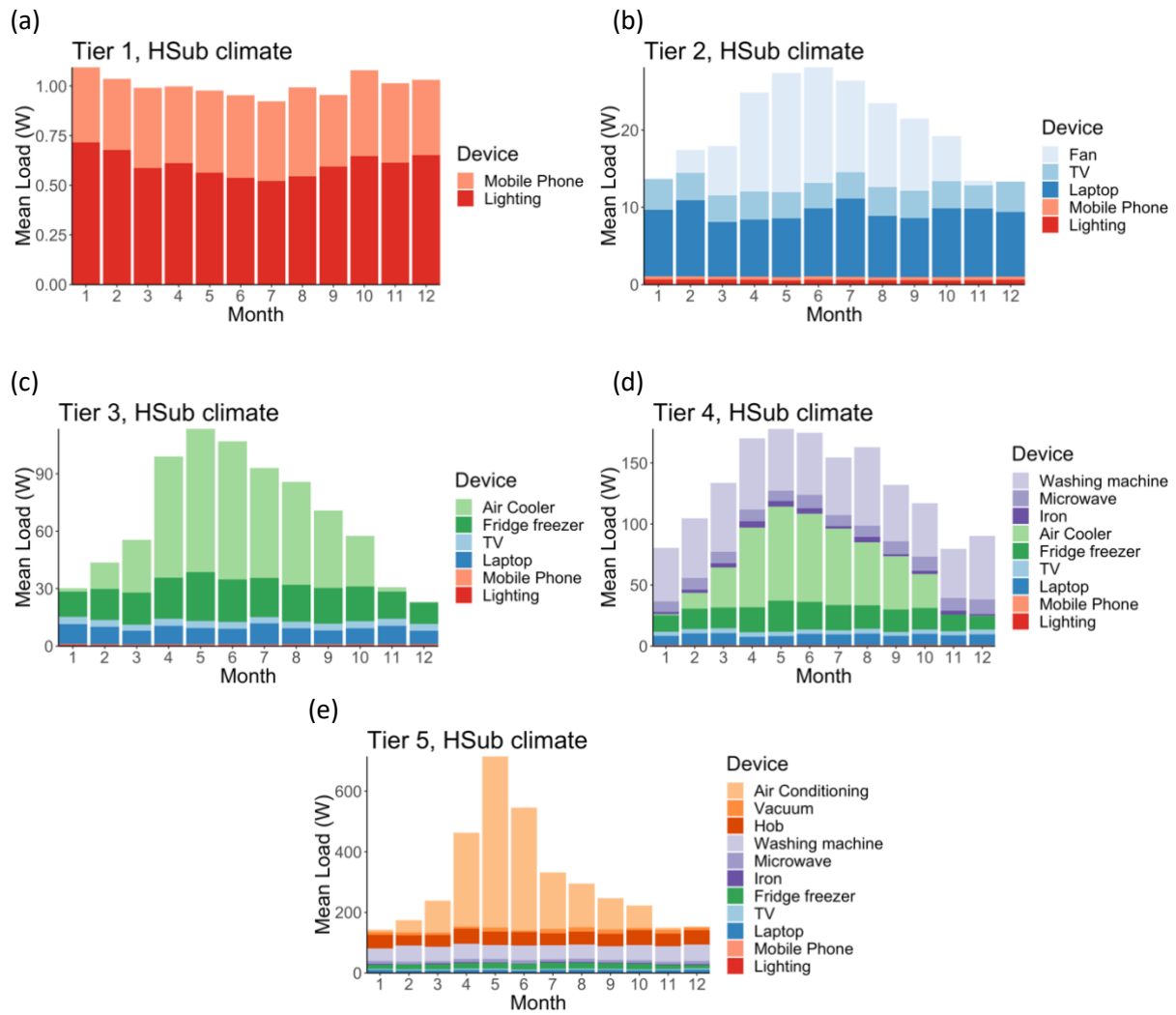


Figure 3 (a-e) Mean monthly load for a simulated household in energy access tiers 1-5 in a humid subtropical climate

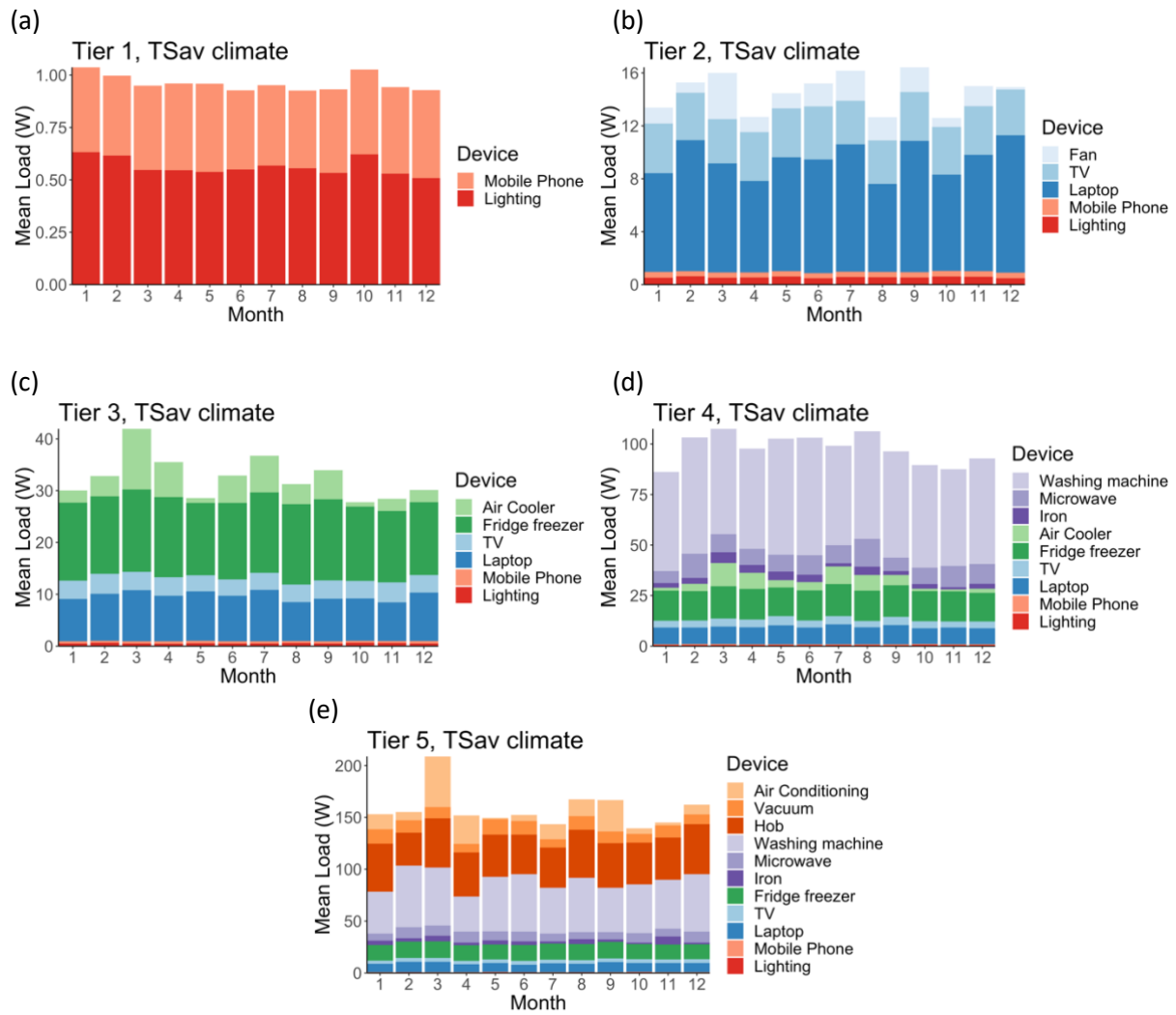


Figure 4 (a-e) Mean monthly load for a simulated household in energy access tiers 1-5 in a tropical savanna climate

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