Energy for Sustainable Development 77 (2023) 101342

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Swarm electrification: Harnessing surplus energy in off-grid solar home systems for universal electricity access

Ida Fuchs [a,*], Sergio Balderrama [b], Sylvain Quoilin [c], Pedro Crespo del Granado [d], Jayaprakash Rajasekharan [a]

[a] Department of Electric Energy, Norwegian University of Science and Technology, Trondheim, Norway
[b] Centro Universitario de Investigacion en Energias, Universidad Mayor de San Simon, Cochabamba, Bolivia
[c] Integrated and Sustainable Energy Systems, University of Liege, Liege, Belgium
[d] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway

ARTICLE INFO

Keywords:
Energy access
Solar home systems
Swarm electrification
Energy sharing
Peer-to-peer

ABSTRACT

Achieving universal access to electricity by 2030, as set out by the Sustainable Development Goals, presents a significant challenge given the current rate of progress. A recent promising concept is swarm electrification. Its central idea is the peer-to-peer energy sharing of surplus energy in solar home systems (SHSs) to connect additional neighbors and grow a bottom-up grid. This paper studies the surplus energy in SHSs and its underlying influencing factors as a basis for swarm electrification. An open-source multi-model-based techno-economic analysis of off-grid SHS including surplus energy as a value is presented. Three distinct household types from the tier 3 category in the Multi-tier framework are compared based on their unique ratios of peak-to-average demand and percentage of load consumption during sun hours. A statistical analysis of surplus energy for each household type is presented and energy sharing with additional households at tier 1–2 is simulated. Two economic analysis methods, including surplus energy, are presented and compared: single-objective cost minimization and multi-objective compromise programming. The study finds that a low ratio of demand during sun hours leads to higher surplus energy volumes, while a peak-to-average ratio alone cannot give such indications. Both economic methods suggest that optimizing the SHS design for tier 3 households involves a slight increase in solar power capacity when considering the expected revenue from selling surplus energy to 2–3 households in tiers 1–2. The total cost for the tier 3 households are reduced by 40% – 64%, additionally to decreasing their own lost load by 4% – 7%, and reducing the up-front cost to get electricity access for the tier 1–2 households by 50% compared to purchasing their own full SHS.

Introduction

Electricity access

The United Nations' Sustainable Development Goals (SDGs) were adopted in 2015 as a universal call to action to end poverty, protect the planet, and ensure that all people enjoy peace and prosperity by 2030. Achieving these goals requires concerted efforts from governments, civil society, the private sector, and individuals worldwide. However, as we approach the halfway mark between 2015 and 2030, progress has been mixed. In particular, the latest tracking report on SDG 7, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all, highlights significant challenges. The report reveals that the target for 2030 is not achievable under the current pace of progress according to the International Energy Agency (IEA). An estimated 670 million people will still lack access to electricity in 2030, and more than 2.1 billion people will continue to rely on traditional methods of cooking with biomass, kerosene, or coal reported by IEA, IRENA, UNSD, World Bank, and WHO (2022).

Describing access to energy is a challenging and intricate task according to Bhatia and Angelou (2014). Thus, the authors propose the Multi-tier Framework (MTF)[1] not defining access to electricity as a binary concept but in five distinct levels, or tiers ($T1 - T5$). In the lower tiers ($T1 - T2$), users typically have access to light, mobile phone charging, and entertainment in the form of radio and TV. In the higher tiers ($T3 - T5$), access includes higher power and energy-intensive household appliances such as refrigerators, kettles, rice cookers, irons, and others. When tracking progress towards SDG 7 and achieve the 2030 goal, households are considered to have access to electricity when

* Corresponding author.
E-mail address: ida.fuchs@ntnu.no (I. Fuchs).

[1] https://mtfenergyaccess.esmap.org/

https://doi.org/10.1016/j.esd.2023.101342
Received 14 August 2023; Received in revised form 11 October 2023; Accepted 1 November 2023
Available online 10 November 2023

Nomenclature

A	Set of all assets
a	Asset
$c_{invest,a}(t)$	Specific investment cost per unit for a in period t
$c_{loastload}(t)$	Specific penalty cost for a unit of lost load in t
$c_{price}(t)$	Price for surplus energy
$c_{salvage,a}(t)$	Specific salvage value per unit for a in period $t = T_{project}$
$DSHR$	Demand during Sun Hours Ratio
$E-SLR$	Expected served load ratio
E_{day}	Total energy for one day
E_{served}	Energy of demand that is served by the SHS
E_{total}	Energy of total demand of a year
$f_i(x)$	Value of the alternative x for criterion i in MOCP
F_i^*	The ideal (best) value for criterion i
f_i^*	The anti-ideal (worst) value for criterion i
i	Criterion in MOCP
$L_v(x)$	Distance to an Utopian solution in MOCP
n	Number of criteria in MOCP
NPC_{assets}	net present cost of the assets
$NPC_{connect}$	Connection cost
$NPC_{invest,a}$	Investment cost for a
$NPC_{lostload}$	Net present cost of the lost load
$NPC_{replace,a}$	Net present cost of replacement of a
NPC_{total}	Total net present cost of SHS
$NPV_{revenue}$	Net present value of the surplus energy revenue
$NPV_{salvage,a}$	Net present value of a at $T_{project}$
$P(t)$	Power in specific time step t
P_{avg}	Average power
P_{ch}	Power of battery charging
P_{demand}	Power of residential demand
P_{dis}	Power of battery discharging
$P_{lostload}$	Power of lost load
P_{peak}	Peak power
P_{PV}	Power of PV generation
$P_{surplus}$	Power of surplus energy
$PADR$	Peak to Average Demand Ratio
q_a	quantity of asset a
$q_a(t)$	The quantity for a in t
$q_{lostload}(t)$	quantity of lost load in t
$q_{surplus}(t)$	Expected quantity of surplus energy that household can sell
r	Interest rate
SER	Surplus Energy Ratio
SLR	Served Load Ratio
t	time step
T_{end}	Ending time of sun hours
T_{start}	Starting time of sun hours
Ti	Tier i in the MTF with $i = 1...5$
v	Parameter for MOCP
W_i	Weight of the criterion i
x	Solution option in MOCP
E-SE	Expected surplus energy
E-SER	Expected surplus energy ratio

Glossary

ConCom	Connection combinations
MEM	Modern Energy Minimum
MOCP	Multi-objective compromise programming
MTF	Multi-tier Framework
PAYG	Pay-as-you-go
Prosumpy	Energy Prosumer analysis toolkit for Python
PV	Photovoltaic
PVGIS	PV Geographical Information System
pvlib	PV library in Python
RAMP	Remote-Areas stochastic Multi-energy load Profiles generator
SDG	Sustainable Development Goal
SEBuy	Surplus Energy Buyer
SESell	Surplus energy seller
SHS	Solar Home System
SOCM	Single-objective cost minimization

they meet the lowest level of the MTF. However, although this represents an improvement in their situation, it does not fully align with the overarching objective of SDG 7, which seeks to achieve universal access to reliable, affordable, and sustainable energy. Additionally, households still face the challenge of obtaining clean cooking solutions. To address this issue, increasing access to higher tiers during the electrification process can not only provide solutions for access to electricity, but it can also help to tackle the problem of clean cooking and even access to clean water by using kettles.

The ambitious level of access to electricity has also been presented by Bazilian et al. (2021) where the authors propose the Modern Energy Minimum (MEM) of 1000 kWh per person per year, inclusive of both household (300 kWh) and non-household electricity consumption (700 kWh). It is better aligned with historical trends and development aspirations for employment, higher incomes, prosperity, and economic transformation. As prices for solar panels and battery technology continue to decrease, and with improved technological advances, aiming for higher tiers or even the MEM is becoming increasingly achievable. Our paper examines the feasibility of such a goal by addressing energy access with Solar Homes Systems (SHSs) at tier 3, which meets the criteria for MEM.

SHSs have played a crucial role in facilitating rural electrification, particularly for the "last mile" communities, and according to World Bank (2022) they will continue to be a prominent approach. They consist of photovoltaic (PV) panels, battery storage and the necessary power electronics to control the system. According to the World Bank, 1.1 billion people will have access to at least $T1$ and above through SHS by 2030. Out of these, around 650 million individuals might become initial users of SHS. This encompasses 464 million people who will adopt SHS as their main electricity source, along with an additional 186 million who will utilize it to supplement an unreliable grid.

Fernandez-Fuentes, Eras Almeida, and Egido Aguilera present the technological innovations in SHS based on the experiences of Bolivia, Peru, and Argentina. The authors define three generations of SHS. The third generation SHS is highly efficient, uses LED lamps, lithium batteries, microelectronic control, and plug-and-play connections. The equipment can be self-managed by users and reflects the technology's high reliability with a minimum maintenance service. Such plug and play components and modular solutions could lead to an acceleration of SHS deployment and enable a bottom-up growth of rural microgrids consisting of interconnected SHS. The growing of such a bottom-up grid is a concept called Swarm Electrification visualized in Fig. 1 and further described in Section "Background". The central premise of the concept is the existence of surplus energy in SHSs, with the primary

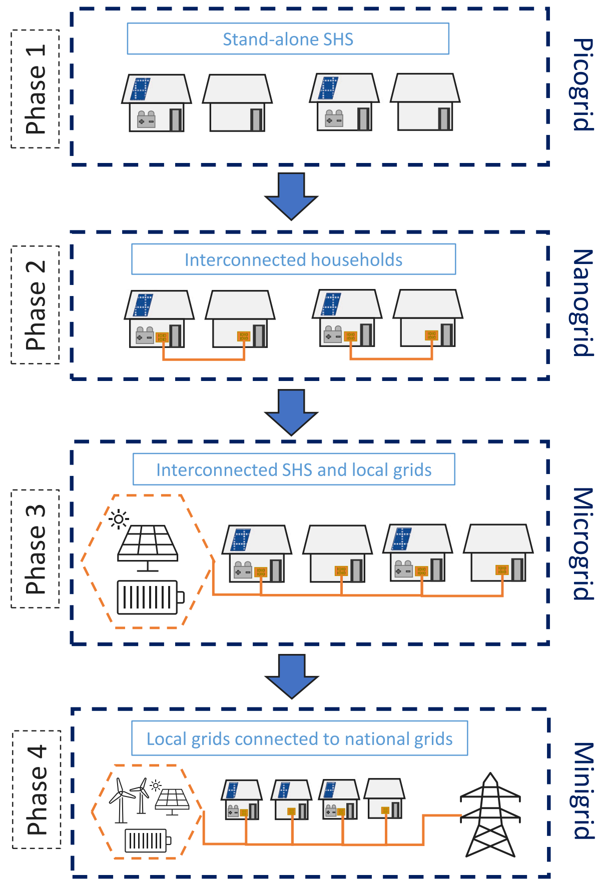

Fig. 1. Swarm electrification's four phases from SHS to national grid.

focus being the accessibility of this surplus energy to accommodate additional users.

Surplus energy

Surplus energy is the energy that cannot be used or stored, i.e. it is curtailed. This curtailment is usually not the case in grid connected SHSs in areas with a stable and reliable grid, nor is there a significant energy demand that cannot be met by the grid (lost load). However, the trading of surplus energy from residential SHSs or simply residential PV systems has become popular in recent years and is currently addressed as active consumers or prosumers in literature. Bjarghov et al. (2021) give a comprehensive review on developments and changes in local electricity markets with increased distributed renewable generation including prosumers and peer-to-peer trading of electricity. The authors identify five challenges that such local electricity markets aim to solve, one of which is the optimal utilization of distributed supply, which essentially refers to the efficient use of surplus energy. This is comparable to the aim for swarm electrification, where such an optimal utilization simply means that the surplus energy is used to connect further households and thus reduce the costs for all involved parties. Kirchhoff, Kebir, Neumann, Heller, and Strunz (2016) compare peer-to-peer electricity trading in local energy communities in Germany with swarm electrification in the Global South. The findings indicate that local energy communities in developing regions and local energy communities in Germany have several common factors for successful achievement. The outcomes illustrate that a significant level of user ownership and the ability to expand the system according to user requirements are particularly encouraging characteristics.

Since peer-to-peer trade of surplus energy from SHS is the basis of swarm electrification, it needs to be studied in depth to quantify the techno-economic benefits of the concept. Kirchhoff (2015) simulated a single SHS of 65 W and a 100 Ah battery for Bangladesh, demonstrating surplus energy levels of 30% of the total generation for one year. This gives an indication that there is a potential, but it does not give knowledge on what influences the amount of surplus energy. Soltowski, Bowes, Strachan, and Anaya-Lara (2018) studied real data from $T1$ and $T2$ SHSs in Rwanda and demonstrate that they both show significant demand diversity and an average surplus energy of 65%. The same authors, (Soltowski et al., 2022), present a field study where they use the fact that up to 70% of the energy generated by SHSs of 50 W installed PV and 17 Ah battery capacity is surplus and effectively goes to waste, due to high solar resource peaks aligning with low demand periods and restricted storage capacity. They demonstrate a successful trial of the interconnection of 7 households with SHSs and surplus energy to a new household without SHS and a community refrigerator. Bhatti and Williams (2021) provide different ways to estimate the surplus energy based on real load profiles in off-grid systems in urban and rural India. They find an average surplus energy through the year of around 50%. The values for the urban and rural households are consistent with the level of solar energy available. The estimated surplus energy for the monsoon months of July and August is 25% based on the reduction in solar output and greater use of fans during humid weather. Although, their study is based on measurements, giving realistic results for the surplus energy estimate, it does not study the specific influence of different load profiles of consumers and its influence on surplus energy and its potential of energy sharing. This was first presented by the same authors as this paper in Fuchs, Balderrama, Del Granado, Quoilin, and Rajasekharan (2023). The study analyzes the dependencies of surplus energy on the size of the SHS, i.e. installed PV capacity and battery capacity and on the stochastic PV generation profile and demand profile of different types of end-users. Further on, the study presents a calculation on how much of the surplus energy can be shared with further households assuming swarm electrification. However, the simulations only cover one year and a more detailed statistical analysis with several years and different stochastic load profiles was still missing in the literature, and is hereby presented by this work.

With a more accurate estimation of expected surplus energy in a SHS and the simulation of the quantity that can be shared or sold further, it becomes possible to include the value of this surplus energy into the sizing process of SHS. This could improve the original decision making when purchasing SHSs considering a community with swarm electrification from the perspective of end-users. However, in typical studies where sizing of SHS is the focus, surplus energy is often not the focus or a parameter that is minimized or avoided, since it is seen as an indicator for an oversized system. Both single-objective and multi-objective optimization methods have been used. Fioriti, Poli, Duenas-Martinez, and Micangeli (2022) defines the concept of multiple design options for a single-objective optimization. The authors propose a novel methodology for sizing stand-alone hybrid energy systems that identifies the optimal solution and post-processes the search history to select second-best options of interest. Balderrama et al. (2019) proposes a two-stage linear programming optimization framework for isolated hybrid microgrids with multiple energy sources. The study focuses on tackling uncertainty in both demand and renewable generation in the planning process and proposes a robust method with little impact on the total net present cost. Although, these studies are clearly relevant, they do not consider single end-users and their potential of economical improvement by including the surplus energy as a value or criterion into the system sizing or investment decision-making process. One example where surplus energy is minimized, is the study of Narayan, Chamseddine, Vega-garita, Qin, and Popovic-gerber (2019) that proposes a genetic algorithm-based multi-objective optimization approach that minimizes the surplus energy, loss of load probability, and battery size while maximizing the battery lifetime. The authors studied the optimal-sized SHSs and show that for demands above $T2$, the present day SHS sizing needs significant improvements. Additionally, they find that the electricity needs of higher tiers of MTF without compromising one or more of the system metrics cannot be achieved purely through standalone SHS at an affordable limit. Higher tiers include high-power appliances that create high power peaks in the demand profiles and significantly influence the sizing of SHS. Such appliances are often those that can improve life-style and help development, e.g. rice cookers, kettles or irons. Therefore, one of the motivations of our paper, is to analyze how the disadvantages in sizing of SHS for such high-power peaks, could be off-set by advantages through sharing the surplus energy with additional households. This requires considering surplus energy as a quantifiable value with the potential to improve the overall economics for the SHS owner. Therefore, it must be considered as a criterion during the system sizing process. Thus, two methods for the economic analysis where surplus energy is included, are presented and compared: single-objective cost minimization and multi-objective compromise programming.

Contributions

The paper's novelty stems from its in-depth examination of the second phase of swarm electrification, achieved through an open-source, multi-model-based techno-economic analysis of off-grid SHS, with a particular emphasis on surplus energy. Unlike previous studies discussed in the literature, which lacked a statistical analysis of surplus energy and its inclusion in investment decision-making for participants in the second phase of swarm electrification, this paper addresses these gaps comprehensively.

The key contributions of this paper are:

- Multi-model-based simulation, statistical analysis and estimation of surplus energy in different typical tier 3 solar home systems for rural Sub-Saharan Africa
- Swarm electrification model for assessment of surplus energy supplying further households at tier 1 and 2
- Including surplus energy as value in solar home system investment decision making process by comparing single-objective cost minimization and multi-objective compromise programming
- Demonstration of 40% – 64% total cost reduction potential for energy access including electric cooking for tier 3 households and 50% up-front cost reductions for connected tier 1 and 2 households

The remainder of this article is organized as follows: In Section "Background" we explain swarm electrification which forms the background of this study. In Section "Methodology" we present the methodology that is used in this paper. First we explain how the surplus energy is modeled, secondly we evaluate how much of the surplus energy could be shared with additional households, and thirdly we propose the economic methods to evaluate the value of the surplus energy integrated in the investment decision making process. In Section "Case study" we present the case study and the input data that is used in the model. In Section "Results" we present the results. This is followed by a discussion and finally a conclusion of the paper.

Background

A new emerging concept that focuses on organically grown bottom-up grids is *swarm electrification* visualized in Fig. 1. It was first introduced by Groh, Philipp, Lasch, and Kirchhoff (2014) and describes a step by step electrification process with four phases.

It starts with individual stand-alone SHS and proceeds with the interconnection of households where the first step of a swarm grid is established. Further, the system grows and step by step new participants or technologies can be added to reach higher levels of electrification. The advantages of the concept are to give electricity to more people, give access to increased power and energy and make electricity more affordable for the involved participants.

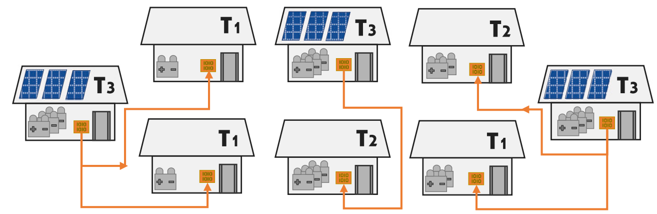

Fig. 2. Swarm electrification — phase 2: Possible connection combinations of $T1$ and $T2$ to $T3$ households.

Sheridan, Sunderland, and Courtney (2023) present a comprehensive review on swarm electrification of 89 scientific papers since 2011, where 90% were published since 2015. The authors highlight the potential of swarm electrification but also identify the need for new business models to make it more financially attractive to investors, customers and end-users as one of the key challenges found in the literature. By reducing dependence on subsidies and non-governmental organizations, a commercially-led electrification program could be established. Our paper addresses the need for new business models by quantifying the value of the surplus energy in the SHS and therewith attracting private investment.

Narayan et al. (2019) demonstrate that the interconnection of SHSs into a bottom-up microgrid results in an increase of electrification level and a decrease of individual system sizes. This is a very important result for increasing the level of energy access and decreasing the costs, however the study mainly represents phase 3 of swarm electrification with a focus on tier $T4$ and $T5$ households. There, a local microgrid is implemented and sharing runs through that network. In contrast, in phase 2 of swarm electrification the emphasize lays on the lower tiers $T1$, $T2$ and $T3$ and their first individual connections into a nanogrids. This is exemplified in Fig. 2.

The assumption is that there are $T3$ households that have or do purchase SHS and are able to sell surplus energy. These household will further be referred to as the Surplus Energy Sellers (SESells). Then, there are the households that are connecting to the SESells to buy the surplus energy. These households are referred to as the Surplus Energy Buyers (SEBuys). High up-front investment costs and high total investment costs are both barriers for energy access. The upfront investment costs are the cost that have to be paid during the initial purchase of the SHS at time step zero. The total costs include the further investment costs as of the replacement of the battery and the penalty costs for lost load. Further, the total cost are reduced by the salvage value of the assets with a remaining lifetime after project lifetime. The upfront investment costs are one of the most crucial barriers for *very low income* households, which are the SEBuys in this study. The SESells are *low and middle* income households and they might consider the total investment costs more than the upfront costs.

To overcome high upfront costs there are financing models like Pay-as-you-go (PAYG) and microfinance. PAYG allows users to pay for a product or service in installments, typically through mobile money or other digital payment systems. It offers the potential to deliver an increasing and faster access to clean affordable energy, however, both the technology and business model are more complex than current alternatives according to Barrie and Cruickshank (2017). Microfinance, on the other hand, is a financial service model that provides small loans, savings accounts, and other financial services to low-income individuals, households, and small businesses who lack access to traditional banking services. Both financing solutions provide support in overcoming the upfront costs, however they do not necessarily help in reducing the total costs. The financing models SESell and SEBuy in phase 2 of swarm electrification could potentially provide upfront reduction (for SEBuy) and total cost reduction (for both SESell and

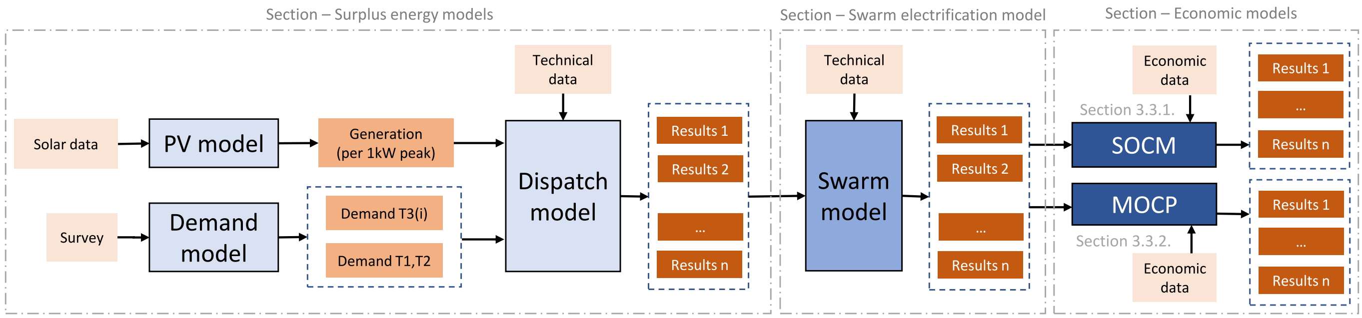

Fig. 3. Overall sequence of models. Light blue: Surplus energy models. Medium blue: Swarm electrification model. Dark blue: Economic models.

Table 1
Comparing finance models.

Cost	PAYGO	Microfinance	SESell	SEBuy
upfront cost reduction	✓	✓	✗	✓
total cost reduction	✗	✗	✓	✓

SEBuy) due to the utilization of surplus energy that otherwise would go to waste. Table 1 shows the potential cost reductions for a SESell and SEBuy compared to PAYG and microfinance. Dumitrescu, Groh, Philipp, and von Hirschhausen (2020) argues that swarm electrification can out-perform existing technical solutions and business models as microfinance and PAYG, because it can bridge between the bottom-up and top-down electrification initiatives without excluding either of them. In this paper, we analyze the economic benefits of purchasing higher tier SHS as a SESell and connect neighbors at lower tier as SEBuy, by adding the value of the surplus energy into the decision-making process for investing in a higher tier SHS.

Methodology

Fig. 3 presents an overview of the different elements of the overall model. Each element is explained in its own subsection in this chapter. The first step are the surplus energy models, including the PV model, the demand model and the dispatch model. The second step is the swarm electrification model, that simulates if the given surpluses can provide sufficient energy to additional households. Third and finally, the economic models Single-objective cost minimization (SOCM) and Multi-objective compromise programming (MOCP) are introduced and explained here. They provide two methods of including the value of the surplus energy into the investment decision process.

Surplus energy models

PV model

The PV generation is modeled by using the methods available in PV library pvlib[2] provided by Holmgren, W. Hansen, and A. Mikofski (2018). For our work, the PV Geographical Information System (PVGIS) is chosen to calculate the PV energy yield for the given location as explained by Huld, Müller, and Gambardella (2012). The combination of both tools, pvlib and PVGIS, gives access to several different irradiation databases and modeling parameters in the Python environment. In order to calculate the output power of the solar panels both the global irradiance and the irradiance components from the dataset called PVGIS-SARAH2 were used. The irradiance components are direct, diffuse, and reflected irradiance. The PV model gives the output PV power per time step for a normalized 1 kW_{peak} SHS for the desired years. This output power is resized according the modeling needs in the further steps.

Demand model

To evaluate the surplus energy in SHS, annual time series for the demand in rural isolated communities have to be used. Such demand profiles can be generated using the open-source stochastic demand modeling tool developed by Lombardi, Balderrama, Quoilin, and Colombo (2019). The model is implemented in Python and available as Remote-Areas stochastic Multi-energy load Profiles generator (RAMP)[3]. Version v0.3.1 was used in this work. RAMP was developed for typical end-users in rural areas, i.e. rural residential loads, rural schools, rural health centers and churches. The model is generic and can be adopted for any region or village of interest by adjusting the input data for the appliances. Every appliance is emulated through the definition of multiple parameters that can be flexibly adjusted based on modeling requirements. The key parameters include the appliances' power capacity, duration of usage, and specific time frames for usage. Additionally, stochastic parameters are added. This creates unique demand profiles each time the model is run. The model allows to create generic demand profiles based on the MTF with specific attributes that are of interest in this study. How the demand profiles and these attributes influence the surplus energy can be studied by introducing load metrics. In this paper we use the Peak to Average Demand Ratio ($PADR$) , referring to the difference between the maximum power demand and the average power demand, which both have significant influence on the design and sizing of the SHS. The formula for calculating the $PADR$ is:

$$PADR = \frac{P_{peak}}{P_{avg}} \tag{1}$$

where P_{peak} is the peak demand and P_{avg} is the average demand over a given time period. In energy access higher $PADR$ occur when introducing high power appliances such as a kettle, a rice cooker or an iron. These appliances could increase lifestyle and improve development, especially for the electrification of cooking. However, they often come with a significant challenge in terms of SHS sizing, due to the high peak power. In general, such appliances require larger SHS and hence lead to higher costs but also more surplus energy.

Another load metric that is relevant for this research describes the correlation between load profile and generation profile, which we define as the Demand during Sun Hours Ratio ($DSHR$) . The $DSHR$ is the ratio of the demand that occurs during the sun hours, where the SHS is generating significant PV power. This percentage of the demand can be covered directly by the PV panels, while all load outside these hours and especially during nighttime has to be covered by a sufficiently sized battery. The formula for calculating the $DSHR$ is:

$$DSHR = \frac{\sum_{t=T_{start}}^{T_{end}} P(t)}{E_{day}} \tag{2}$$

where $P(t)$ is the demand for each time step t. T_{start} and T_{end} define the start and end time of sun hours. E_{day} is the total demand over one day.

[2] https://github.com/pvlib/pvlib-python

[3] https://github.com/RAMP-project/RAMP

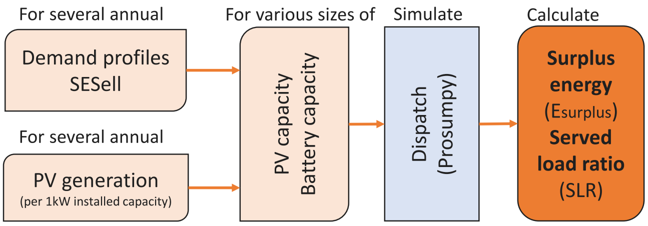

Fig. 4. Dispatch model with its in- and output.

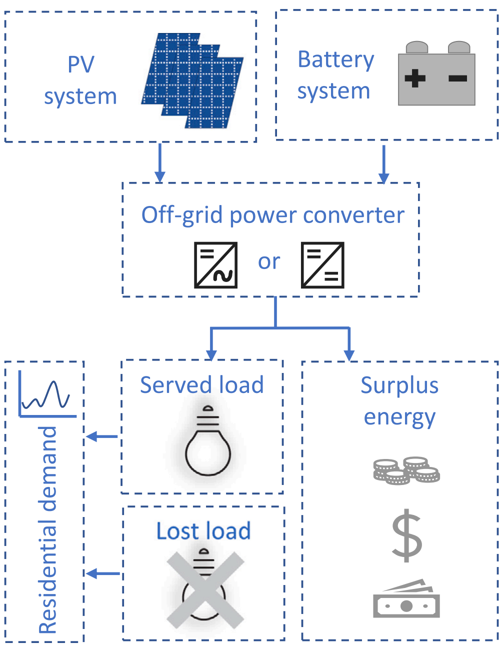

Fig. 5. Solar off-grid system setup including surplus energy and lost load.

Dispatch model

Fig. 4 presents the dispatch model block from Fig. 3 and further describes its in- and outputs.

It uses the demand profiles from the demand model and PV generation yields from the PV model to dispatch the different SHS system sizes and calculate the surplus energy ($E_{surplus}$) and Served Load Ratio (SLR) for each of these SHS sizes. The normalized PV generation for 1 kW$_p$ installed capacity and the simulated demand profiles are the inputs for the model. The model varies PV and battery size and adjusts the PV generation to the modeled size. The surplus energy is calculated for each of the system sizes for each SESell.

For this purpose, the open-source Energy prosumer analysis toolkit for python (Prosumpy[4]) is used. Prosumpy was originally programmed by Quoilin, Kavvadias, Mercier, Pappone, and Zucker (2016) to study the self-consumption of grid connected SHS. However, with only small adaptions the same dispatch model can be used for an off-grid setting as shown in Fig. 5.

The selection of the dispatch strategy aims to optimize the utilization of PV energy. Priority is assigned to using the energy generated by the PV system (P_{PV}) to meet the residential demand (P_{demand}). In cases where the PV energy output exceeds the demand, the surplus is directed towards charging the battery (P_{ch}). Conversely, when the PV energy is insufficient, energy is drawn from the battery (P_{dis}) until the deficit is resolved. In an off-grid system supplementary energy cannot be bought or sold. Instead the options are not supplying the demand resulting in lost load ($P_{lostload}$) , or to have surplus energy ($P_{surplus}$). These behaviors can be synthesized in the power balance equation:

$$P_{demand} = P_{PV} - P_{ch} + P_{dis} - P_{surplus} + P_{lostload} \tag{3}$$

In Prosumpy the dispatch is implemented as logical functions and power flows are calculated and stored for further use. Except the change from grid-connected to an off-grid system the model in Prosumpy is maintained as introduced in Quoilin et al. (2016).

To analyze and compare surplus energy from the different dispatches, specific system metrics need to be defined. Quoilin et al. (2016) use the self-sufficiency rate as the ratio between the self-consumed energy and the total annual energy demand, and the self-consumption rate as the ratio between the self-consumed energy and the annual energy produced by the PV array. Those metrics are common for sizing of PV battery systems according to Weniger, Tjaden, and Quaschning (2014). The self-sufficiency rate indicates how well the self-owned system can serve the demand, while it is assumed the rest of the demand is served by a grid. In an off-grid setting there is no grid, and the fraction of energy that is not served by the self-owned system becomes lost load. However, the fraction that is served, called the Served Load Ratio (SLR) in an off-grid system, is mathematically the same as the self-sufficiency rate for on-grid system and we define it as the percentage of the total demand of the year E_{total} that is served by E_{served}:

$$SLR = \frac{E_{served}}{E_{total}} \tag{4}$$

The self-consumption rate that was used by Quoilin et al. (2016) gives insight into how much of the energy produced by the SHS actually is used to supply the demand, while the remaining percentages of that ratio would inform about the surplus energy. However, since this study focuses on surplus energy, we define the Surplus Energy Ratio (SER) as the percentage of E_{total} that is surplus energy $E_{surplus}$:

$$SER = \frac{E_{surplus}}{E_{total}} \tag{5}$$

The SER gives insight in how much surplus energy the SHS generates compared to the total demand that it tries to serve.

Swarm electrification model

The swarm electrification model presents the approach employed to assess the surplus energy and its viability for supplying electricity to extra households during the second phase of swarm electrification. How much of the surplus energy actually can be shared is dependent on different aspects, that are:

Control aspects:

- Sharing only surplus energy
- Sharing only surplus energy with smart control of battery charging
- Sharing both surplus energy and battery capacity
- Sharing both surplus energy and battery capacity with smart control of battery charging

Infrastructure aspects:

- Bilateral energy sharing (nanogrids between specific households) as in phase 2 of swarm electrification
- Energy sharing into a local network (microgrid and local energy market) as in phase 3 of swarm electrification

Fuchs et al. (2022) present how different energy sharing control aspects influence the SLR for the involved partners. They show that energy sharing of both surplus energy and battery capacity can result in decreasing the SLR for the household that originally had a higher

[4] https://github.com/energy-modelling-toolkit/prosumpy

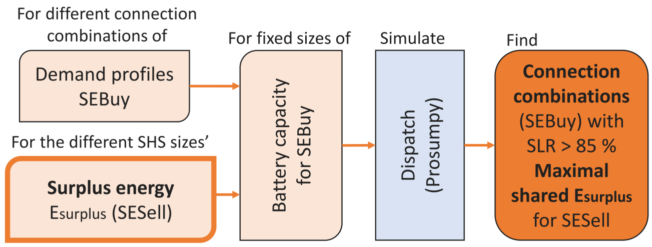

Fig. 6. Swarm electrification model with its in- and outputs.

SLR. This is because the additional connected households use energy during night and discharge the battery of the SESell additionally to the amount it is designed for. Thus, we focus on energy sharing of only surplus energy here, and apply that in phase 2 of swarm electrification. Although, smart control of battery charging could potentially improve the situation, it is often not included in existing available SHS, and will therefore be excluded now.

Fig. 6 shows the principles of the swarm electrification model block from Fig. 3 and further describes its in- and outputs. Demand profiles for SEBuy are used with the assumption that these households must have purchased their own battery, but save the costs of purchasing additional PV panels. Therefore, the simulated surplus energy time series from the dispatch model is used as input for the swarm electrification model instead of PV generation time series. The size of the battery is fixed per household $T1$ and $T2$ to the optimal value of the battery capacity if the households had purchased their own full SHS. The economic implications of these assumptions are discussed in Section “Discussion”.

Further, it is assumed that the SESell can only connect a certain number of SEBuy, and therefore it is of interest to know the connection combinations (ConCom) of SEBuy that are possible to achieve a maximal percentage of surplus energy that is sold. Only solutions that maintain a SLR of at least 85% for the SEBuy are regarded, to make sure that the households get an adequate energy access. The maximal percentage of energy sharing define the percentage of surplus energy for the SESell that can be shared with additional households.

Economic models

Single-objective cost minimization

This section introduces SOCM including the value of the surplus energy. The overall objective function can be written as:

$$\min_{q_a, a\in A} (NPC_{total} - NPV_{revenue}) \tag{6}$$

where NPC_{total} is the total net present cost , $NPV_{revenue}$ is the net present value of the surplus energy revenue and q_a is the quantity of asset a among all assets A. The assets are PV panels, batteries and power inverters. The two decision variable for the optimization are q_{PV} representing the size of the PV system, and $q_{Battery}$ representing the capacity of the battery. The size of the off-grid converter is fixed according to the demand.

A criteria for the sizing of the system is that it is able to meet the demand. This can be included into the decision making in several ways. One way would be to simple set a boundary limit of what is an acceptable value of lost load for the customer and then choose the best solution according to lowest costs. However, to make the SOCM comparable to the MOCP that is presented in the following section, we include the lost load as a penalty cost in the calculation of the NPC_{total}:

$$NPC_{total} = NPC_{assets} + NPC_{lostload} \tag{7}$$

where NPC_{assets} is the net present cost of the assets and $NPC_{lostload}$ is the net present cost of the lost load . The NPC_{assets} is calculated as follows:

$$NPC_{assets} = \sum_{a\in A} NPC_{invest,a} + \sum_{a\in A} NPC_{replace,a} - \sum_{a\in A} NPV_{salvage,a} \tag{8}$$

where $NPC_{invest,a}$ is the investment cost for each asset a of the total set of assets A for the project. Accordingly, $NPC_{replace,a}$ is the net present cost of the replacement cost and $NPV_{salvage,a}$ is the net present value of the asset a at the end of project life time .

The $NPC_{invest,a}$ of asset a is calculated by multiplying the specific cost per unit $c_{invest,a}(t)$ for the asset a with the quantity $q_a(t)$ in period $t = 0$:

$$NPC_{invest,a} = c_{invest,a}(t) \cdot q_a(t) \tag{9}$$

The $NPC_{replace,a}$ of asset a is calculated by the specific cost per unit $c_{invest,a}(t)$ multiplied by the replacement quantity $q_a(t)$ in period $t = T_{replace,a}$:

$$NPC_{replace,a} = c_{invest,a}(t) \cdot q_a(t) \cdot \frac{1}{(1+r)^t} \tag{10}$$

where r is the interest rate . The $NPV_{salvage,a}$ of asset a at the end of the project lifetime $T_{project}$ is calculated by the specific value $c_{salvage,a}(t)$ multiplied by the quantity $q_a(t)$ in period $t = T_{project}$:

$$NPV_{salvage,a} = c_{salvage,a}(t) \cdot q_a(t) \cdot \frac{1}{(1+r)^t} \tag{11}$$

where $c_{salvage,a}(t)$ is the specific salvage value at $t = T_{project}$. Operational costs for SHS are neglected here due to the fact that they are very low compared to investment costs and that they would mainly involve cost of working hours for maintenance, but this is usually done by the private owner. Further, the penalty cost for lost load is calculated as the following:

$$NPV_{lostload} = \sum_{t} c_{lostload}(t) \cdot q_{lostload}(t) \cdot \frac{1}{(1+r)^t} \tag{12}$$

where $c_{loastload}(t)$ is the specific penalty cost for a unit of lost load and $q_{lostload}(t)$ is the quantity of lost load. Finally, the revenue from selling surplus energy is calculated as follows:

$$NPV_{revenue} = \sum_{t} (c_{price}(t) \cdot q_{surplus}(t) \cdot \frac{1}{(1+r)^t}) - NPC_{connect} \tag{13}$$

where $c_{price}(t)$ is the price that surplus energy can be sold for in each period t and $q_{surplus}(t)$ is the simulated expected quantity of surplus energy that the household can sell. How to estimate a realistic quantity of surplus energy that can be sold, was described in the swarm electrification model in Section “Swarm electrification model” in this paper. The $NPC_{connect}$ is a one time connection cost including a smart meter that measures the energy consumption, handles the control of the energy sharing and preferable has an in-build payment function. Such technology can already be found on the market and was introduced in literature and tested in the field several times by Soltowski et al. (2022), Kirchhoff and Strunz (2022) and Richard et al. (2022).

Multi-objective compromise programming

This section introduces MOCP including the value of the surplus energy. Multi-objective optimization is a method that involves optimizing multiple conflicting objectives simultaneously. The goal is to identify a set of solutions that represent a trade-off between the different objectives. Khezri and Mahmoudi (2020) present one way of finding such a trade-off, which is compromise programming. It was successfully implemented for evaluating renewable energy programs, particularly in low-income rural regions by Ferrer-Martí, Ferrer, Sánchez, and Garfí (2018). It involves measuring each solution option against an ideal solution, which is a perfect outcome that satisfies all criteria. Such an outcome cannot be achieved and is therefore called an Utopian solution. Consequently, the best solution is the one that is closest to the Utopian solution. The proximity is determined by the mathematical

Table 2
PV input data.

Parameter	Value
Latitude	3.5°S
Longitude	39.8°E
Altitude	60 m
Timezone	GMT+3
tilt	10°
Azimuth	North

distance $L_v(x)$ between an option x and the Utopian solution, which is based on the metric v, as demonstrated in Eq. (14).

$$L_v(x) = \left[\sum_{i=1}^{n} (W_i)^v \cdot \left(\frac{F_i^* - f_i(x)}{F_i^* - f_i^*} \right)^v \right]^{1/v} \tag{14}$$

Here, n represents the number of criteria; W_i stands for the weight of the criterion i; $f_i(x)$ serves as the value of the alternative x for criterion i; F_i^* signifies the ideal value for criterion i (the best value among all the alternatives); f_i^* constitutes the anti-ideal value for criterion i (the worst value among all the alternatives).

The distance metric $L_v(x)$ can be computed using different values of the parameter v, ranging from 1 to infinity (∞). The choice of the value of v reflects the relative importance given to each criterion's deviation from the ideal value. Higher v values signify a greater emphasis on the maximum deviation. For instance, $L_1(x)$ considers both small and large deviations equally important, while $L_\infty(x)$ takes only the largest deviation among all criteria into account. In this study, a combination of metrics 1 and ∞ was employed, where

$$L_V(x) = \alpha \cdot L_1(x) + [1 - \alpha] \cdot L_\infty(x) \tag{15}$$

with α set to 0.5. This combination has been shown to be effective in previous studies involving multi-criteria analyses of renewable energy programs by Ferrer-Martí et al. (2018).

The aim is to integrate surplus energy as a value into the investment decision process. Thus, we propose to treat the revenue or surplus energy as one of the criteria MOCP, resulting in the following three criteria $i = 1 \ldots 3$: Minimization of costs of assets, maximization of SLR and maximization of revenue from surplus energy. This results in the following value functions: $f_1(x) = NPC_{assets}$, $f_2(x) = SLR$ and $f_3(x) = NPV_{revenue}$.

Case study

Input data for surplus energy calculation

PV data

The location for the PV data calculation is Dzunguni village, Kenya. The coordinates are $[-3.5; 39.8]$. Solar radiation, wind and temperature data from 10 years (2006–2015) are used. The database PVGIS-SARAH2 in PVGIS is used to simulate the PV generation in pvlib. The system is facing north, which is the optimal azimuth on the southern hemisphere. The tilt angle is 10 degrees, which mirrors the inclination of numerous houses within the rural vicinity. Different azimuth angles for the PV panels for the simulated houses are not chosen here, because given a low tilt these angles would not influence the PV generation or energy sharing significantly as it was demonstrated by Fuchs et al. (2022). The energy yield is calculated for each year for 1 kW_p nominal capacity and re-sized according to needs in the further calculations. Table 2 summarizes the input data for the PV generation calculation.

Fig. 7 shows the daily PV generation per 1 kW_p installed capacity. The average daily PV generation is 5.3 kWh/day.

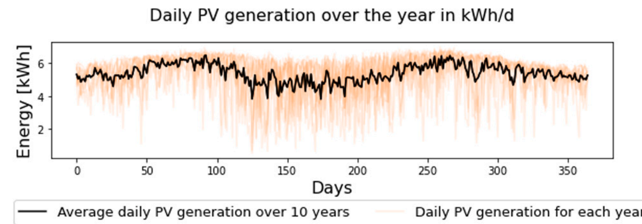

Fig. 7. Daily PV generation output for the years 2006–2015 (orange) and average of all years (black) for a 1 kW_p PV system in Dzunguni village, Kenya.

Table 3
MTF criteria.

	T1	T2	T3	T4	T5
Available power (W)	> 3	> 50	> 200	> 800	> 2000
Daily Energy (Wh/d)	> 12	> 200	> 1000	> 3400	> 8200
Annual energy (kWh/y)	> 4	> 73	> 365	> 1241	>2993

Table 4
Appliances for SE seller households.

Load	Rating P [W]			Quantity q [–]		
	$T3_1$	$T3_2$	$T3_3$	$T3_1$	$T3_2$	$T3_3$
LED light	7	7	7	5	5	5
Phone	3	3	3	3	3	3
Radio	8	8	8	1	1	1
Fan	25	25	25	2	2	2
TV	40	40	40	1	1	1
Tablet	18	18	18	1	1	1
Fridge	100	0	0	1	0	0
Kettle	0	400	400	0	1	1
Rice cooker	0	600	600	0	1	1
Iron	0	750	750	0	1	1

Demand data

As introduced in Section "Electricity access" the MTF is used, to model typical demand profiles for rural households in Kenya. The different levels of access to electricity are clustered in tiers ($T1$-$T5$) defined by several criteria. The relevant criteria for this paper are minimum available peak power and minimum available daily/annual energy, see Table 3 based on Bhatia and Angelou (2014).

In this study we chose $T3$ households for the analysis of surplus energy, because they are comparable to the MEM, as introduced in d. We want to analyze the surplus energy of households with access to different services (different appliances) but still compare to the same level of access as a $T3$. Thus, three different typical demand profiles, $T3_1$, $T3_2$ and $T3_3$ are generated with the demand generator RAMP based on the appliances in Table 4. The appliances' ratings and quantity for each tier used in this study is based on data in literature of comparable studies as in Narayan et al. (2020) and fieldwork in Kenya at Eco Moyo Education Center[5] in February/March and November 2022.

Table 4 shows the ratings and the quantity of the used appliances for each of the three different $T3$ households where surplus energy is modeled. These households represent the SESell. It should be noticed that the $T3_2$ and $T3_3$ have exactly the same number of appliances and ratings. The difference between those two households is the time of use of the high-power appliances, which are kettle, rice cooker and iron. While $T3_2$ uses all high power appliances during daytime when there is PV generation, the other household $T3_3$ uses these appliances during the evening, and therefore has to rely on a battery that is sized accordingly. This is visualized in Fig. 8. The orange curves in Fig. 8(A) show 365 demand profiles in 15 min time resolution for $T3_1$, $T3_2$ and

[5] https://www.ecomoyo.com/

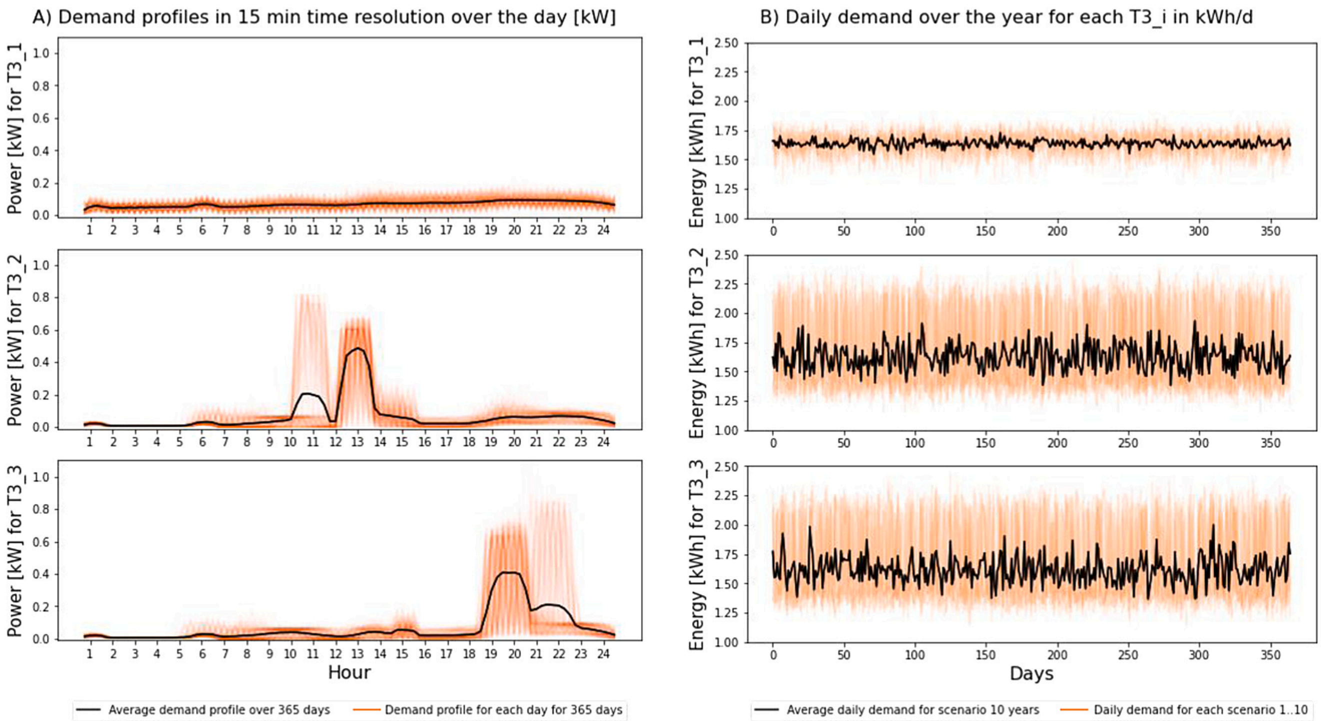

Fig. 8. Demand profiles in (A) and daily energy demand in (B) for households $T3_1$, $T3_2$ and $T3_3$. The demand profiles in (A) give insight on the stochastic variations from day to day, while the daily demand in (B) for all 10 scenarios give insight on stochastic variations from year to year.

Table 5
Key metrics of demand profiles.

	$T3_1$	$T3_2$	$T3_3$
Annual energy demand [kWh]	597	592	591
Average daily energy demand [Wh]	1636	1622	1620
Peak power [W]	224	828	986
Minimum power [W]	2	0	0
Average power [W]	68	68	68
PADR [–]	3	12	15
DSHR [%]	26	64	13

Table 6
Appliances for SE buyer households.

Load	Rating P [W]		Quantity q [–]	
	$T1$	$T2$	$T1$	$T2$
LED light	7	7	3	5
Phone	3	3	2	3
Radio	0	8	0	1
Fan	0	25	0	1
TV	0	40	0	1

$T3_3$. The darker the orange curve area is, the more frequently these values occur each simulated day. The black curves show the average demand profiles over 365 stochastic days. In total, the study uses 3650 daily demand profiles which represent 10 years of stochastic demand. The resulting daily energy demand is plotted in (B) for these 10 scenario years and the average daily demand over these 10 years is plotted in black in (B). (A) gives insight into the stochastic behavior from day to day, while (B) shows the stochastic variations between the 10 years. The households $T3_1$, $T3_2$ and $T3_3$ are representative for a $T3$ demand regarding their energy demand. However, they are different in shape, resulting in a different $PADR$ for $T3_1$ compared with $T3_2$ and $T3_3$. In terms of the MTF you can argue, that the modeled $T3_2$ and $T3_3$ are even achieving the $T4$ available power minimum of 800 W. The difference between $T3_2$ and $T3_3$ is the time of the day when the main consumption happens, in this case the use of the high power appliances. For $T3_2$ the use of these high power appliances is during daytime when there is solar PV generation, and for $T3_3$ this occurs after sunset. This is described by the metric $DSHR$, which is defined as the percentage of demand that occurs during T_{start} = 10:00 and T_{end} = 16:00 of the day. Table 5 shows these key metrics of the modeled T_3 demand profiles.

The purpose of these three different demand profiles is to show how different user preferences influence the sizing and the value of the surplus energy. This is the reason why we introduced the load metrics $PADR$ and $DSHR$, where the $PADR$ gives information on power peaks in the demand and the $DSHR$ gives information on how much energy is used while there is PV generation, which influence the need for storage. The three input files for RAMP for the three households can be shared upon request, including the time of use and the stochastic parameters.

Demand patterns for $T1$ and $T2$ are likewise produced using RAMP to facilitate an analysis of whether the surplus energy from $T3$ households can fulfill the electricity requirements of $T1$ and $T2$. In this study, $T1$ and $T2$ are identified as the SEBuy. Table 6 shows the input data of these two lower tier households and the RAMP input files can be shared upon request.

Dispatch parameters

For the dispatch, it is assumed that the battery can only be charged or discharged at a power level that refers to half of the total capacity. The charging and discharging efficiency for the batteries is set to 0.9 and is controlled by a dc–dc bidirectional power converter. Further, for the dispatch model we assume that all households have a maximal load capacity at 1000 W, which is either supported by an off-grid converter or off-grid inverter, depending on the system type. The converter efficiency is set to 0.95.

To take into consideration stochastic variations of both PV and demand profiles the model uses 10 PV generation years, each with 10 different stochastic demand profiles for each of the 3 households, resulting in 100 runs per household per SHS size.

Table 7
$T1$ and $T2$ connection combinations for swarm model.

ConCom	T1	T1,T1	T2	T1,T1,T1	T1,T2	T1,T1,T2	T2,T2	T1,T2,T2	T2,T2,T2
E_{total} [kWh/a]	65	131	156	196	221	286	312	377	467

Table 8
Economic input data.

	Cost in USD
PV cost per installed kWp	790
Battery cost per installed kWh	210
Inverter cost per installed kWp	190
Battery replacement cost kWh	140
Connection cost for selling surplus energy	50
PV salvage value per kWp after 10 years	200
Lifetime PV in years	20
Lifetime Battery in years	5
Lifetime Converters in years	10
Project life time in years	10
Interest rate in %	5
Selling price USD/kWh	0.2
Penalty cost for lost load in USD/kWh	0.2

Assumptions for swarm electrification

For the swarm electrification model, it is assumed that the SEBuy has purchased a battery of the size that would be optimal if the household had purchased a complete SHS. In our simulations, these sizes are 200 Wh for the $T1$ and 400 Wh for the $T2$. Further, we assume that SESell household can maximal connect three SEBuy. This assumption is due to existing technology introduced by Kirchhoff and Strunz (2022) and due to the fact that a household has limited neighbors in proximity to be connected at a reasonable cost assumption. Therefore all possible combinations SEBuys, $T1$ and $T2$ households, with maximal 3 households connected to the $T3$ SESell, are analyzed in the swarm model. These ConCom and their total annual energy demand are shown in Table 7.

Further, the condition for the energy sharing in the swarm electrification model is that the SEBuy $T1$ and $T2$ can reach a SLR of at least 85% by connecting to a SESell. This level is set to make the option of SEBuy comparable to the option of purchasing complete SHS.

Input data for economic models

The cost input data for the economic model is partially taken from similar studies by Yaldız, Gökçek, Şengör, and Erdinç (2021), Fernandez-Fuentes et al., Balderrama et al. (2019) and partially taken from data collected during field trips to Kenya in February/March and November 2022 (see Table 8).

The project life time is set to 10 years, which means the battery will be replaced once, and the PV panels have a salvage value after the end of project life time.

The connection cost for selling surplus energy includes the controller and connection cables. From the most relevant existing example of swarm electrification by SOLshare (2023), these costs are found to be between $25 - 30 USD$, although they include subsidies according to Siemens (2023). Therefore, the costs are set to $50 USD$ in our study.

The selling price for energy sharing is set to $0.2 USD/kWh$ which reflects the current Kenyan electricity price of 2023. In this way, the national grid serves as a reference in our model, although the actual option of connecting is not an alternative for the households.

The penalty cost for lost load is important for the SESell during the sizing process of the SHS. The assumption is that any lost load could potentially be covered by the another neighbor if the SESell is also a SEBuy. However, we do not model this, we only assume that the penalty cost is not higher than the selling price. For the SEBuy in the total cost calculation the same penalty cost is assumed. However, the SEBuy is not part of the optimization, but the cost changes (upfront cost, total cost) are the results of the outcome of the system optimization for the SESell.

Generally, setting a correct penalty cost for lost load is a challenge. Therefore, multi-objective approaches are preferred as presented by Narayan, Chamseddine, Vega-garita, Qin, and Popovic-gerber (2019). With our assumptions the penalty cost for the lost load does not have a large influence in the SOCM. It does not initiate higher investment in assets, other than the investment that can compete with the alternative grid tariff. This is chosen, because the objective of the paper is to focus on the surplus energy value and its influence on investment costs.

However, when using the MOCP, the SLR is maximized for the SHSs, i.e. the lost load is minimized, as one of the three criteria besides minimization of asset costs and maximization of revenue from selling surplus energy. For the case study the minimization of the asset costs is the main criteria, since this is cash costs that the households have to provide. Thus, the weightings for this demonstration case study are chosen to be 0.4 for the minimization of asset costs, and 0.3 each for the maximization of surplus energy revenue and maximization of SLR.

Results

This section highlights the findings from the methodology (Section "Methodology") and case study (Section "Case study"). It explores the relationship between surplus energy, system sizes, and demand profiles for $T3$ households, and investigates the feasibility of using surplus energy to supply $T1$ and $T2$ households in the second phase of swarm electrification. Additionally, the results of incorporating the value of surplus energy in the investment decision process using two economic methods are presented.

Surplus energy simulations

PV and battery size are varied and the systems' combinations are simulated as described in Section "Dispatch model" for the three different $T3$ demand profiles. Fig. 9 shows the statistical results of the total surplus energy for a year in a *box-and-whisker plot*.

Ten different years with meteorological data for the PV generation and 10 years of stochastic demand are combined into a total of 100 calculations of the total surplus energy. The dispatch is run with 15 min time resolution. For each of the households $T3_1$, $T3_2$ and $T3_3$ the total surplus energy is plotted for all system size combinations that are modeled. The different PV sizes are shown in different colors. The different battery size is plotted along the x-axis. The boxes in the figure extend from the first quartile to the third quartile of the simulated result data for the total surplus energy, with a black line at the median of the data. The whiskers extend from the box by 1.5x the inter-quartile range. It can be observed that almost all data is inside the range of the whiskers, and no outliers (fliers) occur, except a few at the very low PV size combined with large battery installed capacity.

Fig. 10 presents the expected surplus energy (E-SE) for each household in *3D plots* along the battery capacity at the x-axis and PV size along the y-axis. The E-SE is the sum of all values of annual surplus energy for all 100 simulations (10 years each with 10 demand scenarios) divided by the number of simulations $s = 100$.

First of all, and as expected, an increasing PV capacity is the driving influential component for the increase of surplus energy. Secondly, increasing battery storage capacity decreases surplus energy. Nevertheless, although a higher PV capacity will notably augment surplus

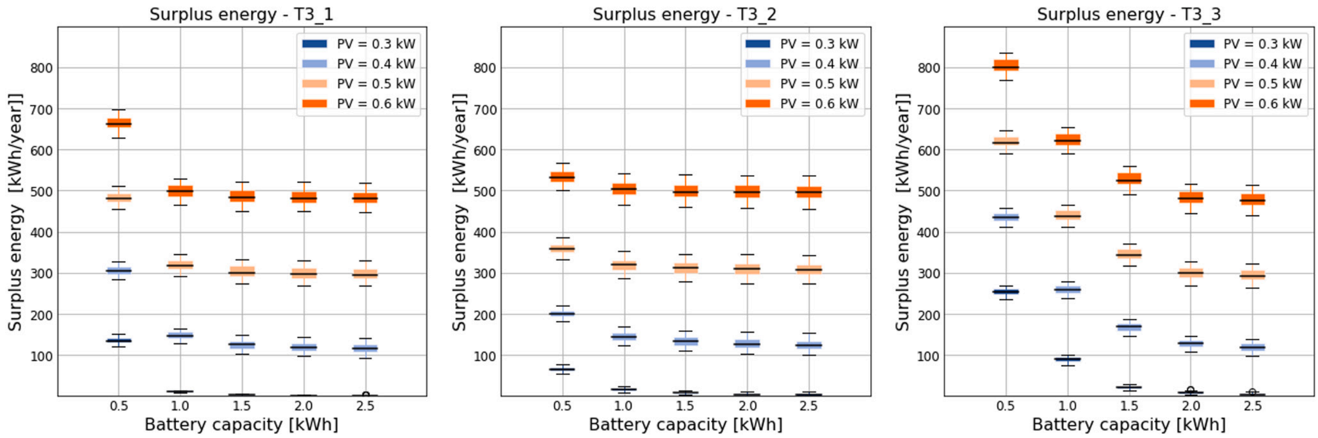

Fig. 9. The statistical results of the annual surplus energies from 100 calculations for each of the three simulated households.

Table 9
E-SLR in % and E-SE in % of the annual demand.

		A) E-SLR in %					B) E-SER in % of total demand				
	PV	Battery [kWh]					Battery [kWh]				
	[kW]	0.5	1	1.5	2	2.5	0.5	1	1.5	2	2.5
$T3_1$	0.3	68	86	88	88	88	23	0	0	0	0
	0.4	70	94	97	98	99	51	25	21	20	19
	0.5	72	97	99	99	100	81	53	51	50	50
	0.6	73	98	99	100	100	111	84	81	81	81
$T3_2$	0.3	79	86	88	88	88	11	3	1	1	1
	0.4	87	94	98	98	99	34	24	22	22	21
	0.5	92	98	99	100	100	61	54	53	52	52
	0.6	94	99	100	100	100	90	85	84	84	84
$T3_3$	0.3	49	74	84	86	87	43	15	4	1	1
	0.4	49	76	90	96	98	74	44	28	22	20
	0.5	50	77	92	98	99	105	74	58	51	50
	0.6	50	78	92	99	100	136	105	89	82	81

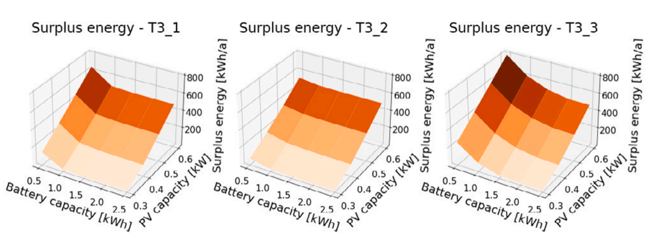

Fig. 10. Expected surplus energy (E-SE) in kWh/year for different SHS sizes.

energy, we observe only a marginal reduction in surplus energy as battery capacity increases beyond a certain threshold. This threshold refers to the SHS sizes where the SLR reaches values close to and above 90 percent, as it can be seen in Table 9. One can observe that the higher the $DSHR$, the lower is the threshold, while the different $PADR$ of the systems does not have a significant influence here.

Table 9 presents the results of the expected SLR ($E - SLR$) for the SHS sizes simulated for each of the three $T3$ households in (A). The $E - SLR$ is the sum of all values of SLR for all 100 simulations (10 years each with 10 demand scenarios) divided by the number of simulations $s = 100$. In (B) the table presents the expected SER ($E - SER$) as a percentage of the total load of each household (each of the households have a similar total load, see Table 5). Seeing these values side by side, the $E - SLR$ and $E - SER$, gives insight in how much surplus energy the system produces compared to the actual load it attempts to supply.

It can be observed that there is not always surplus energy. At low PV sizes and very large battery capacities the system reaches acceptable SLR at $85 - 88\%$, however the amount of surplus energy is between $0 - 1$ kWh per year.

Further, it can be seen that several SHS sizes with low battery capacity cannot fully serve the load (low $E - SLR$) but have a surplus energy much higher than the total load. A further interesting aspect are the systems that have the same SLR but differ strongly in the amount of surplus energy. If not considering the value of surplus energy, an investment decision would possibly be made by purchasing the system with the lowest costs achieving a certain desired SLR. By considering the surplus energy, another system might be optimal. The following economical analysis compares these systems to provide this decision support. However, before this, it has to be estimated how much of the E-SE actually can be shared with neighbors.

Swarm electrification connections

In phase 2 of swarm electrification the total surplus energy from an SHS cannot be shared or sold. Instead, the amount that can be shared is restricted by the system design and load of the households that receive the shared energy. This section provides the results regarding how much surplus energy from $T3$ households can be shared with $T1$ and $T2$ households based on the ConCom of those given in Table 7 in Section "Assumptions for swarm electrification".

Table 10 presents the connection combination that achieve the maximal shared surplus energy under the assumption that $SLR_{T1,T2} > 85\%$. Fig. 11 shows this maximal surplus energy that can be shared. Comparing the three households, it can be seen that household $T3_3$ can share surplus energy in more cases than the other two households. Further, $T3_3$ can share with slightly more $T1/T2$ households and with the higher household load $T2$. This result comes from the fact that $T3_3$

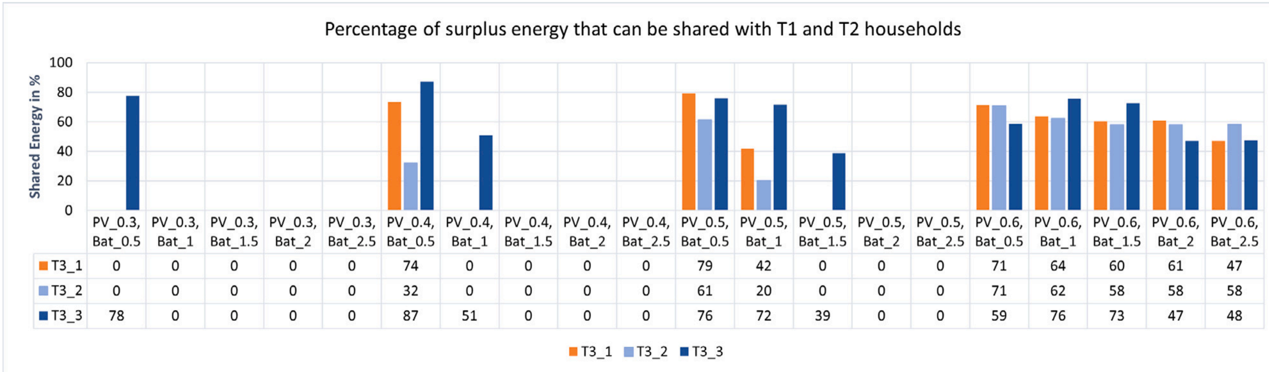

Fig. 11. Maximal percentage of surplus energy that can be shared with the best $T1, T2$ connection combinations from Table 7 assuming $SLR_{T1,T2} > 85\%$.

Table 10
Connection combinations and $SLR_{T1,T2}$ for best solutions.

PV	Bat	Best ConCom			SLR for best ConCom		
[kW]	[kWh]	$T3_1$	$T3_2$	$T3_2$	$T3_1$	$T3_2$	$T3_2$
0.3	0.5	–	–	T1,T1,T1	–	–	86%
0.3	1	–	–	–	–	–	–
0.3	1.5	–	–	–	–	–	–
0.3	2	–	–	–	–	–	–
0.3	2.5	–	–	–	–	–	–
0.4	0.5	T1,T2	T1	T1,T2,T2	85%	87%	86%
0.4	1	–	–	T1,T1	–	–	86%
0.4	1.5	–	–	–	–	–	–
0.4	2	–	–	–	–	–	–
0.4	2.5	–	–	–	–	–	–
0.5	0.5	T1,T2,T2	T1,T2	T2,T2,T2	87%	87%	90%
0.5	1	T1,T1	T1	T2,T2	86%	85%	86%
0.5	1.5	–	–	T1,T1	–	–	87%
0.5	2	–	–	–	–	–	–
0.5	2.5	–	–	–	–	–	–
0.6	0.5	T2,T2,T2	T1,T2,T2	T2,T2,T2	90%	88%	94%
0.6	1	T2,T2	T2,T2	T2,T2,T2	86%	85%	87%
0.6	1.5	T1,T1,T2	T1,T1,T2	T1,T2,T2	86%	86%	86%
0.6	2	T1,T1,T2	T1,T1,T2	T1,T2	85%	85%	86%
0.6	2.5	T1,T2	T1,T1,T2	T1,T2	85%	85%	85%

has a very low $DSHR$ and therewith generally has more direct surplus energy available after the battery of $T3_3$ is fully charged.

Investment decision process

In this section we provide the results from two methods SOCM and MOCP introduced in Section "Economic models" that include the surplus energy as a value in the investment decision process. We analyze if and how the investment decision changes when considering that the household participates in swarm electrification phase 2 and therefore consider the surplus energy as a value.

The achievable cost reductions are presented in Fig. 12(A) and (B). Fig. 12(A) shows the potential in total cost reduction for the $T3$ household. It can be seen that some of the system sizes are reaching significant total cost reductions up to 68%. Such cost reduction could lead to a different optimal solution (different PV and battery size), which we show further down in the section. Analyzing the cost reductions of the three $T3$ households, it can be observed that the household $T3_3$ has higher potential cost reductions than the two other households for several of the SHS sizes. $T3_3$ is the household with a high $PADR$ and low $DSHR$. It needs a larger SHS to achieve the same SLR as the other two households. Therefore, a potential higher cost reduction leads to higher benefits for $T3_3$, and can offset the initial disadvantage.

In Fig. 12(B) the cost changes for the SEBuy ($T1, T2$) are presented when comparing surplus energy purchase from $T3$ to the option of purchasing their own full SHS. SEBuy has a potential of 50% upfront cost reduction for both $T1$ and $T2$, while compared to purchasing their own SHS it shows a total cost increase of 20% and 32% respectively. The cost increase comes from the price that is set for surplus energy. A lower price would share the revenue more equal between the SESell and SEBuy. This is further discussed in Section "Discussion".

Further, the results for the investment decision process are presented, comparing the two introduced methods SOCM and MOCP from Section "Economic models" and how these two results deviate from the sizing without taking surplus energy into account. In Table 11 the objective function values for all SHS sizes for the SOCM in (A) and for the MOCP in (B) are presented. With the given input data from Section "Case study" the optimal solutions show disparity comparing the two methods for $T3_1$, while for the other two $T3$ it is the same. It can be observed that the MOCP gives priority to solutions that reach higher SLR. This is because the criteria of maximization of SLR and therefore minimization of lost load has more impact with this method. Consequently, if the penalty cost in the SOCM was higher, more similar results would have been achieved.

Table 12 presents the benefits of introducing swarm electrification including the value of the surplus energy into the investment decisions. It shows the optimal original system sizes and costs using SOCM, when not considering a phase 2 for swarm electrification, i.e. not considering surplus energy as a value. Then, it shows the new system sizes and their improvements for each $T3$ and both economic methods SOCM and MOCP, when a phase 2 is included into the decision process, i.e. surplus energy as a value is integrated. Additionally, the table lists

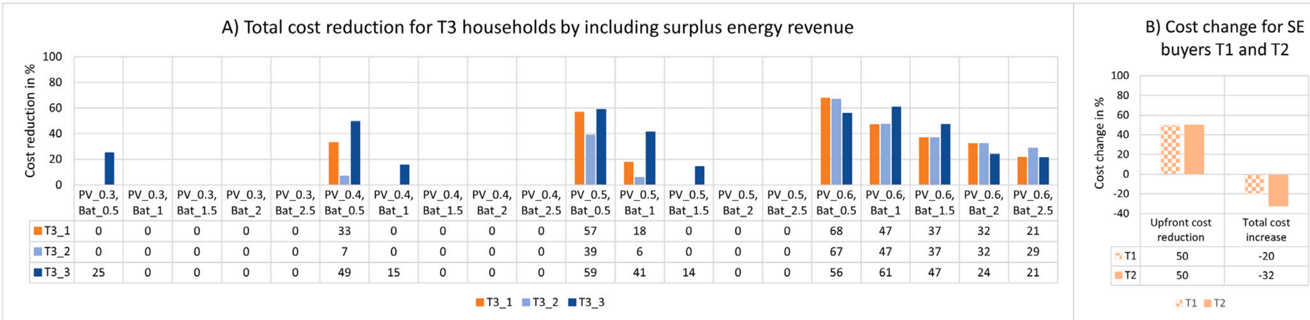

Fig. 12. Potential cost reduction for swarm electrification phase 2. (A) Potential in total cost reduction for the $T3$ household. (B) Cost changes for $T1$, $T2$ comparing surplus energy purchase to the option of purchasing a full SHS.

Table 11
Objective function values for the two economic methods.

	PV $[kW]$	A) $NPC_{Total} - NPV_{SER}$ in USD: Battery [kWh] 0.5	1	1.5	2	2.5	B) $L_p(x)$ in %: Battery [kWh] 0.5	1	1.5	2	2.5
$T3_1$	0.3	846	831	974	1129	1285	45	40	43	47	51
	0.4	595	825	952	1101	1254	38	38	40	44	49
	0.5	406	717	1005	1158	1313	33	32	41	45	52
	0.6	324	492	673	827	1084	30	24	31	39	48
$T3_2$	0.3	741	830	976	1129	1283	45	43	46	50	54
	0.4	681	811	951	1101	1254	38	38	41	44	49
	0.5	461	806	1003	1157	1312	22	36	41	45	52
	0.6	263	481	672	827	983	14	21	29	36	44
$T3_3$	0.3	763	949	1010	1149	1300	39	41	42	45	49
	0.4	549	839	1020	1121	1265	34	35	42	44	49
	0.5	472	616	920	1168	1265	33	26	36	45	52
	0.6	536	437	599	935	1087	34	24	30	41	48

the increased access to electricity for additional households $T1$ and $T2$ with the new solutions.

It can be seen that one of the optimal strategies for all three households is to rather invest in more solar than suggested in the base case. For $T3_1$ the SOCM suggests to reduce the battery size, however this will result in a lower SLR. In general, one can see that the increase of PV panels not only leads to a significant total cost reduction but also a higher SLR for the $T3$ households, although, the initial upfront cost increases slightly. When comparing the optimal solutions among themselves, specifically ($T3_1$, $T3_2$, $T3_3$), it is observed that with the MOCP, the two households with the lower $DSHR$ ($T3_1$, $T3_3$) arrive at the same optimal solution. Additionally, they achieve very similar cost reductions, despite having different optimal solutions in the base case. The household with the high $DSHR$ ($T3_2$) has a solution with a smaller battery than the other two households, and thus it shows the lowest total cost. But it also shows the highest percentage in cost reduction compared to the other households. Although $T3_2$ and $T3_3$ have both high $PADR$ they end up having very different solutions both before and after including surplus energy, showing that the PADR alone cannot give good estimates on the system design, especially not considering swarm electrification.

Table 12
Results.

	$T3_1$	$T3_2$	$T3_3$
Base case without considering surplus energy			
SHS PV in [W]	400	400	300
SHS Battery [Wh]	1000	500	1000
SLR [%]	94	87	74
SHS upfront cost [USD]	716	611	637
SHS total cost [USD]	825	732	949
Including surplus energy with SOCM	$T3_1$	$T3_2$	$T3_3$
SHS PV in [W]	600	600	600
SHS Battery [Wh]	500	500	1000
SLR [%]	73	94	78
SHS upfront cost [USD]	769	769	874
SHS total cost - SE revenue [USD]	324	263	437
Total cost reduction [%]	60	64	53
Additional energy access $T1$	0	1	0
Additional energy access $T2$	3	2	3
Including surplus energy with MOCP	$T3_1$	$T3_2$	$T3_3$
SHS PV in [W]	600	600	600
SHS Battery [Wh]	1000	500	1000
SLR [%]	98	94	78
SHS upfront cost [USD]	874	769	874
SHS total cost - SE revenue [USD]	492	263	437
Total cost reduction [%]	40	64	53
Additional energy access $T1$	0	1	0
Additional energy access $T2$	2	2	3

Discussion

The results of our study in terms of potential total cost reduction between 40%–64% for the $T3$ households and 50% of up-front cost reduction for the $T1$ and $T2$ are significant and cannot be ignored. In this section, we discuss the parameters and assumptions that have a major influence on the results.

Previous studies of Kirchhoff (2015), Soltowski et al. (2018), Soltowski et al. (2022) and Bhatti and Williams (2021) have demonstrated between $30-70\%$ surplus energy in existing systems at $T1$ and $T2$. Our study gives a deeper insight in how surplus energy in $T3$ systems is influenced by different typical load profiles and the SHS design. It reveals surplus energy levels of $30-45\%$ of the total production, or between $50-85\%$ as a percentage of the total demand for SHS designs reaching an SLR of 99%.

The stochasticity of the input parameter PV generation and demand is discussed in the following. For the PV generation, 10 years of historical data are used. The years are 2006–2015 due to the availability of meteorological data in PVGIS. However, these years do not cover the recently fast-changing climate with increased dry periods in the analyzed regions. Less clouds could mean more direct irradiation and would increase the PV generation during the rainy season and thus even increase the benefit from surplus energy selling. However, less rain and increased dry climate could also reduce the PV yield due to soiling, if panels are not regularly cleaned. The demand, was modeled with a stochastic demand generator. Although, the stochasticity is covered by this, larger seasonal changes in the demand or long-term demand growth were not included. Larger seasonal changes could influence the surplus energy in both directions, while demand growth over time would reduce the available surplus energy.

The applicability of the two methods SOCM and MOCP are discussed next. One of the greatest challenges in the SOCM is to describe the penalty cost for lost load in a realistic way. With the MOCP, one does not need to consider that, since the method calculates the lowest distance to each of the used criteria. Instead, in the MOCP method, the modeler has to choose weightings for each criterion, which could influence the optimal solution significantly. However, the establishment of such weightings, where criteria are weighted against each other, is more practicable than finding an absolute value for penalty costs, as it is needed in SOCM. Thus, MOCP could be the better choice here, although both methods would deliver the same optimal solutions, if penalty costs and weightings are designed accordingly.

Our study looks specifically in three different demand profiles that are described by the metrics $PADR$ and $DSHR$. We can observe that households with the same $PADR$ do give very different results in terms of expected surplus energy, optimal SHS and economic improvement potential with swarm electrification. However, including the $DSHR$ helped to explain these differences. The household with a high $PADR$ and high $DSHR$ shows both the best original results, but also the highest potential of improvement with swarm electrification. When having a low $DSHR$ and still high $PADR$ the household has original the most expensive SHS requiring a large battery. However, this household can offset its original expensive situation and reaches the same cost level as a household with a low $PADR$ and low $DSHR$, when including the surplus energy. Since these high $PADR$ are mainly caused by introducing appliances related to electric cooking, this result shows, that including surplus energy as a value can increase the affordability of electric cooking and thus improve sustainable development.

Another aspect for discussion are the assumptions made for SESell and SEBuy in swarm electrification phase 2. The SEBuy need to purchase a battery, which is still a high upfront cost, although lower than for the alternative buying a full SHS. Additionally, the total costs for these SEBuys are higher when they buy surplus energy and only a battery, compared to the alternative of buying their own full SHS. For very low income households, reducing the upfront cost is more important than the total cost, since the households have access to small amounts of cash flow, but they do not have sufficient savings for the initial purchase. However, the higher total costs come mainly from the price that is set for selling surplus energy. This price is set to the same price as the market price for electricity in Kenya in 2022, which is $0.2\$/kWh$. With this price the benefit for the SESell is very high and for the SEBuy there is no benefit in total cost reduction. However, when reducing the price to $0.1\$/kWh$ the total cost increase for $T1$ and $T2$ becomes approximately zero and the optimal system size for the $T3$ remains the same, although the cost reduction decreases because of a lower revenue from the surplus energy selling. Further work could look into the optimal price tariff for the local energy market. However, as there is no other alternative for the service light than buying candles, kerosine and oil lamps, the market price of $0,2\$/kWh$ is already an improvement to consider for the households $T1$ and $T2$.

In this paper, it is analyzed how the consideration of swarm electrification phase 2 and thus including the surplus as a value could help to make improved investment decisions already in phase 1. However, in the same way, one could argue that already in phase 1 the consideration of phase 3 should be made. In phase 3 it is assumed that a local microgrid is formed, which would make it possible for several participants to share energy in the local market, rather than from individual household to household. In that case, the percentage of surplus energy that can be shared could be much larger, if there is deficit in the local community, or much lower if many households with surplus energy are connected. In their study, Narayan et al. (2019) quantifies some of the advantages of phase 3 of swarm electrification, highlighting that greater diversity in load profiles serves as one of the key driving factors for enhanced benefits from energy sharing. Consequently, various system sizes may prove to be optimal under different conditions, thus demanding further research.

Conclusions

In this paper, a multi-model-based techno-economic analysis of off-grid solar home systems that supply typical $T3$ households by swarm electrification in rural areas in Kenya was presented. Three different demand profile types were studied, where one was a rather flat demand profile related to owning a fridge, and two were profiles with typical peaks for electric cooking at two different times of the day. In the simulation, surplus energy was generated, and an assessment was conducted to estimate the potential for sharing this energy with additional households or neighbors within the community. This evaluation specifically focused on the implementation of a bottom-up grid, particularly exploring the possibilities offered by phase 2 of swarm electrification. Then, an investment decision process including the expected revenue from selling that surplus energy was performed with two different methods. Based on the surplus energy analysis, the conclusions are as follows:

- Solar homes systems with low installed photovoltaic capacity and large installed battery capacity with a served load ratio (SLR) of up to 88% do not have surplus energy
- Increasing installed photovoltaic capacity to achieve higher SLRs increases surplus energy faster than the SLR
- Beyond a certain point where the SLRs surpasses 90%, augmenting the installed battery capacity does not lead to a substantial decrease in surplus energy.
- Peak-to-average demand ratio ($PADR$) alone cannot give indications on surplus energy volume
- A low demand during sun hours ratio ($DSHR$) leads to higher surplus energy volumes for systems with a $SLR < 90\%$

Surplus energy from different typical demand profiles of $T3$s was shown to support $T1$ and $T2$ households, resulting in SLR levels surpassing 85%. Swarm electrification can increase the affordability of electric cooking both during day and evening time as demonstrated by the households $T3_2$ and $T3_3$. Based on the economic study that incorporates the value of surplus energy into the sizing and investment decision process, the following conclusions can be drawn:

- Total cost reduction by including surplus energy as a value reaches 40%–64% for the optimal systems for the $T3$ households
- New optimal solutions have increased PV capacity, while battery capacity stays the same
- New optimal systems lead to increased SLR for the $T3$ households by 4%–7%
- Households with high $PADR$ due to appliances for electric cooking can offset their initial disadvantage due to high costs by including surplus energy as a value
- Up-front cost reductions of 50% for connected $T1$ and $T2$ households

The findings of this paper provide valuable insights for improving the efficiency of energy sharing and optimizing the initial sizing of stand-alone solar home systems (SHS) in phase one of swarm electrification. The analysis and methods developed in this paper clearly indicate that it will be possible to enhance the capability for optimal surplus energy sharing among nanogrids in the second phase of swarm electrification.

Future works will concentrate on the interconnection of various existing solar home systems into a nano- or even microgrid (phase three of swarm electrification). More diversified consumption profiles could be studied, and productive uses or different rural services could be included. Demand control and flexibility could be considered. Practical aspects from a power electronics and control viewpoint need to be regarded. Diverse local market regulations can be employed to govern the decentralized sharing of electricity among multiple agents. Finally, swarm electrification can be integrated in large scale rural electrification planning methods.

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.

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

During the preparation of this work the author(s) used ChatGPT in order to improve language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Acknowledgments

This work was supported by the Department of Electric Energy, Norwegian University of Science and Technology (NTNU). The authors would like to thank Eco Moyo Education Centre in Kenya for their collaboration.

References

Balderrama, Sergio, Lombardi, Francesco, Riva, Fabio, Canedo, Walter, Colombo, Emanuela, & Quoilin, Sylvain (2019). A two-stage linear programming optimization framework for isolated hybrid microgrids in a rural context: The case study of the "El Espino" community. *Energy*, [ISSN: 0360-5442] *188*, http://dx.doi.org/10.1016/J.ENERGY.2019.116073.

Barrie, Jack, & Cruickshank, Heather J. (2017). Shedding light on the last mile: A study on the diffusion of Pay As You Go solar home systems in central East Africa. *Energy Policy*, [ISSN: 0301-4215] *107*, http://dx.doi.org/10.1016/J.ENPOL.2017.05.016.

Bazilian, Morgan, Blimpo, Moussa, Bank, World, Culver, Lauren, Kincer, Jacob, Mahadavan, Meera, et al. (2021). The modern energy minimum: The case for a new global electricity consumption threshold. URL https://www.rockefellerfoundation.org/wp-content/uploads/2020/12/Modern-Energy-Minimum-Sept30.pdf.

Bhatia, Mikul, & Angelou, Nicolina (2014). Capturing the multi-dimensionality of energy access. *Livewire Knowledge Note Series*, URL http://documents.worldbank.org/curated/en/937711468320944879/pdf/88699-REVISED-LW16-Fin-Logo-OKR.pdf.

Bhatti, Satyam, & Williams, Arthur (2021). Estimation of surplus energy in off-grid solar home systems. *Renewable Energy and Environmental Sustainability*, *6*, http://dx.doi.org/10.1051/rees/2021024.

Bjarghov, Sigurd, Loschenbrand, Markus, Ibn Saif, A. U. N., Pedrero, Raquel Alonso, Pfeiffer, Christian, Khadem, Shafiuzzaman K., et al. (2021). Developments and challenges in local electricity markets: A comprehensive review. *IEEE Access*, [ISSN: 21693536] *9*, http://dx.doi.org/10.1109/access.2021.3071830.

Dumitrescu, Raluca, Groh, Sebastian, Philipp, Daniel, & von Hirschhausen, Christian (2020). Swarm electrification: From solar home systems to the national grid and back again? In *Green Energy and Technology*. ISBN: 9783030419523, http://dx.doi.org/10.1007/978-3-030-41952-3{_}4.

Fernandez-Fuentes, Miguel H., Eras Almeida, Andrea A., & Egido Aguilera, Miguel A. Characterization of technological innovations in photovoltaic rural electrification, based on the experiences of Bolivia, Peru, and Argentina: Third generation solar home systems. *Sustainability (Switzerland)*, [ISSN: 20711050] *13*, http://dx.doi.org/10.3390/su13063032.

Ferrer-Martí, Laia, Ferrer, Ivet, Sánchez, Elena, & Garfí, Marianna (2018). A multi-criteria decision support tool for the assessment of household biogas digester programmes in rural areas. A case study in Peru. *Renewable and Sustainable Energy Reviews*, [ISSN: 18790690] *95*, http://dx.doi.org/10.1016/j.rser.2018.06.064.

Fioriti, Davide, Poli, Davide, Duenas-Martinez, Pablo, & Micangeli, Andrea (2022). Multiple design options for sizing off-grid microgrids: A novel single-objective approach to support multi-criteria decision making. *Sustainable Energy, Grids and Networks*, [ISSN: 23524677] *30*, Article 100644. http://dx.doi.org/10.1016/j.segan.2022.100644.

Fuchs, Ida, Balderrama, Sergio, Del Granado, Pedro Crespo, Quoilin, Sylvain, & Rajasekharan, Jayaprakash (2023). Surplus energy in solar home systems as driver for bottom-up grids: When grids emerge from the edge. In *2023 IEEE PES grid edge technologies conference & exposition*. ISBN: 978-1-6654-6012-5, http://dx.doi.org/10.1109/GridEdge54130.2023.10102747.

Fuchs, Ida, Myhre Waitz, Anja, Lervik, Kari Thorset, Völler, Steve, Midtgård, Ole-Morten, & Rajasekharan, Jayaprakash (2022). Optimal design and installation of solar home systems for bottom-up grids: Comparative case studies from Kenya and Norway. In *8th world conference on photovoltaic energy conversion*. ISBN: 3-936338-86-8, http://dx.doi.org/10.4229/WCPEC-82022-4CV.1.3.

Groh, Sebastian, Philipp, Daniel, Lasch, Brian Edlefsen, & Kirchhoff, Hannes (2014). Swarm electrification-suggesting a paradigm change through building microgrids bottom-up. In *Proceedings of 2014 3rd international conference on the developments in renewable energy technology* (pp. 1–2). United International University (UIU), ISBN: 9789843378675, http://dx.doi.org/10.1109/icdret.2014.6861710.

Holmgren, William F., W. Hansen, Clifford, & A. Mikofski, Mark (2018). Pvlib Python: a Python package for modeling solar energy systems. *Journal of Open Source Software*, [ISSN: 2475-9066] *3*, http://dx.doi.org/10.21105/joss.00884.

Huld, Thomas, Müller, Richard, & Gambardella, Attilio (2012). A new solar radiation database for estimating PV performance in Europe and Africa. *Solar Energy*, [ISSN: 0038092X] *86*, http://dx.doi.org/10.1016/j.solener.2012.03.006.

IEA, IRENA, UNSD, World Bank, & WHO (2022). *Tracking SDG 7: The energy progress report*. Washington DC: World Bank, URL https://trackingsdg7.esmap.org/.

Khezri, Rahmat, & Mahmoudi, Amin (2020). Review on the state-of-the-art multi-objective optimisation of hybrid standalone/gridconnected energy systems. *IET Generation, Transmission and Distribution*, [ISSN: 17518687] *14*, http://dx.doi.org/10.1049/iet-gtd.2020.0453.

Kirchhoff, Hannes (2015). Identifying hidden resources in solar home systems as the basis for bottom-up grids. *Springer Proceedings in Energy*, http://dx.doi.org/10.1007/978-3-319-15964-5,

Kirchhoff, Hannes, Kebir, Noara, Neumann, Kirsten, Heller, Peter W., & Strunz, Kai (2016). Developing mutual success factors and their application to swarm electrification: microgrids with 100 % renewable energies in the Global South and Germany. *Journal of Cleaner Production*, [ISSN: 09596526] *128*, http://dx.doi.org/10.1016/j.jclepro.2016.03.080.

Kirchhoff, Hannes, & Strunz, Kai (2022). Control and stability of modular DC swarm microgrids. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, [ISSN: 2168-6777] http://dx.doi.org/10.1109/jestpe.2022.3168545.

Lombardi, Francesco, Balderrama, Sergio, Quoilin, Sylvain, & Colombo, Emanuela (2019). Generating high-resolution multi-energy load profiles for remote areas with an open-source stochastic model. *Energy*, [ISSN: 03605442] *177*, http://dx.doi.org/10.1016/j.energy.2019.04.097.

Narayan, Nishant, Chamseddine, Ali, Vega-garita, Victor, Qin, Zian, & Popovic-gerber, Jelena (2019). Exploring the boundaries of solar home systems for off-grid electrification: Optimal SHS sizing for the multi-tier framework for household electricity access. *Applied Energy*, [ISSN: 0306-2619] *240*, http://dx.doi.org/10.1016/j.apenergy.2019.02.053.

Narayan, Nishant, Chamseddine, Ali, Vega-garita, Victor, Qin, Zian, Popovic-gerber, Jelena, Bauer, Pavol, et al. (2019). Quantifying the benefits of a solar home system-based DC microgrid for rural electrification. *Energies*, *12*, http://dx.doi.org/10.3390/en12050938.

Narayan, Nishant, Qin, Zian, Popovic-Gerber, Jelena, Diehl, Jan Carel, Bauer, Pavol, & Zeman, Miroslav (2020). Stochastic load profile construction for the multi-tier framework for household electricity access using off-grid DC appliances. *Energy Efficiency*, [ISSN: 15706478] *13*, http://dx.doi.org/10.1007/s12053-018-9725-6.

Quoilin, Sylvain, Kavvadias, Konstantinos, Mercier, Arnaud, Pappone, Irene, & Zucker, Andreas (2016). Quantifying self-consumption linked to solar home battery systems: Statistical analysis and economic assessment. *Applied Energy*, [ISSN: 03062619] *182*, http://dx.doi.org/10.1016/j.apenergy.2016.08.077.

Richard, Lucas, Boudinet, Cédric, Ranaivoson, Sanda A., Rabarivao, Jean Origio, Befeno, Archille Elia, Frey, David, et al. (2022). Development of a DC microgrid with decentralized production and storage: From the lab to field deployment in rural Africa. *Energies*, [ISSN: 19961073] *15*, http://dx.doi.org/10.3390/en15186727.

Sheridan, Steve, Sunderland, Keith, & Courtney, Jane (2023). Swarm electrification: A comprehensive literature review. In *Renewable and sustainable energy reviews*. [ISSN: 18790690] http://dx.doi.org/10.1016/j.rser.2023.113157.

Siemens (2023). Empowering people network - technologies for basic needs. URL https://empowering-people-network.siemens-stiftung.org/solutions/solbox/. (Accessed 21 June 2023).

SOLshare (2023). Solshare. URL https://solshare.com/. (Accessed 21 June 2023).

Soltowski, Bartosz, Bowes, Jonathan, Strachan, Scott, & Anaya-Lara, O. Limpo (2018). A simulation-based evaluation of the benefits and barriers to interconnected solar home systems in East Africa. *2*, In *2018 IEEE PES/IAS PowerAfrica, vol. 2*. ISBN: 9781538641637, http://dx.doi.org/10.1109/PowerAfrica.2018.8521058.

Soltowski, Bartosz, Stewart, Fraser, Strachan, Scott, Campos-Gaona, David, Anaya-Lara, Olimpo, & Galloway, Stuart (2022). A field trial of off-grid SHS interconnection in Rwanda's northern province. *Energy for Sustainable Development*, [ISSN: 23524669] *66*, http://dx.doi.org/10.1016/j.esd.2021.11.004.

Weniger, Johannes, Tjaden, Tjarko, & Quaschning, Volker (2014). Sizing of residential PV battery systems. *Energy Procedia*, [ISSN: 1876-6102] *46*, http://dx.doi.org/10.1016/J.EGYPRO.2014.01.160.

World Bank (2022). Off-grid solar market trends report 2022: Outlook. Washington, D.C.: World Bank Group, URL http://documents.worldbank.org.

Yaldız, Abdurahman, Gökçek, Tayfur, Şengör, İbrahim, & Erdinç, Ozan (2021). Optimal sizing and economic analysis of photovoltaic distributed generation with battery energy storage system considering peer-to-peer energy trading. *Sustainable Energy, Grids and Networks*, [ISSN: 23524677] *28*, http://dx.doi.org/10.1016/j.segan.2021.100540.