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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.

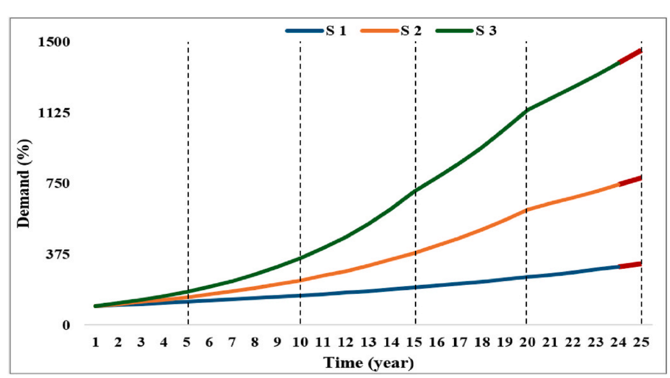


Fig. 1. Considered evolution of demand growth for scenarios 1, 2, and 3 throughout the 25 years. The final year demand (in red) indicates the demand growth considered for SY, while for MY, the full demand growth is considered. Dashed lines represent the investment years in each interval in MYAD.

[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).

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

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

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 (*μc(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

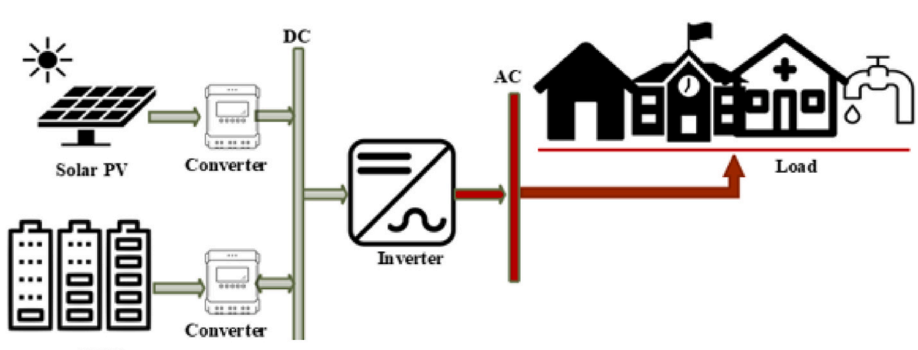


Fig. 2. A schematic diagram of the autonomous solar PV-based mini-grid configuration used in the study.

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.

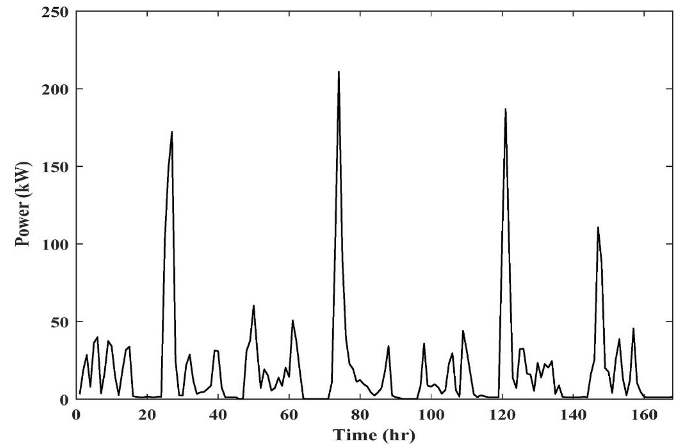


Fig. 3. Measured weekly load profile in Koftu village, used for the initial year in all scenarios of demand development.

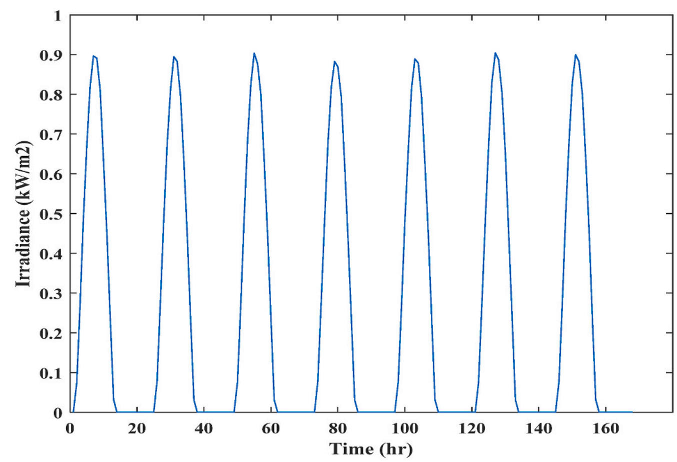


Fig. 4. The calculated weekly average insolation profile for Koftu village [56].

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	[23,42]
Inverter, kW	711	0	650	10	2	10	[23,42]
BESS, kWh	330	0	330	10	2	20	[42,54]

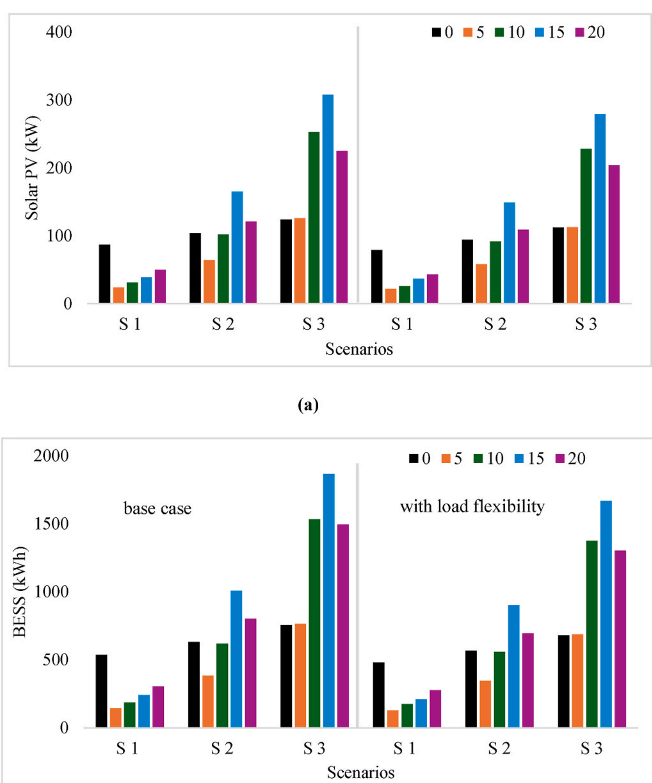
[a] OMC is operation maintenance cost.
[b] RC is replacement cost.
[c] Nrep is the number of replacements over the project lifetime, T.
[d] SV is value of a scrap of the mini-grid components.

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

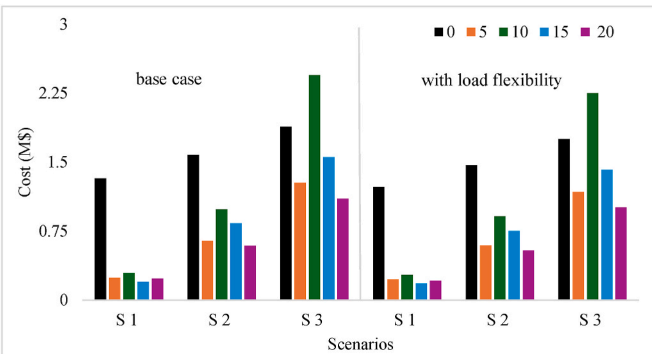


Fig. 6. Calculated cost additions for every five years during the planning horizon for the MYAD approach, both for the base case and with load flexibility for scenarios 1, 2, and 3.

$/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

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

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

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

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

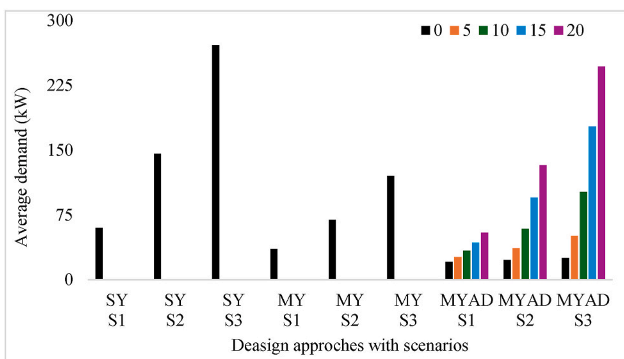
$$PSV = \sum_{j=1}^{N_{rep}+1} SV\left(\frac{1+i}{1+r}\right)^{\frac{T^*j}{N_{rep}+1}}$$

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

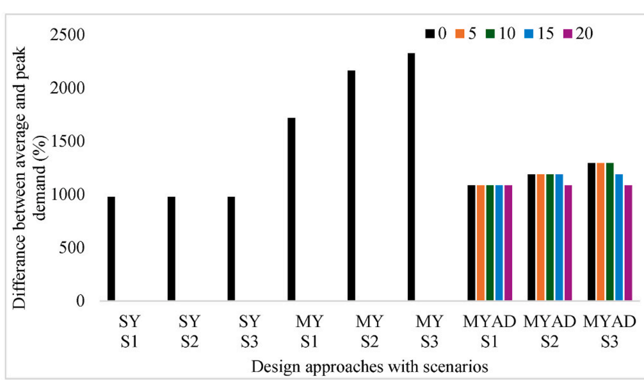
$$SOC_{min} = (1-DOD)C_B$$

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

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

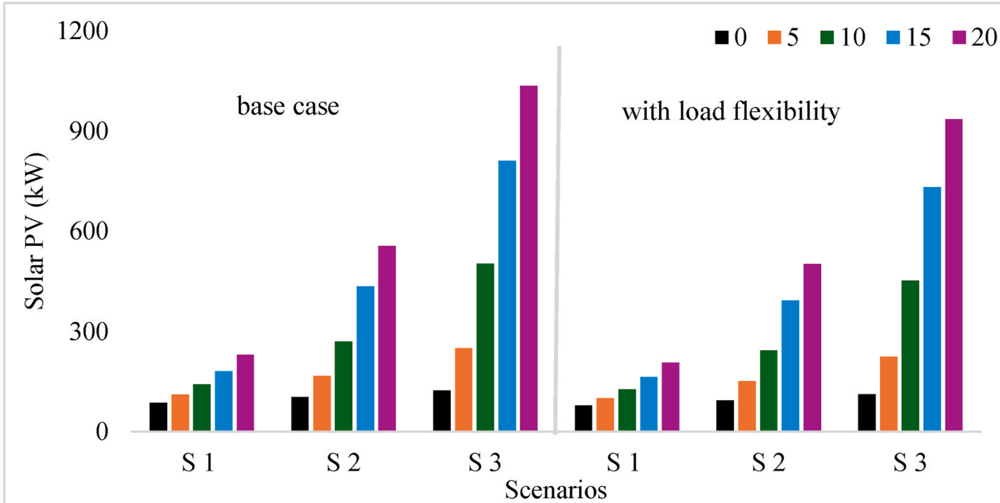


(a)

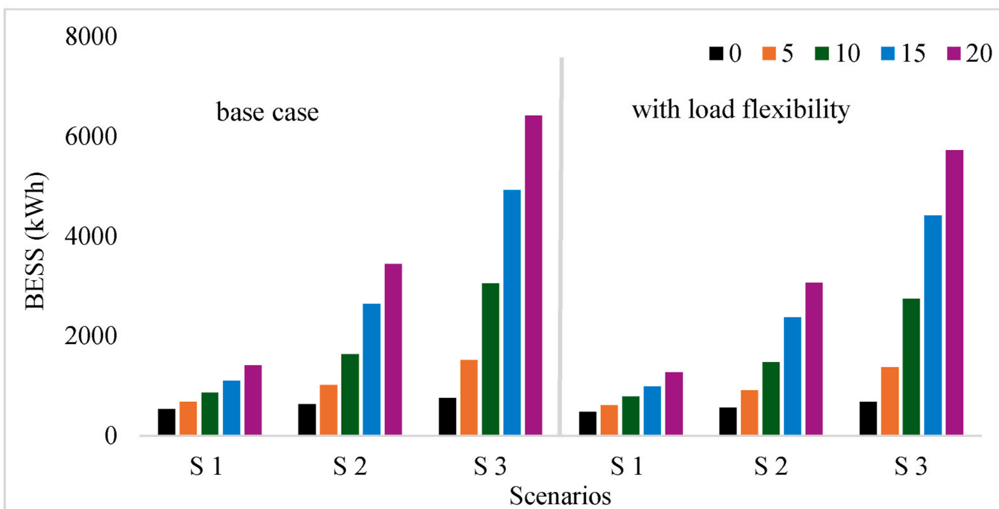


(b)

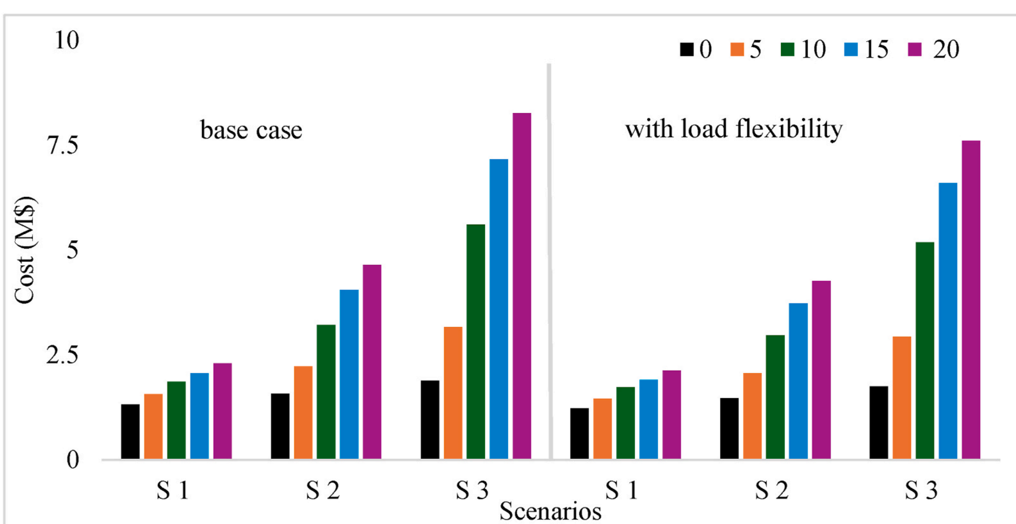
Appendix 3. System capacity and cost in each five years during the planning horizon for MYAD design for the base case and with load flexibility for scenarios 1, 2, and 3: (a) Solar PV, (b) BESS, (c) Cost


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

(a)


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

(b)


10
7.5
5
2.5
0
Cost (M$)
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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