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Leveraging load shedding and daytime loads to improve mini-grid economics

Yuezi Wu [a,*], Alex Wanume [b], Vijay Modi [a]

[a] Department of Mechanical Engineering, Columbia University, United States of America
[b] NOA Uganda Services, Uganda

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ABSTRACT

Mini-grids often face challenges with economic viability due to low and inconsistent electricity demand, when they are being developed in rural areas of Sub-Saharan Africa. This study identifies load profiles that lead to high generation costs in solar PV- and battery-powered mini-grid. The analysis is based on electricity load data from 2124 households and 21 grain mills across 25 mini-grids in Uganda. Our results identify two key load profile aspects that determine the Levelized Cost of Electricity (LCOE): 1) Peak-day to average-day load ratio – Higher peak-day electricity demand increases generation costs. 2) Daytime load fraction – Higher daytime electricity use helps to lower generation costs. Integrating productive loads from grain mills into mini-grids improves both aspects and reduces the LCOE by 23 % compared to mini-grids that serve households alone. Further cost reductions of 15 % are possible by leveraging flexible productive loads scheduling by increasing daytime load fractions. To address the high peak-day to average-day load ratio, a sizing guide is proposed: for every kWh of average daily load, install 0.5 kW of solar capacity and 1.5 kWh of effective battery storage. This sizing cannot meet all loads at all hours. It results in an average load shedding of 1.7 % (maximum 5.1 %) of energy and an average 41 % LCOE reduction compared to systems designed to meet all loads at all hours, across household-only mini-grids. For mini-grids with both household and productive loads but no flexibility allowed, this sizing guide yields an 18 % LCOE reduction with 0.6 % load shedding.

1. Introduction

Access to electricity in developing regions is a fundamental challenge for global sustainable development. In 2023, approximately 666 million people worldwide lacked access to electricity (World Bank, 2025), with the largest share residing in the rural areas of Sub-Saharan Africa (SSA) (World Bank, 2024). Extending national grids to many rural locations is time-consuming and expensive (World Bank, 2023). Mini-grids provide a cost-effective alternative, particularly for villages with moderate electricity demand and population density (Franz et al., 2014; USAID, 2024). A global assessment projects that mini-grids will connect 63 million households by 2030 under a business-as-usual scenario and 111 million households under a universal access scenario (SEforALL and BloombergNEF, 2020). Among the mini-grids built and planned in SSA, the majority are powered by solar photovoltaic (PV) systems (Domegni and Azouma, 2022).

Nevertheless, mini-grid projects face significant challenges, including high hardware procurement costs, limited access to affordable financing services, shortage of local technicians for maintenance, complex regulatory approval processes, and cultural barriers to electricity adoption (Antonanzas-Torres et al., 2021; World Bank, 2022). This paper focuses on mini-grid generation system design and operation, where load uncertainty in unelectrified areas is the primary challenge from this technical perspective (Hartvigsson et al., 2015). A better understanding of electricity demand enables better decisions about system sizing and operational strategies (Gelchu et al., 2023a).

Load uncertainty manifests itself through unreliable consumption estimates and inconsistent load patterns (Ashetehe et al., 2024). It can lead to undersized systems reducing reliability (Babayomi et al., 2023) or oversized systems with low utilization (Sermonis and Murphy, 2024). Traditionally, electricity consumption estimates have relied on interview surveys; however, these often exhibit significant discrepancies when compared with actual measured consumption after electrification (Hartvigsson and Ahlgren, 2018). Studies have explored various approaches to improve estimation accuracy, including satellite imagery analysis with machine learning (Fobi et al., 2022) and hybrid models that integrate machine learning with targeted surveys (Allee et al.,

* Corresponding author.
E-mail address: yw3054@columbia.edu (Y. Wu).

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Nomenclature

Variables and fixed values

A	annualized rate
C	unit capital cost [$/kW] or [$/kWh]
$D_{PUE,n,d}$	daily load of a single PUE customer (indexed by n) at day d [kWh/day]
$D_{PUE,d}$	daily load of PUE customers at day d [kWh/day]
$D_{HH,d}$	daily load of households at day d [kWh/day]
E_{PUE}	hourly load of PUE customers in the system [kW]
$E_{PUE,n}$	hourly load of a single PUE customer (indexed by n) [kW]
E_{HH}	hourly load of households in the system [kW]
f_{day}	daytime load (9AM-5PM) fraction to total energy consumption
G_n	grain mill nameplate capacity of each PUE customer (indexed by n) [kW]
i	discount rate
L	lifespan of the technology [year]
$M_{PUE,n,d}$	daily maximum load of a single PUE customer (indexed by n) at day d [kW]
$R_{pd/ad}$	peak-day to average-day load ratio
S	battery storage state of charge [kWh]
U	utilized electricity from the generation source [kW]
W_{solar}	potential solar-generated electricity [$kW_{generation}$/$kW_{installed}$]
X	technology capacity installed [kW] or [kWh]
α	proportion of electricity load that can be curtailed in load shedding scenarios
γ	increase in battery storage state of charge [kW]
Δ	battery maximum depth of discharge rate
δ	decrease in battery storage state of charge [kW]
η_{batt}	one-way battery storage efficiency
λ	curtailed load in load shedding scenarios

Subscripts and indices

batt	battery storage
d	daily timestep in simulation
HH	household
inv	battery inverter
n	index for PUE customers
PUE	productive use of energy, which is the grain mill in this paper
solar	solar photovoltaic generation system
t	hourly timestep in simulation
tech − list	technology including *solar*, *batt*, *inv*
tech	technology in tech-list

2021).

Recent data-driven studies have enhanced the understanding of rural mini-grid load patterns. Research by (Lorenzoni et al., 2020; Williams et al., 2018) categorized customers and mini-grids by consumption and load patterns, assuming stable social behaviors and weather conditions, to establish representative daily patterns for different customer types. Beyond diurnal patterns, studies (Azimoh et al., 2017; Wassie and Ahlgren, 2024) examined multi-year load profiles from mini-grids in SSA, highlighting seasonal trends and demand growth.

Despite these contributions to load profile analysis, a crucial research gap remains in understanding the relationship between load profiles and system design and operation: what makes a ‘good’ load profile for a solar-battery mini-grid? Rather than describing load patterns, the first research question of this paper focuses on identifying and quantifying the positive and negative aspects in load profiles that enhance or hinder mini-grid sustainability.

In collaboration with NOA Uganda, we collected 8760 hours of load data from over 2000 customers across 25 mini-grids in Uganda. These mini-grids had ample generation capacity, ensuring the load data reflects unrestricted customer behavior. This dataset provides a unique perspective for studying rural electricity load.

There is an additional perspective that mini-grids’ value for economic growth lies in their ability to supply kW to 10-kW level power for agro-processing, commerce, and irrigation (Adamopoulou et al., 2024). These business-oriented loads, known as productive loads, generate income within the community. In turn, these loads enhance mini-grid profitability through higher consumption and payment capacity (Dagnachew et al., 2023). Subsequently, NOA Uganda converted existing diesel machines in the communities to electric machines connected to the mini-grids. The presence of diesel loads ensured that these businesses were already viable and had confirmed energy demand (Modi, 2022). This setup allowed us to examine the impact of productive loads on the generation system sizing.

Through analysis of the load dataset, this paper identifies and quantifies two aspects of load profiles that influence mini-grid generation system sizing. One is the ratio of the peak-day electricity energy usage to the annual average-day electricity energy, which captures the day-to-day load variability. The other is the annual daytime load fraction, defined as the energy consumption from 9 AM to 5 PM as a fraction of the 24 h consumption, which indicates the proportion of demand directly met by solar generation without battery storage.

The load peak is discussed in existing research, such as the hourly-based load factor, which indicates the impact of peak power of the system (Lorenzoni et al., 2020; Scott and Coley, 2021). However, daily aggregation-based metrics, such as the peak-day to average-day load ratio, have received less attention. This distinction matters because peak power can be met by relatively inexpensive inverters, whereas peak-day energy requires battery storage, the most costly component of solar-battery systems (Chaurasia et al., 2022). Meanwhile, mini-grid operators intuitively recognize daytime load as a key metric, yet this paper provides quantitative analyses of its impact on mini-grid generation costs. Guided by these load profile aspects, this paper examines operational measures to manage peak day loads and daytime loads that can lower generation costs.

To manage peak loads, load shedding is a simple yet effective approach by temporarily disconnecting part of the demand. Prior research (Louie and Dauenhauer, 2016; Mbungu et al., 2022) employed models that optimize load shedding in mini-grids and demonstrated its effectiveness in lowering system costs; and field observation has documented a simple everyday fixed-time load shedding method used in mini-grids (Wassie and Ahlgren, 2023). This paper quantifies the benefits of load shedding across our diverse load profiles, confirming its effectiveness. However, existing approaches either rely on model-based scheduling or use fixed schedules that shut down supply at arbitrary times. The former is not operationally implementable, while the latter is inefficient. Through analysis of peak consumption patterns, this paper introduces a targeted curtailment strategy that is easier for operators to apply. This approach selectively restricts consumption for customers who contribute to excessive daily peaks, maintaining system reliability without causing system-wide shutdowns.

Recent studies in Sub-Saharan Africa show that integrating agricultural productive loads affects system sizing and costs. Farthing et al. (2023) found that irrigation and milling increase generation capacity but have site-specific impacts on Levelized Cost of Electricity (LCOE). Wamalwa et al. (2023) reported that incorporating irrigation as a productive load improves capacity utilization and can reduce LCOE by up to

47 %. A World Bank report (2022) showed that increasing daytime productive loads raises load factors and reduces LCOE from $0.38/kWh to $0.28/kWh. These cost reductions are likely to stem from higher mini-grid load factor (van Hove et al., 2022) and increased daytime electricity consumption that matches solar generation patterns (Hartvigsson et al., 2021). This paper explores the grain mill from collected data as productive loads, and tests whether comparable benefits arise in the studied systems. Beyond this, building on prior work on load flexibility (Gelchu et al., 2023b; Kraft and Luh, 2022), we investigate a flexible productive load scheduling strategy to maximize daytime direct solar utilization.

In summary, this paper focuses on understanding key aspects of load profiles affecting solar-battery mini-grid economics and developing targeted strategies. We established a Mini-grid Generation System Design model that optimizes for the least-cost solar and battery combinations and simulates power dispatch. The model is open-source, efficient, and incorporates options for load shedding and productive load shifting. Using real-world data, this paper contributes to the current literature by identifying and quantifying two critical load profile aspects that require greater attention: the peak-day to average-day load ratio and the daytime load fraction. Consequently, we develop practical strategies targeting these aspects. To address peak load days, we demonstrate the effectiveness of load shedding and propose a sizing guide plus an innovative targeted curtailment strategy. To improve the daytime load fraction, we highlight productive loads as significant daytime consumers and show how flexible scheduling can further reduce LCOE. These findings and strategies provide practical contributions to mini-grid development in rural electrification.

2. Data and methodology

2.1. Mini-grid load data

NOA Uganda operates 25 mini-grids in the Lamwo district of Uganda, where customers are equipped with Spark Meters that record electricity consumption at 15 min intervals. There are two customer connection settings: (1) single-phase, which includes households and small businesses, and (2) three-phase, which applies to grain mills. In the studied villages, households and small businesses show similar load patterns, with some sharing meters at the same location. Thus, all single-phase customers are collectively referred to as household loads. Three-phase customers operating grain mills are referred to as productive loads. Electricity consumption data for both customer groups was collected from March 1, 2023, to February 28, 2024.

Several preprocessing steps were applied to the raw data. First, outliers were removed, and the 15 min readings were aggregated to hourly intervals for dispatch simulation. Second, intermittent smart meter disconnections create zero-load gaps, followed by accumulated values upon reconnection. To address these gaps, the accumulated value was redistributed across the preceding zero intervals according to the average diurnal load pattern. Lastly, households with no recorded usage and productive customers with extended data gaps were excluded. Detailed preprocessing steps are provided in Supplementary Material S.1.1. Following preprocessing, the dataset includes data for 2124 households and 21 productive customers across 8760 hours.

2.2. Mini-grid generation system design model

In this paper, the term "productive loads" refers to grain mill loads in textual descriptions. In formulas, figures, and project configurations, the abbreviation "PUE" (Productive Use of Energy) represents these grain mill loads for brevity. This study first examines the impact of integrating productive loads by comparing two project configurations: **"noPUE"** projects, which consist solely of household loads, and **"wPUE"** projects, which combine both productive and household loads. While all 25 mini-grids can be simulated as noPUE projects, only 16 mini-grids that include at least one grain mill are used to create wPUE project scenarios.

To simulate and evaluate the mini-grid projects, we developed the Generation System Design model using linear programming. The model minimizes the annualized costs of solar and battery systems and simulates the hourly energy flow from generation to demand over a one-year period. The LCOE is calculated as the metric to assess the project's economic performance. Fig. 1 presents a schematic representation of the modeled solar-battery mini-grid system. The solar PV array and lead-acid battery storage are connected through dedicated DC/AC inverters to a common AC bus, which supplies household and productive loads. This simplified schematic corresponds to the generation and demand systems in our collaborating mini-grid projects.

Table 1 presents the detailed cost structures and technical specifications for solar and battery systems. In the model configuration, the solar system is treated as a single component with its inverter costs included. The battery system comprises lead-acid battery storage and battery inverters, which are modeled individually. Component costs are annualized according to their individual lifespans using the capital recovery factor.

In the absence of on-site solar measurements, solar generation potential data is obtained from PVGIS SARAH2 (European Commission Joint Research Center, 2024), using the Lamwo district's centroid coordinates. The tool's parameters were set for optimal tilt and zero azimuth angle, using standard crystalline silicon panels and accounting for a 14 % system loss, yielding a solar capacity factor of 17.8 % for 2019. The 2019 solar generation data was reordered (March–December 2019, then January–February 2019) to match the March 2023–February 2024 consumption data. In the modeling, we assume that solar generation potential and the consumption is known in advance.

To address the potential mismatch between 2019 solar data and 2023–24 load data, we conducted sensitivity tests using solar irradiance from different years. We also tested model parameters individually by extending the solar panel lifetime to 25 years and increasing the battery depth of discharge (DoD) to 80 %, each of which reduces annualized generation or storage costs.

To enable load management, two features are incorporated into the model. The first addresses load shedding, where a fixed proportion of annual electricity demand is allowed to be curtailed. The model disconnects certain loads at selected time steps while ensuring that the total curtailed energy does not exceed this predefined share. The timing and magnitude of curtailments are optimized to minimize the total annualized system cost, assuming perfect knowledge of hourly solar generation and electricity demand profiles. The second feature addresses the flexible productive loads, allowing each productive customer's demand to vary within the day while maintaining their total daily energy requirement.

This paper focuses on the design of generation and storage systems. For simplicity, two types of costs are excluded. First, maintenance costs for solar-battery systems are relatively low and thus set to zero. Second, distribution and connection costs are excluded since they become fixed once customers are selected, and our data comes from existing mini-grids with predetermined customers. Furthermore, the Ugandan government provides financial aid for distribution and connection expenses. Lastly, curtailed energy could be met using diesel generators, which are excluded from optimization but calculated in post-processing.

Lastly, this paper introduces the targeted-curtailment strategy. Under this strategy, a customer's power supply is temporarily disconnected if two conditions are met: (1) single-day consumption exceeds 30 times their average daily usage, and (2) single-day consumption surpasses 1 kWh. The customer's connection status is evaluated and reset daily. Implementation requires pre-established average load measurements for each customer, which can be updated periodically as consumption evolves. In this study, annual data were used to determine each household's average daily load. In the load time series, each customer's daily loads were evaluated against the targeted curtailment strategy criteria, resetting at 7 a.m. daily. On days meeting the criteria,

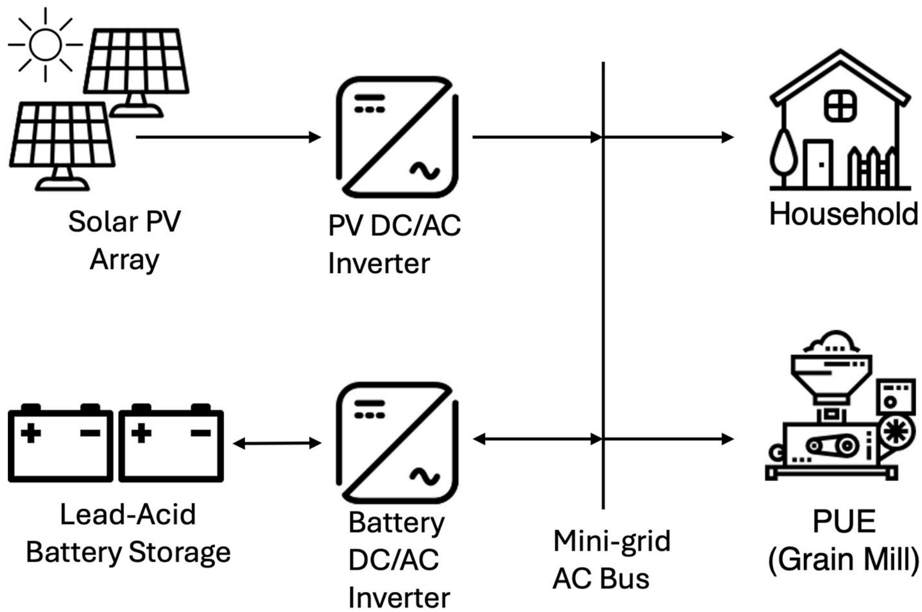

Fig. 1. Schematic of the modeled solar–battery mini-grid system.

Table 1
– Generation system parameters and costs.

Parameters	unit	value
Solar system installation cost [a]	\$/kW	960
Solar system lifespan [b]	year	15
Battery storage installation cost [c]	\$/kWh	181
Battery storage lifespan [b]	year	5
Battery round efficiency [d]	%	80
Battery max depth of discharge [d]	%	60
Battery inverter installation cost [c]	\$/kW	173
Battery inverter lifespan [b]	year	10
Discount rate [e]	%	10

[a] The median solar system cost from (IRENA, 2023) is used, as validated by sector experts.
[b] The lifespans are assumptions made within this paper.
[c] Cost estimates are sourced from (The Rockefeller Foundation, 2020).
[d] Lead-acid battery parameters are sourced from (Dhundhara et al., 2018).
[e] Refers to the Uganda Central Bank Rate (Bank of Uganda, 2024).

consumption from 7 a.m. onward was accumulated; loads within thresholds were supplied, while excess loads triggered curtailment for the remainder of the day. The 07:00 reset was chosen because it aligns with the mini-grid's operational cycle, where nighttime demand is supplied by the battery and solar generation resumes in the morning.

2.3. Model formulation

This model focuses on the energy balance between supply and demand, simplifying electric engineering details. This section introduces the formulations. The objective function is to minimize the annualized system costs, as shown in Eq. (1). The costs are associated with the installed technology capacities, including solar, battery, and battery inverter, denoted as X_{tech}. The cost is then calculated based on the unit cost, C_{tech}, and the annualization rate, $A_{L,i}$. This rate is determined using the discount rate, i, and technology lifespan, L_{tech}, as shown in Eq. (2).

$$obj : minimize\left[\sum_{tech}^{tech-list}\left(X_{tech} * C_{tech} * A_{L,i}\right)\right] \tag{1}$$

$$A_{L,i} = \frac{i*(1+i)^{L_{tech}}}{(1+i)^{L_{tech}} - 1} \tag{2}$$

The system's economic performance is evaluated using the LCOE. It is calculated in Eq. (3) by dividing the total annualized costs by the annual electricity consumption from household (HH) and productive (PUE) customers, expressed in \$/kWh.

$$LCOE = \frac{\sum_{tech}^{tech-list}\left(X_{tech} * C_{tech} * A_{L,i}\right)}{\sum_t\left(E_{HH,t} + E_{PUE,t}\right)} \tag{3}$$

The energy balance of the system is described by Eq. (4). On the left side, the equation includes electricity supplied by solar panels, $U_{solar,t}$, and net battery flow, with γ_t representing charges and δ_t representing discharges. This matches the electricity demand from household, $E_{HH,t}$, and productive, $E_{PUE,t}$, for every time step, t.

$$U_{solar,t} + \delta_t - \gamma_t = E_{HH,t} + E_{PUE,t} \tag{4}$$

$U_{solar,t}$ represents the utilized solar electricity rather than the total electricity generated. It is constrained by the solar system's capacity, X_{solar}, and the potential solar generation, $W_{solar,t}$, from the input time series data, as shown in Eq. (5).

$$U_{solar,t} \le X_{solar} * W_{solar,t} \tag{5}$$

Eq. (6) specifies that the battery charge and discharge rates, adjusted by the one-way efficiency, η_{batt}, should be aligned with changes in the battery state of charge, S. The S_1 at the first hour and the S_T at the last hour are set equal, ensuring consistency in battery simulation.

$$\frac{\delta_t}{\eta_{batt}} - \eta_{batt} * \gamma_t = \begin{cases} S_{t-1} - S_t, t > 1 \\ S_T - S_t, t = 1 \end{cases} \tag{6}$$

In Eq. (7), the battery's state of charge, S_t, should be within the battery storage capacity, X_{batt}, and above the minimum allowable state of charge, which is determined by the maximum DoD, Δ.

$$X_{batt} * (1 - \Delta) \le S_t \le X_{batt} \tag{7}$$

The battery's discharge and charge values are constrained by battery inverter capacity, X_{inv}, in Eq. (8).

$$\gamma_t \le X_{inv} \quad and \quad \delta_t \le X_{inv} \tag{8}$$

The battery inverter capacity should exceed the nameplate capacity of the largest grain mill, denoted as G and indexed by n, as shown in Eq. (9). This condition serves as a practical safeguard for the model's hourly time resolution, which captures energy balances accurately but not instantaneous (sub-hour) power fluctuations. From a modeling standpoint, the inverter capacity is defined to be sufficient to meet the power demand of the largest motor. This does not imply that when the inverter and motor capacities are equal, other loads are curtailed when the grain mill operates; all energy demand is met within the hourly balance.

$$\max_n (G_n) \leq X_{inv} \tag{9}$$

In load shedding scenarios, the variable 'curtailed load' is introduced, denoted as λ_t. The energy balance equation is modified to Eq. (10). This adjustment allows for demand not to be fully met in some hours.

$$U_{solar,t} + \delta_t - \gamma_t = E_{HH,t} + E_{PUE,t} - \lambda_t \tag{10}$$

The aggregated value of the curtailed load is less than a proportion, α, of the annual electricity demand, as shown in Eq. (11). Currently, the model optimizes the load shedding schedules without incurring additional costs.

$$\sum\nolimits_t^{8760} \lambda_t \leq \alpha^* \sum\nolimits_t^{8760} (E_{HH,t} + E_{PUE,t}) \tag{11}$$

The LCOE calculation would be adjusted from Eq. (3) to Eq. (12) in response to the load shedding.

$$LCOE = \frac{\sum_{tech}^{tech-list} (X_{tech}^* C_{tech}^* A_{L,i})}{\sum_t^{8760} (E_{HH,t} + E_{PUE,t} - \lambda_t)} \tag{12}$$

In targeted-curtailment scenario, specific customers are preselected and their curtailed energy is subtracted based on the rule from the project's total load profile to establish new load inputs. Since in this scenario, energy shortages may still occur. These shortages—distinct from targeted curtailment—are referred to as supply deficits. In the model, the same curtailed-load variable λ_t in Eq. (10) is used to represent these supply deficits, but the total curtailed energy constraint in Eq. (11) is omitted. The LCOE is calculated using the same formulation as Eq. (12).

In the flexible productive load scenarios, the productive loads are flexible on a daily basis. For each productive customer, the daily total consumption, $D_{PUE,n,d}$, and maximum power, $M_{PUE,n,d}$, are calculated from the load data. Each day, the hourly productive load for each customer, $E_{PUE,n,t}$, is optimized by the model when the aggregated value equals the fixed daily total consumption, as depicted in Eq. (13).

$$\sum_{t=1+24^*(d-1)}^{24^*d} E_{PUE,n,t} = D_{PUE,n,d}, d = 1, \ldots, 365 \tag{13}$$

Each productive customer has a daily maximum power in kW, $M_{PUE,n,d}$, as shown in Eq. (14).

$$E_{PUE,n,t} \leq M_{PUE,n,d}, t = 1 + 24(d-1), \ldots, 24d \tag{14}$$

These formulations are implemented in Python and solved using Gurobi.

2.4. Scenario settings and two load profile aspects

This section summarizes the scenarios analyzed in this paper. Two configurations are simulated based on customer types (results in Sections 3.1–3.2):

- **noPUE** projects include only household loads.
- **wPUE** projects include both household and productive loads.

Among the 25 sites, 16 include productive loads, so 16 sites have corresponding noPUE projects and wPUE projects, and 9 sites only have noPUE projects. These two configurations serve as the baseline scenarios.

The following cases extend the baseline configurations:

- Model-based **load shedding** (Section 3.3): A fixed share of annual electricity demand (1–15 %) can be curtailed, as formulated in Eqs. 10 and 11. The model optimizes the timing and magnitude of curtailed energy for both noPUE and wPUE projects.
- **Sizing guide** and **targeted curtailment** (Section 3.4): Applied to noPUE projects as an operational approach for managing extreme peak-day demand. The sizing guide recommends installing 0.5 kW of solar capacity and 1.5 kWh of effective battery storage per kWh of average daily load (derived in Section 3.3). And in the targeted curtailment case, customers with unusually high single-day consumption (over 30 times their average and above 1 kWh) are curtailed (proposed in Section 3.4).
- **Flexible productive load** analysis (Section 3.5): Applied only to wPUE projects, allowing productive loads to shift within a 24 h period while maintaining total daily energy use, named 'wPUE Flexible', compared with baseline as 'wPUE Fixed'.

Scenarios are assessed with LCOE and two key load profile aspects. First, the **peak-day to average-day load ratio** quantifies daily variability in electricity use. It is defined as the total energy on the highest-consumption day divided by the mean daily load. Daily energy is calculated from 7 a.m. to 7 a.m. of the following day, rather than midnight to midnight. This was chosen because our findings indicate that the load is consistent from nighttime to early morning when battery continues to supply energy. Starting the day at 7 a.m. yields stronger correlations with LCOE than a midnight start. In Eq. (15), hourly loads are aggregated to daily totals, $D_{HH,d}$ and $D_{PUE,d}$. Only the first 364 days are included, because the final day is incomplete under the 7:00–7:00 definition. In Eq. (16), the ratio, $R_{pd/ad}$, is obtained using the maximum and mean values across all days.

$$\sum_{t=8+24^*(d-1)}^{7+24^*d} E_{HH,t} + E_{PUE,t} = D_{HH,d} + D_{PUE,d}, d = 1, \ldots, 364 \tag{15}$$

$$R_{pd/ad} = \frac{\max_d (D_{HH,d} + D_{PUE,d})}{\operatorname{mean}_d (D_{HH,d} + D_{PUE,d})} \tag{16}$$

Second, the daytime load fraction, representing the proportion of total electricity load occurring between 9 a.m. and 5 p.m., which corresponds to typical solar generation periods, is shown in Eq. (17).

$$f_{day} = \frac{\sum_d^{365} \sum_{t=10+24(d-1)}^{17+24(d-1)} (E_{HH,t} + E_{PUE,t})}{\sum_t^{8760} (E_{HH,t} + E_{PUE,t})} \tag{17}$$

3. Results

3.1. Electricity load overview

The collected load data reveals a sharp contrast in electricity consumption between households and productive customers. Household consumption is low, with the monthly mean of 7.0 kWh and a median of 3.2 kWh. In contrast, productive customers exhibit substantially higher consumption, with a monthly mean of 353.4 kWh and a median of 298.4 kWh. Fig. 2 (a) illustrates the average monthly electricity consumption of households and productive users for each mini-grid, highlighting that the consumption from a small number of productive customers is comparable to the total household consumption in the village.

Fig. 2(b) illustrates the average diurnal load patterns for aggregated households by mini-grid and for each productive customer, alongside average solar generation diurnal patterns. Both household and productive loads peak from late afternoon to evening, whereas solar generation generates most electricity between 9 a.m. and 5 p.m. This mismatch between peak loads and solar generation necessitates battery storage.

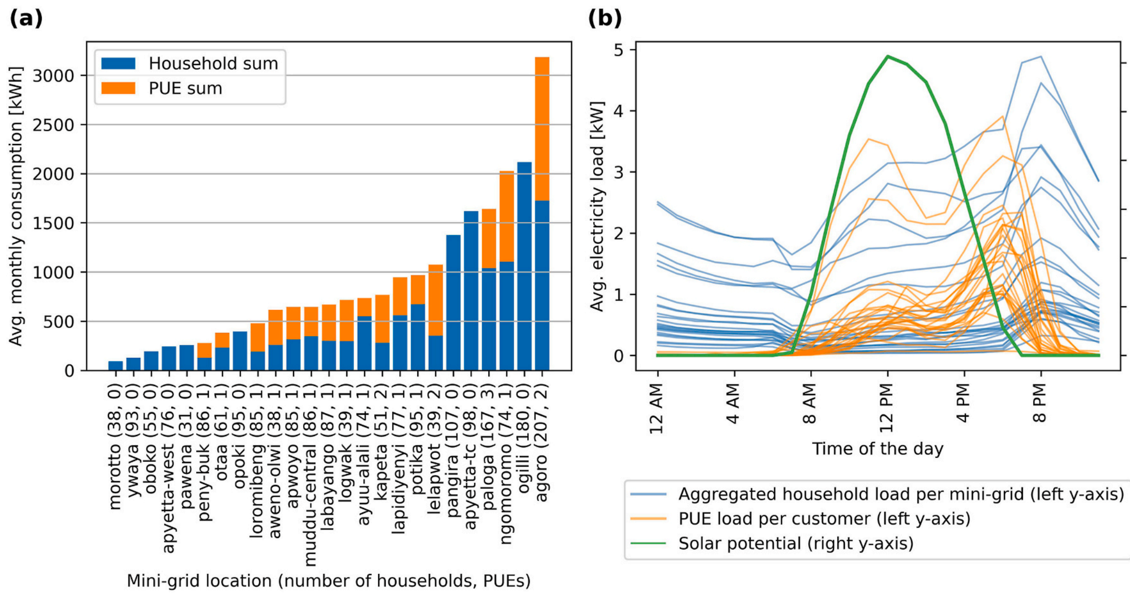

Fig. 2. – Household vs. productive load patterns across mini-grids. (a) Average monthly electricity consumption by aggregated households and aggregated Productive Use of Energy (PUE) customers across mini-grids. (b) The hourly average of diurnal load patterns per mini-grid aggregated households and per PUE customer (left-side y-axis), is compared with the pattern of the average solar generation potential (right-side y-axis).

Household loads are distributed throughout the day, whereas productive loads are concentrated during daylight hours. Given the ample installed capacity of these mini-grids (as shown in Supplementary Fig. S2), the recorded load reflects unconstrained consumption behavior.

3.2. Key load profile aspects

The 25 noPUE projects and the 16 wPUE projects are simulated using the Generation System Design model. On average across all projects, solar contributes about 33 % of the total system costs, battery storage accounts for 63 %, and the battery inverter contributes a small share. Therefore, discussions primarily focus on solar and battery storage. Throughout the results section, "battery" refers to battery storage. The reported capacity represents effective storage by accounting for the maximum DoD rather than the nameplate capacity.

After analyzing various aspects in relation to LCOE, this study identifies the peak-day to average-day load ratio as the primary determinant of solar-battery mini-grid project LCOE. The peak load day requires large solar and battery capacities, leading to underutilization on typical days. The relationship between LCOE and this ratio is depicted in Fig. 3(a). The secondary significant aspect is the daytime load fraction—the proportion of the load occurring between 9 a.m. and 5 p.m. More daytime load supplied by solar reduces reliance on batteries, thereby lowering LCOE. This fraction is inversely correlated with LCOE, as shown in Fig. 3(b).

A linear regression analysis further quantifies the relationship between load profile aspects and LCOE, yielding an R-squared value of 0.880, indicating a strong linear fit. The results are detailed in Table 2,

Table 2
– Impact of load profile aspects on LCOE ($/kWh): a linear regression analysis.

Variable	Coefficient	Std. Error	P-value
Peak-day to average-day load ratio	0.233	0.031	0.000
Daytime load fraction	−0.569	0.287	0.059
Solar availability during peak days	−0.301	0.264	0.265
With or without productive load (Binary)	−0.019	0.065	0.773
Monthly solar potential and load correlation	−0.019	0.090	0.835
Peak-hour to average-hour load ratio	0.001	0.006	0.893
Intercept	0.509	0.217	0.027

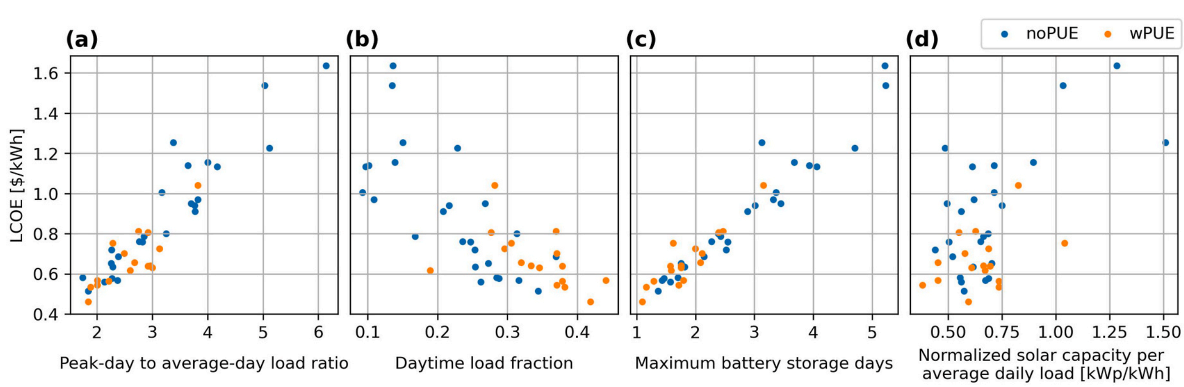

Fig. 3. – Correlation between mini-grid Levelized Cost of Electricity (LCOE) and system factors. Two key load profile aspects influence LCOE: (a) the peak-day to average-day load ratio and (b) the fraction of daytime load (9 a.m.–5 p.m.) to total load. Two generation system components determine LCOE: (c) battery storage capacity and (d) solar capacity. Both capacities are normalized through the division of model output capacities by the average daily load, enabling cross-project comparison. Battery capacity divided by the average daily load represents the maximum number of days the battery can supply the average load. Each graph displays wPUE projects (households and Productive Use of Energy) and noPUE projects (household-only).

with the P-values highlighting the strength of relationships with LCOE. It shows the peak-day to average-day load ratio is highly significant (P-value of 0.000), and the daytime load fraction is significant (P-value of 0.059). Moreover, the coefficients quantify the impacts: decreasing the peak-day to average-day load ratio from 4 to 2 could reduce LCOE by \$0.466/kWh, and increasing the daytime load fraction from 0.2 to 0.4 could lower it by \$0.114/kWh.

Although ‘solar availability during peak days’ has a low P-value, it is beyond the control of mini-grid design due to its dependence on variable weather conditions. The binary variable for including productive loads or not has a high P-value, indicating that customer types with very different loads are not the fundamental reason impacting LCOE. The other two variables in Table 2 may explain the LCOE performance of a few projects but have minimal impact on most. Removing these variables does not reduce the performance of the linear regression. Lastly, the regression analysis includes an intercept. More details about the regression processes and variables are provided in Supplementary Material S.2.2.

Fig. 3 also visualizes the LCOE versus battery and solar capacities in panels (c) and (d). To allow project comparison, capacities are normalized against the average daily load in kWh. The normalized battery storage capacity is expressed as maximum battery storage days, showing how many days a fully charged battery can supply the average load. For example, a project with a daily average load of 40 kWh, maximum battery storage of 3 days, and a normalized solar capacity of 0.6 kW/kWh would require 24 kW peak solar capacity and 120 kWh of effective battery storage.

Fig. 3(c) shows that the maximum battery storage days has an obvious linear relationship with LCOE, with a wide range from 1 to 5 days. This measure is closely tied to the peak-day to average-day load ratio, with a correlation coefficient of 0.93. Moreover, a system with a higher daytime load fraction requires less battery capacity to shift energy from daytime to nighttime, as evidenced by a correlation coefficient of −0.74. However, Fig. 3(d) reveals a weak correlation between LCOE and normalized solar capacity. Most projects feature normalized solar capacities around 0.6 kW per kWh of average daily load, with a variance of ±0.2 kW. Four outliers exceeding 1 kW are attributable to significantly high peak-day to average-day load ratios or low solar availability during peak days.

In conclusion, this analysis illuminates the cascade of influence exerted by the load profile on solar and battery systems, subsequently impacting the mini-grid LCOE. The peak-day to average-day load ratio and the daytime load fraction significantly affect battery storage capacity. Battery storage accounts for approximately two-thirds of the total costs of the electricity supply system, thereby playing a crucial role in determining the LCOE of the mini-grid. Meanwhile, although solar comprises the remaining third of the costs, the load profile’s impact on solar capacity is relatively limited.

In another dimension, Fig. 3 shows the distinctions between projects with and without productive loads. In the 16 sites with grain mills, where both noPUE and wPUE projects were simulated, integration of productive loads decreases the average peak-day to average-day load ratio from 3.1 to 2.6 and raises the average daytime load fraction from 0.22 to 0.34. These changes contribute to an average 23 % decrease in the LCOE (from 0.87 to 0.67 \$/kWh). Integrating productive loads makes more consistent consumption throughout the year and higher daytime usage. Although productive users require the system with larger battery inverters, their contribution to total costs is limited. Combining Figs. 2 and 3, it is evident that integration of productive customers not only increases electricity consumption, but also changes the load profile, leading to higher solar and battery system utilization and lower LCOE.

Sensitivity tests using solar data from different years were conducted to address the mismatch between the load and solar datasets. The results confirm that the main findings are robust to solar variability (Supplementary Material S.2.4). To test parameter uncertainty, we extended the solar lifespan from 15 to 25 years and increased the battery DoD from 60 % to 80 %. These changes reduce LCOE by roughly 5 % and about 16 %, respectively. Because these shifts apply similarly across all projects, the relationships between load profiles and system economics remain unchanged, confirming the robustness of our findings (Supplementary Material S.2.5).

3.3. Load shedding

Given that the peak-day to average-day load ratio is the primary determinant of a solar-battery mini-grid’s LCOE, this study explores load shedding to manage peak loads. The model simulates scenarios by progressively increasing the shed energy from 1 % to 15 % of the annual electricity consumption. The baseline scenario, in which all customer load is met at all hours, is called the “full load” scenario.

Fig. 4(a) illustrates that LCOE decreases as load shedding increases, with the average values and the 10th-90th percentile range across modeled mini-grid projects. This figure shows that applying 5 % load shedding reduces the average LCOE from \$0.81/kWh in the “full load” scenario to \$0.39/kWh, across all noPUE and wPUE projects. This LCOE reduction is primarily attributed to a decrease in the peak-day to average-day load ratio, which declines from 3.0 to 2.0, as shown in Fig. 4(b). The impact of load shedding on LCOE reduction diminishes as load shedding increases from 5 % to 15 %. This occurs because initial load shedding primarily targets a few days with exceptionally high loads, whereas subsequent reductions affect smaller, more frequent peaks.

Analysis shows that a 5 % load shedding strategy effectively reduces LCOE while maintaining essential electricity service reliability. Consequently, this paper further discusses the 5 % load shedding scenario. Fig. 4(b) illustrates changes in normalized solar and battery capacities during a shift from ‘full load’ to a 5 % load shedding scenario. Among all wPUE and noPUE projects, normalized solar capacities decrease from 0.68 to 0.41 kW, and maximum battery storage days declined from 2.46 to 1.03, with battery reductions playing a key role in cost reduction. Solar capacity ranges are consistently similar across both noPUE and wPUE projects. While wPUE projects often feature smaller battery storage capacities than noPUE projects, load shedding narrows the disparity.

Beyond reducing average LCOE and system capacities, load shedding also leads to a convergence in these metrics across projects. At ‘full load’, the variation in LCOEs is significant, and wPUE projects typically have a substantial advantage over noPUE projects. However, as load shedding is implemented, the LCOE ranges (10-90th percentile) narrow for both noPUE and wPUE groups, and the advantage of wPUE projects diminishes. Similarly, solar and battery capacities converge as load shedding is implemented. This convergence results from load shedding eliminating the most challenging peak load events, thereby unifying the peak-day to average-day load ratio across projects.

The observation suggests that allowing load shedding improves the predictability of mini-grid sizing. Accordingly, we examined the capacity requirements of systems with ≤5 % load shedding in Fig. 4(b) to develop a sizing guide. The upper ranges of the box plots provide conservative bounds, showing that such systems require ≤0.5 kW of solar capacity and ≤1.5 kWh of effective battery storage per kWh of average daily load. Therefore, we propose a sizing guide: if a system is designed with 0.5 kW solar and 1.5 kWh battery per kWh of average daily load, load shedding will remain below 5 % and LCOE will be approximately \$0.50/kWh. This provides a simple design rule based on a single metric—the average daily load.

For example, if a project is estimated to consume 40 kWh of electricity per day, a system could be designed with 20 kW of solar and 60 kWh of battery storage. The inverter capacity, not shown in the plot, can be determined as 0.3 kW per kWh of average daily load (Supplementary Material S.2.3). However, wPUE projects should still account for their specific motor limitations when designing battery inverters.

Under these load shedding scenarios, diesel generation offers an alternative supplementary approach. We conducted a computation

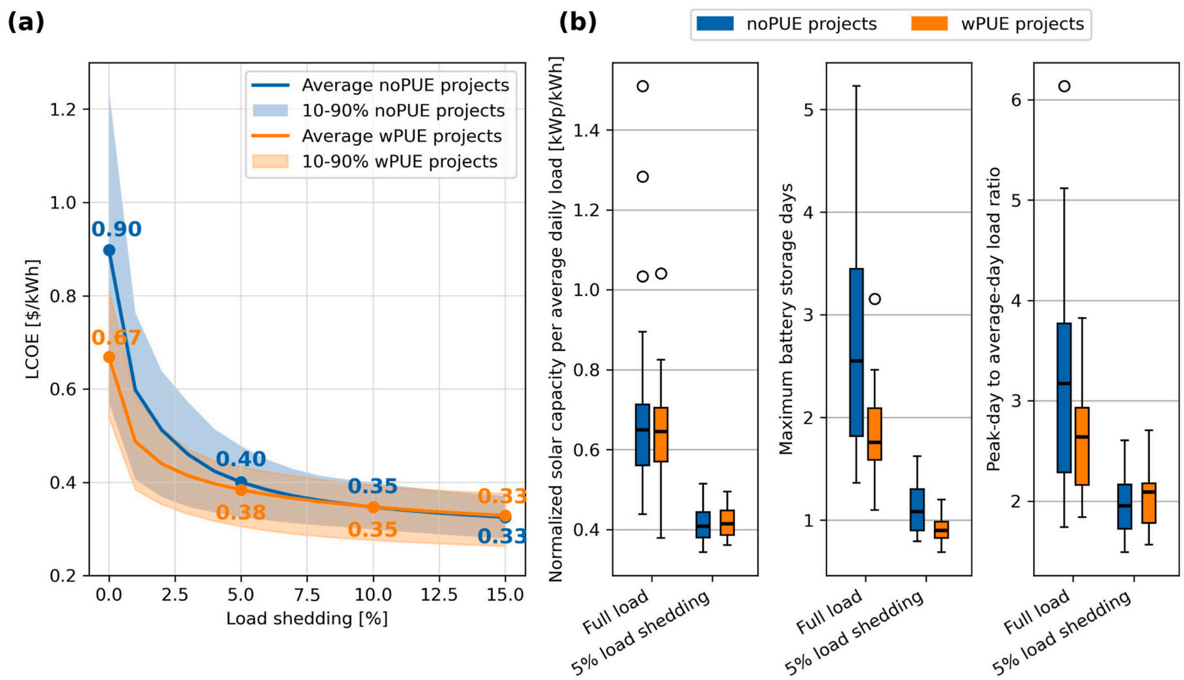

Fig. 4. – Impact of load shedding on the generation system. (a) Reduction in Levelized Cost of Electricity (LCOE) with incremental load shedding from 0 % to 15 %. Solid lines show average values and shaded areas represent the 10th-90th percentile range across modeled mini-grid projects. Load shedding refers to the total power supply cut as a percentage of the total energy demand. (b) Comparison of normalized solar capacity, the maximum number of days the battery can supply the average load, and peak-day to average-day load ratio between full load and 5 % load shedding scenarios. The capacity metrics were normalized using the same approach described in Fig. 3. Each graph displays wPUE projects (households and Productive Use of Energy) and noPUE projects (households only).

where diesel generators supply the curtailed 5 % load in all projects. This supplementary generation resulted in an LCOE of $0.46/kWh, increased from $0.39/kWh, but remains significantly lower than the ‘full load’ scenarios. This finding demonstrates that diesel generation can be an effective strategy to address peak load days when needed. Details regarding the associated assumptions can be found in Supplementary Material S.1.2.

Because increasing battery DoD substantially changes LCOE, we verified whether load shedding remains effective under the 80 % maximum DoD assumption. The results show that 5 % load shedding still reduces LCOE by about half and preserves the sizing-guide values, confirming the load shedding effects and robustness of the sizing guide as well (Supplementary Material S.2.5).

3.4. *Targeted curtailment*

Load shedding has demonstrated a strong capability to reduce LCOE in scenarios where the model optimizes curtailment timing. However,

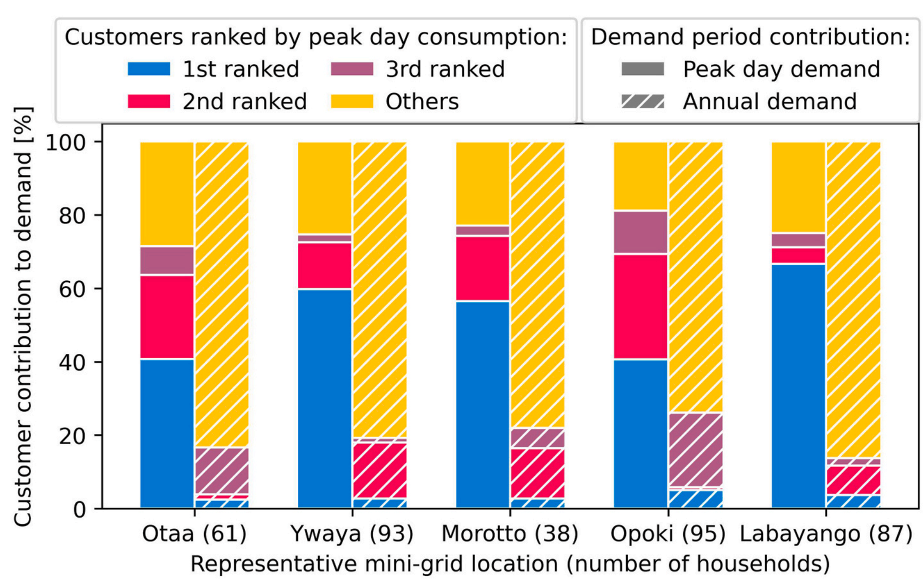

Fig. 5. – Comparison of the peak-day and annual demand shares for selected customers. The left bar for each mini-grid shows the peak-day demand share of the three highest-demand consumers and the remaining consumers (aggregated). The hatched right bar shows the annual demand share for the same customer groups from the peak-day. The figure presents five household-only mini-grids with the highest peak-day to average-day load ratios, with their customer counts shown in parentheses.

real-world applications require a clear and practical approach to implement load shedding. A crucial starting point is understanding the origins of the high peak-day to average-day load ratios. We analyzed five projects with the highest peak-day to average-day load ratio, with none having productive loads. Fig. 5 presents the load distribution on each project's peak consumption day, showing contributions from the three highest-consuming customers and all others combined. The analysis reveals that one or two out of 38–95 customers per project account for over 60 % of the peak-day consumption. However, hatched bars in this figure show that these identified customers do not consistently consume electricity in such high proportions throughout the year. Therefore, special attention should be given to customers who exhibit these infrequent high-demand events.

Given that a few customers significantly contribute to peak-day consumption, we apply the targeted-curtailment strategy to manage these extreme demand events. In this approach, a customer is temporarily disconnected if two conditions are met: (1) single-day consumption exceeds 30 times their average daily usage, and (2) single-day consumption surpasses 1 kWh. Implementation details are described in Section 2.2. This strategy focuses on customers with infrequent but substantial peaks, aiming to manage community-level demand through selective curtailment rather than risking system-wide shortages.

Fig. 6 demonstrates the impact of this targeted curtailment strategy. Among 2124 households, 157 (7.4 %) experienced high-demand events requiring curtailment, with affected customers averaging 16.4 h of curtailment per year. To assess the system-wide impact, we introduced the metric of customer-hours, which is defined as each hour of service experienced by a customer. The total curtailment amounted to 2568 customer-hours, representing 0.014 % of total service hours across all customers.

Given that high peak-day to average-day load ratios are primarily observed among households, this paper experiments with the targeted curtailment strategy exclusively on noPUE projects. Following our proposed sizing guide in Section 3.3 (installing 0.5 kW of solar, 1.5 kWh of battery storage, and 0.3 kW of battery inverter, for each kWh of average daily load), the systems cannot meet all loads at all hours. The unmet energy in these sizing-guided systems is referred to as the supply deficit. We evaluated the effectiveness of the targeted curtailment strategy in managing these supply deficits and mitigating system-level shortages.

Fig. 7 illustrates the load profile over a two-day high-demand period of the Labayango noPUE project under the sizing guide. The left panel demonstrates that without a targeted curtailment strategy, there are 11 h of supply deficit. The right panel shows the load profile after applying curtailment on a single customer who exceeded 30 times their average daily load on both days. This strategy stabilized the system-wide electricity supply for the other 86 customers, reducing their supply deficit to nearly 1 h. This example demonstrates how targeted curtailment can maintain system-wide stability. The same curtailment approach is applied to all customers when their consumption meets the established criteria.

In the original model, supply deficit solutions were not unique due to the objective function treating multiple low-energy deficits per hour similarly to fewer but higher deficits. To address this, binary variables with associated costs were introduced to consolidate deficits into fewer hours without changing the total deficit energy. This ensures a unique solution by minimizing the number of deficit hours while keeping the total curtailed energy unchanged.

Fig. 8 shows the results of all noPUE projects under this guided sizing with or without the targeted curtailment strategy. The 'full load' projects are shown as the benchmark, where we size the generation system to meet all loads at all hours. The 'full load' projects have an average cost of $0.90/kWh, which varies widely based on different load profiles. In contrast, the guided size projects with or without targeted curtailment show an average cost of $0.53/kWh, with minimal variation from total supplied load differences. This economic advantage comes at the expense of the supply deficits. In scenarios with guided sizing but without curtailment, the median project experiences a supply deficit of 1.3 %, with a maximum of 5.1 %, relative to its annual energy demand. Implementing targeted curtailment reduces these deficits, with median total energy deficits decreasing to 0.80 % and maximum deficits to 2.32 %. This reduction corresponds to the amount of curtailment applied.

Despite no change in system size, the targeted curtailment strategy prevents a few customers from consuming all the system's energy, ensuring that more people can meet their basic daily energy requirements. Its effectiveness is measured by the total supply deficit customer-hour. For each project, the number of uncurtailed customers is multiplied by the supply deficit energy ratio to the total uncurtailed demand for each hour. After calculating all hours, these figures are aggregated to determine the total supply deficit customer-hours. Fig. 8 (b) shows that across 25 mini-grid projects with 2124 customers, the total supply deficit reaches 53,082 customer-hours, constituting 0.285 % of the total possible customer-hours calculated from the annual 8760

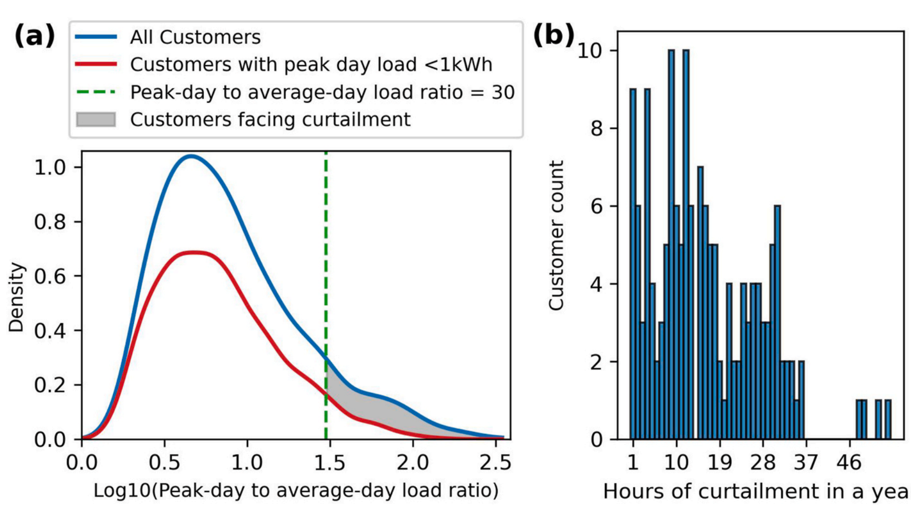

Fig. 6. – Customers targeted for curtailment and their annual curtailment hours. (a) Distribution of peak-day to average-day load ratios for 2124 customers (blue line), with those having peak day loads under 1 kWh (red line). The x-axis shows this ratio on a logarithmic (Log10) scale. The grey area identifies 157 customers targeted for curtailment, selected based on having both peak-day to average-day load ratio above 30 (green dashed line) and peak day load greater than 1 kWh. (b) The frequency of curtailment hours per year for these 157 customers. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

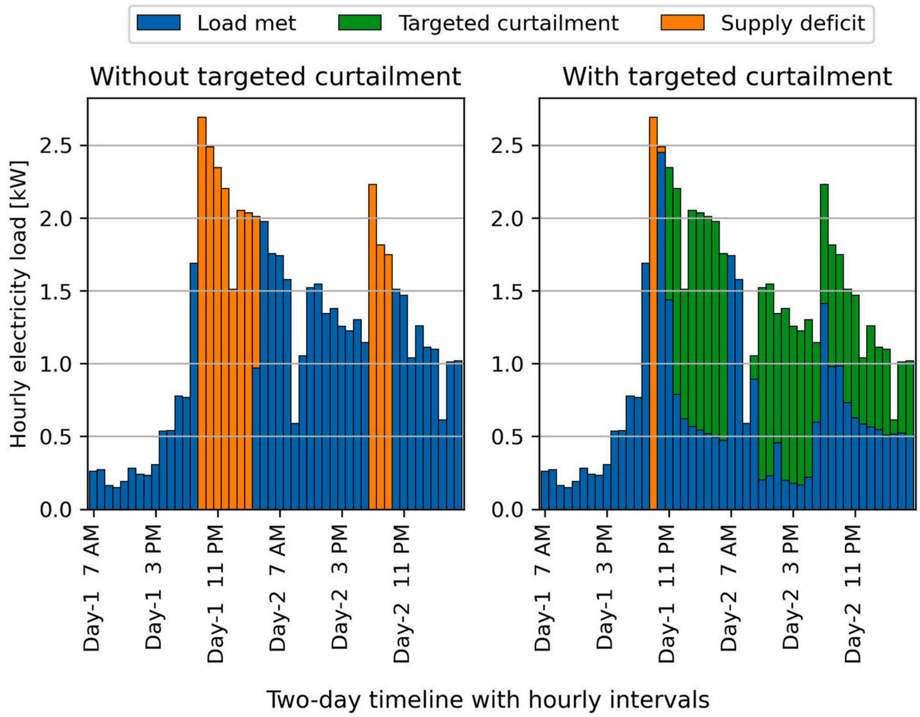

Fig. 7. – Load comparison over a two-day window without (left) and with (right) targeted curtailment, at the household-only Labayango mini-grid. The load is divided into three categories: met by supply (blue), under targeted curtailment (green), and experiencing supply deficit (orange). Targeted curtailment is applied to a single customer whose daily consumption exceeds 30 times their daily average and at least 1 kWh that day. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

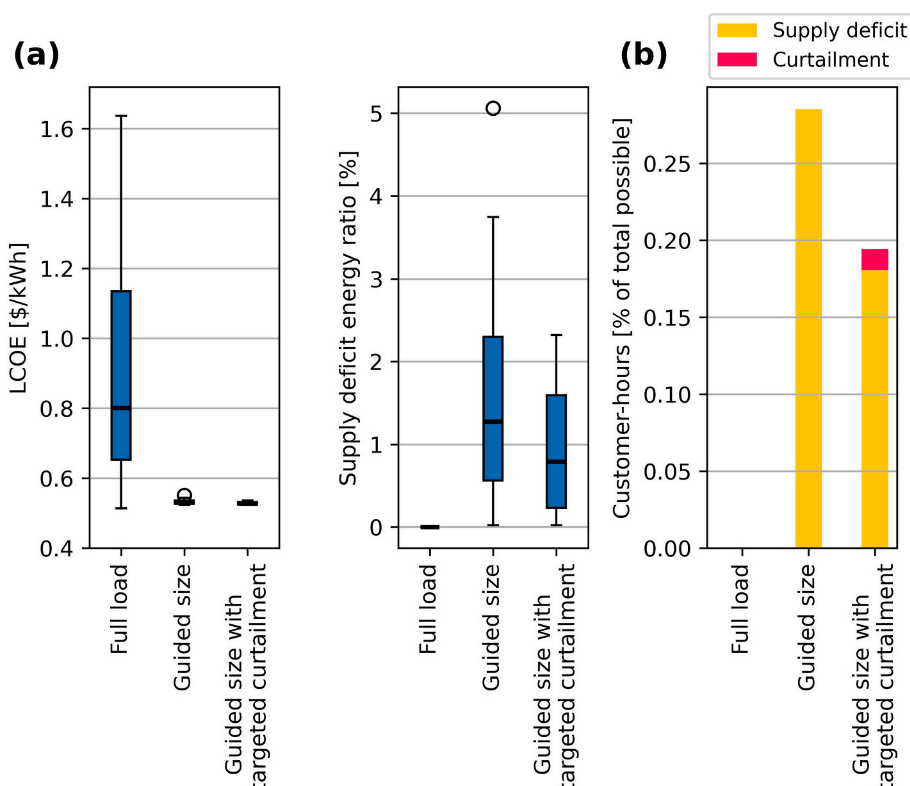

Fig. 8. – System performance under different sizing and curtailment approaches across 25 household-only mini-grids. (a) Distribution of LCOE and supply deficit energy ratio across the mini-grids, and (b) Aggregated supply deficit and targeted curtailment customer-hour expressed as a percentage of total possible service hours across all customers in all mini-grids. Three scenarios are compared: meeting all loads at all hours (full load), guided sizing without and with targeted curtailment. Customer-hour represents each hour of service per customer.

h per customer. With targeted curtailment applied to 0.014 % of customer-hours to the total possible, the supply deficit is reduced to 33,598 customer-hours or 0.181 %. This results in an average annual deficit of just 15.8 h per customer. Lastly, the strategy is particularly beneficial for projects with high peak-day to average-day load ratios caused by a few customers using extremely more electricity than their average. It is much less effective in projects with low peak-day to average-day load ratios.

In summary, the targeted curtailment strategy has proven effective in managing household-only system stability. By disconnecting the few customers who exhibit unexpectedly high peak-day consumption, this strategy ensures a more reliable system-wide electricity supply for the majority of customers.

3.5. Productive load flexibility

To address the daytime load fraction, this section implements an experiment with productive load flexibility, limited to the 16 wPUE projects. This flexibility allows the model to adjust productive load scheduling to match periods of solar availability, while maintaining the same total daily consumption. The wPUE projects discussed earlier in this paper are labeled ‘wPUE Fixed’, and projects with flexible productive loads are labeled ‘wPUE Flexible’. Fig. 9 compares outcomes from ‘wPUE Fixed’ scenarios, ‘wPUE Flexible’ scenarios, and noPUE projects.

In panel (a), implementing productive load flexibility in ‘wPUE Flexible’ leads to an average LCOE reduction of 15 % compared to ‘wPUE Fixed’ scenarios. This improvement builds upon the 23 % reduction already achieved by integrating productive loads into projects. Panel (b) reveals that the decreased battery capacities drive these LCOE reductions, while solar capacities remain unchanged. This reduction in battery capacity is due to an increase in the daytime load fraction from an average of 0.34–0.56, as productive loads are synchronized better with solar generation. These benefits are attributed to changes in the daytime load fraction, with the peak-day to average-day load ratio remaining constant. Lastly, in this test, a higher proportion of the productive load relative to the total load typically leads to significant reductions in LCOE and increases in the daytime load fraction.

4. Discussion

This study identifies two critical load profile aspects that significantly impact the LCOE in solar-battery mini-grids. The primary aspect is the peak-day to average-day load ratio, emphasizing capacities required for peak load days. The secondary aspect is the daytime load ratio, which highlights the benefits of aligning daytime solar generation with electricity load. Accordingly, this paper evaluates strategies such as load shedding to manage peak loads, integrating productive daytime loads, and leveraging productive load flexibility to enhance daytime usage.

In solar-battery mini-grids, we found that system sizing is mainly constrained by daily energy balance rather than power peaks. The conventional load factor is more applicable to hybrid solar–diesel systems, where costs depend on capacity utilization (Lorenzoni et al., 2020; Scott and Coley, 2021; World Bank, 2022). In this analysis, solar-battery systems operate on daily charge–discharge cycles, making daily energy metrics more relevant. As shown in Table S3, the daily indicator correlates strongly with solar and battery capacities, whereas the hourly load factor relates to inverter sizing.

Projects with the highest peak-day to average-day load ratios are primarily influenced by a few customers with sporadic high-demand events, even though their average daily consumption is low. Some mini-grid operators have addressed this by implementing tiered tariffs based on maximum power or energy usage thresholds. This approach prevents unexpected surges, but it may discourage customers with consistently high electricity consumption. The core challenge lies not in consistently high usage customers, but in customers having unexpected high peak-day demands. Another approach involves disconnecting the electricity supply when the battery level drops below a threshold. However, this method is inequitable, as major customers experience power outages due to a few high-consumption users depleting shared resources, despite all paying the same tariff.

Therefore, this paper proposes a curtailment strategy that disconnects customers whose daily consumption exceeds thirty times their average. This strategy effectively manages mini-grids with high peak-day to average-day load ratios, reducing supply deficit hours for the majority of customers. Furthermore, for high-demand special occasions

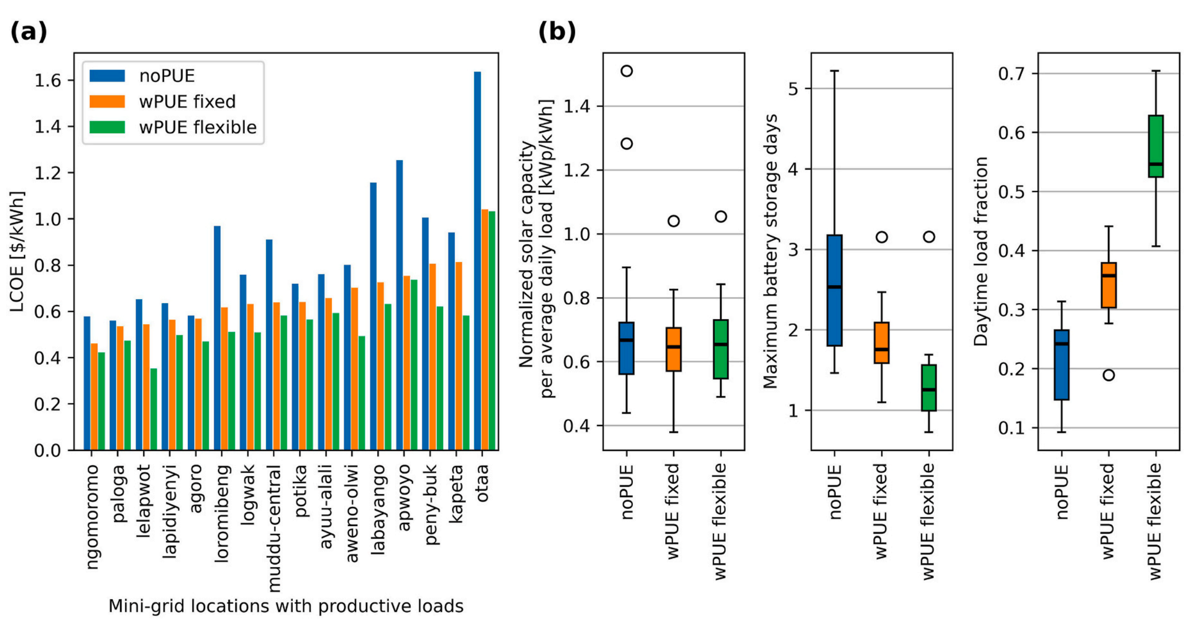

Fig. 9. – Impact of Productive Use of Energy (PUE) flexible scheduling across 16 mini-grids with grain mill as the productive loads. (a) Changes in the Levelized Cost of Electricity (LCOE) under three different setting scenarios: wPUE fixed, representing the unconstrained loads; wPUE flexible, involving the redistribution of the same total electricity use over every 24 hours; and noPUE, with no productive loads. (b) Distribution of system parameters: normalized solar capacity over average daily load, the maximum number of days the battery can supply the average load, and the fraction of daytime load (9 a.m.–5 p.m.) to total load.

(e.g., weddings), operators of multiple mini-grids in a region could offer battery pack or diesel generator rental services. This rental service could be expanded to nearby unelectrified villages or houses. Additionally, the same high-demand event has a smaller impact on the peak-day to average-day load ratio in higher-demand mini-grids compared to lower-demand ones, because the former ones have a higher denominator. So, targeted curtailment provides more benefits in projects with smaller demand profiles.

This paper explores flexible load rescheduling to improve the daytime load ratio. Rescheduling household loads that typically peak during the evening and night poses challenges, so we tested flexible productive load, which naturally occurs during the daytime. For implementation, it's more efficient to collaborate with a single productive customer with high demand than coordinating with multiple smaller customers.

In this study, the electric mills examined are converted from existing diesel-powered mills rather than newly established businesses with uncertain demand. These mills already operate with consistent and confirmed energy needs, so their electrification provides substantial benefits to mini-grid operations. This suggests that prioritizing the electrification of existing fossil-fuel-based businesses can be especially advantageous.

Grain mill owners may consider alternative energy solutions, such as standalone electricity systems or diesel operations. First, standalone systems typically have higher LCOE than mini-grids (Supplementary Material S.2.6). For diesel mills, assuming 25 % machine efficiency and diesel at $1.4 per liter, the operational cost is $0.53/kWh when converted to electrical equivalent. Diesel machines may offer lower operational energy costs than electricity when connection costs are added. In this situation, because productive loads reduce the mini-grid LCOE and thereby enhance household electrification in the community, mini-grid operators and governments should consider offering benefits to productive customers, such as subsidizing their electrification transition or giving lower tariffs.

This paper proposes a sizing guide for mini-grid design that strategically accepts a small amount of unmet energy to achieve reasonable generation costs. In the studied projects, this sizing approach results in an average load shed of 1.7 %, with a maximum of 5.1 %. To address equity concerns, we introduce a targeted curtailment strategy that reduces supply deficit customer-hours by 37 %. This combined approach of strategic sizing and targeted curtailment can be effectively implemented in mini-grid design and operation, with particularly strong results in household-only mini-grids as demonstrated in the results section.

One limitation of this combined approach is the requirement for estimation of average community load—a challenging task that researchers have attempted to address. This paper does not resolve this issue; it only provides a framework for system design once such estimates are available. A second limitation is the exclusion of distribution and connection costs, as the paper focuses on load profiles and generation systems. Nonetheless, distribution and connection costs are significant. Especially when system demand is low, the per-kWh costs associated with these expenses can be very high.

Moreover, the optimization model in this paper has inherent limitations. It assumes perfect knowledge of the data to present ideal results instead of considering uncertainties. Its hourly time resolution limits the representation of short-term power dynamics, meaning instantaneous kW requirements (i.e., battery inverter size) may not be fully captured in the design. Lastly, LCOE is used as the main comparison metric, but its value can vary under different parameter and cost assumptions. Overall, these simplifications affect the absolute LCOE and warrant caution when comparing with other studies. However, they do not fundamentally influence comparative trends across scenarios, such as identifying key load-profile aspects or assessing the effects of load shedding.

In summary, this paper offers several recommendations for mini-grid operators and policymakers: (1) focus on two critical load profile aspects: the peak-day to average-day load ratio (primary) and daytime load fraction (secondary), which should guide strategy development; (2) prioritize productive loads integration to improve load profiles, implementing flexible scheduling where applicable; (3) balance generation costs against system reliability levels, as small load shedding can substantially reduce generation costs; (4) apply the proposed sizing guide once average demand is predicted for cost-effective system design; (5) implement targeted curtailment for customers whose consumption unexpectedly exceeds their typical usage, ensuring reliable operation for the entire community.

5. Conclusion

This study analyzed one-year of hourly load data from 2124 households and 21 grain mills across 25 mini-grids in Uganda. We developed an open-source Mini-grid Generation System Design model to simulate these load profiles, providing valuable insights into rural mini-grid generation costs. Simulations were conducted for two project configurations: household-only projects, and projects combining households with grain mills as productive loads. The analysis identified two critical load profile aspects that significantly influence generation costs. The peak-day to average-day load ratio is the primary aspect, with higher ratios leading to significant LCOE increases. The daytime load fraction is the secondary aspect, where higher fractions demonstrated potential for LCOE reduction. These findings suggest that strategies to improve mini-grid generation design and operation should prioritize managing these two aspects.

Our findings confirm and expand upon previous research on the importance of productive loads in mini-grid development. Integrating productive loads can lower the peak-day to average-day load ratio and increase the daytime load ratio, resulting in lower LCOEs compared to household-only systems. Furthermore, when productive loads operate on flexible schedules, mini-grids can achieve higher daytime load fractions, leading to additional LCOE reductions. These results suggest mini-grid operators should establish cooperation agreements with productive users to encourage daytime electricity consumption.

This research demonstrates that load shedding during rare peak-day events can significantly reduce generation costs. It represents a crucial trade-off between system reliability and cost-effectiveness, where a minor reduction in reliability yields substantial cost savings. Based on this trade-off, we propose a sizing guide with one input metric - estimated average daily load. This sizing framework maintains the unmet load below 5 % across simulated projects while ensuring economically viable mini-grid LCOEs. Additionally, this paper revealed that extreme peak-day loads in some household-only projects come from a single customer who consumes much less during all other days. We propose a targeted curtailment strategy that limits usage when a customer's single-day consumption exceeds thirty times their average. This strategy prevents system-wide blackouts and increases system equity.

This paper provides actionable insights and strategies for optimizing mini-grid design and operation. Future work could focus on two areas not addressed in this study: improving load estimation accuracy prior to local electrification and integrating distribution systems design within the simulation models. Both aspects are crucial for broadening the scope of this research and advancing mini-grid development strategies.

CRediT authorship contribution statement

Yuezi Wu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Alex Wanume:** Writing – review & editing, Validation, Resources, Conceptualization. **Vijay Modi:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude (Anthropic) in order to improve the readability, grammar, and language clarity of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2025.115004.

Data availability

The code and sample data for the Generation System Design model in this study are available at: github.com/SEL-Columbia/mini-grid_generation_system_design.

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