Addis Ababa University

Investigation of the Impacts of Demand-Side Factors on the Planning, Operation, and Tariff Design of Rural Mini-Grids

Doctoral Dissertation of:

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To My Parents and Beloved Teachers.

“The best and most beautiful things in the world cannot be seen or even touched, they must be felt with the heart.”

Helen Keller

Declaration

This PhD dissertation is a presentation of my own work. Any material used from other sources has been clearly identified and properly acknowledged and cited.

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Abstract

Electricity is essential for socio-economic development, quality of life, and environmental protection. Despite significant improvements in rural electrification, millions of people in rural areas of developing countries, especially in sub-Saharan Africa, still lack access to electricity. Off-grid mini-grid systems are a promising alternative to traditional grid expansion, but ensuring their economic viability remains a significant challenge. To enhance economic viability, most studies have focused on supply-side solutions; however, many mini-grid programs in developing countries are still failing for various reasons, including inadequate integration of demand-side factors such as load estimation, demand development, demand-side management, and load composition.

The thesis aims to address mini-grid economic viability challenges by examining how demand-side factors impact the planning, operational and tariff design of mini-grids, focusing on four key specific objectives. First, comparing interview- and measurement-based load profile estimation methods, identifying load categories and specific appliances responsible for significant differences. The impact of these differences between methods and the difference in load profile resolution on mini-grid sizing and cost is also examined using the PSO algorithm. The findings reveal that interview-based methods underestimate peak loads, daily energy use, and system costs (by up to 52%). The underestimation is more pronounced for household load categories, due to appliances with high power ratings and cyclic operation (e.g. electric cooking appliances). Hourly electric load estimation methods also lead to (9%) cost underestimation.

Second, exploring the advantages of a multi-year-adaptive design approach on cost-optimal long-term mini-grid component sizing under different demand evolution scenarios. PSO algorithm is used with measured loads to determine component sizes under three demand evolution scenarios and various design approaches. The results show that the multi-year-adaptive approach helps to manage demand evolution challenges. It leads to significant cost-savings in higher demand evolution scenarios compared to multi-year and single-year approaches. These cost-savings increase with load flexibility (up to 4% with 10% flexibility), higher discount rates (up to 9.4% with rates from 7% to 20 %), and component cost reductions (up to 3.6% per 1% reduction). The study demonstrates how an adaptive approach can be utilized to optimize mini-grid component sizing and enhance cost efficiency.

Third, determining the impacts of demand-side management implementation and shifting hours of electric cooking operation on the cost-efficient mini-grid sizing. To determine the impact of demand-side management and shifting hours on mini-grid sizing and cost, a shifting strategy is applied based on classification into high- and low priority loads. The results indicate that implementing demand-side management on different load categories leads to significant variations in potential levelized cost of energy reductions. Household and productive use load categories have the largest capacity to reduce the levelized cost of energy. Shifting hours of electric cooking in the household impacts the size of the mini-grid component, resulting in a system cost reduction.

Finally, the thesis examines the impact of load compositions on the economic viability of rural mini-grids, addressing the challenges of revenue and tariff settings due to future demand uncertainties in already installed mini-grids. Using normalized high-resolution measurements of households and productive users load profiles, the study determines the optimal load composition that maximizes mini-grid revenue. Results indicate that for a system with fixed capacity, there is an optimal mix of household and productive users that leads to high revenue. However, this composition changes with differentiated tariffs between households and productive users. Additionally, analysis using a mini-grid with spare capacity and three future load composition scenarios under five tariff structures (fixed energy, fixed and variable, time-of-use, power, and hybrid) shows that future load compositions significantly impact cost-reflective tariffs and users' monthly bills, with the impact varying across the tariff structures.

Keywords: Mini-grid; load estimation method; multi-year-adaptive design approach; demand uncertainty; demand-side management; load categories; load composition; tariff structures

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Abbreviations and acronyms

AVRm	Average peak power during off-peak hours
AVRn	Average peak power during peak hours
AVRT	Total average peak hour
PDF	Probability Density Function
BC	Base case
CF	Capacity Factor
CH	Church
CL	Community load
D	Total energy usage
DG	Diesel generator
DR	Demand response
DSM	Demand-side management
EEA	Ethiopian energy agency
EEU	Ethiopian Electric Utility
FET	Fixed energy tariff
fop	Off-peak factor
fp	Peak factor
FVT	Fixed and variable tariff
HET	Energy component of hybrid tariff
HH	Household
HPT	Power component of hybrid tariff
HT	Hybrid tariff
IEA	International Energy Agency
LCOE	Levelized cost of electricity
M	Millers
MEB	Monthly electricity bill
MILP	Mixed-integer linear programming
MY	Multi-year
MYAD	Multi-year adaptive
PSO	Particle swarm algorithm
PT	Power tariff
PU	Productive use
PV	Photovoltaic
RES	Renewable energy sources
RR	Revenue requirement
SCH	School
SDG	Sustainable development goals
SHS	Solar home system
SSA	sub- Saharan Africa
SY	Single-year
ToU	Time of use
Tp	Peak tariff

TPC	Total present cost
UEAP	Universal Electricity Access Program
UN	United Nations
WP	Water pumps
WS	Workshops

1. Introduction

In this chapter the background of the thesis along with the identified problem of statement of the thesis are presented. Additionally, it outlines the main and specific objectives, the research questions, and the key scientific contributions of the thesis, along with the resulting scientific publications.

1.1.Background

The United Nations (UN), consisting of 193 member states, adopted the 2030 Agenda for Sustainable Development on September 5, 2015. The 17 Sustainable Development goals (SDG) outlined in this agenda includes a subset specifically aimed at improving people's living standards [1]. Among these goals, SDG 7 emphasizes access to affordable and clean energy, such as electricity, which is a key enabler of socio-economic development and enhanced living conditions. Electricity facilitates lighting, modern appliances, and comfort while driving progress in sectors like healthcare, education, and agriculture through the operation of essential tools and equipment [2]. Notably, modern energy system transformation is vital for achieving all SDGs, with ~65% of targets linked to energy-related actions [3].

Despite significant global progress in increasing electric access, increasing from 83% in 2010 to 91% in 2020, substantial challenges persist, particularly in the Global South [4]. In 2023, 750 million people still lacked access to electricity, a decrease of only 10 million from 2022, according to the International Energy Agency (IEA) [5]. The majority of those without access reside in developing countries, especially in rural areas of sub-Saharan Africa (SSA), which constitutes a significant portion of the global energy gap [4]. The IEA projects that by 2030, approximately 660 million people will still lack electricity access, with 85%, around 560 million, residing in SSA [4].

Communities lacking electricity often rely on inefficient and harmful energy sources, such as biomass, kerosene, and diesel generators. These practices not only harm the environment and contribute to global warming but also pose significant health risks due to fumes and fire hazards. Moreover, many of these communities depend on agriculture, yet limited electricity access restricts agricultural commercialization by preventing value-added processing and other productivity-enhancing measures [6].

To advance the broader SDG in SSA, fostering an innovative and sustainable energy transition in rural areas is essential for expanding electricity access [1]. Previous efforts to increase electricity access mainly relied on extending the centralized national grids, known as grid extension. In SSA, government-controlled utilities oversee grid extension efforts. However, unsustainable economies and high debt levels have constrained government budgets in many SSA countries, making it challenging to achieve SDG 7 through grid extension alone [4]. This risk increased in 2020 due to the COVID-19 pandemic and continued population growth, which resulted in the highest number of people without electricity in the SSA for the first time since 2013 [7].

Users in rural areas of SSA often exhibit distinct electricity demand characteristics and driving factors, which differ significantly from those of users connected to main grids [8]. The electricity demand in rural areas of SSA is characterized by dispersed consumers, low consumption, and typically low-income levels [9]. The geographical remoteness and low electricity consumption of rural users make grid extensions inefficient and costly, driving up electricity tariffs [10], while low-income levels limit their willingness to pay for electricity [11].

In recent years, both the performance of renewable energy technologies (RETs) and energy storage have improved, and their capital costs have decreased [12]. Among RETs, solar photovoltaic (PV) systems are gaining traction in SSA [13]. However, their costs in SSA are still much higher than the world average due to political, financial, and technological risks [14]. Additionally, countries in SSA have an abundance of renewable energy resources (RES), such as solar PV, wind power, small-scale hydropower, biomass, etc. Due to the potential of these resources, the remoteness and isolation of rural communities, and the low cost-effectiveness of grid extension for rural electrification, other off-grid electrification options are emerging, such as the solar home systems and mini-grids.

Solar Home Systems (SHSs), which are devices composed of a rooftop solar panel and a small battery that supply electricity for a few low-consuming household appliances, are used to electrify rural areas. They are usually designed to directly serve DC loads for lighting, and cell phone charging, but also larger appliances such as TVs or fridges. Despite their affordability, SHSs positively impact the rural quality of life or improve rural living [15]. However, SHSs are inadequate for fostering the economic development of rural areas, which is largely driven by productive users [16].

Productive use of electricity (PU) can be defined as the use of electricity in operations that enhance revenue or improve economic value. Some studies have defined it more broadly, including the use of energy, both electrical and non-electric, for activities that enhance welfare and income outcomes, such as gender equality, health, and education [17]. This study defines productive use based on the first definition, focusing on economic activities rather than a broader interpretation that includes electricity consumption for improving well-being.

Productive uses demand more power and energy than households (HHs), with their average monthly electricity consumption often more than three times higher than that of typical households [18]. In order to supply electricity for productive uses, larger systems, such as mini-grids, are needed rather than solar home systems. Mini-grids are electric power generation and distribution systems that may provide electricity to just a few customers in a remote settlement or bring power to hundreds of thousands of customers in a town or city [13].

In the literature, the distinction between 'micro-grid' and 'mini-grid' is defined from a supply-side perspective. Some define micro-grids as systems in the range of tens to hundreds of kW, while mini-grids are associated with larger decentralized systems in the MW scale. Other literature provides varying definitions based on connectivity, and operational characteristics. However, due to the dynamic nature of electricity demand and its expansion over time and across different areas, strict size-based definitions are limiting. In this study, the term 'mini-grid' is used interchangeably to describe both terms.

Mini-grids can be either fully isolated from the national grid (off-grid) or connected to it. Mini-grids can be developed or operated by state utilities, private companies, communities, non-governmental organizations, or a mix of different players such as public-private partnerships. The mini-grids can run on diesel, RES (solar PV, hydro, wind, biomass, etc.), or as RES-diesel hybrids (HRES) [19].

Mini-grids are considered the most economically feasible solution for generating the electricity needed to achieve SDG 7, according to IEA [5]. The World Bank estimates that in 2019, 47 million people worldwide were connected to 19,000 mini-grids, mostly hydro and diesel-powered, at a total investment cost of $28 billion [19]. In order to reach universal access by 2030, 490 million people will have to be served by at least 210,000 mini-grids, mostly solar PV based, requiring an investment of $220 billion [19]. However, the costs of mini-grids are still expensive for non-electrified rural areas, especially in SSA countries [20]. As a result, most mini-grids in SSA depend on grants and subsidies to cover at least 30% of their investment costs [21]. To support the SDG 7 goal, the UN has allocated more than half of the estimated $45 billion annual budget to mini-grids and isolated power systems [22].

The economic viability of mini-grids (the ability to generate sufficient revenue to cover both capital and operational costs while ensuring long-term financial sustainability) depends on accurate planning to meet demand. Oversizing the system in anticipation of growing demand leads to a poor system economy, hindering cost recovery and increasing tariffs and upfront costs [23,24], while undersizing results in poor performance and reliability, potentially slowing down local development by failing to meet demand growth or providing unreliable supply, thus limiting growth [24,25].

Mini-grid planning involves a defined set of actions in the selection (viz. identifying, sizing, and designing) of suitable technology mixes, and this may be guided by optimization based on appropriate criteria (viz. mathematical programming) and matching of available energy resources with the demand [26]. Based on the time scale considered during planning, the planning horizon can be divided into short-term (from one month to one year), medium-term (from one to ten years), and long-term[1] (beyond fifteen years) [27,28].

Mini-grids initial investment cost depends on the size of the installed components. The sizing of components of a mini-grid in a cost-optimal manner (minimized investment and running cost) is tied to the demand knowledge [29]. To acquire demand knowledge, it is necessary to conduct demand assessment, load profile estimation, and analysis [30].

Demand assessment is conducted to estimate electricity demand and develop a corresponding load profile that indicates the variation of electricity demand or load over a specific time interval. The terms "electricity demand" and "load" are often used interchangeably but have differences. Electricity demand refers to the amount of electricity consumption desired by consumers at a given time, while load is the actual electricity consumption of consumers. In the literature, various methods are employed to estimate the electricity demand in non-electrified rural areas. Among them: (*i*) Tier-based method - assigning pre-defined consumption tiers to different areas or users [31]. (*ii*) Relying on observed data from communities having similar socio-economic characteristics method - this is based on the assumption that communities that share similar socio-economic and geographical traits will share similar electricity demand [24]. (*iii*) Load Archetypes method - estimating electricity demand by defining load profiles for different user categories, which are then applied to simulate the overall load of a community [32]. (*IV*) Interview method - estimating electricity demand by

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[1] The lifetime of mini-grids depends on the selected renewable energy sources [35].

gathering data on appliance usage through interviews [29]. (*V*) Measurement method-estimating load profiles from data collected through electricity measuring equipment [30].

The demand assessment methods can be categorized into top-down (econometric) and bottom-up (end-use) approaches. The top-down approach is based on large, aggregated data sets and uses mathematical methods to estimate demand and its evolution over time. The bottom-up approach is based on the behavior of every single user and summing up the effects at the community level. Due to the high socio-technical complexity faced in rural areas, it is difficult for top-down approaches to estimate demand efficiently. The bottom-up approaches relatively can produce a more realistic load profile but, they suffer from a lack of data in developing countries [29].

In mini-grid planning, different design approaches are utilized, mostly aiming for the least-cost sizes to meet future electricity demand [27,33]. The commonly used "static/single-year" design approach determines the component size and costs by using a representative, mostly single-year, demand profile [34], assuming a constant demand. The multi-year approach, which considers demand evolution over the full planning horizon to determine component size and cost, is also utilized [35]. Additionally, an adaptive design is an iterative approach that makes investment decisions for a specific period of time, typically annually, by increasing the system's capacity to meet both past and expected future demand growth [23,35].

The mini-grids are often powered by RES. The output of RES is variable and is not known with perfect accuracy [36]. This variability necessitates the incorporation of expensive energy storage to minimize the effects of intermittence [37], or the installation of additional generation capacity [38]. There are also demand variations on sub-hourly, hourly, daily, and/or seasonal timeframes [39]. Given the intermittency of RESs, the evolving costs and performance characteristics of individual technologies, and the uncertainties in the electricity demand, an energy management system is required in mini-grids.

Flexibility can broadly be defined as a system's ability to cope with variability in supply and demand side while maintaining reliability at a reasonable cost over different time horizons. Flexibility can be divided into short-term (i.e., flexibility adequacy) and long-term (i.e., system adequacy). Flexibility adequacy refers to the short-term ability to keep the system balanced, whereas system adequacy (the primary concern of the system) refers to the system's long-term ability to meet its demand [23,40]. In mini-grids, load flexibility refers to a system's ability to adjust electricity demand based on supply conditions, particularly to accommodate the variability of RESs such as solar and wind. This involves shifting or reducing loads during peak times or when the generation is low, as well as increasing demand when there is excess generation [41].

Flexible generation units, like hydropower or gas power, can provide flexibility in the supply side [42]. On the demand side, load flexibility can be achieved by demand-side management (DSM) [41]. DSM is a strategy that enables the interaction between consumer and utility, being geared towards improving energy efficiency through demand profile modifications. There are six broadly discussed and implemented techniques for DSM, including peak clipping, valley filling, load shifting, load building, strategic conservation, and strategic load growth [43]. Load shifting refers to the possibility of shifting electricity demand in time, either to offset peak demand or to off-peak periods. It is the most commonly used DSM strategy, categorizing loads based on various criteria [43]. The demand response (DR) program is a branch of DSM that aims to motivate and influence electricity consumers to reshape their energy demands in return for benefits offered by utility companies [37].

Once the technical solution is determined, a suitable business model is identified to ensure the financial sustainability of the project. Within this step, the financial strategy for energy service provision is established, and the tariff is set [31]. This is crucial because generating a reasonable return on investment, typically dependent on these set tariffs, is essential for mini-grids to be perceived as commercially viable and to secure their long-term economic sustainability [44].

In SSA countries, mini-grid tariffs are calculated using five methodologies: (i) uniform national tariff, matching with main grid tariff; (ii) efficient new entrant approach, which sets a benchmark tariff estimated as the cost of service for a new market entrant; (iii) bid tariff, set by the lowest price bid in a competitive process; (iv) individualized cost-based tariff, tailored to each mini-grids cost recovery limit by the regulator; and (v) willing buyer/willing seller model, where tariffs are agreed upon between the developer and customers [45].

Countries like Ethiopia (for capacity greater than 200kW), Kenya, and Rwanda have adopted individualized cost-based tariffs, which help ensure cost recovery for developers and attract private investment by reflecting project-specific costs. However, this approach faces challenges in regulating mini-grids as infrastructure due to long payback periods and uncertainties, such as the potential arrival of the main grid and future demand fluctuations [45].

Tariffs determined using different methodologies can have distinct structures, such as energy-based, power-based, or hybrid tariffs (HT), which combine both. Energy-based tariffs depend on metered energy usage, encouraging energy conservation, while power-based tariffs (PT) are based on maximum power consumption and aim to limit peak usage. Energy-based tariffs can either be fixed (fixed energy tariff, FET) or vary over time, such as time-of-use (ToU) tariffs, which can support DSM strategies [46].

Block tariffs are another approach, charging different rates based on usage levels and applying additional fees for exceeding thresholds [47]. Furthermore, the fixed and variable tariff (FVT) is an energy-based tariff structure where the fixed rate covers a predetermined cost per connection, and the variable rate depends on energy consumption within a specific time period, typically one month. Tariffs can also be tailored to specific load categories, such as households, productive uses, and community loads (CL), reflecting their varying usage patterns [47]. The varying shares of these load categories within the system, particularly households, and productive uses in this thesis, is called load composition.

1.2. Overview of the energy sector and mini-grids in Ethiopia

Ethiopia, with a landmass of 1.1 million square kilometers, is the third-largest and second-most populous nation in SSA, with an estimated population of approximately 120 million. The country is rich in renewable energy resources and benefits from geographically advantageous locations. Ethiopia has an estimated exploitable hydropower potential of 45,000MW, solar energy potential of 106GW with an average insolation of 5.5kWh/m^2 even during the rainy season, wind energy potential of 10,000MW with average wind speeds of 3.5–5.5m/s for 6 hours per day, geothermal energy potential of 7,000MW, and 15–30 million tons of agricultural waste that can be utilized for energy generation. Ethiopia also holds the second-highest installed electricity generation capacity in SSA, at 4.5GW, with hydropower accounting for nearly 90% of the total generation capacity [48,49].

Despite Ethiopia's massive potential in diversified energy sources, the electricity access rate remains low. According to World Bank data from 2022, electricity access is only 43% in rural areas and 94% in urban areas, resulting in approximately 55% total access to electricity nationwide [4]. Studies reveal that around 89% of Ethiopia's total energy consumption in households is dedicated to cooking, with a significant portion used for baking injera. Preparation of injera, the cultural staple bread food item in Ethiopia, is known for its intensive energy consuming cooking, requiring 5–6 kW per cooker [50]. Due to limited electricity access, a large proportion of the population, particularly in rural areas, continues to depend on non-renewable and unclean energy sources [51].

According to Ethiopia's National Electrification Plan (NEP 2.0), the Ministry of Water, Irrigation, and Energy, responsible for planning and promoting energy sector development, aims to achieve universal electricity access by 2025 [52]. The plan envisions meeting 65% of the country's electricity demand through the national grid, while the remaining 35% will be supplied by off-grid solutions, primarily solar home systems and solar PV mini-grids. According to the Ethiopian Energy Agency (EEA) mini-grid is defined as "*an off-grid electricity generation and distribution system, i.e. a set of electricity generators and possibly energy storage systems (distributed or embedded) interconnected to a distribution network that supplies electricity to a localized group of customers with maximum capacity up to 10MW and is not connected to the national grid"* [53].

According to NEP 2.0, there are two main approaches to implementing mini-grid projects in rural areas. The first involves government-led initiatives, where the Ethiopian Electric Utility (EEU)[2] identifies 250 off-grid rural sites that are not yet connected to the national grid and require electrification through solar PV-based mini-grids. The second approach invites private companies to bid on these projects as part of the Universal Electricity Access Program (UEAP) [52]. By 2024, the EEU and private companies had constructed fourteen solar PV-battery mini-grids with capacities ranging from 75kWp to 725kWp, out of the planned 250, with additional projects still under construction. Table 1 presents the capacity and location of these mini-grids. This indicates that, despite various efforts to implement off-grid solutions, Ethiopia continues to face significant challenges in achieving full electrification by 2030.

Table 1. Installed mini-grids in Ethiopia [54]

No	Location	Capacity (kW)	Installed (year)	No	Location	Capacity (kW)	Installed (year)
1	Koftu	250	2018	8	Biltu	75	2021
2	Qorelle	325	2020	9	Behima	200	2021
3	Alebasa	275	2020	10	Wassel	300	2021
4	Uguge	175	2021	11	Bambaho	275	2021
5	Tum	550	2021	12	Kursewad	75	2021
6	Omorate	375	2021	13	Daratole	725	2024
7	Mino	225	2021	14	Higlole	600	2024

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

1.3. Problem statement

While mini-grids are crucial for enhancing electricity access in rural areas of developing countries and achieving SDG 7, one of the significant challenges remain in ensuring their economic viability for effectively expanding access [55]. Most existing studies on ensuring the economic viability of mini-grids have focused on the supply side, addressing aspects such as selecting appropriate technologies, optimizing component sizing, and minimizing upfront and operational costs through various optimization algorithms and management systems. Despite these efforts, many mini-grid programs in developing countries are still failing due to various reasons, including socio-economic dynamics and regulatory challenges [10].

The socio-economic characteristics of users, including their living habits and perceptions of technologies, are primarily reflected in their electricity demand characteristics [33]. To address the challenges related to the economic viability of mini-grids, it is crucial to examine the demand-side constraints and potential. Although few studies have examined the impact of electricity demand dynamics and usage behaviors of rural communities on the economic viability of mini-grids, they highlight the need to account for such changes in off-grid mini-grid planning [25,56]. However, there remains a lack of understanding, particularly regarding how demand-side factors such as load estimation, future demand development, demand-side management, and load composition impact the planning, operation, and tariff design of mini-grids.

Among these demand-side factors, load estimation is particularly challenging in mini-grid planning for developing countries because of the lack of reliable, high-resolution data on electricity demand, particularly in rural areas. This lack of data can impact the ability to design and implement economically viable mini-grids. Interviews used to collect appliance ownership and usage data are the most common method for estimating electricity load profiles; however, these estimates often lack accuracy [32]. For instance, in Ethiopia, load estimation for mini-grid design have typically been conducted using data that is often inaccurate, outdated, or insufficient, such as the number of households in a town or satellite imagery, rather than through extensive and detailed on-site demand assessments [25]. This can hinder the deployment of solutions aimed at improving access to electricity in rural areas, such as the design of economically viable mini-grids. Thus, to minimize the effects of uncertainties in load estimation, it is essential to understand the errors that occur in the estimation methods.

Electricity demand development over time is subject to significant uncertainties [57]. As a result, mini-grids often face challenges due to these uncertainties, which hinder realistic planning by failing to account for socio-economic dynamics and productive use growth [10]. This is largely attributed to the complex socio-economic dynamics in areas with little or no historical consumption data, frequent policy changes, and erratic technology diffusion [27]. Minimizing the impact of uncertainties in demand development needs mini-grid design approaches that help to deal with the uncertainty in future demand.

Due to the typically low electricity usage of customers in rural areas, mini-grids often struggle to generate the critical revenue needed for financial viability [16]. This challenge is particularly pronounced in villages comprised solely of households, where providing affordable electricity to geographically remote communities with dispersed populations, low usage levels, and incomes averaging $1.50 a day poses significant difficulties [52,58]. Consequently, in SSA, private investors have been hesitant to invest in mini-grids due to high levels of uncertainty and an unbalanced risk-return profile [57].

Demand-side management implementation strategies, implemented in various ways, are critical to the economic viability of mini-grids and need to be examined thoroughly. While demand-side management implementation has been studied at both the system and appliance levels, controlling each appliance poses challenges in rural areas, such as increasing cost. Additionally, studies focus more on productive users. Therefore, to fully exploit the potential of demand-side management in rural areas, a strategy that reduces infrastructure costs and expands its application from productive uses to households and community loads is essential. This requires an analysis of its implementation strategy impact on mini-grid cost efficiency across different load categories.

Mini-grids are often designed with the expectation of becoming economically viable once installed, and this may attract commercial funding. However, low electricity usage by both households and productive users in rural areas limit the revenue and hinder the economic viability of mini-grids [16]. Economic viability also depends on the ability to recover costs through cost-reflective tariffs. Yet, a significant gap between electricity cost-reflective tariffs and actual costs complicates long-term financing and cost recovery [59]. Designing these tariffs is further complicated by demand uncertainties, which affect not only the rate of demand growth but also the composition of that demand. This indicates the need to examine the impact of load composition on revenue and tariff design.

Therefore, investigating and understanding the impact of demand-side factors, including load estimation, future demand development, demand-side management, and load composition, is crucial to ensuring the economic viability of mini-grids, particularly for achieving both global and local electrification goals.

1.4. Objective

1.4.1. Main objective

To develop economically viable mini-grids in rural areas, it is essential to address the knowledge gaps in the existing literature regarding key barriers on the demand side that can affect the supply side of mini-grids. Therefore, the main objective of the thesis is to examine the impact of demand-side factors on the planning, operation, and tariff design of rural mini-grids, with a focus on improving their economic viability.

The findings of this thesis will thereby contribute to scientific knowledge that helps to address the low electrification rates in rural areas and developing countries at large. Additionally, it will support the establishment of mini-grids as a solution to transform the electrification conditions of rural communities in developing countries.

1.4.2. Specific objective

To achieve the main objectives of this thesis, the specific objectives and main research questions addressed in the thesis are:

Specific objective 1: To compare electricity load estimation methods in rural mini-grids, focusing on a case study in Ethiopia.

This will be used to answer the following research questions.

- How do electric load profile estimations using interviews and measurements differ in the case of Ethiopia?
- How may the electric load estimation methods differences impact mini-grid sizing and cost estimation?
- How may hourly electric load estimation impact mini-grid sizing and cost estimation?

Specific objective 2: To explore the advantages of design approaches for cost-optimal long-term mini-grid design under future demand uncertainty.

This will be used to answer the following research questions.

- What are the long-term advantages of a design approach that combines the multi-year and adaptive (multi-year-adaptive) design approach in terms of mini-grid component sizing and cost compared to the single-year and multi-year design approaches under different demand growth assumptions?

- How do the impacts of load flexibility, varying discount rates, and future mini-grid component cost reductions differ across the various design approaches?

Specific objective 3: To determine the impact of demand-side management on the sizing and cost of mini-grids.

This will be used to answer the following research questions.

- What is the impact of DSM implementation at the category level on the cost-efficiencies of solar PV and HRES-based off-grid mini-grids in rural areas?
- How large is the impact of DSM implementation at the category level on the cost-efficiencies of solar PV and HRES-based off-grid mini-grids in rural areas, as compared to the impact of load flexibility?
- How does cost-efficient components sizing and the cost of mini-grids vary due to shifting hours of cooking?

Specific objective 4: To examine the impact of load compositions on the economic viability of rural mini-grids.

This will be used to answer the following research questions.

- What composition of household and productive use loads leads to the maximum revenue in systems with fixed capacity?
- How can the future mini-grid load composition impact the monthly electricity bills of users?

1.5. Scientific contribution

The main scientific contributions of this work, which are used to answer the research questions, are summarized here.

Paper I provides a comparative analysis of interview- and measurement-based load profile estimation methods in the case of Ethiopia. This paper explains the differences between load profile estimations derived from interview and measurement methods, identifies the load categories responsible for these differences, and examines the specific appliances that contribute to the differences between the two methods. Furthermore, the paper provides an understanding of the extent to which these differences and the difference in load profile resolution can impact the cost and sizes of mini-grid systems.

Paper II explores the advantages of a multi-year-adaptive design approach on cost-optimal long-term mini-grid components sizing under three demand growth scenarios. It also evaluates how load flexibility, varying discount rates, and potential future reductions in mini-grid component costs differ across design approaches. By examining these, the paper adds to the understanding of how the multi-year-adaptive design approaches can be further developed to optimize mini-grid component sizing and cost efficiency while handling long-term uncertainties.

Paper III examines the impacts of DSM implementation on the cost efficiency of mini-grids, focusing on load categories rather than individual systems or appliances. It also evaluates the potential of DSM implementation across various load categories to enhance mini-grid cost efficiency in rural areas and compares this to the impact of load flexibility.

Paper IV explores how shifting the hours of electric cooking operation affects the sizing and cost of mini-grids. It provides cost-optimal cooking hours that contribute to improving the economic viability of mini-grids, with a particular focus on Ethiopia.

Paper V presents a load management approach to optimize the combination of household and productive users in a mini-grid to maximize revenue. It also demonstrates how an optimized combination of household and productive users can enhance revenue generation in a mini-grid with fixed capacity.

Paper VI examines the impact of future mini-grid load compositions on monthly electricity bills of different users. It also evaluates how future load composition and tariff structures influence the design of cost-reflective tariffs, resulting in variations in system revenue collected from different load categories in a mini-grid with fixed capacity. Furthermore, the paper provides policy implications in designing cost-reflective tariffs, implementing equitable subsidies, and ensuring the protection of low-usage households.

List of publications

The thesis is based on the work in the following papers (listed as I-VI).

I. Gelchu MA, Ehnberg J, Ahlgren EO. Comparison of electricity load estimation methods in rural mini-grids: Case study in Ethiopia. IEEE PES/IAS PowerAfrica, Institute of Electrical and Electronics Engineers; 2023, p. 1–5. https://doi.org/10.1109/PowerAfrica57932.2023.10363276.

II. Gelchu MA, Ehnberg J, Shiferaw D, Ahlgren EO. Exploring the advantages of a multi-year-adaptive approach on cost-optimal long-term mini-grid design under different demand evolution scenarios. Smart Energy 2025;18:100178. https://doi.org/10.1016/J.SEGY.2025.100178.

III. Gelchu MA, Ehnberg J, Shiferaw D, Ahlgren EO. Impact of demand-side management on the sizing of autonomous solar PV-based mini-grids. Energy 2023;278:127884. https://doi.org/10.1016/j.energy.2023.127884.

IV. Gelchu MA, Ehnberg J, Ahlgren EO. Impact of cooking appliances shifting hours in rural mini-grids: Case study in Ethiopia. IEEE PES/IAS PowerAfrica, Institute of Electrical and Electronics Engineers; 2023, p. 1–3. https://doi.org/10.1109/PowerAfrica57932.2023.10363284.

V. Gelchu MA, Ehnberg J, Ahlgren EO, Hartvigsson E. Improving load factors as a smart management approach - A developing country mini-grid case study. IEEE PES/IAS PowerAfrica, Institute of Electrical and Electronics Engineers; 2021, p. 1–3. https://doi.org/10.1109/PowerAfrica52236.2021.9543147.

VI. Gelchu MA, Ehnberg J, Shiferaw D, Ahlgren EO. Determining the impact of future load compositions on monthly electricity bills under different tariff structures in a rural solar PV mini-grid. Working paper 2025.

Contributions of authors

Milky Ali is the principal author of all the papers. Professor Erik O. Ahlgren and Associate Professor Jimmy Ehnberg contributed by providing conceptual ideas, feedback on methodology and analysis throughout the studies, and editing of all the papers. Dr. Dereje Shiferaw contributed by providing feedback, discussions, reviewing and editing papers II, III, and VI. Dr. Elias Hartvigsson contributed by providing discussions, reviewing, and editing paper V.

Other publications by the author, not included in the thesis:

i. Gelchu MA, Ehnberg J. Analysis of load composition impact on the bankability of rural mini-grids. IEEE PES/IAS PowerAfrica, Institute of Electrical and Electronics Engineers; 2024, p. 1–5. https://doi.org/10.1109/PowerAfrica61624.2024.10759417.

ii. Ehnberg J, Gelchu MA, Uwitije PD. Assessing cable sizing for PV microgrids: economic and environmental factors in focus - A case study of Ethiopia and Rwanda.

IEEE PES/IAS PowerAfrica, Institute of Electrical and Electronics Engineers, 2024, p.1–5. https://doi.org/10.1109/PowerAfrica61624.2024.10759427.

1.6. Thesis outline

The thesis is outlined as follows: **Chapter 2** presents a literature review on load estimation, mini-grid design approaches, demand-side management and tariffs. **Chapter 3** presents the research design of this thesis. This includes the methods employed in the study, including the formulation of the research problem, the development of scenarios, the selection of the case study area, and the data utilized to achieve the thesis objectives. **Chapter 4** presents the results and analysis of the study. In **Chapter 5**, the discussion of the results is presented by interpreting the findings, comparing them with existing literature, exploring their implications, and addressing the limitations. **Chapter 6** presents reflection on the selected methodology and the data used in this thesis. Finally, **Chapter 7** concludes the thesis, summarizing the key findings and suggesting areas for future research.

2. Demand-side factors considerations for enhancing mini-grid economic viability: A review

This chapter reviews existing studies relevant to the scope of the thesis, focusing on key factors such as load estimation, mini-grid design approaches, demand-side management, and tariff settings, with an emphasis on their economic implications.

2.1. Load estimation

To enhance interview-based demand assessment in rural areas, various studies propose different methods and software tools. One approach involves estimating load profiles using data from already electrified areas with similar socio-economic and geographical characteristics [60]. Another study developed a stochastic bottom-up model-based software tool called *LoadProGen*, which correlates the load factor with the coincidence factor, representing the probability of simultaneous load peaks among electrical appliances used by customers [61]. Additionally, a stochastic bottom-up model was proposed to determine load profiles by considering the instantaneous working times of appliances, users' working habits, and their economic status [62]. However, these methods, in [24,60–63], rely heavily on data from interview as their initial input, making them prone to significant uncertainty. Furthermore, machine learning models, which require extensive historical data for accurate predictions, have been applied to estimate electricity demand for new customers in unelectrified areas [24,63].

Studies also examined the differences between load profile estimation methods based on interviews and those based on measurements. A study on mini-grid in Tanzania show that interview-based load profile estimation underestimates the load factor and capacity factor from 34 to 117%. It also shows underestimation in energy use by 48-117% and peak loads by 11% [29]. Another study revealed that the average energy use estimated using interviews prior to mini-grid implementation is more than four times higher than the actual measured energy [60].

Although the comparison between interview and measurement methods was estimated in studies [29] and [60], they did not evaluate the impact on mini-grid sizing and cost estimation. Additionally, these comparisons did not consider community loads or include metrics such as responsibility factor, which is relevant for assessing the impact of DSM (which can help to mitigate the uncertainty in estimation) at the planning stage. Comparing interview and measurement methods across all load categories could link these categories to the system's total load profile and clarify the connection between customers and load categories load profile.

Due to the difference in load profile estimation methods studies have examined their impact on mini-grid size and cost. A study on seven small-scale mini-grids in Malawi indicates that component sizing scales proportionately with load estimation uncertainty. The cost of over-estimating the load ranges from approximately \$1.92 to \$6.02 per watt-hour, while under-estimation can significantly degrade reliability [64]. The minimized cost (cost efficiency) of mini-grid configurations, especially those relying on a large share of renewable energy sources, is significantly affected by stochastic load profile formulation methods that utilize interview data [65].

The sizing and costs of mini-grid are heavily affected by the methods used to size system components. Studies in [64] and [65] have examined the effect of load estimation methods on mini-grid sizing and costs using intuitive and numerical method. An intuitive sizing method assumes a worst-case scenario and a numerical method relies on average daily load but lacks detailed load profile characteristics. These methods often lead to low-quality sizing solutions. As a result, they limit the analysis of how interview-based load profiles compare with actual measurements in sizing and cost estimation of mini-grid. On the other hand, most sizing software's relay on hourly load profiles [60]. However, the impact of load profile resolution (hourly) on mini-grid sizing and cost has not been examined.

Therefore, it is important to compare load estimation methods by examining the differences in each load category and considering metrics relevant to DSM implementation. Additionally, the impact of load estimation methods and load profile resolution on the sizing and costs of mini-grids needs to be determined using advanced methods such as metaheuristic algorithms.

2.2. Mini-grid design approaches

Various studies explore different mini-grid design approaches, often relying on single-year design approaches with different optimization algorithms and tools to achieve high-quality solutions. These algorithms include iterative optimization techniques [66], HOMER software [67–70], and dynamic programming algorithm [71]. HOMER is a powerful tool for designing hybrid systems, but it has significant limitations, especially in its restricted flexibility to adjust the operating strategy and objective function. Moreover, the software depends on several simplifications during the component sizing and optimization process, which can greatly impact the accuracy of the results. Consequently, while HOMER may find the lowest-cost solution, this result is not always the optimal solution, but rather the best option based on the available data provided for each component.

Additionally, various metaheuristic algorithms are employed, including genetic algorithm (GA) [72], and particle swarm optimization (PSO) [73–76], Non-dominated Sorting Genetic Algorithm (NSGA-II) [77], Virus Colony Search (VCS) algorithm [38], metaheuristic Gray Wolf Optimization (GWO) algorithm [78], harmony search algorithm [79], and simulated annealing algorithm [80]), and machine learning algorithms [12]. Among these algorithms, the PSO algorithm produces higher quality results than iterative techniques HOMER and most metaheuristic algorithms. It also requires less simulation time compared to most metaheuristic algorithms [75], especially in single-objective optimization. However, machine learning algorithms and hybrid metaheuristic algorithms are even faster and more efficient than PSO, although machine learning algorithms require substantial historical data for training [81].

Several studies have also employed multi-year approaches that account for evolving demand over the planning horizon [34,35,82–84]. Despite using different assumptions to represent demand throughout the planning year, predicting future demand in rural areas remains challenging. Consequently, both single-year and multi-year approaches are susceptible to uncertainties regarding future demand [34,35]. To address these uncertainties in future demand, various design approaches have been proposed in studies.

Among the proposed approaches, an adaptive design approach is one. This approach reduces the impact of future demand uncertainties since decisions are made annually [35]. Additionally, a comparison between a multi-year and adaptive approach, as opposed to a single-year approach, revealed total cost reductions [35]. In rural areas of SSA, where skilled labor is scarce, project management and financial services may not be consistently available each year [85]. This indicates the challenges of implementing adaptive approach under this circumstance. Conversely, study [35] suggests that to address these uncertainties, future work can explore hybrid approaches that combine multi-year and adaptive (multi-year-adaptive) approach.

A flexible and adaptive design approach is also proposed for distribution capacity, transformation capacity, and protection system levels [23]. This approach can reduce initial investment costs while allowing the system capacity to expand in a controlled manner to meet future demand. A multi-step based capacity expansion approach for medium-term planning is presented [86]. Furthermore, a multi-year capacity expansion model using mixed-integer linear programming (MILP) is proposed [84], but it lacks incorporation of an operating strategy. Incorporating an operational strategy into mini-grid design could improve both the optimality and computational efficiency of the design [87]. To address this gap, some studies have explored a multi-year capacity expansion approach that incorporates a load-following operational strategy [34,82]. However, this load-following strategy can lead to an increase in investment costs by over 15% compared to other strategies that better balance supply and demand [87].

The aforementioned studies [34,84] are based on hybrid solar PV-based mini-grids with battery energy storage systems (BESS) and diesel generators. However, in rural areas of SSA, diesel generators are not cost-efficient and rarely used due to the high fuel and maintenance costs, making diesel-based systems less visible in these regions [25,88]. Additionally, [84,86] utilized interview-based load profiles. However, this method often lead to the under or over estimation of both the component size and costs of mini-grids [29,88].

On the other hand, in the past decade, the cost of mini-grid components such as solar PV panels and BESS have dropped by more than 80% [89]. Further cost reduction is expected in the future due to different reason, such as due to technological development, expanded manufacturing, and increased competition [35]. However, the aforementioned studies in mini-grid designing have not examined the impact of such cost reductions. Additionally, the impact of discount rates is not examined.

The discount rate, which reflects the cost of capital, risk, and expected returns on investments, is essential for determining long-term costs and advantages [90]. The discount rate in developing countries is higher than in developed countries. For instance, in SSA, it can exceed 18%, making it a crucial factor in determining the long-term size of mini-grids [91]. However, the impact of discount rates is not examined in the aforementioned studies.

Therefore, to fully explore the potential of 100% renewable energy-based off-grid mini-grids in rural areas of developing countries, it is essential to investigate hybrid design approaches. These approaches combine the benefits of multi-year and adaptive designs to address uncertainties in demand evolution and economic viability of mini-grid. Additionally, it is crucial to determine the impacts of load flexibility, varying discount rates, and future component cost reductions across these design approaches in the long-term sizing of mini-grids, while also utilizing actual load data.

2.3. Demand-side management

The impact of DSM on the cost-efficiency of mini-grids has been studied using different types of objective function. Optimizing demand combinations in order to much with the available power supply help to reduce electricity costs [92,93]. DSM-based optimization was proposed and implemented in HRES sizing, revealing that the proposed management system lower the initial capital cost of mini-grids for residential customers in rural areas [94]. A load management that categorizes the demand into high- and low-priority loads was applied for HRES sizing and indicated its potential to reduce electricity costs [95]. DSM approach based on a flexible load priority list was implemented to minimize the operational cost of a mini-grid without shedding critical loads [96]. Additionally, DSM using load shifting and frequency-based pricing was proposed to maximize utilization of renewable resources and system frequency [97].

The impact of demand response, which incentivizes and influences consumers to reshape their usage in exchange for benefits offered by the operator, has been also studied with various objectives. These include total cost reduction [38,40], enhancing economic performance and supply-demand balance [98], and increasing the revenue and enhancing supply-demand matching [99].

The aforementioned studies examined the impact of DSM more on the cost-efficiency of mini-grids, indicated that DSM has a more significant impact on energy storage components than on other components. This is indicates that DSM is crucial in areas with highly uncertain and peaky loads, which often necessitate oversized RES and energy storage systems to ensure adequate reliability and resilience [100]. However, these studies primarily focused on HRES-based mini-grids rather than 100% renewable energy-based off-grid mini-grids. Additionally, in the aforementioned studies, while the impact of DSM on the cost-efficiency of mini-grids was determined by incorporating DSM strategies into mini-grid sizing, demand-side uncertainties related to inaccurate load profile estimations and supply-side uncertainties linked to intermittency were not considered.

There are studies examining the effects of demand-side and supply-side uncertainties on DSM implementation for mini-grid sizing, showing that these uncertainties affect the costs and reliability of mini-grids, though they were modeled differently across studies [38,77,101,102]. For instance, one study [77] used Chance Constrained Programming to model supply-side uncertainties, while another study [101] applied the same approach to model uncertainties on both the load and supply sides. Uncertainties related to both load and supply sides have also been modeled using different distribution functions [38,102].

Furthermore, the impacts of DSM implementation strategies have been studied either at the system level or appliance level, such as household appliances [92–95]. However, controlling each appliance is challenging and increases cost, as each needs to be connected to the controller via cables or communication networks, especially in rural areas [43]. Despite these challenges, DSM implementation in rural mini-grids need to be expanded from productive uses to include household and community loads, as the evolving grid demands increased flexibility [103].

Therefore, to fully exploit DSM implementation in rural areas, a strategy that requires low-cost for control and communication network infrastructure is essential [104]. In this regard, it is important to investigate the potential impact of DSM implementation on the cost-efficiency of mini-grids by considering different load categories, rather than focusing solely on the appliance level. Thus, the impact of DSM implementation rather than at appliance level on the cost-efficiency of mini-grids need to be determined by incorporating both load-side and supply-side uncertainties, as neglecting these uncertainties could lead to inaccurate sizing and cost estimations [29].

2.4. Mini-grid tariffs

There is a broad consensus that cost-reflective tariffs are essential for economic viability and scaling up mini-grids [45]. However, the deployment of mini-grids has been slowed by a lack of private sector investment, often due to unfavorable policies and tariffs that are too low for investors to recover their total cost [22]. In many SSA countries, highly subsidized uniform national tariffs are used, often set to match the main grid tariff and below the actual costs incurred by mini-grids [44]. Mini-grid tariffs in Africa generally range from $0.05 to $0.30 per kWh, yet studies show that operators need to charge between $0.50 and $1.00 per kWh to recover costs[22]. While users seek affordable electricity and are willing to pay, this mismatch calls for rethinking tariff structures and cost-recovery strategies to ensure the sustainability of rural mini-grids [22].

Various studies have explored solutions to achieve the critical revenue needed to recover total costs, especially when demand is lower than anticipated. One approach emphasizes increasing the share of productive users and suggests that partnering them with microfinance organizations could help developers encourage productive use [10]. Other studies have also proposed integrating productive uses to stimulate demand [58,105] and expanding the mini-grid capacity to meet the needs of productive users [82].

Additionally, the formation of public-private community partnerships is recommended to increase the economic viability of mini-grid, with communities playing a key role as partners [106]. A combination of household and productive electricity use offers both technical and economic benefits for the operator [55,107]. Increasing income flows without needing to expand the generation system would improve the economic viability of mini-grids. Therefore, it is crucial to analyze the different combinations of load categories, particularly household and productive use, to maximize the revenue in a system with fixed capacity.

The aforementioned studies [58,82,105] indicated that the importance of productive uses in enhancing the economic viability of mini-grids. However, it remains uncertain which loads will grow and dominate future demand, indicating the uncertainty of load compositions in future demand. This uncertainty arises from the fact that demand patterns and energy requirements can change depending on characteristics and economic activities of the community after electrification. Additionally, studies examine the drivers of electricity usage patterns [15] and long-term forecasting methods [16]. However, to the best of the authors knowledge, no study has determined future load compositions impact on monthly electricity bills of different users within the system.

3. Research design

This chapter outlines the research design, detailing the methods employed in the study, including the formulation of the research problem, the development of scenarios, the selection of the case study area, and the data utilized to achieve the thesis objectives.

3.1.Framework of the thesis

The thesis follows a mixed research approach, organized in a step-by-step framework as outlined in Figure 1. First, it compares interview and measurement-based load profile estimation methods, focusing on load categories and assessing the impact of hourly resolution load estimation on mini-grid sizing and costs. Next, the study assesses various design approaches for long-term mini-grid component sizing under three demand growth scenarios, taking into account load flexibility, varying discount rates, and potential future reductions in component costs. The study then examines the effect of DSM implementation at the load category level and shifting hour of cooking on off-grid mini-grid cost-efficiency. Finally, it investigates the impact of load compositions on revenue and monthly bill of users using five tariff structures and analyzes their impact on users' electricity bills. Detailed methods for each component are outlined in the following section.

3.2. Comparing load estimation methods

To compare interview and measurement methods of load estimation, metrics essential for analyzing load profiles that impact mini-grids size and costs are utilized. These metrics include peak load, daily energy use, and load factor. Additionally, metrics such as the coincidence factor and responsibility factor, which are crucial for DSM implementation and analysis, are also considered. These metrics are used to compare the two methods, interview-based and measurement-based, across total load and load categories such as households, productive uses, and community loads. Furthermore, to examine the impact of load estimation methods and hourly resolution on mini-grid size and cost, the minimized cost and size are determined based on load profiles estimated using both methods. This comparison of load profile estimation methods is based on a selected case study area in Ethiopia.

3.2.1. Case

In comparing the two load estimation methods, a case study mini-grid located in Koftu (8.83°, 39.05°), 40km southwest of Addis Ababa, Ethiopia, is used. This rural village is served by an off-grid mini-grid comprising a solar PV capacity of 250kW (distributed in two sites with 200 kW and 50kW), a diesel generator with a capacity of 50kW, and a BESS of 1000kWh. Designed to serve approximately 2,884 people across 366 households, the system currently connects 146 households, a school, a water pump, a church, and a health center (which does not use electricity). In December 2018, the mini-grid was funded by the Ministry of Trade, Industry, and Energy of the Republic of Korea in recognition of the friendship between Ethiopia and Korea.

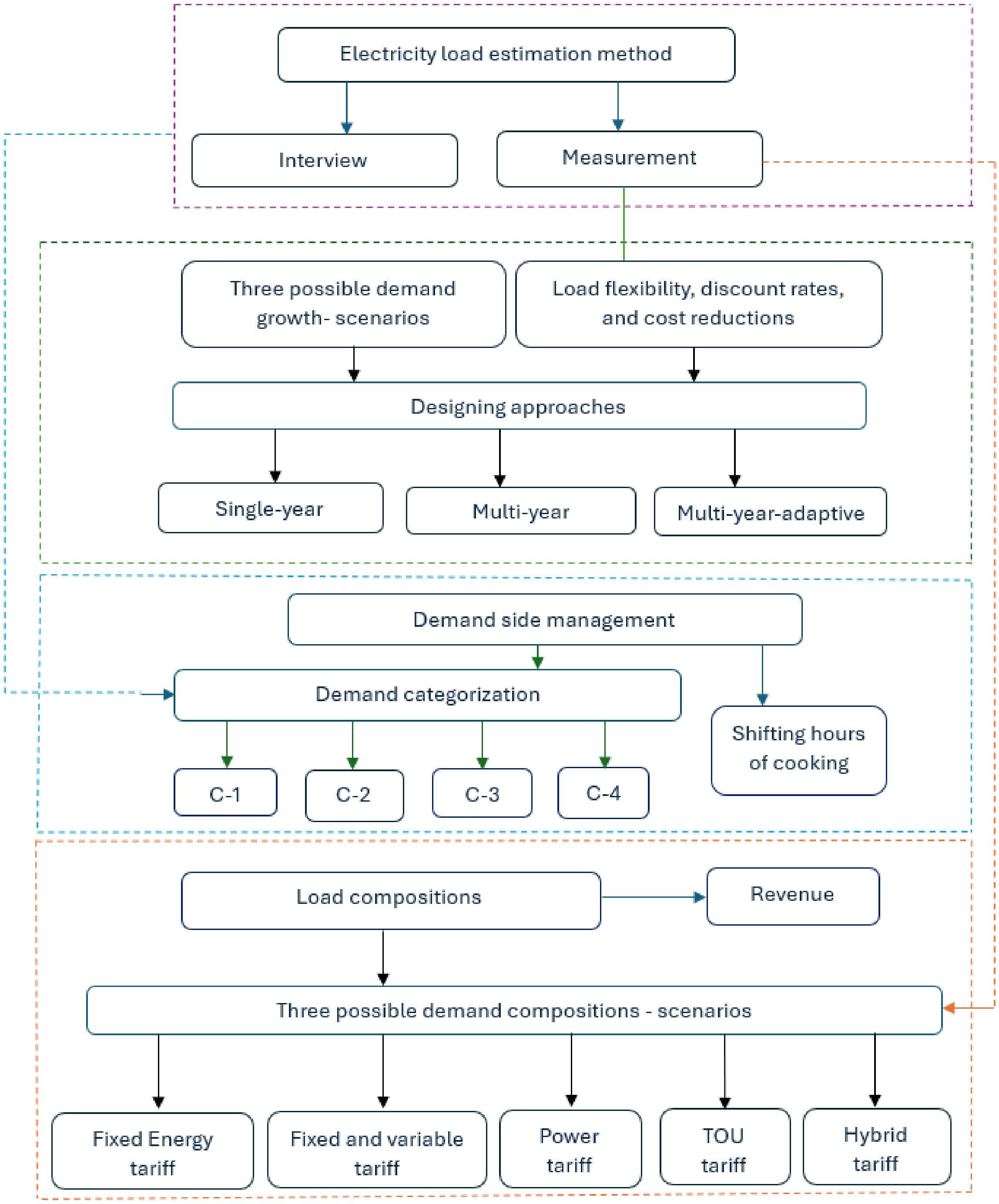

Figure 1. The thesis framework follows a step-by-step approach: load assessment, design approach, demand-side management, and tariff design.

3.2.2. Calculation of used metrics

The peak load, energy per day, load factor, coincidence factors and responsibility factors are used metrics in comparation of the load estimation methods. Peak load is the highest power demand over specific interval, whereas energy per day is the sum of energy use in specific intervals divided by the number of days in the interval. The load factor, calculated using Eq. (1), is the ratio of average load ($P_{L, AVg}$) to peak load ($P_{L, peak}$), indicating energy utilization efficiency [107].

$$\text{Load factor} = \frac{P_{L, AVg}}{P_{L, peak}} \tag{1}$$

The coincidence factor for each load categories, calculated using Eq. (2), is the ratio of systems peak load to the sum of peak load of each load category (i) [29].

$$\text{Coincidence factor} = \frac{P_{L, peak}}{\sum P_{L, peak, i}} \tag{2}$$

The responsibility factor, calculated using Eq. (3), is the ratio of an individual load categories' power at system peak time to each load categories peak load. This metric shows each load's contribution to the system peak and guides DSM strategy implementation [108].

$$\text{Responsibility factor}_i = \frac{P_{L, i}(\text{at system peak})}{P_{L, peak, i}} \tag{3}$$

3.2.3. Load profile estimation

To estimate interview and measurement-based load profiles, a representative sample of users was selected using a mixed sampling approach. Among the 146 households connected to a mini-grid, stratified sampling was used to categorize households into low, medium, and high electricity usage users, ensuring representation across usage levels. A sample of 26 households was selected, consisting of 13 low-usage, 8 medium-usage, and 5 high-usage users. This distribution balanced proportional representation (50% low usage, 30% medium usage, and 20% high usage) with the need for sufficient data across all groups to understand diverse consumption patterns. Additionally, the recommendation of local EEU operator is considered to select specific households among the connected ones, considering socio-economic diversity and energy meter readings.

For measurement purposes, three households, one from each usage category (low, medium, and high), were selected from the interview sample. Non-household loads, including productive uses and community loads, were included using census sampling due to their small number. These included a water pump, a church, and a primary school, where the water pump represents productive use, while the church and primary school serve as community loads. The health center was excluded due to its lack of power usage, despite being connected. The interviews and measurements were collected from November 28 to December 15, 2021

To estimate interview-and measurement-based load profiles, bottom-up demand modeling was applied for households, productive uses, and community loads. The load profile for each sample user in households, productive use, and community loads are estimated and scaled to the total number of users in each load categories. These profiles are then summed up to obtain the total weekly load profile for the case study area.

3.2.3.1. Interview-based load profiles

To estimate interview-based load profiles, based on recommendation in [29], questionnaires with predefined questions were used to guide discussions. Questions were asked in no particular order to facilitate open discussions and gather more information. Interviews were divided into weekday and weekends to account for different load patterns and conducted in both Afaan-Oromo and Amharic languages. The questionnaire covered the type and number of appliances, their usage times, and nominal voltage.

Load profiles for each sample user were estimated without considering the coincidence factor and appliance efficiency. The contribution of each appliance to the load profiles at time t (E_t) is given by (4) [29].

$$E_t=\frac{N}{n}\sum_{m}^{n} P_{m,t}\cdot fc \tag{4}$$

Where n and N is the total number of sample users and total number of users in each load category. The power rating of the appliance at time t is $P_{m,t}$ and fc refers to the appliance's functioning cycle, or the duration it remains on once it is on.

3.2.3.2. Measurement- based load profiles

The measurements are carried out using four FLUKE a3000 FC AC current clamp meters for two weeks, one week for household and another week for PU and CLs. The FLUKE a3000 FC AC current clamp meters can measure and store minimum, maximum, and average TRMS current every minute for up to 400A AC and save up to 65,000 readings. The meters are connected to the connection point of a power meter, which was installed by the utility to measure the power consumption of the users.

The measured average current is multiplied by the nominal voltage (220V for single-phase and 380V for three-phase) to estimate sample users' measurement-based load profiles and is scaled to the total number of users in each load category and summed. The resolution of estimated measurement-based load profiles is per minute.

3.2.4. Sizing

In the section below the mini-grid configuration and problem formulation used for mini-grid sizing are presented.

3.2.4.1. Mini-grid configuration

In comparing the load estimation methods, the configuration of Koftu mini-grid is utilized. This configuration includes a solar PV, BESS, converter, and an inverter on the supply side, while excluding the unused diesel generator, which is not operational. It provides electricity to various loads, including households, a school, a healthcare facility, and a water pump. The schematic diagram of this system is presented in Figure 2.

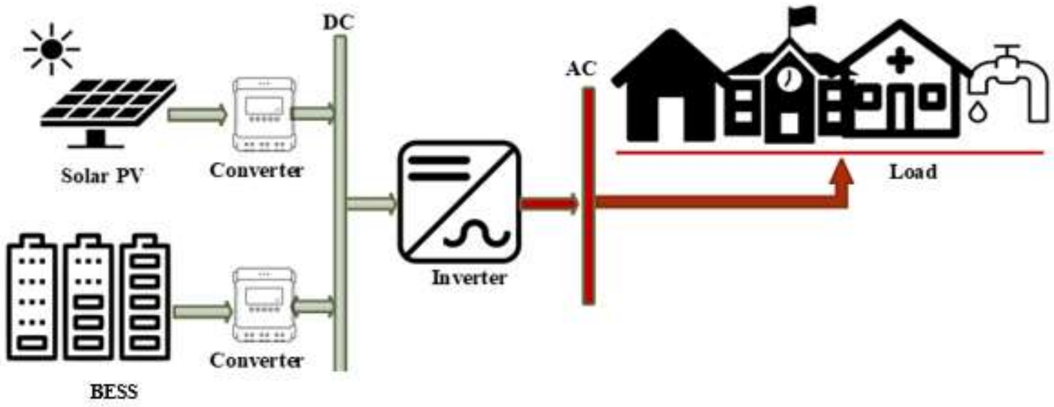

Figure 2. The schematic diagram of the mini-grid configuration used for load estimation comparison.

3.2.4.2. Optimization problem formulation for mini-grid sizing

An optimization problem for mini-grid component sizing is formulated using objectives, variables, and constraints. Levelized cost of energy (LCOE) and total present cost (TPC) are common objective functions for mini-grid sizing. LCOE is used to compare mini-grids of varying sizes, while TPC is more suitable for comparing mini-grids of similar sizes [82]. To examine the impact of different electric load estimation methods and load profile resolution on mini-grid sizing and cost in rural areas, this study uses TPC minimization as the objective function, calculated by Eq. (5).

$$TPC = IC + OMC + RC - PSV \tag{5}$$

where IC represents the initial capital cost, including the component price, civil work, and installation cost, calculated using Eq. (6). OMC stands for the operation and maintenance cost, calculated using Eq. (7). RC is the replacement cost, calculated using Eq. (10), and PSV is the present scrappage value of the mini-grid components (SV), calculated using Eq. (11).

$$IC = IC_{PV} + IC_B + IC_{Iv} \tag{6}$$

$$\mathrm{OMC} = \mathrm{OMC_{PV}} + \mathrm{OMC_B} + \mathrm{OMC_{IV}} \tag{7}$$

$$\mathrm{OMC} = \mathrm{OMC_0}\left(\frac{1+\mathrm{i}}{\mathrm{r}-\mathrm{i}}\right)\left(1-\left(\frac{1+\mathrm{i}}{1+\mathrm{r}}\right)^{\mathrm{T}}\right) \quad \mathrm{r} \neq \mathrm{i} \tag{8}$$

$$\mathrm{OMC} = \mathrm{OMC_0} \times \mathrm{T} \qquad \mathrm{r} = \mathrm{i} \tag{9}$$

$$\mathrm{RC} = \sum_{\mathrm{j}=1}^{\mathrm{N_{rep}}}\left(\mathrm{C_{RC}} \times \mathrm{C_V} \times \left(\frac{1+\mathrm{i}}{1+\mathrm{r}}\right)^{\frac{\mathrm{T}*\mathrm{j}}{(\mathrm{N_{rep}}+1)}}\right) \tag{10}$$

$$\mathrm{PSV} = \sum_{\mathrm{j}=1}^{\mathrm{N_{rep}}+1} \mathrm{SV}\left(\frac{1+\mathrm{i}}{1+\mathrm{r}}\right)^{\frac{\mathrm{T}*\mathrm{j}}{\mathrm{N_{rep}}+1}} \tag{11}$$

Where IC_{pv}, IC_B, IC_{Iv} are the initial capital costs for solar PV, BESS, and inverter. OMC_0, $\mathrm{OMC_{PV}}$, $\mathrm{OMC_B}$ and $\mathrm{OMC_{IV}}$ are solar PV, BESS and inverter operation and maintenance cost, i is the inflation rate of replacement units, r real interest rate, CRC is the nominal capacity of the replacement units (solar PV in (kW); BESS in (kWh) and inverter in (kW)). C_V is the cost of replacement units (solar PV ($/kW); BESS ($/kWh) and inverter ($/kW)), and N_{rep} is the number of unit replacements over the system life period, T.

The mini-grid sizing is subject to different constraints. Security constraint ensures a total demand and supply energy match, as shown in Eq. (12). The BESS constraint ensures the state of charge of a BESS (SOC) at any time t should lie between the minimum (SOC_{min}) and the full capacity of the BESS ($SOC_{\max}$), shown in Eq. (13). The maximum charge quantity of the BESS ($SOC_{\max}$) takes the value of the nominal capacity of the BESS (C_B), and the minimum charge quantity of the BESS (SOC_{min}), is determined using the maximum depth of discharge (DOD).

$$E_{dem} \leq E_{sup} \tag{12}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{13}$$

where E_{dem} and E_{sup} are, respectively, the total energy demand required and supplied.

3.2.5. Optimization algorithm used for mini-grid sizing

A PSO algorithm is applied to evaluate how electric load estimation methods and differences in load profile resolution affect the size and cost of mini-grids in rural areas. PSO is a widely used metaheuristic optimization algorithm for solving complex sizing problems in mini-grids. In this algorithm (Figure 3), a potential solution is represented by each particle in the swarm, which is evaluated for fitness using the objective function. In this study, particles represent the size of a mini-grid component, while TPC serves as the objective function. Each particle adjusts its movement based on its own best position (${X_i}^p$) and the global best (${X_i}^p$) of the swarm [74,109]. The process continues until the defined criteria, such as reaching the maximum iteration, are satisfied.

The position update equation, using Eq. (14), and the velocity update equation, using Eq. (15) are the two main equations utilized for PSO implementation. Additionally, parameters in optimization algorithm are to be modified in each iteration to converge towards the optimal solution. These steps are repeated until the stopping conditions are met.

$$V_i(t+1) = \mathrm{w}V_i(t) + C_1 r_1\left({X_i}^p(t) - X_i(t)\right) + C_2 r_2\left({X_i}^g(t) - X_i(t)\right) \tag{14}$$

In the PSO algorithm, the population is represented by X, r1, and r2 denote random numbers, t indicates the iteration number, C_1 and C_2 are acceleration coefficients, and w is the inertia weight used to enhance convergence speed. The inertia weight is calculated for each iteration using a linear decreasing function, as shown in Eq. (16). This method of determining inertia weight has been shown to minimize inaccuracy more effectively than alternative approaches [110].

$${X_i}^{(g+1)} = {X_i}^{(g)} + {V_i}^{(g+1)} \tag{15}$$

where ${X_i}^{(g)}$ is the global best solution, and ${X_i}^p$ is the best particle position.

$$w_i = w_{max} - \frac{w_{max} - w_{min}}{i_{max}} \times i \tag{16}$$

where w_{max} and w_{min} are the maximum and minimum inertia weights, respectively, and i represents the particle index.

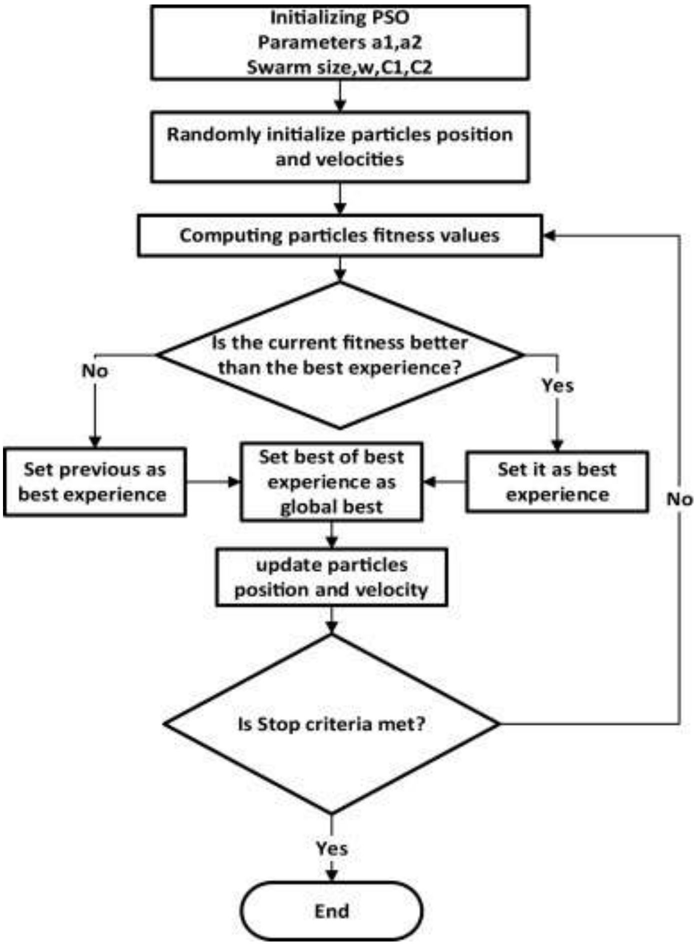

Figure 3. Flowchart for the PSO algorithm.

3.2.6. Modeling of mini-grid component

In cost-optimal mini-grid component sizing, system modeling plays a crucial role; thus, mini-grid component modeling is presented in the section below.

3.2.6.1. Solar PV

A solar PV system generates electricity by directly transforming solar irradiance into electricity output. The electricity output of solar PV array, as a function of on the average irradiance in hour t (θ_t), total solar cells areas (PVA), and instantaneous PV cell efficiency (μc(t)) is determined using by Eq. (17) [111]. The instantaneous PV cell efficiency and the total solar cells areas required to supply the load demand are calculated by Eq. (18) and (19) [109]:

$$P_{pv} = \theta_t \times PVA \times \mu_c(t) \tag{17}$$

$$\mu_c(t) = \mu_{cr}[1 - \beta_t(T_c(t) - T_{cr})] \tag{18}$$

$$PVA = \frac{1}{24}\sum_{t=1}^{24}\frac{P_{L,av}(t)F_s}{H_t\mu_c(t)\eta_{pc}V_F} \tag{19}$$

where β_t is the temperature coefficient for silicon cells, μ_{cr} and T_{cr} are the theoretical solar cell efficiency and temperature, respectively. F_s is the safety factor, V_F is the factor of variability, which considers the impact of yearly radiation variation, and η_{pc} is the power conditioning system efficiency [74].

3.2.6.2. Battery energy storage system

The excess electrical energy generated by the solar PV system is stored in the BESS. When the solar PV output falls short of meeting the demand, the stored energy in the BESS is discharged. The charging and discharging of the BESS are influenced by the solar PV output and the BESS's state of charge at any given moment. The state of charge of the BESS at a specific time is represented by Eq. (20) and Eq. (21) [74]:

$$SOC(t+1) = SOC(t)(1-\sigma) + P_B(t)\eta_B \qquad \text{charging mode} \tag{20}$$

$$SOC(t+1) = SOC(t)(1-\sigma) - P_B(t)/\eta_B \qquad \text{discharging mode} \tag{21}$$

where SOC is state of charge of BESS, η_B is efficiency of BESS, and σ is self-discharge rate of BESS. $P_B(t)$ represents the power used for charging or discharging of the BESS at time t and calculated using Eq. (22).

$$P_B(t) = P_{PV}(t) - \frac{P_L(t)}{\eta_{inv}} \tag{22}$$

Where $P_{PV}(t)$ and $P_L(t)$ is the total power generated and required by the mini-grid system, respectively.

3.2.6.3. Inverter

Inverters convert direct current to alternating current and must be capable of handling the maximum anticipated alternating current loads at any hour of the day, with their size determined using Eq. (23) [111]:

$$P_{inv} = \frac{P_{peak}}{\eta_{inv}} \tag{23}$$

where P_{peak} is the maximum load, and η_{inv} is inverter efficiency.

3.2.7. Data and assumptions used

In estimating load profiles, all appliances are assumed to operate continuously (fc = 100%), except for high power appliances intermittently, such as stoves, electric mitad (traditional Ethiopian food baking machine), and water pumps. A functioning cycle of 50% is assumed for stoves, mitad, and water pumps. The estimated load profiles based on interview method are calculated on an hourly basis.

The weekly insolation profile of Koftu village is shown in Figure 4. The economic and technical parameters used for mini-grid components sizing are listed in Table 2.

Table 2. Economic and technical parameters used for mini-grid components sizing.

Component, unit	Price ($)	OMC[3] ($/year)	RC [4] ($)	T (year)	Nrep[5]	SV[6] (%)	Reference
Solar PV, kW	1,500	50	300	25	0	10	[112]
Civil Work, solar PV, kW	40%	1%	40%	25	0	20	[74]
Inverter, kW	711	0	650	10	2	10	[74]
BESS, kWh	330	0	330	10	2	20	[113]

The PSO algorithm uses a population size of 100, an acceleration factor of 2, maximum and minimum inertial weights of 0.9 and 0.4, respectively, and a maximum of 100 iterations, which is also used as stopping criteria [110]. The study assumes a discount rate of 7% [114], an inflation rate of 8.1% [115], and a planning horizon of 25 years, based on the maximum lifetime of the system components [27].

3.3. Comparing mini-grid design approaches

To explore the advantages of multi-year-adaptive approach by comparing with the multi-year and single-year approaches on mini-grid sizing and cost, the optimization problem formulated in Section 3.2.4.2 is applied. Using this problem formulation, the size and cost for both single-year and multi-year approaches, reflecting the upfront investment needed for the entire planning horizon, are calculated. For the multi-year adaptive approach, additional component sizes and costs are calculated at specific intervals including the initial calculations. These costs calculated at specific intervals are then aggregated using a discount rate to determine the total cost over the planning horizon.

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[3] OMC is operation maintenance cost.
[4] RC is replacement cost.
[5] Nrep is the number of replacements over the project lifetime, T.
[6] SV is value of a scrap of the mini-grid components.

The objective function used in the sizing of a mini-grid based on the design approaches minimizes the TPC, which is defined in Eq. (5) in Section 3.2.4.3. Additionally, to account for the uncertainty of future demand on mini-grid sizing, three distinct demand evolution scenarios are developed. In the scenario development, a measured weekly load profile from a specific case study mini-grid is used. The demand evolution scenarios and input data are specifically tailored to an Ethiopian context, with details available in Sections 3.3.1 and 3.3.3.

To determine how the impact of load flexibility, varying discount rates, and future mini-grid component cost reductions on sizing and cost differ across the various design approaches, the formulated optimization problem is used. The results are then compared with the base case, which does not include load flexibility. In this study, the load flexibility at each hour t is determines the amount of electricity load that is shiftable and is calculated using Eq. (24):

$$L(t) = P(t) \times Lf \tag{24}$$

where $L(t)$ is the flexible load at hour t. $P(t)$ is the load at hour t, and Lf is the percentage of load flexibility.

3.3.1. Scenarios

Lack of data and demand uncertainty, especially in unelectrified rural areas, present significant challenges for mini-grid sizing [57]. In order to represent these uncertainties, it is a common procedure to develop scenarios of demand development, offering descriptive pathways that indicate the possible future size and costs of mini-grids may evolve [116]. This study applies three distinct demand growth scenarios, low, medium, and high, to represent varying levels of demand growth. Previous studies and historical trends in Ethiopia are utilized to develop the three scenarios, since the study is based on the Ethiopian context.

The average annual electricity demand growth rate across all load categories in the Ethiopian national grid from 2001 to 2017 is 13% [117]. Additionally, the annual average electricity demand forecasted for rural households in Ethiopia from 2012 to 2030 is 9.7% [118].]. In newly electrified areas of Ethiopia using solar PV-based mini-grids, the annual demand growth in the initial years has been observed to reach as high as 38% to 54% [18]. However, demand growth may slow down (saturation) may occur from the expected or exciting due to various reasons. For instance, in the case of Ethiopia, the adoption of improved energy-efficient appliances and DSM can result in up to 41% energy savings from the total electricity demand [117]. Additionally, there are other factors contributing to lower demand growth, including low-income levels, limited economic development and productive use activities, lack of knowledge about electricity usage, and local climatic conditions [55]. Consequently, the study considers the following three scenarios:

- Scenario 11 (S-11) assumes low demand growth. In S-11, an annual demand growth of 5% is assumed.
- Scenario 12 (S-12) assumes medium demand growth. In scenario S-12, an annual demand growth rate of 10% is assumed. This rate corresponds with the annual average electricity demand growth observed in rural households, from which most of the electricity demand in rural areas comes.
- Scenario 13 (S-13) assumes high demand growth. In S-13, an annual demand growth of 15% is assumed.

In scenario 11, a constant demand growth is considered over the entire planning horizon. However, for scenarios 12 and 13, saturation is considered after some years over the planning horizon. Specifically, in scenario 12, a 5% demand growth is considered during the final five years of the planning horizon. In scenario 13, 10% demand growth followed by a 5% growth is considered for the last two five-year intervals. Consequently, by the end of the planning horizon, the initial demand increases by 3.2 times in scenario 11, 7.8 times in scenario 12, and 14.5 times in scenario 13. The respective demand growth evolution over the planning horizon is presented in Figure 5.

3.3.2. Mini-grid design approaches

The optimal mini-grid component size and cost are determined in different ways in the three design approaches (single-year, multi-year, and multi-year-adaptive):

- In the single-year (SY) design approach, based on the demand at the planning horizon end year.
- In the multi-year (MY) design approach, by considering each year's demand evolution for the entire planning horizon.
- In the multi-year-adaptive (MYAD) design approach, for investment years in each interval (every five years).

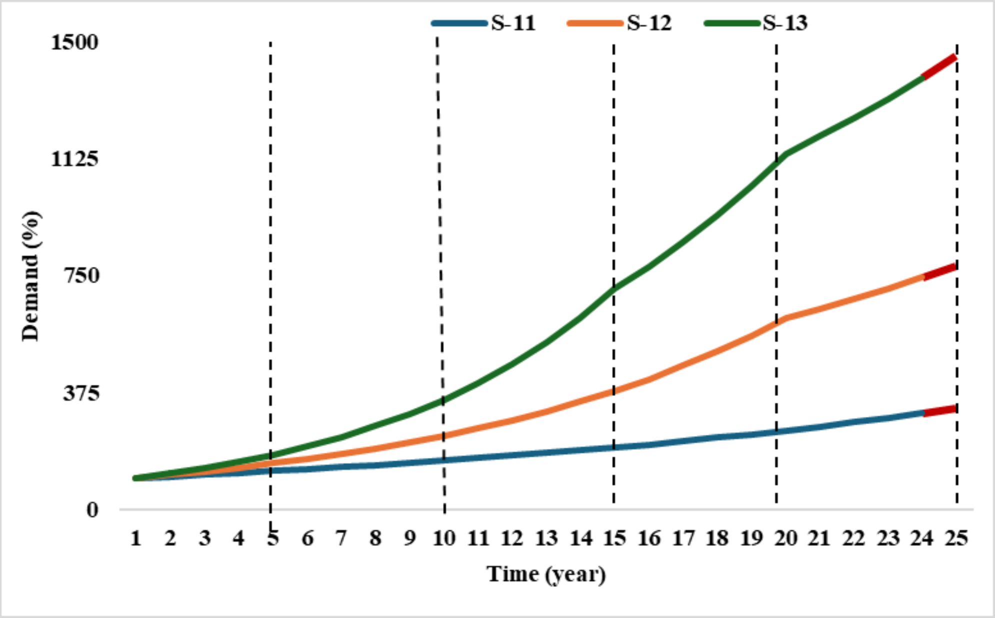

Figure 4. Evolution of demand for scenarios 11, 12, and 13. The final year demand (in red) indicates the demand growth considered for SY, while for MY, full growth evolution is utilized. Dashed lines represent the investment years in each interval in MYAD.

3.3.3. Data and assumptions

Rural electrification in SSA is dominated by off-grid solar PV-based mini-grid [119]. Thus, for mini-grid sizing, data from Koftu village, which is powered by solar PV-based mini-grid, is used as case study. In comparing design approaches for mini-grid sizing, only the solar PV and BESS are considered, as they have a significant impact than inverters [82]. However, the cost comparison includes inverters in addition to solar PV and BESS. Additionally, Koftu village weekly insolation profile is presented in Figure 5. The irradiance profile depicted in Figure 5 is based on average weekly solar irradiation values. This approach was adopted due to the relatively low intra-day and seasonal variability of solar irradiation in many parts of Ethiopia. As a result, the profile appears smooth and exhibits minimal day-to-day fluctuations.

The comparison of design approaches with load flexibility assumes a 10% load flexibility. In the base case a discount rate of 7% is applied, reflecting the risk-free assumption and the interest rate in Ethiopia [114]. In order to analyze the impact of discount rates on the TPC of the mini-grid, the study also considered higher rates of 15% and 20%. Additionally, an inflation rate of 8.1% [115] and a planning horizon of 25 years[7] are applied.

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[7] Determined by the maximum lifetime of the system components based on [27].

The costs of solar PV and BESS have decreased at an average annual rate of 8% in recent years, but this trend may not continue indefinitely [89]. Therefore, to evaluate the impact of future components cost reductions on the TPC of mini-grid across the design approaches, cost reduction of 2%, 3%, and 4% per year are considered for solar PV and BESS. Additionally, component sizes for each design approach are determined using the data described in Section 3.2.7.

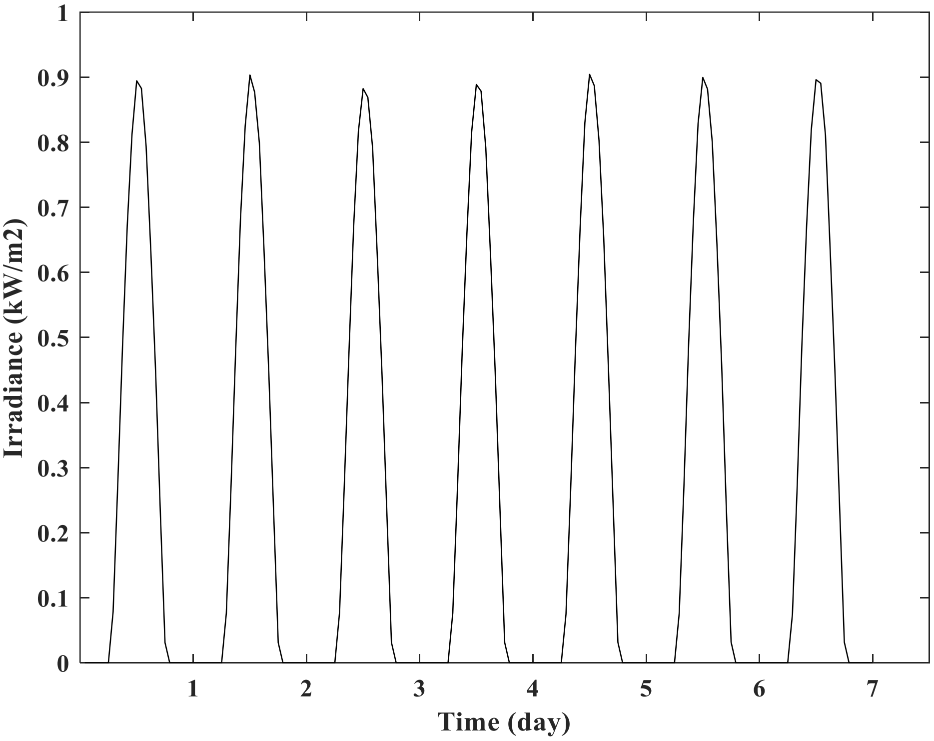


Figure 5. Koftu village weekly insolation profile [120].

3.4. Determining the impact of demand-side management

3.4.1. Determining the impact of demand-side management at the category level

To determine the impact of DSM implementation at the load category level on the sizing and cost of mini-grids, the demand of a given case study system is categorized. The optimal, cost-efficient sizing of the mini-grid is determined using a PSO algorithm described in Section 3.2.5. This sizing is analyzed using two different mini-grid configurations, each employing a different operating strategy. The optimized sizing is then compared with a load flexibility application impact in determining the optimal size of off-grid mini-grid components. A detailed description of the demand categorization, the two configurations, problem formulation, implemented operating strategies, and the modeling of mini-grid components is provided.

3.4.1.1. Demand categorization

The type of electricity consumers in the rural mini-grids, including households, productive use and community consumers exhibit different load profile patterns in a static load profile model [43]. Implementing financial incentives, such as time-of-use tariffs tailored to these distinct load categories, is one of the most effective strategies for encouraging load shifting from peak to off-peak times. This approach is particularly effective in resource-constrained mini-grids in developing countries [39]. Therefore, to evaluate the impact of DSM on the cost efficiency of off-grid rural mini-grids, this study categorizes demand into four distinct load categories, each with distinct load profile patterns: household loads (C-1); community loads (C-2); productive uses with nighttime loads (C-3); and productive uses without nighttime loads (C-4).

A bottom-up methodology is employed to model the weekly load profile for each load category. This approach relies on interview data collected by the EEU in the case study village. The data provides information on appliance types, quantities, power ratings, and usage probabilities. Each appliance's specific load profile is then estimated by multiplying its power rating by its probability of use. These appliance-specific load profiles are aggregated to estimate the overall load profile for each load category.

3.4.1.2. Mini-grid configurations

The two off-grid mini-grid configurations utilized in this study: Configuration 1 consists of solar PV and BESS, making it a 100% RES based off-grid mini-grid; Configuration 2 represents a HRES based off-grid mini-grid, where a diesel generator (DG) is added to the solar PV and BESS. Figure 6 presents a schematic diagram of the off-grid mini-grid system for both 100% RES and HRES based configurations.

3.4.1.3. Optimization problem formulation for determining the impact of DSM on mini-grid cost-efficiency

To determine the impact of DSM implementation at the category level on the cost-efficiency of the mini-grid, an optimization problem is formulated based on the mini-grid sizing optimization problem presented in Section 3.2.5. In this formulation, component sizing is determined using a priority-based load-shifting operating strategy. Additionally, the minimization of LCOE, calculated based on Eq. (25), is considered as the objective function.

To analyze the impact across different load categories, sixteen combinations of the four load categories are compared with the No DSM case (i.e., mini-grid component sizing without load prioritization) in a priority-based manner. To compare the impacts of DSM implementation at the category level with load flexibility, the shiftable load, considered a low-priority load in the implemented DSM operating strategy, is calculated and considered based on Section 3.3.

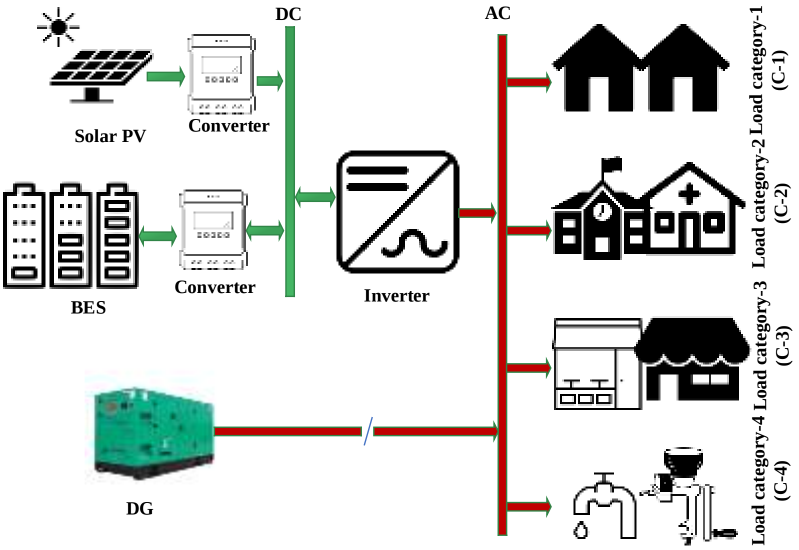


Figure 6. Schematic of the off-grid mini-grid system, showing the load categories for Configurations 1 and 2.

In this study, the effect of uncertainties on both the demand-side (due to inaccurate load profile estimations) and the supply-side (due to intermittency) on mini-grid sizing based on demand-side management is considered and determined. This approach enhances the formulated optimization. Additionally, the results of the optimization using PSO are validated using an iterative method. In both the determination of the impact of uncertainties and the validation of optimization, 10% load flexibility is considered. The objective function and constraints utilized in this study are detailed in the subsequent sections.

3.4.1.4. Objective function

LCOE, calculated using Eq. (23), is used as the objective function of the optimization problem.

$$LCOE = \frac{TPV \times CRF}{LAE} \tag{25}$$

where LAE is the annual load demand (the summation of all demand per year), and CRF is the capital recovery factor, which depends on the rate of annual interest (r) and plant life (T), as shown in Eq. (26) [41]. The TPC is determined using Eq. (5) in Section 3.2.4.3. For configuration 2, besides the TPC determined based on Eq. (5) for configuration 1, additional factors are included: initial capital cost, operation maintenance cost, replacement cost, fuel costs (FC), and present scrappage value of the Dg.

$$CRF = \frac{r(1+r)^T}{(1+r)^T - 1} \tag{26}$$

The fuel cost of the DG is calculated using Eq. (27), where $DG_h$is the total operating hours of the DG during T and P_f is the fuel price per liter ($/L) [121].

$$FC = D_f(t)DG_hP_f \tag{27}$$

3.4.1.5. Operating strategy

Typical energy management systems in mini-grids operate based on priority-list rules, where assets are dispatched in a pre-set economic order: first renewable sources, then batteries, and lastly diesel generators. Notable techniques include load-following and cycle-charging operating strategies. The typical load-following strategy aims to minimize operating costs using straightforward priority-list rules, dispatching RESs first, then energy stored in the BESS, and lastly the diesel generators. Conversely, in the cycle-charging strategy, once the generator is activated, it recharges the BESS until it is full or a preset threshold [34,122]. Although both load-following and cycle-charging strategies may be sub-optimal, they require minimal computational time, making them suitable for preliminary designs [87].

The operating strategy employed in this thesis incorporates a priority list for load categories, in addition to supply-side technology. A load-shifting strategy is applied to manage load categories based on priority, classifying loads into high-priority loads (HPLs) and low-priority loads (LPLs). High-priority loads are non-shiftable and must be supplied at their operating time as specified by the user. Conversely, low-priority loads can be rescheduled and shiftable to a time when there is sufficient electric power generation from solar PV and the BESS is fully charged. The maximum shifting time is 24 hours. Thus, the operating strategy maximizes the energy served to high-priority loads and minimizes it for low-priority loads. The flowcharts for the operating strategies used in configurations 1 and 2 are presented in Figure 7 and Figure 8.

The step-by-step description of the operational strategy flowchart for the two configurations is as follows:

Configuration 1: The electrical power from solar PV in hour t (Ppv(t)) is first utilized to meet the high-priority load for that hour. Any surplus energy, (PBC(t)), based on the efficiency of the inverter (η_{inv}), is added to the available energy in the BESS (charging) from the previous period. This stored energy is then used to supply the high-priority loads during periods when the electrical power generated by the solar PV is insufficient (discharging) to meet the demand, denoted as PBD(t).

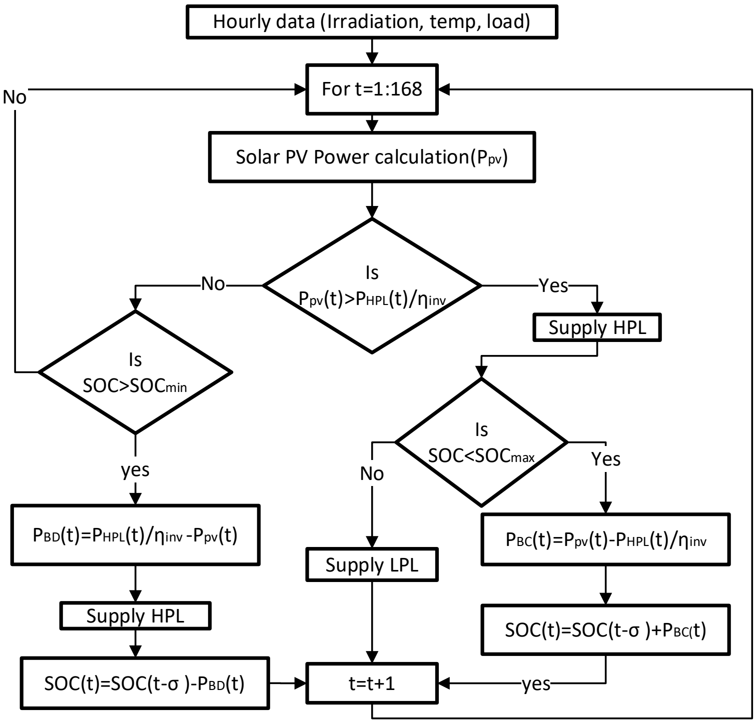


Figure 7. Flowchart of the operating strategy for Configuration 1.

The states of charge of the BESS, which is affected by the BESS self-discharge rate, must remain between its minimum and maximum states of charge, i.e., $SOC_{min} \leq SOC \leq SOC_{max}$. During the charging phase, the BESS should not exceed its maximum SOC (SOC_{max}), and during discharge, it should not fall below the minimum states of charge. Low-priority loads are supplied when there is excess energy from solar PV, and the BESS reaches SOC_{max}. These low-priority loads are then shifted to a later time when there is sufficient electricity generation from the solar PV, and the BESS is at SOC_{max}.

For Configuration 2, all the steps described for Configuration 1 are applied, with the exception that the electrical power generated from solar PV and the stored energy in the BESS may not be sufficient to meet the high-priority load demand. In this case, the high-priority loads will be supplied by the DG, denoted as PDG(t).

3.4.1.6. Modeling of mini-grid component

In Section 3.2.6, the mathematical modeling of solar PV, BESS and inverter is presented. To incorporate uncertainties in solar PV generation, a probabilistic model for solar PV output is applied to the presented solar PV model. Additionally, Beta Probability Density Function (PDF) is used to model the distribution of solar irradiance, as illustrated in Eq. (28) [38].

$$f(\theta)\begin{cases}\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha)+\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1} & 0\le\theta\le 1,\alpha\ge 0,\beta\ge 0\\ 0 & otherwise\end{cases} \tag{28}$$

where α and β are elements of the Beta PDF. The μ and σ terms represent the mean and standard deviation of the Beta PDF, respectively.

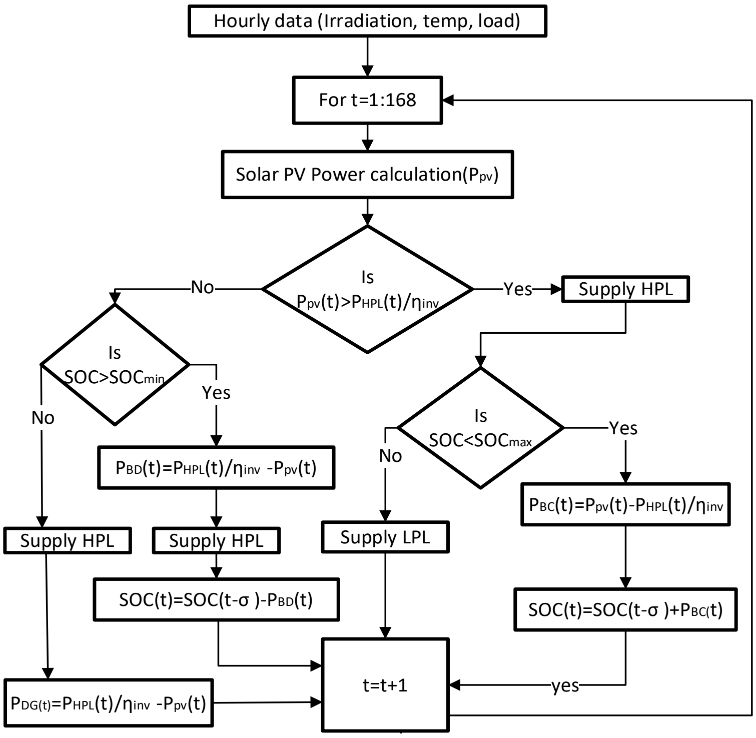


Figure 8. Flowchart of the operating strategy for Configuration 2.

The probability of the solar irradiance θ can be calculated using Eq. (29):

$$P(\theta)=\int_{\theta_c}^{\theta_d} f(\theta)d\theta \tag{29}$$

The instantaneous PV cell efficiency is determined based on the cell temperature [109]:

When the energy supplied by the solar PV and BESS is insufficient to meet high-priority loads, a DG is utilized. The fuel consumption of the DG is contingent upon its output power at each time-step, as illustrated in Eq. (30) [74]:

$$D_f(t)=\alpha_D P_{Dg}(t)+\beta_D P_{Dgr} \tag{30}$$

where $D_f(t)$ is the hourly fuel consumption of the DG, P_{Dg} is the average power per hour of the DG, P_{Dgr} is the rated power of the DG, and α_D and β_D are the coefficients of the fuel consumption curve.

In the modeling of the electricity demand, uncertainties related to the demand are modeled using a normal distribution function [38]:

$$f_{load}(L_d) = \frac{1}{\sqrt{2\pi\sigma_{L_d}{}^2}} exp\left({-\left(L_d - L_{d_{mean}}\right)^2} \Big/ {2\sigma^2 L_d} \right) \tag{31}$$

3.4.1.7. Case, data, and assumptions

The selected case study area for this study is Bada village, located in the Afar region of north-eastern Ethiopia at a latitude of 14.309° and a longitude of 40.072°. Bada village is currently not electrified, but the EEU has chosen it for the implementation of an off-grid solar PV-based mini-grid. The weekly insolation of the Bada village collected from PVGIS, is shown in Figure 10 [123].

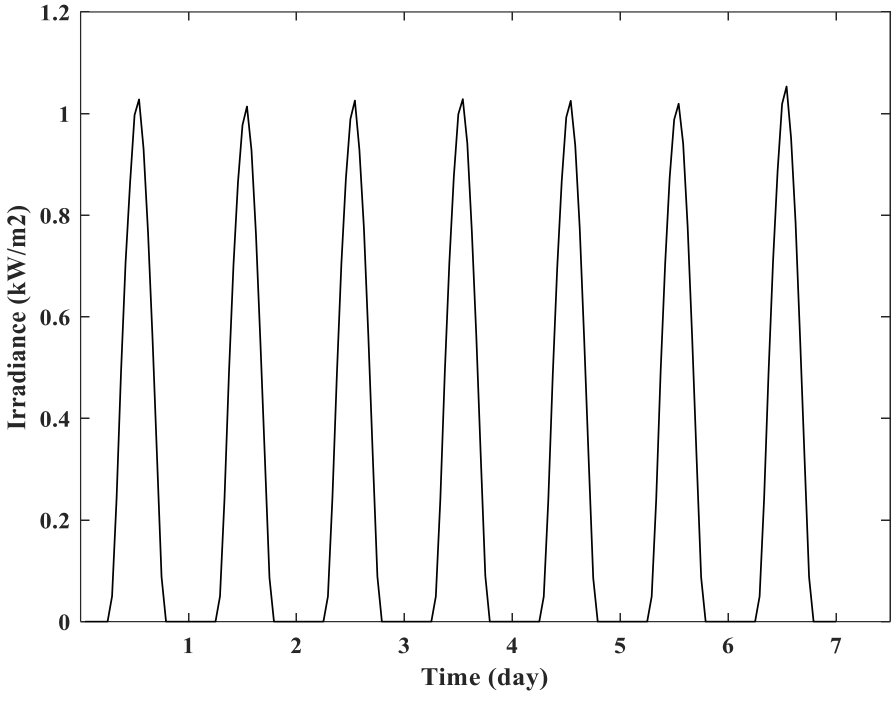


Figure 9. Weekly insolation profile of the Bada village.

Based on the data collected by the EEU and the load categorization described in Section 3.4.1, the load categorization for Bada Village is presented in Table 3.

Table 3. Load categories for Bada village.

Load categories	Number and types of loads
C-1	2,500 households
C-2	1 clinic, 1 health center, 1 animal clinic, 4 pharmacies, 2 kindergartens, 2 elementary schools, 4 mosques, 8 government offices, 1 farmer training center, and 2 storehouses
C-3	200 mini-shops, 1 barber, 10 tailors, 8 hotels, and 1 video hall
C-4	5 flour millers, and 1 water pump

To estimate the weekly load profile for each load category, a bottom-up methodology is employed. This approach considers the types and number of appliances, their power ratings, and the probability of their use. Additionally, for the water pumping system, a minimum of 100 liters of water per day per family and 2400 liters per day for each pair of one health center and one primary school is used [68]. In estimating load profile for miller, two operating days, Thursday and Saturday (market days in the village), are taken into account.

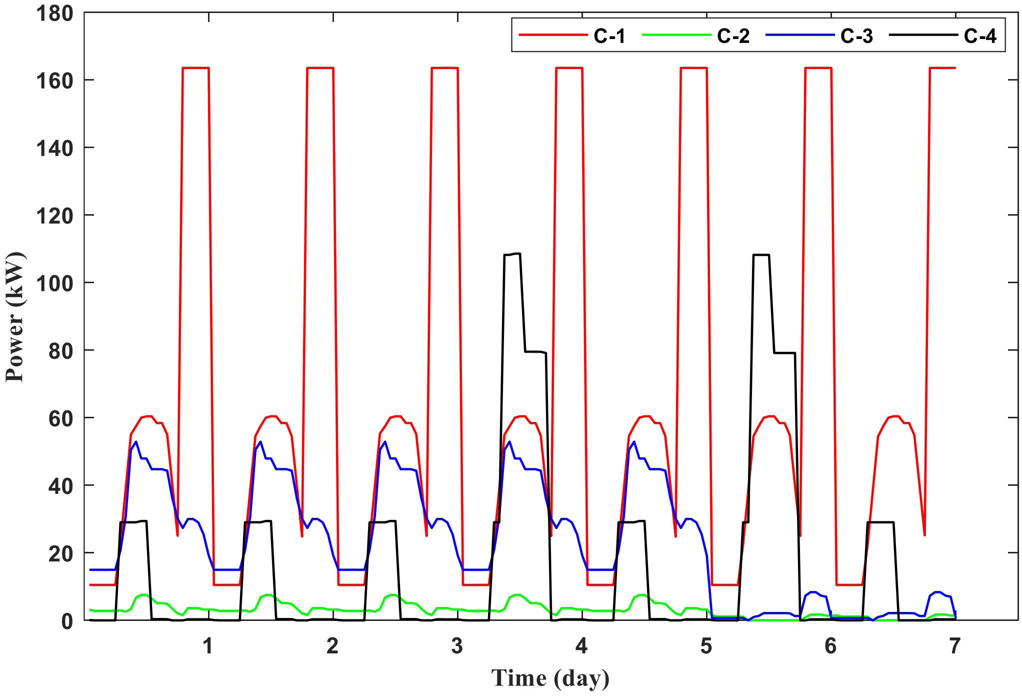


Figure 10. Weekly load profiles for the different load categories in the Bada village.

This study utilizes the economic and technical parameters of mini-grid components, along with PSO parameters detailed in section 3.2.7. The fuel price is set at $0.62 per liter. Uncertainty levels of 5% for solar irradiance and 11% for load profile estimation are taken into account.

3.4.2. Determining the impact of cooking appliances shifting hours on cost-efficiency of mini-grid

Using the measured weekly load profile estimated in Koftu, this study determines the impact of shifting cooking appliance usage times on cost-efficient mini-grid sizing and cost. The cost-efficient mini-grid sizing is analyzed by identifying one hour of higher cooking appliance usage in the Koftu mini-grid and shifting this higher usage to different hours of the day. The study utilizes the problem formulation and mini-grid component modeling, data and assumptions described in Section 3.2. Mini-grid sizing is determined for two cases: Case 1 involves shifting 100% of the one-hour cooking load, while Case 2 involves shifting 50% of the one-hour cooking load.

3.5. Determining the impact of load composition

3.5.1. Determining the impact of load composition on revenue of min-grid

For determining the impact of different load combinations (particularly household and productive users) on mini-grid revenue, two metrics are used: load factor and revenue. The load factor measures the utilization of generated energy during a given period relative to the maximum energy that could have been utilized in that period, which is especially important in systems based on renewables. High-resolution (per minute) measured load profiles of households and various types of productive uses are employed to calculate the load factors and revenues. The load profiles of household and productive use are normalized based on daily electricity consumption, enabling direct comparison and verification of electricity consumption between households and productive uses. Once the load profiles are normalized, they are combined in different ratios to examine the variations in daily load factor and revenue. The most favorable load composition is identified based on the analyzed data. In this study, two cases are explored: Case 1 includes all loads, and Case 2 removes the most atypical load profile of the households among the measured load profiles of households.

In determining the impact of load composition on revenue, the tariff used plays a crucial role. Additionally, differentiated tariffs exist between household and productive uses [55]. To examine the impact of tariff differences on the revenue, both identical tariffs and a 10% tariff difference are utilized. The revenue is normalized to the 100% household load, which serves as the baseline.

3.5.1.1. Case, data and assumptions

The load data for household and productive electricity use collected from a community-based mini-grid in southwestern Tanzania (refer to Appendix B for details) were utilized [55]. The household profiles consist of two low-consuming households and two high-consuming households. Among the three households, two low-consuming and one high-consuming, electricity usage patterns are similar, typically featuring an afternoon/evening peak. However, the second high-consuming household exhibits a significantly higher peak, likely due to the use of appliances such as a heater or cooker.

The measured loads for productive use include a bar, a workshop, and two mills, which are representative of typical productive users. These productive loads show considerably higher peak loads during the day compared to households. The bar maintains a relatively steady load profile during its operating period, while the mills and workshop experience interspersed periods of higher power demand with minimal demand [55].

3.5.2. Determining the impact of future mini-grid load composition on monthly bill of users

To determine the impact of future mini-grid load composition on users' monthly bills, the required tariff is calculated to ensure the recovery of the mini-grid investment costs through monthly revenue from bill. This calculation considers various scenarios of load composition developments within the system. Five tariff structures, FET, FVT, ToU, PT, and HT, are analyzed. These tariff structures serve different purposes, such as promoting renewable energy use, managing peak demand, and encouraging energy efficiency [22]. Their utilization and benefits depend on multiple factors, including user behavior, regulatory requirements, and the specific objectives of power suppliers and decision-makers [44].Therefore, to determine the impact of future load compositions on monthly electricity bills, the study calculates and compares users' monthly electricity bills using the calculated cost-reflective tariffs based on the considered different tariff structures and future mini-grid load compositions. Based on the quantitative findings, the study explores potential policy implications.

The calculation utilizes realistic demand data derived from measured load data from a specific case. The measured demand includes connected loads categorized into three household types (HH-1 representing low usage, HH-2 representing medium usage, and HH-3 representing high usage), productive uses, and community loads. Household load categorization follows a multi-tier framework that classifies electricity consumption into distinct tiers: Tier 1 (low usage) for consumption of ≥ 0.012kWh and 0.003kW; Tier 2 (moderately low usage) for consumption of ≥ 0.2kWh and 0.05kW; Tier 3 (medium usage) for consumption of ≥ 1kWh and 0.2kW; Tier 4 (high usage) for consumption of ≥ 3.4kWh and 0.8kW; and Tier 5 (very high usage) for consumption of ≥ 8.2kWh and 2kW [124].

3.5.2.1. System description

Due to the anticipated future load growth in mini-grids and uncertainty regarding future demand evolution, the initial generation capacity must significantly exceed the initial demand. Otherwise, demand would quickly reach its limit, constraining further growth. In the early stages of a mini-grid's operation, there is substantial uncertainty about how demand will evolve, whether it will primarily consist of household demand or productive use demand and whether it will grow rapidly or at a slower pace. This study takes this uncertainty into account by assuming a fixed-capacity system with sufficient spare capacity to accommodate future growth. Solar PV is assumed to be the main energy source, as it accounted for 50% of operational mini-grids in 2020 [125].

3.5.2.2. Load composition scenarios

The growth in electricity demand results from both increased consumption by existing users and new connections, which include households and productive users. Productive uses can be classified based on their usage patterns and frequency into daily and non-daily categories, each with distinct energy needs and consumption behaviors.

Daily productive uses are typically shops, small bars, and workshops, although their electricity usage varies. Shops and small bars have peak loads in the evening, similar to households. Workshops typically operate during the daytime and exhibit higher power demand compared to shops and small bars [29,41].

Non-daily productive uses, on the other hand, are types of loads that are not used daily. Examples include millers (M), which run three to four days per week, typically on market days when a large quantity of grains are collected, and water pumps (WP) used for drinking water and irrigation. In rural areas, certain families may use millers monthly, generally once or twice a month [126]. Water pumps operate in cycles rather than daily, and millers usage is more prevalent in rural areas compared to water pumps for irrigation [126,127].

To represent these different possible load developments, three alternative future load composition scenarios are formulated based on demand growth from households and the two types of productive uses.

- Scenario 1 (S-21): assumes that the demand growth comes entirely from households.
- Scenario 2 (S-22): assumes that the demand growth comes from households and daily productive uses.

- Scenario 3 (S-23): assumes that the demand growth comes from households and non-daily productive uses.

In determining the load profile for each scenario, the base case (BC) load profile of existing connected loads in the specific case study area is considered. In each scenario, the number of load types contributing to demand growth is determined based on the system's capacity. This involves incrementally adding one user at a time to the base case demand while evaluating the system's energy and power limits as constraints. Once these limits are reached, the maximum number of new connections is identified and used to develop load profiles for the three alternative future load compositions. This demand growth is assumed to occur at any point during the lifetime of the mini-grid. Furthermore, in S-2 and S-3, to account for potential alternative load compositions within mini-grids, the study considers a mix of respective HHs and PUs using the method presented in Section 3.5.1.

3.5.2.3. Cost-reflective tariff determination

To ensure the tariff is cost-reflective, it should, at a minimum, recover the investment costs associated with mini-grids. In the study, in determining the cost-reflective tariff, the TPC is used to calculate the monthly revenue requirement (RR) over the mini-grid lifetime in months (T), as shown in Eq. (32). The TPC is calculated using initial investment cost, replacement cost, operation and maintenance cost, and based on the allowed rate of return on investment [44,53].

$$RR = \frac{TPC}{T} \ (\$) \tag{32}$$

The calculation of the cost-reflective tariff, based on the tariff structure considered, is described below.

Fixed energy tariff

The cost-reflective tariff using the FET structure is the ratio of the required RR of the system to the monthly (m) energy usage for each user (i), as shown in Eq. (33).

$$FET = \frac{(RR)_m}{\sum_t^m D_{t,i}} \left(\frac{\$}{kW}\right) \tag{33}$$

Fixed and variable tariff

The FVT structure includes both a fixed tariff (FT) component and a variable tariff (VT) component. The FT is calculated based on the RR to return the TPC of the distribution system only ($(DC)_m$) and then divided it by the total number of users (n) as shown in Eq. (34). On the other hand, the VT, is calculated using in Eq. (33), but the RR utilized in this equation does not account for the $(DC)_m$, as shown in Eq. (35).

$$FT = \frac{(DC)_m}{n}(\$) \tag{34}$$

$$VT = \frac{(RR)_m - (DC)_m}{\sum_t^m D_{t,i}}\left(\frac{\$}{kW}\right) \tag{35}$$

Time of use

The ToU tariff structure involves setting tariff rates (prices for peak and off-peak hours) and determination of tariff shape (duration of peak and off-peak hours), with peak hours being periods of highest demand and off-peak hours occurring outside these times. To calculate the peak tariff (T_P), the peak factor (f_p) is multiplied by the RR and divided by the expected total energy usage (D) during peak hours (N), as shown in Eq. 36). Similarly, to determine the off-peak tariff (T_{OP}), the off-peak factor (f_{op}) is multiplied by RR and divided by the expected total energy usage during off-peak hours (M), as shown in Eq. 37. The f_p is obtained by dividing the average peak power during peak hours (AVR_n) by the total average peak hour (AVR_T) (Eq. 41), while the f_{op} is determined by dividing the average peak power during off-peak hours (AVR_m), by the AVR_T (Eq. 42), where AVR_T is calculated using Eq. 40.

$$T_P = \frac{RR_T \times f_p}{\sum_n^N D_n}\left(\frac{\$}{kW}\right) \tag{36}$$

$$T_{OP} = \frac{RR_T \times f_{op}}{\sum_m^M D_m}\left(\frac{\$}{kW}\right) \tag{37}$$

$$AVR_n = \frac{\sum_n^N D_n}{N}\left(\frac{kW}{hr}\right) \tag{38}$$

$$AVR_m = \frac{\sum_m^M D_m}{M}\left(\frac{kW}{hr}\right) \tag{39}$$

$$AVR_T = AVR_n + AVR_m \quad \left(\frac{kW}{hr}\right) \tag{40}$$

$$f_p = \frac{AVR_n}{AVR_T} \tag{41}$$

$$f_{op} = \frac{AVR_m}{AVR_T} \tag{42}$$

Power tariff

The cost-reflective tariff using PT is calculated by dividing the RR by the sum of the peak demand for each load ($D_{p,i}$), as shown in Eq. (43).

$$PT = \frac{(RR)_m}{\sum_i^I D_{p,i}} \left(\frac{\frac{\$}{kW}}{month} \right) \tag{43}$$

Hybrid tariff

The cost-reflective tariff using HT is calculated by combining both the energy and power tariff components. The energy tariff component (HET) is determined by using 50% of the RR from Eq. (32), while the power tariff component (HPT) is calculated using the remaining 50% of the RR, as shown in Eq. (43).

3.5.2.4. Monthly electricity bill

Monthly electricity bill (MEB) for each user is calculated using the cost-reflective tariffs based on FET, FVT, ToU, PT, and HT structures, using Eq. 44, 45, 46, 47, and 48, respectively.

$$MEB_{ET} = FET * \sum_i^I D_i \ (\$) \tag{44}$$

$$MEB_{FVT} = FT + VT * \sum_i^I D_i \ (\$) \tag{45}$$

$$MEB_{TOU} = T_{P,N} * \sum_n^N D_n + T_{OP,M} * \sum_m^M D_m \ (\$) \tag{46}$$

$$MEB_{PT} = PT * D_{p,i} \ (\$) \tag{47}$$

$$MEB_{HT} = HET * \sum_i^I D_i \ + \ HPT * D_{p,i} \ (\$) \tag{48}$$

Where $MEB_{ET}, MEB_{FVT}, MEB_{TOU}, MEB_{PT}, and\ MEB_{HT}$ are the monthly electricity bills of users calculated using FET, FVT, ToU, PT, and HT structure, respectively.

3.5.2.5. Case, data, and assumptions

The selected case is a solar PV-based mini-grid located in Koftu, described in Section 3.2.1. A 2021 survey showed that 146 households, 1 church (CH), 1 school (SCH), and 1 water pump (WP) are connected. The measured demand of the connected load over one week, from December 6 to 13, 2021, shows that only 27% of the generated energy is consumed, indicating a significantly larger supply capacity than the demand [88]. The daily energy use and peak power for each load type are listed in Table 4.

Table 4. Daily energy use and peak power of the load types in the case.

Load types	Energy per day (kWh)	Peak power (kW)
HH-1	0.08	0.02
HH-2	2	0.7
HH-3	6	2
CH	0.6	0.05
SCH	14	3
WP	9	7

The TPC of the selected mini-grid is \$2.56M, calculated with a 7% discount rate and based on the economic and technical parameters of the mini-grid components in Table 2, excluding the diesel generators and the distribution system [88]. In SSA, the initial cost of distribution networks, metering elements, and end-user devices averages 21% of their TPC [128]. This study considers the distribution cost, with an additional 4% for operational and maintenance costs [128], to be 25% of the overall TPC, totaling \$0.85M.

In scenario formulation, medium household demand (HH-2) from the Koftu mini-grid is considered in S-21. In Scenario S-22, WS is considered to represent a daily PU, while M is considered to represent a non-daily PU in S-23. However, demand data from a mini-grid located in southwestern Tanzania [29] is used for WS and M since the Koftu mini-grid has only one PU (a WP). The daily energy use and peak power for WS and M used in the scenario development are presented in Table 5.

Table 5. Daily energy use and peak power of the WS and M load types.

Load types	Energy per day (kWh)	Peak power (kW)
WS	18	16
M	26	14

The energy per day ratio of HH-2 to WS and M is 9:1 and 13:1, respectively. Based on the method described in Section 3.5.1, the highest load factor occurs when WS and M account for approximately 71% and 89% of the shares, respectively, with the remaining shares coming from HH-2 in S-22 and S-23. With this mix, the energy ratio between HH and WS, calculated on a one-to-one basis, shifts to 22:1, while the ratio between HH and M shifts to 104:1. These energy ratios are considered in the formulation of future demand growth for S-22 and S-23.

The load types and energy per day for demand growth in each scenario are shown in Table 6. The number of new HHs in S-21 is similar to that in S-22 and S-23. However, in addition to these HHs, S-22 includes WS, and S-23 includes M, with the number of WS higher compared to M. This difference is due to the non-coincident peak times of the load types with BC: HHs peak during the morning and evening, while WS and M peak around midday. The total demand per day in BC is 430 kWh/day, whereas for S-21, S-22, and S-23, it is shown in Table 6. This difference in daily usage results in varying levels of excess energy, with S-22 exhibiting 12% and 10% lower excess energy compared to S-21 and S-23, respectively.

Table 6. Number of load types and excess energy per day for each load composition scenario.

Scenarios	Load type	Number of load types	Total demand (kWh/day)
S-21	HH-2	225	887
S-22	WS	10	1065
	HH-2	224	
S-23	M	2	936
	HH-2	224	

To determine the peak and off-peak hours for calculating the cost-reflective tariff using a ToU tariff structure, the load profiles are considered, as shown in Figure 11. The peak load in the system occurs in the early morning, from 6 a.m. to 10 a.m., and in the evening, from 6 p.m. to 6 a.m. Therefore, peak hours are defined as the morning period from 6 a.m. to 10 a.m. and the evening period from 6 p.m. to 6 a.m., while off-peak hours are those during the day, from 10 a.m. to 6 p.m.

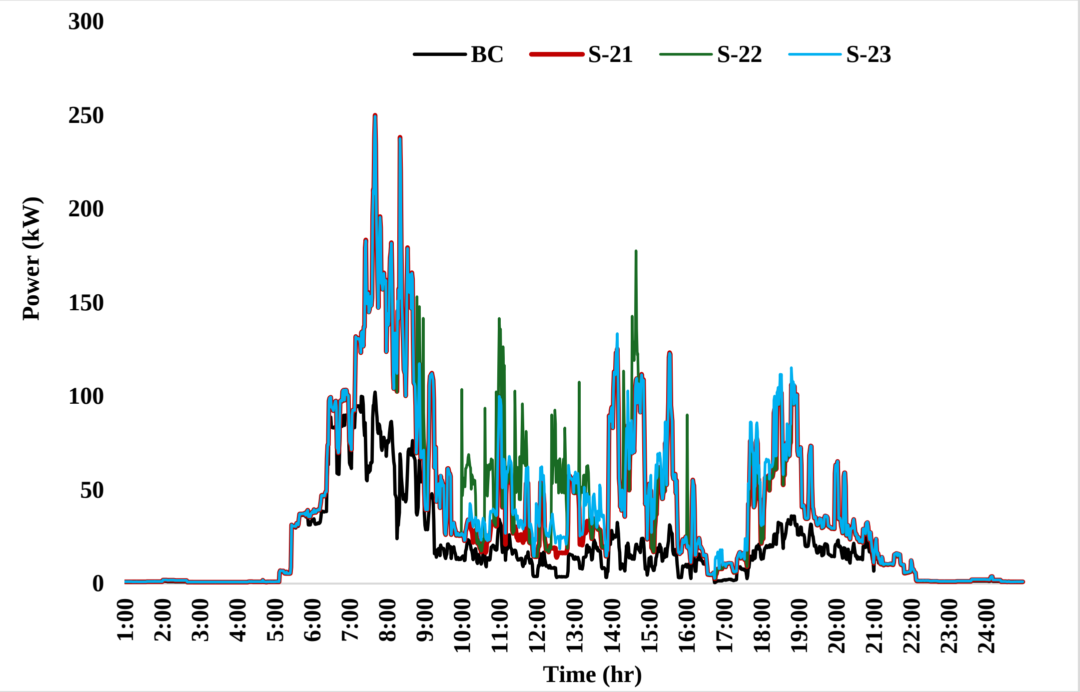


Figure 11. Load profiles for the base case and each load composition scenario.

4. Results and analysis

This chapter summarizes the results and analysis of the thesis.

4.1. Comparison of load estimation methods

The estimated load profiles, based on interviews and measurements, are shown in Figure 12. These profiles are presented per hour and per minute, respectively. The load profiles for households, productive uses, and community loads, estimated from both interviews and measurements, are presented in Figures 13a, 13b, and 13c, respectively. The interview- and measurement-based load profiles both show similar peak loads of 79 kW during the nighttime for each day, as shown in Figure 12. However, the measured data indicates a higher peak load (over 150 kW) during the morning hours for about six hours each week. This morning peak, as shown in the measurement-based load profile, is attributed to cooking appliances (such as electric mitads and stoves) used in households, as depicted in Figure 13a. Notably, the base load is overestimated in interviews by 274% compared to the base load in measurements, which is 66 W.

The high peak demand shown in the measurements, particularly during early morning hours, is driven by the simultaneous use of high-power appliances such as electric stoves and traditional electric mitads for injera baking. The operation of these appliances across multiple households leads to a load coincidence effect, increasing instantaneous power demand. This phenomenon is captured in the measured data but is absent in the interview-derived estimates. The difference is likely due to underreporting or limited respondent awareness regarding appliance usage patterns. This indicates the limitations of relying solely on interview data for load estimation and impacts the design of mini-grid systems.

The estimated performance metrics for weekday, weekend, and weekly load profiles, based on interviews and measurements, are presented in Table 7. According to Table 7, on weekdays, both the energy per day and the load factor are lower compared to weekends, with a reduction of 4% and 5% for interview data, and 4% and 20% for measurement data, respectively. This is because the system is dominated by households and has higher usage on weekends. While there is no difference in peak load between weekdays and weekends in the interview data, the measurement data indicates that the weekday peak load is 15% higher than the weekend peak load. Conversely, in the weekly load profile, the interview data underestimated the peak load by 70% compared to the measurement data. Additionally, daily energy consumption is underestimated by interviews by 21% compared to measurements. However, interviews overestimated the load factor by 162% compared to the measurement data.

The performance metrics show significant differences across the load categories. The estimated metrics for each load category are presented in Table 8. The peak load of the household load category is significantly higher than that of productive uses and community loads for both load estimation methods. This indicates that, although per-customer energy usage in households is lower, the number of households is much higher than that of productive uses and community loads. Consequently, the impact of household load categories is higher than other categories in the total load profile estimation. As a result, households contribute 61% and 90% of the total energy in the interview- and measurement-based load profiles, respectively. Therefore, the difference between the two load estimation methods in the total load profiles is primarily due to households. However, the peak load of households and productive uses in the interview-based load profile is underestimated compared to the measurement-based profile, whereas this is not the case for community loads.

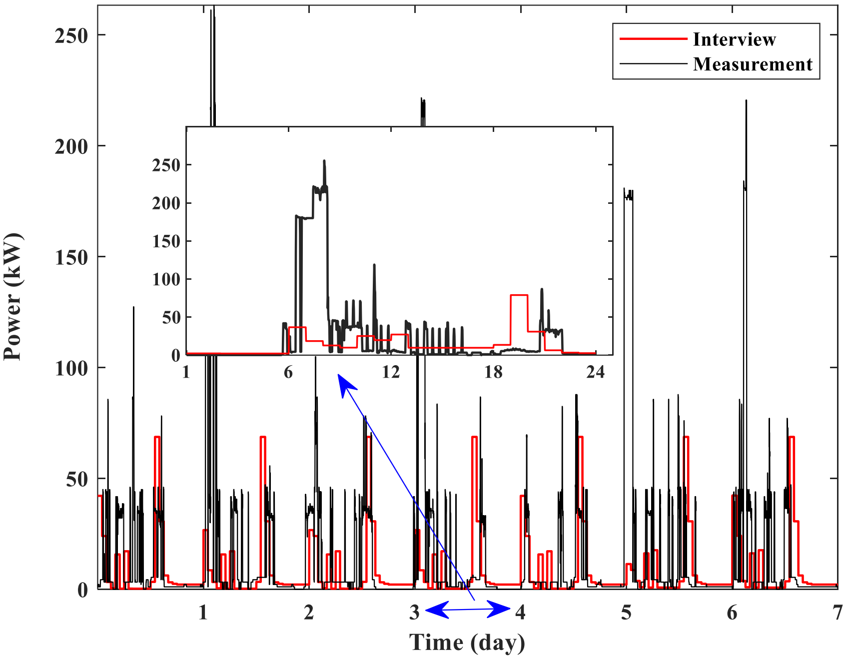
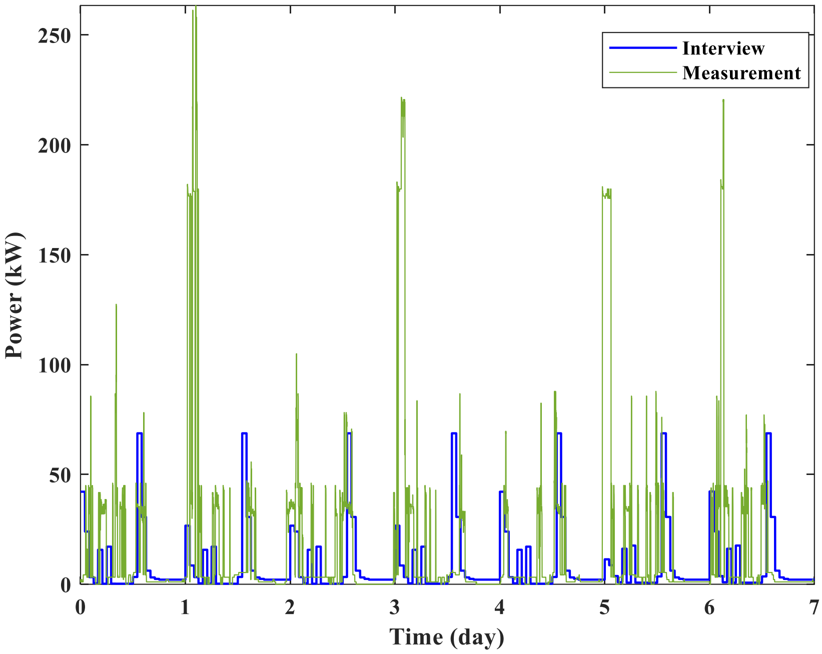
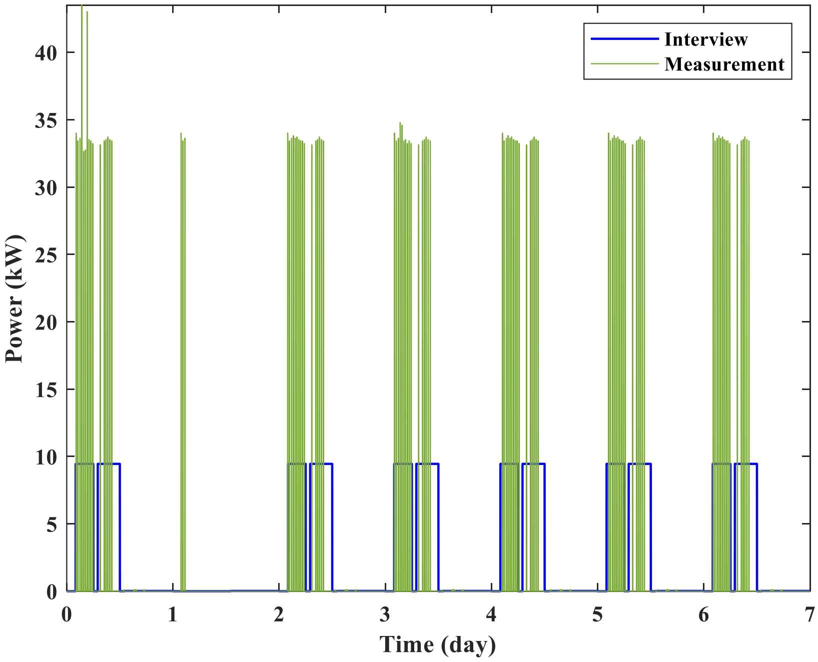


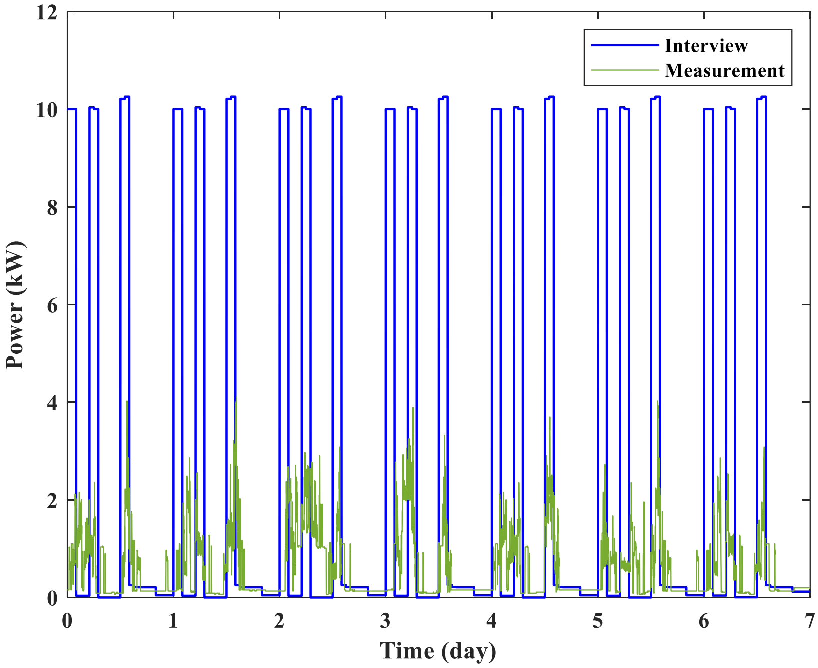
Figure 12. *Total interview- and measurement-based load profiles and in-zoomed one day (day 4) load profile.*


Interview
Measurement
Power (kW)
Time (day)
0
50
100
150
200
250
0
1
2
3
4
5
6
7

(a)


Interview
Measurement
Power (kW)
Time (day)
0
5
10
15
20
25
30
35
40
0
1
2
3
4
5
6
7

(b)



(c)

Figure 13. Load categories load profiles estimated based on interviews and measurements. (a) Household, (b)productive use, and (c) community

The estimated load factor for all load categories indicates that the interview method overestimated the load factor compared to the measurement method. This difference, shown in Table 8, aligns with the difference in total load profiles shown in Table 7. Among the load categories, the difference between the load factor estimated based on interviews and measurements is more significant in productive use, where the load factor is overestimated by 12 times in interviews compared to measurements.

On the other hand, the coincidence of these load categories indicates that it is overestimated in interviews (0.85) compared to measurements (0.89). The responsibility of households and productive uses load categories for the peak load of the total load profile shows the same contribution in both interview and measurement methods. However, the community load categories responsibility factor is underestimated by 68% in measurement method.

Table 7. Performance metrics for the total load profiles estimated based on interview and measurement methods.

Metrics	Interview			Measurement		
	Weekday	Weekend	Weekly	Weekday	Weekend	Weekly
Peak load (kW)	79	79	79	265	223	265
Energy (kWh)	346	361	350	440	467	448
Load factor	0.182	0.190	0.185	0.069	0.087	0.071

Table 8. Performance metrics for load categories load profiles estimated based on interview and measurement methods.

Metrics	Interview			Measurement		
	HH	PU	CL	HH	PU	CL
Peak load (kW)	68	9	10	263	43	4
Energy (kWh)	215	73	62	407	27	14
Load factor	0.130	0.322	0.252	0.064	0.026	0.144
Responsibility factor	0.9	0.001	1	0.9	0	0.32

The results indicate that different load profile estimation methods can lead to varying mini-grid component sizing and costs. The estimated cost-optimal mini-grid component size and cost based on the total estimated load profile from interview and measurement methods are presented in Table 9. Among the mini-grid components, the BESS size is more significantly impacted compared to solar PV due to the significant difference in total energy and peak load between the two estimation methods, as shown in Tables 7 and 8. Specifically, BESS sizes are underestimated by 55% and solar PV by 43% when sizing is based on interview data compared to measured data, resulting in a 52% underestimation of TPC in interviews.

Converting the estimated total load profile from per minute to per hour resolution leads to underestimation of component sizes and costs. As shown in Table 9, BESS and solar PV sizes are underestimated by 55% and 43%, respectively, in per hour resolution load profiles compared to per minute load profiles, resulting in a 9% underestimation of TPC from per minute. This difference is due to a 24% reduction in peak load in the per hour compared to the per minute load profile, reducing from 265 kW to 200 kW.

Table 9. The size of mini-grid components based on interviews and measurement method.

	Interview	Measurement	
	Per hour	Per hour	Per minute
BESS (kWh)	204	449	455
Solar PV (kW)	56	73	98
TPC (M$)	0.579	1.105	1.217

4.2. Comparison of single-year, multi-year, and multi-year-adaptive design approaches

Based on the method presented in Section 3.3, this section details the cost-optimal mini-grid component sizes and costs using SY, MY, and MYAD design approaches under three demand growth scenarios

4.2.1. Comparison of single-year, multi-year and multi-year-adaptive design approaches on mini-grid component sizing

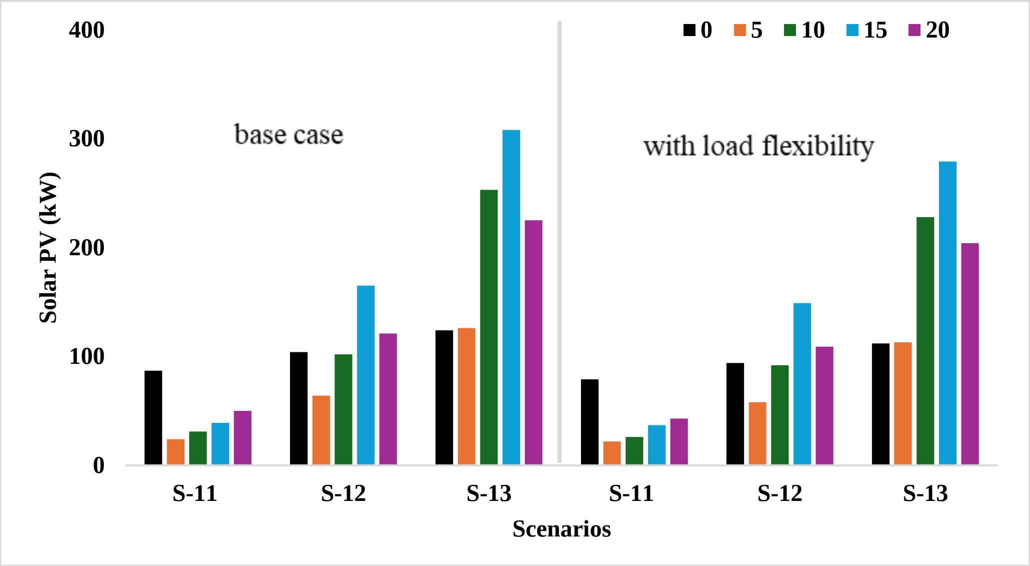
The required additional cost-optimal mini-grid component size in MYAD shows variation across the demand growth scenarios. The required additional solar PV and BESS sizes in the MYAD approach for every five years during the planning horizon, for scenarios 11, 12, and 13, both in the base case and with load flexibility, are shown in Figures 14a and 14b. In scenario 11, as depicted in Figure 14, the required additional solar PV and BESS sizes during the planning horizon are significantly lower than the initial component size for the first five year (initial capacity). In scenario 12, the smaller additional solar PV and BESS size requirements are only observed in the second five years but are higher than the initial capacity in the other five years of the planning horizon. Additionally, in scenario 13, the calculated results indicate that the additional size requirements are equal to or greater than the initial capacity, with smaller additions during demand growth saturation intervals compared to previous year's requirements.

The total mini-grid component size required over the full planning horizon in MYAD results in larger reduced component sizes that depend on demand growth, compared to the SY and MY approaches. The total solar PV and BESS sizes required over the full planning horizon based on the SY, MY, and MYAD design approach for both base case and with load flexibility for scenarios 1, 2, and 3 are shown in Table 2. In MYAD, the initial solar PV and BESS capacity required is smaller than the required size over the full planning horizon, shown in Table 2. This smaller initial capacity requirement compared to the total required component size is significant for higher demand growth scenarios compared to other scenarios. However, these scenarios show consistent relative reductions of 62%, 81%, and 88% for both solar PV and BESS when compared to the sizes needed at the end of the planning horizon in scenarios 11, 12, and 13, respectively. Although this relative reduction decreases over the planning horizon, it remains more significant for higher demand growth scenarios.

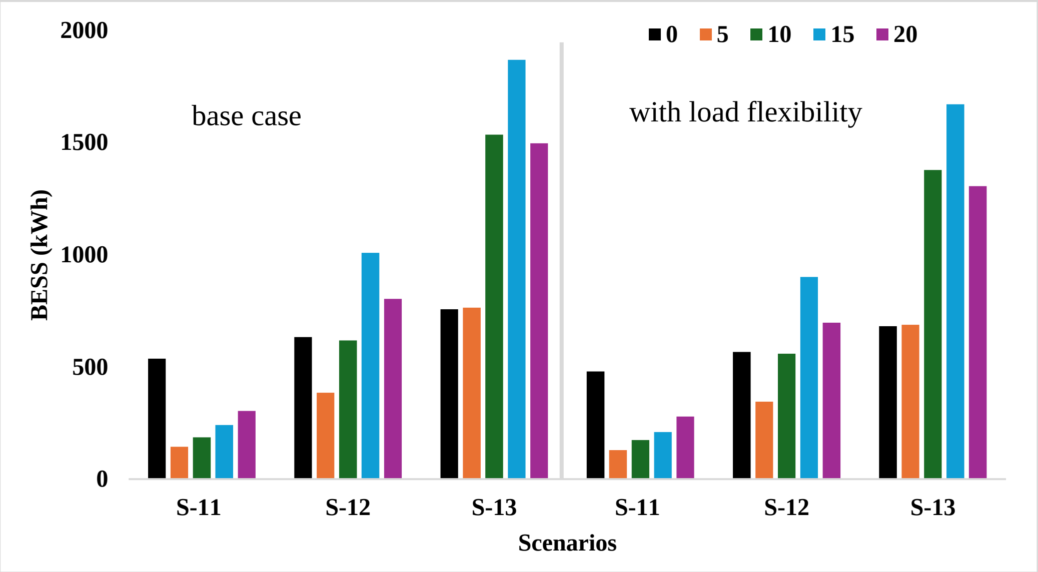
The MYAD approach results also reduces the total solar PV and BESS sizes required compared to the SY and MY approaches. As detailed in Table 10, with higher demand growth, MYAD reduces the required solar PV capacity by 7%, 11%, and 16% compared to SY for scenarios 11, 12, and 13, respectively, and by 10% and 3% compared to MY for scenarios 12 and 13, respectively. This required capacity in scenario 11 is 2% larger than in MY, leading to surplus capacity. Similarly, MYAD reduces BESS size by 7%, 11%, and 15% compared to the SY and by 7%, 2%, and 4% compared to the MY for scenarios 11, 12, and 13, respectively. The larger reduction in BESS size in scenario 11, even compared to scenarios 12 and 13, explains the reason for higher solar PV capacity in MYAD for this scenario compared to MY. This indicates how varying demand evolutions impact the cost-optimal system sizing.

The impact of different design approaches on cost-optimal mini-grid sizing is influenced by how they account for projected demand evolutions over the planning horizon (see Appendix C for average demands and the percentage differences between peak and average demand). The SY approach, which does not consider potential demand evolution, results in a higher average demand (see Appendix D). This may lead to larger solar PV capacity in SY approach. In contrast, the MY approach, which considers demand evolution over the planning horizon, shows a greater disparity between peak and average demands compared to MYAD and SY. This necessitates a larger BESS capacity in MY than in MYAD and SY to consistently meet demand. Additionally, the cost differences between mini-grid components also affect the capacity variations among these approaches.

The impact of load flexibility on mini-grid sizing varies based on the design approaches. The effect of implementing 10% load flexibility on cost-optimal mini-grid component sizing across the different design approaches is presented in Table 10. As detailed in Table 10, different design approaches show varying levels of solar PV and BESS size reduction when 10% load flexibility is applied. In the SY and MY approaches, solar PV size remains largely unchanged or shows minimal reduction, while there is a reduction in BESS size. In MY, the 10% load flexibility application results in a more substantial reduction in BESS size than in SY and MYAD approaches. This indicates that load flexibility application is more evident in the design approach that considers demand evolution and significantly influences the size of the component responsible for managing demand variability, which is the BESS in this case.



(a)



(b)

Figure 14. Calculated system additions for every five years during the planning horizon for the MYAD approach under scenarios 1, 2, and 3 for the base case and with load flexibility: (a) Solar PV, (b) BESS.

Additionally, Table 10 reveals that the solar PV/BESS ratio ranges between 0.15 and 0.2 kW/kWh across all scenarios and design approaches. This relatively low ratio stems from the high morning energy demand in the case study area, primarily due to cooking appliances. Such demand patterns require a larger BESS capacity to ensure sufficient energy supply during these peak periods. Implementing various DSM strategies, such as shifting cooking appliance usage to midday, could potentially reduce BESS size requirements, enhancing system cost-efficiency.

Table 10. Mini-grid component size under scenarios 1, 2, and 3, for the SY, MY, and MYAD approaches for the base case and with load flexibility.

		Design approach					
		base case			with load flexibility		
Scenarios	Components	SY	MY	MYAD	SY	MY	MYAD
S-11	Solar PV (kW)	248	227	231	249	227	207
	BESS (kWh)	1522	1516	1412	1389	1300	1272
S-12	Solar PV (kW)	628	616	556	632	616	502
	BESS (kWh)	3857	3523	3447	3519	3067	3069
S-13	Solar PV (kW)	1232	1070	1036	1223	1070	936
	BESS (kWh)	7512	6706	6420	6852	5878	5721

4.2.2. Comparison of design approaches on mini-grid total present cost

The MYAD approach leads to lower initial investment requirements compared to the total investment required. In Figure 15, the required additional investments for MYAD, for each five-year interval over the planning horizon, are presented. In MYAD, the initial costs comprise 74%, 53%, and 39% of the total TPC required by the end of the planning horizon for scenarios 11, 12, and 13, respectively. In scenario 11, characterized by lower demand growth, the MYAD approach results in additional capacity installations that represent a smaller portion of the TPC in later years compared to scenarios with higher demand growth. This is because the initially installed components already meet a significant part of the demand. Consequently, the MYAD approach offers substantial cost savings, especially when demand increases sharply.

MYAD leads to considerable cost savings compared to both SY and MY approaches. Table 11 presents the TPC over the planning horizon for various approaches. The cost savings of MYAD are more significant in scenarios with higher demand growth. With a 7% discount rate, MYAD reduces the TPC by 52%, 68%, and 74% compared to SY, and by 51%, 66%, and 70% compared to MY for scenarios 11, 12, and 13, respectively. These savings are primarily due to the postponement of additional investments, which lowers upfront costs. Moreover, the approach reduces component replacement costs, especially for BESS and inverters, as well as operation and maintenance expenses. It also enhances the scrappage value, contributing to a lower TPC. The replacement cost for solar PV is zero because the project's lifespan aligns with that of the solar PV system.

The application of load flexibility in MYAD results in greater TPC savings than the base case. As shown in Table 11, using a 7% discount rate, applying 10% load flexibility in MYAD boosts TPC savings by 4% compared to SY and by 2% compared to MY, relative to the base case. The LCOE for the SY approach is 0.58$/kWh, which decreases to 0.56$/kWh with load flexibility. However, the LCOE is lower for both MY and MYAD compared to the SY approach.

The reduction in TPC with MYAD compared to SY and MY becomes more significant as the discount rate increases, indicating higher cost savings at greater rates. Table 11 presents the estimated TPC for various discount rates and design approaches. For instance, in scenario 11, the TPC reduction increases by up to 6.1% compared to SY and by 4.1% compared to MY when the discount rate is increased to 15% and 20%, respectively, compared to the 7% discount rate. Similarly, in scenario 13, the relative reduction in TPC increases by up to 6.3% compared to MY and 9.4% compared to SY at a 15% discount rate, and by 5.6% and 8.3% at a 20% rate, respectively. Scenario 12 shows a relative reduction that falls between the results of scenario 11 and 13.

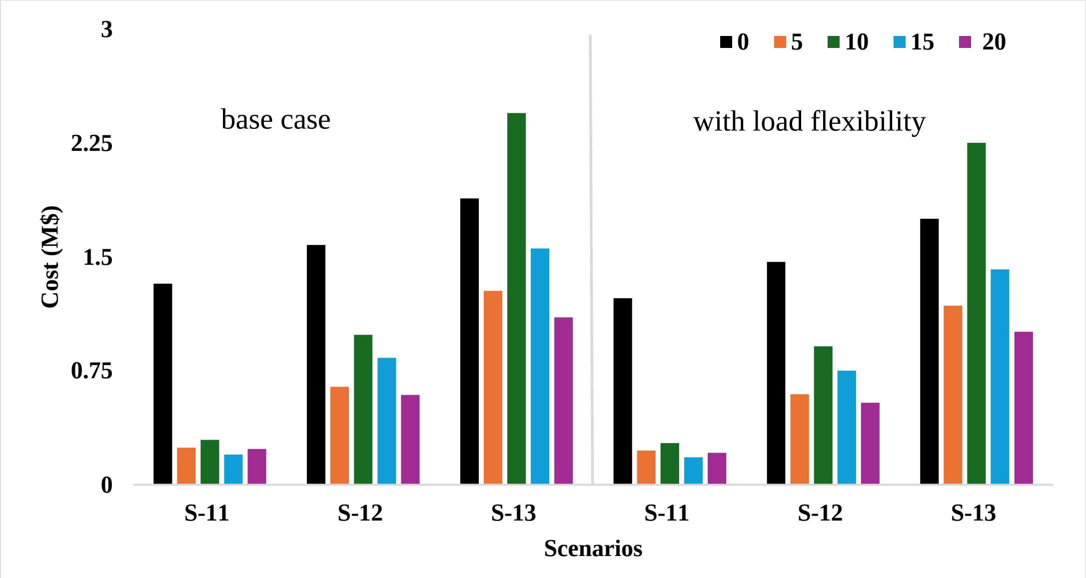


Figure 15. Cost additions for every five years during the planning horizon for the MYAD approach for the base case and with load flexibility for scenarios 11, 12, and 13.

The reduction in TPC with MYAD compared to SY and MY also becomes more significant with future component cost reductions. The total present cost required over the planning horizon for the MYAD approach under different annual cost reductions and mini-grid component cost reductions is presented in Table 12. As shown in Table 12, the relative TPC reduction with MYAD increases by 2.4%, 3.1%, and 3.2% compared to SY, and by 2.5%, 3.3%, and 3.6% compared to MY, for each 1% annual decrease in solar PV and BESS costs.

Table 11. Total present cost in M$ required over the planning horizon for the SY, MY, and MYAD approaches for scenarios 11, 12, and 13 for the base case for different discount rates and with load flexibility.

Scenario	Design approach											
	base case									with load flexibility		
	SY			MY			MYAD			SY	MY	MYAD
	discount rate											
	7%	15%	20%	7%	15%	20%	7%	15%	20%	7%		
S-11	3.7	2.2	1.8	3.6	2.1	1.7	1.8	1.0	0.7	3.6	3.4	1.6
S-12	9.5	5.6	4.6	8.8	5.2	4.3	3.0	1.5	1.1	9.1	8.3	2.8
S-13	18.5	10.9	8.9	16.3	9.6	7.8	4.9	2.3	1.6	17.8	15.4	4.5

Table 12. Total present cost in M$ required over the planning horizon for the MYAD approach under different annual cost reductions.

Scenario	Annual cost reduction of solar PV (per kW) and BESS (per kWh)		
	2%	3%	4%
S-11	1.7	1.7	1.7
S-12	2.8	2.7	2.6
S-13	4.5	4.3	4.1

4.3. Impact of demand side management

This section presents the impact of DSM implementation at the category level on the cost-optimal off-grid mini-grid sizing. It also provides an analysis comparing this impact of DSM implementation at the category level with load flexibility.

4.3.1. Impact of DSM implementation on the cost-efficiency of mini-grids

The cost-efficient sizes of the off-grid mini-grid components for each combination of load categories with implemented DSM in Configurations 1 and 2 are shown in Figures 16, a, and b. The size of the BESS, charged during higher levels of solar PV power production and discharged during peak demand hours, is highly influenced by the shiftable loads through the DSM implementation, as compared with the sizing of solar PV and DG.

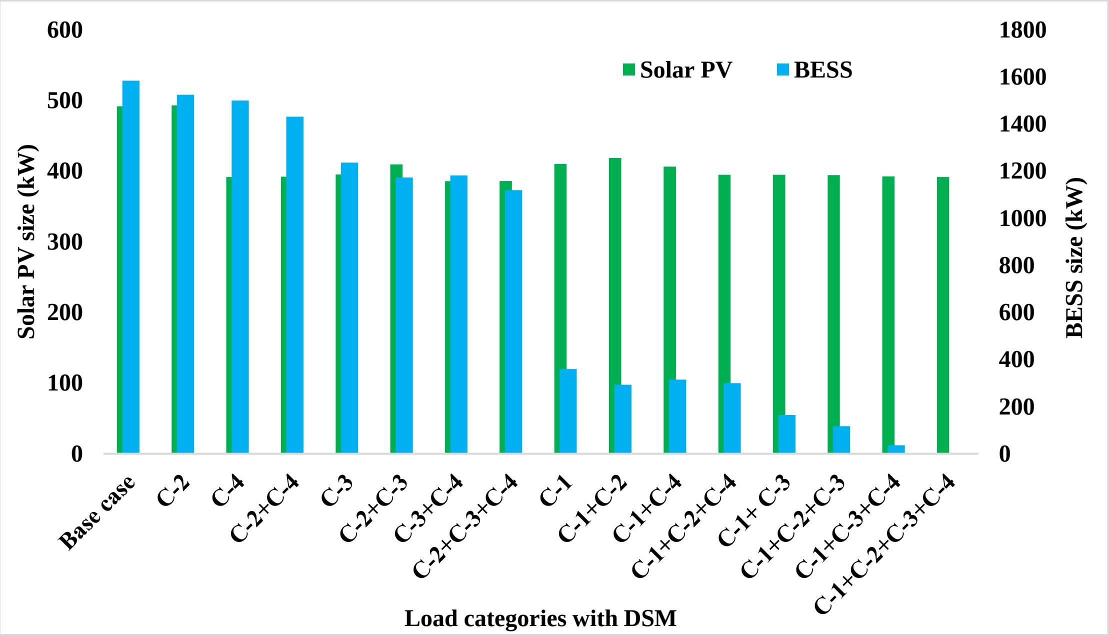
As shown in Figure 16, a and b, different load categories with DSM have different impacts on the BESS, solar PV, and DG sizing. In both configurations, DSM implementation in all load categories will result in reduced power from solar PV (391.6 kW) and no need for BESS, since all loads are low-priority loads and are scheduled for hours with higher production of solar PV power. In Configuration 2, DSM implementation in all load categories results in no need for

DG, thereby reducing the levels of CO_2 emissions and operational costs. The cost-optimal sizes of the BESS and solar PV in the No DSM case (base case), whereby all loads are high-priority loads and operate at their scheduled times, are 1,584kWh and 491.8kW in Configuration 1 and 1,491kWh and 476.5kW in Configuration 2, respectively.

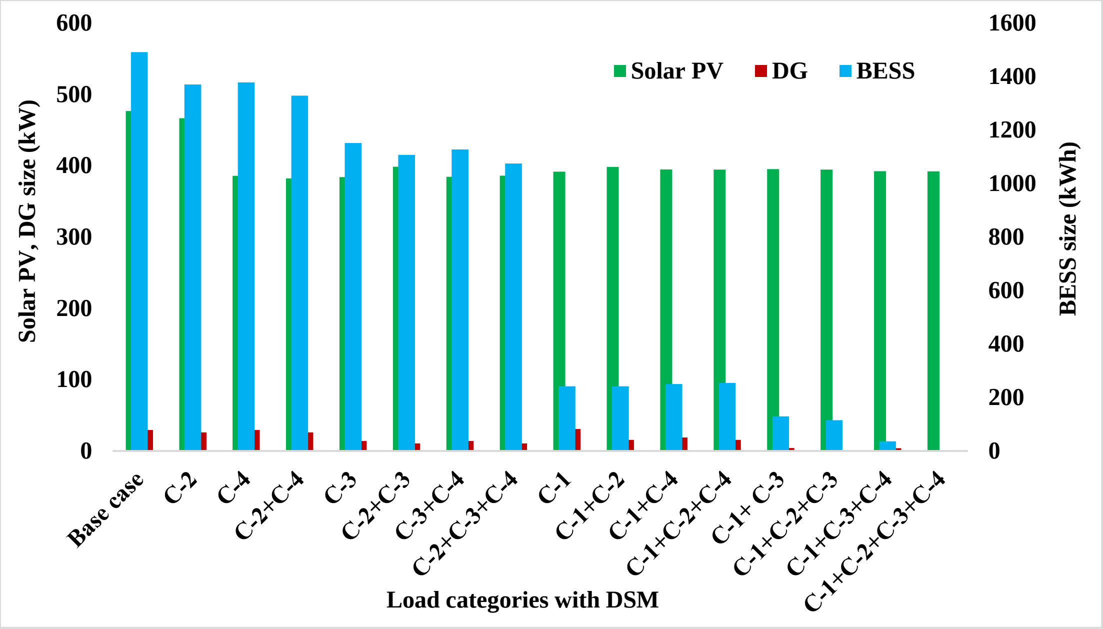
Among the load categories, DSM implementation in C-1 has a greater impact than the other load categories, reducing the BESS and solar PV by 1,224kWh (77.2%) and 81.5kW (16.5%) in Configuration 1, and by 1,249kWh (83.7%) and 85kW (17.8%) in Configuration 2, respectively, as compared to the No DSM case. DSM implementation in C-3, C-4, and C-2, in descending order of impact, reduces the cost-optimal BESS size by 21.9%, 5.3%, and 3.7%, respectively, as compared to the No DSM case, as shown in Figure 16a. DSM implementation in C-3 and C-4 reduces the cost-optimal solar PV size by 19.6% and 20.3%, respectively, as compared to the No DSM case. However, for DSM implementation in C-2, the cost-optimal solar PV size is nearly equal to that in the No DSM case. In C-2, community load, demand is concentrated to the daytime, when there is a higher level of solar PV power production. This indicates that the shifting strategy has a lower impact for C-2.

In Configuration 2, DSM implementation reduces the cost-optimal BESS size by 22.7%, 7.5%, and 8%, and the cost-optimal solar PV size by 19.4%, 19%, and 2.1% for C-3, C-4, and C-2, respectively, as compared to the No DSM case, as shown in Figure 16b. DSM implementation in C-3, with peak demand coinciding with solar PV power production, results in lower DG size than for other load categories, as shown in Figure 16b. In the No DSM case, the cost-optimal DG size is 29.5kW, which is only 6% of the solar PV size, whereas DSM implementation in C-1, C-3, C-4, and C-2 results in cost-optimal DG sizes of 31kW, 14kW, 29kW, and 26kW, respectively.

The LCOE values, calculated using Eq. (2), for Configuration l (LCOE-1) and Configuration 2 (LCOE-2) are shown in Figure 17. In Configuration 2, DG supplies peak loads. As a result, the BESS and solar PV needed to meet peak loads are reduced, resulting in a lower LCOE, thus LCOE-2 is lower than LCOE-1. DSM implementation in C-1, greatly reduces the size of the BESS and reduces the levels of solar PV and DG more than in other load categories, leading to a dramatic decrease in LCOE: LCOE-1 is reduced by 45.8% and LCOE-2 by 47.6%, as compared to the No DSM case. DSM implementation in C-3, C-4, and C-2 reduces the LCOE-1 by 20.7%, 13%, and 1.6%, and LCOE-2 by 21.8%, 13.2%, and 5.1%, respectively, compared to the No DSM case.



(a)



(b)

Figure 16. Optimal component sizes for different load categories with DSM in: (a) Configuration 1; and (b) Configuration 2.

4.3.2. Impact of load flexibility on the cost-efficiency of mini-grids

To determine the impact of load flexibility on the cost-efficiency of mini-grids, different levels of load flexibility, considering low-priority loads in the implemented DSM operating strategy, are used in the cost-optimal component sizing for Configurations 1 and 2, as shown in Figure 18, a and b. The BESS size is particularly strongly influenced by load flexibility and is reduced, on average, by 29.8% for every 10% increase in load flexibility for both configurations, resulting in no need for BESS for 100% load flexibility (an ideal case). This is because flexible demand can be shifted to align with periods of peak solar generation, thereby maximizing the direct utilization of solar energy and minimizing the mismatch between supply and demand.

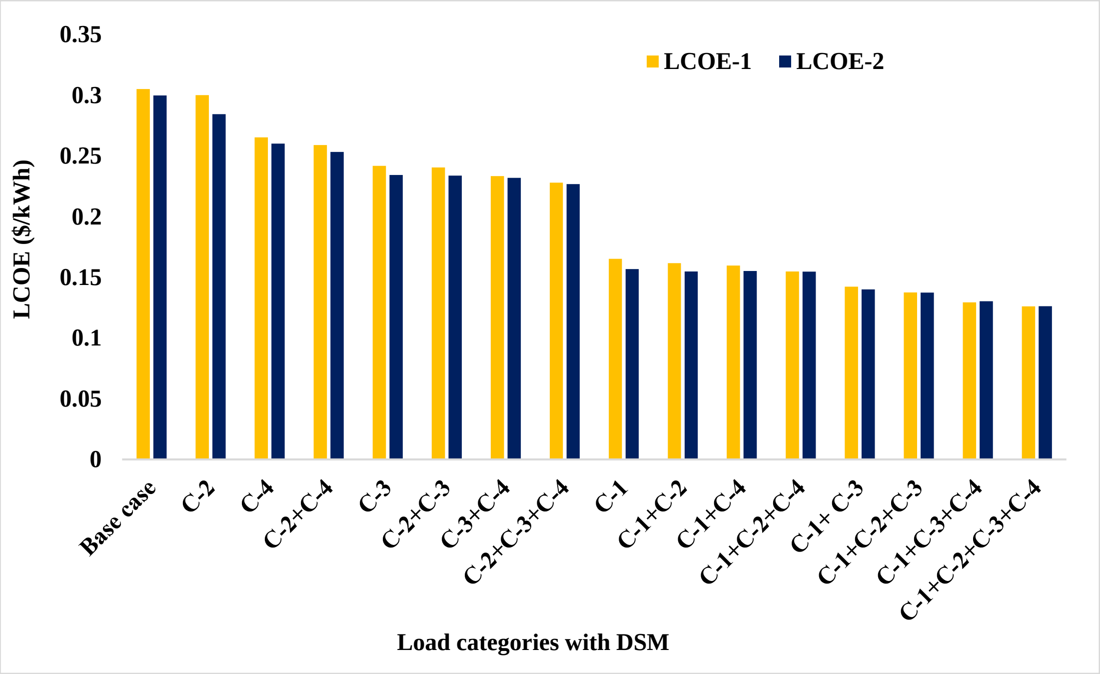
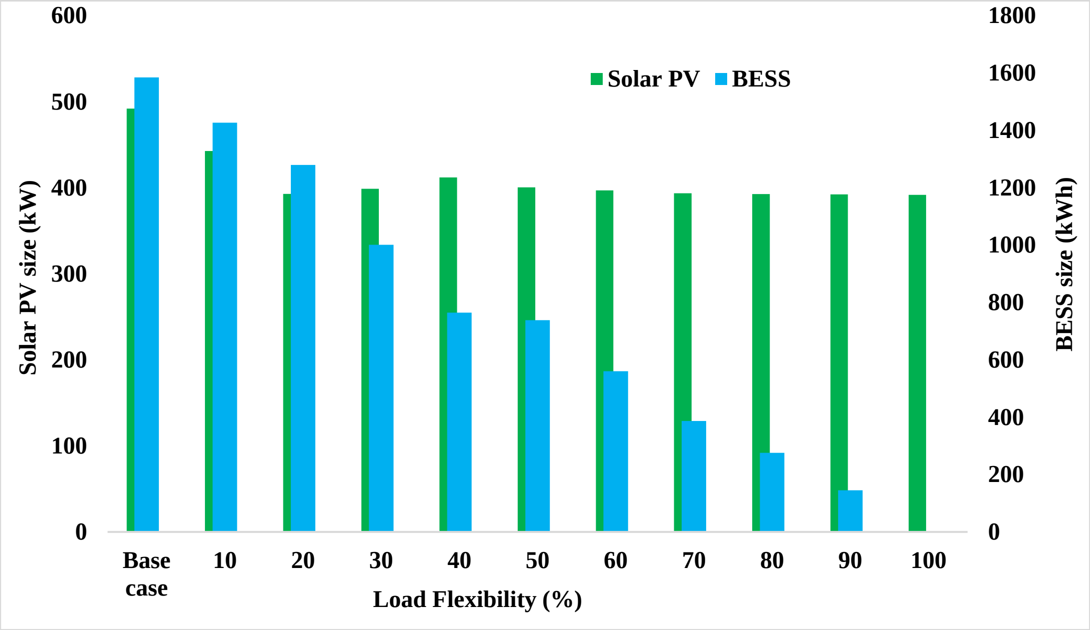
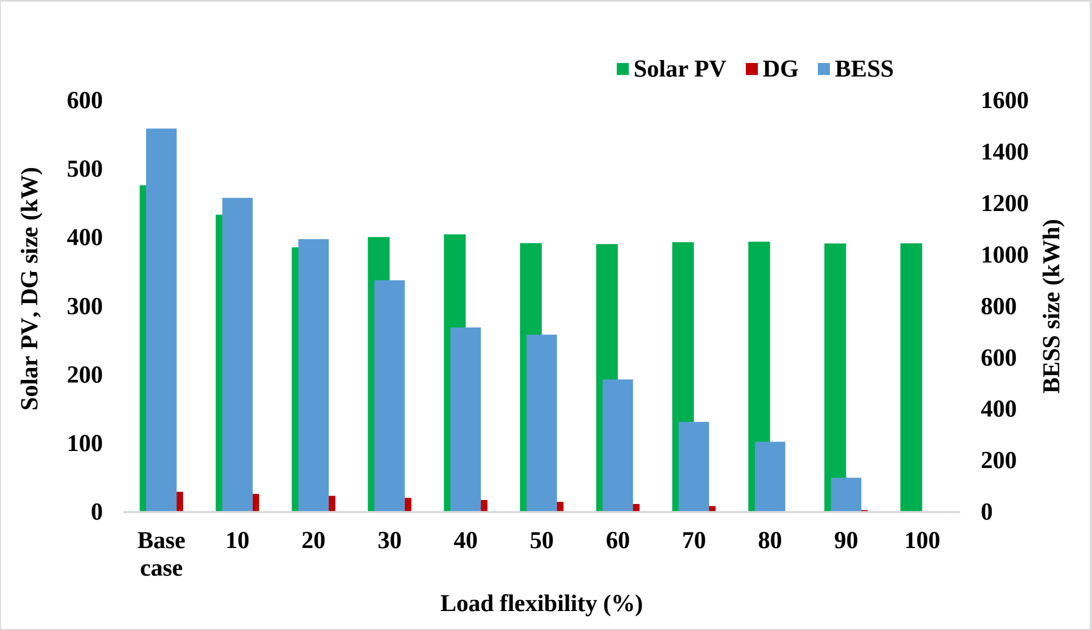


Figure 17. LCOE-1 and LCOE-2 values for different load categories with DSM.

The cost-optimal solar PV size is reduced, on average, by 2.1% for every 10% increase in load flexibility in Configuration 1, Figure 18a, and in Configuration 2, Figure 18b, on average by 1.8%. DG, which is only available in Configuration 2, is reduced, on average, by 12.1% for every 10% increase in load flexibility.



(a)



(b)

Figure 18. Optimal component sizes for different percentages of load flexibility in: (a) Configuration 1; and (b) Configuration 2.

The impacts of load flexibility on the LCOE values for Configuration 1 (LCOE-1) and Configuration 2 (LCOE-2) are shown in Figure 19. Load flexibility reduces the LCOE by, on average, 8.4% and 8.2% for every 10% increase in load flexibility for Configurations 1 and 2, respectively.

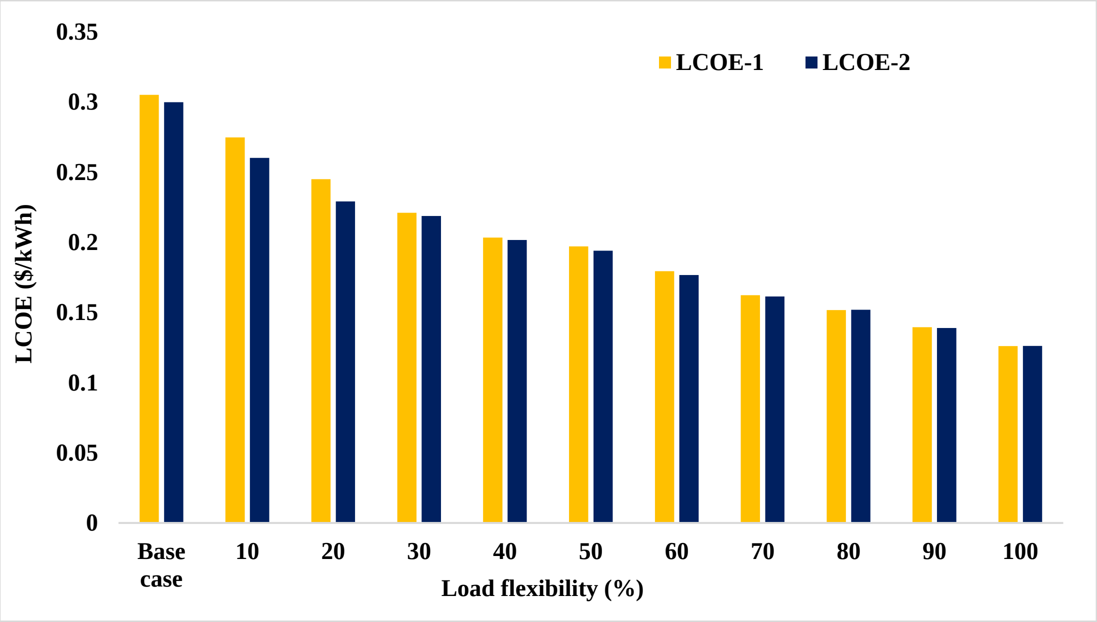


Figure 19. LCOE-1 and LCOE-2 values for different percentages of load flexibility.

4.3.3. Comparison of the impacts of DSM implementation at category level and load flexibility on the cost-efficiency of mini-grids

DSM implementation at the category level has the same impact as that achieved by using a higher load flexibility, as shown in Figures 17 and 19. The DSM implemented in all the load categories reduces the LCOE-1 by 58.7% and LCOE-2 by 58%, as compared to the No DSM case, shown in Figure 17. This is equal to the result of 100% load flexibility, Figure 19.

The DSM implementation in C-1, Figure 17, reduces LCOE-1 and LCOE-2 to almost the same extent as 55% and 58% load flexibility for Configurations 1 and 2 respectively, Figure 19. C-3, C-4, and C-2, Figure 17, have the capacity to reduce the LCOE to almost the same extent as 25%, 16%, and 2% load flexibility for Configuration 1, and 26%, 16%, and 6% load flexibility for Configuration 1, respectively, Figure 19.

In addition, as shown by a comparison of Figure 17 and Figure 19, the difference between LCOE-1 and LCOE-2 diminishes with shiftable load categories, low-priority loads, and percentage of load flexibility. This indicates that as shiftable load categories and load flexibility increase, DSM implementation will increase the cost-competitiveness of a 100% RES-based off-grid mini-grid (Configuration 1).

4.3.4. Comparison of mini-grid sizing with and without considering uncertainty and validation of the PSO result

The cost-optimal size of the mini-grid with and without consideration of load and supply side uncertainties for Configuration 1 and 2 is shown in Appendix C. Cost-optimal sizing without considering uncertainties reduces the size of the BESS and DG more than the solar PV, as shown in Appendix C, since peak load variations caused by uncertainties is met by BESS and DG. In Configuration 1, the cost-optimal size of the BESS and the solar PV are reduced by 3.2% and 2.4%, and in Configuration 2 by 2.5%, 2.6%, and 2.6% for the BESS, solar PV, and DG, respectively.

The cost-optimal size of the mini-grid for resulting from the use of an iterative method in the case of 10% load flexibility is shown in Table 13. In finding the cost-optimal size of the mini-grid components, the results obtained from the PSO algorithm and the iterative method are almost the same for both configurations, but the accuracy of the cost-optimal solution differs. The convergence characteristic of the PSO algorithm for the cost-optimal sizing with and without considering uncertainty is shown in Figure 20. As shown in the convergence characteristics of the PSO, the LCOE decreases as the number of iterations increases and finally converges to the optimal value.

Table 13. Optimal size of mini-grid with and without considering uncertainty using PSO and Iterative method for configuration 1 and 2.

Component, unit	Configuration 1			Configuration 2		
	With uncertainty		Without uncertainty	With uncertainty		Without uncertainty
	Iteration	PSO	PSO	Iteration	PSO	PSO
Solar PV, kW	441.6	442.6	432.1	441.6	433.5	422.9
BESS, kWh	446	1425	1380	1410	1221.5	1189.9
DG, kW	0	0	0	26.5	26.5	25.8

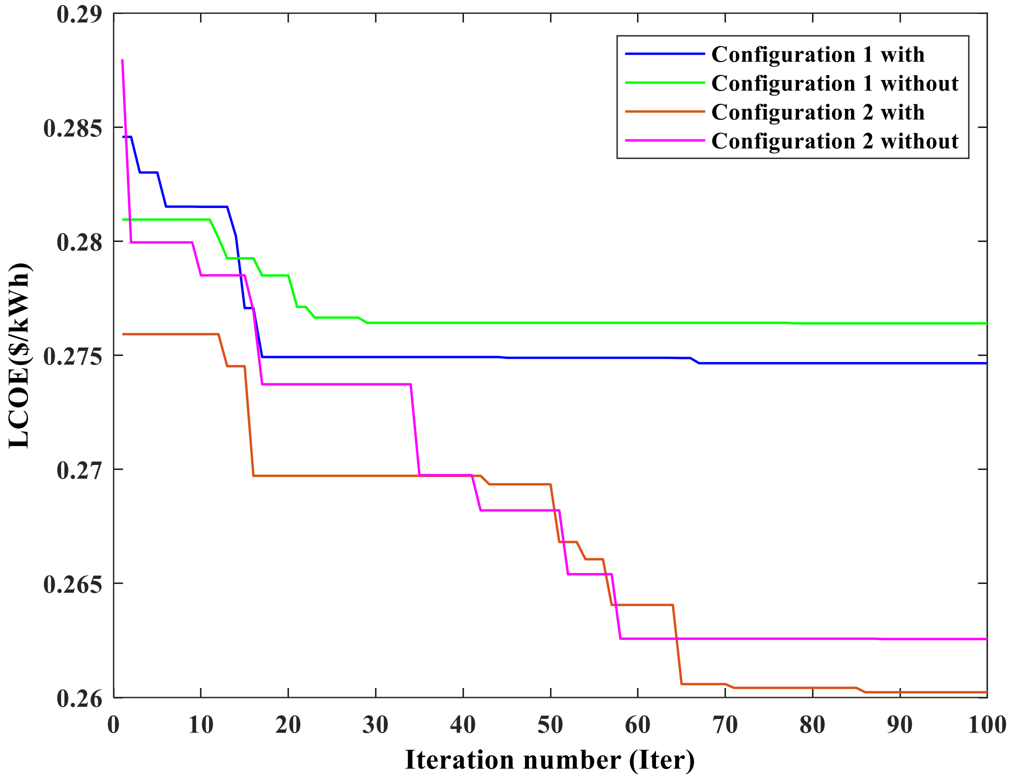


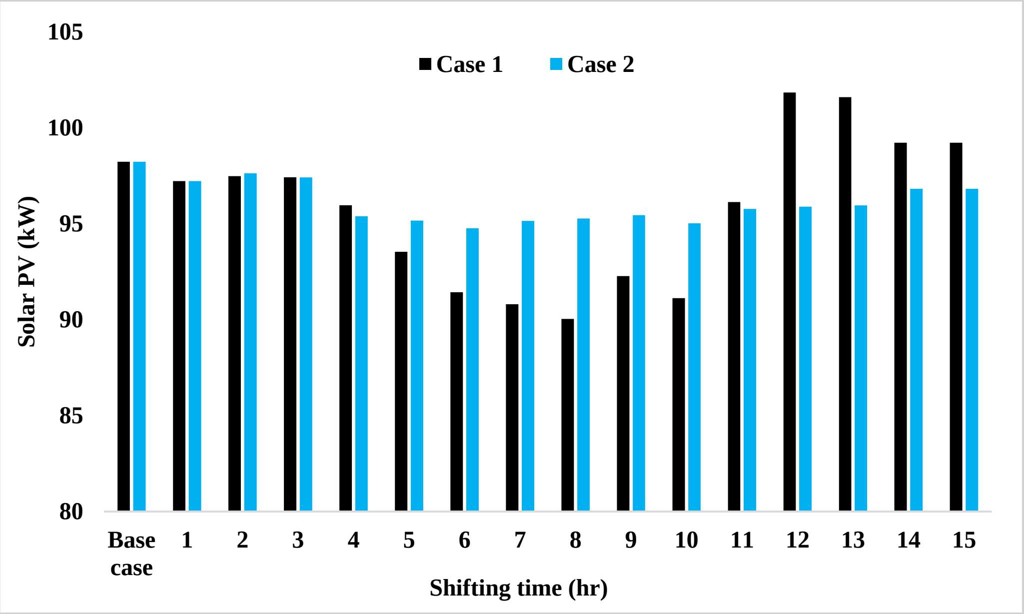
Figure 20. Convergence characteristics of the PSO algorithm for optimal size of mini-grid with and without considering uncertainty.

4.3.5. Impact of cooking appliances shifting hours on cost-efficiency of mini-grid

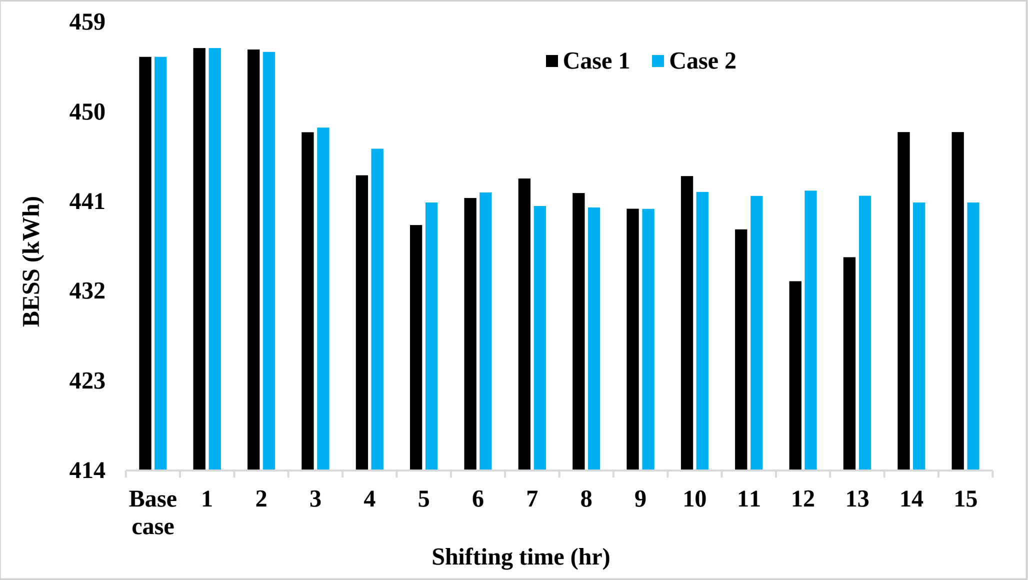
The peak load in the Koftu system occurs in the early morning, from 8 AM to 9 AM, with a total load profile peak of 265 kW. This peak is primarily caused by the household load category, which peaks at 263 kW during the same hour. The second highest peak load, 250 kW, occurs between 6 AM and 8 AM. In cases 1 and 2, the peak load shifts every hour from 8 AM to 9 AM to 11 PM. In case 1, the maximum peak load is 332 kW, which is 25% higher than the base case peak load. However, in case 2, the peak load remains at 261 kW for all shifting hours, which is 1.2% lower than the base case peak load.

Based on different cooking appliance shifting hours, Figure 21 shows the cost-optimal size of the BESS, solar PV, and TPC of the mini-grid. The size of BESS is reduced by up to 3% for both cases 1 and 2 compared to the base case, as shown in Figure 21. In the base case, where cooking appliance shifting is not considered, the sizes of BESS and solar PV are 455 kWh and 98 kW, respectively, resulting in a TPC of $1.217 million. Shifting cooking appliances reduces the solar PV size by up to 8% in case 1 and 3% in case 2.

The reduction in BESS and solar PV sizes can be higher if the second peak loads, occurring between 6 AM and 8 AM, are shifted to the afternoon, as they are 5% lower than the first peak. This reduction is achieved by shifting cooking appliance operating times to any time in the afternoon between 1 PM and 5 PM, decreasing the mini-grid TPC by up to 3% in both cases. However, the TPC of case 1 is higher than the base case if cooking is shifted from 8 AM to 9 AM to 12 AM and between 7 PM and 9 PM. This is because additional load during these hours increases rather than decreases the peak load compared to the base peak load. Additionally, if 100% of cooking appliances are shifted in case 1, customer satisfaction may decrease.



(a)



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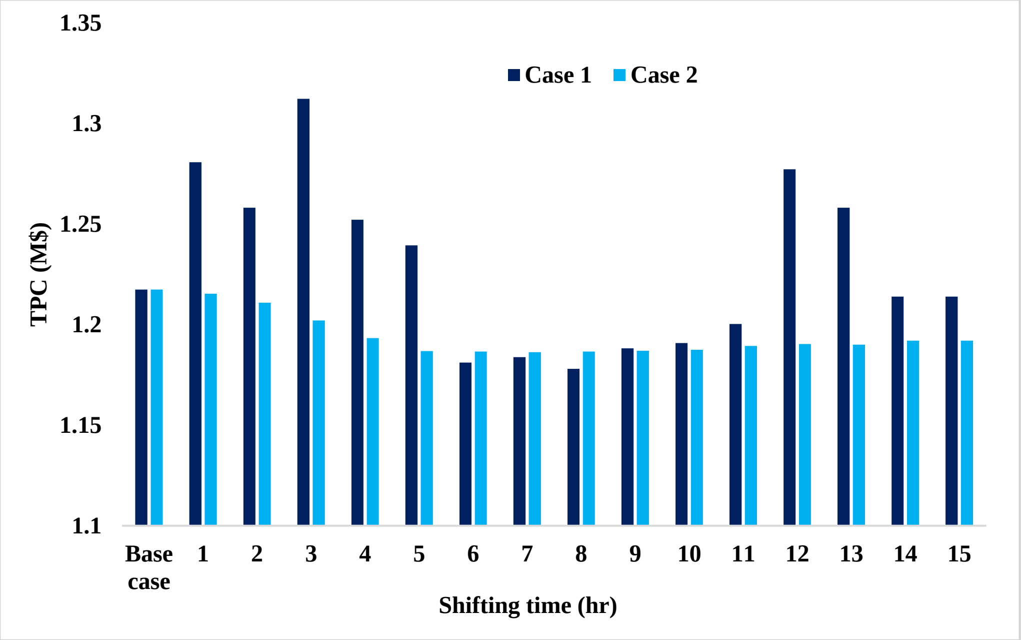


(C)

Figure 21. Calculated size and cost of mini-grid for the different shifting hours of cooking appliance: (a) Solar PV, (b) BESS (C) TPC

4.4. Impact of load composition

The cost-reflective tariff and monthly bill of users calculated based on the different tariff structures for each load composition scenario are presented in this section.

4.4.1. Load factor and revenue optimization

The load factor changes due to different compositions of the household and productive use of electricity for the two cases shown in Figure 22. As shown in Figure 22, the highest load factor arises when the composition of loads is approximately 50 % productive use. The increase in the load factor is expected to be around 20 to 40 % compared with 100 % household loads and 100 to 500 % compared with 100 % productive use, dependent on load behavior. The measurements indicate there is a 11:1 ratio in average energy usage for household and productive use. Thus, with the 50 % composition, this indicates that there should be 11 times more households' customers than productive users to reach the maximum load factor.

How the total revenue changes due to the load composition is shown in Figure 23. The solid lines show how the total revenues change for both case 1 and 2 when household and productive use have the same tariff, the maximum point will be the same as for the load factor optimization. With an increase of the tariff of 10 % for the productive use customers, the optimum is shifted by about 3-5 percentage points towards a lower household share as indicated with the dashed line in Figure 23. The shift makes the maximum number of household's customers to be 10 times more than the number of productive use customers to reach maximum revenue.

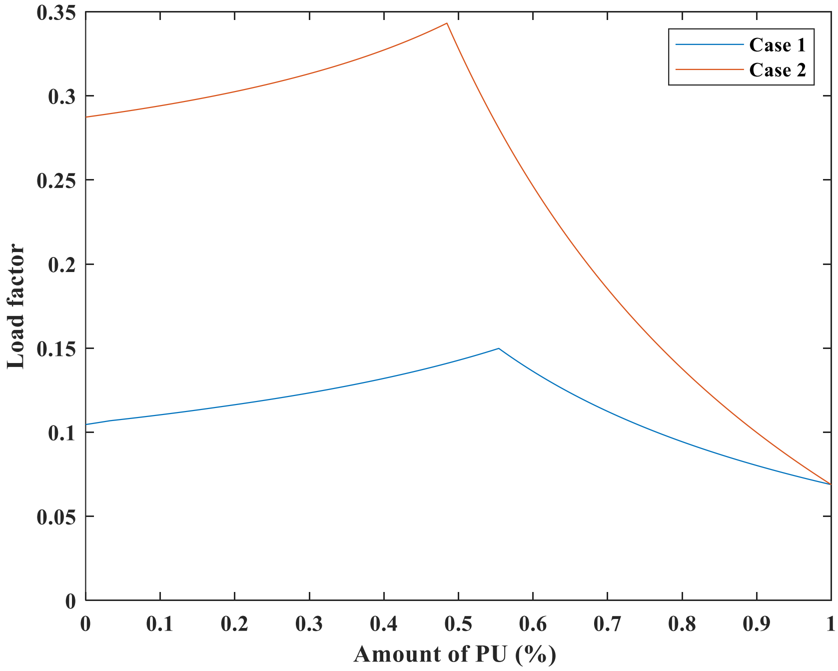


Figure 22. How the load factor changes due to different compositions of the household and productive use of electricity for two cases.

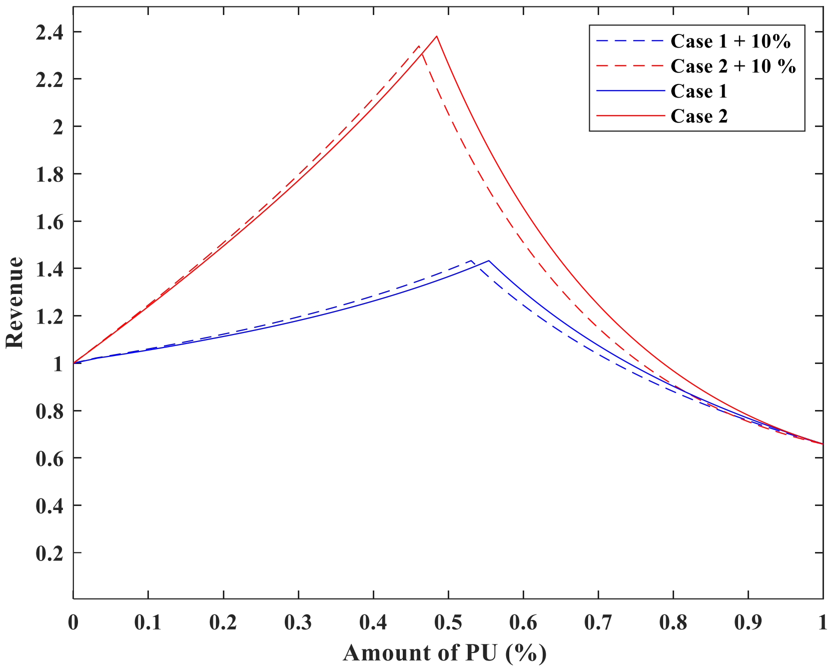


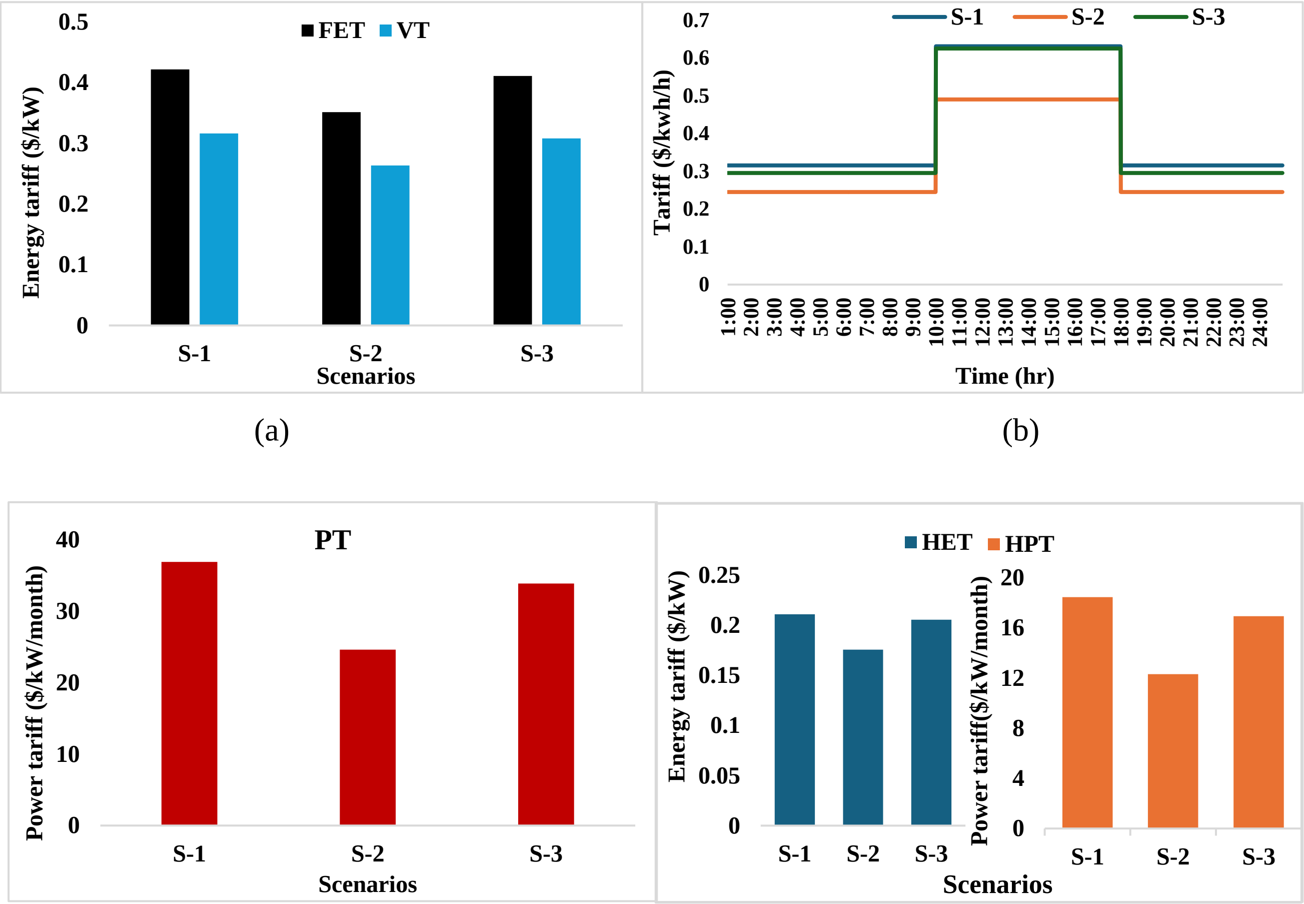
Figure 23. Normalized revenue for different compositions of household and productive load. Two different cases are investigated. The dashed line is the revenue for with a 10 % increase of tariffs for productive use.

4.4.2. Cost-reflective tariff

Cost-reflective tariffs for scenarios 21, scenario 22, and scenario 33 are shown in Figure 24. The tariff structures depending on total energy usage, FET, VT of FVT (shown in Figure 24a), and HET of HT (shown in Figure 24d), exhibit different cost-reflective tariffs for each scenario but show the same relative differences between scenarios. Specifically, the cost-reflective tariff for scenario 22 is 17% and 15% lower than scenario 21 and scenario 23. Among these tariff structures, the cost-reflective tariff calculated using VT of FVT and HET of HT results in reductions of 25% and 50%, respectively, compared to FET calculated for each scenario. This is because the FT in FVT distributes 25% of TPC among users, averaging 7.5$/month per user, while the HET in HT is based on 50% of the total RR. FT is 2% lower for scenario 22 compared to scenario 21 and scenario 23 due to a 2% higher number of users. The cost-reflective tariffs calculated using energy-based tariff structures are lower than the implied tariff (1.75$/kWh) that unconnected customers in SSA would pay for energy generation through alternative means like kerosene or batteries [22,44].

The cost-reflective ToU-based tariff, shown in Figure 24b, reveals that higher energy usage during peak hours compared to off-peak hours, shown in all scenarios, results in peak-hour tariffs that are 50% lower than off-peak tariffs in all scenarios. Due to these differences in energy usage in peak and off-peak hours among scenarios, peak and off-peak tariffs in scenario 22 exhibit the lowest tariff compared to scenario 21 and scenario 23. Specifically, the peak and off-peak rates in scenario 22 are 22.3% lower than those in scenario 21, and 17% and 21.6% lower than those in scenario 23, respectively.

The sum of each user's peak load can vary depending on load composition, even with a fixed mini-grid capacity. The cost-reflective tariff based on the PT structure, which depends on the total peak load, is shown in Figure 24c. As shown in Figure 24c, scenario 22, which has a high peak load sum, results in power tariffs that are 33% and 27% lower than those in scenario 21 and scenario 23, respectively. On the other hand, the cost-reflective tariff based on the HT structure that distributes the required revenue evenly to energy and power tariff components is shown in Figure 24d. Both HET and HPT tariffs are 50% lower than FET and PT while maintaining the same relative differences shown in FET and PT across scenarios.



(a) (b)

(c) (d)

Figure 24. Cost-reflective tariff for each scenario based on the different tariff structures: (a) FET and VT of FVT, (b) ToU, (c) PT, (d) HT.

4.4.3. Monthly bill

The monthly electricity bills of different users, presented in Table 13, exhibit significant variations based on the type of tariff structure used to calculate cost-reflective tariff and load composition, particularly noticeable when compared to the commonly employed tariff structure, FET. Lower monthly bills for users (HH-1, HH-2, HH-3, CH, SCH, and WP) are shown in scenario 22, where a low cost-reflective tariff is yielded compared to scenario 21 and scenario 23. The average reductions for all users shown in scenario 22 are between 12% and 33% when compared to in scenario 21 and between 10% to 27% when compared to in scenario 23, with the lowest and highest reduction in FV and PT structures, respectively. Yet, productive uses and community loads show monthly bill reductions from similar tariff structures in different load composition scenarios, but not for households, as shown in Table 13. Productive use and community loads show significant reductions in monthly bills under FVT and PT and, respectively. FVT reduces the monthly bill of users having higher consumption in the system, reducing productive uses' bills by over 17% compared to FET. PT shows a bill reduction of over 75% for CH and over 40% for SCH compared to FET. However, productive uses bills under PT are more than 100% higher compared to those under FVT.

On the other hand, the extent of reduction and the tariff structure that leads to reduced bills varies across different household usage levels and load compositions. Table 13 shows that PT tariff structures lead to lower monthly bills than other tariff structures for household users in scenario 22, showing reductions of 14% or more compared to FET. Whereas in scenario 21 and scenario 23, the ToU tariff shows a reduced bill for HH-1 (reducing 25% or more compared to FET), while FET shows a reduced bill for HH-2 (5% bill reduction compared to FV and ToU). Additionally, the monthly bill for HH-1 under ToU tariffs shows a reduction, although it is slightly higher than PT. However, FV tariffs significantly increase monthly bills for low-usage users like HH-1 and CH, by more than 8 and 2 times, respectively, compared to FET in all scenarios. HH-3 exhibits a reduction in monthly bills under different tariff structures in scenario 21 (under FVT) and scenario 23 (under PT), resulting in reductions of 15% or more when compared to FET.

The calculated monthly electricity bill using FET in all scenarios is lower than the implied tariff. However, the monthly bill for HH-1 in scenario 22 is 69 times higher than the amount calculated under the old tariff in Ethiopia, and 28 times higher compared to the amount under the new tariff (see Appendix E for the old and new electricity tariffs in Ethiopia and Appendix F for the monthly bills of users based on these tariffs). This difference is more pronounced in scenario 21 and scenario 23, with increases of 6% and 5%, respectively. While CH follows the same pattern as HH-1, other households, as well as productive uses and community loads, show monthly bills 5 to 11 times higher compared to those calculated using the new tariff in Ethiopia.

The variations in load composition significantly affect total revenue collection, even when using old and new tariffs in Ethiopia, with scenario 22 generating the highest revenue compared to scenario 21 and scenario 23. The total monthly revenue of the mini-grid calculated using the cost-reflective tariff is higher compared to when it is calculated with the electricity tariff in Ethiopia (see Appendix G). Specifically, the total monthly revenue under the cost-reflective tariff is significantly 21, 16, and 20 times higher for scenario 21, scenario 22, and scenario 23, respectively, compared to the old tariff, but this reduces to 12, 9, and 11 times under the new tariff.

Table 14. Monthly bills for each user, calculated based on the cost-reflective tariff in different tariff structures for each scenario. Colour coding indicates the cost level: the highest costs are shown in red and the lowest costs in green within each user and scenario.

Scenarios	Types of users	Monthly bill ($)				
		Tariff structures				
		FET	FVT	ToU	PT	HB
S-1	HH-1	0.98	8.34	0.73	0.81	0.90
	HH-2	25.68	26.87	27.47	27.71	26.70
	HH-3	79.18	66.99	68.70	69.57	74.37
	CH	7.85	13.49	6.19	1.97	4.91
	SCH	171.99	136.60	178.72	103.30	137.65
	WP	113.34	92.61	142.05	265.04	189.19
S-2	HH-1	0.82	8.04	0.57	0.54	0.68
	HH-2	21.39	23.47	21.34	18.49	19.94
	HH-3	65.94	56.88	53.37	46.41	56.17
	CH	6.54	12.33	4.81	1.31	3.93
	SCH	143.23	114.85	138.83	68.92	106.07
	WP	94.39	78.22	110.35	176.82	135.60
	WS	189.82	149.79	252.59	380.59	285.21
S-3	HH-1	0.95	8.30	0.69	0.75	0.85
	HH-2	25.02	26.35	26.62	25.44	25.23
	HH-3	77.14	65.44	65.35	63.86	70.50
	CH	7.65	13.32	5.83	1.81	4.73
	SCH	167.55	133.25	172.77	94.83	131.19
	WP	110.42	90.40	139.22	243.30	176.86
	M	157.23	125.51	217.08	479.27	318.25

🟥 High

🟩 Low

The monthly distribution of RR among households, productive uses, and community loads is shown in Figure 25. Different tariff structures impact the total RR collected from these load types. In scenario 22 and scenario 23, where there are more productive uses, ToU, and PT tariffs reduce households bills and shift RR collection to productive uses, by reducing the households share by 5% and 17% in scenario 22, and by 2% and 7% in scenario 23 compared to FET. The HB tariff structure also shifts more RR to productive uses, reducing the households share by 8% in scenario 22 and 3% in scenario 23. Conversely, FV relatively reduces the RR share from productive uses.

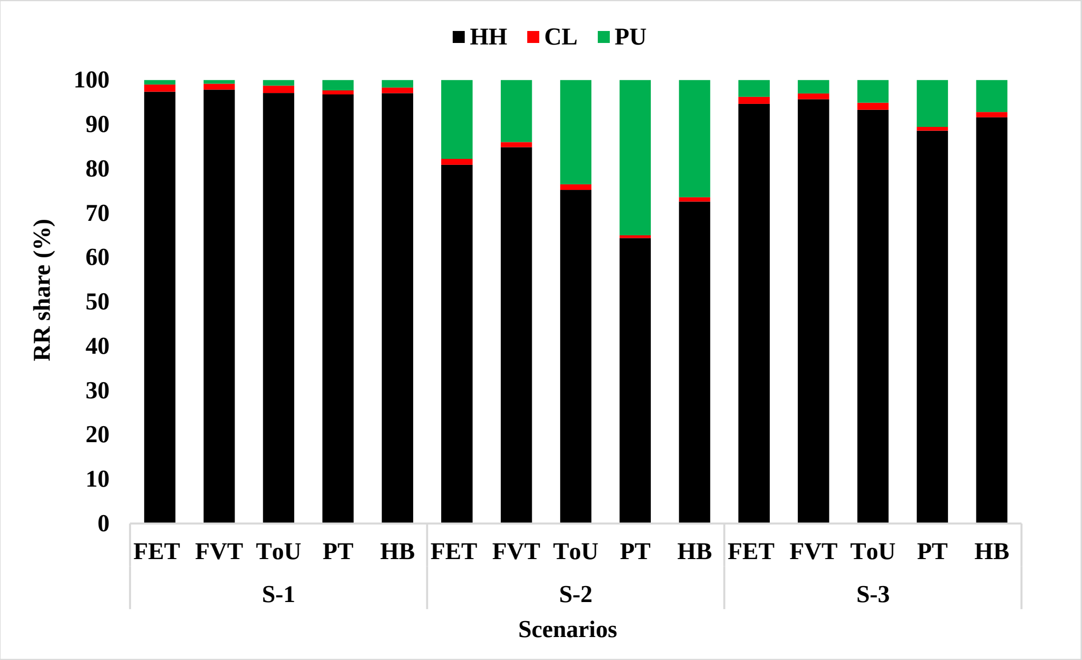


Figure 25. Percentage shares of revenue from household, productive use and community load from the total revenue, under the different tariff structures for each scenario.

5. Discussion

This chapter discusses the results and analysis of the thesis, by interpreting the findings, comparing them with existing literature, exploring their implications, and addressing the limitations

5.1. Interviews- and measurements-based electric load estimation

This study conducts comparative analysis of interviews- and measurements-based methods for electric load estimation and examines their effects on the sizing and cost of mini-grid components. The comparison of the interview- and measurement-based methods was examined in both the total and load categories of the load profile. The impact of the load estimation method difference on the sizing and cost of mini-grid were studied using the weekly load profile and PSO algorithm. In previous studies, the two methods were compared in estimating the total load profile, and the impact on mini-grid component sizing and cost was analyzed using the average daily load and a worst-case scenario. In addition, the impact of using hourly resolution load profile estimation on mini-grid sizing and cost is examined. This was done using a case village in a rural area of Ethiopia.

The findings show that using the interview- based electric load estimation can underestimate the peak load, energy per day and cost, which can have a significant impact on investment decisions. However, interview-based load estimation can overestimate the load factor because of underestimation of peak load. This can have impact in income estimation since the higher load factor implies higher mini-grid income [29].

Among the load categories, a significant difference between the methods is shown for household demands due to peak load underestimation of the load profile of appliances with high power ratings and cyclic operation in households. The study also indicates that while the main difference is indeed in the household, the specific appliance or type of usage that causes this difference also plays a significant role. According to the findings of this study, the main difference in electricity demand estimation arises from cooking appliances used within the communities, specifically from mitad. This implies that improvements of interview assessments of appliances with high power ratings and cyclic operation, and time change (e.g., load shifting in cooking, particularly mitad) could have a significant impact on the outcome and would be required when these types of assessments are used. This also implies that in particular mini-grid modeling of systems dominated by household users' needs to pay attention to this.

The responsibility factor difference of load categories between the methods is modest but higher in the community load. This indicates that, in planning and operation of mini-grids, matching the required demand and supply by implementing demand side management for instance should consider the difference that can be expected in load estimation methods.

The result of this study indicates that the main difference between interviews- and measurements-based methods for electric load estimation is cooking appliances. The type of cooking used varies from one area to another because of consumer behavior, socio-economic factors, time considerations, environmental factors, and technological differences. This highlights that the consideration of electricity demand in relation to religion or cultural behavior, as well as the socio-economic aspects, is of paramount importance prior to initiating data collection. Additionally, it is essential to emphasize appliances with high power ratings and cyclic operation that are unique to the area, rather than focusing solely on commonly found appliances in other areas when estimating load profiles based on data from an electrified area with a similar socio-economic and geographical context.

The interview and measurement assessments in per hour resolution show different impact on mini-grid sizing and cost than the per minute measurement. High-resolution per minute load profiles reveal peak loads not captured in low resolutions. These peak loads are often missed in interviews and underestimated when converting per minute load profile to per hour. Consequently, mini-grid sizing based on hourly data underestimates the battery energy storage system size, leading to different cost estimations. This highlights that using hourly-resolution data can underestimate the size and cost of technologies needed to meet peak loads. Therefore, understanding how load profile estimation methods and resolutions impact mini-grid sizing and total present cost is crucial. This knowledge helps mini-grid operators assess the risks of interview-based methods and supports them in considering the costs and benefits of conducting detailed load estimations [60].

5.2. Advantages of a multi-year-adaptive design approach

This study explores and quantifies the advantages of the multi-year-adaptive approach on long-term mini-grid component sizing and associated costs under different demand growth scenarios. The study also evaluates the impact of load flexibility, varying discount rates, and potential future mini-grid component cost reductions across single-year, multi-year, and multi-year-adaptive design approaches. By examining these, this study adds to the understanding of how the multi-year-adaptive design approach can be further developed to improve mini-grid component sizing and cost efficiency while handling long-term uncertainties.

The multi-year-adaptive approach results in lower component sizes, leading to total present cost reductions compared to the multi-year and single-year approaches, in line with results of previous studies showing that adaptive designs yield greater cost savings than the multi-year and single-year approaches [34,35,84,86]. The result of the solar PV/BESS ratio (0.15 to 0.2kW/kWh) also aligns with an earlier study that reported a ratio of 0.12 to 0.19 [86] while a study on eleven operational mini-grids run by private investors showed a considerably higher ratio of 0.56kW/kWh [129]. The solar PV/BESS ratio reflects robustness, indicating the system's ability to operate normally without significant performance degradation despite disturbances, uncertainties, and changes in demand, inputs, and energy resource conditions, and enhancing the reliability of the mini-grid [82]. The calculated LCOE also aligns with previous studies, reporting values for solar PV-based mini-grids just above 0.25 to 0.61$/kWh [84,130].

The demand-supply energy matching constraint ensures that the load is fully met at all times, since load curtailment is not considered in this study. This often increases system size and cost, as components must be scaled to handle peak demand and lower generation. Additionally, the SOC constraints for the BESS, which limits its operation between minimum and maximum SOC levels, affect BESS sizing by requiring larger capacities to provide adequate usable energy while ensuring safe operational limits. These constraints are intermittently binding; SOC_{min} binds during peak demand periods, while SOC_{max} binds during high energy generation periods. Therefore, these constraints impact overall system sizing and cost [82].

The development of mini-grids involves various stages, each influencing the type and amount of investment required. The earlier the stage, the riskier the project [131]. The multi-year-adaptive design approach provides additional investment decision options, either at the component or system level, unlike the multi-year and single-year approaches requiring decisions at the outset. This postponement of additional investment decisions allows for considerations of both present and future component costs and the potential national grid connection in subsequent stages [23].

The final-year demand consideration in SY led to overcapacity and underutilization early on, creating economic inefficiency and financing challenges. The perfect foresight demand evolution requirement is challenging in MY due to the difficulty of predicting the future.

Conversely, while SY remains the prevailing real-world investment strategy, MYAD offers certain advantages. However, MY remains a valuable benchmark, as evidenced by previous research such as [34,35,82–84].

The postponement of additional component installations will not only lower the upfront cost but also further decrease the overall total cost. This cost-saving further increases with the application of load flexibility, a high discount rate, and future component cost reductions. The cost savings achieved by postponing additional investment decisions in multi-year-adaptive approach highlight that it also minimizes the cost of the expansion strategy by implementing the expansion in multiple stages rather than all at once. It also enables the utilization of historical demand growth knowledge, which can help in later investment decisions and reduce uncertainties related to load estimation and forecasting [35]. However, the cost savings in MYAD, rather than all at once in SY and MY, can be impacted by economies of scale, which were not explicitly modeled in this study. These could influence investment decisions by favoring larger initial capacity installations in SY and MY compared to MYAD.

The multi-year-adaptive approach shortens the load forecasting time horizon for mini-grid sizing compared to multi-year approach. In our case, the forecasting period is reduced by a factor of five-to-five years, from twenty-five years to five years. This highlights that multi-year-adaptive approach will help to deal with future demand uncertainties in long-term mini-grid sizing. On the other hand, while the MYAD approach splits the full planning horizon into five-year periods for adaptability, the approach is not fully decoupled. Each stage builds upon the previous one by carrying over installed capacities and operational constraints (operation and maintenance and replacement). This ensures continuity and allows the model to account for long-term impacts, thereby reducing the risk of suboptimal mini-grid designs.

Compared to stochastically optimal system sizing, which provides a static system size with sufficient operational flexibility to account for variability and uncertainties in future demand by considering multiple random potential future demand scenarios [84], the multi-year-adaptive approach dynamically updates plans as circumstances involve. For instance, if demand development follows scenario 11 for the first five years but then shifts to scenario 12 or 13, the multi-year-adaptive approach allows plan updates based on the evolved demand in scenario 12 or 13. However, it remains flexible and does not strictly adhere to the demand trajectory of scenario 12 or 13, allowing for further updates as conditions change in subsequent periods. This highlights that the MYAD approach reduces the impact of unforeseen demand spikes or drops, thus reducing reliance on future assumptions. Additionally, by reducing reliance on static mini-grid design in stochastic system sizing, the MYAD approach offers a practical and flexible way to address future long-term demand uncertainty and ensures more robust system sizing decisions over time.

Timely component additions are essential for system reliability and economics since they reduce the mismatch between demand and supply, enhance power availability, and decrease system costs. However, the time interval for adding components over the planning horizon must exceed the lead time (the time between the initiation and completion of the process) [132]. From this perspective, the multi-year-adaptive approach is more flexible than both the multi-year and single-year approaches. This highlights how the multi-year-adaptive approach can greatly increase the sustainability and scalability of mini-grids in rural areas by lowering financial risks, optimizing resource allocation, and minimizing the possibility of oversized or underutilized systems. It is also more realistic compared to the adaptive approach, which adds additional mini-grid components every year, which certainly is challenging to implement in rural areas. This indicates that the decision on when to add additional mini-grid components should be based on different criteria (cost, reliability, environment, and social considerations, etc.), of which many depend on the local context.

The multi-year-adaptive approach leads to significant cost savings in scenarios with higher demand growth, which is highly likely in rural villages [28,41]. For villages with slower demand growth, there is a smaller total present cost share in later years, resulting in less cost savings compared to a village with higher demand growth (could be corresponding to a larger village along a road, villages closer to urban areas, etc.). This highlights that the multi-year-adaptive approach, offering more flexibility than the multi-year and single-year approaches, seems to be a more economical and favorable choice, especially at higher demand growth. Additionally, villages with higher demand growth can increase the cost-efficiency of the system if the growth is from productive load categories [82].

Initial up-front costs are a major obstacle for mini-grid investment, especially in rural areas with limited access to financial tools and banking services [85]. Thus, total cost constraints in rural areas are limiting wider access to basic electricity. This stresses the importance of the multi-year-adaptive initial investment cost reduction enabling available financial resources to be used for basic access also at other sites instead of for oversized systems in a few villages. Moreover, this reduction in initial investment costs provides opportunities to secure additional funding for subsequent investments [86]. This shows how crucial decisions regarding initial investments are, as they serve as a foundation for all subsequent investments in the system.

Operation and maintenance costs increase based on the actual capacity installed and used in any given year [84]. In the multi-year-adaptive approach, increasing capacity based on demand growth will lead to reduced replacement, and operation and maintenance costs. The postponement of additional component installations, particularly battery energy storage, contributes to reduced system costs and possibly also environmental impacts. The reduction in operation and maintenance costs can have a significant impact, especially on technologies with higher operation and maintenance costs. Additionally, the development of a system with demand growth helps operators to acquire technical skills (especially in smart systems) gradually [23] for rural mini-grids in SSA having a lack of skilled personnel [39].

Mini-grids are established in order to provide electricity for the rural population in their service area while balancing customer satisfaction and financial viability [60]. Cost savings increase with the application of load flexibility in the multi-year-adaptive approach compared to the multi-year and single-year approaches. These results highlight that the load flexibility application in the multi-year-adaptive approach enhances techno-economic benefits by reducing uncertainties and costs compared to the multi-year and single-year approaches. However, the implementation of load flexibility needs continuous commitment from users and may have lower social acceptance. Additionally, implementation through customer incentives-based DSM incurs additional costs related to control and communication systems. However, expenses can be reduced by implementing DSM at the load categories rather than at the appliance level [41].

The multi-year-adaptive approach cost savings will be larger in contexts with higher general risk considerations and higher discount rates as in many developing countries, even if major differences also occur between countries that are comparable with respect to their state of economic development [133]. The cost savings shown between the design approaches, because of the discount rate, highlight the significance of the multi-year-adaptive approach is more in the context of developing countries.

The cost savings from multi-year-adaptive approach also increase with future component cost reductions (both market-driven and those resulting from supportive policies and incentives). This highlights the advantage of the multi-year-adaptive approach not only in the planning phase but also during system operation. For instance, if subsidies or regulatory changes are introduced after system installation, leading to lower component costs, the multi-year-adaptive approach would allow developers to benefit from these reductions by incorporating them into future stages of the project. This emphasizes the advantage of the multi-year-adaptive approach in minimizing the risks associated with future cost fluctuations and highlights its suitability for environments where future cost reductions or regulations changes are uncertain, offering a more risk-averse strategy for mini-grid development.

The multi-year-adaptive approach requires more frequent sizing and field visits to upgrade capacity, which can be challenging for mini-grids facing issues such as limited infrastructure (like rugged landscapes and dense forests) or lack of transportation. Additionally, harsh weather conditions, security concerns (including conflict in the area), limited or unreliable communication, and resource constraints can limit the applicability of the approach. On the other hand, mini-grid settings with fewer such challenges are more likely to successfully implement this approach, although they may still incur some costs [125], but these are certainly less in many cases than the potentially huge cost savings.

Component degradation both affects the performance of a mini-grid system and increases its system costs [82]. Charge and discharge cycles also influence battery replacement costs [84]. This study does not take this influence into account but its effect would be smaller for MYAD compared to SY and MY due to lower initial and total capacity.

Measured electricity load data, representing realistic load data, were used to represent the initial year demand. The use of a one-week load profile to represent a full one-year load profile introduces a simplification, especially in regions with marked seasonal demand variations. However, this should not have much effect in Ethiopia since seasonal demand variations are modest due to minimal weather fluctuations throughout the year and no marked seasonally dependent changes of social behaviors.

Furthermore, the study is based on data from a specific case study area. The demand in this area has a high morning peak due to the mitad use for bread (injera) baking. This is typical for Ethiopia, but such a high morning peak is otherwise less common. The high morning peak results in a low solar PV/BESS ratio, as would any high demand peak do, especially high demands outside of the PV generation time. Higher electricity demands during early mornings and evenings are more likely in areas dominated by residential demands and in villages where a large population shares work in agriculture (individuals spend the majority of daytime on farming activities) [29]. However, the main findings of the study, particularly the significant reduction in initial and overall components leading to initial and overall cost reductions and helping in addressing uncertainties about future demand by the MYAD approach, should be valid in most developing contexts.

5.3. DSM implementation at the category level and the cost-efficiency of mini-grids

The impacts of DSM implementation using a load-shifting strategy on the cost-efficiency of off-grid mini-grids in non-electrified rural areas were determined. DSM analyses have often been implemented on small systems in developed countries. However, this study focuses on the mini-grids in rural areas of developing countries rather than in developed countries, broadening the geographic focus area of DSM. The impact of DSM implementation was determined at the category level rather than at the appliance level for four load categories: household loads (C-1), community loads (C-2), productive uses with nighttime loads (C-3), and productive uses without nighttime loads (C-4), each with different load profiles. While each individual appliance must be operated within the load categories, it is unrealistic that a utility would individually control end uses, which are typically aggregated by demand response service providers. For this reason, individual appliance impacts are aggregated into categories without losing appliance-level constraint fidelity [103]. This examination of DSM implementation at the category level regarding the cost-efficiency of mini-grids provides insights into the system-wide impacts of each load category on the techno-economics of mini-grids, rather than focusing on the appliance level.

The component sizing was carried out for each combination of the four load categories using a PSO algorithm. Load-side and supply-side uncertainties were also considered, but not their development with time. The applied load-shifting strategy was conducted in a priority-based fashion, with Configuration 1 supplying high-priority loads at the scheduled time and low-priority loads only when there is sufficient power generation from solar PV and the BESS is full. In Configuration 2, the high-priority loads were supplied using the DG when neither solar PV generation nor BESS was sufficient.

In contrast to the day-ahead DSM strategy, which has been studied to determine the optimal time when low-priority loads can be curtailed for higher levels of user satisfaction [43], the load-shifting strategy applied in this study does not include load curtailment, thus increasing system reliability. However, the results of the study are in line with those of previous studies [92–95], regarding how the cost-efficiency of mini-grids is impacted by a priority-based shifting strategy.

The result reveals that the cost-effectiveness of rural mini-grids depends on the load category mix considered when DSM is implemented. Among the load categories, the productive use category, C-3, with a night-time load, has a greater impact on the cost-efficiency of mini-grids than C-4, without a night-time load. This emphasizes that productive loads can increase the cost-efficiency of mini-grids, but not all productive loads have equal impact. The impact of DSM implementation in C-1, reducing the size of off-grid mini-grid components and the LCOE, will likely become more important due to the increase in household connections in rural areas [43]. C-3, while having a weaker impact than C-1, has the capacity to increase the load factor of the mini-grid and improve its cost-efficiency [58]. However, balancing different load categories is crucial for creating a cost-efficient mini-grid in rural areas [107].

The variation in LCOE reduction observed for the different categories indicates that different DSM strategies (such as demand response), based on category level, can have a different impact on system operation. However, system operators can choose a type of DSM implementation that reflects their own perspectives. Importantly, depending on the ownership and business model of the mini-grid, the relationship between the utility and its customers may differ significantly, including in relation to the priority given to the load categories [134].

In a mini-grid framework, DSM implementation can be achieved through mechanisms such as time-of-use electricity tariffs. These tariffs allow the control of each load category based on its load profiles by applying different electricity rates at various times of the day. This pricing signal encourages users to shift non-essential loads to off-peak periods. Implementing this may require a smart metering infrastructure at the user level rather than at the appliance level. However, the effectiveness of this DSM implementation and the degree of user responsiveness to pricing signals or control commands can significantly impact the reliability and overall efficiency of the DSM strategy. Uncertainties related to customer behavior and participation can influence the operational and economic performance of the mini-grid.

DSM implementation at the category level offers advantages over the appliance level, such as reduced infrastructure and fewer operational and maintenance challenges. Rural mini-grids require communication infrastructure and distributed smart meters for electricity usage control, but this approach reduces system complexity as the number of users increases. Additionally, category-level DSM implementation is less affected by load estimation uncertainties.

Considering the order of impact among the load categories in terms of creating a cost-efficient mini-grid, C-1, the household category, is the most significant followed by C-3, the productive use category, followed by C-2 and C-4. Due to their load profiles, the capacity of DSM implementation in C-1 and C-3 to reduce the LCOE is almost equal to the impacts achieved by 55% and 25%, and 58% and 26% load flexibility for solar PV-based and HRES-based off-grid mini-grids, respectively. C-1 and C-3 are the main contributors to the night-time peak demand when there is no solar PV power production and, thus, more BESS is required to ensure supply. C-2 and C-4, on the other hand, have peak demand during the daytime, when there is higher solar PV power production. However, C-2 + C-4 have a higher peak and energy demand than C-2 and C-4, resulting in a lower LCOE than C-2 and C-4, but higher than C-1 and C-3. Thus, the implementation of a load-shifting strategy in these categories would have a weaker impact on reducing the BESS size and, therefore, a weaker impact on the LCOE.

DSM implementation in C-1, C-3, C-4, and C-2 enhances the cost-competitiveness of solar PV-based, 100% RES-based off-grid mini-grids by reducing the BESS and solar PV size. This contributes to decarbonization in the energy sector. Policy should encourage DSM implementation in C-1 and C-3 for rural area electrification using 100% RES-based mini-grids. However, DSM implementation requires reduced user consumption, such as reduced lighting in C-1 and decreased consumption from low-priority loads like TVs, refrigerators, radios, mobile charging, and other entertainment appliances in C-3.

Household consumers, which have a higher impact, in rural areas are characterized by low demand and they are likely to resist shifting the load of certain appliances, such as lighting. However, there are appliances that consume a significant amount of energy and have high peak power demands, such as cooking appliances. The results of this study indicate that shifting either 100% or 50% of the morning peak load consumption to midday hours can reduce the total present cost of the mini-grid. For instance, in the case of Ethiopia, where injera, a commonly consumed food that requires high energy consumption, is only baked four to five times per week, there exists the potential to shift the usage of electric mitad and/or stoves to mid-day. However, failure to implement such a shift result in challenges and peaks being added to the system, which are attributed to economic growth, increased demand for new electric appliances, and the growth of village size. This, in turn, leads to a greater need for distribution cables and transformers to accommodate the morning peak loads. The impact becomes even more pronounced when more households are connected to the mini-grid. Consequently, there is a heightened risk of surpassing the maximum power capabilities of the local distribution transformer when a large number of cooking appliances or appliances with high power ratings and cyclic operations are connected [135].

On the other hand, even if in the case area of this study the productive use, agricultural loads are low but their operation is much more flexible than that of other productive users [103]. The implications of this additional flexibility from agricultural loads, which are more likely in rural areas, are significant in the cost-efficiency of mini-grids.

5.4. Load composition, revenue and monthly bill

5.4.1. Load composition and revenue

The impact of the load composition is crucial for increasing the economic viability of the small off-grid mini-grids. Revenue can be increased, which could be used to financially promote a transition to the optimum composition based on methods proposed in [10], generating systematic knowledge on different options for configuring and managing mini-grids. More productive use will not only lead to more a sound financial situation for the grid operator but also generate income for the area [16].

Optimizing load composition is a key action that can improve financial revenues in off-grid RES-based mini-grids. This can be implemented as part of a smart management strategy and combined with demand-side management or even load frequency control. There is significant potential value in demand-side management in renewable-based systems, as shown in [136] for wind power.

Although the focus of this study has been on economic benefits, there are also environmental benefits. Power sources with low running costs are often renewables with a lower environmental impact. Avoiding over-capacity also has less negative environmental impact, reducing impacts from manufacturing, transport, and waste handling.

5.4.2. Load composition and monthly bill

To determine the impact of load composition on the monthly bill of users, an installed solar PV-based mini-grid designed with a larger capacity to deal with future demand uncertainties was used. The cost-reflective tariff necessary to recover the required revenue to cover the total present cost of the mini-grid was determined for five commonly used tariff structures: fixed energy tariff, fixed and variable tariff, time-of-use tariff, power tariff, and hybrid tariff combining both energy and power tariffs.

The fixed energy tariff is commonly known as a flat-rate tariff or simple energy tariff, widely used for residential and small-scale users due to its simplicity. The fixed and variable tariff, also referred to as a two-part tariff, combines a customer charge (fixed) with an energy charge (variable). The time-of-use tariff, known as time-based pricing or dynamic pricing, is popular in advanced grids to encourage demand-side management. The power tariff is commonly recognized as a demand charge or capacity tariff, typically applied to industrial and large commercial users. Finally, the hybrid tariff integrates energy and demand charges and is known as a combined energy and demand tariff, balancing costs and incentives for energy consumption and peak demand management [137].

This analysis takes into account anticipated future load growth and calculates tariffs based on demand-side profiles, under the premise that revenue generated from electricity sales must completely cover the investment costs of the mini-grid. Given that the supply side is constrained by the pre-installed infrastructure and the associated investment, the cost-reflective tariff is established using various tariff structures that accommodate uncertainties in future demand. These calculations examine different potential load growth scenarios, emphasizing the expected mix of load categories, specifically households and productive users (load composition), that are predicted to drive demand growth, while simultaneously addressing the uncertainties inherent in demand development.

The results indicate that the future load composition of a mini-grid can significantly impact the monthly bill of users that depends on cost-reflective tariffs. The cost-reflective tariff is lower for load compositions consisting of more daily productive use compared to more household and non-daily productive use. However, the magnitude of this difference depends on the tariff structure used to calculate the cost-reflective tariff. Specifically, it is more significant with power-based tariffs (33% and 27%) than with energy-based tariffs (17% and 15%), highlighting the significant impact of the peak load sum of users compared to aggregate energy usage in the system. The time-of-use and hybrid tariff structures show differences that fall between energy and power-based tariffs. Additionally, the fixed tariff component of the fixed and variable tariff structure, dependent on the number of users, shows a modest (2%) reduction by the future mini-grid load composition.

The low cost-reflective tariff for the future mini-grid load composition that consists of more daily productive use, 0.351$/kWh, is more than 11 times higher than the old average price of 0.03$/kWh paid by household users in Ethiopia. Following a tariff reform starting on September 11, 2024, which raises the average price to 0.07$/kWh through quarterly price adjustments and the largest increase in four years, the tariff of the future load composition that consists of more daily productive use remains more than 4 times higher [138]. This difference between the electricity tariff in Ethiopia and calculated cost-reflective tariff indicates that the revenues generated from electricity sales under both the existing and newly revised tariff structures in Ethiopia are insufficient to recover the investment costs of mini-grid projects. Furthermore, the findings suggest that achieving economic viability for off-grid mini-grids in Ethiopia will require additional measures. These include promoting daily productive uses of electricity (to increase demand and revenue) and implementing appropriate incentive mechanisms and tariff restructuring. Such measures are particularly important for private mini-grid developers, who face significant disincentives under the current low tariff rates, making it difficult for them to achieve sustainable operations and attract further investment [82].

The new tariff shows a higher rate in Ethiopian birr (ETB) compared to the old tariff, but the new tariff becomes higher than the old tariff by the final quarter of 2025/26. This is due to Ethiopia's recent shift to a market-driven floating exchange rate, which led to an exchange rate increase of around 55%, from 53 to 123.6 ETB/USD, based on the commercial bank exchange rate on 28/09/2024 [139]. This highlights the importance of regularly evaluating tariff structures and exchange rates to ensure the long-term viability and financial sustainability of mini-grid systems within dynamic economic contexts.

The calculated bill for low-usage households is low in all scenarios except under the fixed and variable tariff structure compared to the average monthly bill of 257 birr ($4.5) and the median of 179 birr ($3.1) for households in urban Ethiopia [59]. Conversely, the bill for medium and high-usage households is high. Additionally, the future mini-grid load composition also shows an impact on the revenue of the system, even with old and new electricity tariffs in Ethiopia, which are based on block tariffs, highlighting that the impact of load composition is also present in the block tariff structure. This result also highlights that in countries such as Ethiopia, which mandates mini-grid tariff reviews every four years [53], the importance of considering the impacts of future mini-grid load composition and tariff structures during tariff revisions as a key factor alongside other factors.

The load composition in rural areas of SSA is more likely dominated by households [140]. The result of this study highlights that a system with a higher proportion of households, especially during the initial lifespan of the system, limits the connection of new demand growth from households and non-daily productive use, compared to daily productive use, resulting in a low cost-reflective tariff. In this regard, using time-of-use tariffs can encourage demand growth in the system, especially in a system with a fixed capacity. Demand growth can be achieved through time-of-use tariffs, for instance, by incentivizing electric mills to operate during peak solar hours rather than operating during morning hours. This timing benefits them as they often use sunlight to dry their products, resulting in higher-quality, drier flour [16] and allow to connect new users to the system. Additionally, using water pumps for irrigation and millers during harvesting time can increase demand growth per year rather than using just one of them. This demand growth can lead to reduced tariffs and help address challenges posed by high rates, such as the limited ability of rural populations to afford electricity [55] [82]. However, the implementation of time-of-use tariffs requires advanced metering technology, which may increase the required revenue and cost-reflective tariff, which can affect residential electricity consumers based on their income and availability [141].

The result of this study shows that the impact of future mini-grid load composition may significantly impact users' monthly bills, potentially affecting profitability, but the effect varies depending on the tariff structure used. In evaluating the sensitivity of the different tariff structures for users, the analysis highlights notable impacts on the monthly bill of users, where the impact varies based on the type of load categories. Among the tariff structures, the power tariff can reduce monthly bills for community load categories by more than 40%, but it increases bills for productive use by over 100% compared to the fixed energy tariff. In the load composition entirely consisting of households, high-usage households behave similarly to productive uses, resulting in low monthly bills under fixed and variable tariff structures. On the other hand, in load compositions with more household and non-daily productive use, lower and medium-usage households experience reduced bills under time-of-use and fixed energy tariff structures, respectively. Notably, the relative reduction in monthly bills is more pronounced for lower usage households (more than eight times under fixed and variable compared to fixed energy tariff structure), highlighting the importance of selecting appropriate tariff structures based on usage levels. Additionally, these higher reductions in monthly bills by time-of-use tariff for households highlight the significance of implementing demand-side management for lower and medium-usage households. Furthermore, the result also highlights that power tariffs can be less advantageous for productive uses and high-usage households. However, power tariffs can provide more stable revenue and better cost recovery, even if users reduce energy consumption, particularly in systems with more non-daily productive uses [141].

Most SSA countries recognize cross-subsidies that can be integrated into the tariffs of mini-grids [53]. The difference shown in monthly electricity bills and the percentage shares of collected required revenue per month suggests that certain tariff structures can incentivize specific users while penalizing others. Consequently, the impact of load composition may lead to the need for additional subsidies or incentives if they are not properly accounted for. This highlights the importance of considering the potential scale of subsidies or other grants required to facilitate mini-grid development within existing regulatory frameworks, taking into account the effect of the mini-grid load composition and the different tariff structures.

To support private mini-grid operators facing challenges from low domestic utility tariffs that hinder cost recovery, technology-specific feed-in tariffs play a vital role[142]. In countries with feed-in tariffs, such as Kenya, mini-grid operators receive a fixed price for every unit of energy generated but sell energy to users at a different, often lower price compared to they received [143]. In this regard, the result of this study shows that mini-grids with more daily productive uses have financial advantages, depending on the tariff structure, compared to those with mainly household and non-daily productive loads. Furthermore, the differences in collected required revenue among the three load categories highlight that the impact of load composition can lead to high monthly bills for households and impose substantial fiscal burdens on governments providing subsidies for households if the impact is not taken into account.

The findings also indicate that mini-grid developers should select sites in rural communities with existing economic activity or with productive use loads. To enhance revenue, some developers have adapted their business models by adjusting tariff structures and encouraging productive use loads. For instance, through appliance financing. However, this study highlights the importance of a comprehensive approach when selecting mini-grid sites and business models that consider the impact of load composition. Additionally, it is crucial to evaluate used business models that stimulate demand by considering the resulting future load composition. This evaluation is essential for ensuring the mini-grid's long-term sustainability, effectively meeting the community's energy needs, and maintaining reasonable tariffs while securing a viable return on investment.

In the study, an installed solar PV-based mini-grid designed with spare capacity to allow for future demand growth was used. The study develops load composition scenarios based on various categories, rather than focusing on specific appliances. This approach provides more generalizable insights instead of solely focusing on a specific type of appliance or equipment load. Additionally, using a fixed-capacity mini-grid allows to observe the impact while maintaining a constant total present cost, despite uncertainties in load composition. However, the case study area used in this study, characterized by a high morning peak due to mitad use for injera baking, a common practice in Ethiopia, limits the capacity for connecting additional daily and non-daily productive uses. Despite this, the findings, particularly regarding the impact of future mini-grid load composition on users' monthly electricity bills, are likely applicable to many developing countries contexts.

Further significant policy implications can be drawn from the findings of the study. First, governments often implement policies to expand access to services for low-income households. In this regard, during tariff setting and revisions, it is crucial to pay particular attention to low-usage households, as they are significantly affected by the future mini-grid load composition. Therefore, it is important to consider the impact of load composition uncertainty in mini-grids, both pre-and post-electrification, when making tariff decisions and revisions to ensure fair and affordable pricing among users and to implement time use of tariffs to protect low-usage households while maintaining profitability for investors.

Second, considering the impact of future mini-grid load composition is critical for effective subsidies. Therefore, when formulating policies to support specific types of appliances and load categories, it would be case-specific for effective subsidization. This approach encourages private actors and ensures the long-term sustainability of the mini-grid.

Third, while the productive use of electricity reduces the cost-reflective tariff, the extent of this reduction varies depending on the type of productive use. Therefore, when designing tariffs and financial models, it is crucial to consider both the type and extent of daily and non-daily productive uses.

6. Reflections on the selected method and data

As pointed in the problem statement of the thesis one of the main challenges that hinder rural electrification using mini-grids is economic viability. The methodological approach adopted in this thesis was designed to provide a comprehensive understanding of how demand-side factors influence the economic viability of mini-grids. The study combined empirical data collection, optimization modeling, and scenario analysis to address different aspects of mini-grid planning and operation. While the selected methods effectively captured key insights, certain limitations and areas for improvement are presented in this chapter.

This thesis explores the impact of load profile estimation by comparing interview-based methods with measured load profiles for off-grid mini-grids. While interview-based methods are popular due to their simplicity and practicality in resource-limited rural areas, they often lack accuracy because respondents estimate their future electricity needs, leading to potential inaccuracies. Although this study aims to assess load estimation methods in non-electrified rural areas, it is conducted in electrified communities where residents are already aware of their electricity usage and appliances. In non-electrified areas, interview-based assessments rely on users' expectations of future consumption, making accurate estimates more challenging. The difference shown in this study can be used as the minimum possible error for interview methods in areas without prior electricity, and it highlights the need for methodological improvements. This study proposes a hybrid approach, combining interview-based methods with direct measurement in electrified rural areas with similar socio-economic characteristics. However, it does not specifically evaluate how this approach improves load estimation accuracy in non-electrified areas. This gap presents an opportunity for further research to refine and validate hybrid methods for off-grid energy planning.

The interview-based load profile estimation method used in this study lacks stochastic modeling of appliance usage. This can affect its ability to accurately capture the characteristics of appliances, especially appliances with high power ratings and cyclic operation. Without accounting for the randomness and variability in appliance usage, the interview method may not fully capture electricity consumption patterns and lead to potential inaccuracies in load estimation. However, despite this limitation, comparing interview-based methods and direct measurements without incorporating stochastic modeling offers valuable input for stochastic modeling. The result can be used to enhance the modeling of the stochastic properties of load profiles by basing the modeling of the probability of randomness on real settings rather than assumptions.

The interview-based method used in this study also overlooks the reliance on traditional fuels in the village, such as woody biomass and fossil fuels, for cooking appliances. Since cooking appliances significantly contribute to the difference between interview- and measured-based load profiles, neglecting them in load profile estimation can lead to inaccuracies in future load estimates. However, this study highlights potential solutions to address these challenges. Specifically, it suggests a multi-year-adaptive design approach and implementing demand-side management strategies, such as shifting cooking appliance usage to different hours of the day.

Despite the prevalence of single-year design approaches in mini-grid planning across SSA due to funding and logistical constraints, this study clearly presents the advantages of a multi-year adaptive design approach, presenting it as a potential alternative solution. This design approach is essential for dealing with uncertainties in future demand, especially as communities transition to modern energy sources and behaviors evolve. From a long-term planning perspective, the multi-year adaptive design creates a flexible system capable of adjusting to evolving demand, whether due to population growth, technological adoption, or shifts in energy use behaviors.

Long-term mini-grid planning is inherently subject to uncertainties related to load flexibility, discount rates, and potential future cost reductions for mini-grid components. In most existing studies, these uncertainties are addressed as separate phases: mini-grid design focuses on system sizing and operation, while financial modeling assesses economic feasibility. By combining these elements, this study provides a more comprehensive perspective on the uncertainties influencing mini-grid design. However, one limitation remains: political or policy changes impact these uncertainties, which are difficult to quantify, may affect the findings, particularly in highly dynamic regions. Although measured electricity load data was used to represent initial-year demand, the reliance on a one-week load profile to approximate a full year introduces simplifications and remains a limitation, particularly in regions with significant seasonal demand variations. Furthermore, stochastic modeling was not considered during the optimization of the cost and size of the mini-grid based on the utilized design approaches. Instead, to represent potential future demand development, the study used multiple demand growth scenarios.

The impact of demand-side management at the category level, instead of at the appliance level, is determined by using four load categories, with categorization based on grouping similar load profile characteristics. Each load category is defined by distinct load profile patterns. This approach is particularly useful in areas with limited historical consumption data, a common challenge in unelectrified rural regions. However, in areas with more data availability, clustering techniques can be applied to achieve more precise load categorization, enhancing analysis and optimization.

This approach offered methodological insights into how demand-side management implementation can enhance mini-grid economic viability. However, the success of demand-side management depends on the elasticity of demand and the willingness of users to adjust their consumption patterns, which is not explicitly explored in this study. Socio-cultural factors that influence energy use behavior were also not explicitly explored in this study but could offer valuable insights for improving demand-side management implementation. Additionally, while the study examined the potential capacity of different load categories for demand-side management and compared it with load flexibility, it did not quantify the cost-effectiveness of demand-side management at the category level compared to the appliance level, nor did it examine its impact on the long-term lifetime of storage systems.

In mini-grid components modeling, the battery energy storage system was modeled using a state of charge-based approach, without a detailed battery degradation model. While the state of charge framework captures short-term energy availability and operational dynamics, it does not account for long-term performance deterioration from degradation mechanisms such as capacity fade and increased internal resistance. These processes are influenced by several operational factors, including frequent deep cycling, sustained operation at extreme state of charge levels, high charge/discharge rates, and ambient temperature fluctuations [82]. Although integrating a degradation model could enhance the practicality of the simulation, it may also constrain the generalizability of the results, particularly in the comparative assessments of load profile estimation methods and context of demand-side management. However, in the comparative analysis of different mini-grid design approaches, system sizing and cost were evaluated relative to each other rather than across varying load development scenarios. This may obscure the impact of load dynamics on battery degradation.

The analysis of load compositions, revenue and tariff setting provides important insights into the financial sustainability of mini-grids. The findings demonstrate the importance of optimizing the mix of household and productive-use loads to maximize revenue under various tariff structures, addressing a critical challenge in mini-grid economics. However, the study assumes a fixed capacity system and predefined demand growth scenarios based on the two types of productive users, which may not fully capture real-setting in load evolution. Additionally, the study doesn't consider the impact of tariff setting on users' consumption.

In this thesis, PSO algorithm is used to optimize mini-grid component sizing by minimizing system costs under different demand scenarios. One of the key advantages of PSO is its ability to handle complex, multi-dimensional optimization problems while maintaining computational efficiency. Compared to traditional deterministic optimization methods, PSO offers flexibility in searching for global optima without requiring detailed mathematical formulations of the objective function. While the PSO method is validated through iterative methods and previous studies, hybrid PSO variants can achieve better optimization of mini-grid components by enhancing accuracy and efficiency.

Therefore, the novelty of this study lies in its examination of differences between load profile estimation methods across load categories and its evaluation of the impact of electric load estimation methods and load profile resolution on mini-grid sizing and cost estimation. This is achieved by using a more advanced method, the PSO algorithm, compared to the average daily load and worst-case scenario methods used in previous studies. Additionally, it quantifies the advantages of multi-year adaptive design by using measured load data from a real setting and an entirely renewables-based mini-grid. The study includes operating strategies in the optimization of multi-year adaptive design and extends the investigation of design approaches by considering load flexibility, discount rate, and future component cost reduction uncertainties.

The study also presents a smart management strategy aimed at improving load factors by optimizing the composition of household and productive-use loads, enhancing economic viability without the need to increase generation capacity. Furthermore, it introduces a novel methodological approach to demand-side management at the category level rather than the appliance level, leading to cost-efficiency improvements in autonomous mini-grids. Lastly, it presents a methodological approach to determining cost-reflective tariffs based on the demand side and determining the impact of load composition on user bills.

7. Conclusions and future work

7.1. Conclusions

This thesis examines the impact of load profile estimation methods, design approaches, demand-side management, and the load composition of different types of users on the economic viability of rural mini-grids. The findings of this thesis from six separate but inline studies, three journals and three conferences, show the critical role of demand-side factors in the planning, operation, and tariff design of rural mini-grids, which are vital for the economic viability of mini-grids.

The result reveals that commonly used interview-based load profile estimation methods in rural areas significantly underestimate peak load and energy demands compared to measurement methods, leading to substantial underestimation of mini-grid costs. The underestimation is more significant in household load categories than in productive use and community load categories. This is primarily due to cooking appliances in household load categories, which have high power ratings and cyclic operation. The study also found that hourly resolution based electric load estimation can result in different cost estimations compared to per minute, impacting investment decisions. Therefore, improving interview-based assessments for high-power appliances and their cyclic operation is crucial for enhancing load profile estimation in rural areas, particularly for household-dominated communities. Additionally, to improve load estimation, it is essential to identify high-power appliances that are region-specific, such as the mitad in Ethiopia, through a careful examination of consumer behavior.

The findings indicate that a multi-year-adaptive design approach helps to deal with uncertainties about future demand through its adaptive component. Compared to the other multi-year and single-year design approaches studied, it also results in significant mini-grid component size and cost reductions. High-demand growth scenarios, the application of load flexibility, and a high discount rate combined with future component cost reductions further increase the cost savings achieved through the multi-year adaptive approach. Therefore, since investment costs in general and initial up-front costs in particular are major obstacles for mini-grid investments, and high demand growth is to be expected even with uncertainties in its estimation, in many locations where mini-grids are constructed, the findings underline the importance of considering the multi-year-adaptive design approach when investments are made. To further enhance the advantages of the multi-year-adaptive design approach, it is crucial to couple it with strategies promoting load flexibility and to implement it in regions with higher discount rates. Additionally, it helps to factor in the potential future mini-grid component cost reductions, whether market-driven or supported by policies and incentives, in long term mini-grid planning.

The analysis of demand-side management implementation at a category level reveals significant variations in mini-grid component sizes and reductions in levelized cost of energy. These variations impact the economic viability of mini-grids. Battery energy storage is more affected by demand-side management than solar PV and diesel-fueled generators. Among the load categories, households and productive uses with nighttime loads have the greatest potential to reduce levelized cost of energy. Furthermore, implementing demand-side management at the category level in rural mini-grids, rather than at the appliance level, can reduce initial, operational, and maintenance costs. It also simplifies the complexity associated with controlling and connecting appliances. Therefore, due to its cost-effectiveness and ease of integration with tariff settings, such as time-of-use electricity tariffs, implementing demand-side management at the category level is more advantageous than at the appliance level when considering demand-side management implementation in mini-grids.

The result also reveals that correctly combining the number of household and productive users can enhance the revenue of a mini-grid. However, the share of productive users should not be too high. For systems with a fixed capacity, there is a specific mix that achieves a high load factor in the composition of households and productive use of electricity and enhancing the economic viability of a mini-grid.

Finally, the findings show that mini-grid load composition significantly impacts users' monthly bills, which in turn can impact the economic viability of mini-grids. The impact of future mini-grid load composition on users' monthly bills depends on the tariff structure. Mini-grid load compositions with daily productive uses result in lower cost-reflective tariffs compared to those composed entirely of household and non-daily productive uses. The future mini-grid load composition affects monthly electricity bills differently across load categories, with households being more affected. Therefore, it is important to consider the future load composition effect when setting tariffs and designing policies in mini-grids, such as subsidies, especially in protecting low-usage households in tariff decisions.

Collectively, the thesis emphasizes the need for improved interview-based load profile estimation for better mini-grid planning, the benefits of multi-year adaptive designing to address future demand uncertainties, and the significance of implementing demand-side management at the load category level rather than the appliance level. It highlights the importance of balancing household and productive users to maximize revenue and operational efficiency and considering future load composition when designing cost-reflective tariffs to ensure profitability and economic viability. Therefore, the thesis further emphasizes the importance of an integrated mini-grid planning framework that incorporates demand-side factors, which have often been overlooked, alongside widely studied supply-side considerations to enhance the economic viability of mini-grids in rural areas, particularly in regions with limited data and uncertain demand forecasts.

By addressing these aspects, the thesis contributes to filling critical research gaps and provides valuable frameworks for policymakers, investors, and mini-grid developers. It supports rural electrification efforts and contributes to the development of technologies and strategies that enhance clean energy access and its productive use. Ultimately, this research aligns with and advances global sustainability efforts, particularly contributing to achieving the United Nations' Sustainable Development Goals.

7.2. Future work

The findings of this study indicate several potential areas for future research. One direction is the examination of hybrid methods that combine interviews and measurements from electrified areas with similar socio-economic and geographical contexts to improve accuracy in estimating load profiles of unelectrified areas. The integration of Geographic Information System tools to estimate the total population catchment and other critical factors can be considered in this examination.

The advantages of the multi-year adaptive design approach can also be explored by accounting for uncertainties regarding the arrival of the main grid to mini-grids, particularly in rural areas that are feasible for connection but not yet connected. Further work on demand-side management can enhance load categorization through clustering algorithms and improve prioritization, as well as examine the impact of load categorization on the long-term lifetime of different types of storage systems. Future research could investigate the effects of load compositions on mini-grid economic viability and reliability while considering options such as capacity expansion. Additionally, research could examine how load compositions influence the selection of different storage technologies to enhance mini-grid economic viability and reliability.

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Appendices

Appendix A. Published/Submitted Papers

Paper I

2023 IEEE PES/IAS PowerAfrica

Comparison Of Electricity Load Estimation Methods In Rural Mini-Grids: Case Study In Ethiopia.

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***Abstract*—To provide electricity to unelectrified sub-Saharan Africa rural areas, mini-grids could play a key role. Mini-grid components size and investment cost, which is high for rural customers, need load profile knowledge for the design of a cost-efficient system. However, load profiles may vary based on the estimation method used, which leads to different mini-grid sizes and costs. This study compares interview and measurement load profile estimation methods in the case of Ethiopia. The impact of hourly electric load estimation on mini-grid sizing and cost is also determined. The result indicates that the interview method shows significant underestimation in peak load, energy per day and cost. The peak load and energy per day are underestimated by 70% and 21%, while load factor is overestimated by 162% in interviews. This leads to a 52% cost underestimation. In addition, hourly electric load estimation is prone to error that leads to a 9% cost underestimation.**

Keywords— Interview, load estimation, load profile, measurement, mini-grid

I. INTRODUCTION

Reliable and affordable energy, the seventh United Nations Sustainable Development Goal (UNSDG), is recognized as an essential factor for the socio-economic development and economic growth of any country to meet basic human needs. However, achieving UNSDG 7 is an ongoing struggle for sub-Saharan Africa (SSA) countries [1].

To provide electricity to unelectrified rural areas in SSA countries, mini-grids could play a key role. Mini-grids are electric power generation and distribution systems that may provide electricity to just a few customers in a remote settlement or bring power to hundreds of thousands of customers in a town or city [2]. However, mini-grids are still expensive in non-electrified rural areas, especially in SSA countries [1].

Mini-grids initial investment cost depends on the size of the installed components, which need the load profile knowledge to design a cost-efficient system [3]. However, load profile estimation is one of the greatest challenges in non-electrified rural areas [4].

Interviews and measurements are the common methods used for estimating load profiles. Load profiles estimated based on interviews (interview-based load profiles), commonly used, are estimated based on appliances and usage data collected through interviews. However, individuals without access may underestimate or overestimate their electricity demand without first realizing electrification opportunities [3]. Measurement-based load profiles are estimated based on measurement data collected using electricity measuring equipment. This requires equipment, which can be expensive, and technical knowledge, and it is difficult to get measurable electricity usage in non-electrified rural areas. Measurement-based load profiles improve time resolution and can reveal load profile knowledge not obtained from interview-based load profiles, but incorrect handling of the measuring equipment results in inaccurate estimations [4].

Previous studies have focused on the differences between interviews and measurements. In particular, the load factor and capacity factor are underestimated by 34–117% in interview assessments, which also underestimate energy use and peak loads, by 48-117% and 11%, respectively [3]. The average energy estimated using interviews prior to mini-grid implementation is more than four times that of the measured [5].

As a result of these differences in load profile estimation methods, studies examined the electric load estimation uncertainty impact on mini-grid size and cost-efficiency. A study on seven small-scale mini-grids shows component sizing scales proportionately with load estimation uncertainty [6]. The optimal (cost-efficient) system configuration is also significantly affected by stochastic load profiles formulation methods using interview data [7].

Mini-grid sizing and cost depend on the sizing method used. A majority of computer aided sizing methods uses a load profiles in hourly basis [5]. However, in the above studies, [6] and [7], electric load estimation uncertainty impact on mini-grid sizing and cost was studied based on an intuitive sizing method, considering a worst-case scenario, and a numerical method, using average daily load, which lacks additional load profile characteristics. Heuristic algorithms, such as particle swarm optimization (PSO), yield high quality solutions in mini-grid sizing [8]. In addition, the impact of hourly resolution load profile estimation on mini-grid sizing and cost is not examined.

On the other hand, in [3] and [5], they compared interviews and measurement methods without examining their impact on mini-grid sizing and cost estimation. In addition, the comparison of the two methods between load categories doesn't include community loads (CLs) and metrics more relevant to assessing the impact of demand-side management (DSM) at the planning stage.

Based on the identified knowledge gaps, this study aims to examine the differences between load profile estimation methods by considering metrics that are important for DSM

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implementation. The impact of the two methods of electric load estimation difference, and the difference in load profile resolution on the size and cost estimation of rural area mini-grids is also examined using PSO algorithm. The main research questions addressed in this study are:

- How do electric load profile estimations using interviews and measurements differ in the case of Ethiopia?
- How may the electric load estimation methods differences impact mini-grid sizing and cost estimation?
- How may hourly electric load estimation impact mini-grid sizing and cost estimation?

II. CASE STUDY AND ASSUMPTIONS USED

The rural community of Koftu (8.83°, 39.05°), located 40km southwest of Addis Ababa, Ethiopia is used as a case study village. The Koftu village is electrified by a solar PV-based autonomous mini-grid constructed by the Ministry of Trade, Industry, and Energy of the Republic of Korea in recognition of the friendship between the federal democratic Republic of Ethiopia and the Republic of Korea in December 2018.

The mini-grid contains 250kW of solar power at two sites with 200kW and 50kW each, as well as a 50kW diesel generator and a 1000kWh battery capacity. The mini-grid is expected to be able to supply a population of approximately 2884 distributed in 366 households, but so far only 146 households, 1 school, 1 water pump, 1 health center (not using power), and 1 church has been connected to the mini-grid.

During sampling, 26 households (HHs) were selected for interviews of which 3, representing low, medium and high electricity usage, were used for the measurements. There are just one productive use (PU) (a water pump) and two CLs (a church and a primary school) and thus all these three non-household loads were used for both interviews and measurement. The health center was excluded due to lack of power usage (connected but no power use due to lack of electronic appliances). Interview and measurement data were collected between November 28 and December 15, 2021.

Used economic and technical parameters of the mini-grid components are listed in Table I. A function cycle of 50% is considered for Stoves, Mitad, and water pump. Mini-grid configuration containing solar PV and battery energy storage (BES) is considered in this study.

III. METHOD

To compare the electric load estimation methods, the performance metrics and optimal sizing of mini-grid components are estimated using interview- and measurement-based load profiles, for a selected case study area in Ethiopia, Koftu. A random sampling method with 29 sampling sizes for interviews and 3 for measurements are used.

Performance metrics are peak load, energy per day, load factor, coincidence factor, and responsibility factor. These metrics are compared for the total load profiles and load categories in the case study area. The load categories are HH, PU, and CL.

TABLE I. ECONOMIC AND TECHNICAL PARAMETERS OF THE MINI-GRID COMPONENTS.

Components	Price ($)	OMC ($/year)	RC ($)	Time (year)	SV (%)
Solar PV, kW	1500	50	300	25	10
Inverter, kW	711	0	650	10	10
BES, kWh	330	0	330	10	20

The peak load is the maximum power demand at a specific time. Energy per day is the total energy in each day divided by the total days. Load factor is the ratio of the mean electricity load used ($P_{L,\,Avg}$) within a specified time interval divided by the peak load at a specific time ($P_{L,\,peak}$). It is the measure of electrical energy utilization during a specific time [9].

$$\text{Load factor} = \frac{P_{L,\,Avg}}{P_{L,\,peak}} \qquad (1)$$

The coincidence factor, which indicates the probability of load peaking at the same time, is estimated by dividing the system's peak load by the sum of each load category's peak loads (i) [3].

$$\text{Coincidence factor} = \frac{P_{L,\,peak}}{\sum P_{L,\,peak,\,i}} \qquad (2)$$

The responsibility factor is the electricity power of an individual load at the system peak time divided by the peak of each load. It indicates the share of the individual load peak contribution to the system peak, which can be used as a DSM guideline [10].

$$\text{Responsibility factor}_i = \frac{P_{L,\,i}(\text{at system peak})}{P_{L,\,peak,\,i}} \qquad (3)$$

A. *Load profile estimation*

In estimating interview- and measurement-based load profiles, the respective load profiles for HH, PU, and CL categories are determined using representative sample users, using bottom-up demand modeling.

The representative sample users were selected within the case study area based on the recommendation of the Ethiopian Electric Utility operator (to represent the socio-economic variability of the case area) and their power meter readings since the users in the case study area are electrified. The load profile for each sample user in each load category is estimated and scaled to the total number of users in HHs, PUs, and CLs. The load profiles of each load category are summed to get the total weekly load profile for the case study area.

1) *Interview-based load profiles*

To estimate interview-based load profiles, interviews are conducted based on the interview protocol recommended in [3], with predefined questions to guide the discussion. The questions were not asked in any particular order to put respondents at ease and facilitate an open discussion, resulting in more information.

Self-developed questionnaire is used, and it includes questions about the type, number, time of electricity usage, and nominal voltage of appliances used. Weekend load patterns may differ from weekday load patterns; thus, the questionnaire is divided into two sections: weekday and weekend. Interviews are conducted in Afaan-Oromo and Amharic languages.

The load profiles of each sample user are estimated without considering appliances coincidence factor and efficiency. The contribution of each appliance to estimating the load profile for each load category at the time t (E_t) is given by (4) [3].

$$E_t = \frac{N}{n} \sum_{m}^{n} P_{m,t} \cdot fc \tag{4}$$

where n is the total number of sample users in the load categories, and N is the total number of users in each load category. $P_{m,t}$ is the power rating of the appliance at time *t* and fc is the functioning cycle of the appliance, on–off time of appliance once it is on.

All appliances are modelled with an assumption of continuous operation (fc = 100%) except for appliances used over shorter periods at high power, such as stoves, mitad (the conventional electric injera (Ethiopian food) baking machine), and water pumps. Interview-based load profiles are hourly.

2) Measurement-based load profiles

The measurements are carried out using four FLUKE a3000 FC AC current clamp meters for two weeks, one week for households and another week for PU and CLs. The FLUKE a3000 FC AC current clamp meters measure and store minimum, maximum, and average TRMS current every minute for up to 400A AC. The meter can store up to 65,000 readings.

The meters are connected to the connection point of a power meter, which was installed by the utility to measure power consumption. The measured average current is multiplied by the nominal voltage (220V for single-phase and 380V for three-phase) to estimate sample users' measurement-based load profiles and scaled to the total number of users in each load category. Estimated measurement-based load profiles are per minute.

B. Sizing

In this study, a PSO algorithm is used for mini-grid sizing based on the estimated load profiles. Sizing of the mini-grid components is determined by considering the minimization of total present cost (TPC) as an objective function. The problem formulation and mini-grid component modeling used in this study is based on in [8].

IV. RESULTS

The estimated total interview- and measurement-based load profiles, per hour and minute, respectively, are shown in Fig. 1. The load profiles of HH, PU, and CL are estimated based on interview and measurement and shown in Fig. 2, 3 and 4, respectively.

As shown in Fig. 1, the interview and measurement have nearly the same peak load (79kW) during night-time for each day, but the measurement indicates a peak load (>150kW) that occurs during the morning time for around 6 hours, per week. The morning peak load shown in the measurement-based load profile comes from cooking appliances (stove and mitad) in households, as shown in Fig. 2. Interviews overestimate the base load by 274% compared to the measured base load, 66W.

The performance metrics for total interview- and measurement-based load profiles are calculated for weekday, weekend, and weekly load profiles, and shown in Table II and III. As shown in Table II, peak load and energy per day are underestimated in interviews by 70% and 21%, respectively. However, the load factor is overestimated by 162%.The energy per day and load factor in the weekend is higher than the weekday, by 4% and 5%, in total interviews and 4% and 20% in total measurements, respectively. There is no difference in peak load between the weekday and weekend in interviews. However, in measurements, weekday peak load is 15% higher than weekend peak load.

The performance metrics for the interview- and measurement-based load profiles are calculated for each load category and shown in Table IV. As shown in Table IV, the HH peak load is much higher than PU and CL peak loads for both interviews and measurement since the peak load of HH and PU is underestimated in interviews, but not for CL.

Even if the per customer usage in HH is less, the number of HH is much higher than PU and CL, where 61% and 90% of the energy in the total interview-and measurement-based load profile comes from the HH. So that the difference between the two methods described above, in total interview- and measurement-based load profiles, mainly comes from the HH.

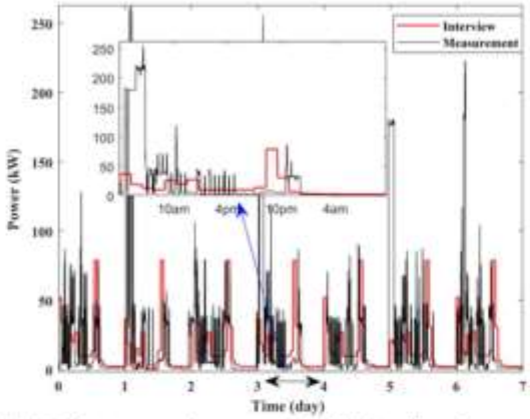

Fig. 1. *Total interview- and measurement-based load profiles and in-zoomed one day (day 4) load profile.*

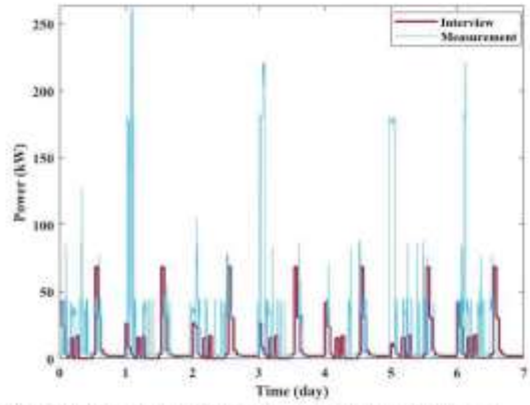

Fig. 2. *Household load profiles based on interview and measurement.*

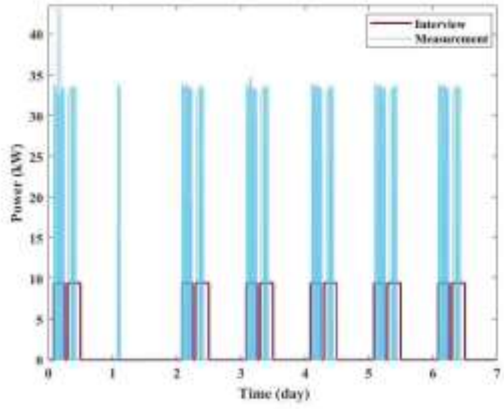

Fig. 3. *Productive use load profiles based on interview and measurement.*

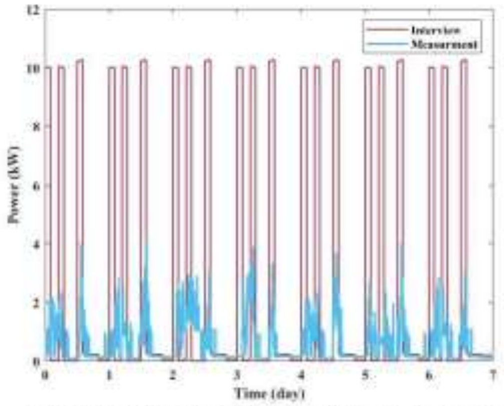

Fig. 4. *Community load profiles based on interview and measurement.*

As shown in Table IV, the load factor is overestimated in interview for all load categories, which is in line with the difference in total load profiles shown in Table II and III and results in studies [3]. However, the difference in load factor is higher in PU than HH and CL, where the load factor of PU in the interview is overestimated by 12 times.

The coincidence factor of load categories, calculated using (2), for measurement, 0.89, is higher than interview, 0.85. The responsibility factor calculated using (3), for HH and PU is the same in both interview and measurement, but not for CL, which is 68% lower in the measurement method.

TABLE II. PERFORMANCE METRICS FOR TOTAL INTERVIEW-BASED LOAD PROFILE

Metrics	Weekday	Weekend	Weekly
Peak load (kW)	79	79	79
Energy (kWh)	346	361	350
Load factor	0.182	0.190	0.185

TABLE III. PERFORMANCE METRICS FOR TOTAL MEASUREMENT-BASED LOAD PROFILE

Metrics	weekday	weekend	weekly
Peak load (kW)	265	223	265
Energy (kWh)	440	467	448
Load factor	0.0693	0.0873	0.0705

TABLE IV. PERFORMANCE METRICS FOR LOAD CATEGORIES

Load category	Metrics	Interview	Measurement
HH	Peak load (kW)	68	263
	Energy (kWh)	215	407
	Load factor	0.130	0.064
	Responsibility factor	0.9	0.9
PU	Peak load (kW)	9	43
	Energy (kWh)	73	27
	Load factor	0.322	0.026
	Responsibility factor	0.001	0
CL	Peak load (kW)	10	4
	Energy (kWh)	62	14
	Load factor	0.252	0.144
	Responsibility factor	1	0.32

TABLE V. THE OPTIMAL SIZE OF MINI-GRID COMPONENTS

	Interview	Measurement	
	Per hour	*Per hour*	*Per minute*
BES (kWh)	204	449	455
Solar PV (kW)	56	73	98
TPC (M$)	0.579	1.105	1.217

The optimal mini-grid components sizes for interview- and measurement-based load profiles, per hour and minute, are shown in Table V. The optimal BES and solar PV sizes are underestimated by 55% and 43%, respectively, when it is calculated using interviews, resulting in a 52% underestimation of TPC. This difference in size is mainly due to the underestimation of total energy and peak load in the interview method shown in Table II and III.

The peak load is reduced to 200kW from 265kW when the per minute measurement-based load profile is converted to an hourly load profile, a 24% reduction from the per minute profile. As a result of this conversion, the BES and solar PV sizes are underestimated by 1.3% and 25% compared to per minute measurements. This reduction in BES and solar PV size underestimates the TPC by 9% from per minute measurements.

V. DISCUSSION

This study aims to compare two electric load estimation methods and their impact on mini-grid component sizing and cost. The scientific contributions of this study are: first, the comparison of the interview and measurement methods was examined in load categories. Second, the impact of the load estimation method difference on mini-grid components was studied using the weekly load profile and PSO algorithm. Previously, similar studies compared the total load profile estimation the two methods but impact on mini-grid components were studied using average daily load and a worst-case scenario. In addition, the impact of using hourly resolution load profile estimation on mini-grid sizing and cost is examined. This was done using a case village in a rural area of Ethiopia.

Interview and measurement methods show a significant difference in load factor metrics, where the productive use showing the larger difference than in other load categories. The lower load factor implies lower mini-grid income [3]. However, productive use impacts mini-grid income considerably, even if it requires an optimal combination of load categories [9].

Results show that, due to appliances with high power ratings and cyclic operation, the household load category is underestimated compared to the productive use and community loads. This implies that improvements of interview assessments of appliances with high power ratings and cyclic operation, and time change (e.g., load shifting in cooking) could have a significant impact on the outcome and would be required when these types of assessments are used. This also implies that in particular mini-grid modeling of systems dominated by household users' needs to pay attention to this.

It could be worthwhile to target the load categories with higher responsibility, and higher contribution to the peak system, using DSM [10]. According to the results, the responsibility factor of the community load differs between interview and measurement-based load profile, 68% lower in measurement. This indicates that, in planning and operation of mini-grids, matching the required demand and supply by implementing DSM for instance should consider the difference that can be expected in load estimation methods.

The interview and measurement assessments in per hour resolution show different impact on mini-grid sizing and cost than the per minute measurement assessment. Since high resolution load profiles, per minute, show peak loads not shown in low resolution. This peak load is not shown in the interviews and reduced when the per minute load profile is converted to per hour. As a result of the peak load differences, mini-grid sizing indicates that the BES size is reduced based on interview and measurement per hour data, resulting in different cost estimations. Therefore, electric load estimation using different methods and/or resolution can result in different cost estimations, which can have a significant impact on investment decisions.

An understanding of how load profile estimation methods impact mini-grid sizing and total present cost will assist mini-grid operators in assessing the risk of load profile estimation methods at the planning stage and also provides them support for considering the costs and benefits of conducting interviews for load estimation [5].

Different techniques have been developed recently to improve load profiles estimation methods. For instance, using data from an electrified area with a similar socio-economic and geographical context [5], and a stochastic bottom-up model based on the coincidence factor [7]. However, they rely on interview data as primary input data.

The main difference between interview and measurement data is in the morning peak time, due to appliances with high power ratings and cyclic operation. Interview-based load profiles can be improved to a certain extent if appliances with high power ratings and cyclic operation are considered without affecting peak loads and energy consumption.

The use of a hybrid interview and measurement method may improve load profile estimations in rural areas. Identifying the type, number, and time of electricity usage using interviews together with measured appliance load profiles (e.g., appliances with high power ratings and cyclic operation) and taking the coincidence factor into account, rather than using the power rating of such appliances. Measured appliance load profile data from electrified areas with similar socio-economic and geographical contexts can be used. Future studies may address this.

VI. CONCLUSION

In this study, interview and measurement methods used for load profile estimation in rural area are compared in the case of Ethiopia. The results indicate that the interview method shows a significant underestimation of the peak load, energy per day and cost of mini-grids. Among the load categories, the significant underestimation is for household demands rather than for the productive use and community loads. This is due to peak load underestimation of appliances with high power ratings and cyclic operation in households. In the interviews, peak load and energy per day are underestimated by 70% and 21%, while the load factor is overestimated by 162%. This leads to a 52% underestimation of cost. In addition, hourly electric load estimation is prone to errors leading to a 9% cost underestimation.

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Paper II

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Exploring the advantages of a multi-year-adaptive approach on cost-optimal long-term mini-grid design under different demand evolution scenarios

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ABSTRACT

Mini-grids are essential for rural electrification in sub-Saharan Africa, but due to uncertainty about future demand evolution in non-electrified communities, cost-optimal long-term sizing and design is particularly difficult. Standard, non-adaptive design approaches single-year and multi-year, are highly susceptible to demand evolution uncertainties. Despite potentially great advantages there is a lack of studies investigating adaptive design approaches. Thus, this study, using particle swarm optimization, explores the advantages of a multi-year-adaptive approach on cost-optimal long-term solar PV mini-grid component sizing under three demand evolution scenarios, considering the impacts of load flexibility, varying discount rates, and potential future mini-grid component cost reductions. The results show that the multi-year-adaptive approach helps to manage demand evolution challenges. It leads to significant cost-savings, up to three-quarters, in higher demand evolution scenarios, compared to multi-year and single-year approaches. These cost-savings increase with load flexibility (up to 4 % with 10 % flexibility), higher discount rates (up to 9.4 % with rates from 7 % to 20 %), and component cost reductions (up to 3.6 % per 1 % reduction). The study demonstrates how an adaptive approach can be utilized to optimize mini-grid component sizing and enhance cost efficiency.

1. Introduction

More than half a billion people will still lack reliable and affordable electricity in 2040 [1], the majority of whom live in rural areas of sub-Saharan Africa (SSA) [2]. Many factors contribute to this low electrification rate, including a lack of necessary investment capital, low power demands, and a lack of proper planning and policies [3].

Mini-grids are seen as a promising solution for rural electrification in SSA [4]. Mini-grid planning involves selection (viz. identifying, sizing, and designing) of suitable technology mixes, and this may be guided by optimization based on appropriate criteria (viz. mathematical programming) and matching of available energy resources with the demand [5]. Based on the time scale considered during planning, the planning horizon can be divided into short-term (from one month to one year), medium-term (from one to ten years), and long-term[1] (beyond ten years) [1,6].

To size mini-grid components in a cost-optimal manner (minimized investment and running cost), demand development needs to be taken into account [7]. However, estimations of long-term future electricity demand are challenging in rural areas, especially with no prior electricity access and use [8,9]. Such demand estimations are often subject to large uncertainties [10] due to the complex socio-economic dynamics affecting electricity demand developments in areas with no or very low historical consumption, frequent policy changes, and erratic technology diffusion [1]. These uncertainties about future electricity demand may negatively affect mini-grid sizing and cost [10]. Oversizing the system in anticipation of growing demand leads to a poor system economy [11], while undersizing results in poor performance and reliability [12].

The load forecasting literature presents two remedial methods. (*i*) reducing the forecasting horizon to less than half of the data history

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[1] The lifetime of mini-grids depends on the selected renewable energy technology [27].

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length, resulting in more accurate forecasts; (*ii*) developing probabilistic demand forecasts to understand and manage the possible impact of potential demand growth [13]. Another approach is to use the arbitrary trend method that incorporates justified assumptions based on literature and historical trends, which may capture the complexities behind the evolution of electricity demand. The use of the arbitrary trend method is usually combined with multiple demand evolutions, enabling uncertainties associated with assumptions about future demand evolution to be addressed [1].

In mini-grid planning, different design approaches are utilized, mostly aiming for cost-optimal sizes to meet future electricity demand [1,14]. A single-year design approach is commonly used in studies to determine the component size and costs by using a representative, mostly single-year, demand profile [4], assuming constant demand over the full planning horizon. This design approach simplifies system design but using this approach for long-term sizing, especially in rural communities with high demand growth, may not ensure long-term sustainability.

In the studies applying the single-year design approach for mini-grid sizing, various optimization algorithms and tools are utilized to yield high-quality solutions. These include iterative optimization techniques [15], HOMER [16–19], metaheuristic algorithms (dynamic programming algorithm [20], genetic algorithm (GA) [21], and particle swarm optimization (PSO) [22–24]) and machine learning algorithms [25]. The PSO algorithm is powerful, well known, and yields high-quality solutions in a shorter simulation time than iterative techniques, HOMER, and most heuristic algorithms for mini-grid sizing [24], especially in single objective optimization. Machine learning algorithms are also faster and more efficient at yielding high-quality solutions than heuristic algorithms but require significant amounts of historical data at the training stage [26]. The multi-year approach, which considers evolving demand over the full planning horizon to determine component size and cost, is also used [27]. However, due to the difficulty in estimating future demand in rural areas, both single-year and multi-year approaches are susceptible to uncertainties about future demand [4,27].

An adaptive approach is an iterative approach that makes investment decisions for a specific period of time, typically annually, by increasing the system's capacity to meet both past and expected future demand growth [11,27]. This design approach reduces the impact of future demand uncertainties since decisions are made annually. However, access to skilled labor and financial services may not always be readily available every year in rural areas of SSA [28]. Implementing an adaptive approach can thus be challenging under these circumstances. Specifically [27], recommends exploring hybrid approaches combining multi-year and adaptive approaches (multi-year-adaptive approach) for future work.

To address uncertainties about future demand, a flexible and adaptive approach is also proposed for the distribution systems, allowing the system capacity to grow in a controlled manner [11]. Additionally, a multi-step approach for medium-term planning is presented, whereby installed capacity is expanded according to demand evolution [29]. A multi-year-based capacity expansion using mixed-integer linear programming (MILP) is also presented [30]. However, in Ref. [30], no actual operating strategy was utilized, which is common in typical MILP approaches. Including an operating strategy could enhance both the optimality and computational efficiency of the solution [31]. Building upon the limitation of [30], [4,32,33] examines multi-year based capacity expansion while considering a load-following operating strategy (prioritizing energy sources to meet the demand), but the load-following operating strategy can increase the investment by more than 15 % compared to the application of operating strategies that can help to mitigate supply-demand imbalances [31].

The aforementioned studies [4,30] are based on solar PV-based mini-grids with battery energy storage systems (BESS) and diesel generators. However, in rural areas of SSA, diesel generators are rarely used due to the high diesel cost, as well as the maintenance and operational expenses involved, making diesel-based systems less feasible in these regions [8,12]. Additionally [29,30], utilized synthesized load profiles derived from initial load assessments based on interviews, but interview-based assessments may result in an underestimation of both the size and cost of mini-grids [8,9].

Studies have also investigated approaches to deal with supply-side uncertainties for mini-grid, such as long-term power generation estimation [34], investment estimations [35], expansion planning under grid outage risks [36], and expansion planning under the uncertain arrival of the main grid [37]. The cost of essential supply-side mini-grid components like solar PV panels and BESS has decreased by over 80 % in the past decade [38]. Due to technological development, production expansion, and increased competition, further mini-grid component cost reductions are anticipated [27]. However, the above studies have not adequately captured such cost reductions. Additionally, the discount rate, which reflects the capital cost, risk, and expected return on investments, plays a crucial role in determining costs and long-term benefits [39]. In SSA, the discount rate can reach more than 18 %, making it a critical factor in long-term mini-grid sizing [40].

Temporal electricity demand variations can impact cost-optimal component sizing [14]. Flexibility can broadly be defined as a system's ability to cope with variability in demand while maintaining reliability at a reasonable cost over different time horizons. Flexibility can be divided into short-term (i.e., flexibility adequacy) and long-term (i.e., system adequacy). Flexibility adequacy refers to the short-term ability to keep the system balanced, whereas system adequacy (the primary concern of the system) refers to the system's long-term ability to meet its demand [11,41]. Load flexibility can be achieved by demand-side management (DSM) including load shifting [42], which refers to the possibility of shifting electricity demand in time, either to offset peak demand or to off-peak periods.

While there are studies that examined its application in the short-term, load flexibility is also significant and plays a crucial role in balancing supply and demand in the long-term [43]. In some rural areas, DSM is implemented through load management to address electricity shortages [44] and load scheduling to prevent system overloads [45] in mini-grids.

The studies presented above [15–24], on mini-grid sizing indicate that most designs rely on a single-year approach, simplifying sizing, while only a few focus on multi-year approaches, [4,27,30,32,33], but both of which are susceptible to uncertainty about future demand. To realize the potential of mini-grids in developing countries, it is crucial to design them smartly to deal with the impacts of the uncertainty about future demand. Previous studies [11,27,29,30,32,33], have proposed different approaches to address this uncertainty. However, none of these studies examine hybrid methods that combine the advantages of multi-year and adaptive designs while considering the effects of load flexibility, varying discount rates, and future component cost reductions for sizing 100 % renewable energy-based autonomous mini-grids based on measured load data. Thus, this study aims to explore the advantages of a multi-year-adaptive approach on long-term mini-grid component sizing and cost under different demand evolution assumptions. It is guided by these main research questions:

- What are the long-term advantages of a multi-year-adaptive design approach in terms of mini-grid component sizing and cost compared to the single-year and multi-year design approaches under different demand evolution assumptions?
- How do the impacts of load flexibility, varying discount rates, and future mini-grid components cost reductions differ across the various design approaches?

The overall problem formulation is generic and applies to most non-electrified rural settings in SSA, but the actual calculations carried out are based on a single case. A solar PV-based mini-grid, which is entirely based on RES and operating autonomously, was chosen as the case, as it is the currently dominating off-grid electrification solution in SSA, and due to its flexibility and modularity [46]. The demand evolution scenarios applied, and data used for the calculations are from an Ethiopian setting.

The novelty of this study is due to its quantification of multi-year-adaptive design advantages by using measured load data from a real setting and an entirely renewables-based mini-grid; its inclusion of operating strategies into the optimizations of multi-year-adaptive design; and its extension of the design approaches investigation by considering load flexibility, discount rate, and future component cost reduction uncertainties.

2. Method

In order to represent future demand uncertainties, this study builds upon three demand evolution scenarios in an off-grid mini-grid setting. To obtain a realistic load profile for the calculations, measured weekly electrical demand load data over one week, December 6–13, 2021, from a recently solar PV electrified village were used.

To explore the long-term advantages of a multi-year-adaptive design approach for mini-grid component sizing and cost compared to single-year and multi-year design approaches under the three demand evolution scenarios, a mini-grid component sizing-based optimization problem was formulated and utilized. The optimization problem considers the cost-minimization objective function. It also ensures that demand is met, taking into account different load growth assumptions and design approaches.

To compare design approaches through mini-grid component sizing, only the solar PV and BESS components were considered, as they demonstrate higher impacts than inverters [32]. However, the cost comparison includes solar PV, BESS, and inverter components costs. The mini-grid component size and cost for single-year and multi-year were calculated once initially, indicating the initial investment for the full planning horizon. The additional component sizes and costs in the multi-year-adaptive approach were calculated for each specific time interval. The estimated additional costs were aggregated to calculate the total cost over the planning horizon, using a discount rate.

To determine how load flexibility, varying discount rates, and future mini-grid component cost reductions differ across the various design approaches, the formulated optimization problem was used, and its result was compared with the base case (without load flexibility). Load flexibility, as used in this study, indicates the amount of shiftable electricity load from 1 h to another hour. In the case of design approaches applying load flexibility, a certain percentage of demand at each time t is considered a shiftable load. A priority-based operating strategy,[2] classifying loads as shiftable and non-shiftable for each hour, while also prioritizing energy sources, as in the load-flowing operating strategy, was used. In addition, to address the uncertainty regarding the future discount rate and future mini-grid component cost reductions, the assumptions of these were varied in a sensitivity analysis. Detailed descriptions of the scenarios, design approaches, problem formulation, and optimization methods used are provided in the following sections.

2.1. Scenarios

In rural areas without access to electricity, the uncertainty of future demand poses challenges to mini-grid sizing [10]. To mitigate this, multiple demand evolution scenarios might be developed providing a set of descriptive pathways indicating how future mini-grid size and costs need to be developed [47]. Therefore, three different demand evolution scenarios representing low, medium, and high demand growth were developed and applied in this study. They offer a set of descriptive pathways showing how future demand may develop.

Since the study is based on an Ethiopian case, the assumed growth of the three scenarios is based on Ethiopian electricity demand growth. The average annual electricity demand growth rate for all load types in the Ethiopian national grid is 13 % [43] and is expected to grow by over 14 % annually, with rural households' demand expected to grow at a rate of 9.7 % per year [48]. In recently electrified localities, demand growth has been shown to be as high as 38 % and 54 % per year in the first years following electrification [49]. However, demand growth saturation may occur, slowing down growth rates due to various reasons, among them the adoption of improved energy-efficient appliances and DSM, which can result in up to 41 % energy savings [43]. Demand growth can also be low due to low income levels, limited economic development and productive use activities, poor prior knowledge about electricity usage and its benefits, and local climatic conditions [50]. This results in the following three scenarios:

- Scenario 1 (S 1) represents a generally low demand growth. In S 1, a demand growth of 5 % per year is assumed.
- Scenario 2 (S 2) represents medium demand growth, corresponding to the annual average electricity demand growth in rural households since most of the rural area demand is from households. In S 2, a demand growth of 10 % per year is assumed.
- Scenario 3 (S 3) represents high demand growth for all load types. In S 3, a demand growth of 15 % is assumed.

Scenarios 2 and 3 do not consider constant growth over the entire planning horizon but instead reflect saturation after some years. Thus, for scenario 2, a 5 % demand growth was considered for the last five years of the planning horizon, whereas for scenario 3, 10 % and 5 % demand growth were considered for the last two five years, respectively. In this way, scenarios 1, 2, and 3 increase the initial demand by 3.2, 7.8, and 14.5 times, respectively, at the planning horizon end year. The respective demand growth evolution over the planning horizon is shown in Fig. 1.

2.2. Design approaches

The optimal mini-grid component size and cost are determined in different ways in the three design approaches (single-year, multi-year, and multi-year-adaptive):

- In the single-year (SY) design approach, based on the demand at the planning horizon end year.
- In the multi-year (MY) design approach, by considering each year's demand evolution for the entire planning horizon.

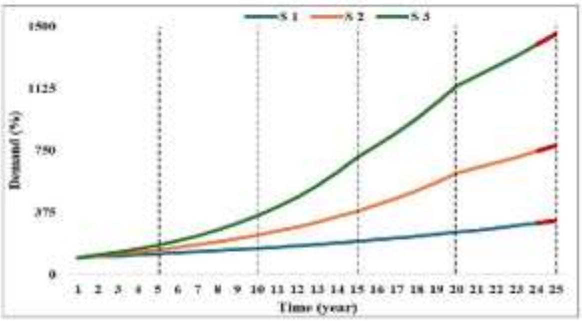

Fig. 1. Considered evolution of demand growth for scenarios 1, 2, and 3 throughout the 25 years. The final year demand (in red) indicates the demand growth considered for SY, while for MY, the full demand growth is considered. Dashed lines represent the investment years in each interval in MYAD.

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[2] A detailed description of the priority-based operating strategy is given in Ref. [42].

- In the multi-year-adaptive (MYAD) design approach, for investment years in each interval (every five years).

2.3. Problem formulation

A component-sizing-based optimization problem was formulated based on the mini-grid configuration used and sizing (variables, objective, and constraints). Each of them is explained in the following section.

2.3.1. Mini-grid configuration

The main components of the studied mini-grid include solar PV, the BESS with a converter, and an inverter on the supply side. These provide electricity to various load types. The schematic diagram of the studied mini-grid is shown in Fig. 2.

2.3.2. Sizing

To compare design approaches with different demand evolutions, minimization of the total present cost (TPC), calculated using Eq. (1), is used as the objective function for sizing:

$$TPC = IC + OMC + RC - PSV \tag{1}$$

where *IC* is the initial cost that includes the capital cost (component price, balance of system cost, installation cost, and soft costs), and the cost of civil work. *OMC* is the operation and maintenance cost, *RC* is the replacement cost, and *PSV* is the present scrappage value of the mini-grid. The mini-grid components considered are solar PV, BESS, and inverter. Appendix 1 provides detailed equations of OMC, RC, and PSV.

The mini-grid sizing, at every time step, is subject to the constraint of ensuring a total demand-supply energy match without load curtailment (loss of load), thereby increasing system reliability, for both base and with flexibility cases, shown in Eq. (2). Additionally, a BESS constraint, where the state of charge of a BESS (SOC) at any time *t* should lie between the minimum (SOC_{min}) and the full capacity of the BESS (SOC_{max}), shown in Eq. (3). The maximum charge quantity of the BESS (SOC_{max}) takes the value of the nominal capacity of the BESS (C_B) and the minimum charge quantity of the BESS (SOC_{min}) is determined using the maximum depth of discharge (DOD).

$$E_{dem} \leq E_{sup} \tag{2}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{3}$$

where E_{dem} and E_{sup}, respectively, are the total energy demand required and the total energy demand supplied in the autonomous mini-grid.

2.4. Optimization method

The PSO algorithm was used for mini-grid sizing based on the design approaches used. In PSO, the objective function (TPC) is determined by generating and calculating the value of each random population of decision variables or particles. In this study, the particles are the sizes of mini-grid components. In each iteration, the objective function of each particle was evaluated, with each particle's solution saved as its personal best, and the best solution across all particles saved as the global best. Moreover, in each iteration, particles position and velocity are updated based on personal and global best. This will continue until the maximum iteration is reached.

The following parameters are used for the PSO algorithm: population size of 100, maximum and minimum inertia weight of 0.9 and 0.4, respectively [42,51], acceleration factor of 2, and the maximum number of iterations is 100.

2.5. Mini-grid component modeling

In cost-optimal mini-grid component sizing, system modeling plays a crucial role; thus, mini-grid component modeling is presented in the section below.

2.5.1. Modeling the solar PV output

The electricity output of solar PV was estimated based on the average irradiance in hour *t* (θ_t), surface size of the cell (*PVA*), and instantaneous PV cell efficiency ($\mu c(t)$), expressed by Eq. (4) [52]. The instantaneous PV cell efficiency and *PVA* were calculated by Eqs. (5) and (6) [53]:

$$P_{pv} = \theta_t \times PVA \times \mu_c(t) \tag{4}$$

$$\mu_c(t) = \mu_{cr}[1 - \beta_t(T_c(t) - T_{cr})] \tag{5}$$

$$PVA = \frac{1}{24}\sum_{t=1}^{24}\frac{P_{L,av}(t)F_s}{H_t\mu_c(t)\eta_{pc}V_F} \tag{6}$$

where β_t is the temperature coefficient for silicon cells, μ_{cr} and T_{cr} are the theoretical solar cell efficiency and temperature, respectively. F_s is the safety factor, V_F is the factor of variability, and η_{pc} is the power conditioning system efficiency [23].

2.5.2. Battery energy storage system

The surplus electrical energy from the solar PV is stored in the BESS and discharged from the BESS when the solar PV output is not sufficient to supply the demand. BESS charging and discharging depends on the solar PV output and the BESS state of the charge at any given time. The BESS state of charge at a specified time is expressed in Eq. (7) and Eq. (8) [23]:

$$SOC(t+1) = SOC(t)(1-\sigma) + P_B(t)\eta_B \text{ charging mode} \tag{7}$$

$$SOC(t+1) = SOC(t)(1-\sigma) - P_B(t)\eta_B \text{ discharging mode} \tag{8}$$

where *SOC* is the BESS state of charge, η_B is the BESS efficiency, and σ is the BESS self-discharge rate. $P_B(t)$ represents the charging or discharging

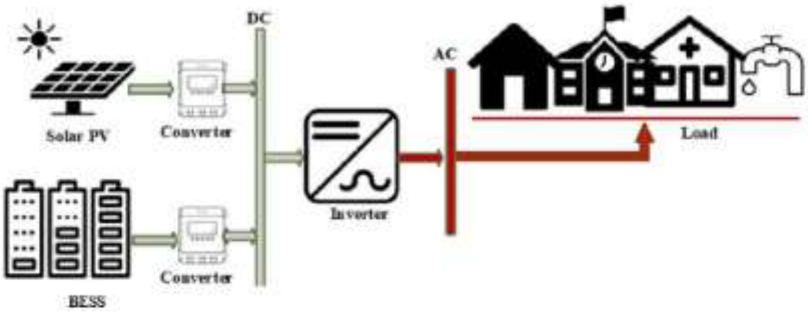


Fig. 2. A schematic diagram of the autonomous solar PV-based mini-grid configuration used in the study.

power of the BESS at time *t*.

2.5.3. *Power inverter*

An inverter is used for converting DC to AC and must be able to manage the maximum expected AC loads for any of the hours of the day. The size of the inverter was calculated using Eq. (9) [52]:

$$P_{inv} = \frac{P_{peak}}{\eta_{inv}} \tag{9}$$

where P_{peak} is the peak of the demand and η_{inv} is the efficiency of the inverter.

3. Case, data, and assumptions

3.1. *Case*

The Koftu village, located at 8.83°, 39.05°, 40 km southwest of Addis Ababa, Ethiopia, is supplied by a solar PV-based autonomous mini-grid since 2018. The mini-grid uses 250 kW of solar power installed at two sites with 200 kW and 50 kW each, a 50 kW diesel generator, and 1000 kWh of battery capacity, designed using a single-year approach.

3.2. *Data used*

In determining the component size for the SY, MY, and MYAD approaches, the economic and technical parameters of the mini-grid components, PSO parameters, demand data, solar irradiance data, and assumptions were utilized. The economic and technical parameters of the mini-grid components used are presented in Table 1. The economic data used in this study is based on the scientific literature [23,42,54,55].

Electricity consumption data were measured data in the Koftu village using FLUKE a3000 FC AC clamp meters. To reduce computational sizing time, a one-week load profile was utilized to represent a one-year load profile. Hourly load profiles were constructed and used based on the collected per-minute demand load data. The insolation profile used is also based on data representative of the Koftu village. The measured weekly load profile and insolation for Koftu village are shown in Figs. 3 and 4, respectively.

The peak load poses a challenge for mini-grid sizing and matching, particularly when dealing with highly fluctuating RES. In the load profile, Fig. 3, the peak load occurs during the morning hours due to the usage of cooking appliances such as stoves and mitad (the conventional electric injera (Ethiopian food) baking machine) in households. This morning peak is 2–4 times higher than the evening peak load, in contrast to commonly known load profiles in rural mini-grids.

The assumptions used in this study include 10 % load flexibility. A baseline discount rate of 7 % was considered based on the risk-free assumption and the interest rate of the National Bank of Ethiopia [57]. To examine the effect of the discount rate on the TPC of the system, in addition to the baseline discount rate of 7 %, higher discount rates of 15 % and 20 % were also considered. An inflation rate of 8.1 % [58], and a project life of 25 years, determined by the maximum lifetime of the system components, in accordance with [1], was applied.

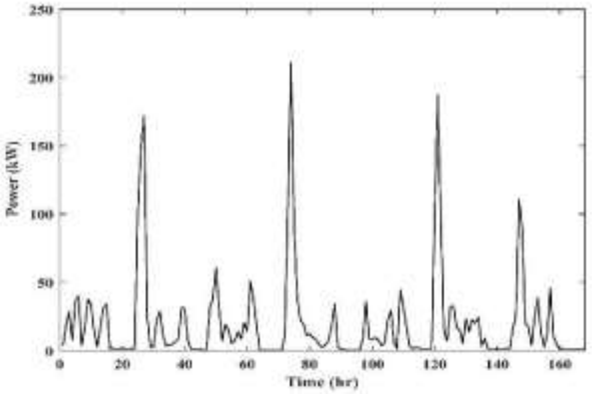


Fig. 3. Measured weekly load profile in Koftu village, used for the initial year in all scenarios of demand development.

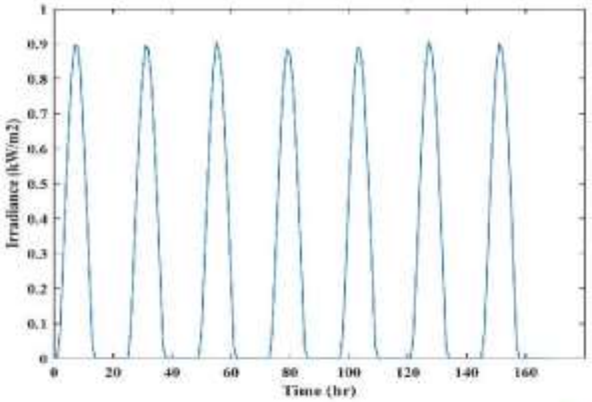


Fig. 4. The calculated weekly average insolation profile for Koftu village [56].

Even if studies indicate that the costs of solar PV and BESS have dropped with an average yearly reduction of 8 % in recent years, it is expected that the rate of cost reduction may not continue at that pace [38]. Thus, to examine the effect of cost reductions for solar PV and BESS, annual cost reduction rates of 2 %, 3 %, and 4 % were applied.

4. Result and analysis

In this section, the calculation results are presented; the cost-optimal mini-grid components size calculated using Eq. (4) and Eq. (7), and costs using Eq. (1) for the three approaches, SY, MY, and MYAD under the three demand evolution scenarios.

Table 1
Economic and technical parameters of the mini-grid components.

Component, unit	Capital cost ($)	OMC[a]($/year)	RC [b]($)	T(year)	Nrep[c]	SV[d] (%)	Reference
Solar PV, kW	1500	50	300	25	0	10	[42,55]
Civil Work, solar PV, kW	40 %	1 %	40 %	25	0	20	[25,42]
Inverter, kW	711	0	650	10	2	10	[23,42]
BESS, kWh	330	0	330	10	2	20	[42,54]

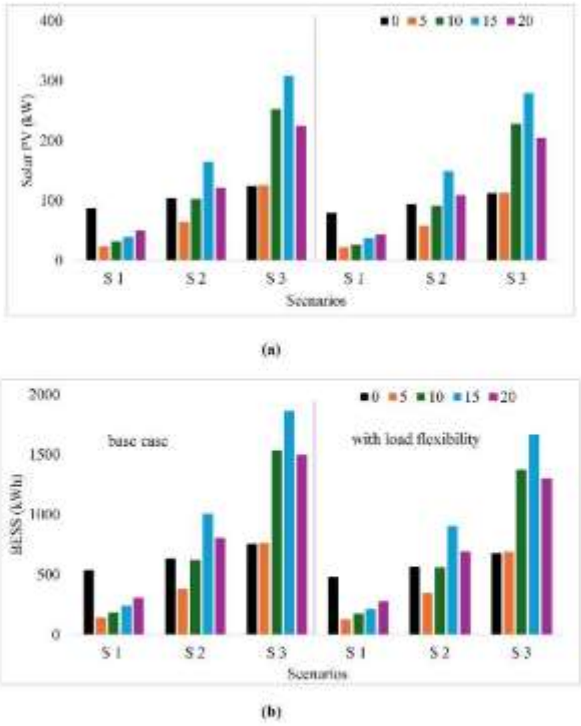
[a] OMC is operation maintenance cost.
[b] RC is replacement cost.
[c] Nrep is the number of replacements over the project lifetime, T.
[d] SV is value of a scrap of the mini-grid components.

4.1. Comparison of design approaches on mini-grid component sizing

The additional solar PV and BESS size requirement in MYAD varies across the three scenarios and depends on demand growth. The calculated system additions for every five years during the planning horizon for the MYAD approach, for scenarios 1, 2, and 3, for both base case and with load flexibility, are shown in Fig. 5a and b. As shown in the figure, in scenario 1, the additional component size is smaller than the initial component size for the first five years (initial capacity). However, in scenarios 2 and 3, the additional size requirements are equal to or higher than the initial size or the previous year's requirements, and also smaller during demand growth saturation.

In MYAD, compared to the required component size over the full planning horizon, the initial capacity is smaller for the higher demand growth scenarios, but they exhibit the same relative reduction of 62 %, 81 %, and 88 %, for both solar PV and BESS, when compared with the respective sizes needed at the end of the planning horizon in scenarios 1, 2, and 3, respectively. This relative reduction decreases with the planning horizon, but it is larger for higher demand growth scenarios.

With higher demand growth, the MYAD approach results in larger reduced component sizes compared to the SY and MY approaches over the entire planning horizon. As shown in Table 2, MYAD reduces the solar PV size by 7 %, 11 %, and 16 % compared to the SY for scenarios 1, 2, and 3, respectively, and by 10 % and 3 % compared to the MY for scenarios 2 and 3, respectively. However, in scenario 1, it is 2 % larger than in MY, leading to excess electricity production. MYAD also reduces BESS size by 7 %, 11 %, and 15 % compared to the SY and by 7 %, 2 %, and 4 % compared to the MY for scenarios 1, 2, and 3, respectively. This indicates that the higher relative reduction in BESS size in scenario 1 (even compared to scenarios 2 and 3) is the reason for the higher solar PV capacity in scenario 1 in MYAD compared to MY. This shows the impact of the different demand evolution scenarios on the optimized system [30].



(a)

(b)

Fig. 5. Calculated system additions for every five years during the planning horizon for the MYAD approach under scenarios 1, 2, and 3, both for the base case and with load flexibility: (a) Solar PV, (b) BESS.

The differences regarding how the design approaches take into account the likely demand evolution over the planning horizon impact the resulting optimized system design and sizing (see Appendix 2 for average demands and percentage differences between peak demand and average demand). The lack of consideration of a likely demand evolution in the SY approach leads to a higher average demand (see Appendix 2) and can result in higher solar PV capacity in SY than in the MY and MYAD approaches. On the other hand, the accounting for demand evolution in MY increases the relative difference between peak and average demands compared to MYAD and SY. This leads to a higher BESS capacity being required in MY than in SY and MYAD to ensure that demand is always met. The cost difference between solar PV and BESS can also impact the resulting capacity difference between the approaches.

Load flexibility affects mini-grid component sizing [42]. The effect of applying 10 % load flexibility is shown in Table 2. The design approaches demonstrate varying degrees of component size reduction with the application of load flexibility. MYAD exhibits a relatively higher overall component size reduction than SY and MY. In SY and MY, there is either no difference or only a slight difference in solar PV size, but there is a reduction in BESS size. In MY, with the application of load flexibility, there is a higher reduction in BESS size than in SY and MYAD. This is because load flexibility has a higher impact on the component responsible for managing the demand variability, the BESS in this case.

As shown in Table 2, the solar PV/BESS ratio ranges from 0.15 to 0.2kW/kWh for all scenarios in all design approaches. However, the result in Table 2 is a low ratio value due to very high morning loads in the case study area caused by cooking appliances, resulting in a larger BESS size. This BESS size can potentially be reduced through different DSM strategies, such as shifting the usage of cooking appliances to midday [59].

4.2. Comparison of design approaches on mini-grid total present cost

The calculated cost additions for every five years during the planning horizon are shown in Fig. 6. The MYAD approach results in reduced initial investment requirements. The initial cost requirement constitutes 74 %, 53 %, and 39 % of the total TPC required at the planning horizon end year for scenarios 1, 2, and 3, respectively. In MYAD, lower demand growth, such as in scenario 1, results in the installation of additional capacity representing a smaller share of TPC in subsequent years than in higher demand growth scenarios since initially installed components already satisfy a substantial portion of the demand. This shows that the MYAD approach in particular leads to very large cost-savings when demand is growing sharply.

These results indicate that MYAD results in significant cost savings compared to MY and SY. The TPC over the planning horizon for the different approaches is shown in Table 3. The cost-savings of MYAD compared to MY and SY are larger in the higher demand growth scenarios. Using a 7 % discount rate, MYAD reduces the TPC by 51 %, 66 %, and 70 % compared to MY and 52 %, 68 %, and 74 % compared to SY for scenarios 1, 2, and 3, respectively. The cost-savings in the MYAD approach stem from postponing additional investments, thus reducing immediate costs. Postponing investments also reduces component replacement costs, particularly for BESS and inverters, operation and maintenance costs, and increases the scrappage value. These cost reductions result in a lower TPC, with savings increasing at a high discount rate. The replacement cost for solar PV is zero since the project's lifespan matches the solar PV's.

Load flexibility application in MYAD shows a higher TPC saving than for the base case. As shown in Table 3, using a 7 % discount rate, compared to TPC savings from MYAD in the base case, applying 10 % load flexibility in MYAD increases TPC savings by 2 % and 4 % compared to MY and SY, respectively. The LCOE for the SY approach is 0.58

Table 2
Calculated mini-grid component size under scenarios 1, 2, and 3, for the SY, MY, and MYAD approaches for the base case and with load flexibility.

Scenarios	Components	Design approach					
		base case			with load flexibility		
		SY	MY	MYAD	SY	MY	MYAD
S 1	Solar PV (kW)	248	227	231	249	227	207
	BESS (kWh)	1522	1516	1412	1389	1300	1272
S 2	Solar PV (kW)	628	616	556	632	616	502
	BESS (kWh)	3857	3523	3447	3519	3067	3069
S 3	Solar PV (kW)	1232	1070	1036	1223	1070	936
	BESS (kWh)	7512	6706	6420	6852	5878	5721

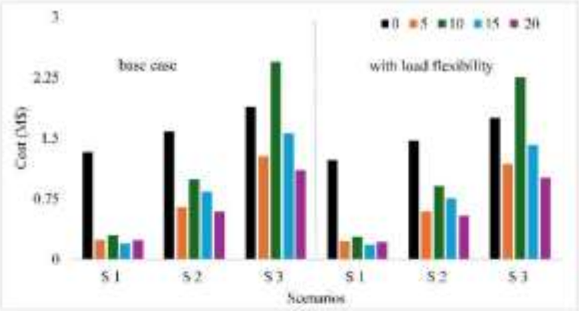


Fig. 6. Calculated cost additions for every five years during the planning horizon for the MYAD approach, both for the base case and with load flexibility for scenarios 1, 2, and 3.

$/kWh, and with the application of load flexibility, it decreases to 0.56 $/kWh. However, the LCOE is lower for the MY and MYAD than for the SY approach.

The estimated TPC for different discount rates is shown in Table 3. The TPC reduction in MYAD compared to MY and SY increases under higher discount rates, highlighting greater cost savings at higher rates. As shown in Table 3, compared to the TPC reduction with a 7 % discount rate, in S-1, the reduction in TPC increases relatively by up to 4.1 % and 6.1 % compared to MY and SY when the discount rate is raised to 15 % and 20 %, respectively. Similarly, in S-3, the reduction in TPC increases by up to 6.3 % and 9.4 % compared to MY and by 5.6 % and 8.3 % compared to SY when the discount rate increases to 15 % and 20 %, respectively. The relative reduction in S-2 falls between the results of S-1 and S-3.

The effect of the MYAD postponement of additional investment increases with increasing annual component cost reductions as shown in Table 4 for the TPC required over the planning horizon. For every 1 % annual reduction in solar PV and BESS costs, the cost-savings of MYAD relative to MY and SY improve by 2.5 %, 3.3 %, and 3.6 % compared to MY, and by 2.4 %, 3.1 %, and 3.2 % compared to SY for scenarios 1, 2, and 3, respectively.

5. Discussion

This study explores and quantifies the advantages of the MYAD approach on long-term mini-grid component sizing and associated costs under different demand evolution scenarios, linking future demand uncertainty to various village level demand developments. To determine cost-optimal component sizes, the PSO algorithm was used along with a measured load profile. In contrast to previous studies focusing on the analysis of mini-grid design approaches, this study compares the application of load flexibility across design approaches on system adequacy, going beyond previous studies' focus on flexibility adequacy. Additionally, a priority-based operating strategy is used. Furthermore, this study compares the design approaches under different discount rates and potential future cost reductions in mini-grid components. By examining these, this study adds to the understanding of how the MYAD design approach can be further developed for cost-efficient optimization of mini-grid component sizing.

This study mainly contributes by: (*i*) quantifying the advantages of the MYAD design approach in terms of component sizing and cost-savings under different demand evolution scenarios compared to other design approaches; and (*ii*) indicating how sizing and cost-savings differ in mini-grid design approaches when load flexibility is applied, under different discount rates and potential future mini-grid components cost reductions.

The MYAD approach results in lower component sizes, leading to total present cost reductions compared to the MY and SY approaches, in line with results of previous studies showing that adaptive designs yield greater cost-savings than the MY and SY approaches [4,27,29,30]. The result of the solar PV/BESS ratio (0.15–0.2kW/kWh) also aligns with an

Table 4
Total present cost in M$ required over the planning horizon for the MYAD approach under different annual cost reductions.

Scenario	Annual cost reduction of solar PV (per kW) and BESS (per kWh)		
	2 %	3 %	4 %
S 1	1.7	1.7	1.7
S 2	2.8	2.7	2.6
S 3	4.5	4.3	4.1

Table 3
Total present cost in M$ required over the planning horizon for the SY, MY, and MYAD approaches for scenarios 1, 2, and 3 for the base case for different discount rates and with load flexibility.

Scenario	Design approach											
	base case									with load flexibility		
	SY			MY			MYAD			SY	MY	MYAD
	discount rate											
	7 %	15 %	20 %	7 %	15 %	20 %	7 %	15 %	20 %	7 %		
S 1	3.7	2.2	1.8	3.6	2.1	1.7	1.8	1.0	0.7	3.6	3.4	1.6
S 2	9.5	5.6	4.6	8.8	5.2	4.3	3.0	1.5	1.1	9.1	8.3	2.8
S 3	18.5	10.9	8.9	16.3	9.6	7.8	4.9	2.3	1.6	17.8	15.4	4.5

earlier study that reported a ratio of 0.12–0.19 [29] while a study on eleven operational mini-grids run by private investors showed a considerably higher ratio of 0.56kW/kWh [60]. The solar PV/BESS ratio reflects robustness, indicating the system's ability to operate normally without significant performance degradation despite disturbances, uncertainties, and changes in demand, inputs, and energy resource conditions, and enhancing the reliability of the mini-grid [32]. The calculated LCOE also aligns with previous studies, reporting values for solar PV-based mini-grids just above 0.25 to 0.61$/kWh [30,61].

The demand-supply energy matching constraint ensures that the load is fully met at all times, since load curtailment is not considered in this study. This often increases system size and cost, as components must be scaled to handle peak demand and lower generation. Additionally, the *SOC* constraints for the BESS, which limits its operation between minimum and maximum *SOC* levels, affect BESS sizing by requiring larger capacities to provide adequate useable energy while ensuring safe operational limits. These constraints are intermittently binding; SOC_{min} binds during peak demand periods, while SOC_{max} binds during high energy generation periods. Therefore, these constraints impact overall system sizing and cost [32].

Mini-grid developmental stages determine the type of investment and financial resources required for funding. The earlier the stage, the riskier the project [62]. The MYAD approach gives additional investment decision options (either at the component or system level), unlike the MY and SY approaches requiring decisions at the outset. This postponement of additional investment decisions allows for considerations of both present and future component costs and the potential national grid connection in subsequent stages [11]. However, the final-year demand consideration in SY led to overcapacity and underutilization early on, creating economic inefficiency and challenges in financing. On the other hand, the perfect foresight demand evolution requirement makes MY less realistic compared to adaptive approaches like MYAD, which better reflect real-world investment strategies. However, MY remains a valuable benchmark, as evidenced by previous research such as [4,27,30,32,33].

The postponement of additional component installations will not only lower the upfront cost but also further decrease the overall total cost. This cost-saving further increases with the application of load flexibility, a high discount rate, and future component cost reductions. The cost-savings achieved by postponing additional investment decisions in MYAD highlight that it also minimizes the cost of the expansion strategy by implementing the expansion in multiple stages rather than all at once. It also enables the utilization of historical demand growth knowledge, which can help in later investment decisions and reduce uncertainties related to load estimation and forecasting [27]. However, the cost savings in MYAD, rather than all at once in SY and MY, can be impacted by economies of scale, which were not explicitly modeled in this study. These could influence investment decisions by favoring larger initial capacity installations in SY and MY compared to MYAD.

The MYAD approach shortens the load forecasting time horizon for mini-grid sizing compared to MY. In our case, it is reduced by a factor of five to five years. This highlights that MYAD will help to deal with future demand uncertainties in long-term mini-grid sizing. Stochastically optimal system sizing provides a fixed system size with the flexibility to handle future demand uncertainties and variability [30]. In contrast, the MYAD approach updates plans dynamically as circumstances change. For instance, if demand development follows scenario 1 for the first five years but then shifts to scenario 2 or 3, the MYAD approach allows plan updates based on the evolved demand in scenario 2 or 3. However, it remains flexible and does not strictly adhere to the demand trajectory of scenario 2 or 3, allowing for further updates as conditions change in subsequent periods. This highlights that the MYAD approach reduces the impact of unforeseen demand spikes or drops, thus reducing reliance on future assumptions. Additionally, by reducing reliance on static mini-grid design in stochastic system sizing, the MYAD approach offers a practical and flexible way to address future long-term demand uncertainty and ensures more robust system sizing decisions over time.

Timely component additions are essential for system reliability and economics since they reduce the mismatch between demand and supply, enhance power availability, and decrease system costs. However, the time interval when additional components are added over the planning horizon must exceed the lead time (the time between the initiation and completion of the process) [13]. From this perspective, the MYAD approach is more flexible than both the MY and SY approaches. This indicates how the MYAD approach can greatly increase the sustainability and scalability of mini-grids in rural areas by lowering financial risks, optimizing resource allocation, and minimizing the possibility of oversized or underutilized systems. It is also more realistic compared to the adaptive approach, which adds additional mini-grid components every year, which certainly is challenging to implement in rural areas. This indicates that the decision on when to add additional mini-grid components should be based on different criteria (cost, reliability, environment, and social considerations, etc.), of which many depend on the local context.

The MYAD approach leads to significant cost savings in scenarios with higher demand growth, which is highly likely in rural villages [28]. For villages with slower demand growth, there is a smaller TPC share in later years, resulting in less cost-savings compared to a village with higher demand growth (could be corresponding to a larger village along a road, villages closer to urban areas, etc.). This highlights that the MYAD approach, offering more flexibility than the MY and SY approaches, seems to be a more economical and favorable choice, especially at higher demand growth. Additionally, villages with higher demand growth can increase the cost-efficiency and bankability of the system if the growth is from productive load categories [32].

Initial up-front costs are a major obstacle for mini-grid investment, especially in rural areas with limited access to financial tools and banking services [28]. Thus, total cost constraints in rural areas are limiting wider access to basic electricity. This stresses the importance of the MYAD initial investment cost reduction enabling available financial resources to be used for basic access also at other sites instead of for oversized systems in a few villages. Moreover, this reduction in initial investment costs provides opportunities to secure additional funding for subsequent investments [29]. This shows how crucial decisions regarding initial investments are, as they serve as a foundation for all subsequent investments in the system.

Operation and maintenance costs increase based on the actual capacity installed and used in any given year [30]. In the MYAD approach, increasing capacity based on demand growth will lead to reduced replacement, and operation and maintenance costs. The postponement of additional component installations, particularly battery energy storage, contributes to reduced system costs and possibly also environmental impacts. The reduction in operation and maintenance costs can have a significant impact, especially on technologies with higher operation and maintenance costs. Additionally, the development of a system with demand growth helps operators to acquire technical skills (especially in smart systems) gradually [11] for rural mini-grids in SSA having a lack of skilled personnel [63].

Mini-grids are established in order to provide electricity for the rural population in their service area while balancing customer satisfaction and financial viability [64]. The results highlight that the load flexibility application in the MYAD approach enhances techno-economic benefits by reducing uncertainties and costs compared to the MY and SY approaches. However, it requires users' commitment, may have lower social acceptance, and incurs additional costs for implementing DSM. Implementing DSM at the load categories rather than the appliance level reduces the additional costs [42].

The MYAD cost-savings will be larger in contexts with higher general risk considerations and higher discount rates as in many developing countries, even if major differences also occur between countries that are comparable with respect to their state of economic development

[65]. The cost-savings shown between the design approaches, because of the discount rate, highlight the significance of the MYAD design approach is more in the context of developing countries.

The increase in cost-savings in MYAD, by future component cost reductions (both market-driven and those resulting from supportive policies and incentives), highlights MYAD's advantage not only in the planning phase but also during system operation. For instance, if subsidies or regulatory changes are introduced after system installation, leading to lower component costs, the MYAD approach would allow developers to benefit from these reductions by incorporating them into future stages of the project. This highlights the advantage of the MYAD approach in minimizing the risks associated with future cost fluctuations and its suitability for environments where future cost reductions or changes in regulations are uncertain, providing a more risk-averse strategy for mini-grid development.

The MYAD requires more frequent sizing and field visits to upgrade capacity, which can be challenging for mini-grids facing issues such as limited infrastructure (like rugged landscapes and dense forests) or lack of transportation. Additionally, harsh weather conditions, security concerns (including conflict in the area), limited or unreliable communication, and resource constraints can limit the applicability of the approach. On the other hand, mini-grid settings with fewer such challenges are more likely to successfully implement this approach, although they may still incur some costs [66], but these are certainly less in many cases than the potentially huge cost-savings.

Component degradation affects both the performance of a mini-grid system and increases its system costs [32]. Charge and discharge cycles also influence battery replacement costs [30]. This study does not take this influence into account but its effect would be smaller for MYAD compared to SY and MY due to lower initial and total capacity.

Measured electricity load data, representing realistic load data, were used to represent the initial year demand. The use of a one-week load profile to represent a full one-year load profile introduces a simplification, especially in regions with marked seasonal demand variations. However, this should not have much effect in Ethiopia since seasonal demand variations are modest due to minimal weather fluctuations throughout the year and no marked seasonally dependent changes in social behaviors.

Furthermore, the study is based on data from a specific case study area. The demand in this area has a high morning peak due to the mitad use for bread (injera) baking. This is typical for Ethiopia, but such a high morning peak is otherwise less common. The high morning peak results in a low solar PV/BESS ratio, as would any high demand peak do, especially high demands outside of the PV generation time. Higher electricity demands during early mornings and evenings are more likely in areas dominated by residential demands and in villages where a large population shares work in agriculture (individuals spend the majority of daytime on farming activities) [9]. However, the main findings of the study, particularly the significant reduction in initial and overall components leading to initial and overall cost reductions and helping in addressing uncertainties about future demand by the MYAD approach, should be valid in most developing contexts.

6. Conclusions

This study investigates and quantifies the possible advantages of the multi-year-adaptive design approach for off-grid mini-grids in terms of mini-grid component sizing and cost under three different demand evolution scenarios based on real setting demand data. The study also evaluates the impact of load flexibility, varying discount rates, and potential future mini-grid component cost reductions across single-year, multi-year, and multi-year-adaptive design approaches. To determine cost-optimal component sizes over a 25-year project life across various design approaches, particle swarm optimization was used.

Our findings show how the multi-year-adaptive design approach helps to address the uncertainty about future demand evolution in previously non-electrified areas, and thus of particular relevance for rural electrification in SSA. Compared to the other two design approaches studied, it also results in significant mini-grid component size and cost reductions, specifically during the early years of the studied system's project lifetime. The size reductions are particularly large in high demand growth scenarios, resulting in a reduction of the initial investment cost by up to 60 %. These component size reductions lead to significant total present cost savings (51 %, 66 %, and 70 % when compared to the multi-year and 52 %, 68 %, and 74 % when compared to single-year design approaches for low, medium, and high demand growth scenarios, respectively). The application of 10 % load flexibility leads to modest total present cost reductions, 2 % and 4 % larger reductions in the multi-year-adaptive than in the multi-year and single-year approaches, respectively. A high discount rate combined with future component cost reductions further increases the cost savings achieved through the multi-year adaptive approach. In this study, a relatively low solar PV/BESS ratio was found due to very high morning loads in the case study area due to the mitad use for bread (injera) baking.

Since investment costs in general and the initial up-front cost in particular, are major obstacles for mini-grid investments and high demand growth is to be expected in many locations where mini-grids are constructed, the study findings underline that the multi-year-adaptive design approach ought to be considered when investments are made. To further enhance the advantages of the multi-year-adaptive design approach, coupling it with strategies promoting load flexibility is crucial, and implementing it in regions with higher discount rates provides additional benefits. Additionally, potential future mini-grid component cost reductions, whether market-driven or supported by policies and incentives, should be factored in. Further research can explore the benefits of the approach, such as enhancing system reliability, environmental impacts, and its practical application.

CRediT authorship contribution statement

Milky Ali Gelchu: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Jimmy Ehnberg:** Supervision. **Dereje Shiferaw:** Supervision. **Erik O. Ahlgren:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

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 1. Used equations

$$CRF = \frac{r(1+r)^T}{(1+r)^T - 1}$$

$$IOMC = OMC_0\left(\frac{1+i}{r-i}\right)\left(1 - \left(\frac{1+i}{1+r}\right)^T\right) \quad r \neq i$$

$$OMC = OMC_0 \times T \quad r = i$$

$$RC = \sum_{j=1}^{N_{rep}} \left(C_{RC} \times C_V \times \left(\frac{1+i}{1+r}\right)^{\frac{T*j}{(N_{rep}+1)}}\right)$$

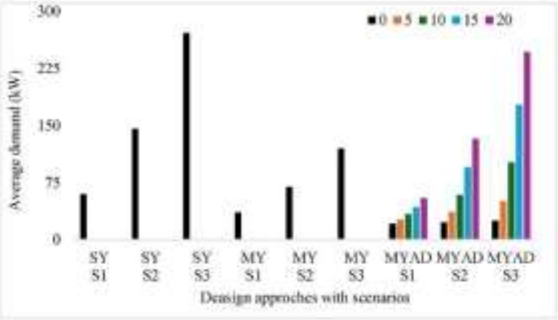
$$PSV = \sum_{j=1}^{N_{rep}+1} SV\left(\frac{1+i}{1+r}\right)^{\frac{T*j}{N_{rep}+1}}$$

$$SOC(t+1) = SOC(t)(1-\sigma)$$

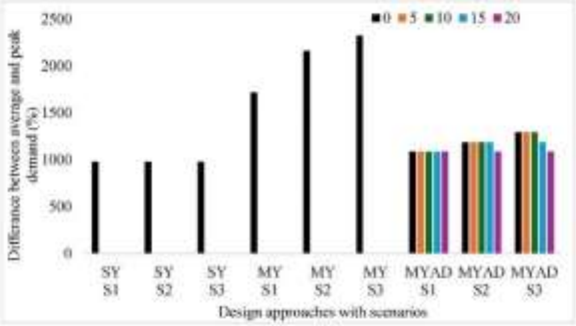
$$SOC_{min} = (1 - DOD)C_B$$

$$T_c(t) = T_a + 3H_t(t)$$

Appendix 2. Demand characteristics in demand profile used for the design approaches: (a)Average demand, (b) Percentage difference between average and peak demand

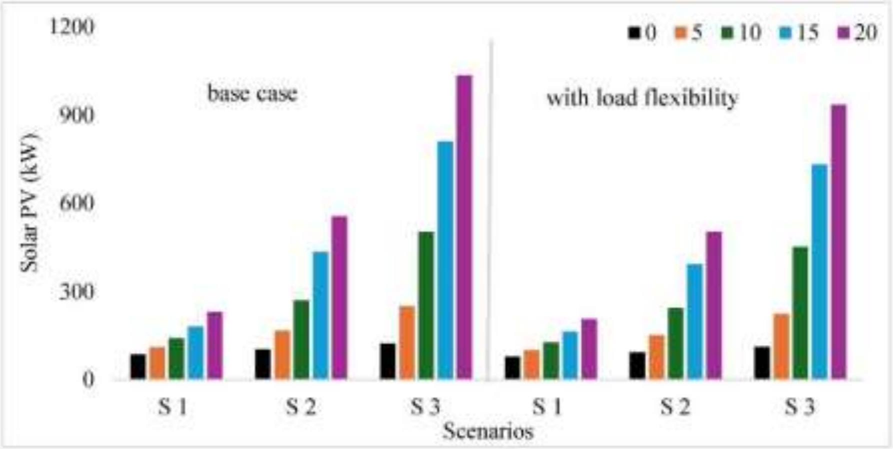


(a)



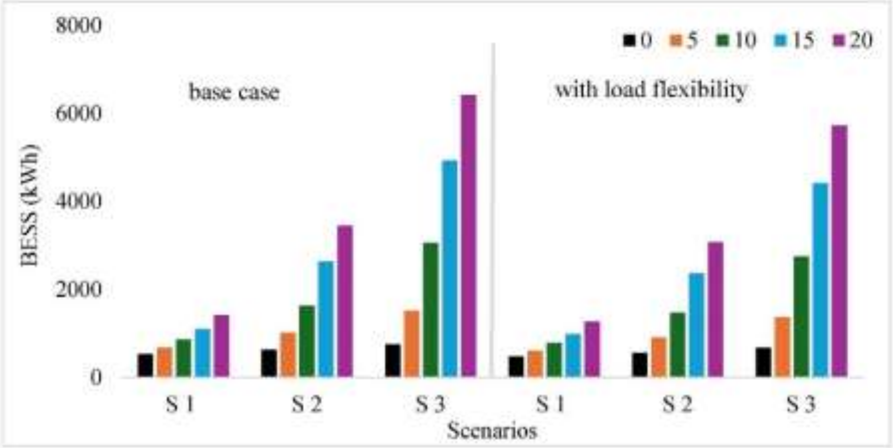
(b)

Appendix 3. System capacity and cost in each five years during the planning horizon for MYAD design for the base case and with load flexibility for scenarios 1, 2, and 3: (a) Solar PV, (b) BESS, (c) Cost



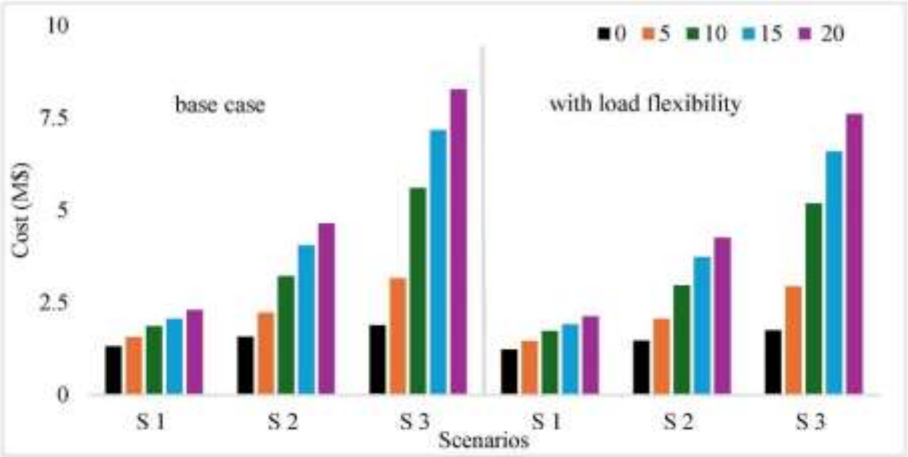
Solar PV (kW)
1200
900
600
300
0
0 5 10 15 20
base case
with load flexibility
S 1
S 2
S 3
S 1
S 2
S 3
Scenarios

(a)



BESS (kWh)
8000
6000
4000
2000
0
0 5 10 15 20
base case
with load flexibility
S 1
S 2
S 3
S 1
S 2
S 3
Scenarios

(b)



Cost (M$)
10
7.5
5
2.5
0
0 5 10 15 20
base case
with load flexibility
S 1
S 2
S 3
S 1
S 2
S 3
Scenarios

(c)

Data availability

Data will be made available on request.

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Paper III

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Impact of demand-side management on the sizing of autonomous solar PV-based mini-grids

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A R T I C L E I N F O

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A B S T R A C T

Solar PV-based autonomous mini-grids represent an economically affordable and robust electrification option for rural communities. However, the initial investment cost for renewable energy technologies such as solar PV remains high for rural communities. Implementation of demand-side management (DSM) could increase the cost-efficiency of mini-grids in rural areas. This requires demand-side knowledge, but little is still known of electricity demands in recently electrified areas and, in particular, of how DSM implementation could impact mini-grids. The few studies available focus either on systems or on appliance levels while this study aims to determine cost-efficiency impacts of DSM implementation at a category level. A shifting strategy is applied based on classification into high priority loads and low priority loads. Autonomous rural mini-grid components sizing for four different load categories and load flexibility are carried out using particle swarm optimization. The results show that different load category combinations result in large variations in terms of possible levelized energy cost reductions and, thus, in terms of the cost-optimal sizing of the mini-grid components. The DSM implementation on the household and productive use categories have the largest capacity of reducing the levelized energy cost, by 45.8% and 20.7%, respectively, compared to the no demand-side management case.

Credit author statement

We certify that all authors have participated sufficiently in this research work from intellectual conception, and design of the research objectives, analysis and interpretation of the result and writing of the manuscript. The contribution of each author is provided hereafter. Milky Ali Gelchu: Conceptualization, Methodology, Software, Writing-Original Draft and Writing - Review and Editing. Jimmy Ehnberg: Conceptualization, Supervision, Reviewing, and Editing. Dereje Shiferaw: Conceptualization, Supervision, Reviewing, and Editing. Erik O. Ahlgren: Conceptualization, Supervision, Writing – Review, and Editing.

1. Introduction

Access to affordable electricity is a vital enabling factor for human development, and improving this access in developing countries is one part of the seventh United Nations Sustainable Development Goal (UNSDG) [1]. One billion people, representing 13% of the world's population, lacked access to electricity in Year 2017. Roughly half of these people live in sub-Saharan Africa (SSA), with a large majority inhabiting rural areas [2]. UNSDG stipulates the need for an innovative sustainable energy transformation for rural areas [1].

Autonomous mini-grids constitute an economically affordable and robust electrification option for non-electrified areas in which extensions to the electric grid are not techno-economically feasible [3]. Mini-grids are electric power generation and distribution systems that provide electricity to a few customers in a remote settlement or bring power to hundreds of thousands of customers in a town or city. Mini-grids can be either fully isolated from the national grid (autonomous) or connected to it [4].

Mini-grids are a fundamental "building block of the Smart Grid" [5]. Studies define the term "Smart Grid" in various ways, but most of the definitions share the idea that the Smart Grid is a stable, efficient and reliable system [6]. Among the definitions, the European Technology Platform defines a Smart Grid as: "*an electricity network that can intelligently integrate the actions of all users connected to it - generators,*

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consumers, and those that do both to efficiently deliver sustainable, economic, and secure electricity supplies" [7].

In recent years, the capital costs of renewable energy technologies (RETs) have been decreasing [3]. Among RETs, solar photovoltaic (PV) systems are gaining traction in SSA [4], although costs in SSA are still much higher than the world average due to political, financial, and technological risks [8].

There are many non-electrified areas in SSA countries receiving high levels of solar irradiation. E.g. Ethiopia, with an rural electricity access rate of 27%, has a potential total solar electricity reserve of 2.199 million TWh/annum with average insolation level of 5.25 kWh/m^2 [9]. Thus, solar PV- and battery energy storage (BES)-based autonomous mini-grids represent potential sustainable and reliable solutions for the electrification of rural areas [10].

The initial investment cost for solar PVs remains high for rural communities, and financial viability has been achieved until now only through heavy subsidization of this cost [11]. Consequently, in SSA, private stakeholders have been reluctant to invest in mini-grids due to the high level of uncertainty and the uncertain investment risk-return profile [12].

Mini-grid supply-side optimization and component sizing have been studied with different optimization methods in order to overcome the aforementioned barriers to mini-grid investments. While an iterative optimization technique for solar PV system sizing has been presented [13], it is usually time-consuming and may not provide accurate results. The Hybrid Optimization of Multiple Energy Resources (HOMER) software has been used for sizing hybrid renewable energy sources (HRES) [14]. However, it lacks flexibility in relation to altering the operating strategy and objective function.

In supply-side optimization studies, heuristic optimization algorithms have also been used, including a dynamic programming algorithm used for sizing of energy storage [5], a genetic algorithm (GA) used for optimal sizing of a PV-diesel-battery system [15], Non-dominated Sorting Genetic Algorithm (NSGA-II) used for HRES sizing based on different objectives [16], Virus Colony Search (VCS) algorithm [17], metaheuristic Gray Wolf Optimization (GWO) algorithm [18], and Particle Swarm Optimization (PSO) algorithms used for optimal sizing of different renewable energy source combinations [19–21]. The PSO algorithm yields high-quality solutions in a shorter simulation time than the iterative, HOMER, and most of the heuristic algorithms described above [20,22].

In recent years, machine learning algorithms are also used in supply-side optimization. They have short computational time and high exploration efficiency compared to heuristic algorithms. However, machine learning algorithms require significant amounts of historical data at the training stage [23].

On the supply side, the output of renewable energy sources (RES) is variable and is not known with perfect accuracy (referred to as 'uncertainty') [24]. This uncertainty necessitates the incorporation of expensive BES to minimize the effects of intermittence [25], the installation of additional generation capacity, or load flexibility [17]. There are also demand variations on sub-hourly, hourly, daily, and/or seasonal timeframes [26].

Flexibility is the ability of the system to cope with variations in generation and load. Flexibility cannot be provided solely by flexible generation units, e.g., hydropower or gas power, as it also requires a set of policies and control methods to manage the electrical loads, referred to as Demand-Side Management (DSM) [7]. Load flexibility can involve the shifting of the electricity demand to another time to offset the peak demand or to maximize the use of electricity from RES [26].

DSM is a Smart Grid strategy that enables the interaction between consumer and utility, being geared towards improving energy efficiency through demand profile modifications. There are six broadly discussed and implemented techniques for DSM including: peak clipping, valley filling, load shifting, load building, strategic conservation, and strategic load growth [27]. Load shifting, which is the most commonly used DSM strategy, is performed by load categorization based on various criteria [27].

Different studies examined how DSM implementation for different load profiles affects the cost-effectiveness of mini-grids. Optimized demand combinations that can be met using the available supplied power to reduce the cost of electricity [28,29]. DSM-based optimization was proposed and implemented for HRES sizing to reduce the initial capital cost of mini-grids [11]. Smart Grid concept-based load management, which divides the load profile into high and low priority loads, was applied for HRES sizing for electricity cost minimization [30]. An energy management strategy was proposed and implemented with DSM to minimize the operating cost of energy storage system of mini-grid [31]. DSM was implemented by using a flexible load priority list to minimize the operational cost without shedding critical loads in a mini-grid [32]. DSM using load shifting and frequency-based pricing was proposed to maximize utilization of renewable resources and system frequency [33].

The demand response (DR) program is a branch of DSM that aims to motivate and influence electricity consumers to reshape their energy demands in return for benefits offered by utility companies [25]. The impact of DR has been studied with different objectives, for instance, for total cost reduction [17], for financial and load balancing [34], to achieve supply–demand balance and increase profit of power suppliers [35], and for power system planning using techno-economical optimization to reduce the total cost [36].

The above-presented studies investigated the impact of DSM on the cost-efficiency of HRES-based mini-grids rather than that of 100% RES-based autonomous mini-grids. Further, the impacts of DSM implementation strategies have been studied either at the system level or appliance level, e.g., household appliances [11,28–30], but the control of each appliance is not an easy task as every appliance needs to be connected to the controller through cable or communication networks, especially in rural areas [27]. Thus, for the full exploitation of DSM implementation in rural areas, a low cost control and communication network infrastructure is essential [37].

In the aforementioned studies, even if the impact of DSM on the cost-efficiency of mini-grids was determined by incorporating DSM into the mini-grid sizing methodology, there were no consideration of the load-side uncertainties related to inaccurate load profile estimations or of the supply-side uncertainties linked to intermittency. Some studies have examined the effects of such uncertainties in relation to DSM implementation for mini-grids sizing and shown that the load and supply-side uncertainties impacts the optimum economic and reliability design of mini-grids, but the uncertainties were modeled differently in the studies [16,17,38,39]. For example, one study [16] used Chance Constrained Programming (CCP) to address the supply-side uncertainties, whereas another study [38] used CCP to model both the load-side and supply-side uncertainties. Uncertainties linked to both the load and supply sides have also been modeled using different distribution functions [17,39].

Based on the identified knowledge gaps, this study investigates the potential impact on cost-efficiency of DSM implementation by addressing different load categories (rather than looking only at the appliance level). In addition, the impacts on cost-efficiency of DSM implementation and load flexibility are compared.

The main research questions addressed in this study are:

- What is the impact of DSM implementation at the category level on the cost-efficiencies of solar PV and HRES-based autonomous mini-grids in rural areas?
- How large is the impact of DSM implementation at the category level on the cost-efficiencies of solar PV and HRES-based autonomous mini-grids in rural areas, as compared to the impact of load flexibility?

The remainder of this paper is structured as follows. The method used, configurations, and modeling of the components of the mini-grid are described in Section 2. Section 3 describes the data used, section 4 describes the results and analysis, section 5 discusses the results and section 6 draws some overall conclusions from the work.

2. Method

The electricity demand distribution in rural areas of SSA is characterized by dispersed consumers, low consumption, and low income levels of the consumers [40]. Low income levels affect the willingness to pay for electricity, which in turn depends on the electricity tariff, in that strong willingness to pay is associated with a low electricity tariff [41]. Thus, the impact of DSM implementation at the category level on the sizing of a cost-efficient, solar PV-based, autonomous mini-grid is determined on the basis of levelized energy cost (LEC) minimization.

The optimal, cost-efficient sizing of autonomous mini-grid components based on LEC minimization is determined using a PSO algorithm, characterized by easy implementation, robustness, computation efficiency compared with other existing heuristic algorithms and exhibiting good performance in solving these types of problems [22,42]. To validate the results obtained from the PSO algorithm an iterative method is used.

To study the impact of DSM implementation at the category level on the configuration of the autonomous mini-grid, two different configurations are used. Similarly, the impact of DSM implementation at the category level is compared with load flexibility by determining the optimal sizing of autonomous mini-grid components. For this, conditions representing a village in northeastern Ethiopia is used.

In the following sections, the demand categorization, mini-grid configurations used, problem formulation, operating strategy used for DSM, method of optimization, and the modeling of mini-grid components are described.

2.1. *Demand categorization*

In a static model of the load profiles in the rural mini-grids, the productive use and community types of electricity consumers have been shown to present different load profile patterns than the household consumers [27]. These different load profile patterns can be used to design a financial incentive entailing different tariff settings for different load categories to encourage load-shifting from peak to off-peak periods (time-of-use tariffs), which is the most effective measure to implement DSM.

To determine the impact of DSM on the cost efficiency of an autonomous rural mini-grid, this study proposes the implementation of DSM for four load categories with different load profile patterns. The four load categories are: household loads (C-1); community loads (C-2); productive use (PU) loads having night time load (C-3); and PU loads not having night time load (C-4).

The sizing of mini-grids requires knowledge of the electricity load profile [43]. Load profiles may exhibit variability. However, most of the variations are limited in developing SSA countries, since weather conditions are similar throughout the year and social behaviors are essentially unchanging [44]. In the sizing of a cost-efficient autonomous mini-grid system, weekly load profiles are used for each load category.

To model the weekly load profile for each load category, a bottom-up methodology is applied. The load profiles are estimated based on data collected by the Ethiopian Electric Utility (EEU), the state-owned power utility. The collected data include appliance type and number, power rating, and probability of being used. An appliance-specific load profile is estimated for each appliance by multiplying the appliance power rating by the appliance probability of use. A load profile for each load category is estimated by summing up the appliance-specific load profiles.

2.2. *Configurations*

Two configurations of an autonomous mini-grid are used. Configuration 1 contains only solar PV and BES and is, thus, a 100% RES-based autonomous mini-grid. Configuration 2 represents a HRES-based autonomous mini-grid in which a diesel generator (DG) is added to the solar PV and BES. A schematic of the autonomous mini-grid system with both configurations is presented in Fig. 1.

2.3. *Problem formulation*

In this study, the impact of DSM implementation at category level on the cost-efficiency of mini-grid is formulated as an optimization problem, which determines the component sizing using a priority-based load shifting strategy. The objective function is minimization of the LEC. To determine the impact difference among the load categories, sixteen combinations of the four load categories are compared with the No DSM case (i.e., mini-grid component sizing without load prioritization) in a priority-based fashion. For comparison of the impact of DSM implementation at a category level with load flexibility, different percentages of load flexibility for the two configurations are used. The load flexibility at each hour t determines the amount of electricity load that is shiftable. The shiftable load which is considered a low-priority load in the implemented DSM operating strategy is calculated using Eq. (1):

$$L(t) = P(t) \times Lf \tag{1}$$

where $L(t)$ is the flexible load at hour t, $P(t)$ is the load at hour t, and Lf is the percentage of load flexibility.

To increase the robustness of the optimization problem, load-side uncertainties related to inaccurate load profile estimations and supply-side uncertainties related to intermittency are considered. To determine how the uncertainties impact the mini-grid sizing, component sizing with and without uncertainties considered is calculated. In addition, the validation of the results is examined using an iterative method. In determining the impact of uncertainties and validation of the results using an iterative method, a 10% load flexibility case is used. The objective function and constraints used for this study are explained in the following sections.

2.3.1. *Objective function*

The levelized energy cost (LEC) is the objective function of the optimization problem. It is an indicator for the cost-reflective tariff and is calculated as:

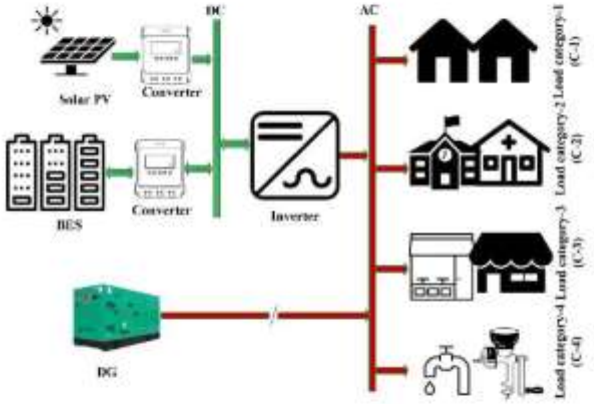


Fig. 1. Schematic of the autonomous mini-grid system, showing the load categories for Configurations 1 and 2.

$$LEC = \frac{TPV \times CRF}{LAE} \tag{2}$$

where *LAE* is the annual load demand (the summation of all demand per year), and *CRF* is the capital recovery factor, which depends on the rate of annual interest (r) and plant life (T). *TPV* is the total present cost of the entire system and is calculated as:

$$TPV = IC + OMC + RC + FC - PSV \tag{3}$$

where *IC* is the initial capital cost, *OMC* is the operation maintenance cost, *RC* is the replacement cost, *FC* is the fuel costs, and *PSV* is the present scrappage value of the mini-grid components. The initial capital cost includes the component price, the cost of civil work, and the installation cost for the autonomous mini-grid components.

The fuel cost of the DG is calculated as:

$$FC = D_f(t) DG_h P_f \tag{4}$$

where DG_h is the total operating hours of the DG during time *T*, and P_f is the fuel price per liter [30].

2.3.2. Design constraints

The mini-grid sizing is subject to various constraints. Security constraints to enforce the autonomous mini-grid should cover the required energy demand-supply and are expressed as:

$$E_{dem} \leq E_{sup} \tag{5}$$

where E_{dem} and E_{sup}, respectively, are the total energy demand required and the total energy demand supplied in the autonomous mini-grid.

In addition, there is the BES constraint: the state of charge of a BES (SOC) at any time *t* should lie between the minimum (SOC_{min}) and the full capacity of the BES (SOC_{max}). This limit of a state of charge is expressed by Eq. (6), where the maximum charge quantity of the BES (SOC_{max}) takes the value of the nominal capacity of the BES (C_B), and the minimum charge quantity of the BES (SOC_{min}), is determined using the maximum depth of discharge (DOD):

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{6}$$

2.4. Operating strategy

A load-shifting strategy operating strategy is used to manage load categories in a priority-based fashion based on a classification into high-priority loads (HPLs) and low-priority loads (LPLs). HPLs are non-shiftable loads and are, therefore, allowed to operate at their scheduled time by the user. In contrast, LPLs are shiftable loads which can be shifted to a time when there is sufficient electric power generation from solar PV and the BES is full. The maximum allowed shifting time is 24 h. Thus, the used operating strategy maximizes the hours of energy served for HPLs and minimizes them for LPLs. The flowcharts of the operating strategies used for Configurations 1 and 2 are shown in Figs. 2 and 3, respectively.

The step-by-step description of the flowchart used for the configurations operational strategy is as follows. For Configuration 1, the electrical power from solar PV in hour *t*, ($P_{pv}(t)$), is first used to satisfy the HPL in that hour, and the remaining energy, ($P_{BC}(t)$), expressed based on the efficiency of the inverter (η_{inv}), if any, is added to the available energy in the BES (charging) from the previous period. This stored energy is used to supply the HPLs during the period when the electrical power generated from solar PV is insufficient to satisfy (discharging) $P_{BD}(t)$. However, the state of charge of the BES (SOC), expressed based on the BES self-discharge rate (σ), is less than the maximum state of charge (SOC_{max}) during charging, and the BES must be above its minimum state of charge (SOC_{min}) during discharge. The

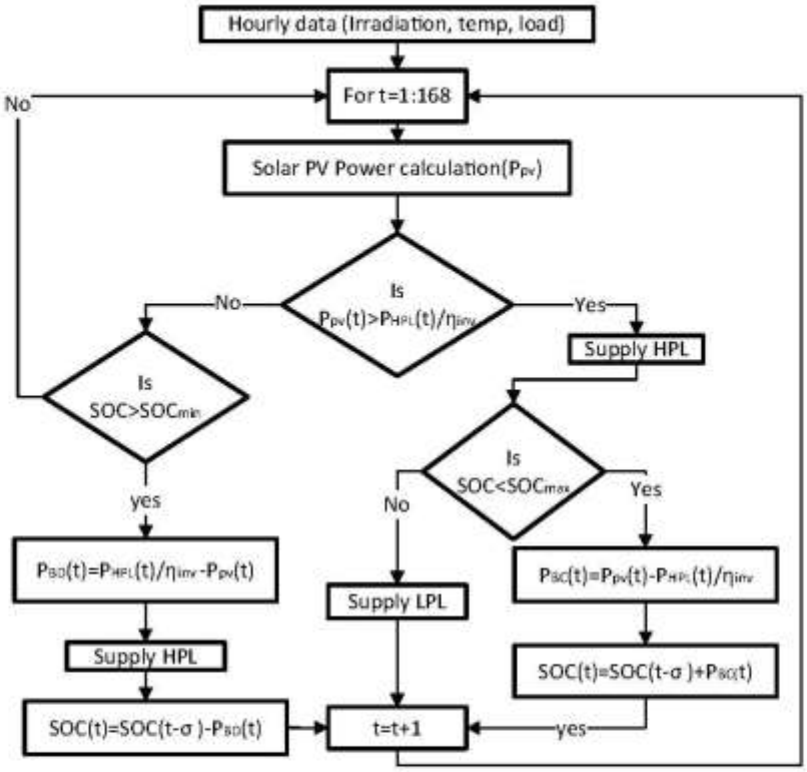


Fig. 2. Flowchart of the operating strategy for Configuration 1.

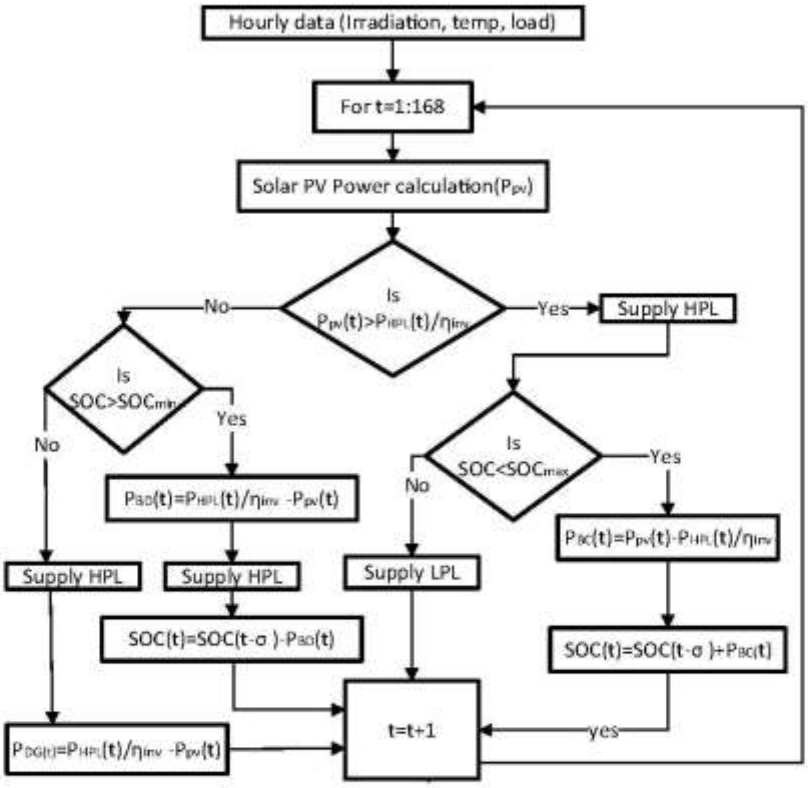


Fig. 3. Flowchart of the operating strategy for Configuration 2.

LPLs are supplied when there is excess energy from solar PV and the BES is equal to SOC_{max}. Thus, the LPL is shifted to a time where there is sufficient electricity generation from the solar PV and the BES is equal to SOC_{max}.

All the steps described for Configuration 1 are applied in Configuration 2, with the exception that the electrical power generated from solar PV and stored energy in the BES is not sufficient to supply the HPL, which means that in this case the HPLs will be supplied using the DG ($P_{DG}(t)$).

2.5. *Method of optimization*

The PSO algorithm is used to identify the optimal sizes of the components of the autonomous mini-grid, while minimizing the LEC as an objective function using the MATLAB software.

PSO is one of the most popular heuristic optimization algorithms used to solve optimization problems. In the PSO algorithm (Fig. 4), each particle (swarm) represents a potential solution, and these solutions are assessed by the optimization objective function to determine their fitness. In the PSO algorithm, each particle modifies its movement according to the best position achieved previously by the particle (X_i^P) and the global best (X_i^g) position of the entire population (to which it belongs) [45,46].

The two equations used for PSO are the position update equation [Eq. (7)] and the velocity update equation, [Eq. (8)]. These are to be modified in each iteration of the PSO algorithm, so as to converge to the optimum.

$$V_i(t+1) = wV_i(t) + C_1 r_1 (X_i^P(t) - X_i(t)) + C_2 r_2 (X_i^g(t) - X_i(t)) \tag{7}$$

The PSO algorithm represents the population as the term X, r_1 and r_2 represent random numbers, t represents the iteration number, C_1 and C_2 represent the coefficients of acceleration, and w is the inertia weight that is used to improve the speed of convergence. The inertia weight is calculated for each iteration using a linear deceasing inertia weight, which has the lowest inaccuracy compared to other inertia weights [22]:

$$X_i^{(g+1)} = X_i^{(g)} + V_i^{(g+1)} \tag{8}$$

where $X_i^{(g)}$ is the global best solution, and X_i^P is the best personal position. The above steps are performed until the stopping conditions are met.

$$w_i = w_{min} - \frac{w_{max} - w_{min}}{i_{max}} \times i \tag{9}$$

where w_{max} and w_{min} are the maximum and minimum inertia weights, respectively, and i represents the particle index.

2.6. *Modeling of system components*

The modeling of the mini-grid components is a significant step in the optimization for different configurations. The mathematical modeling of each mini-grid component is described in the next section.

2.6.1. *Modeling the solar PV output*

The power of a solar PV array as a function of the solar irradiance and the ambient temperature is defined by Eq. (10) [47].

$$P_{pv} = \theta_t \times PVA \times \mu_c(t) \tag{10}$$

where θ_t is the average irradiance in hour t, PVA is the surface size of the cell, and $\mu c(t)$ is the instantaneous PV cell efficiency.

However, solar PV generation cannot generate a constant electrical power output. Therefore, a probabilistic model of PV output, the Beta

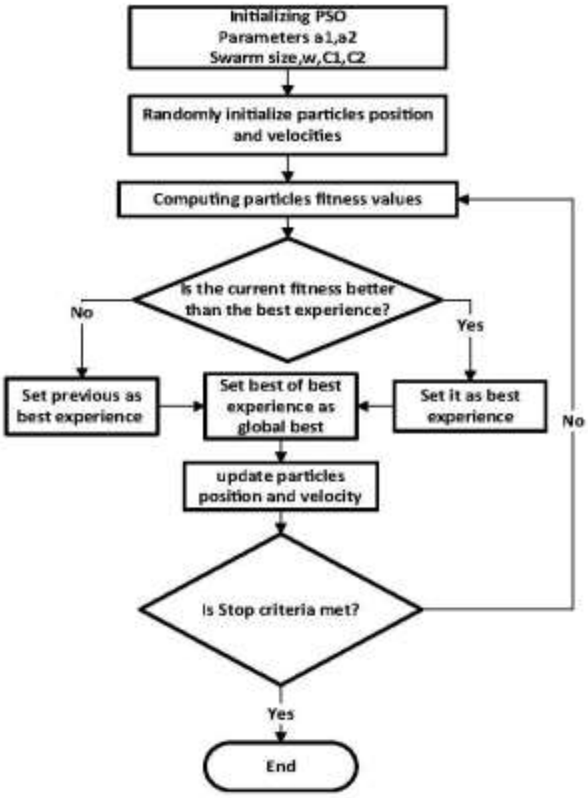


Fig. 4. Flowchart for the PSO algorithm.

PDF, is used to model the distribution of the solar irradiance, as shown in Eq. (11): [17].

$$f(\theta)\begin{cases}\dfrac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha)+\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1} & 0\le\theta\le 1,\alpha\ge 0,\beta\ge 0\\ 0 & otherwise\end{cases} \tag{11}$$

where α and β are elements of the Beta distribution function. The μ and σ terms represent the mean and standard deviation of the Beta PDF, respectively.

The probability of the solar irradiance θ can be calculated using Eq. (12):

$$P(\theta)=\int_{\theta_i}^{\theta_j} f(\theta)d\theta \tag{12}$$

The instantaneous PV cell efficiency can be calculated in terms of the cell temperature as [46]:

$$\mu_c(t)=\mu_{cr}[1-\beta_t(T_c(t)-T_{cr})] \tag{13}$$

where β_t is the temperature coefficient, in the range of 0.004–0.006 for silicon cells. The terms μ_{cr} and T_{cr} are the theoretical solar cell efficiency and temperature, respectively.

The value of *PVA*, which is the total solar cell area required to supply the load demand, can be calculated from Eq. (14):

$$PVA=\frac{1}{24}\sum_{t=1}^{24}\frac{P_{L,av}(t)F_s}{H_{\beta}\mu_c(t)\eta_{pc}V_F} \tag{14}$$

where F_s is the safety factor, which includes the possible allowance of insolation data inaccuracy, V_F is the factor of variability, which considers the impact of yearly radiation variation, and η_{pc} is the power conditioning system efficiency [45].

2.6.2. Battery energy storage (BES)

BES charging and discharging depends on the energy production and state of the charge of the BES at any given time. The state of the charge of the BES at a specified time is expressed by Eq. (15) and Eq. (16) [45]:

$$SOC(t+1)=SOC(t)(1-\sigma)+P_B(t)\eta_B \quad \text{charging mode} \tag{15}$$

$$SOC(t+1)=SOC(t)(1-\sigma)-P_B(t)/\eta_B \quad \text{discharging mode} \tag{16}$$

$$\text{where } P_B(t)=P_{PV}(t)-\frac{P_{HPL}(t)}{\eta_{inv}} \tag{17}$$

$P_{PV}(t)$ and $P_{HPL}(t)$ are the total power levels produced by the mini-grid system and required by the HPL at time *t*, respectively, *SOC* is the state of charge of the BES, η_B is the efficiency of the BES, and σ is the BES self-discharge rate. $P_B(t)$ represents the charging or discharging power of the BES at time *t*.

2.6.3. Power inverter

Inverters, which are responsible for converting DC to AC, is calculated using Eq. (18) [47]:

$$P_{inv}=\frac{P_{peak}}{\eta_{inv}} \tag{18}$$

where P_{peak} is the peak of the load demand, and η_{inv} is the efficiency of the inverter.

2.6.4. Diesel generator model

A DG is used to meet the HPLs in case the energy provided by the solar PV and BES is insufficient. The amount of fuel consumed by the DG depends upon its output power at each time-step [45]:

$$D_f(t)=\alpha_D P_{Dg}(t)+\beta_D P_{Dgr} \tag{19}$$

where $D_f(t)$ is the hourly fuel consumption of the DG, P_{Dg} is the average power per hour of the DG, P_{Dgr} is the rated power of the DG, and α_D and β_D are the coefficients of the fuel consumption curve.

2.6.5. Demand modeling

In the modeling of the electricity demand, uncertainties related to the demand are modeled using a normal distribution function [17]:

$$f_{load}(L_d)=\frac{1}{\sqrt{2\pi\sigma_{L_d}{}^2}}exp\left(-(L_d-L_{d_{mean}})^2/2\sigma^2L_d\right) \tag{20}$$

3. Data used

The Bada village was selected as a case for this study. It is situated in a rural setting in the Afar region of northeastern Ethiopia (latitude, 14.309° and longitude, 40.072°). The village is currently non-electrified. It has been selected by the EEU for implementation of an autonomous, solar PV-based mini-grid. The weather data for the village collected from the Photovoltaic Geographical Information System (PVGIS) are shown in Fig. 5 [48]. Weekly load profiles, estimated based on interview data collected by EEU (as described in Section 2.1), are shown in Fig. 6.

Based on the data collected by the EEU and the load categorization described in Section 2.1, the load categorization for Bada village is shown in Table 1.

For the weekly load profile estimation, the following assumptions are applied: for water pumping, a minimum demand of 100 L of water per day per family and 2400 L/day for a health center and a primary school, each [12], and for the miller load profile estimation, two market days

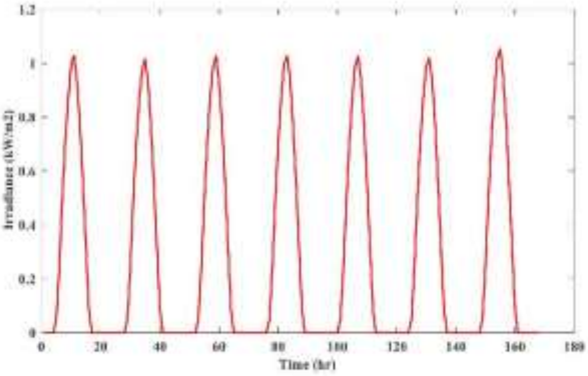


Fig. 5. Insolation profile of the Bada village.

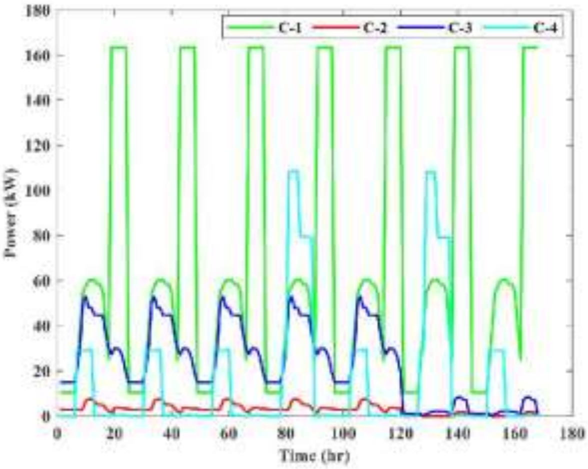


Fig. 6. Weekly load curves for the different load categories in the Bada village.

Table 1
Load categories for Bada village.

Load categories	Number and types of loads
C-1	2500 households
C-2	One clinic, One health center, One animal clinic, four pharmacies, two kindergartens, two elementary schools, four mosques, eight government offices, one farmer training center, and two storehouses
C-3	200 mini-shops, 1 barber, 10 tailors, 8 hotels, and 1 video hall
C-4	Five flour millers, and one water pump

(Thursday and Saturday).

3.1. Economic and technical parameters of the mini-grid components

The economic and technical parameters of the mini-grid components used are listed in Table 2. The fuel price considered is 0.62 \$/L. Uncertainty levels of 5% and 11% are considered for the solar irradiance and load profile estimation, respectively. Other assumptions applied are an interest rate of 7% [49], inflation rate of 8.1%, and a project lifetime of 25 years [14].

When sizing the autonomous mini-grid components, the parameters used for the PSO algorithm are: particle size (n) of 100, maximum inertia weight of 0.9, and minimum inertia weight (w_{min}) of 0.4, since the inertia weight from 0.9 to 0.4 provides the best result as demonstrated by experimental testing [22]. To balance particle and global best, the acceleration factors c_1 and c_2 are set to the same value, 2. A maximum of 100 iterations (max_{ite}) is used as a stopping criterion.

4. Results and analysis

In this study, based on the sizing of the autonomous mini-grid components, the impacts of DSM implementation at category level on the cost-efficiency of an autonomous mini-grid in a non-electrified rural area are determined. The impacts of DSM implementation at the category level are also compared with load flexibility based on the sizing of the autonomous mini-grid components. To determine the optimal, cost-efficient sizes of the autonomous mini-grid components, calculated using Eq. (1), Eq. (10), Eq. (17) and Eq. (19), for each combination of the four load categories with DSM and different percentages of load flexibility, a PSO algorithm is used.

4.1. Impact of DSM implementation at category level on the cost-efficiency of mini-grids

The optimal sizes of the autonomous mini-grid components for each combination of load categories with implemented DSM in Configurations 1 and 2 are shown in Fig. 7a and b. The size of the BES, charged during higher levels of solar PV power production and discharged during peak demand hours, is highly influenced by the shiftable loads through the DSM implementation, as compared with the sizing of solar PV and DG.

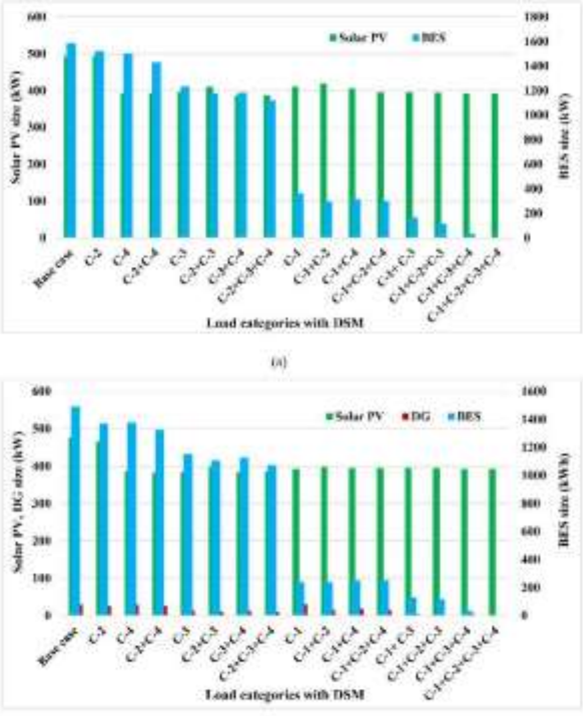
As shown in Fig. 7a and b, different load categories with DSM have different impacts on the BES, solar PV, and DG sizing. In both configurations, DSM implementation in all load categories will result in reduced power from solar PV (391.6 kW) and no need for BES, since all loads are LPLs and are scheduled for hours with higher production of solar PV power. In Configuration 2, DSM implementation in all load categories results in no need for DG, thereby reducing the levels of CO_2 emissions and operational costs. The optimal sizes of the BES and solar PV in the No DSM case (base case), whereby all loads are HPLs and operate at their scheduled times, are 1584 kWh and 491.8 kW in Configuration 1 and 1491 kWh and 476.5 kW in Configuration 2, respectively.

Among the load categories, DSM implementation in C-1 has a greater impact than the other load categories, reducing the BES and solar PV by 1224 kWh (77.2%) and 81.5 kW (16.5%) in Configuration 1, and by

Table 2
Economic and technical parameters of the mini-grid components.

Component, unit	Price (\$)	OMC (\$/year)	RC (\$)	T(year)	Nrep	SV[a] (%)	Reference
Solar PV, kW	1500	50	300	25	0	10	[50]
Civil Work, solar PV, kW	40%	1%	40%	25	0	20	[45]
Inverter, kW	711	0	650	10	2	10	[45]
BES, kWh	330	0	330	10	2	20	[51]
DG, kW	850	20	800	10	2	20	[38]

[a] SV is value of a scrap of the mini-grid components.



(a)

(b)

Fig. 7. Optimal component sizes for different load categories with DSM in: (a) Configuration 1; and (b) Configuration 2.

1249 kWh (83.7%) and 85 kW (17.8%) in Configuration 2, respectively, as compared to the No DSM case. DSM implementation in C-3, C-4, and C-2, in descending order of impact, reduces the optimal BES size by 21.9%, 5.3%, and 3.7%, respectively, as compared to the No DSM case, as shown in Fig. 7a. DSM implementation in C-3 and C-4 reduces the optimal solar PV size by 19.6% and 20.3%, respectively, as compared to the No DSM case. However, for DSM implementation in C-2, the optimal solar PV size is nearly equal to that in the No DSM case. In C-2, community load, demand is concentrated to the daytime, when there is a higher level of solar PV power production. This indicates that the shifting strategy has a lower impact for C-2.

In Configuration 2, DSM implementation reduces the optimal BES size by 22.7%, 7.5%, and 8%, and the optimal solar PV size by 19.4%, 19%, and 2.1% for C-3, C-4, and C-2, respectively, as compared to the No DSM case, as shown in Fig. 7b.

DSM implementation in C-3, with peak demand coinciding with solar PV power production, results in lower DG size than for other load categories, as shown in Fig. 7b. In the No DSM case, the optimal DG size is 29.5 kW, which is only 6% of the solar PV size, whereas DSM implementation in C-1, C-3, C-4, and C-2 results in optimal DG sizes of 31 kW, 14 kW, 29 kW, and 26 kW, respectively.

The LEC values, calculated using Eq. (2), for Configuration 1 (LEC-1) and Configuration 2 (LEC-2) are shown in Fig. 8. In Configuration 2, DG supplies peak loads. As a result, the BES and solar PV needed to meet peak loads are reduced, resulting in a lower LEC, thus LEC-2 is lower than LEC-1. DSM implementation in C-1, greatly reduces the size of the BES and reduces the levels of solar PV and DG more than in other load categories, leads to a dramatic decrease in LEC: LEC-1 is reduced by 45.8% and LEC-2 by 47.6%, as compared to the No DSM case. DSM implementation in C-3, C-4, and C-2 reduces the LEC-1 by 20.7%, 13%, and 1.6%, and LEC-2 by 21.8%, 13.2%, and 5.1%, respectively, compared to the No DSM case.

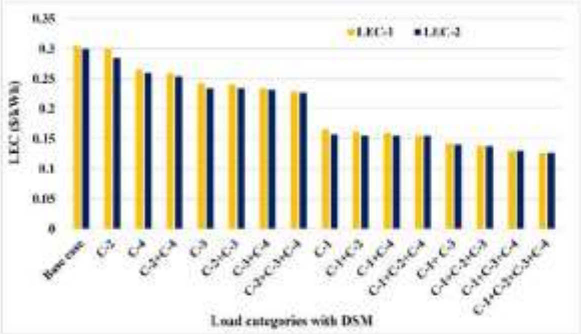
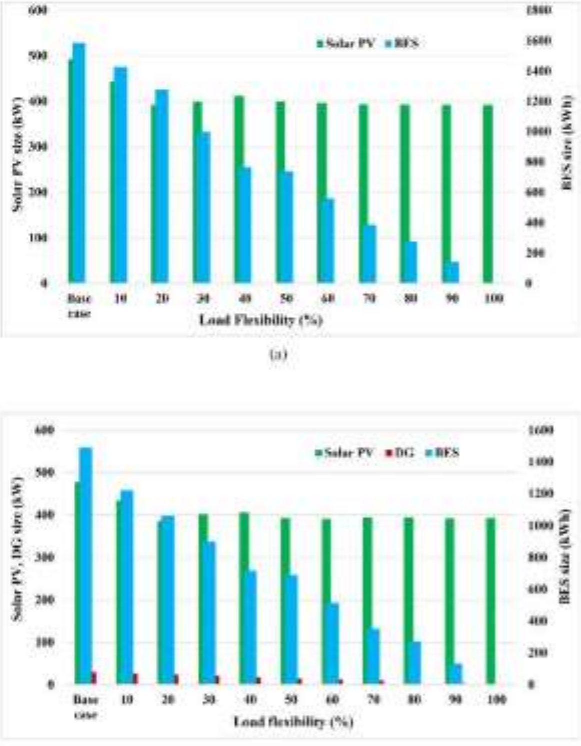


Fig. 8. LEC-1 and LEC-2 values for different load categories with DSM.

4.2. Impact of load flexibility on the cost-efficiency of mini-grids

To determine the impact of load flexibility on the cost-efficiency of mini-grids, different levels of load flexibility, calculated using Eq. (1) and considering LPL in the implemented DSM operating strategy, are used in the optimal component sizing for Configurations 1 and 2, as shown in Fig. 9a and b. The BES size is particularly strongly influenced by load flexibility and is reduced, on average, by 29.8% for every 10% increase in load flexibility for both configurations, resulting in no need for BES for 100% load flexibility (an ideal case).

The optimal solar PV size is reduced, on average, by 2.1% for every



(a)

(b)

Fig. 9. Optimal component sizes for different percentages of load flexibility in: (a) Configuration 1; and (b) Configuration 2.

10% increase in load flexibility in Configuration 1, Fig. 9a, and in Configuration 2, Fig. 9b, on average by 1.8%. DG, which is only available in Configuration 2, is reduced, on average, by 12.1% for every 10% increase in load flexibility.

The impacts of load flexibility on the LEC values for Configuration 1 (LEC-1) and Configuration 2 (LEC-2) are shown in Fig. 10. Load flexibility reduces the LEC by, on average, 8.4% and 8.2% for every 10% increase in load flexibility for Configurations 1 and 2, respectively.

4.3. *Comparison of the impacts of DSM implementation at category level and load flexibility on the cost-efficiency of mini-grids*

As shown in Figs. 8 and 10, DSM implementation at category level has the same impact as that achieved by using a higher load flexibility. The DSM implemented in all the load categories reduces the LEC-1 by 58.7% and LEC-2 by 58%, as compared to the No DSM case, shown in Fig. 8. This is equal to the result for 100% load flexibility, Fig. 10.

The DSM implementation in C-1, Fig. 8, reduces LEC-1 and LEC-2 to almost the same extent as 55% and 58% load flexibility for Configurations 1 and 2 respectively, Fig. 10. C-3, C-4, and C-2, Fig. 8, have the capacity to reduce the LEC to almost the same extent as 25%, 16%, and 2% load flexibility for Configuration 1, and 26%, 16%, and 6% load flexibility for Configuration 1, respectively, Fig. 10.

In addition, as shown by comparison of Figs. 8 and 10, the difference between LEC-1 and LEC-2 diminishes with shiftable load categories, LPL, and percentage of load flexibility. This indicates that as shiftable load categories and load flexibility increases, DSM implementation will increase the cost-competitiveness of a 100% RES-based autonomous grid (Configuration 1).

4.4. *Comparison of mini-grid sizing with and without considering uncertainty and validation of the PSO result*

The optimal size of the mini-grid with and without consideration of load and supply side uncertainties for Configuration 1 and 2 is shown in Appendix B. Optimal sizing without considering uncertainties reduces the size of the BES and DG more than the solar PV, as shown in Appendix B since peak load variations caused by uncertainties is met by BES and DG. In Configuration 1, the optimal size of the BES and the solar PV are reduced by 3.2% and 2.4%, and in Configuration 2 by 2.5%, 2.6%, and 2.6% for the BES, solar PV, and DG, respectively.

The optimal size of the mini-grid for resulting from the use of an iterative method in the case of 10% load flexibility is shown in Appendix B. In finding the cost optimal size of the mini-grid components, the results obtained from the PSO algorithm and the iterative method are almost the same for both configurations, but the accuracy of the optimal solution differs. The convergence characteristics of the PSO algorithm for the optimal sizing with and without considering uncertainty is shown in Appendix C. As shown in the convergence characteristics of the PSO, the LCE decreases as the number of iterations increases and finally converges to the optimal value.

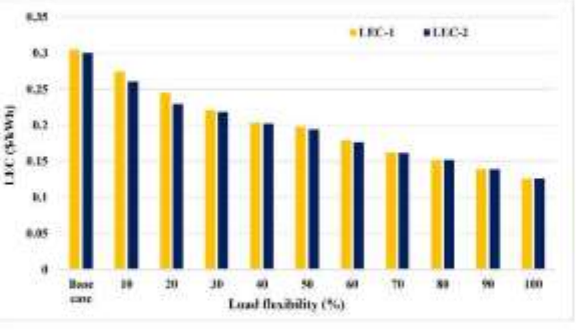


Fig. 10. LEC-1 and LEC-2 values for different percentages of load flexibility.

5. Discussion

The impacts of DSM implementation using a load-shifting strategy on the cost-efficiency of autonomous mini-grids in non-electrified rural areas were determined. The impact was determined at category level rather than at appliance level for four load categories with different load profiles. This is a novelty, since previous similar studies have determined the impact at appliance level.

The component sizing was carried out for each combination of the four load categories using a PSO algorithm. Load-side and supply-side uncertainties were also considered, but not their development with time. The applied load-shifting strategy was conducted in a priority-based fashion, with Configuration 1 supplying HPLs at the scheduled time and LPLs only when there is sufficient power generation from solar PV and the BES is full. In Configuration 2, the HPLs were supplied using the DG when neither solar PV generation nor BES is sufficient.

In contrast to the day-ahead DSM strategy, which has been studied to determine the optimal time when LPLs can be curtailed for higher levels of user satisfaction [27], the load-shifting strategy applied in this study does not include load curtailment, thus increasing system reliability. However, the results of the study are in line with those of previous studies [11,28–30], regarding how the cost-efficiency of mini-grids is impacted by a priority-based shifting strategy.

The results show that different category combinations result in large variability in terms of possible LEC reductions and, thus, in terms of the optimal sizing of cost-efficient BES, solar PV, and DG. This indicates that the cost-effectiveness of rural mini-grid depends on the load category mix considered for HPL and LPL when DSM is implemented.

Considering the order of impact among the load categories in terms of creating a cost-efficient mini-grid, C-1, the household category, is the most significant followed by C-3, the productive use category, followed by C-2 and C-4. Due to their load profiles, the capacity of the DSM implementation in C-1 and C-3 to reduce the LEC is almost equal to the impacts achieved by 55% and 25%, and 58% and 26% load flexibility for solar PV-based and HRES-based autonomous mini-grids, respectively. C-1 and C-3 are the main contributors to the night-time peak demand when there is no solar PV power production and, thus, more BES is required to ensure the supply. C-2 and C-4, on the other hand, have peak demand during the daytime, when there is higher solar PV power production. However, C-2 + C-4 have a higher peak and energy demand than C-2 and C-4, resulting in a lower LEC than C-2 and C-4, but higher than C-1 and C-3. Thus, the implementation of a load-shifting strategy in these categories would have a weaker impact on reducing the BES size and, therefore, a weaker impact on the LEC.

In Configuration 1 and 2, the productive use category, C-3, with a night time load, have a greater impact on the cost-efficiency of mini-grids than productive use category, C-4, without night time load. This indicates that productive loads can increase the cost-efficiency of mini-grids [52,53], but not all productive loads have equal impact. The impact of DSM implementation in C-1, reducing the size of the autonomous mini-grid components and the LEC, will likely become more important with each year due to the pronounced increase in household connections compared to other types of loads in rural areas [27]. While C-3 has a weaker impact than C-1, it has the capacity to increase the load factor of the mini-grid and improve the cost-efficiency of the mini-grid [52]. However, balancing different load categories is an important factor, in addition to DSM implementation at the category level to create a cost-efficient mini-grid in rural areas [53].

The variation in LEC reduction observed for the different categories indicates that different tariff structures, based on category level, would be required for system operation. Thus, DSM implementation at category level can be used with smart pricing methods such as time of use (TOU) electricity tariffs, which are more effective in mini-grids that have poor availability of skilled personnel [26] and have the capacity to handle voltage dip and power deviations in mini-grids [17]. DSM with a TOU electricity tariff enables the control of each load category based on its load profiles, using different electricity tariffs for different load categories at different times of the day. However, system operators can choose a type of DSM implementation that reflects their own perspectives. Importantly, depending on the ownership and business model of the mini-grid, the relationship between the utility and its customers may differ significantly, including in relation to the priority given to the load categories [54].

DSM implementation requires use of communication infrastructure and distributed smart meters that sense and control the electricity usage. As the users number increases, and thus system complexity, this need increases exponentially [55]. However, less infrastructure is needed at category level than at appliance level. This indicates that DSM at category level in rural mini-grids will reduce the operational and maintenance challenges by decreasing the complexity linked to controlling and connecting appliances, which is associated with appliance level DSM implementation [11,28–30].

In category level DSM implementation, aggregated load estimations are sufficient [56].Thus, DSM implementation at category level is less impacted by load estimation uncertainties since over and under appliance load estimations offset each other [57].

DSM implementation in C-1, followed by C-3, C-4, and C-2 in order of impact, increases the cost-competitiveness of solar PV-based, 100% RES, autonomous mini-grids by significantly reducing the BES and reducing the solar PV size. In this way, DSM contributes to decarbonization of the energy sector by promoting 100% RES-based autonomous mini-grids.

The contribution of DSM to energy sector decarbonization indicates a need for policies encouraging implementation of DSM in C-1 and C-3 rather than in C-4 and C-2 for rural area electrification using 100% RES-based autonomous mini-grids. This also indicates that DSM applied in combination with RETs subsidies creates options for 100% RES-based rural area electrification.

DSM implementation at category level requires a reduction in the level of consumption by users, which certainly is a limitation to its application. In C-1, lighting is one of the main reasons for the night-time peak demand, and reduced lighting is required to create a cost-efficient autonomous mini-grid. In addition to C-1, C-3 also requires decreased consumption from LPLs such as TVs, refrigerators, radios, mobile charging, and other appliances used for entertainment. As a result, the creation of more-cost-efficient autonomous mini-grids by DSM implementation at category level will require decreased user consumption, in turn, affecting user satisfaction.

Further studies of DSM implementation at category level could involve increased categorization and load prioritization, as well as implementation of other DSM strategies, e.g., the use of different tariff settings in demand response programs, consideration of user satisfaction and integration of alternative storage systems, such as pumped hydro storage.

6. Conclusions

In this study, we investigate ways in which DSM implementation contributes to cost-efficient, autonomous mini-grids in non-electrified rural areas. DSM exerts impacts on four load categories through a load-shifting strategy. The results show that DSM implementation has a stronger impact on reducing BES than solar PV and the use of a diesel-fueled generator. Load categories C-1 (household) and C-3 (productive use) show the highest cost-efficiency impacts, reducing the LEC to extents that are almost equal to those achieved by 55% and 25%, and 58% and 26% load flexibility for solar PV-based and HRES-based autonomous mini-grids, respectively. In comparison to DSM implementation in C-1 and C-3, implementation in C-4 and C-2 have lower impacts. However, C-4 and C-2 can reduce LEC to almost the same extent as achieved by 16% and 2% load flexibility for solar PV-based autonomous mini-grids, and 16% and 6% load flexibility for HRES-based autonomous mini-grids, respectively. Therefore, DSM implementation in C-1 and C-3 will increase the cost-competitiveness of 100% RES-based autonomous mini-grids in non-electrified rural areas, as compared to the C-4 and C-2 load categories. The study adds methodological novelty through its approach of investigating mini-grid DSM implementation impacts at the category level.

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 on request.

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Appendix A. Used equations

$$CRF = \frac{r(1+r)^T}{(1+r)^T - 1}$$

$$IOMC = OMC_0\left(\frac{1+i}{r-i}\right)\left(1-\left(\frac{1+i}{1+r}\right)^T\right) \quad r \neq i$$

$$OMC = OMC_0 \times T \quad r = i$$

$$RC = \sum_{j=1}^{N_{rep}}\left(C_{RC} \times C_Y \times \left(\frac{1+i}{1+r}\right)^{\frac{Tj}{(N_{rep}+1)}}\right)$$

$$PSV = \sum_{j=1}^{N_{rep}+1} SV\left(\frac{1+i}{1+r}\right)^{\frac{Tj}{N_{rep}+1}}$$

$$SOC(t+1) = SOC(t)(1-\sigma)$$

$$SOC_{min} = (1 - DOD)C_B$$

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1\right)$$

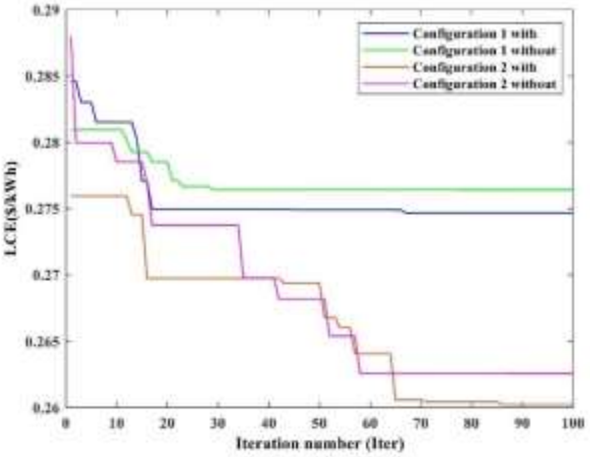
$$\alpha = \frac{\mu \times \beta}{1-\mu}$$

$$T_c(t) = T_a + 3H_i(t)$$

Appendix B. Optimal size of mini grid with and without considering uncertainty using PSO and Iterative method

Component, unit	Configuration 1			Configuration 2		
	With uncertainty		Without uncertainty	With uncertainty		Without uncertainty
	Iteration	PSO	PSO	Iteration	PSO	PSO
Solar PV, kW	441.6	442.6	432.1	441.6	433.5	422.9
BES, kWh	1446	1425	1380	1410	1221.5	1189.9
DG, kW	0	0	0	26.5	26.5	25.8

Appendix C. Convergence characteristics of the PSO algorithm



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Paper IV

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Impact Of Cooking Appliances Shifting Hours In Rural Mini-Grids: Case Study In Ethiopia.

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***Abstract*— Cooking is an essential aspect of daily life in any community. Electric cooking appliances have high power ratings and cyclic operations and thus contribute strongly to a system peak load. Optimal component sizing and cost are highly impacted by the peak loads. Thus, this study investigates how shifting hours of operation may impact mini-grid component sizing and their cost in a village in Ethiopia. The results indicate that shifting hours of electric cooking impacts the size of battery energy storage and solar PV, resulting in a system cost reduction. The results show that cooking appliance shifting to mid-day has a minor impact on optimal component sizing and the cost of mini-grids (total present cost reduced only by 3%).**

Keywords*—cooking appliance, cost reduction, load shifting, mini-grid, solar *PV

I. INTRODUCTION

Cooking is an essential aspect of daily life in any community. Electric cooking has the potential to improve the quality of life for people who cook using biomass. This is both by improving health by eradicating harmful emissions and by removing the need to collect fuelwood, thus freeing up time for other activities [1]. However, in rural areas of developing countries, access to electricity for household consumption is still a luxury.

In Ethiopia, for example, about 55 percent of the population lacks access to electricity. Due to this low access to electricity, households rely upon traditional methods of cooking based on as burning of wood and charcoal [2].

To alleviate the problem of lacking access to electricity, the Government of Ethiopia has started to implement off-grid solar mini-grid solutions, to reach full electrification by 2030 [3]. However, the investment cost of mini-grids to supply rural households of Ethiopia poses a challenge [2].

Several studies have been conducted on the optimal sizing of mini-grids and the optimal combinations of renewable energy sources, as well as the various demand side management (DSM) measures based on different categorization techniques, and division of appliances into shiftable and non-shiftable loads. However, it could also be valuable to target specifically appliances with high power ratings and cyclic operations, e.g., in DSM, since these appliances contribute much to the peak loads.

Preparation of injera, the cultural staple bread food item in Ethiopia, is known for its intensive energy consuming cooking. Injera baking on the traditional three-stone stoves (95% of the population of Ethiopia still relies on traditional biomass fuels for cooking), with an efficiency of 5-15%, consumes huge amounts of firewood and is thus the cause of deforestation, global warming and household air pollution [4].

Several initiatives have been taken to promote clean energy and the use of local, sustainable, and green cooking appliances. Electrical injera stoves (mitads) are a sound alternative in Ethiopia. It is estimated that the power consumed by existing electric mitads is 3.5-6 kW per cooker [4].

In rural areas, due to cooking appliances, system peak loads are mostly caused by households. Cooking appliances, stoves and mitads, have high power ratings and cyclic operations. When appliances operate cyclically, they use a lot of energy initially, then stop using it until their temperature drops below a threshold, when they start drawing power again.

The system peak load is a challenge for mini-grid sizing and matching especially with highly fluctuating renewable energy sources. Using energy-efficient appliances can reduce 38% of household peak load [5]. In efficiency improvement studies of electric mitads, up to 45% energy reduction has been possible. However, this also implies a higher retail price [4]. Thus, cooking, among the least favorable to be included in DSM, contributes the most to the peak in mini-grids [5].

DSM can be based on different measures to reduce the system peak load. Load shifting is one of the types of DSM. Shifting is when users reduce their consumption by turning it off during low solar PV electricity generation and increase during higher solar PV electricity generation.

Therefore, it is necessary to know the capacity of cooking appliances in households during peak load time. It is also important to know how sizing and the cost of mini-grid is impacted by the hourly shifting of cooking. Thus, this study examines the impact of cooking appliance load shifting at different hours of the day and how this affects optimal component sizing and the cost of mini-grids. The research questions of this study are:

- How does cost-efficient components sizing and the cost of mini-grids vary due to shifting hours of cooking?
- What are the cost-efficient shifting hours for cooking?

II. CASE STUDY

To identify the impact of shifting hours of cooking appliances on the cost-efficient sizing and cost of mini-grids, load profile estimation is required and for this, a case study area is selected in a rural area of Ethiopia.

In this study, Koftu, a mini-grid located in a rural area of Ethiopia, is used as case. Koftu (8.83°, 39.05°) is located 40km southwest of Addis Ababa, Ethiopia. The mini-grid uses 250kW solar power installed at two sites with 200kW and

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50kW each, a 50kW diesel generator, and 1000kWh battery capacity. The mini-grid is designed to supply 2884 households and 366 schools but has so far only been connected to 146 households, 1 school, 1 water pump, 1 health center (not using electricity), and 1 church.

III. METHOD

The load profile of Koftu is estimated by selecting ample users based on recommendations from the Ethiopian Electric utility operator and their electricity usage. For measurements, FLUKE a3000 FC AC current clamp meters were used. These measure minimum, maximum, and average TRMS currents for up to 400A AC every minute. Measurements were taken between November 28 and December 15, 2021.

The measured average current is multiplied by 220V for single-phase and 380V for three-phase to estimate sample users' measurement-based load profiles and scaled to the total number of users in each load category and summed to get the total weekly load profile.

Based on the weekly load profile estimated in Koftu, the impact of shifting time of cooking appliances on the optimal components sizing and cost of mini-grids is determined. The optimal mini-grid sizing is determined by shifting cooking appliances for different hours of the day. The objective function was used to find cost-efficient (optimal) sizing of mini-grid components is minimization of total present cost (TPC) based on the data in Table I. This study uses the formulation and mini-grid components modeling in [6].

To see the impact difference of shifting, two cases are studied: Case 1) assumes shifting of 100% of, one hour cooking load while case 2) assumes shifting of 50% of the one-hour cooking load. Optimal mini-grids sizing is carried out for the two cases. The impact of any temperature difference during the day is not considered.

TABLE I. ECONOMIC AND TECHNICAL PARAMETERS OF THE MINI-GRID COMPONENTS.

Components	Price ($)	OMC[a] ($/year)	RC[b] ($)	Time (year)	SV[c] (%)
Solar PV, kW	1500	50	300	25	10
Inverter, kW	711	0	650	10	10
BES, kWh	330	0	330	10	20

[a] Operation and maintenance cost, [b] Replacement cost, [c] Scrap of the mini-grid components

IV. RESULTS

The estimated total load profile of Koftu is shown in Fig. 1. The peak load in the system occurs in the early morning, from 8am-9am. The peak load of the total load profile is 265kW. This peak load is caused by the household load category. Household peak load is 263kW, which coincides with the peak hour of the total load profile. The second highest peak loads, 250kW, occurs between 6am-8am.

The morning peaks are due to electric cooking, as confirmed through interviews conducted in parallel with the measurements. This indicates that the characteristics of the appliance having high power and cyclic operation need to be given more emphasis than other appliances in the household since they can increase system peak load. This is especially important for mini-grid built to electrify households or having few productive use and community load, e.g., Koftu.

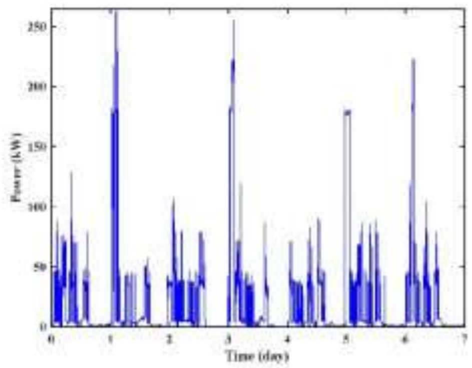

Fig. 1. *Total estimated load profile of Koftu.*

Thus, for case 1 and 2 we examine how the peak load shifts every hour, from 8am-9am to 11pm. The peak load for case 1 varies based on the shifting hour. In case 1, the maximum peak load is 332kW, which is higher than the base case peak load by 25%. However, in case 2 the peak load is 261kW for all shifting hours, which is 1.2% lower than the base case peak load.

Based on different cooking appliance shifting hours, Fig. 2, 3 and 4, show the optimal size of the BES, solar PV and TPC of the mini-grid, respectively. As shown in Fig. 2, the size BES reduced up to 3% for case 1 and 2 as compared to the base case.

The size of BES and solar PV in base case, where cooking appliance shifting is not taken into account, is 455kWh and 98kW, resulting in 1.217M$. The shifting of cooking appliances reduces solar PV size by up to 8% and 3% in case 1 and 2, respectively. The reduction in BES and solar PV can be higher if the second peak loads, occurring between 6am-8am, are shifted to the afternoon since it is 5% lower than the first peak. This reduction in BES and solar PV size is achieved by shifting cooking appliance operating time to any time in the afternoon between 1pm-5pm. This reduction decreases the mini-grid TPC up to 3% in both cases.

Total present cost of case 1 is higher than the base case if cooking is shifted from 8am-9am to 12am and between 7pm to 9pm. This is because there is additional load during these hours and shifting of the load to those hours will increase rather than decrease the peak load compared to the base peak load. In addition, if 100% cooking appliances are shifted, case 1, customer satisfaction may decrease.

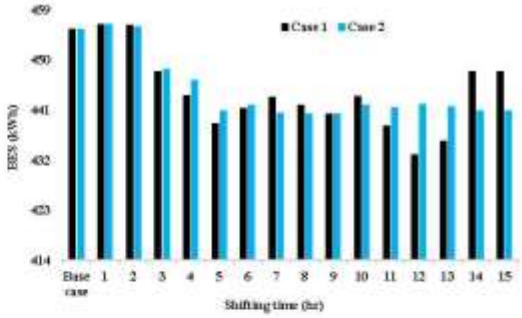

Fig. 2. Optimal BES size for the different shifting hour of cooking appliance.

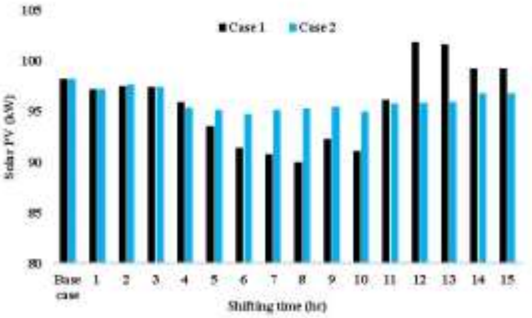

Fig. 3. *Optimal solar PV size for the different shifting hours of cooking appliance.*

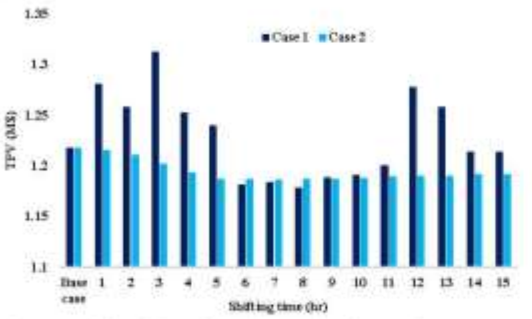

Fig. 4. *TPV for the different shifting hours of cooking appliance.*

V. DISCUSSION

The impact of shifting hours of cooking was studied on the optimal components sizing and cost of mini-grids. The result shows that case 1, shifting 100% consumption of the morning peak load, does not show any difference compared to case 2, where 50% of the morning peak load was shifted. Thus, a shifting of half of the cooking to mid-day hours the total present cost can be reduced. As injera is only baked four to five times per week, there could be a potential of shifting the electric mitad and/or stoves usage to mid-day.

With economic growth, due to new electric appliance demands including cooking appliances, and village size growth, further challenges and peaks are added. The peak loads in the morning will increase the need for and planning of distribution cable and transformers. With more households connected to the mini-grid, this impact becomes larger because most of the loads in Koftu are not connected as planned yet. Thus, there is an increasing risk of exceeding the maximum power capabilities of the local distribution transformer when a large number of cooking appliances or appliances with high power ratings and cyclic operations are connected [7].

One way to reduce the financial risks associated with mini-grid development is to build adaptive and flexible systems that can follow the development of the load and thereby the development of local community [8]. Thus, cost-efficient optimization of adaptive and flexible mini-grid systems will be addressed in future work.

VI. CONCLUSION

The impact of shifting hours of cooking appliances is examined using optimal components sizing and cost of mini-grids. The result shows cooking appliances shifting to mid-day has an impact on the optimal components sizing and cost of mini-grids. It can reduce the total present cost by 3% compared to case without shifting cooking appliance.

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Paper V

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Improving load factors as a smart management approach - a developing country mini-grid case study

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***Abstract*— One option to improve electricity access to the one billion people currently lacking electricity access is autonomous mini-grids. Most of the unelectrified communities are located in rural areas far from the current grids. Rural area communities are characterized by geographical remoteness, dispersed consumers, low consumption, and limited ability to pay. The low consumption and limited ability to pay can affect the revenue of the mini-grid operator and owner, often leading to low cost-effectiveness of the mini-grid. However, as shown in the current work, correctly combining the number of household and productive users in a mini-grid can increase revenue by 40 % compared to only households if an equal tariff is considered for both customer groups.**

Keywords—mini-grid, productive use, rural electrification, household use, increased revenue.

I. INTRODUCTION

Electricity is essential as an enabler of social and economic development and thus contribute to poverty reduction. Electricity access, together with access to modern cooking fuels, is the seventh United Nations Sustainable Development Goal (UNSDG) for 2030 [1]. However, globally one billion people, or 13%, still lacked access to electricity in 2017. Roughly half of these people live in sub-Saharan Africa, and a majority of them live in rural areas [2].

In remote areas with low population density, renewable-based autonomous mini-grids is one option to improve electricity access. Currently, renewable energy technologies are characterized by high initial capital costs but low operational costs. The high capital cost can be a challenge for many rural communities, since they are mainly characterized by geographical remoteness, dispersed consumers, low consumption and low income. In addition, they often have difficulties to attract capital for long-term investment [3].

Rural electrification is a persistent challenge throughout the world. In rural development, modern energy has been, and in most cases still are, looked at as having two distinct uses: productive use (PU) and household use (HH).

Productive use refers to the direct and indirect use of electricity to produce goods or services for the production of income or value. Productive use of electricity in rural areas is expected to result in increased rural productivity, greater economic growth, and a rise in rural employment, which is expected to lead to raised incomes and reduced migration of the rural poor to urban areas [4].

Electricity in households in rural areas is mainly used for lighting, mobile phones charging, and operation of a few small appliances plus radios and sometimes TV sets. Household use of electricity is expected to positively impact the rural quality of life or improve rural living [5].

Because of the typically low electricity usage of household and productive use customers, mini-grids often have problems to reach the critical revenue needed for financial viability [4]. For instance, in Sub-Saharan African private players have been hesitant to invest in mini-grids due to the high level of uncertainty and unbalanced risk-return profile [6].

The literature has an abundance of studies examining rural electrification and barriers to renewable energy deployment to solve this problem. For instance, in [7] they described productive use as especially important to make mini-grids financially viable and that partnering with microfinance organizations could be a way forward for mini-grid developers to foster productive use.

To achieve the economic viability of autonomous mini-grids it is suggested in [8] to form public-private community partnerships, involving communities as crucial partners. In [9] they indicate that a mixture of household use and productive use of electricity provides both technical and economic benefits for the operator.

Increasing income flows without having to increase the power output of the generation system would have positive impacts on mini-grids economic viability. Therefore, the aim of this study is to find an optimal composition of household and productive use loads to maximize the revenue in systems with fixed capacity.

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II. CASE STUDY

Measurements were done in an autonomous community-based mini-grid built by the Italian NGO ACRA. The mini-grid, located in south-western Tanzania, generates power for about 1145 households, 344 small productive users, and 55 large productive users (e.g. millers and small industries). The mini-grid uses a small-scale hydropower plant: consisting of two 150 kW Pelton turbines and started suppling in January 2017.

Electricity usage of the customers were measured using an Amprobe 16-TRMS clamp on current meters. The device has a measuring frequency of 5Hz and store values each minute (maximum, minimum, and average current for a duration of 3.5 days. Power is calculated based on the measured current and rated voltage of the customer i.e. 230 V for single-phase customers and 400 V for three phase customers.

The measured load data for household use and productive use of electricity in [9] is used. The measured load profiles of household use consider low-consuming households (Household 1a and 2a) and high-consuming households (Household 1b and 2b). Household 1a, 2a and 1b shows similar electricity usage typical for a household with an afternoon/evening peak. Household 2b shows a very high peak, which is likely caused by either a heater or cooker.

The measured productive use of electricity loads considers a bar, a workshop and two mills. Their demand behaviors are quite typical for productive users. The distribution is thus considered representative. They have a considerable higher power demand during the day compared to the households. The bar is characterized by a comparably flat load profile during its opening hours. The mills and workshop are characterized by very high peak loads with periods of very low loads [9]. All productive loads are considered typical for its type.

III. METHOD

The study focuses on two metrics (load factor and revenue) for measuring the impact from different combinations of household and productive users. The daily load factor is the ratio of the mean electricity consumption used over the day in relation to the peak consumption in a specific day. The load factor is thus a measure of the capacity efficiency of the system or how well the generation capacity is adapted to the demand. It is the measure of the utilisation of electrical energy during a given period to the maximum energy which would have been utilised in that period, especially important in systems based on renewables.

High-resolution measurements of households and different types of productive uses of electricity are used to calculate the load factors and revenue streams. The combined times series for household and productive use are normalized based on daily electricity consumption. The normalization method of daily electricity consumption enables a direct comparison and verification of electricity consumption in household and productive use. The combination leading to maximum revenue for the mini-grid operator is selected as the optimal point. In total, the measurements include four households and four productive users.

After the load profiles have been normalized, they are combined at different shares to analyse the change in daily load factor and revenue.

The most favourable composition of the loads is dependent on the measured loads. To get an indication of the dependence two cases are investigated: with all loads (case 1) and with the removal of the most untypical load curve of the households (case 2) which is previous section called Household 2b.

The daily revenues are based on electricity tariffs. Two cases are investigated. Case one uses an identical tariff for household and productive users. Since differentiated tariffs exist between household and productive use [9] the impact of the an additional 10 % tariff is investigated to study the impact of the differentiation. The revenue is normalised to the 100 % household loads since that is considered the base load situation.

Due to the different typical electricity use of household and productive use is significantly different the number on customers, household and productive use, are estimated. The estimation is based on the same measured data used in the rest of the study.

IV. LOAD FACTOR OPTIMISATION

As shown in Figure 1 the highest load factor arises when the composition of loads is approximately 50 % productive use. The increase in the load factor is expected to be around 20 to 40 % compared with 100 % household loads and 100 to 500 % compared with 100 % productive use, dependent on load behaviour.

The measurements indicate there is a 11:1 ratio in average energy usage for household and productive use. Thus, with the 50 % composition this indicates that there should be 11 times more households' customers than productive users to reach the optimal load factor.

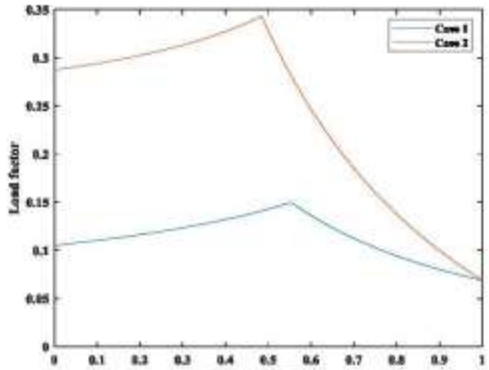

Figure 1. How the load factor changes due to different compositions of the household and productive use of electricity for two cases.

V. REVENUE OPTIMISATION

Figure 2 shows how the total revenue changes due to the load composition. The solid lines show how the total revenues changes for both case 1 and 2 when household and productive use have the same tariff, the optimal point will be the same as for the load factor optimisation.

With an increase of the tariff of 10 % for the productive use customers the optimum is shifted with about 3-5 percentage points towards a lower household share as indicated with the dashed line in the figure. The shift makes the optimal number of household's customers to be 10 times more than number of productive use customers to reach maximum revenue.

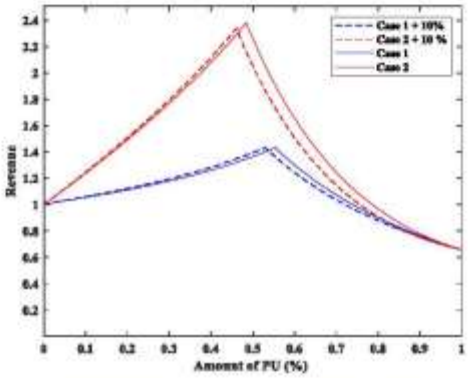

Figure 2. Normalized revenue for different compositions of household and productive load. Two different cases are investigated. The dashed line is the revenue for with a 10 % increase of tariffs for productive use.

VI. DISCUSSION

The impact of the load composition was shown to be important to increase the economic viability of the small autonomous mini-grids. The revenue can be increased which could be used to financially promote a transition to the optimum composition based on methods proposed in [7]. More productive use will not only lead to more a sound financial situation for the grid operator but also to income to the area [4].

Design of the load composition is a first step in actions that could improve financial revenues in autonomous renewable based mini-grids. This can be combined with demand side management or even with load frequency control. There is a large potential value of demand side management in renewable based systems as shown in [10] for wind power.

Even though the focus in this study has been on financial benefits there are also environmental benefits as power sources with low running costs are often renewables with a lower environmental impact. Avoiding over-capacity has also less negative environmental impact, both reduced impacts from manufacturing and, transport, and from waste handlings.

VII. CONCLUSION

For system with a fixed capacity there is an optimum when it comes to the composition of household and productive use of electricity. If the same energy tariff applies for both of the type of customers, the optimum is around 11 times more household than productive use customer. However, this changes with differentiated tariffs.

VIII. FUTURE WORK

The economic and technical benefits of optimal combinations of household and productive use need to be studied further. This might include variations of customers types, different tariff settings/structures and different sources or combinations of sources of power supply like solar, hydro and wind. A larger dataset with more variation might also affect the optimal combination. Extending the analysis with end-uses for productive use, rather than specific load profiles could allow for an analysis of developmental aspects related to technical and economic aspects.

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Paper VI

Determining the impact of future load compositions on monthly electricity bills under different tariff structures in a rural solar PV mini-grid

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Abstract

Renewables-based mini-grids can significantly increase electricity access in rural, non-electrified areas. Despite their potential, mini-grid deployment has been slower than expected due to low profitability in areas with initially low demand. Tariff settings that would increase profitability are challenging due to future demand uncertainties. While previous studies have explored how tariff settings affect demand and productive use increases profitability, the impact of future load composition on users' monthly bills remains unexplored. This study determines the impact of future load compositions on monthly electricity bills under different tariff structures in a rural solar PV mini-grid. By combining a case with an already installed solar PV-based mini-grid with spare capacity for future demand evolution and three future load composition scenarios, the study calculates users monthly bills using calculated cost-reflective tariffs for five different structures (fixed energy, fixed and variable, time-of-use, power, and hybrid). The results show that future load compositions significantly affect cost-reflective tariffs and users' monthly bills, with the effect depending on the tariff structure. Power-based tariffs show a reduction compared to energy-based tariffs in load compositions with more daily productive use compared to household and non-daily productive uses. The effect on the monthly bills is significant for lower-usage households.

Keywords: solar PV mini-grid, future load composition, load categories, productive use, monthly bill, tariff structures

1. Introduction

Renewable energy-based mini-grids play a crucial role in improving electricity access in rural areas of sub-Saharan Africa (SSA), where the majority of the people without electricity access are living, and are thus key to achieving the United Nations (UN) Sustainable Development Goal (SDG) 7. However, high upfront investment costs, despite low operational costs, hinder their economic viability and pose a significant challenge in expanding electricity access in rural areas [1]. As a result, most mini-grids in SSA depend on grants and subsidies to cover at least 30% of their investment costs [2]. To support SDG 7, the UN has allocated more than half of the estimated $45 billion annual budget to mini-grids and isolated power systems [3].

To ensure the economic viability of mini-grids, it is essential that mini-grids are perceived as commercially viable, generating a reasonable return on investment, which is typically contingent on tariffs [4]. In SSA countries, mini-grid tariffs are calculated using five methodologies: (*i*) uniform national tariff, matching with main grid tariff; (*ii*) efficient new entrant approach, which sets a benchmark tariff estimated as the cost of service for a new market entrant; (*iii*) bid tariff, set by the lowest price bid in a competitive process; (*iv*) individualized cost-based tariff, tailored to each mini-grids cost recovery limit by regulator; and (*v*) willing buyer/willing seller model, where tariffs are agreed upon between the developer and customers [5].

Many SSA countries use highly subsidized uniform national tariffs, often set equivalent to the main grid tariff and below the actual costs incurred by mini-grids, to achieve fairness and affordability for users with electricity access [4]. Some countries, such as Ethiopia (for capacity greater than 200kW), Kenya, and Rwanda, use individualized cost-based tariffs, which help to ensure cost recovery for developers and attract private investment by reflecting project-specific costs. However, this methodology faces challenges in regulating mini-grids as infrastructure due to the long payback periods requirement and uncertainties, such as main grid arrival and future demand uncertainties [5].

Tariff settings based on different methodologies may have distinct structures, including energy-based, power-based, and hybrid tariffs. Energy-based tariffs are contingent on metered energy usage and encourage energy conservation. They can be fixed energy tariffs (FET) or vary over time, such as time-of-use (ToU) tariffs, which allow for demand-side management (DSM) [7]. The fixed and variable tariff (FVT) is an energy-based tariff, where the fixed rate tariff has a predetermined cost per connection, whereas the variable tariff depends upon the energy consumption within a certain amount of time, typically one month. Block tariffs are another option, which charges different rates based on usage levels and additional fees for exceeding thresholds [6]. Power tariffs (PT) are based on maximum power and thus could limit peak usage. Hybrid tariffs (HT) are a combination of energy and power-based tariffs. Tariffs can be tailored to specific load categories, such as households (HH), community (CL), and productive use of electricity (PU)[1], reflecting their varied usage patterns. In this study, load compositions refer to the mix of electricity demand from different load categories, specifically from HHs and PUs, in a mini-grid.

To ensure the economic viability of mini-grids, various solutions and policies have been proposed by studies. Nevertheless, especially in villages solely comprised of HH, a significant challenge lies in providing affordable electricity to geographically remote communities in rural areas with dispersed populations, low demands, and living on $1.5 a day, at a reasonable electricity tariff [7] [8]. Consequently, studies suggest the integration of PUs to stimulate demand [8,9], improve load factors, and thereby reduce the levelized cost of electricity (LCOE) [10], and capacity expansion to meet the demand from PUs [11]. However, the share of PUs to HHs should not be too high [12].

The aforementioned studies [8] [9] [10] [11] [12] highlight the pivotal role of PUs in enhancing the economic sustainability of mini-grids. However, it remains uncertain which loads will grow and dominate future demand, indicating the uncertainty of load compositions in future demand. This uncertainty can be influenced by the characteristics and economic activities of the community after electrification. Studies utilize multiple scenarios in order to represent the uncertainty of future demand [13] and assess the impact of various tariff types on the electricity consumption of different users [14]. Additionally, studies examine the drivers of electricity usage patterns [15] and long-term forecasting methods [16]. Yet, to the best of the authors' knowledge, no study has determined the impact of load composition on the monthly bills of users that depend on cost-reflective tariffs, defined as the minimum tariff required to recover investment costs for mini-grids. Thus, the study aims to determines the impact of future load compositions on monthly electricity bills under different tariff structures in a rural solar PV mini-grid.

The problem formulation in this study is based on a conceptual feedback loop, as shown in Fig. 1, where a mix of user load characteristics (orange arrow) influences system load composition, which in turn impacts tariff settings (black arrows) based on policy decisions (blue arrow). These tariffs affect users' monthly bills (black arrow), potentially altering users' load characteristics (orange arrow). The study focuses on quantifying the black arrows, which represents how load composition affects tariffs and how tariffs impact monthly bills, while also discussing the policy implications (blue arrow) and the effects of tariff structures on consumer behavior and system load (orange arrow) by incorporating factors such as subsidies, demand-side management, and peak-hour pricing.

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[1] Productive use of electricity is any application of electricity energy services in activities that increase income or enhance economic value [34].

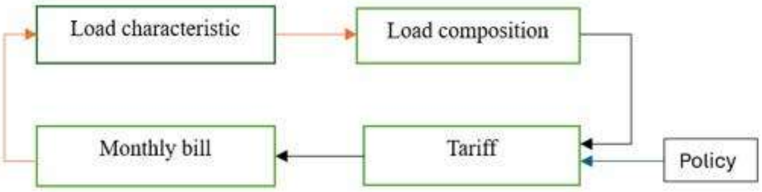

Fig.1. Conceptual feedback loop of load composition and users' monthly bill.

2. Method

To determine the impact of future load compositions on monthly electricity bills, the study employs a quantitative research approach. The determination of this impact involves calculating the cost-reflective tariff required for recovering the investment cost of mini-grids through the collected monthly revenue. This is done under alternative load composition evolutions (scenarios).

The calculation of the cost-reflective tariff utilizes FET, FVT, ToU, PT, and HT tariff structures (pricing mechanisms used for different purposes). These tariff structures can be used for different purposes based on the business model and incentives associated with the mini-grid [3], including recovering costs, promoting the use of renewable energy sources, managing peak demand, and encouraging energy efficiency. The utilization and benefits of each tariff structure are influenced by several factors, such as user behavior, regulatory requirements, and the specific objectives of power suppliers and decision-makers [4].

System revenue can depend on the efficiency of the system's capacity. To represent the different possible load developments, a method is employed to identify a combination that leads to a high load factor, which serves as a measure of the system's capacity efficiency. The study determines the mix of HHs and PUs by normalizing and combining their respective demands. This method is adapted from [12].

Therefore, to determine the impact of future load compositions on monthly electricity bills, the study calculates and compares users' monthly electricity bills using the calculated cost-reflective tariffs based on the considered different tariff structures and future mini-grid load compositions. Based on the quantitative findings, the study explores potential policy implications.

The calculation uses realistic demand data based on measured load data from a specific case. The measured demand of the connected load, based on three categories of HHs (HH-1 representing low usage, HH-2 representing medium usage, and HH-3 representing high usage), PU, and CLs are used. Household load categorization follows a multi-tier framework that classifies electricity consumption into distinct tiers: Tier 1 (low usage) is for consumption of ≥ 0.012kWh and 0.003kW; Tier 2 (moderate low usage) is for consumption of ≥ 0.2kWh and 0.05kW; Tier 3 (medium usage) is for consumption of ≥ 1kWh and 0.2kW; Tier 4 (high usage) is for consumption of ≥ 3.4kWh and 0.8kW; Tier 5 (very high usage) is for consumption of ≥ 8.2kWh and 2kW [17]. The framework, summarizing the steps taken during the study, is shown in Fig. 2.

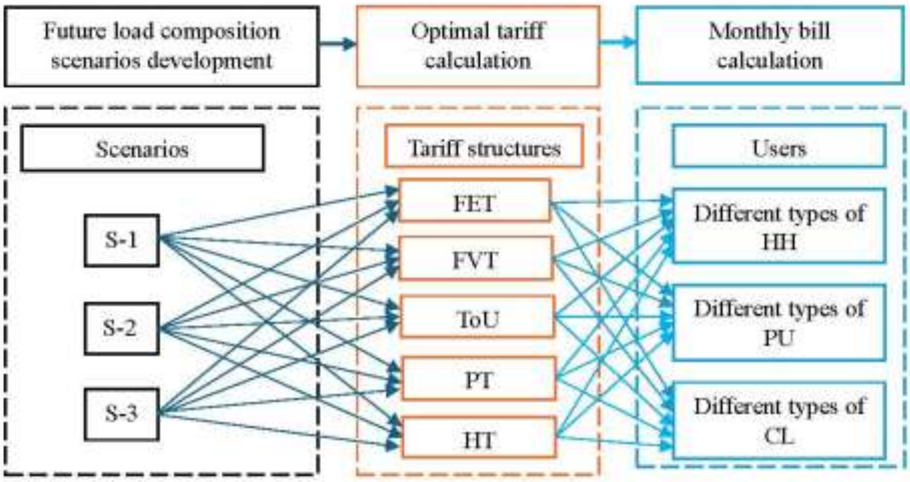

Fig. 2. The framework of the study.

2.1. System description

Due to expected future load growth in mini-grids and the uncertainty about the future demand evolution, the initial generation capacity must be well above the initial demand, or else demand would soon reach its limit and further growth be constrained. Thus, in the early life of a mini-grid, there is considerable uncertainty about how demand will evolve, if it is to be mainly household demand or productive use demand, and if it will develop rapidly or more slowly. This is the point of departure of the system considered in this study, which assumes a fixed-capacity supply with considerable spare capacity for future demand development. Supply is assumed to be covered by solar PV, as this is now the most common for new systems and accounted for 50% of operational mini-grids in 2020 [18].

2.2. Load composition scenarios

The growth of electricity demand is due both to increased consumption by already connected users and connection by new users, HHs, and PUs. PUs can be classified based on their usage patterns and frequency into daily and non-daily PUs, each with distinct energy needs and consumption behaviors.

The most common types of daily PUs are shops, small bars, and workshops. However, their electricity usage characteristics differ. Shops and small bars have peak loads in the evening, similar to HHs, while workshops (WSs) are typically used during the daytime and have a higher demand compared to shops and small bars [19,20].

Non-daily PUs, on the other hand, are load types that are not used daily. Examples include millers (Ms), which operate three or four days per week, mostly during market days when more grains are collected, and water pumps (WPs) for irrigation. Additionally, in rural areas, certain families often use M monthly, typically once or twice per month [21]. WPs can be used for irrigation, operating in cycles rather than daily. Additionally, Ms are more likely to be used in rural areas compared to WPs for irrigation [21,22].

To represent these different possible load developments, three alternative future load composition scenarios are formulated based on the demand growth of HHs and the two types of PUs.

- Scenario 1 (S-1) assumes that the demand growth is entirely from HHs.
- Scenario 2 (S-2) assumes that the demand growth from HHs and daily PUs.
- Scenario 3 (S-3) assumes that the demand growth from HHs and non-daily PUs.

In determining the load profile for each scenario, the base case (BC) load profile of existing connected loads in the specific case study area is considered. In each scenario, the number of load types contributing to demand growth is determined based on the system's capacity. This involves incrementally adding one user at a time to the base case demand while evaluating the system's energy and power limits as constraints. Once these limits are reached, the maximum number of new connections is identified and used to develop load profiles for the three alternative future load compositions. This demand growth is assumed to occur at any point during the lifetime of the mini-grid. Furthermore, in S-2 and S-3, to account for potential alternative load compositions within mini-grids, the study considers a mix of respective HHs and PUs based on the method described in Section 2.

2.3. Calculation of cost-reflective tariffs

To ensure that the tariff is cost-reflective, it should at least recover the total investment cost, including replacement cost and operation and maintenance cost of the mini-grid. For determining the cost-reflective tariff, the total present cost (TPC) is used to calculate the monthly revenue requirement (RR) over the mini-grid lifetime in months (T), as shown in Eq. (1). The TPC is calculated using the initial investment cost, replacement cost, and operation and maintenance cost [4,23].

$$RR = \frac{TPC}{T} \ (\$) \tag{1}$$

The calculation of the different cost-reflective tariffs, based on the tariff structure considered, is described below.

Fixed energy tariff

The cost-reflective tariff using the FET structure is calculated by dividing the required RR of the system by the monthly (m) energy usage for each user (i) as [24]:

$$FET = \frac{(RR)_m}{\sum_t^m D_{t,i}} (\$/kW) \tag{2}$$

Fixed and variable tariff

The FVT structure includes both a fixed tariff (FT) component and a variable tariff (VT) component. The FT is calculated based on the RR to return the TPC of the distribution system only ($(DC)_m$) and then divided it by the total number of users (n) as shown in Eq. (3). On the other hand, the VT, is calculated using in Eq. (2), but the RR utilized in this equation does not account for the $(DC)_m$, as shown in Eq. (4) [24].

$$FT = \frac{(DC)_m}{n} (\$) \tag{3}$$

$$VT = \frac{(RR)_m - (DC)_m}{\sum_t^m D_{t,i}} (\$/kW) \tag{4}$$

Time of use

The ToU tariff structure involves setting tariff rates (price for peak and off-peak hours) and determination of tariff shape (duration of peak and off-peak hours), with peak hours being periods of highest demand and off-peak hours occurring outside these times. To calculate the peak tariff (T_P), the peak factor (f_p) is multiplied by the RR and divided by the expected total energy usage (D) during peak hours (N) (as shown in Eq. 5). Similarly, to determine the off-peak tariff (T_{OP}), the off-peak factor (f_{op}) is multiplied by RR and divided by the expected total energy usage during off-peak hours (M) (as shown in Eq. 6). The f_p is obtained by dividing the average peak power during peak hours (AVR_n) by the total average peak hour (AVR_T) (as shown in Eq. 10), while the f_{op} is determined by dividing the average peak power during off-peak hours (AVR_m), by the AVR_T (as shown in Eq. 11), where AVR_T is calculated using Eq. 9. The AVR_n and AVR_m is calculated using Eq. 7 and 8, respectively [24].

$$T_P = \frac{RR_T \times f_p}{\sum_n^N D_n} (\$/kW) \tag{5}$$

$$T_{OP} = \frac{RR_T \times f_{op}}{\sum_m^M D_m} (\$/kW) \tag{6}$$

$$AVR_n = \frac{\sum_n^N D_n}{N} \; (kW/hr) \tag{7}$$

$$AVR_m = \frac{\sum_m^M D_m}{M} (kW/hr) \tag{8}$$

$$AVR_T = AVR_n + AVR_m \;\; (kW/hr) \tag{9}$$

$$f_p = \frac{AVR_n}{AVR_T} \tag{10}$$

$$f_{op} = \frac{AVR_m}{AVR_T} \tag{11}$$

Power tariff

The cost-reflective tariff using PT is calculated by dividing the RR by the sum of the peak demand for each load ($D_{p,i}$), as shown in Eq. (12).

$$PT = \frac{(RR)_m}{\sum_i^I D_{p,i}} (\$/kW/month) \tag{12}$$

Hybrid tariff

The cost-reflective tariff using HT is calculated by combining the energy and power tariff types. The energy tariff component (HET) is calculated by using 50% of the RR calculated using Eq. (2), while the power tariff (HPT) is calculated based on the rest 50% of the RR, using Eq. (12).

2.4. Monthly electricity bill

The monthly electricity bill (MEB) for each user category is calculated using the cost-reflective tariffs based on the FET, FVT, ToU, PT, and HT structures, using Eq. 12, 13, 14, 15, and 16, respectively [24].

$$MEB_{ET} = ET * \sum_i^I D_i \; (\$) \tag{13}$$

$$MEB_{FVT} = FT + VT * \sum_i^I D_i \;\; (\$) \tag{14}$$

$$MEB_{TOU} = T_{P,N} * \sum_n^N D_n + T_{OP,M} * \sum_m^M D_m \;\; (\$) \tag{15}$$

$$MEB_{PT} = PT * D_{p,i} \;\; (\$) \tag{16}$$

$$MEB_{HT} = HET * \sum_i^I D_i \; + HPT * D_{p,i} \;\; (\$) \tag{17}$$

Where $MEB_{ET}, MEB_{FVT}, MEB_{TOU}, MEB_{PT}, and\ MEB_{HT}$ are the monthly electricity bills of users calculated using FET, FVT, ToU, PT, and HT structure, respectively.

3. Case, data, and assumptions

A case with characteristics of recently installed mini-grids, with a considerably larger supply capacity than demand, was selected. Below, the selected case is presented together with actual case-based data inputs and other assumptions used for the calculations.

3.1. Case

The selected case is a solar PV-based mini-grid located in Koftu (8.83°, 39.05°), Ethiopia, 40km southwest of Addis Ababa, established in year 2018. The mini-grid consists of 250kW of solar PV, a 50kW diesel generator, and a 1000kWh battery energy storage system (BESS) capacity. Excluding the diesel generator, the mini-grid is capable of generating 1553kWh per day. A survey in 2021 showed that 146 HHs, 1 church (CH), 1 school (SCH), and 1 WP are connected. The measured demand of the connected load over one week, from December 6 to 13, 2021, indicates that only 27% of the generated energy is consumed, indicating a considerably larger supply capacity than demand [25]. The measured demand is in per minute. The measured daily energy use and peak power for each load type in the Koftu mini-grid are listed in Table 1.

Table 1. Measured daily energy use and peak power data of each load type in the Koftu mini-grid [25].

Load types	Daily energy use (kWh)	Peak power (kW)
HH-1	0.08	0.02
HH-2	2	0.7
HH-3	6	2
CH	0.6	0.05
SCH	14	3
WP	9	7

3.2. Data and assumptions used

The TPC of the selected mini-grid is $2.56M, calculated with a 7% discount rate and based on the economic and technical parameters of the mini-grid components shown in Table 2 excluding the diesel generators and the distribution system. In SSA, the initial cost of distribution networks, metering elements, and end-user devices averages 21% of their TPC [26]. This study considers the distribution cost, with an additional 4% for operational and maintenance costs [26], to be 25% of the overall TPC, totaling $0.85M.

Table. 2. Economic and technical parameters of the mini-grid components.

Component, unit	Price ($)	OMC[2] ($/year)	RC [3] ($)	T (year)	Nrep[4]	SV[5] (%)	Reference
Solar PV, kW	1,500	50	300	25	0	10	[27]
Civil Work, solar PV, kW	40%	1%	40%	25	0	20	[28]
Inverter, kW	711	0	650	10	2	10	[28]
BESS, kWh	330	0	330	10	2	20	[29]

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[2] OMC is operation maintenance cost.

[3] RC is replacement cost.

[4] Nrep is the number of replacements over the project lifetime, T.

[5] SV is value of a scrap of the mini-grid components.

The measured medium usage household (HH-2) load profile from the Koftu mini-grid is assumed to represent household demand growth in all scenarios. In S-2, WS is representing a daily PU, while M is representing a non-daily PU in S-3. However, WSs and Ms demand assumptions are from a mini-grid in southwestern Tanzania [19] since there is no connected WS and M in the Koftu mini-grid. The daily energy use and peak power for WS and M used in the scenarios are presented in Table 3.

Table 3. Assumed daily energy use and peak power of the WS and M load types based upon measured data from a mini-grid in southwestern Tanzania [19].

Load types	Daily energy use (kWh)	Peak power (kW)
WS	18	16
M	26	14

The daily energy ratio of HH to WS and M is 9:1 and 13:1, respectively. The mix of HHs and PUs in S-2 and S-3, determined using the method outlined in [12], shows that WS accounts for 71% of the daily energy in S-2, while M accounts for about 89% in S-3, with the rest coming from HHs. Based on this mix, the daily energy ratio between HH and WS shifts to 22:1 and the ratio between HH and M shifts to 104:1. The calculated mix of respective HHs and PUs is considered to represent future demand growth in S-2 and S-3.

The load types and daily energy for each scenario, determined based on the method in section 2.2, are shown in Table 4. The number of new HH in S-1 is similar to those in S-2 and S-3. However, in addition to HH, S-2 includes WS, and S-3 includes M, with the number of WS higher than M. This difference is due to the non-coincident peak times of the HH with BC; HH peak is during the morning and evening, while WS and M peak midday. The total daily energy in BC is 430kWh/day. The daily energy differences between the scenarios result in varying excess energy compared to the installed capacity, with S-2 showing 12% and 10% lower excess energy than S-1 and S-3, respectively.

Table 4. Number of load types and daily energy use, used in the formulation of each scenario.

Scenarios	Load type	Number of load types	Total daily energy use (kWh/day)
S-1	HH-2	225	887
S-2	WS	10	1065
	HH-2	224	
S-3	M	2	936
	HH-2	224	

To determine the peak and off-peak hours, in calculating the cost-reflective tariff using a ToU tariff structure, the BC load profile is considered (shown in Fig. 3). The BC peak load occurs in the early morning and evening. Thus, the assumed peak hours are the periods from 1 to 10 and from 18 to 24, while the off-peak hours are the periods from 10 to 18 during the day.

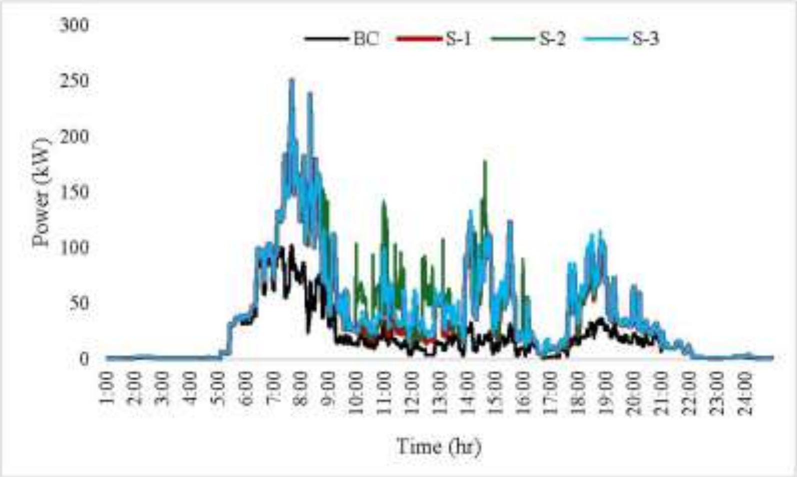


Fig. 3. Load profiles for the base case and the three scenarios.

4. Result and Analysis

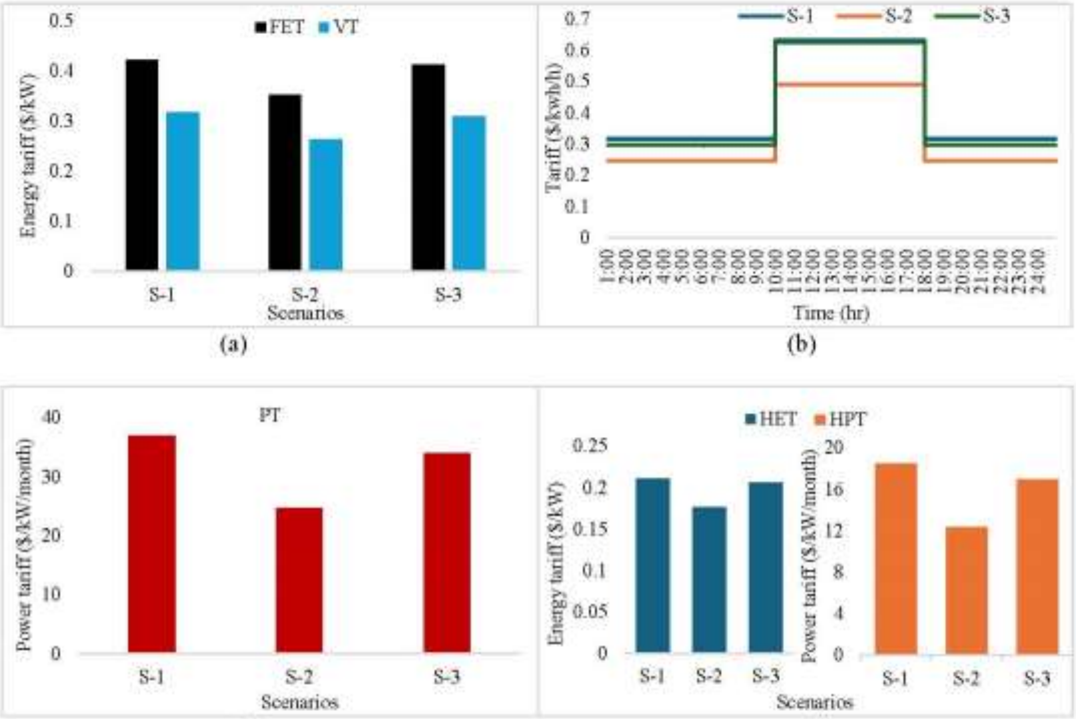
The cost-reflective tariffs and monthly bills of users calculated based on the different tariff structures for each load composition scenario are presented in this section.

4.1. Cost-reflective tariffs

For each scenario (S-1, S-2, and S-3), the cost-reflective tariffs, calculated using Eq. 2-12, are shown in Fig. 4. The tariff structures based on energy use, FET, VT of FVT (Fig. 4a), and HET of HT (Fig. 4d), exhibit different cost-reflective tariffs while showing the same relative differences between scenarios. Specifically, for S-2, the cost-reflective tariff is 17% and 15% lower than S-1 and S-3, respectively. In each scenario, the cost-reflective tariff calculated using VT of FVT and HET of HT results in reductions of 25% and 50%, respectively, compared to that calculated using FET. This is because the FT in FVT distributes 25% of TPC among users, averaging $7.5/month per user, while the HET in HT is based on 50% of the total RR. S-2 shows a 2% lower FT compared to S-1 and S-3 due to a 2% higher number of users.

As shown in all scenarios, the cost-reflective ToU-based tariff (Fig. 4b) reveals that higher energy usage during peak hours, compared to off-peak hours, results in peak-hour tariffs that are 50% lower than off-peak tariffs. Due to differences in energy usage in peak and off-peak hours among scenarios, S-2 exhibits the lowest peak and off-peak tariffs compared to S-1 and S-3. Specifically, the peak and off-peak rates in S-2 are 22.3% lower than those in S-1, and 17% and 21.6% lower than those in S-3, respectively.

The sum of each user's peak load will vary depending on the future load composition, even with a fixed mini-grid capacity. The cost-reflective tariff based on the PT structure, which depends on the total peak load, is shown in Fig. 4c. As shown in Fig. 4c in the scenario, S-2, which has a high peak load sum, results in power tariffs that are 33% and 27% lower than those in S-1 and S-3, respectively. On the other hand, the cost-reflective tariff based on the HT structure that distributes the required revenue evenly to energy and power tariff components is shown in Fig. 4d. Both HET and HPT tariffs are 50% lower than FET and PT while maintaining the same relative differences shown in FET and PT across scenarios.



(a) (b)

(c) (d)

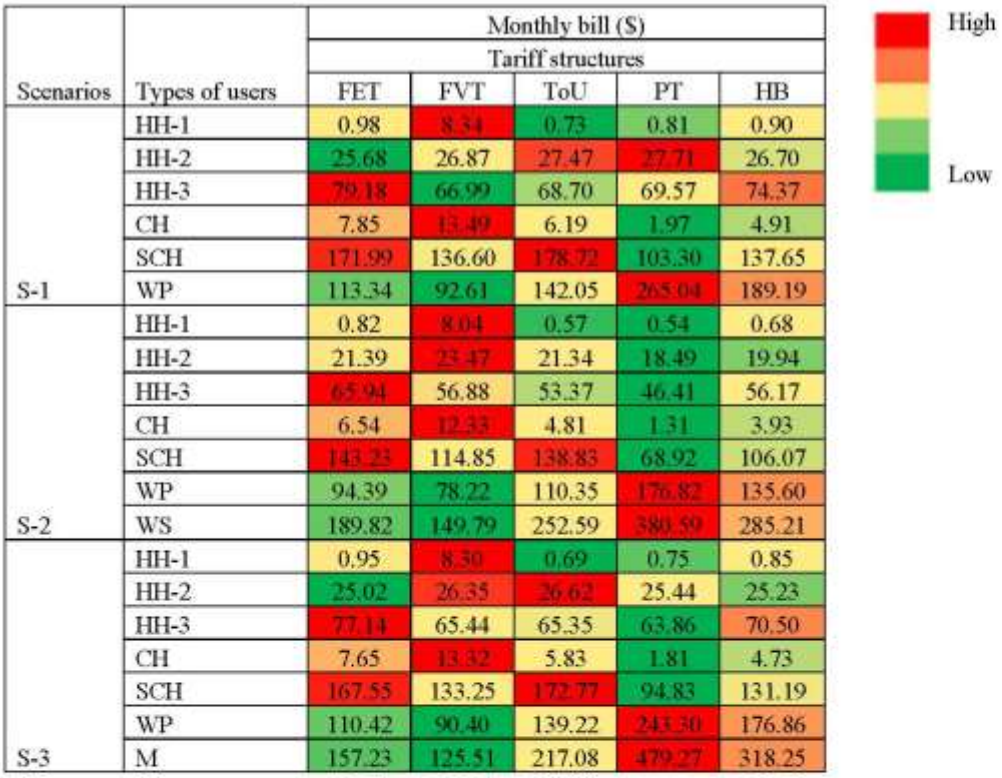
Fig. 4. Cost-reflective tariff for each scenario based on the different tariff structures: (a) FET and VT of FVT, (b) ToU, (c) PT, (d) HT.

4.2. Monthly electricity bill

The monthly electricity bills of different users, presented in Table 5, exhibit significant variations based on the type of tariff structure used to calculate cost-reflective tariff and load composition, particularly noticeable when compared to the commonly employed tariff structure, FET. In S-2, lower monthly bills for users (HH-1, HH-2, HH-3, CH, SCH, and WP) are shown, where a low cost-reflective tariff is yielded compared to S-1 and S-3. The average reductions for all users shown in S-2 are between 12% and 33% when compared to in S-1 and between 10% to 27% when compared to in S-3, with the lowest and highest reduction in FV and PT structures, respectively. Yet, CL and PUs show monthly bill reductions from similar tariff structures in different load composition scenarios, but not for HHs, as shown in Table 3. CL and PUs show significant reductions in monthly bills under PT and FVT, respectively. PT shows a bill reduction of over 75% for CH and over 40% for SCH compared to FET. FVT reduces the monthly bill of users having higher consumption in the system, reducing PUs' bills by over 17% compared to FET. However, PUs' bills under PT are more than 100% higher compared to those under FVT.

The extent of reduction and the tariff structure that leads to reduced bills vary across HH usage levels and load compositions. Table 5 shows that PT tariff structures lead to lower monthly bills than other tariff structures for HH users in S-2, showing reductions of 14% or more compared to FET. Whereas in S-1 and S-3, the ToU tariff shows a reduced bill for HH-1 (reducing 25% or more compared to FET), while FET shows a reduced bill for HH-2 (5% bill reduction compared to FVT and ToU). Additionally, the monthly bill for HH-1 under ToU tariffs shows a reduction, although it is slightly higher than PT. However, FVT significantly increases monthly bills for low-usage users like HH-1 and CH, by more than 8 and 2 times, respectively, compared to FET in all scenarios. HH-3 exhibits a reduction in monthly bills under different tariff structures in S-1 (under FVT) and S-3 (under PT), resulting in reductions of 15% or more when compared to FET.

Table. 5. Monthly bills for each user, calculated based on the cost-reflective tariff in different tariff structures for each scenario. Color coding indicates the cost level: the highest costs are shown in red and the lowest costs are in green for each user and scenario.



Scenarios	Types of users	Monthly bill ($)				
		Tariff structures				
		FET	FVT	ToU	PT	HB
S-1	HH-1	0.98	8.34	0.73	0.81	0.90
	HH-2	25.68	26.87	27.47	27.71	26.70
	HH-3	79.18	66.99	68.70	69.57	74.37
	CH	7.85	13.49	6.19	1.97	4.91
	SCH	171.99	136.60	178.72	103.30	137.65
	WP	113.34	92.61	142.05	265.04	189.19
S-2	HH-1	0.82	8.04	0.57	0.54	0.68
	HH-2	21.39	23.47	21.34	18.49	19.94
	HH-3	65.94	56.88	53.37	46.41	56.17
	CH	6.54	12.33	4.81	1.31	3.93
	SCH	143.23	114.85	138.83	68.92	106.07
	WP	94.39	78.22	110.35	176.82	135.60
	WS	189.82	149.79	252.59	380.59	285.21
S-3	HH-1	0.95	8.30	0.69	0.75	0.85
	HH-2	25.02	26.35	26.62	25.44	25.23
	HH-3	77.14	65.44	65.35	63.86	70.50
	CH	7.65	13.32	5.83	1.81	4.73
	SCH	167.55	133.25	172.77	94.83	131.19
	WP	110.42	90.40	139.22	243.30	176.86
	M	157.23	125.51	217.08	479.27	318.25

In all scenarios, the calculated monthly electricity bill using FET is lower than the tariff in Ethiopia. The monthly bill for HH-1 in S-2 is 69 times higher than the amount calculated under the old tariff in Ethiopia and 28 times higher compared to the amount under the new tariff (see Appendix A for the old and new electricity tariffs in Ethiopia and Appendix B for the monthly bills of users based on these tariffs). This difference is more pronounced in S-1 and S-3, with increases of 6% and 5%, respectively. While CH follows the same pattern as HH-1, other HHs, as well as CL and PUs, show monthly bills 5 to 11 times higher compared to those calculated using the new tariff in Ethiopia.

The variations in load composition significantly affect total revenue collection, even when using old and new tariffs in Ethiopia, with S-2 generating the highest revenue compared to S-1 and S-3. The total monthly revenue of the mini-grid calculated using the cost-reflective tariff is higher compared to when it is calculated with the electricity tariff in Ethiopia (see Appendix C). Specifically, the total monthly revenue under the cost-reflective tariff is significantly 21, 16, and 20 times higher for S-1, S-2, and S-3, respectively, compared to the old tariff, but this reduces to 12, 9, and 11 times under the new tariff.

The monthly distribution of RR among HH, CL, and PU is shown in Fig. 5. The tariff structures impact the total RR collected from these load types differently. In S-2 and S-3, where there are more PUs, ToU, and PT tariffs reduce HH bills and shift RR collection to PUs, by reducing the HH share by 5% and 17% in S-2, and by 2% and 7% in S-3 compared to FET. The HB tariff structure also shifts more RR to PUs, reducing the HH share by 8% in S-2 and 3% in S-3. Conversely, FV relatively reduces the RR share from productive uses.

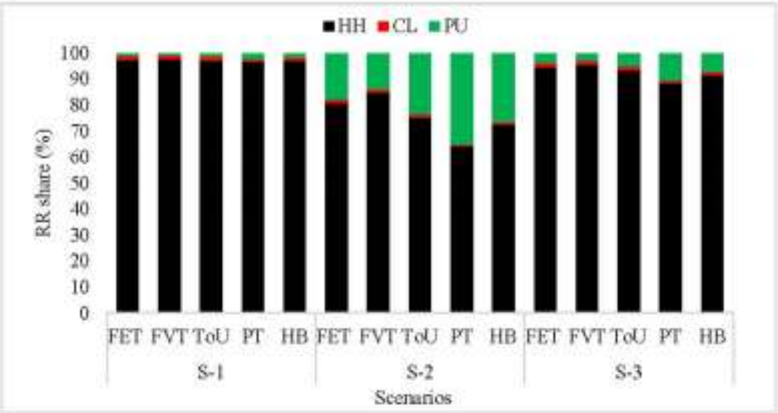


Fig. 5. Percentage shares of revenue from household, community, and productive use, under the different tariff structures for each scenario.

5. Discussion

The results of the study show how future mini-grid load compositions significantly impact the monthly bill of users that depend on cost-reflective tariffs, which are lower for load compositions consisting of more daily productive use compared to more household and non-daily productive use. The magnitude of this difference depends on the tariff structure. It is more significant with power-based tariffs than with energy-based tariffs. This highlights the significant impact of the peak load sum of users compared to the systems that aggregate energy usage. The impact of future mini-grid load compositions on the monthly bills of users shows differences that fall between energy- and power-based tariffs for time-of-use and hybrid tariff structures. Additionally, the fixed tariff component of the fixed and variable tariff structure shows a modest (2%) difference among the future mini-grid load composition.

The calculated cost-reflective tariff, determined using the fixed energy tariff structure, aligns with previous studies, reporting values for solar PV-based mini-grids just above $0.25 to 0.61/kWh [30]. However, these cost-reflective tariffs are lower than the implied tariff ($1.75/kWh) that unconnected customers in SSA would pay for energy generation through alternative means like kerosene or batteries [3,4]. Additionally, the calculated monthly electricity bill using a fixed energy tariff in all future load composition scenarios is lower than the implied tariff.

The calculated low cost-reflective tariff for the future load composition with more daily productive use, $0.351/kWh, is more than eleven times higher than the old average tariff, $0.03/kWh, paid by household users in Ethiopia. In Ethiopia, a new tariff was implemented on September 11, 2024, which raises the average price to $0.07/kWh through quarterly price adjustments and the largest increase in four years [31]. This new tariff is still more than four times higher than the calculated low cost-reflective tariff. This shows that both current and revised tariffs in Ethiopia are insufficient to cover mini-grid investment costs, highlighting the need for additional measures to ensure economic viability.

The future mini-grid load composition also shows an impact on the revenue of the mini-grid, even with old and new block tariffs in Ethiopia. This highlights the importance of considering the impact of future mini-grid load composition as a key factor, alongside other considerations, during tariff revisions, which occur every four years in Ethiopia [23]. However, connecting to a system with changing tariffs may pose risks, including price volatility, long-term investment challenges, reluctance to adopt demand-side management strategies, and ensuring profitability [32].

Households are typically the primary users in rural areas of SSA. This study highlights that a system with a higher proportion of household connections, especially during the initial lifespan, limits the connection of new users and restricts demand growth. The limitation on demand growth results in high cost-reflective tariffs. Therefore, implementing tariffs that encourage demand growth, especially in a system with a fixed capacity, is crucial. Increased demand can lead to reduced tariffs, addressing challenges posed by high rates, such as the limited ability of rural populations to afford electricity [1] [11]. This would be important for lower-usage households, governments, and the profitability of investors.

Demand growth can be achieved through time-of-use tariffs. For instance, incentivizing electric mills to operate during peak solar hours rather than in the morning. This timing benefits users, as they often use sunlight to dry their products, resulting in higher-quality, drier flour [10]. Additionally, using water pumps for irrigation and millers during harvesting can further increase annual demand growth. However, calculating the time-of-use tariff based on supply rather than demand may be necessary. Implementing time-of-use tariffs may also require advanced metering technology, which could raise costs and necessitate demand flexibility from users [14].

The impact of future mini-grid load composition on users' monthly bills can significantly affect profitability, with the effect varying depending on the tariff structure employed. Evaluating the sensitivity of different tariff structures reveals significant impacts on monthly bills and revenue collection from load categories. Power tariffs can reduce monthly bills for community loads by more than 40%, but they can increase bills for productive use by over 100% compared to fixed energy tariffs. In the future load composition with only households, high-usage households behave similarly to productive uses. This finding indicates that power tariffs may be less advantageous for productive uses and high-usage households. However, power tariffs can provide more stable revenue and better cost recovery, even if users reduce energy consumption, particularly in systems with more non-daily productive uses [14]. Furthermore, the differences in collected required revenue among the three load categories highlight that load compositions with more household and non-daily productive use can lead to increased revenue collection from households. This can affect households and governments or utilities providing subsidies for households if the impact of load composition is not taken into account.

On the other hand, in load compositions with more household and non-daily productive use, low- and medium-usage households experience reduced bills under time-of-use and fixed energy tariff structures, respectively. Notably, the relative reduction in monthly bills is more pronounced for low-usage households (more than eight times under fixed and variable compared to fixed energy tariff structure), highlighting the importance of selecting appropriate tariff structures based on usage levels. These reductions in monthly bills for low-usage households and the ability to connect additional productive uses under the time-of-use tariff indicate that, for villages like Koftu, implementing a time-of-use tariff is the most advantageous option. The higher reductions in monthly bills by time-of-use tariffs for households also highlight the significance of implementing demand-side management for low and medium-usage households.

Most SSA countries recognize cross-subsidies that can be integrated into the tariffs [23]. The differences in monthly electricity bills and the percentage shares of collected required revenue per month indicate that certain tariff structures can incentivize specific users while penalizing others. Consequently, this may create a need for additional subsidies or incentives for the penalized users. This highlights the importance of considering the impact of the mini-grid load composition and the different tariff structures in cross-subsidies.

To support private mini-grid operators facing challenges from low tariffs, some countries use feed-in tariffs, where operators receive fixed prices for every unit of energy generated. However, the energy is sold to users at a different, often lower price compared to the feed-in tariff [33]. In this regard, this study shows that mini-grids with future load composition with more daily productive uses may have financial advantages compared to those with mainly household and non-daily productive loads. These findings highlight that mini-grid developers can select sites in rural communities with existing economic activity or productive use loads.

To enhance revenue, some developers have adapted their business models by adjusting tariff structures and encouraging productive use loads. For instance, through appliance financing. However, the result of this study highlights the importance of adopting a comprehensive approach in business models that take load composition impact into account. Additionally, it is crucial to evaluate used business models that stimulate demand by considering the resulting future load composition. This evaluation is essential for ensuring the mini-grid's long-term sustainability, effectively meeting the community's energy needs, and maintaining reasonable bills while securing a viable return on investment.

In this study, an installed solar PV-based mini-grid designed with spare capacity to allow for future demand growth was used. The study develops future load composition scenarios based on load categories rather than specific appliances, offering more generalizable insights. Using a fixed-capacity mini-grid helps to determine the impact of load composition while maintaining a constant total present cost. Additionally, the case study area used is characterized by a high morning peak. This high morning peak is less common. Despite this, the findings of the study are likely applicable to many developing countries' contexts. The main contribution of the study is: (*i*) to indicate how the cost-reflective tariff is impacted by the future mini-grid load composition and tariff structures; and (*ii*) to indicate how the monthly bill of mini-grid users is impacted by the future mini-grid load composition and tariff structures. The study adds methodological novelty by estimating cost-reflective tariffs from the demand side, considering the load composition rather than the supply side. As future work, this study can be expanded by considering additional case study areas, as the current analysis is based on data from a specific case study area.

6. Conclusion and policy implications

This study determines the impact of mini-grid load compositions under various tariff structures on the monthly electricity bills of rural solar PV mini-grid users. The findings indicate that the future mini-grid load composition can significantly affect users' monthly bills, with the effect varying depending on the tariff structure. A mini-grid load composition with more daily productive uses results in a lower cost-reflective tariff compared to household and non-daily productive uses, with reductions of 33% and 27% under power-based tariff structures and 17% and 15% under energy-based tariffs.

The impact of future mini-grid load composition on users' monthly bills varies across load categories. Among the load categories, households are more significantly impacted compared to community and productive use. Community and productive users can have reduced monthly bills under power and fixed and variable tariff structures, respectively. While low- and medium-usage households can see reduced bills under time-of-use and fixed energy tariffs, respectively, low-usage households may face significantly higher bills, up to eight times more, under fixed and variable tariffs compared to fixed energy tariffs. These findings emphasize the importance of considering the impact of future mini-grid load composition for ensuring the economic viability and sustainability of mini-grids.

Further significant policy implications can be drawn from the findings of the study. First, governments often implement policies to expand access to services for low-income households. In this regard, during tariff setting and revisions, it is crucial to pay particular attention to low-usage households, as they are significantly affected by the future mini-grid load composition. Therefore, it is important to consider the impact of load composition uncertainty in mini-grids, both pre-and post-electrification, when making tariff decisions and revisions to ensure fair and affordable pricing among users and to implement time use of tariffs to protect low-usage households while maintaining profitability for investors.

Second, considering the impact of future mini-grid load composition is critical for effective subsidies. Therefore, when formulating policies to support specific types of appliances and load categories, it would be case-specific for effective subsidization. This approach encourages private actors and ensures the long-term sustainability of the mini-grid.

Third, while the productive use of electricity reduces the cost-reflective tariff, the extent of this reduction varies depending on the type of productive use. Therefore, when designing tariffs and financial models, it is crucial to consider both the type and extent of daily and non-daily productive uses.

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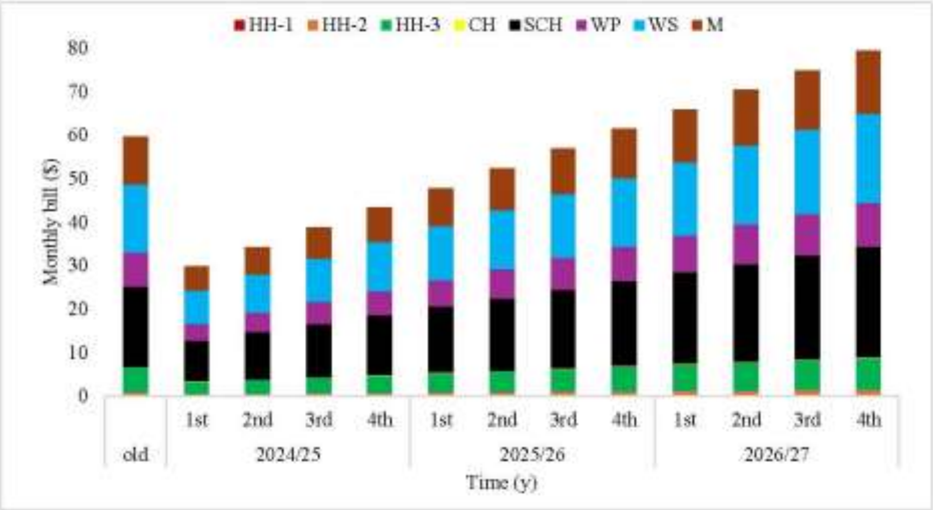
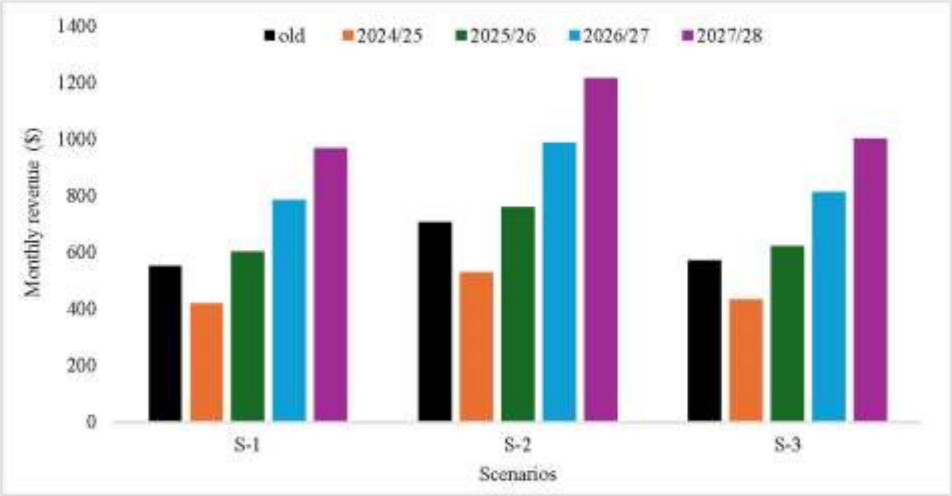
Appendix A. Old and new electricity tariff in Ethiopia

	Old tariff (ETB)	New tariff (ETB)															
		2024/25				2025/26				2026/27				2027/28			
Monthly electricity consumption (kWh)		1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Up to 50 kWh	0,27	0.35	0.43	0.52	0.6	0.68	0.76	0.84	0.92	1	1.08	1.16	1.24	1.32	1.4	1.48	1.56
Up to100 kWh	0.77	0.95	1.13	1.31	1.49	1.67	1.85	2.03	2.21	2.39	2.57	2.76	2.94	3.12	3.3	3.48	3.66
Up to 200 kWh	1.63	1.89	2.15	2.41	2.67	2.93	3.19	3.45	3.72	3.98	4.24	4.5	4.76	5.02	5.28	5.55	5.81
Up to 300 kWh	2	2.46	2.92	3.38	3.84	4.3	4.76	5.22	5.68	6.14	6.6	7.06	7.52	7.98	8.44	8.89	9.35
Up to 400 kWh	2.2	2.66	3.12	3.57	4.03	4.49	4.95	5.41	5.86	6.32	6.78	7.24	7.7	8.15	8.61	9.07	9.53
Up to 500 kWh	2.41	2.85	3.29	3.73	4.17	4.62	5.06	5.5	5.94	6.39	6.83	7.27	7.71	8.16	8.6	9.04	9.48
Above 500 kWh	2.48	2.92	3.35	3.79	4.23	4.66	5.1	5.54	5.97	6.41	6.84	7.28	7.72	8.15	8.59	9.03	9.46
Small industry	1.53	1.76	2.02	2.29	2.56	2.82	3.09	3.36	3.62	3.88	4.15	4.41	4.68	4.93	5.2	5.46	5.73

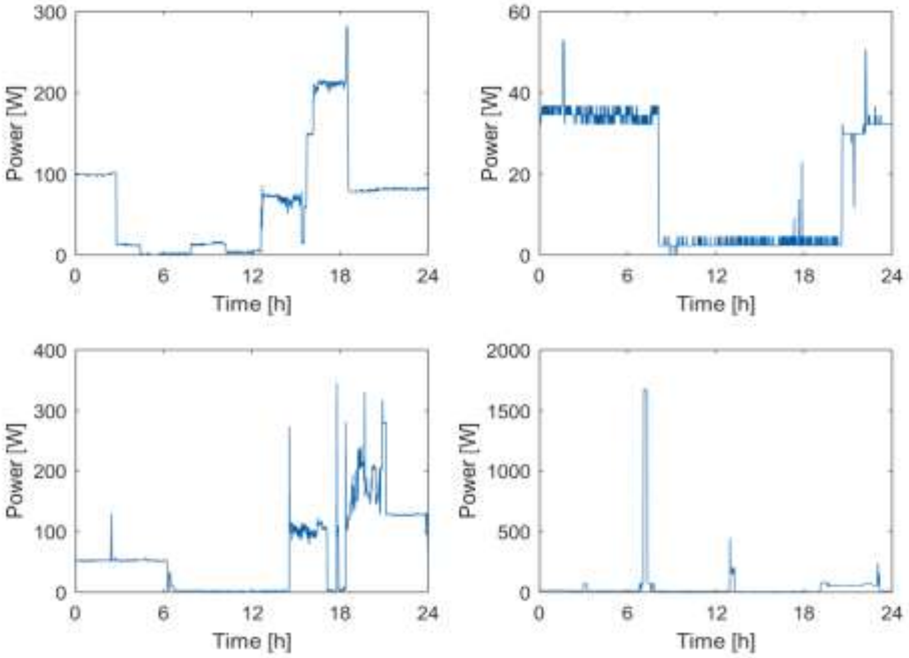
Appendix B. Monthly bill of users based on the electricity tariff in Ethiopia



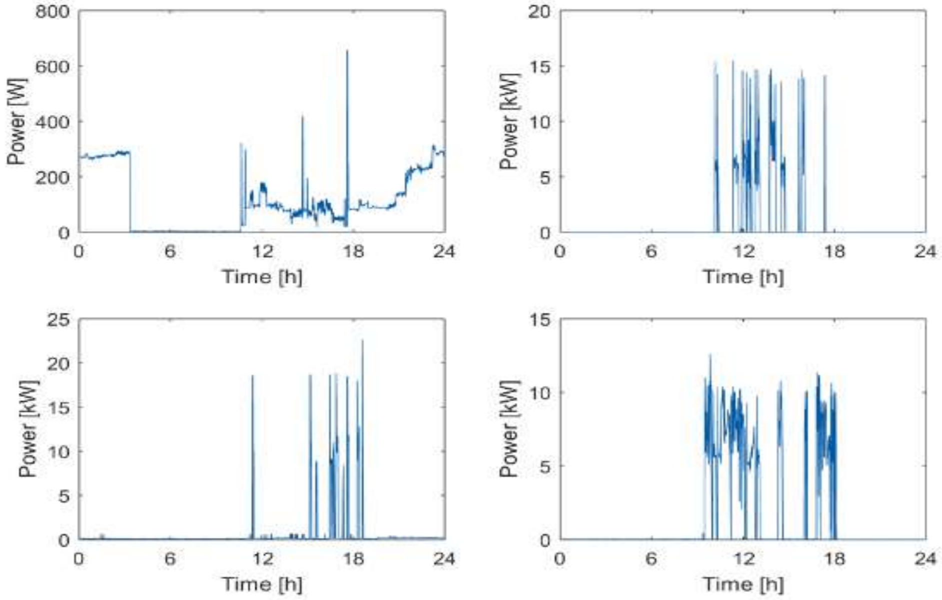
Appendix C. Total monthly revenue based on the electricity tariff in Ethiopia



Appendix B. The measured load data for household use and productive use of electricity used from [55]: (a) household, (b) productive use

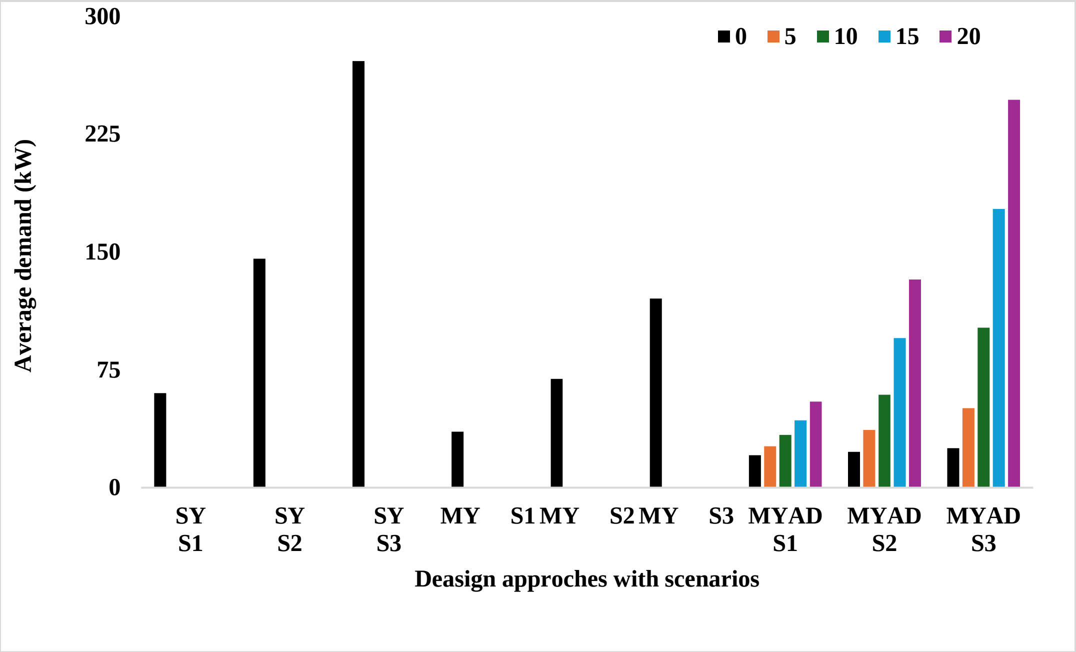


(a)

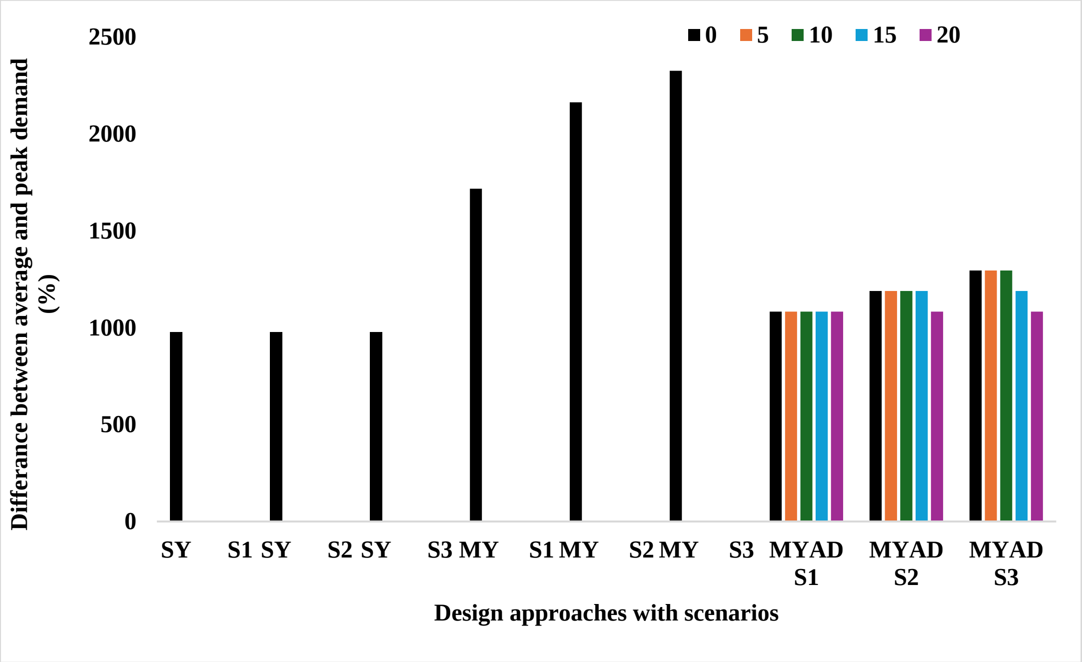


(b)

Appendix C. Demand characteristics in demand profile used for the design approaches: (a)Average demand, (b) Percentage difference between average and peak demand

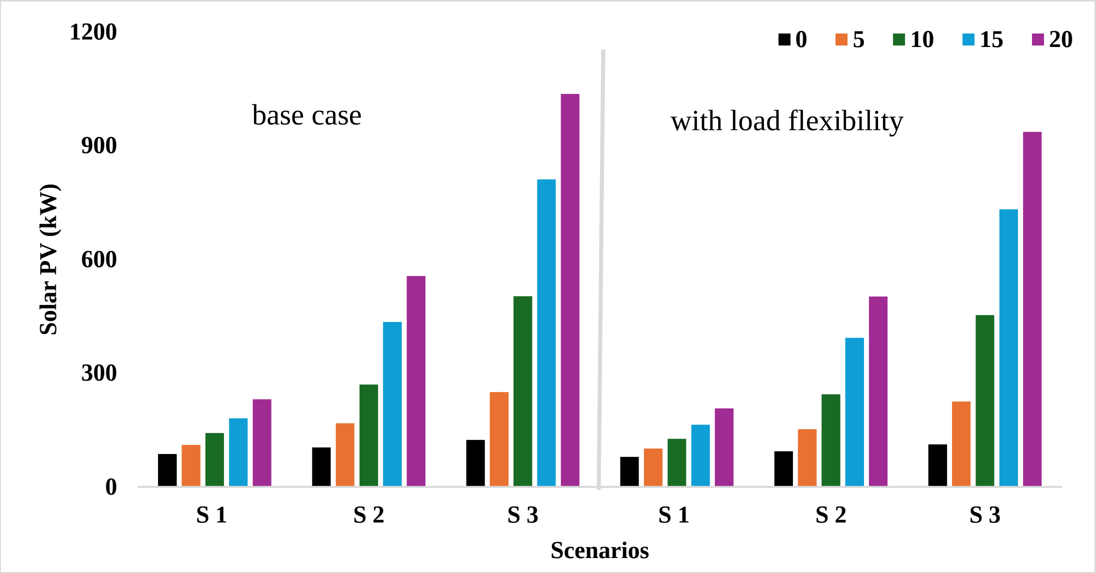


(a)

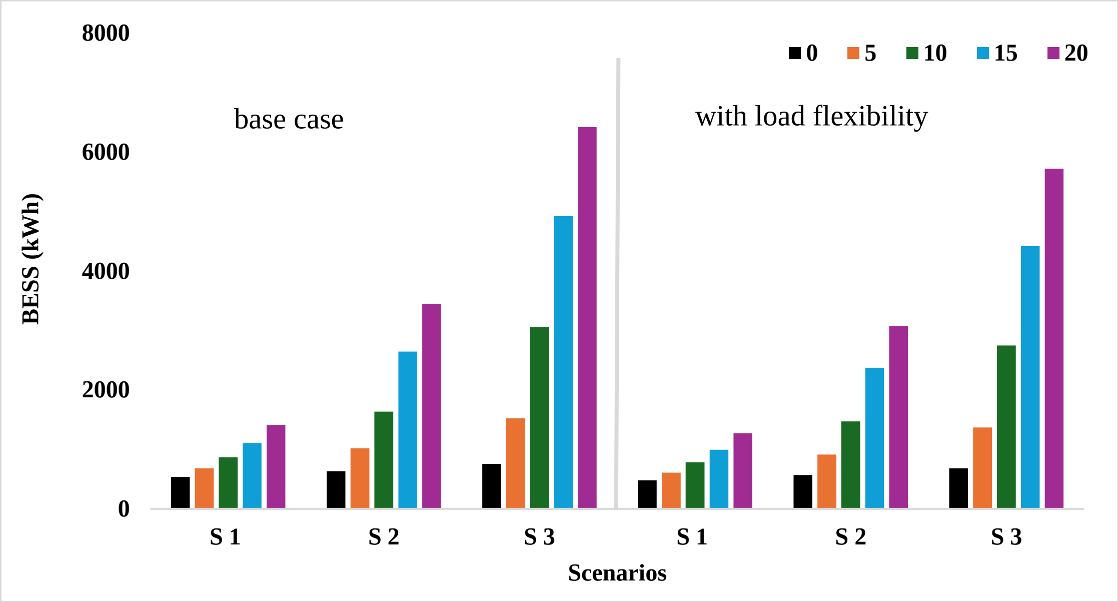


(b)

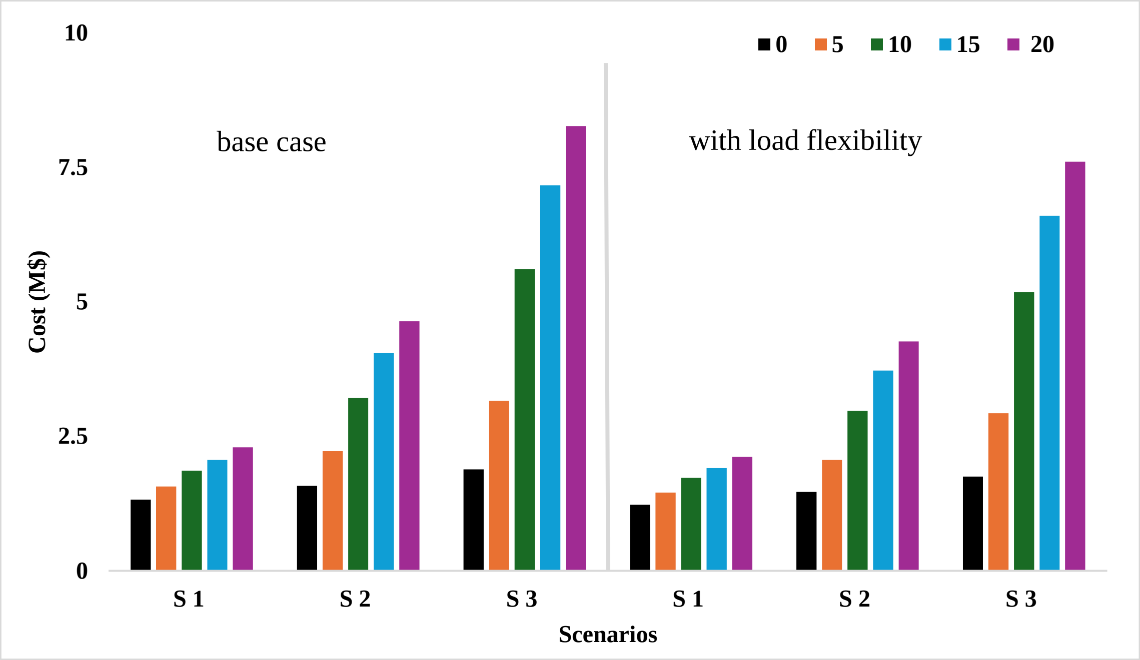
Appendix D. System capacity and cost in each five years during the planning horizon for MYAD design for the base case and with load flexibility for scenarios 1, 2, and 3: (a) Solar PV, (b) BESS, (c) Cost



(a)



(b)

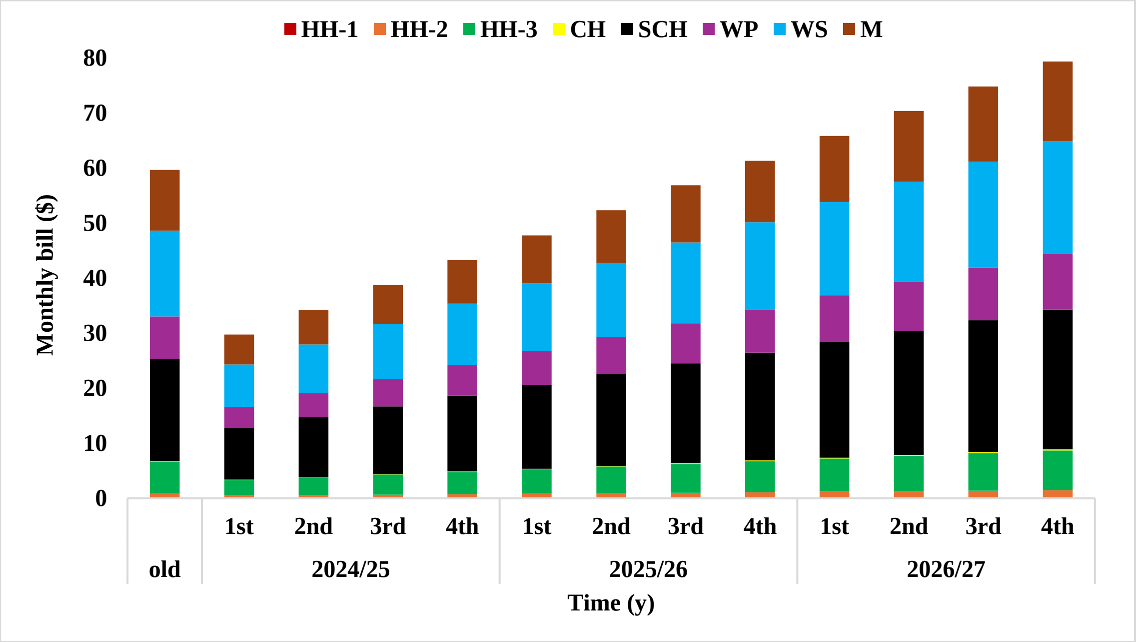


(c)

Appendix E. Old and new electricity tariff in Ethiopia

	Old tariff (ETB)	New tariff (ETB)															
		2024/25				2025/26				2026/27				2027/28			
Monthly electricity consumption (kWh)		1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Up to 50 kWh	0.27	0.35	0.43	0.52	0.6	0.68	0.76	0.84	0.92	1	1.08	1.16	1.24	1.32	1.4	1.48	1.56
Up to100 kWh	0.77	0.95	1.13	1.31	1.49	1.67	1.85	2.03	2.21	2.39	2.57	2.76	2.94	3.12	3.3	3.48	3.66
Up to 200 kWh	1.63	1.89	2.15	2.41	2.67	2.93	3.19	3.45	3.72	3.98	4.24	4.5	4.76	5.02	5.28	5.55	5.81
Up to 300 kWh	2	2.46	2.92	3.38	3.84	4.3	4.76	5.22	5.68	6.14	6.6	7.06	7.52	7.98	8.44	8.89	9.35
Up to 400 kWh	2.2	2.66	3.12	3.57	4.03	4.49	4.95	5.41	5.86	6.32	6.78	7.24	7.7	8.15	8.61	9.07	9.53
Up to 500 kWh	2.41	2.85	3.29	3.73	4.17	4.62	5.06	5.5	5.94	6.39	6.83	7.27	7.71	8.16	8.6	9.04	9.48
Above 500 kWh	2.48	2.92	3.35	3.79	4.23	4.66	5.1	5.54	5.97	6.41	6.84	7.28	7.72	8.15	8.59	9.03	9.46
Small industry	1.53	1.76	2.02	2.29	2.56	2.82	3.09	3.36	3.62	3.88	4.15	4.41	4.68	4.93	5.2	5.46	5.73

Appendix F. Monthly bill of users based on the electricity tariff in Ethiopia



Appendix G. Total monthly revenue based on the electricity tariff in Ethiopia