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Understanding the load profiles and electricity consumption patterns of PV mini-grid customers in rural off-grid east africa: A data-driven study

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ABSTRACT

This paper analyzes the load profiles and electricity consumption patterns of different customer types electrified by off-grid solar photovoltaic (PV) mini-grids in two remote towns in Ethiopia using metered data collected over a 20-month period and a survey of 238 customers. Findings show that the load profiles of mini-grid customers differ significantly across locations, sectors, and time. The load curves at site one (Omorate) are interrupted and completely shed off for 13 h every day due to the demand consistently exceeding the generation. By contrast, the mini-grid at site two (Tum) generates enough electricity to meet the demand continuously. The average daily electricity consumption at Omorate, 1065 kW h, is more than 1.5 times the consumption at Tum, 640 kW h; despite the fact that the mini-grid at Omorate has a significantly lower installed capacity than the one at Tum. At both sites, the monthly consumption of productive users is more than three times that of households. At both sites, demand for electricity has significantly increased over time, but at varying rates. Regression analyses showed significant differences in the factors influencing electricity consumption between the two towns. Key policy implications of the study are discussed for informed planning of rural electrification through mini-grids.

1. Introduction

Providing electricity access to rural communities in sub-Saharan Africa (SSA) is challenging, particularly in remote areas where national power grid extension is economically unfeasible (IEA, 2021; Sharma et al., 2020). An increasingly relevant part of the solution for rural electrification in off-grid areas of SSA are distributed renewable energy systems such as photovoltaic (PV) mini-grids (MGs). Studies and reports (Wassie and Ahlgren, 2023; UNDP, 2022) indicate that the use of PV MGs with storage batteries and backup diesel generators (DG) is growing in many SSA countries including Angola, Ethiopia, Kenya, Senegal, Sierra Leone and Tanzania. Given the global efforts to realize the seventh Sustainable Development Goal (SDG-7) of the United Nations, renewable off-grid MG solutions are expected to play an important role in achieving clean and affordable universal electricity access by 2030 (UNDP, 2022).

Nevertheless, emerging evidence suggest that progress in renewable MGs development has largely been patchy between and within countries, across rural areas, and between communities (Katre et al., 2019; Okoko et al., 2022). Among the major obstacles to scaling up distributed renewable MGs in SSA are high upfront costs, demand uncertainty and poor financial viability (Okoko et al., 2022). The latter two challenges, in particular, stem from lack of reliable data and thorough understanding of the load profiles, and energy consumption patterns of rural communities and businesses to be electrified using these MGs (Lorenzoni et al., 2020). This is because understanding consumer loads and energy consumption patterns is vital for optimal designing and sizing of techno-economically viable MGs (Lorenzoni et al., 2020; Mandelli et al., 2016a; Pedersen, 2016). Furthermore, understanding the dynamics of electricity demand of MG customers is instrumental for identifying suitable demand management strategies. As Peters et al. (2019) pointed out; electricity demand is a major concern to consider when investing in rural electrification projects through MGs. This is due to the fact that insufficient demand negatively affects the commercial viability of MGs, while excess demand may seriously jeopardize the reliability and quality of power supply (Wassie and Ahlgren, 2023; Peters et al., 2019). In both scenarios, there are severe repercussions for the power company, the consumers and the rural electrification projects.

However, little research has been done to analyze the load profiles and electricity consumption patterns of rural households (HHs) and small and medium enterprises (SMEs) electrified by off-grid renewable MGs based on actual data. Previous studies have mainly focused on issues such as the technoeconomic feasibility of MGs, and demand

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Abbreviations

AC	Alternating Current
DG	Diesel Generator
DSM	Demand Side Management
EEU	Ethiopian Electric Utility (Electricity supplier)
EMCS	Energy Management and Control System of the Mini-grid
ETB	Ethiopian Birr (Ethiopian Currency)
HHs	Households
LED	Light-emitting Diode
m.a.s.l.	Meters above sea level
MG	Mini-grid
MLR	Multiple Linear Regression
MoWE	Ministry of Water and Energy of Ethiopia
NEP	National Electrification Plan of the Federal Democratic Republic of Ethiopia
PV	Photovoltaic
PVG	Photovoltaic Generator
SDG	United Nations Sustainable Development Goals
SMEs	Small and Medium Enterprises
SSA	Sub-Saharan Africa
UEAP	Universal Electricity Access Program
UN	United Nations

forecasting (Hartvigsson and Ahlgren, 2018; Lombardi et al., 2019; Scott and Coley, 2021; Hartvigsson et al., 2021; Mandelli et al., 2016b). Furthermore, the majority of the studies that have been conducted on rural electricity consumption in developing countries were typically based on national level aggregated survey data from consumers electrified by conventional power grids (Ye et al., 2018; Zou and Luo, 2019; Agrawal et al., 2020). Few studies have examined rural electricity consumption using disaggregated data, albeit from conventional power grids. For instance, using a survey data, Nsangou (2022) analyzed rural household electricity consumption in southern Cameroon and showed that factors related to appliance ownership and income have significant influence on electricity consumption. A study in rural China (Li et al., 2016) showed that electricity consumption varies significantly across villages. Similarly, using a micro-level data from grid-connected rural HHs in Nigeria, Isihak (Isihak et al., 2020) found that the daily electricity consumption per HH ranged from 0.38 to 20.56 kW h.

Notwithstanding, rural communities in remote isolated areas may have different energy demand characteristics and drivers than do customers connected to conventional power grids. Distributed renewable MGs are also different from conventional power grids in terms of their energy sources, operations and energy storage systems. To the best of the authors' knowledge, only a handful of studies (Scott and Coley, 2021; Hartvigsson et al., 2021) have been conducted hitherto to characterize the load profiles of MG-electrified rural households and SMEs in SSA. Even these studies were focused either on comparison of static load profiles across sites (Scott and Coley, 2021) or dimensioning of MGs based on actual load profiles (Hartvigsson et al., 2021). As a result, electricity [1]demand of off-grid MG customers, demand dynamics over time and the factors driving the demand remain poorly understood. In light of these knowledge gaps, this study aims to analyze the load (demand) profiles, electricity consumption patterns, and drivers of energy demand of rural households and SMEs powered by off-grid PV MGs in two remote small towns in Ethiopia using micro-level disaggregated metered data.

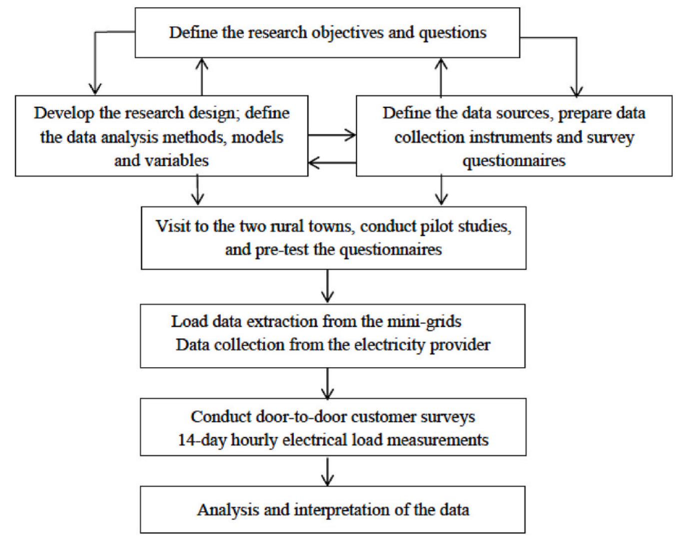

Fig. 1. Flow chart of the processes and steps followed when conducting the study.

Specifically, the paper addresses the following research questions.

- How do the load profiles and electricity demand patterns of the two towns compare and change over time?
- How do the daily and monthly electricity consumptions of different consumer types (sectors) compare and change over time?
- What drives the variation in energy consumption among consumers and between locations?
- What does the data imply for policy making and optimal sizing of off-grid PV mini-grids?

This study is novel in many ways. First, it primarily relies on disaggregated metered load data, and therefore provides more accurate information and evidence-based explanations on the electricity demand characteristics of off-grid rural communities. This enables policy-makers and mini-grid developers to construct policies and MG solutions that are grounded on real-world experience and actual electricity demand in the rural settings. Second, for developing nations like Ethiopia where a significant proportion of their population lives in rural inaccessible areas, this study provides valuable insights and analyses into understanding the potentials and pitfalls of rural electrification through renewable MGs. Third, the study adds to the emerging body of knowledge and literature on the dynamics and drivers of electricity demand in the context of off-grid communities in SSA. Moreover, findings and lessons from the study may assist PV MG operators and managers identify appropriate operational and energy management strategies.

2. Methodology

2.1. Research design

A data-driven case study approach combining quantitative and qualitative research methods was used to conduct this study. A data-driven approach is a strategic decision-making process based on *analysis* and interpretation of hard data and facts, rather than on observation or intuition. This makes the data-driven approach best suited for analyzing measured data and gaining practical understanding of the load profiles and consumption patterns of different consumer types as well as their dynamics over time. The case study method, on the other hand, allows us to undertake in-depth analyses of the relationships

[1] In this paper demand or 'load' refers to the amount of electrical power (kW) required at a given point in time to satisfy the needs of all connected appliances and systems; while consumption stands for the total amount of energy(kWh) used by the consumer per day, per month or per year. Demand is thus the immediate rate of consumption.

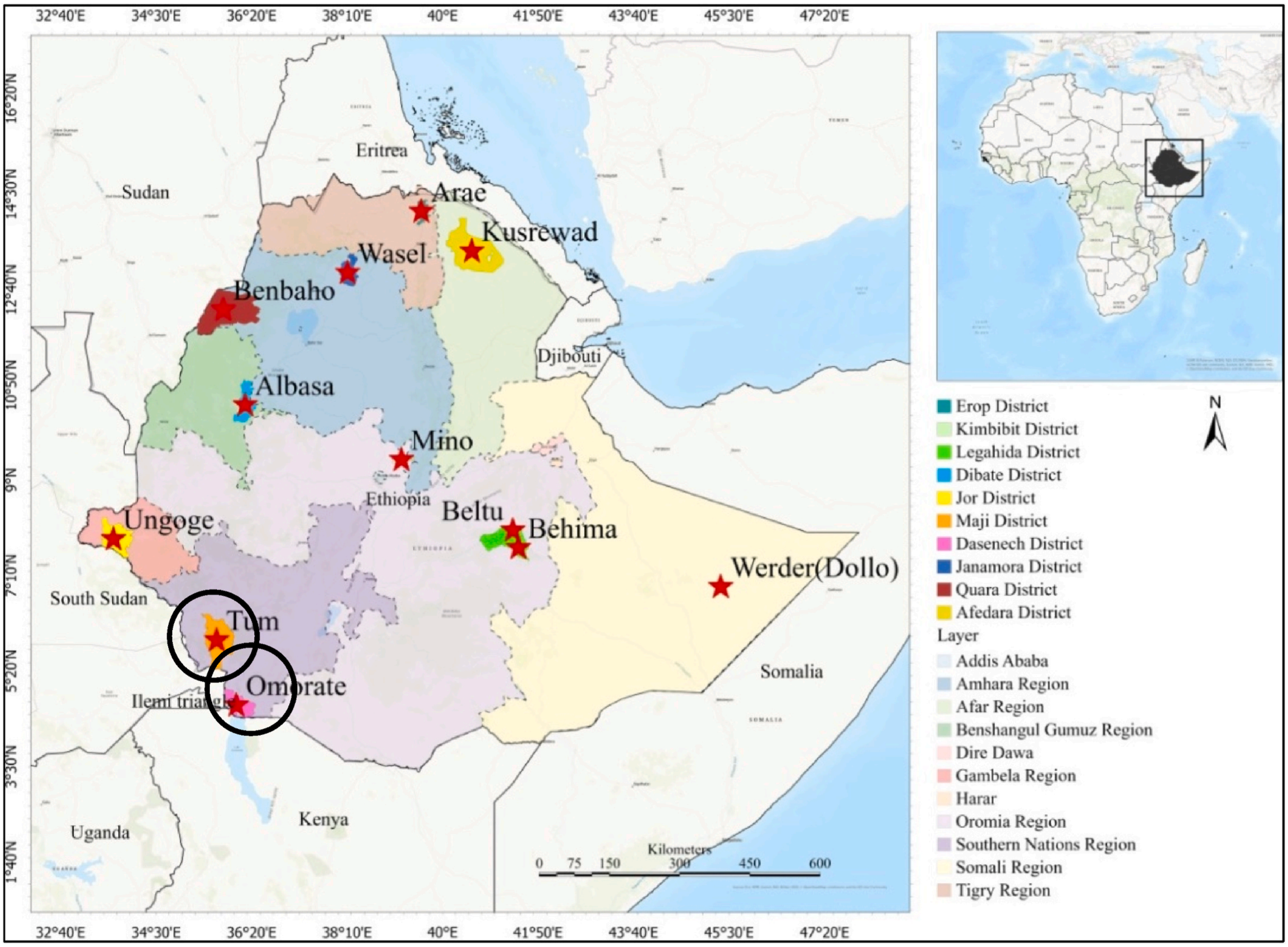

Fig. 2. Location map of Omorate and Tum towns in Southern Ethiopia along with other 10 towns where solar PV mini-grids have been installed for rural electrification (Source: EEU (EEU, 2022)).

between electricity consumption and the various driving factors within a defined real-life situation, based on data collected from various sources. The study follows six iterative processes adapted from Yin (2014) and Crowe et al. (2011). The flow chart in Fig. 1 depicts these processes and steps.

2.2. Description of the case study sites

According to the national electrification plan (NEP 2.0) of the government of Ethiopia, the country aims to achieve universal electricity access by 2025 through generating 65% of its power demand from national grids and 35% using distributed renewable energy technologies, particularly stand-alone PV systems and off-grid PV MGs (MoWE, 2019). Given that 80% of Ethiopia's 120 million people lives in rural areas, realizing the universal electricity access goal hence depends on the deployment of off-grid PV MGs and stand-alone PV systems. In view of that, the Ministry of Water and Energy (MoWE) of Ethiopia and the Ethiopian Electric Utility ([2]EEU) identified 250 off-grid rural towns that are disconnected from the national grid and need to be electrified through PV-Diesel hybrid mini-grids under the country's Universal Electricity Access Program (UEAP). By 2021, twelve PV-battery MGs with rated capacity ranging from 75 kWp to 550 kWp were built out of the 250 planned. The Omorate and Tum towns, where the present study was carried out, were thus among these twelve first-batch off-grid towns to be electrified through PV MGs. In February 2021, the EEU signed a contract with SinoSoar (a Chinese renewable energy company) for the construction of additional 25 (second-batch) PV-battery MGs with capacity ranging from 75 kWp to 2000 kWp. In January 2023, the EEU signed yet another agreement with Masdar (a United Arab Emirates' renewable energy company) for the joint development of a solar project with a capacity of 500 MW. These agreements and initiatives signify that the future potential for solar power systems in Ethiopia's energy sector is promising. However, the total installed generation capacity of solar PV systems including MGs and stand-alone PV systems, which are primarily used for telecom towers (network towers), in the country thus far is only approx. 14 MW (Mulatu et al., 2023). And therefore, photovoltaic generation currently covers only 0.3% of Ethiopia's 4500 MW total installed generation capacity.

As indicated earlier this study was conducted in two remote small towns, named Omorate (site 1) and Tum (site 2), in rural southern Ethiopia (Fig. 2). Both towns are powered by decentralized PV MGs. The two towns were chosen for the comparable age of their MGs, expected similarities in electricity demand, and the availability of metered data as well as the fact that they were among the first 12 off-grid towns to be electrified using PV MGs in Ethiopia. Omorate is located between

[2] Ethiopian Electric Utility (EEU) is a state-owned utility company that manages power distribution and sales from all power plants in Ethiopia including mini-grids.

Table 1
Distribution of sampled households, SMEs and institutions at each site.

Consumer type	Omorate		Tum		Total samples
	Total number (N)	Sample size (n)	Total number (N)	Sample size (n)	
Households	301	68	384	60	128
SMEs	112	50	40	40	90
Institutions	30	10	26	10	20
Total	443	128	450	110	238

4°80′16″N Latitude and 36°3′29″ E Longitude with an average elevation of 368 m. a.s.l. Tum is situated between 6°15′16″N Latitude and 35°31′18″ E Longitude with an average elevation of 1439 m. a.s.l. The mean annual temperature at Omorate is 29.2 °C whereas at Tum it is 21.6 °C. In 2021, Omorate had a total population of 3, 852 with approx. 770 HHs, while Tum had a population of 4856 with approx. 950 HHs. The MG at Omorate has a total installed capacity of 375 kWp and is equipped with a 600 kW h storage battery. The MG at Tum, in contrast, has a total installed capacity of 550 kWp and is equipped with a 750 kW h battery. Both MGs began producing electricity around May 1, 2021. By December 2021, the number of MG customers in Omorate had risen to 443; of which 301 (68%) were [3]ordinary HHs, 112 (25%) were [4]SMEs - typically HH-based businesses, and 30 (7%) were state/public institutions. Over the same period, the number of MG consumers at Tum had grown to 450, with 384 (85%) households, 40 (9%) SMEs, and 26 (6%) institutions.

2.3. Data sources

2.3.1. Hourly power generation and load data at the two MG sites

This study is based on four datasets: 1) hourly load and power data from the MGs, 2) hourly load measurements of sample customers using smart meters, 3) monthly electricity consumption data obtained from the EEU, and 4) data generated through customer surveys and in-depth interviews. The hourly load and power generation data at MG level were retrieved directly from the energy management and control system (EMCS) of each MG in the form of daily reports. The daily load report, for example, provides detailed information on the hourly electrical load P (kW) in each feeder, the peak load, distribution of loads etc. Similarly, the daily power report provides detailed information on the hourly electricity generation by the PV, electricity generated by the DGs, hourly battery charging and discharging power etc. Appendix A presents an example of a daily load report retrieved from the EMCS of the MG at Tum.

2.3.2. Monthly metered electricity consumption data

The monthly metered energy consumption data for all MG customers at each site were obtained directly from the EEU district offices. The data contains detailed information on the customer's name and address, the type of customer (domestic, SMEs, or institution), billing month, monthly electricity consumption quantity, consumption charge, tariff category, and monthly fixed service charge. Since both MGs began operating around May 1, 2021, metered consumption data were only available for the first 20 months at the time of the field data collection (December 2022).

2.3.3. Door-to-door customer surveys and key informant interviews

Door-to-door surveys were conducted at both sites using purposive random sampling. At first, all customers listed in the EEU billing list were identified and grouped into three separate categories (HHs, SMEs, and Institutions) as per the EEU's customer classification. A random sampling of roughly 20–40% was then used to select sample HHs, SMEs and Institutions in each town. The purpose of conducting the surveys was to collect relevant socioeconomic and appliance use data from the customers, and thereby to conduct a regression analysis and validate the results of the metered data analysis with those of the survey. The survey data consists of demographic data, dwelling type and number of rooms, monthly income, appliances ownership and use, monthly consumption energy quantities and charges, type of electricity service (productive or domestic), frequency and duration of power interruptions per week etc. All electrical appliances of survey customers were identified and sorted into two categories [5]:HH appliances and [6] other appliances. The surveys were conducted through face-to-face interviews from 1 to December 31, 2022 using semi-structured questionnaires that were designed, pre-tested and revised following pilot studies and Yin's (Yin, 2014) guidelines. The final sample sizes at each site are presented in Table 1. During the same period, frequent field visits to both MG sites and in-depth interviews with MG operators and more than 15 key informants were conducted at each site including regional and local EEU staff, local political administrators and community leaders.

2.3.4. Hourly electrical load measurement for different consumer types using smart meters

Since the load data retrieved from the MGs in section 2.3.1 is town level aggregated data, high resolution hourly electrical load data by consumer type was measured to examine the variations in the daily load profiles among the different sectors. Accordingly, we measured the hourly electrical loads of 20 randomly selected households, 20 SMEs and 5 institutions at each site, using smart electric meters, as representative samples. The electrical load measurements were made in both towns for 14 consecutive days covering 24 h from 15 to December 28, 2022. Appendix B presents a summary of a 14-day hourly load measurement for a hotel owner at Omorate, as an example. Based on the measured load data, the average daily energy consumptions of the three consumer types or sectors were calculated for each town.

2.4. Data analysis

This study is mainly data-driven and descriptive. As such, it mostly utilizes descriptive statics, load duration curves, and graphs to characterize, illustrate and comparatively analyze electrical load profiles and consumption patterns across the different customer types and the two

[3] In this paper, ordinary households stands for those households that use electricity primarily for household purposes while SMEs refers to those households that use electricity primarily for productive purposes. Institutions on the other hand, refer to government offices, public schools, health centers, churches and mosques etc.

[4] Since almost all SMEs were household-based businesses, SMEs are treated in this analysis as 'households that use electricity for income-generating/productive purposes' rather than a separate class of observations. Doing so enables us to better understand the influence of productive use (SMEs) on household electricity demand.

[5] **Household appliances** refer to all domestic uses including electric bulbs, boilers, cooking stoves, juice makers, coffee makers, irons, cooling fans, refrigerators, freezers, rechargeable LEDs, radios, TVs, speakers etc.

[6] **Other appliances and equipment** in this study refers to all power-intensive appliances (≥1 kW) typically used for productive purposes by SMEs including welding machines, air compressors, electric drills, large dough mixers, hair dryers, coffee machines for commercial use, and other high-wattage electric machines.

Table 2
Definition of the independent variables.

Variable	Variable definition/description
[a]Gender	Dummy: 1 = if the HH head or SME owner is Female, 0 = if Male
Age	Age of the HH head or SME owner in years
Educational level	Total number of years of schooling of the HH head or SME owner
Household size	Total number of family members in the household
[a]Dwelling type	Dummy: 1 = if the house is made of brick/concrete, 0 = if the house is traditional, made of mud or wood.
Number of rooms	Total number of rooms in the building/house
log (monthly per capita income of the HH)	The log-transformed average gross monthly per capita income of the HH in Ethiopian Birr (ETB) from all income sources
log (net monthly income of the SME owner)	The log-transformed average net monthly income of the SME owner household from all business activities in ETB
No of refrigerators	Total number of refrigerators the customer owns and uses
No of electric cooking stoves	Total number of electric cookstoves the customer owns and uses
No of space cooling fans	Total number of space cooling fans the customer owns and uses
No of other (high-wattage) appliances and equipment	Total number of other (≥1 kW) electrical appliances and equipment the customer owns and uses
[a]Private PV ownership	Dummy: 1 = if the customer owns private PV system, 0 = if the customer does not own private PV systems
[a]Productive use of power	Dummy: 1 = if the customer uses MG electricity for productive purposes, 0 = if the customer does not use MG electricity for productive or income-generating purposes

[a] All categories in the categorical variables with a value of zero are reference categories.

towns. The average hourly power generated by each MG, and energy consumed by all loads at each site were calculated over the 20-month period (610 days) of the MGs' operation. The dynamics of monthly electricity consumption among the different customer types over the same period was analyzed based on EEU's metered dataset and classification of customers.

In order to determine the effect of the load-shedding on the demand at Omorate, we applied the [7]Multiple Imputation (MI) method of predicting missing data using predictive-mean matching (PMM) technique (Seaman et al., 2012). Data imputation using MI derives imputations from observed values by building a model based up on the distribution of the incomplete data and real values from other observations. The main justification for using the PMM method is that it delivers more accurate estimates of multiple missing data when the variable is not normally distributed (Seaman et al., 2012). As will be seen in the results section 3.1.1, the daily loads in Omorate are not normally distributed. The MI method is embedded in many software packages such as STATA, R, and SAS in the form of 'Multiple Imputations by Chained Equations (MICE)'. The multiple imputations in this study were performed by using STATA version 16.

Following the works of Laicane (Laicane et al., 2015) and Kim (2020), Multiple Linear Regression (MLR) analyses were performed to investigate the factors affecting the electricity consumption of HHs and SMEs in each town. However, the factors influencing the electricity consumption of institutions were not analyzed. This is because the majority of the institutions in both towns are either government sector offices or public/state institutions whose electricity consumption is relatively less impacted by the local socio-economic and appliance factors. Also, as Table 3 will show, there is little difference in the average daily electricity usage of institutions between the two sites. Accordingly, two separate MLR analyses, one for HHs and one for SMEs, were carried out for each of the two towns. The dependent variable, log (kWh per month), in all of the four regression equations is the natural logarithm of the mean monthly electricity consumption per customer, while the independent or predictor variables (shown in Table 2) were chosen based on our recent work (Wassie and Ahlgren, 2023) and review of relevant earlier studies (Ye et al., 2018; Zou and Luo, 2019; Agrawal et al., 2020; Li et al., 2016). Equation (1) presents the general MLR model that was used to analyze the association between the predictors and electricity consumption of HHs and SMEs in each town.

$$\log(Y_{ij}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots \dots + \beta_n X_n + \varepsilon \quad (1)$$

Where: $\log(Y_{ij})$ is the dependent variable, i.e., the log-transformed average monthly consumption of customer i (HH, SME) in town j, X_1 through X_n are the independent or explanatory variables, β_0 is the intercept (the value of $\log(Y_{ij})$ when all of the independent variables (X_1 to X_n) are equal to zero), β_1 through β_n are the parameter estimates (regression coefficients), and ε is the error term.

3. Results and discussion

3.1. Load profiles and demand analysis of the two towns

3.1.1. Hourly load and power generation at the two sites

Using the hourly load and AC power data retrieved from the EMCS of each MG, the monthly average daily load and power generation curves for each location were established as shown in Figs. 3–6. Fig. 3 illustrates that except for the first three months of the MG's operation (May through July 2021), the daily load curves at Omorate are consistently interrupted and near zero kW for a significant portion of the day. This is because following the rapid surge both in the number of customers and demand per customer, the MG at Omorate was no longer able to fully meet the load requirement. As a result, a complete load-shedding of 8–13 h each day has been in effect in two time slots; from 17:00/18:00 to 19:00 and again from 21:00/22:00 to 08:00 since August 2021. The load-shedding is used by MG operators as a demand side management (DSM) strategy to save power during 'low demand' hours and supply it during peak evening hours. As of December 2022, the load at Omorate was being shed off for 13 h a day.

Fig. 3 also depicts that the load curves at Omorate follow roughly similar distribution patterns (shape) with the peak loads (maximum demands) occurring in the evening; and a stable and high demand (loads) through much of the day-time until the load is shed off at 17:00/18:00.

On the other hand, the power generation curves at Omorate, Fig. 4, illustrate that both the hourly generation patterns and magnitudes of the power produced by the MG vary between months. This is atypical of a PV generator (PVG) in an equatorial climate where the daily solar irradiance usually follows a similar distribution pattern throughout the year.

Unlike the load curves observed at Omorate, the load curves at Tum (Fig. 5) are unbroken throughout the day, and customers receive 24 h of electricity service since the MG produces sufficient electricity to meet the demand. Compared to the somewhat stacked, or clustered, load curves seen at Omorate, the size of the loads at Tum grows noticeably over time. As a result, the average amount of energy consumed at hour h in Tum in December 2022 is almost twice the energy consumed at hour h in May 2021. Furthermore, the load curves at Tum exhibit a more or less

[7] A detailed description of the MI method using predictive-mean matching can be found in Seaman et al. (2012).

Table 3
Summary statistics of average daily electricity consumption of the three sectors.

Sector	Location	No of days	Min (kWh)	Median (kWh)	Mean (kWh)	Max (kWh)	St. Dev. (kWh)
HHs	Omorate	14	0.14	1.31	1.49	7.33	0.81
	Tum	14	0.09	0.50	0.80	2.37	0.53
SMEs	Omorate	14	0.54	4.03	5.01	29.0	6.21
	Tum	14	0.19	2.03	3.23	17.13	2.13
Institutions	Omorate	14	0.49	2.75	3.01	16.08	2.81
	Tum	14	0.37	2.54	2.85	14.75	2.90

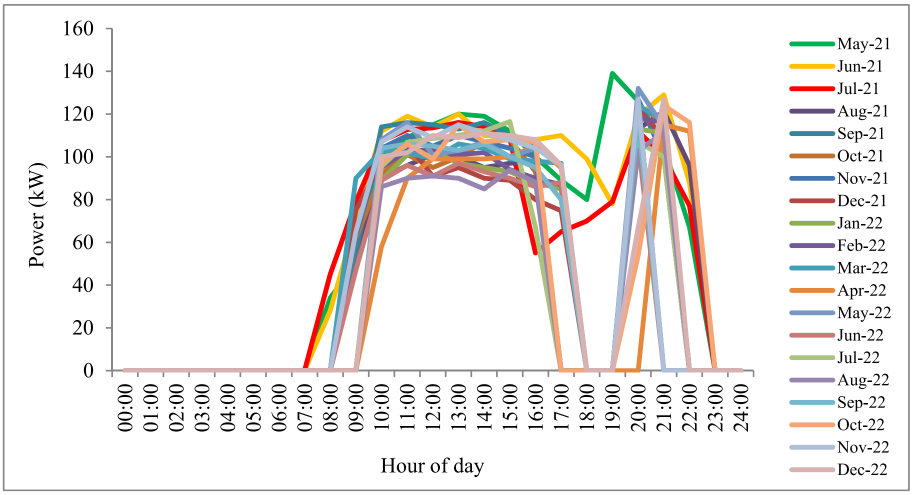

Fig. 3. Monthly average daily load profiles at Omorate over the 20 month-period.

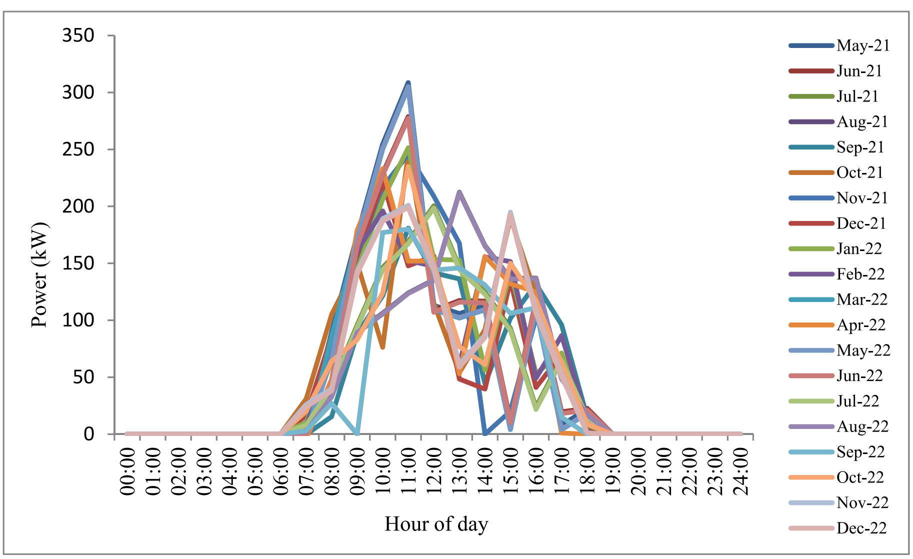

Fig. 4. Monthly average daily PV power generation at Omorate over the 20 month-period.

consistent distribution pattern, with the peak demand typically occurring late in the evening (around 20:00) and two smaller peaks occurring in the morning (08:00) and midday (12–13:00).

A comparative quantitative analysis of the average hourly electricity generation from each MG, and the electricity delivered to all loads in each town over the 610 days is given in Fig. 7. The figure affirms that the load profiles of the two towns exhibit significantly differing characteristics and distribution patterns. At Omorate, the load spikes to 90 kW within an hour of connecting to the power feeder, and stays above 90 kW h for most of the day. The load is shed off at 17:00 and reconnected around 19:00. Fig. 7 further displays that the power generated by the PVG at Omorate is below the instantaneous load demand even when the irradiance is still plentiful, between 15:00 and 18:00. As a result, there is not much energy left in the battery to service the high evening demand for more than 2 h. In contrast, the PVG at Tum produces sufficient power (beyond meeting the instantaneous load) throughout the daytime; and the load is stable and remains around 30 kW for most of the daytime.

At both sites, the peak load occurs in the late evening hours. The

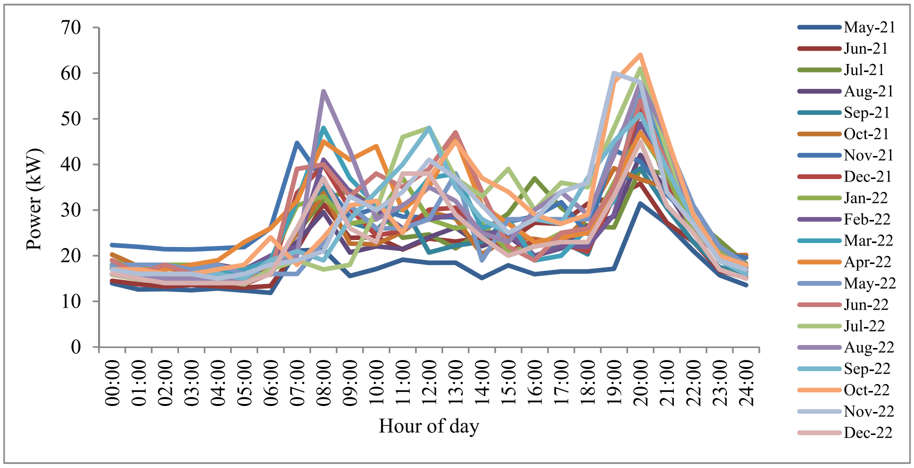

Fig. 5. Monthly average daily load profiles at Tum over the 20 month-period.

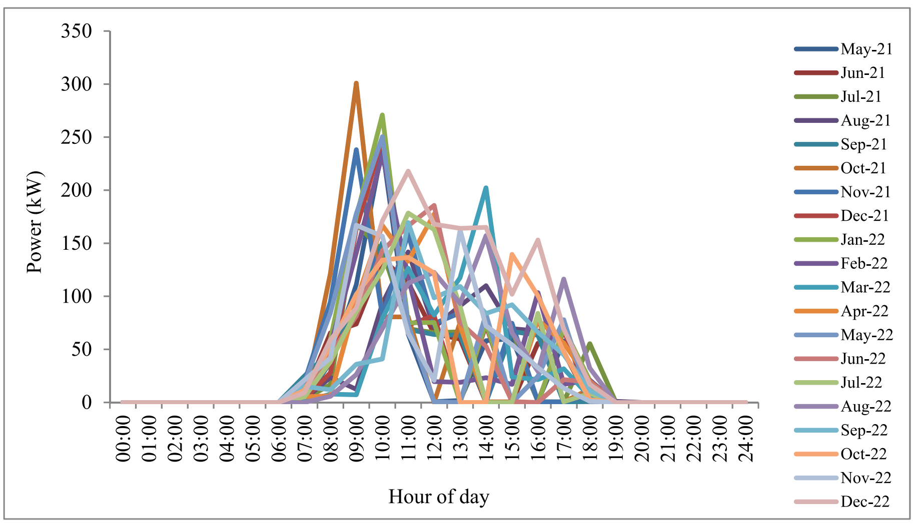

Fig. 6. Monthly average daily PV power generation at Tum over the 20 month-period.

reason is that at this time of the day most lighting units are turned on and most of the [8]businesses are open. Another contributing factor for the timing of the peak load at Omorate could be that the load-shedding at around 21:00 is dictating the shape of the load curve, such that the highest demand occurs right before the load is shed off. Despite the parallelism in the timing of the peak loads, the peak load at Omorate (128 kW) is almost three times that of the peak load at Tum (48 kW), and the midday minor peak at Omorate, 110 kW, is three times the morning minor peak at Tum, 33 kW.

The substantial difference in load profiles between the two towns can be attributed to three main factors. The first is differences in key demand variables between the two towns. As can be seen in Table 1, the proportion of SMEs in the total number of customers at Omorate, 25%, is almost three times that of SMEs at Tum, 9%. From our field visits and on-site load measurements, it was evident that productive users were mostly responsible for the peak loads at both sites through the day and at the evening. Hence, a higher number of productive users at Omorate means higher consumption. The average stock of electrical appliances per customer at Omorate is 4.2 while at Tum it is 2.8. The mean monthly income per customer in Omorate is calculated to be ETB 11,000 while it is ETB 9300 at Tum. Studies indicate that households with more appliances and higher incomes use more electricity than those with fewer appliances (Ye et al., 2018; Nsangou, 2022).

The second important element that contributed to the significant difference might be the prior exposure to and experience with the use of electricity by customers in Omorate. According to the town administration officials and elderlies we interviewed as well as our on-site verification, the Omorate town used to be powered by large diesel generator set for more than a decade up until 2016. But, due to technical malfunctions and the significant expense needed for maintenance, the DG has stopped operating since 2016. This indicates that the MG customers in Omorate already had a considerable amount of prior knowledge and experience about the use of electricity and its socioeconomic, health and other benefits. Moreover, many of these former DG consumers may have kept their electrical equipment while awaiting the arrival of the PV MG. Evidently, 44% of the MG customers surveyed in Omorate stated they tried to utilize the MG electricity for cooking, whereas only 11% of the respondents in Tum, mostly SMEs, reported of cooking with electricity. The cumulative effect of all of these may have led to the surge in energy demand at Omorate within three months of operationalization of the MG, thus overwhelming the MG's capacity. In contrast, MG customers in Tum had little to no prior experience with electricity, relying solely on traditional kerosene lamps and dry-cell

[8] Because of the hot equatorial climate that prevails throughout the Omo Valley, locals typically begin to stroll around, mingle, and drink beer in the late afternoon and into the evening.

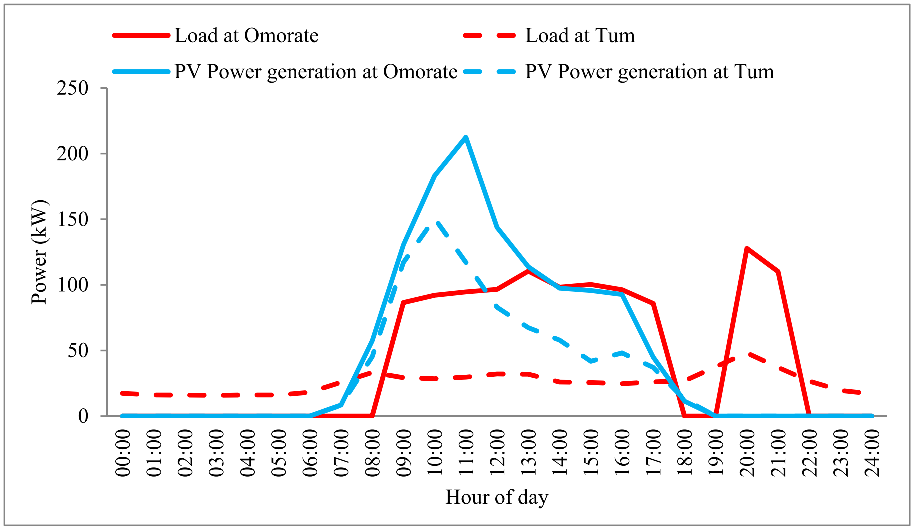

Fig. 7. Hourly mean power generation and hourly mean load at each site (based on data retrieved from the EMCS of the MGs over the 610 days).

powered hand torches, and this may have contributed to the relatively low demand and sluggish demand growth.

The third factor for the disparity in load profiles between the two towns may stem from location-specific variables including access to appliance markets, local climatic conditions, and economic and business activities of the locals. Although both towns are located in remote areas, Omorate has better road access that connects it to a nearby big town (Jinka) situated within 150 km distance. More importantly, the road between Omorate and Jinka is relatively safe and there is good access to public transportation. As a result, appliances are comparatively cheaper in Omorate than in Tum, although much more expensive than in mainland urban areas. Conversely, Tum has poor access to appliance markets, and one has to travel more than 178 km on an unsecure and dangerous route to purchase appliances at Mizan-Aman, the nearest big town. Moreover, in Omorate where the mean annual maximum temperature reaches up to 42°*C*, many HHs, businesses and institutions use refrigerators and cooling fans. In contrast, only a few customers use refrigerators and cooling fans in Tum, where the mean annual maximum temperature does not exceed 30 °C.

3.1.2. Dynamics in load (demand) profiles of the two towns over time

The load curves of the two towns *discussed in section 3.1.1 have shown* significant differences *in the daily demand profiles* both in terms of size and hourly distribution patterns. Therefore, it may be useful to compare the average daily *load* curves of each site in the early days of the MGs' operation (May 2021) with the present (December 2022) to gain insights into how the demand at each site has evolved *over time.* The results, Figs. 8 and 9, show that the demand at Omorate has completely changed from an uninterrupted, stable, and relatively low load (on average 45 kW/h) in May 2021 to a high and unquenchable load demand (on average 98 kW/h) that is routinely interrupted and suppressed by daily load-shedding in December 2022.

When the uninterrupted (unsuppressed) load curve in December 2022, shown by the broken line in Fig. 8, was constructed using the MI method described in section 2.4, the result shows that the total daily unsuppressed energy requirement at Omorate in December 2022 was 1808 kW h but the actual average consumption per day in December 2022 was only 1100 kW h. This means that 708 kW h (close to 40%) of the daily critical load is unmet due to the load-shedding. This is the sum of the area between the interrupted load curve and the uninterrupted load curve, which amounts to an average unmet load of 54 kW for each hour of load-shedding. In fact, it is possible that part of the consumption during the uninterrupted hours would have been consumed during the interrupted hours if all hours were uninterrupted. As such, one might argue that the MI constructed curve may have inflated the unmet load. However, given the significant latent demand particularly from productive users (i.e., electricity demand that would exist if there were no generation capacity shortages and power interruptions), it is highly unlikely that the calculated unmet load of 54 kW h per hour of load-shedding and consumption of 1808 kW h/day are overestimated.

Fig. 9 shows that the daily load at Tum, too, has changed sizably. The evening peak load has nearly doubled from 27 kW in May 2021 to 48 kW in December 2022. The morning minor peak has risen from 23 kW in May 2021 to 40 kW in December 2022. Yet, when compared to the load curve at Omorate, the shape of the load curve at Tum has remained largely consistent over time.

3.1.3. Daily electricity consumption and its dynamics at the two sites

Based on the daily load data retrieved from the EMCS of each MG, the average daily electricity consumption over the 20-month period was calculated to be 1065 kW h at Omorate and 640 kW h at Tum. This shows that the mean daily consumption at Omorate is more than one and half times the consumption at Tum, despite the fact that the MG at Omorate has a total installed capacity of 375 kWp and that at Tum has 550 kWp; and that both MGs have a similar number of customers. However, the average daily consumption varies significantly from a minimum of 441 kW h to a maximum of 1575 kW h at Omorate, and from a minimum of 340 kW h to a maximum of 858 kW h at Tum. Prior studies analyzing the electricity demand of rural towns in SSA are generally scarce. However, Mwakitalima and King'ondu (Mwakitalima and King'ondu, 2015) assessed the electricity demand of Kikwe, a remote off-grid small town in Tanzania with a total population of 2500 in 2015. According to their findings the average total daily electricity demand of the town was 757 kW h. This implies that, relative to its population size, Kikwe has a larger daily electricity demand than Omorate and Tum.

Analysis of the temporal dynamics of the total daily energy consumption based on the same dataset over the same time period (Fig. 10) illustrates that the average daily consumption at Tum has climbed steadily from around 420 kW h in May 2021 to 800 kW h in December 2022. The results indicate that the daily electricity usage at Tum has risen by 90% *over the* 20-month *period, while it* has apparently stagnated or slightly declined in Omorate from around 1100 kW h per day in May 2021 to 1008 kW h per day in December 2022. However, as demonstrated by the reconstructed load curve in section 3.1.2., the demand in Omorate has in fact increased, albeit the supply was unable to satisfy the demand. According to our results, when the daily uninterrupted load curve at Omorate is reconstructed (Fig. 8), the total average daily

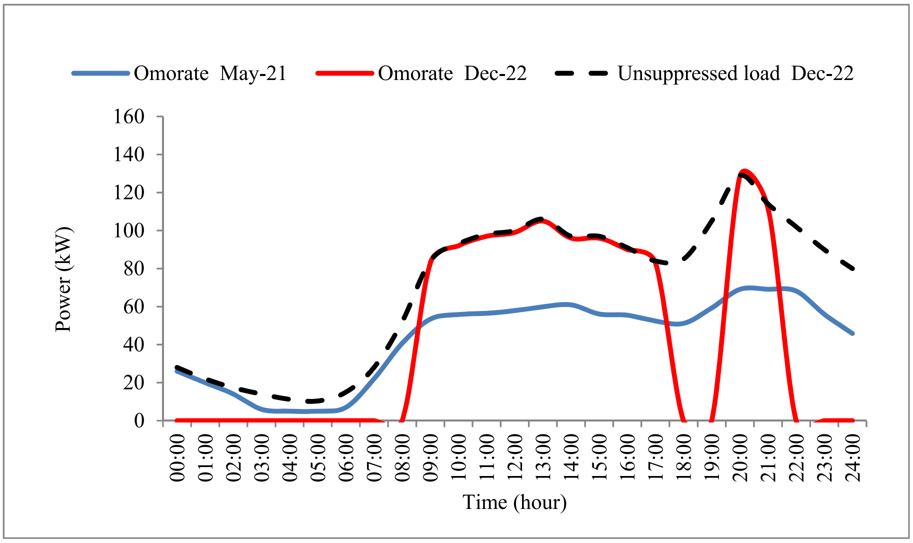

Fig. 8. The average daily load profiles at Omorate in May 2021 and December 2022.

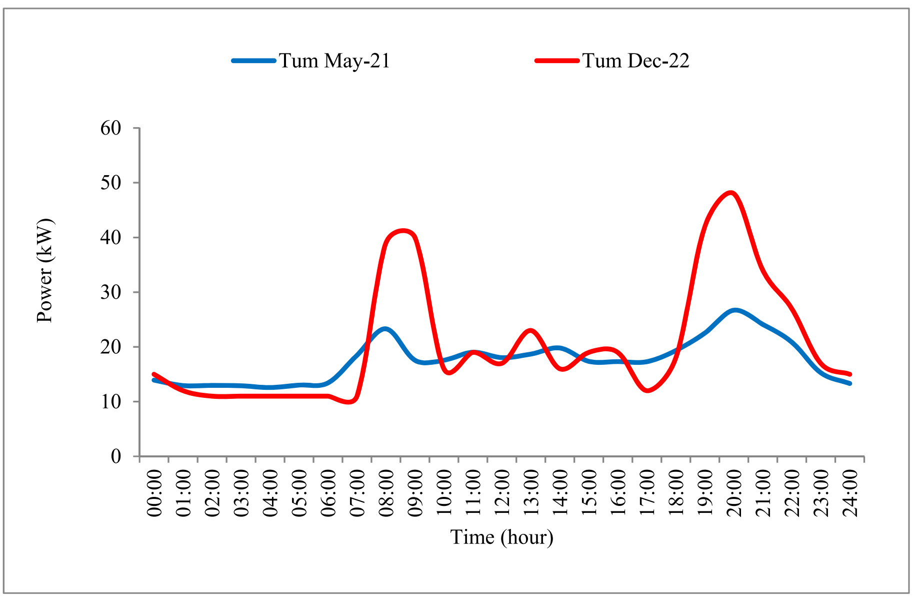

Fig. 9. The average load profiles at Tum in May 2021 and December 2022.

electricity consumption increases from 1100 kW h in May 2021 to 1808 kW h in December 2022. This shows that the mean daily electricity consumption in Omorate has increased by 64% over the 20-month period. The MI, however, only estimates missing critical load values during the load-shedding hours. Therefore, the true value of unsuppressed electricity consumption and its growth rate, had there not been load-shedding, are unknown. In reality, the total daily power consumption is probably much higher than the predicted 1808 kW h/day. The finding substantiates our recent study on the same MG (Wassie and Ahlgren, 2023) which showed that rather than a saturation of customers' demand for electricity, the stagnation in daily consumption is associated with the PV generation and battery capacity constraints relative to the demand.

The gradually rising consumption trends at Tum and the ever-increasing load-shedding hours (from 8 h in early August 2021 to 13 h in December 2022) at Omorate demonstrate that demand for electricity has *expanded significantly* at both sites *over time*. Notwithstanding, the data in Fig. 10 shows little seasonal variation in electricity consumption at town (aggregate) level. However, as will be discussed in Section 3.4., the consumption of productive users at Omorate during the dry months is relatively higher than the consumption during the rainy months. It was also found that the weekend loads at Omorate are higher than the weekday loads (Appendix B).

The primary reason for the higher weekend loads in Omorate compared to weekday loads could be that the town serves as a local market and trade hub, drawing in locals from up to 30 km away on the weekends for shopping, dining, socializing, meetings and beer-drinking. Consequently, this raises the energy usage of SMEs, which are responsible for more than 50% of the town's electricity consumption. Given that a significant number of the SMEs in Omorate are in the service sector, the higher consumption on weekend days is most likely the result of increased business activity. By contrast, the variations between weekday and weekend loads at Tum are only marginal. This could be, in part, the result of decreased weekend demand of institutions offsetting the increased weekend consumption by HHs and SMEs. These results have direct implications for MG sizing in rural areas. The frequent fluctuations in daily loads at Omorate are likely caused by inconsistencies in power generation, weather conditions, load-shedding

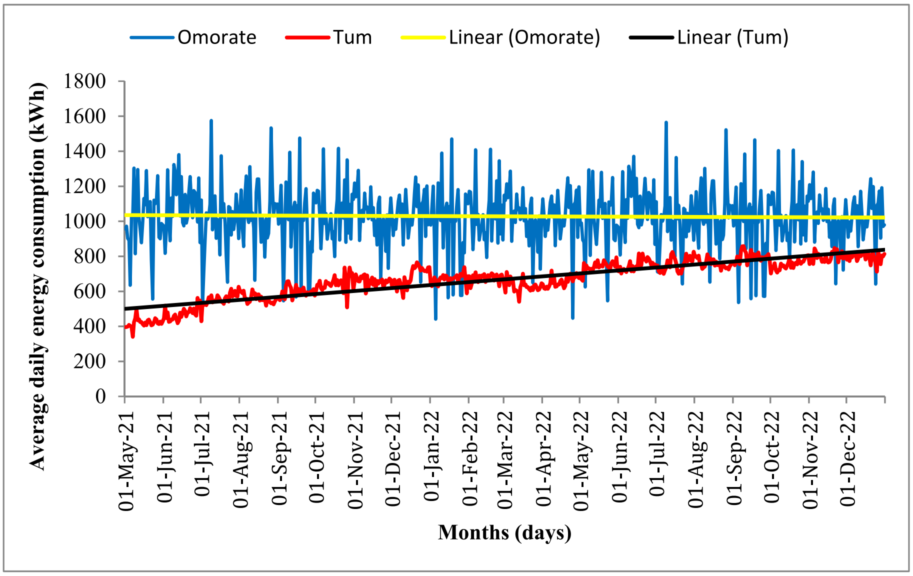

Fig. 10. Dynamics of the average daily total energy consumption from all customers in each site over the 20-month period.

hours, or technical and operational issues rather than fluctuations in demand per se. Our findings corroborate prior research by Hartvigsson et al. (2021), but they disagree with Katre et al. (2019), who found insignificant temporal dynamics in the electricity consumption of MG-electrified HHs in rural India. The causes for the disparity can be attributed to differences in socio-cultural settings, availability of alternative energy resources, and important demand determinant variables between the research areas.

3.2. Load profiles and daily energy consumptions by sector

In this section, the load profiles and energy consumption patterns of the three sectors (HHs, SMEs, and institutions) powered by the MGs in the two towns are discussed. As indicated in section 2.3.4, the daily electrical load data for the sampled customers representing each sector were gathered through direct measurement using smart meters. Using this measured data; the 14-day average daily load curves were created and analyzed by customer type for each town. The results, presented in Figs. 11 and 12, display that the load profiles and distribution patterns between the three customer types within each site as well as between the two sites are markedly different. At both towns, the average week-day peak load, both for HHs and SMEs; occur in the late evening hours. However, the average week-day peak load per HH at Omorate 0.16 kW is nearly twice that of the peak load per HH at Tum 0.09 kW. Likewise, the week-day peak load per SME at Omorate (0.6 kW) is twice that of the peak load per SME at Tum (0.31 kW). The figures also illustrate that the load curves of HHs and SMEs at each site appear to follow similar distribution patterns, despite having significantly different sizes. Our findings run counter to earlier studies (Hartvigsson and Ahlgren, 2018; Scott and Coley, 2021) that showed distinct load curve shapes for HHs and SMEs in rural SSA. Figs. 11 and 12 further depict that the peak load of institutions at Omorate occurs at around 15:00 while at Tum it occurs at 11:00.

One possible explanation for the similarities in the load distribution between the HHs and SMEs at Omorate could be that the extended daily load-shedding has compelled HHs and SMEs to adopt similar patterns of electricity use throughout the day.

On the other hand, the fact that most of the SMEs at Tum are in the service sector may account for the similarities in the shape of the load curves of HHs and SMEs. The SMEs in Tum were typically busier in the

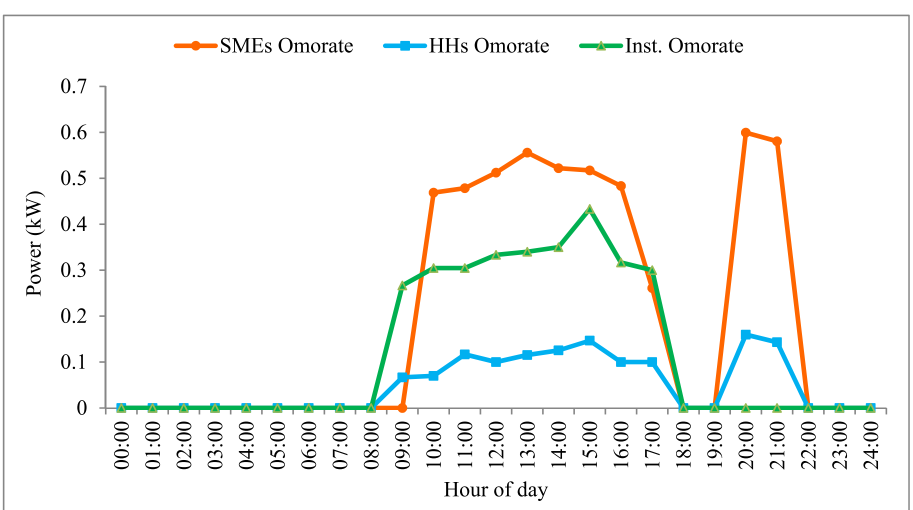

Fig. 11. Average week-day load profiles of HHs, SMEs and institutions at Omorate in December 2022 (based on the 14-day measured load data using smart meters).

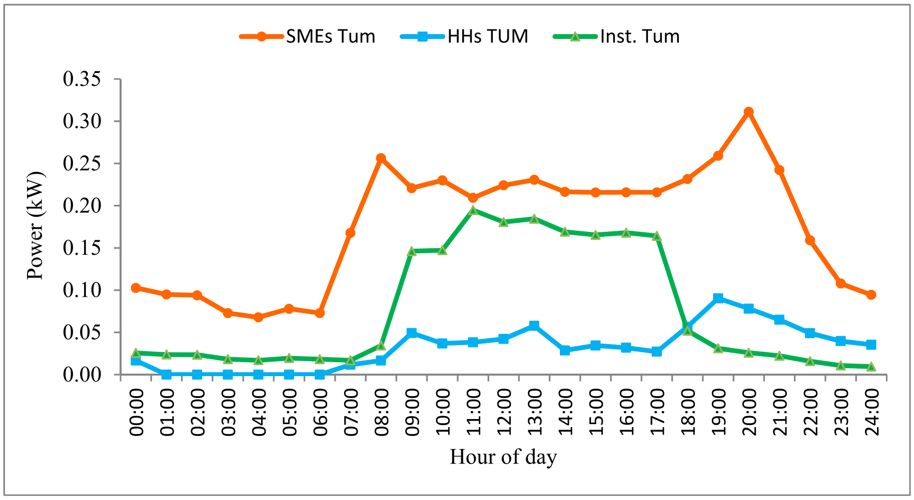

Fig. 12. Average week-day load profiles of HHs, SMEs and institutions at Tum in December 2022 (based on the 14-day measured load data using smart meters).

morning, midday, and evening hours, when HHs are actively using electricity. The effect of the high temperatures in Omorate and the resulting increased power consumption for air conditioning, especially among government sector workplaces, could be one possible cause for the differences in the timing of the peak load of institutions between the two sites.

Based on the same 14-day measured load data, the average daily energy consumption of the three customer types in each town was calculated as presented in Table 3. According to the results, *HHs at Omorate consume on average* 1.49 kW h per *day. In contrast, HHs at Tum consume on average 0.*8 *kW h* per *day. Similarly, the average daily electricity consumption* of *productive use customers at Omorate* 5.01 kW h *is almost twice the daily mean consumption* of *productive users at Tum 3.*23 *kW h. The results reveal that, in both towns,* productive users *consume more than three times the daily consumption of HHs.* Hartvigsson et al. (Hartvigsson and Ahlgren, 2018) and Scott and Coley (2021) also found significantly higher consumption by productive users from distributed MGs installed in Tanzania. On another note, the mean daily energy consumption of institutions did not differ much between the two sites. The fact that the median values in Table 3 are below the mean for all three sectors illustrates that the distribution of the load data is skewed to the right, i.e., the daily consumption of the majority of the consumers in each group are clustered around the left tail of the distributions.

The findings in Table 3 point out that the daily power consumptions of the three customer types are significantly different both within and between the two towns. While the daily consumptions of SMEs and HHs at Omorate are severely impacted by the load-shedding, the consumptions of HHs and SMEs at Tum exhibit those of typical domestic and productive users in rural SSA (Hartvigsson et al., 2021; Mandelli et al., 2016b). Moreover, as can be seen from the sample measured data in Appendix B, productive users generally consume more energy during the weekend days than during the weekdays. Likewise, significant differences were observed between weekend and weekday consumptions of HHs at Omorate, but not at Tum. The higher electricity consumption of SMEs is essentially related to the fact that SMEs are primarily engaged in income generating activities that involve substantial power use, such as garages, hotels/restaurants, local breweries, bakeries, and beauty salons. According to the survey data, 46% of the total sampled SMEs (in Omorate and Tum) were established after the launch of the MG services. This suggests that the introduction of the MG service may have served as the impetus for the creation of new businesses and enterprises. Appendix C presents a summary of the main electricity use types by sector in the study areas.

3.3. Monthly electricity consumption patterns and dynamics by sector

In this section, the mean monthly electricity consumption of the different consumer types and its dynamics over the 20-month period is analyzed using the EEU's metered dataset and customers' classification. The summary statistics of the average monthly electricity consumption by sector, shown in Table 4, generally substantiates the daily average energy consumptions calculated from the 14-day load measurements of representative samples (Table 3). The data in Table 4 shows that HHs typically consume 45 kW h per month in Omorate and 22 kW h per month at Tum, indicating that the mean monthly consumption of HHs at Omorate is more than twice that of their counterparts at Tum. Similarly, SMEs at Omorate consume more electricity each month (on average 159 kW h) than SMEs at Tum (on average 90 kW h). However, the mean monthly consumption of institutions at Omorate is only marginally higher than that of the institutions at Tum.

A further analysis of the EEU dataset shows that SMEs at Omorate consume over half of the total energy supplied by the MG (on average 51%) each month, while representing only 25% of the total number of customers. In Tum, SMEs account for 28% of the total monthly consumption despite making up only 9% of the total customers. It is also found that about 50% of the HHs at Omorate consume less than 50 kW h per month, while 70% of HHs at Tum use less than 20 kW h per month. By contrast, SMEs at Omorate consume up to 800 kW h per month.

These results once again highlight the significant differences in electricity consumption across the two towns and between the three sectors discussed in sections 3.1 and 3.2, respectively. Our results have significant policy implications which underline the importance of understanding the energy demands and lad profiles of SMEs in determining rural electricity demand especially in off-grid areas. In line with our findings, Agrawal et al. (2020) reported that rural HHs in India consumed on average 39 kW h per month. Comparable results were also found by Sharma et al. (2020).

Analysis of the dynamics of monthly energy consumption over the 20-month period, shown in Figs. 13 and 14, reveals differing patterns between the two towns and across the three sectors. The average monthly consumption per HH at Omorate has dropped from 175 kW h in May 2021 to 36 kW h in December 2022 (79% decline); while at Tum it has grown from 25 kW h in May 2021 to 37 kW h in December 2022 (48% increase). Similarly, the average monthly consumption per SME at Omorate has plunged from about 665 kW h in May 2021 to 200 kW h in December 2022 (70% decline); whereas it has steadily climbed up at Tum from 89 kW h in May 2021 to 124 kW h in December 2022 (39%

Table 4
Summary statistics of monthly electricity consumption by sector in the two towns.

Sector	Location	Min (kWh)	Median (kWh)	Mean (kWh)	Max (kWh)	St. Dev. (kWh)	% Demand
Households	Omorate	3.14	41.4	45.4	200.5	22.8	40.0
	Tum	2.5	13.6	22.2	61.5	14.9	56.3
Productive users/SMEs	Omorate	12.0	110.9	158.5	800.1	170.8	50.7
	Tum	5.3	55.86	89.9	192.5	55.7	28.1
State/public institutions	Omorate	7.7	85.0	98.1	434.1	100.8	9.2
	Tum	6.2	76.6	90.4	398.3	80.1	15.6

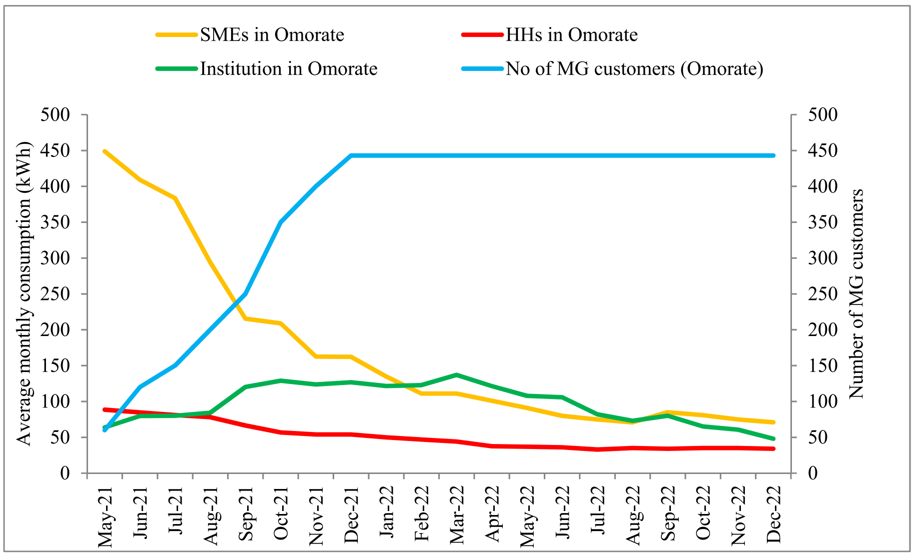

Fig. 13. Mean monthly electricity consumption per customer for the different customer types over the 20-month period at Omorate (based on EEU's metered data and customer classification).

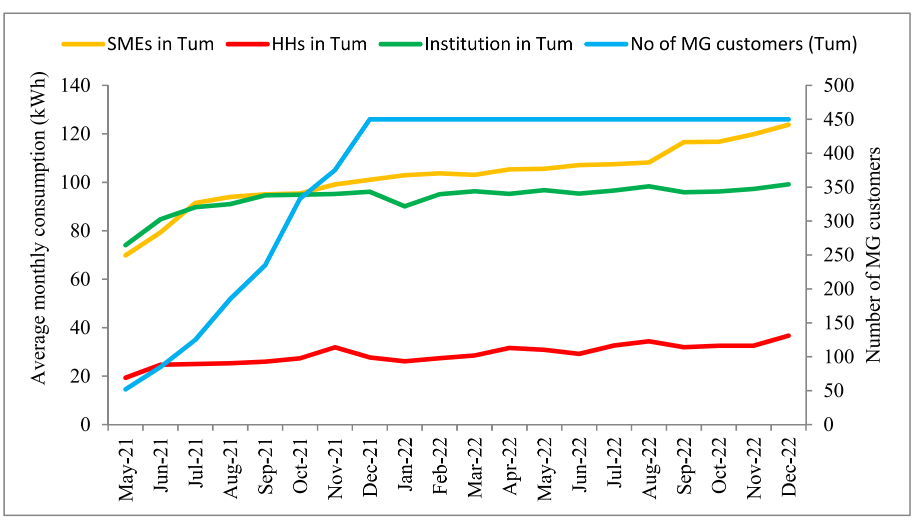

Fig. 14. Mean monthly electricity consumption per customer for the different customer types over the 20-month period at Tum (based on EEU's metered data and customer classification).

increase). By contrast, the monthly consumption per institution at Tum has marginally increased over time, while it has marginally decreased at Omorate.

Figs. 13 and 14 also show that the number of MG customers grew sharply at both sites but the energy supplied by the MG at Omorate has remained essentially unchanged (see Fig. 10). As a result, the monthly consumptions of HHs and SMEs, in particular, have dropped significantly. The flat line of in the number of MG customers as of December 2021 indicates that the EEU has ceased providing connections to new customers at both sites since then. In terms of seasonal variation in energy consumption, the mean monthly consumption of SMEs at Omorate during the dry months (July through March) was found to be 132 kW h/month compared to 108 kW h/month during the rainy months (April through June), indicating a 22% increase in mean

Table 5
Multiple Linear Regression (MLR) results for HHs in Omorate.

Regression Statistics						
Multiple R		0.864		St. Error		0.563
R Square		0.746		Observations		68
Adjusted R Square		0.708				
ANOVA						
	df	SS		MS	F	Significance F
Regression	13	50.34		3.87	12.21	0.000
Residual	54	17.13		0.32		
Total	67	67.47				
	Coeff.	St. Error	t Stat	P-value	Lower 95%	Upper 95%
Gender	0.07	0.19	0.37	0.714	−0.30	0.44
Age	0.01	0.01	1.25	0.218	0.00	0.02
Education level	0.03	0.02	1.59	0.117	−0.01	0.08
HH size	0.05	0.06	0.99	0.326	−0.06	0.17
Dwelling type	0.16**	0.22	2.12	0.039	−0.27	0.59
No of rooms	0.11**	0.07	2.08	0.041	−0.02	0.24
log (monthly per capita income)	0.08*	0.12	1.72	0.092	−0.24	0.24
No of refrigerators	0.27***	0.23	3.57	0.000	−0.17	0.72
No of cooking stoves	0.21	0.31	1.01	0.317	−0.39	0.81
No of cooling fans	0.20**	0.18	2.42	0.018	−0.15	0.55
No of other appliances	0.04	0.24	0.85	0.401	−0.43	0.51
Private PV ownership	−0.13	0.19	−1.05	0.286	−0.50	0.23
Productive use of power	0.02	0.24	0.07	0.948	−0.45	0.49
Constant (intercept)	2.72**	1.69	2.60	0.011	−0.60	6.03

*p < 0.1; **p < 0.05; ***p < 0.01 significance levels.

Table 6
Multiple Linear Regression results for HHs in Tum.

Regression Statistics						
Multiple R		0.926		St. Error		0.353
R Square		0.857		Observations		60
Adjusted R Square		0.817				
ANOVA						
	df	SS		MS	F	Significance F
Regression	13	34.42		2.65	21.23	0.000
Residual	46	5.74		0.12		
Total	59	40.16				
	Coeff.	St. Error	t Stat	P-value	Lower 95%	Upper 95%
Gender	0.14	0.11	1.21	0.233	−0.09	0.37
Age	0.00	0.00	−0.36	0.722	−0.01	0.01
Education level	0.04**	0.01	2.63	0.011	0.01	0.07
HH size	0.10***	0.03	3.04	0.004	0.03	0.16
Dwelling type	0.35**	0.17	2.11	0.040	0.02	0.68
No of rooms	0.15**	0.04	2.31	0.024	0.07	0.24
log (monthly per capita income)	0.12**	0.11	2.10	0.041	−0.20	0.29
No of refrigerators	0.05	0.16	0.31	0.758	−0.27	0.37
No of cooking stoves	0.23	0.17	1.04	0.151	−0.10	0.56
No of cooling fans	0.00	0.01	0.16	0.873	−0.02	0.02
No of other appliances	0.42	0.32	1.32	0.191	−0.22	1.07
Private PV ownership	−0.01	0.25	−0.02	0.984	−0.51	0.50
Productive use of power	0.22	0.27	0.82	0.417	−0.31	0.75
Constant (intercept)	0.02	0.87	0.02	0.984	−1.73	1.77

*p < 0.1; **p < 0.05; ***p < 0.01 significance levels.

monthly consumption of SMEs during the dry months. Similarly, the monthly consumption of HHs at Omorate was found to be marginally higher in dry months than in wet months. The variation in energy consumption of SMEs and HHs between the dry and rainy seasons at Omorate could be related to two factors. The first is that energy consumption is higher during the dry months since many HHs, and SMEs use air conditioning and refrigeration. In contrast, during the rainy season, consumption is relatively low because the weather is cooler, which means less power is needed for space cooling. Although both towns have an equatorial climate, it is worth noting that Omorate is situated at the heart of the Omo Valley where the annual average maximum temperature ranges from 35 to 42.8 °C, while at Tum it ranges from 24 to 30 °C. Second, during the rainy season the amount of incoming solar energy can be lower, resulting in less electricity being produced by the PVG.

The increase in consumption over time at Tum was expected as electricity usage increases with increase in access to electricity, awareness, appliance ownership and the use of electricity for various purposes. On the other hand, the stalling of monthly consumption per SMEs and per HHs at Omorate is due to the generation capacity shortage relative to the demand as discussed earlier in this paper and also reported in our

Table 7
Multiple Linear Regression results for SMEs in Omorate.

Regression Statistics			
Multiple R	0.884	St. Error	0.595
R Square	0.765	Observations	50
Adjusted R Square	0.663		

ANOVA	df	SS	MS	F	Significance F
Regression	13	22.30	1.72	2.71	0.009
Residual	36	22.76	0.63		
Total	49	45.06			

	Coeff.	St. Error	t Stat	P-value	Lower 95%	Upper 95%
Gender	−0.46	0.28	−1.63	0.111	−1.03	0.11
Age	−0.03	0.02	−1.65	0.107	−0.06	0.01
Education level	0.00	0.04	−0.11	0.912	−0.08	0.07
HH size	0.10**	0.04	2.12	0.041	0.00	0.19
Dwelling type	0.31	0.52	0.59	0.561	−0.71	1.33
No of rooms	0.28	0.37	0.77	0.222	−0.44	1.01
log (net monthly income)	0.16**	0.10	2.39	0.010	−0.03	0.36
No of refrigerators/freezers	0.38**	0.23	1.93	0.029	−0.07	0.83
No of cooking stoves	0.42	0.47	0.56	0.577	−0.50	1.34
No of cooling fans	0.15*	0.26	1.75	0.089	−0.39	0.68
No of other appliances	0.97***	0.36	3.04	0.004	0.25	1.67
Private PV ownership	−0.37	0.31	−1.18	0.247	−1.00	0.27
Productive use of power	1.21***	0.42	2.92	0.006	0.37	2.05
Constant (intercept)	4.44**	2.17	2.05	0.048	0.05	8.84

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$ significance levels.

recent study (Wassie and Ahlgren, 2023). In congruence with our results, a study in Tanzania (Hartvigsson et al., 2021) found that over a period of 30 months, the electricity consumption of HHs and SMEs electrified by an off-grid MG grew by 56% and 37%, respectively.

4. Drivers of electricity consumption

4.1. Factors affecting electricity consumption of HHs

The results of the regression analyses for the factors determining the electricity consumption of ordinary HHs in Omorate and Tum are presented in Tables 5 and 6, respectively. Both regression models have satisfactory goodness-of-fit (Adj. $R^2 = 0.708$ and Adj. $R^2 = 0.817$) indicating that the predictor variables included in each equation sufficiently explain the variation in electricity usage among HHs in each town. The parameter estimates (regression coefficients) in Table 5 reveal that HH electricity consumption in Omorate is significantly influenced by appliance ownership (total number of refrigerators and cooling fans the HH owns) and dwelling factors (whether the HH lives in 'modern' brick/concrete house or traditional house, and the total number of rooms). According to the model estimates, a one unit increase in the number of refrigerators (standard 250 L) that the HH owns may increase the average monthly electricity consumption of the HH by 27% ($p < 0.01$), keeping other variables in the model constant. Similarly, compared with HHs living in traditional mud or wooden houses (the reference category), HHs living in 'modern' brick or concrete houses consume 16% ($p < 0.05$) more electricity per month. These results reinforce findings of previous studies (Ye et al., 2018; Nsangou, 2022) which reported that appliance ownership and dwelling factors are among the major predictors of rural HH electricity consumption in developing countries.

The coefficient for per capita income indicates that a 1% increase in the monthly per capita income of the HH may increase the HH's monthly electricity usage by 8% ($p < 0.1$), holding other variables constant. While the coefficient for per capita income appears to be sizable, it is statistically weakly significant ($p < 0.1$). In contrast to our finding, Ye et al. (2018) and Rahut et al. (2016) reported that rural HH electricity consumption is significantly and strongly influenced by per capita income. There are two possible explanations for the weak effect of per capita income in Omorate. The first is that per capita income perhaps influences HH electricity consumption indirectly by affecting the HH's ability to purchase and utilize appliances. The second is that electricity demand in Omorate may have become income-inelastic (i.e., is not sensitive to changes in income). Earlier studies in South Africa (Ye et al., 2018) and India (Basumatary et al., 2021) have also shown that rural HH electricity demand is income inelastic.

Table 5 further elucidates that, despite the positive relationship, sociodemographic factors such as the gender, age, and education level of the HH head as well as family size have no significant influence on electricity consumption. This might be due to two reasons. The first is that most HHs in Omorate are well aware of the benefits of access to electricity since Omorate used to be powered by a large diesel genset up until 2016. The second may be that other determinants such as the HH's appliances ownership and disposable income have stronger effects.

In contrast to the HHs in Omorate, the regression coefficients in Table 6 show that HH electricity consumption in Tum is significantly influenced by family size ($p < 0.01$), education level of the HH head ($p < 0.05$), dwelling type and number of rooms ($p < 0.05$), and monthly per capita income ($p < 0.05$). As can be seen from the results in Table 6, some of the variables affecting the electricity consumption of HHs in Tum are distinct from those affecting HHs in Omorate. Whereas the effect of HH size was insignificant in Omorate, in Tum, the average monthly electricity consumption of a HH statistically significantly increases by 10% for every one person added to the family size ($p < 0.01$), keeping other variables constant. It is also worth noting that monthly per capita income of the HH has stronger and more significant ($P < 0.05$) effect on HH electricity consumption in Tum than in Omorate. These findings clearly demonstrate that, while income and dwelling factors affect the electricity consumption of HHs in both towns, appliance ownership and access to appliances exert a more significant positive effect in Omorate than in Tum. In contrast, the education level of the HH head and HH size play a major role in determining the electricity consumption of HHs in Tum. The latter results are in agreement with previous research (Ye et al., 2018; Aziz and Chowdhury, 2021), which reported that HHs with larger family size and higher educational attainment consume more electricity.

Table 8
Multiple Linear Regression results for SMEs in Tum.

Regression Statistics			
Multiple R	0.867	St. Error	0.718
R Square	0.751	Observations	40
Adjusted R Square	0.652		

ANOVA	df	SS	MS	F	Significance F
Regression	13	31.43	2.42	4.70	0.000
Residual	26	13.39	0.51		
Total	39	44.81			

	Coeff.	St. Error	t Stat	P-value	Lower 95%	Upper 95%
Gender	−0.18	0.32	−0.57	0.574	−0.85	0.48
Age	−0.02**	0.01	−2.14	0.042	−0.04	0.00
Education level	0.00	0.03	0.09	0.927	−0.06	0.07
HH size	0.03	0.07	0.42	0.678	−0.11	0.16
Dwelling type	0.19	0.16	0.79	0.439	−0.12	0.50
No of rooms	−0.07	0.05	−0.86	0.398	−0.17	0.04
log (net monthly income)	0.15**	0.16	2.10	0.046	−0.17	0.47
No of refrigerators	0.40	0.32	1.24	0.226	−0.26	1.06
No of cooking stoves	0.25***	0.62	3.05	0.002	−0.96	1.47
No of cooling fans	0.01	0.02	0.17	0.432	−0.03	0.05
No of other appliances	0.55**	0.28	1.97	0.027	−0.02	1.13
Private PV ownership	−0.23	0.11	−1.05	0.305	−0.45	−0.02
Productive use of power	1.09***	0.25	4.28	0.000	0.56	1.61
Constant (intercept)	0.60	2.74	0.22	0.828	−5.03	6.24

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$ significance levels.

It is evident from the results in Tables 5 and 6 that the drivers of HH electricity consumption in the two towns differ considerably. As discussed earlier in Section 3.1.1., the notable differences in the factors influencing HH consumption between the two towns are attributable to appliances ownership, HHs' income, and location-dependent variables such as access to electrical appliances and cost of appliances, local livelihoods as well as prior awareness. Noticeably, HHs in Omorate who generally own a higher number of refrigerators, space cooling fans, and 'other high wattage appliances' consume more electricity than HHs in Tum who own fewer number of appliances. Geographic location is another key variable since it affects the local climate, and HHs' livelihoods and access to appliance markets. Our findings from the EEU data analysis have demonstrated that customers in Omorate - where the climate is hot and there is lengthy daily load-shedding - consume significantly more electricity than their counterparts at Tum, where there is no load-shedding, and the climate is modest. Also, HHs in Omorate had previously used electricity or were familiar with it while HHs in Tum had no prior acquaintance with electricity. In accord with our results, a study conducted in four SSA countries (Rahut et al., 2017) found that accessibility of appliance markets and the level of remoteness of the village/town greatly influence HH electricity consumption. Gaunt et al. (Gaunt, 2005) also identified access to and cost of appliances among the major determinants of electricity demand in rural South Africa. The significant effect of local climate and extreme temperatures on energy demand has been documented by some previous studies (Li et al., 2018; Ali et al., 2013).

4.2. Factors affecting electricity consumption of SMEs

Tabless 7 and 8 report results of the MLR analyses for factors affecting the electricity consumption of SMEs in Omorate and Tum, respectively. In both models, the adj. R^2 value is higher than 0.65, which indicates that both models explain at least 65% of the variation in electricity consumption among SMEs within each town. The coefficients in Table 7 reveal that the electricity consumption of SMEs in Omorate is significantly influenced by productive use of electricity, number of other (power intensive) appliances, number of refrigerators/freezers, number of space cooling fans, the net monthly income of the SMEs and HH size. The large and significant coefficient for productive use clearly shows that the electricity consumption of SMEs in Omorate highly depends on whether the SME utilizes power for productive purposes or not. Evidently, compared to SMEs that do not primarily use electricity for productive purposes (such as small retail shops and grocery stores), productive user SMEs (such as beauty salons, restaurants, wood workshops) consume 121% more electricity per month ($p < 0.01$). The strong effect of productive use on electricity demand of SMEs in Omorate is further evidenced by the significant coefficients for the number of refrigerators and freezers ($p < 0.05$) and the number of 'other (power intensive) appliances/equipment' ($p < 0.01$). According to the results in Table 7, a one unit increase in the number of high-wattage electrical appliances (such as welding machines, air compressors, drills, or hair dryers) that the SME owns is associated with a 97% increase in monthly power consumption, keeping other variables constant.

Whereas the influence of per capita income on the electricity consumption of HHs in Omorate was modest (see Table 5), a 1% rise in the SME's net monthly income is associated with a 16% increase in monthly electricity consumption. This finding illustrates how a gain in net income can increase the electricity demand of rural SMEs since it provides them with more cash to expand and intensify their commercial operations. It is also found that an increase in HH size significantly increases the electricity consumption of SMEs in Omorate ($p < 0.05$). This might be because as family size increases, so does the productive workforce available for operating SMEs, which in turn enhances the income-generating activities and ultimately increases power consumption.

In alignment with the results for SMEs in Omorate, the coefficients in Table 8 illustrate that the electricity consumption of SMEs in Tum is significantly influenced by productive use of power ($p < 0.01$), number of other (power intensive) appliances, number of electric coking stoves, and the net monthly income of the SME. The results establish that productive use of electricity is a major driver of electricity consumption. The reasons as to why productive users consume more electricity are explained in section 3.2. However, the weight of influence of productive use and number of high-wattage appliances on electricity consumption of SMEs in Tum is less than that in Omorate. This may be due to the limited access to appliances in Tum along with the largely farming-related economic activity in the town. The age of the SME owner is negatively and significantly associated with electricity consumption ($p < 0.05$). One possible explanation for this might be that the younger generations have better access to education and knowledge on how to take advantage of electricity access for income-generating activities. Interestingly, the number of refrigerators and cooling fans have no significant influence on the electricity consumption of both HHs and SMEs in Tum. This is in stark contrast to the findings in Omorate where both variables have significant influence on the energy consumption of HHs and SMEs. There are several reasons for this. First, the climate in Tum is relatively cooler than in Omorate, therefore only a few SMEs use refrigerators and cooling fans. Second, compared to Omorate, SMEs in Tum have less access to electrical appliances. Third, the purchasing power of SMEs in Tum is lower than that of SMEs in Omorate.

Overall, findings of the MLR analyses highlight that a spectrum of factors influence the electricity consumption of MG customers in the study areas. These factors can be summarized into five major categories: the customer's appliances stock and access to appliances, sociodemographic factors, income level, location and the type of customers served (ordinary HHs, non-productive user small businesses, productive user enterprises). However, these factors differ markedly between sectors (HHs vs SMEs) and across the two towns. Additionally, the MLR results demonstrate how location and context-specific variables including prior awareness on electricity use influence the electricity consumption of HHs and SMEs due to their confounding effects. As such, the regression analyses consolidate our earlier findings and conclusions drawn from the EEU metered data and the 14-day measured data. The implication is that rural electrification planners and policy makers should take into account the influence of context-specific demand variables, in addition to the more traditional determinants such as income and appliances use, when sizing and deploying off-grid PV MGs.

4.2.1. Generalizability of our findings

In contrast to most studies on energy consumption, which mainly rely on data from sample surveys, this research has made use of high quality, measured data from both the supply and demand sides. These datasets have been thoroughly analyzed in the paper across sites, sectors, and time periods. As a result, many of the findings – including the variations in electricity consumption across towns, between HHs and SMEs and over time – as well as the significant effects of appliances ownership, productive use of electricity and the local climate are generalizable and applicable to comparable situations in rural areas of east Africa and the wider SSA. However, some of the study's findings, including the load-shedding and its effect may have more to do with the particular circumstances in Omorate, and the limited installed capacity of the mini-grid.

5. Conclusions and policy implications

A data-driven analysis of the electrical load profiles, consumption patterns and demand drivers of different consumer types electrified through off-grid photovoltaic (PV) mini-grids in two remote small towns (namely Omorate and Tum) in Ethiopia was conducted using metered data spanning 20 months and a survey of 238 customers. Findings indicate that the load profiles and electricity consumption patterns of mini-grid customers differ significantly between the two sites, across customer types (households, productive users, and institutions), and over time. The load curves at Omorate are consistently interrupted and close to zero kW for a significant portion of the day (13 h each day) due to load-shedding as a result of demand exceeding generation capacity. By contrast, the load curves at Tum are continuous throughout the day, and the mini-grid produces enough power to meet the demand. However, reconstructing the uninterrupted (unsuppressed) daily load curve at Omorate revealed that the demand has in fact grown at least by 64% during the 20-month period. Over the same period, the daily energy consumption at Tum has increased by 90%. Although the mini-grid at Omorate has a significantly lower installed capacity than the one at Tum, and that both mini-grids have comparable number of customers, the average daily energy consumption at Omorate, 1065 kW h, was found to be more than 1.5 times the daily consumption at Tum, 640 kW h. *At* both sites, the *mean monthly electricity consumption* of *productive users (SMEs) is more than three times that of ordinary households.* Multiple regression analyses of the drivers of electricity consumption revealed that the factors determining electricity consumption, especially among households, differ considerably across the two towns. Furthermore, the analyses showed that, in addition to traditional economic factors such as the customer's income level, access to and ownership of appliances, prior knowledge of the customer about electricity usage, and local climatic conditions significantly influence electricity consumption.

A number of important policy implications can be drawn from this study. First, the study highlights that rural energy policy makers in east Africa, to a much greater extent, should take into account the local context, (including accessibility of electrical appliances, type and intensity of business activities, climatic conditions, and income level and lifestyle of customers), when planning off-grid electrification through PV mini-grids. Second, the excess demand at Omorate and, conversely, the comparatively lower demand at Tum, indicate that PV mini-grid capacity dimensioning should be based on accurate demand forecasting and load profile calibration, as well as an understanding of current and prospective energy consumption patterns and dynamics across villages. Third, the high share of productive users in the total energy consumption at both sites, particularly at Omorate despite the protracted load-shedding, demonstrates the crucial role that productive use of power plays in determining rural electricity demand. This suggests that mini-grid developers must also make sure that the systems satisfy the energy needs of rural enterprises, in addition to fulfilling the needs of ordinary households, to maximize the mini-grids' financial profitability and development impact. Fourth, despite some studies suggesting that off-grid mini-grids might not be economically viable in rural SSA due to insufficient demand for electricity (Peters et al., 2019), the high consumption levels and unmet load at Omorate imply otherwise. It follows that with proper dimensioning, operation, pricing strategy and policy support, renewable mini-grids may in fact be attractive investments for electricity providers as well as consumers. Fifth, the regression analyses showed that installing the mini-grids does not necessarily result in energy consumption. It is therefore imperative that energy ministries and electricity providers in low-income nations facilitate access to affordable electrical appliances and raise awareness in order to create sustainable electricity demand.

CRediT authorship contribution statement

Yibeltal T. Wassie: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Erik O. Ahlgren:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

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.

Data availability

Data will be made available

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Appendix A. A sample daily load report retrieved from the MG at Tum

Site	TUM						Date: 2022-12-16					
	Load 1						Load 2					
Time:	Ia(A)	Ib(A)	Ic(A)	P(KW)	Q (kvar)	COS	Ia(A)	Ib(A)	Ic(A)	P(KW)	Q (kvar)	COS
00:00	25	27	29	17	7	0.93	0	0	0	0	0	0.00
01:00	25	27	29	17	7	0.92	0	0	0	0	0	0.00
02:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
03:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
04:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
05:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
06:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
07:00	0	0	0	0	0	0.00	0	0	0	0	0	0.00
08:00	44	57	51	34	9	0.98	0	0	0	0	0	0.00
09:00	44	49	46	31	7	0.96	0	0	0	0	0	0.00
10:00	50	49	49	33	8	0.97	0	0	0	0	0	0.00
11:00	49	56	65	38	8	0.98	0	0	0	0	0	0.00
12:00	51	47	63	36	8	0.98	0	0	0	0	0	0.00
13:00	62	65	56	41	9	0.98	0	0	0	0	0	0.00
14:00	44	55	48	33	8	0.97	0	0	0	0	0	0.00
15:00	37	44	45	27	8	0.96	0	0	0	0	0	0.00
16:00	45	51	50	32	8	0.97	0	0	0	0	0	0.00
17:00	35	58	50	31	10	0.95	0	0	0	0	0	0.00
18:00	52	73	56	40	7	0.99	0	0	0	0	0	0.00
19:00	87	103	97	66	6	1.00	0	0	0	0	0	0.00
20:00	84	97	87	61	5	1.00	0	0	0	0	0	0.00
21:00	57	62	66	41	6	0.99	0	0	0	0	0	0.00
22:00	39	47	45	29	6	0.98	0	0	0	0	0	0.00
23:00	32	35	37	22	6	0.96	0	0	0	0	0	0.00
24:00	26	26	30	18	6	0.94	0	0	0	0	0	0.00

Appendix B. Summary of a 14-day hourly electrical load of a typical hotel owner at Omorate, from 15 to December 28, 2022, as an example. (Source: own measurement using a smart-meter)

Time	Measured total energy consumption per day (kWh)													
	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed
00:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
01:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
02:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
03:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
04:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
05:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
06:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
07:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
08:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
09:00	0.50	0.34	0.00	0.00	0.43	0.53	0.27	0.58	0.31	0.00	0.74	0.37	0.68	0.35
10:00	0.52	0.35	1.00	0.80	0.45	0.54	0.28	0.61	0.32	1.02	0.74	0.39	0.69	0.36
11:00	0.57	0.39	1.08	0.90	0.49	0.59	0.31	0.66	0.36	1.11	0.83	0.42	0.75	0.40
12:00	0.58	0.44	1.11	0.90	0.50	0.61	0.28	0.73	0.41	1.04	0.93	0.43	0.83	0.41
13:00	0.63	0.40	1.09	1.00	0.50	0.66	0.32	0.67	0.37	1.13	0.83	0.48	0.77	0.46
14:00	0.58	0.39	1.19	0.90	0.55	0.60	0.32	0.62	0.36	1.22	0.83	0.43	0.76	0.41
15:00	0.53	0.36	1.01	0.80	0.45	0.55	0.36	0.67	0.33	1.13	0.74	0.39	0.70	0.36
16:00	0.19	0.30	0.45	0.30	0.15	0.20	0.06	0.24	0.09	0.52	0.27	0.12	0.28	0.10
17:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.00	0.00	0.48
19:00	0.00	0.69	0.61	0.00	0.73	0.93	0.40	0.81	0.46	1.05	0.93	0.00	0.92	0.50
20:00	0.70	0.97	0.58	1.00	0.70	0.90	0.58	0.77	0.00	1.40	1.02	0.70	0.88	0.00
21:00	0.67	0.00	0.00	1.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.73	0.00	0.00
22:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total	**5.47**	**4.63**	**8.12**	**7.70**	**4.95**	**6.11**	**3.18**	**6.36**	**3.45**	**9.62**	**7.86**	**4.46**	**7.26**	**3.83**

*All Wednesdays and Fridays are fasting days among Orthodox Christian adherents in Ethiopia.

Appendix C. The main electricity services/uses of the different customer groups

No	Customer type (sector)	Main electricity services	Frequency	
			Omorate (n = 68)	Tum (n = 60)
1	**Households (domestic use)**	Home lighting	68	60
		Mobile phone charging	58	49
		TV and/Radio service	55	22
		Refrigeration/cooling	51	7
		Space cooling/fans	45	0
		Cooking and heating/stoves	30	11
		Coffee maker/boilers	6	3
2	**Small and medium enterprises (SMEs)**		**(n = 50)**	**(n = 40)**
	Retail goods and cold drinks stores	Lighting, refrigerators, cooling fans	18	6
	Fast foods, beverages and traditional coffee shops	Lighting, refrigeration cooking stoves, boilers	5	7
	Bars, restaurants, and traditional 'beer-like' beverage makers	Refrigeration, deep freezers, cooking, lighting	5	6
	Women's and Men's beauty salons	Hair styling machines	5	5
	Hotels and pensions	Deep freezers, refrigerators, lighting and cooking	4	3
	Mobile phone charging and electronic shops	Lighting, maintenance and phone-charging	1	4
	Garage, wood and metal workshops	Welding, compressors, low-power sawing, air pumping,	2	1
	Motorcycle and bicycle repair service	Light-welding and pumping	2	1
	Juice makers and sport/game zones	Juice machine operating	2	1
	Bakeries	Dough mixing	1	2
	Photo studios	Background lighting	2	1
	Photocopy, computer and printing services	Photocopying, printing, laminating, typing	1	1
	Tailor and ironing	Tailoring and ironing	1	1
	Private clinic/pharmacy	Lighting, cooling	1	1
3	**Institutions**		**(n = 10)**	**(n = 10)**
	Government sector offices and administrations	Computer use, documentation,	3	2
	Churches/Mosques	Lighting, speakers	1	1
	Bank (ATM service)	Banking, networking	1	1
	Health centers, clinics and pharmacies	Laboratory, deep-freezing of vaccines and storage of medicine, space cooling,	1	1
	Schools and colleagues	Lighting, TV-education laboratory, workshop	2	2
	Police stations and prisons	Lighting, space cooling	1	1
	Military/refugee camps	Lighting, space cooling	1	1
	State/district prisons	Lighting, space cooling	0	1
4	**Streetlights**	Lighting	14	0

*n = sample size.

References

Agrawal, S., et al., 2020. Influence of Improved Supply on Household Electricity Consumption Evidence from Rural India. Energy, 118544.

Ali, M., Iqbal, M.J., Sharif, M., 2013. Relationship between extreme temperature and electricity demand in Pakistan. Int. J. Energy Environ. Eng. 4, 36.

Aziz, S., Chowdhury, S.A., 2021. Determinants of off-grid electrification choice and expenditure: evidence from Bangladesh. Energy 219, 119578.

Basumatary, S., Devi, M., Basumatary, K., 2021. Determinants of household electricity demand in rural India: a case study of the impacts of government subsidies and surcharges. Int. J. Energy Econ. Pol. 11 (6), 243–249.

Crowe, S., et al., 2011. The case study approach. BMC Med. Res. Methodol. 11 (100).

EEU, 2022. Ethiopian Electric Utility, Project Portfolio Management: Projects Status. http://www.ethiopianelectricutility.gov.et/contents/project-and-program. (Accessed 2 December 2022).

Gaunt, C.T., 2005. Meeting electrification's social objectives in South Africa, and implications for developing countries. Energy Pol. 33, 1309–1317.

Hartvigsson, E., Ahlgren, E.O., 2018. Comparison of load profiles in a mini-grid: assessment of performance metrics using measured and interview-based data. Energy Sustain. Dev. 43, 186–195.

Hartvigsson, E., et al., 2021. Linking household and productive use of electricity with mini-grid dimensioning and operation. Energy Sustain. Dev. 60, 82–89.

IEA, 2021. Tracking SDG7: the Energy Progress Report. The International Energy Agency, 2021. https://www.iea.org/reports/tracking-sdg7-the-energy-progress-report-2021. (Accessed 3 November 2022).

Isihak, S., et al., 2020. The evolution of rural household electricity demand in grid-connected communities in developing countries: result of a survey. Future Cities Environ. 6 (1), 1–11, 10.

Katre, A., Tozzi, A., Bhattacharyya, S., 2019. Sustainability of community-owned mini-grids: evidence from India. Energy, Sustain. Soc. 9 (2).

Kim, M.J., 2020. Understanding the determinants on household electricity consumption in Korea: OLS regression and quantile regression. Electr. J. 33 (7), 106802.

Laicane, I., et al., 2015. Comparative multiple regression analysis of household electricity use in Latvia: using smart meter data to examine the effect of different household characteristics. Energy Proc. 72, 49–56.

Li, G., Sun, J., Dai, A., 2016. Village differences in rural household energy consumption within the Loess hilly region of China. Energ Sustain. Soc. 6, 33.

Li, Y., Pizer, W.A., Wu, L., 2018. Climate change and residential electricity consumption in the Yangtze River Delta, China. Proc. Natl. Acad. Sci. U. S. A. 116 (2), 472–477, 8.

Lombardi, F., et al., 2019. Generating high-resolution multi-energy load profiles for remote areas with an open-source stochastic model. Energy 177, 433–444.

Lorenzoni, L., et al., 2020. Classification and modeling of load profiles of isolated mini-grids in developing countries: a data-driven approach. Energy Sustain. Dev. 59, 208–225.

Mandelli, S., et al., 2016a. Off-grid systems for rural electrification in developing countries: definitions, classification and a comprehensive literature review. Renew. Sustain. Energy Rev. 58, 1621–1646.

Mandelli, S., et al., 2016b. Effect of load profile uncertainty on the optimum sizing of off-grid PV systems for rural electrification. Sustain. Energy Technol. Assessments 18, 34–47.

MoWE, 2019. National electrification plan (NEP 2.0) of the federal democratic republic of Ethiopia, Vol (1), pp, 45-52. Ministry of Water and Energy. Addis Ababa, Ethiopia. https://www.powermag.com/wp-content/uploads/2020/08/ethiopia-national-electrification-program.pdf. (Accessed 25 November 2022).

Mulatu, A.B., Negash, W.A., Teshome, M., 2023. The status of solar energy utilization and development in Ethiopia. J. Fund. Renew. Energy Appl. 13 (307).

Mwakitalima, I.J., King'ondu, C.K., 2015. Electricity demand evaluation for rural electrification. A case study of Kikwe village in Tanzania. Int. J. Eng. Res. Technol. 4 (6).

Nsangou, J.C., 2022. Explaining household electricity consumption using quantile regression, decision tree and artificial neural network. Energy 250, 123856.

Okoko, A., et al., 2022. Are mini grids a solution to energy poverty? A case of mini-grids in Kenya. In: Paper Presented at the DSA 2022 Online Conference. University College London, UK, pp. 6–8. July 2022.

Pedersen, M.B., 2016. Deconstructing the concept of renewable energy-based mini-grids for rural electrification in East Africa. WIRES Energy and Environ. 5 (5), 570–587.

Peters, J., Sievert, M., Toman, M., 2019. Rural electrification through mini-grids: challenges ahead. Energy Pol. 132, 27–31.

Rahut, D.B., Behera, B., Ali, A., 2016. Household energy choice and consumption intensity: empirical evidence from Bhutan. Renew. Sustain. Energy Rev. 53, 993–1009.

Rahut, D.B., et al., 2017. A ladder within a ladder: understanding the factors influencing a household's domestic use of electricity in four African countries. Energy Econ. 66 (C), 167–181.

Scott, N., Coley, W., 2021. Understanding load profiles of mini-grid customers in Tanzania. Energies 14 (14), 4207.
Seaman, S.R., Bartlett, J.W., White, I.R., 2012. Multiple imputation of missing covariates with non-linear effects and interactions: an evaluation of statistical methods. BMC Med. Res. Methodol. 12 (1), 46.
Sharma, A., Agrawal, A., Urpelainen, J., 2020. The Adoption and Use of Solar Mini-Grids in Grid-Electrified Indian Villages, vol. 55. Energy for Sustainable Development, pp. 139–150.
UNDP, 2022. The Africa Mini-Grids Program. United Nation's Development Program (UNDP). https://www.undp.org/energy/publications/brochure-africa-minigrids-program. (Accessed 3 October 2022).
Wassie, Y.T., Ahlgren, E.O., 2023. Performance and reliability analysis of an off-grid PV mini-grid system in rural tropical Africa: a case study in southern Ethiopia. Dev. Eng. 8, 100106.
Ye, Y., Kocha, S.F., Zhang, J., 2018. Determinants of household electricity consumption in South Africa. Energy Econ. 75, 120–133.
Yin, R.K., 2014. Case Study Research. Design and Methods, fifth ed. Sage publications, Thousand Oaks, CA, USA.
Zou, B., Luo, B., 2019. Rural household energy consumption characteristics and determinants in China. Energy 182, 814–823.