Extend: A Framework for Increasing Energy Access by Interconnecting Solar Home Systems

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ABSTRACT

The means of electrifying households and the resulting electricity networks are rapidly evolving. Traditionally, an extension of existing centralized grids was the only prominent technique, but now electrification is seeing massive expansion via decentralized solar home systems (SHSs). These systems consist of a low-wattage photovoltaic (PV) panel (typically 5-100W), a battery, a collection of energy-efficient DC appliances, and a charge controller. Spurred by significant advances and reduced costs in solar, batteries, energy-efficient appliances, and mobile money-driven business models, SHSs have proliferated rapidly, with tens of millions of systems now deployed, primarily in regions with otherwise low rates of electricity access.

In this work, we profile a large deployment of solar home systems in Western Kenya to ascertain the dominant generation and consumption patterns. We note that there are often substantial mismatches between generation and consumption, and that PV overgeneration presents an opportunity via networking of households. We consider the opportunity to leverage system interconnection to enable increased connectivity among households, challenging typical electricity system architecture by effectively creating ad hoc electricity grids at the edges of the overall electricity network. Further, we consider the potential to integrate households without SHSs ("passive nodes") into these electricity networks, as a low-cost opportunity to increase electrification rates. Considering energy curtailment, the spatial distribution of households, and infrastructure costs, we build a decision problem for interconnecting existing SHSs with passive nodes. Our analysis shows that compared to the all-SHS solutions that are presently achieving widespread deployment, we show that interconnecting existing SHSs can increase electrification rates by more than 25% and reduce average costs by up to 30% per household.

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CCS CONCEPTS

• **Computing methodologies** → *Discrete-event simulation*; • **Applied computing** → *Decision analysis*; • **Hardware** → **Power networks**.

KEYWORDS

Renewable energy, simulation, energy access, power networks

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1 INTRODUCTION

Globally 840 million people still have no access to electricity and 87% of them live in rural areas despite the recent improvements in sustainable energy technologies that have accelerated energy access in countries with unreliable or poor electrification rates [4]. Communities in remote locations face serious challenges to reach universal access since grid extensions have high economic costs, time constraints, and terrain difficulties. As a result, only 30% of rural areas are expected to be electrified from the central grid [2, 26].

However, household electrification is no longer limited to extension of centralized grids. In the most recent decade, due to technology advances and cost reductions in solar photovoltaics (PV), batteries, electronics for charge control, and energy-efficient appliances, new classes of decentralized systems for electricity access have emerged. These include microgrids, which are microcosms of centralized grids that have received significant attention, as well as solar home systems (SHSs), which are comprised of a PV panel, battery, charge controller, and a few appliances. The proliferation of these systems is crucial to meeting the UN Sustainable Development Goal 7, whose aim is to "ensure access to affordable, reliable, sustainable and modern energy for all" by 2030. To meet this universal electrification goal by 2030, it is estimated that decentralized systems will be needed to provide access to 60% of households in rural regions by 2030[4].

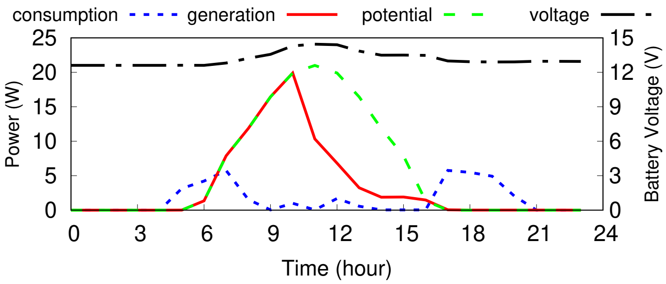

Figure 1: The solar energy generation (red), energy consumption (blue), the maximum generation potential (green), and the battery voltage (black) on a typical day for an example solar home system.

In this work, we focus on a new opportunity that has emerged from the widespread deployment of solar home systems in certain communities, typically with low electrification rates otherwise. In particular, the low costs of PV panels and the mismatch of electricity generation and consumption patterns result in curtailment of this renewable generation due to insufficient consumption. Figure 1 shows the interplay between generation, consumption, and storage on a typical day for an SHS. We explore the potential to interconnect SHSs and non-electrified households as a low-cost means to increase household electrification. We build our analysis upon an empirical dataset of solar generation and electricity consumption among 14.5k SHS customers in Western Kenya, a dataset of locations of all of the structures in the same region, and models of the solar generation for the region. Considering energy curtailment, spatial distribution of households, and infrastructure costs, we build a decision problem for interconnecting SHSs with "passive nodes" (non-electrified households). To understand the sensitivity of this interconnection problem, we consider the effects of topology, increased consumption, and initial SHS penetration. Our results hint at the potential benefits of alternative architectures to electricity networks, exploring the space between traditional centralized electricity grids and fully decentralized solar home systems.

2 BACKGROUND AND RELATED WORK

As grid extensions become infeasible in rural areas due to difficult access and high connection costs, Off-Grid Solar technologies (OGS) have facilitated electrification at different tier levels [12]. There are two main approaches used by OGS technologies: microgrids and solar home systems. Existing literature on the context of shorter distribution distances has typically proposed architectures to reach rural electrification using solar PV-based DC microgrids. They offer approximately 20% more efficiency than AC microgrids and reduced AC/DC conversion and distribution costs [21, 29]. These Low Voltage Direct Current (LVDC) distribution networks usually use one of the following architectures [25]:

i) *centralized generation and storage.* In [20], the authors propose a 250W solar PV-based microgrid that can supply households in the vicinity of 100 to 150 meters with 136Wh of load per day per household. A centralized monitoring system represents one of the main advantages of this architecture given its simplicity and low cost. However, this type of architecture is prone to higher distribution losses and a lack of flexibility for future expansions since the sizing and load analysis of the microgrid is required beforehand.

ii) *centralized generation and distributed storage:* Madduri et. al. [21] designed a microgrid that can meet the electricity needs of households within a 1 km radius. The system provides a Power Management Unit (PMU) per household that can digitally communicate information such as electricity price, state of charge of batteries, credits, and energy usage. Additionally, the microgrid has a distributed control scheme to mitigate variability in grid power. Distributed storage reduces losses and decouples individual household loads from communal energy use at night-time. However, large centralized generation and robust power electronic devices are required to implement the power-sharing schemes, increasing the complexity and costs of this solution.

iii) *distributed generation and distributed storage:*. In [25], the authors propose a distributed generation and distributed storage architecture that consists of several solar PV-based nanogrids. Their implementation offers bidirectional power flow and distributed voltage droop control which are implemented through the duty cycle control of a modified flyback converter. Another ad-hoc DC microgrid is presented in [15] which presents a peer-to-peer electricity network enabled by PMUs. However, these implementations require several subscribing households to make financial sense. Microgrid developers perform a substantial assessment of the candidate communities before planning a deployment due to the high risks in the investment arising from uncertain energy demand in the target community [30]. Also, the sophisticated power control components represent a higher capital cost which further constrains the opportunity to provide tier 1 and 2 energy access.

Solar home systems have played a key role to fill the energy access gap among lower energy consumers. Figure 2 illustrates the layout of a typical SHS. For example, in Kenya, which leads the African continent in SHS deployments, there were more than 400k SHS deployed as of 2016 [11]. The majority of these products are pico solar (<11Wp) used for tier 1 electrification and plug and play SHS of less than 1kW. Even though these devices are reducing the energy poverty gap, there are still many people that cannot afford such devices. Approximately 10% of the world's population lives on less than $1.90 a day which makes it difficult to afford down payments of tier 1 products that have total installed costs between 4.3 to 14.2 $/Watt [14]. There are several mechanisms that have intended to reduce the affordability gap such as Pay as you Go (PaYGo), supply-side incentives to develop new markets and serve more users, and demand-side subsidies. However, there are still 240 million people that belong to this gap which requires $ 6.1 to 7.7 billion in external investment for OGS companies and up to $3.4 billion of public funding to bridge the affordability gap [8]. Although financial access constitutes the main constraint, SHSs are heavily subutilized [9] which creates opportunities to optimize the use of these devices.

None of the aforementioned microgrid implementations address the interconnection of existing SHS infrastructure with the neighboring households with and without any storage device. In our previous work on sharing SHS infrastructure [9], considerations about time of use and increased consumption patterns were not taken into account. In this work, we analyze these gaps and show

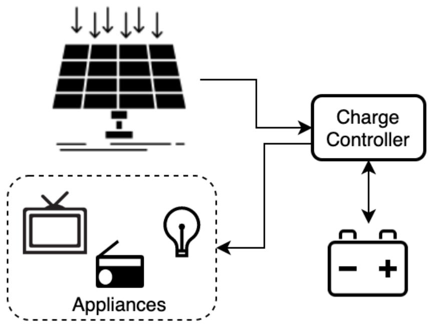

Figure 2: Layout of a typical solar home system consisting of a solar panel, charge controller, battery, and appliances connected through a ready-board.

the opportunities to electrify neighboring households from existing SHSs in a more realistic setting.

3 EXTEND: OVERVIEW

Extend explores the opportunities to increase tier 1 and 2 electrification using existing SHS infrastructure. The idea is to share the untapped energy generation potential of existing SHSs by connecting them to non-SHS nodes. The energy transaction is unidirectional and our simulation approach considers different topologies, the cost of making a connection, the energy sharing potential of the parent SHS, and the energy demand pattern of the child home when deciding on a connection. We leverage the energy consumption and solar generation profiles of real solar home systems deployed in Kenya and Geographic Information System (GIS) data of building structures in the same region for our simulation.

In this section, we outline (1) the details of the SHS and spatial distribution datasets, (2) how we use the dataset to build solar energy generation, energy consumption, and solar generation potential models, (3) the details of additional models such as battery, connection cost, and losses, and (4) the *Extend* simulation logic.

3.1 Datasets

To evaluate the potential increase in electrification by connecting SHSs to passive nodes, we must accurately depict the solar energy generation and energy consumption patterns of the SHSs. This requires that we have the ground truth data of solar energy generation and consumption from actual SHSs. For this work, we use a dataset collected over 23 months of more than 14.5K 50W SHSs deployed in Western Kenya.

This dataset provides measurements of voltage, the current coming in from the solar panel (generation), and current coming out from the charge controller (consumption) at 15-minute granularity. We transform these data to obtain hourly energy measurements in watt-hour units and aggregate daily measurements for each SHS to understand time of use patterns. Figure 5 illustrates clusters of consumption and generation patterns from this dataset. Using agglomerative hierarchical clustering techniques [17], we identify 5 clusters that describe the consumption and generation profiles. In terms of consumption, all the clusters show an evening peak between 6 and 10 pm and a slight increment of consumption in the morning that match the use of lighting loads. Besides, almost 50% of the SHSs consume less than 20kWh a year, which is only 23% of the expected capacity of these systems; further, only 2.7% of SHS owners in this dataset have a high utilization consuming ~76 kWh a year (90% of the expected capacity).

An important aspect of the planning of power infrastructure deployment is the analysis of the variation of consumption of prospect customers over time. Figure 4(a) shows the percentage change in average monthly consumption and generation between 2017 and 2018. More than 80% of the SHSs had only ±6% change in generation and ±10% in consumption during that time frame. Also, figure 4(b) illustrates the correlation between average consumption during weekdays and weekends for each SHS. The red dotted line shows the result of linear regression with an R-squared of 0.995 for the equation $weekday = weekend$. This information suggests that in the short term and at different time frames, the low consumption and generation changes would allow an eventual networking strategy to endure without the need to upgrade the infrastructure required to meet future loads.

Besides SHS data, we use the spatial distribution of structures in our analysis. This dataset was collected from satellite imagery and consists of more than 360K geographic location of structures in Homa Bay County, Kenya. It allows us to evaluate the impact of the spatial distribution of households and the opportunities of networking based on real layouts. While not all structures represent households in practice, we make that assumption here, as it would be difficult to classify each structure properly from satellite imagery.

In our simulation setup, we use SHS consumption and generation profiles from this dataset and the spatial distribution of households. However, there is significant prior work on developing model-based and data-driven approaches to modeling the energy demand of consumers. Similarly, there has been work on the modeling of the power output of solar sites. While we do not use those approaches, we outline relevant work along with the models we used for the scenarios when large-scale ground truth data are not available.

3.2 Models

In this section, we describe various models that we use in our simulation to account for estimating SHS generation potential, battery charge/discharge characteristics, consumption patterns, and energy distribution costs.

3.2.1 Energy Consumption. Our approach requires an energy consumption model to estimate the energy demand of a solar home system (SHS) or a non-SHS system that is to be electrified. The modeling can be done using either a model-driven or a data-driven approach. In a model-driven approach, the energy consumption pattern for a site is generated by using energy demand signatures of different appliances. The signatures are multiplexed over time to match the expected aggregate demand curve for a home. Model-driven approaches are useful for scenarios where no prior data are available. In a data-driven approach, historical data from actual SHSs are used to generate a distribution of energy demand patterns and simulation logic assigns energy consumption to homes from this distribution. This approach better reflects the ground-truth energy demands of homes.

Figure 3: Layout of a scenario for energy sharing using star topology in one of the regions of Homa Bay County, Kenya. Each blue box shows the connections accomplished for each SHS in the area and its respective average daily energy generation potential and consumption. Squares illustrate SHSs and circles passive nodes. The yellow box shows an example household candidate that is not networked given the conditions of losses or load.

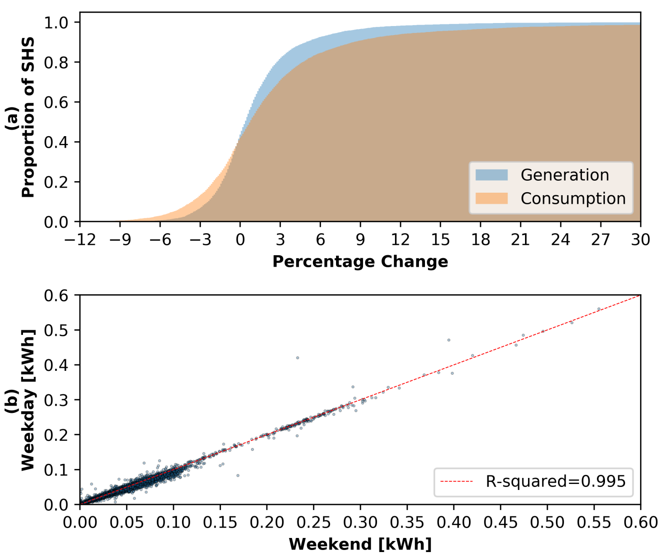

Figure 4: (a) CDF of the average monthly percentage change in generation and consumption between 2017 and 2018. (b) Comparison of average consumption during weekdays and weekends for each SHS. The best fit (y=x) is shown in red.

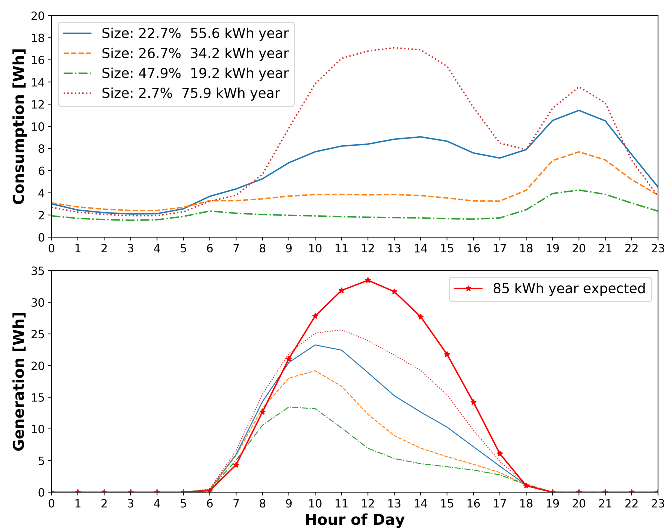

Figure 5: Clusters of the 90th percentile of daily energy consumption and generation. The legend provides cluster size (in %) and average yearly consumption. The red line illustrates the potential solar generation in the region.

The most accurate approach is to use the raw data from actual SHS deployments, an approach that we adopt in developing our energy consumption model. To illustrate the typical energy consumption behaviors of consumers in this dataset, we clustered the energy consumption profiles of SHSs. Figure 5 (top) depicts the four major energy demand patterns in the historical data. This demand pattern is not well-suited for high solar energy utilization if the battery is not sized properly. As a result, most of the homes do not realize their energy generation potential. It should be noted that these clusters are generated only for illustration purposes. We assign the actual energy demand patterns from our SHS dataset to the homes with or without SHSs. These energy consumption data are available at 15-minute granularity and we downsample the data to generate hourly consumption profiles.

3.2.2 Solar Energy Generation. Modeling power output for a solar PV site can be done using physical modeling approaches or machine learning techniques. However, both approaches implicitly assume sufficiently large load or a battery that does not restrict solar power generation. Therefore, an estimation of solar energy generation patterns for SHS systems with curtailed generation using the modeling approaches would require simulation of a solar system with a limited battery backup, a setup that would provide a restricted power generation curve. Simulation setup with a physical modeling approach can be used for scenarios when historical generation data from the actual SHS are not available, but the physical parameters for the site including location, capacity, tilt, and orientation are known.

The SHS dataset provides the ground truth solar generation data for each of the solar home systems. Figure 5 (bottom) depicts the four major energy generation patterns in the historical data. We can also observe a common generation curtailment between 9 and 11 a.m. where solar panels are producing only the amount of energy to fully recharge the batteries after evening use and satisfy the small energy demand. In our simulation setup we only consider the solar generation potential since we expect to avoid the curtailment as nodes are networked to existing SHS infrastructure.

3.2.3 Solar Generation Potential. Our approach uses a solar generation potential model to estimate how much energy an SHS would have produced if it were not restricted by the fully charged battery and the low energy consumption of an isolated solar home system, as depicted in Figure 1. The generation potential model should take into account the effect of system capacity, installation parameters such as tilt and orientation, and most importantly weather, i.e., cloud cover. This model would provide the expected weather-adjusted generation for a solar home system over the simulation horizon at the desired time resolution, i.e., minutes, hours, or days.

Solar generation potential can be modeled using a variety of different approaches. Prior work [9] has used PVWatts to estimate a site's annual energy generation potential [10]. While PVWatts is good for estimating a site's annual energy potential, its hourly level estimates can be highly inaccurate [5]. Another approach is to use machine learning techniques to model a site's generation potential using the data from existing solar home systems. However, this problem is different from typical ML-based modeling approaches [28] because the historical solar generation does not convey information about generation potential throughout the day. An accurate approach would use the time periods when solar home systems produce unrestricted generation, i.e. the first half of the day. We leave the design and accuracy analysis of this approach for future work.

Our implementation leverages Solar-TK [5], an open-source solar performance model, to estimate a site's generation potential based on its location, time, physical characteristics, cloud cover, and temperature. Solar-TK first generates a clear-sky maximum generation model by inferring the physical parameters of a site, such as capacity, tilt, orientation, and temperature coefficient, from historical data. It next incorporates the effect of weather, i.e., cloud cover, on the clear-sky generation to determine the expected weather-adjusted output. Solar-TK fetches the temperature and cloud cover data from Weather Underground and Darksky; both sources provide hourly historical weather data for Homa Bay County, Kenya.

3.2.4 Battery Model. The size of a battery and the energy stored in it determine the amount of additional solar energy that can be stored and how much energy consumers can withdraw from the battery. Our simulation logic uses a battery model to imitate the behavior of the sealed lead-acid batteries used in a typical SHS setup. A battery model should accurately depict how the state of charge (*SoC*) changes as it is charged or discharged and how its life degrades over time. There is a lot of work on increasing the life of lead-acid batteries by only controlling the externally controllable factors such as charging/discharging rates and the allowed depth of discharge (*DoD*). Prior work reports that the life of lead-acid batteries depends upon the number of bad recharges, time since last full recharge, and the lowest state of charge since last full recharge [6]. While enhancing the lifetime of battery backups is an important problem, the existing charge controllers in SHSs do not employ explicit control mechanisms for life enhancement. Their passive approach to battery lifetime enhancement only constrains the charging/discharging rates and the minimum state of charge allowed.

We use a battery model that is extensively utilized in prior work on peak-reduction in industrialized countries, demand response, and analyzing the impact of battery backups on stressed grids of developing countries [6, 22–24]. This model requires setting the battery capacity, maximum charge rate, maximum discharge rate, and the maximum depth of discharge. The battery used by SHSs in our dataset is a 17Ah, 12V battery, with a total storage capacity of 204Wh. We set the maximum depth of discharge to 45% as it minimizes the battery cost by balancing the usable storage capacity with the lifetime for a typical battery designed for home photovoltaic (PV) installations [22]. For the charge rate, sealed lead-acid batteries are capable of fast charging up to a $C/3$ rate, i.e., charging to full capacity in three hours [19]. We set the charge rate limit to $C/4$. Finally, the discharge rate has a huge impact on the usable capacity according to Peukert's law, However, the consumption profiles in our dataset suggest that the maximum discharge rate is ≈25W. This discharge rate is less than 15% of usable capacity and we can expect to extract all of the usable capacity at such low rates. For modeling purposes and to allow the connection of new nodes to the same battery, we set the discharge rate limit to C.

3.2.5 Connection Cost. To evaluate the benefits of connecting a non-served home (passive node) to an existing SHS, we need to compare the cost of the connection to the potential revenue from the excess energy. A connection between a passive node and an existing SHS requires four components: a cable, a ready board where users plug their appliances, a charge controller, and a battery. While the cable and ready board costs apply to every connection, battery and charge controller costs occur only when we assume that the connecting passive node is deploying its own battery. In such cases, we assume that the home is deploying a similar battery, 12V 17Ah, to the existing SHS.

According to the most recent cost and market report for Africa from the International Renewable Energy Agency (IRENA) [16], for a typical sub-1kW SHS, which is between 4.3 and 14.2 USD/Watt, the installation cost is approximately 2 USD/Watt including the ready board. The charge controller costs approximately 0.7 USD/Watt and the storage component accounts for the largest share of the entire infrastructure at \$140. The cost split between battery, installation+ready board, and the charge controller is 29%, 7%, and 20%, respectively. For the cable's cost, a 50 Watt SHS requires 14 AWG (1.5 mm diameter approximately) cable that costs around 0.58 USD/meter in Kenya [18].

3.2.6 Losses Model. To accurately model the available energy in the system, we need to model the losses incurred when energy is transferred from the SHS to a passive node with or without the battery. We assume that this connection is made at the voltage generated by the solar panel or the battery, both of which are around 12V. This low voltage connection incurs significant losses but avoids the cost and complexity of stepping up and down the voltage level of connection. For our setup, we only consider the I^2R losses, where I is the current and R is the resistance of the cable. The cable resistance depends upon its material, the temperature, the length, and the gauge. We use a per meter resistance value of 0.0082 Ohms/meter for a 14 AWG wire made of copper and assume a constant temperature.

Algorithm 1: Simulation Algorithm

```
Data: Iterations, nodes, patches, cons, gen, topology
Result: Electrification, connection costs per household.
initialization;
while it < iterations do
    Randomly select a patch;
    Randomly assign roles and consumption profile to
      nodes;
    for each SHS node do
        Select all the nodes within 40m;
        Build the adjacency matrix with selected nodes;
        Get networked nodes using A_topology(dist_matrix)
    end
    Calculate number of connections and costs;
end
```

3.3 Simulation logic

There are four main components of our simulation: the patch, SHS node, passive node, and conformed graph. We split Homa Bay County into independent patches of 1 km^2 and select the set of spatial structures belonging to the given patch. The simulation logic is initialized with this set of structures that belong to a randomly selected patch of the region, the proportion and PV size of SHS nodes, battery capacities, a proportion of passive nodes that are battery-less, and a networking algorithm that generates either a star or Minimum Spanning Tree (MST) topology. Each structure in the patch has a role: SHS, passive node with storage, or passive node without storage. These roles are randomly assigned using the proportions of SHS and battery nodes specified in the initialization. We use a default proportion of SHS of 30%, which is the proportion of off-grid households in Kenya that have a solar product. [3] Nodes with storage are assigned lead-acid batteries of 17Ah which is the capacity of the SHS batteries in our dataset. For the simulation logic,

Algorithm 2: $A_{topology}$: Star

```
Data: Adjacency matrix, SHS node
Result: Graph of connected nodes
Initialize list of nodes connected so far;
while Neighboring nodes available do
    Connect nearest node;
    Calculate cable losses;
    Run battery models with consumption and generation
      profiles, and losses;
    if SoC > 1 − DoD for entire time frame then
        Add node to list and update resulting graph;
    end
end
```

our battery model initializes the SoC of these batteries at 70%, a middle point between full charge and the recommended Depth of Discharge (DoD) for lead-acid batteries (40% SoC).

After initialization, our simulation constructs graphs in the selected patch based on a star or MST topology with root in the SHS node. Each graph is built with the nodes that are located in a vicinity of 40 meters based on a given networking algorithm for the topology. We choose this conservative distance due to the impact of losses in DC networks at 12V. Algorithm 1 shows the generic procedure where *cons* and *gen* represent daily consumption and generation profiles. Algorithms 2 and 3 illustrate the operation of star and MST algorithm respectively. Algorithm 2 simply evaluates the opportunity to connect each neighboring node from closest to furthest iteratively. In contrast, algorithm 3 first calculates the MST using Prim's algorithm (lines 1-11)[7] and then evaluates the conditions to connect neighbors. In both cases, we use a strict policy which requires that the SoC of the batteries cannot be lower than the DoD at any given time.

Finally, we build a Monte Carlo simulation that uses the randomly sampled graphs and calculates electrification cost and rates given the output of the battery model. If the state of charge of the SHS is not completely depleted after a current state topology and for all the hours of day, our algorithm keeps discovering the next node in the topology and evaluates the opportunity to connect. This randomized approach allows us to reduce the bias to a specific scenario and measure electrification increase in the long run.

Our Monte Carlo approach numerically is used to evaluate expectations of random variables [27]. In our case, the goal is to understand opportunities to augment electrification rates given a randomized sample of conditions. In order to reach convergence in our setting, we evaluate the number of iterations that reduce the variation of our results. Figure 6 shows the variance of an experiment as the number of iterations increases. For our experiments, we used ten thousand iterations since it presents low variability at a tractable running time of around 3 hours.

4 EVALUATION

In this section, we vary simulation parameters such as topologies to interconnect underserved neighbors, the proportion of SHS nodes, the scale of consumption patterns, and the proportion of passive nodes with storage. We analyze the opportunities for networking

Algorithm 3: $A_{topology}$: Minimum Spanning Tree (MST)

Data: Adjacency matrix, SHS node
Result: MST graph of connected nodes
Initialize list of nodes connected so far;
Initialize all nodes;
for *each node in adjacency matrix* **do**
  Set min(distance(node,connecting nodes)) to ∞;
  Set parents of node to NIL ;
end
Set min(distance(SHS,connecting nodes)) to zero;
Build a min-priority queue Q of the graph based on the minimum distance of connecting nodes;
while *Q is not empty* **do**
  Extract node v with min (Q);
  for *each node in adjacency matrix(v)* **do**
    if *node in Q and distance(v, node) < min(distance(v,connecting nodes))* **then**
      Set parent of node to v;
      Set min(distance(v,connecting nodes)) to distance(v,node)
    end
  end
end
Traverse resulting graph;
for *each node in graph* **do**
  Calculate cable losses;
  Run battery models with consumption and generation profiles, and losses;
  if *SoC* $> 1 - $ *DoD for entire time frame* **then**
    Add node to list and update resulting graph;
  end
end

SHS in real settings and the impact that each one of these parameters has on electrification and connection costs.

4.1 Evaluation Metrics

We observe the impact of simulation parameters using two specific metrics: electrification and cost of the distribution (or connection) per household. Electrification is computed as the proportion of nodes connected from the entire number of nodes in the selected geography. For costs per household, we use our model described in Section 3.2.5 and all the structures in a selected geographical area are assumed to be a household. The total cost of the original SHSs and the cost of connecting nodes with each other is divided by the total number of households in a given geographical area to compute the cost per household. A combination of these two metrics allows us to assess this electrification strategy against the current cost incurred in traditional energy access mechanisms.

4.2 Electrification and Cost

Three key parameters affect the electrification increase and the cost incurred to achieve that electrification level: topology used for connections, consumption and generation profiles of SHS and

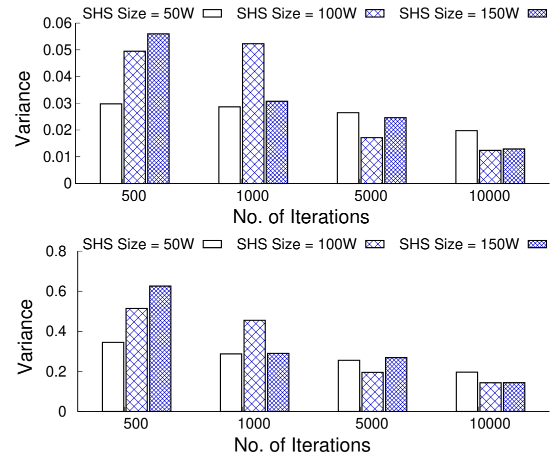

Figure 6: Variance in number of nodes connected (top) and electrification achieved (bottom) decreases as the no. of iteration increase.

passive nodes, and whether the passive nodes have storage. Next, we evaluate the impact of these parameters.

4.2.1 Effect of Topology. Algorithms 2 and 3 present two connection strategies based on star and MST topologies. We evaluate the impact of this parameter in the connection cost per household as we vary the proportion of SHSs present. Figure 7 illustrates the result of a simulation where each line represents a connection strategy and its impact on the cost and cable length. The top graph shows that both strategies present a negligible difference in cost which becomes less noticeable as the proportion of SHS increases. Different topologies affect the number of power lines that need to be deployed. As we expect, MST is more efficient in the amount of cable required; however, in this scenario, low-voltage lines account for less than 8% of the distribution cost where the difference in average length is at most 10 meters (bottom graph). Even though this difference is relevant in terms of power losses in DC networks, costs are not heavily impacted by this factor.

4.2.2 Impact of Changes in the Consumption Profiles. To better understand the effect of consumption profiles in long term infrastructure deployment, we evaluate the possible electrification rate when we use different scale factors for the consumption patterns. The U.S. Energy Information Administration estimates that worldwide renewable energy consumption increases by 3.1% per year [1] which demands that energy infrastructure should last to attend the future necessities of users. Among electricity consumers in Kenya, demand also rises sharply, especially in initial years after connection [13]. In this experiment, we want to observe the robustness of our networking strategy when the energy demand increases.

Figure 8 illustrates the effect of increasing consumption profiles by a given factor as we vary the proportion of SHSs. Each line shows the electrification rate at actual, 2x, and 3x consumption increases. The vertical line represents an approximation of today's proportion of off-grid households in Kenya that have a solar product [3] and the red dotted line illustrates the baseline electrification with only SHS nodes. As a result, higher increments of energy

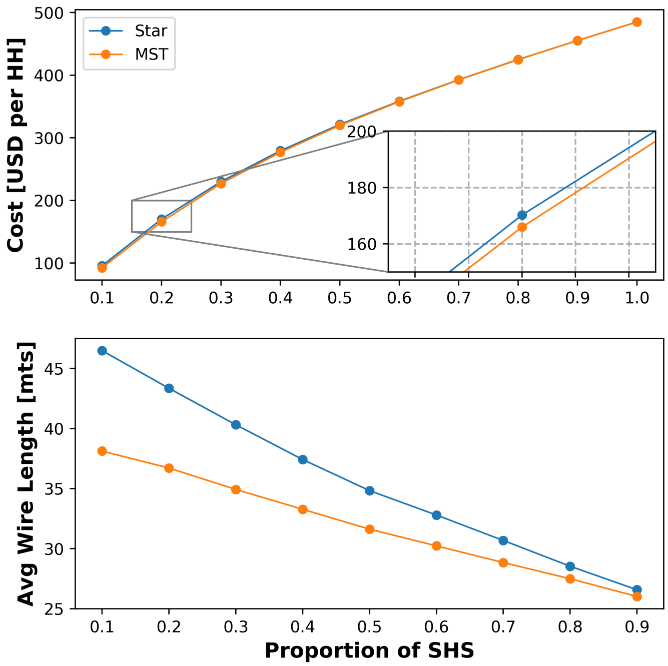

Figure 7: Impact of different interconnection strategies as proportion of SHS increase. Top: Distribution cost per household (USD per HH) where star and Minimum Spanning Tree (MST) present low cost differences for proportions of SHS less than 40%. The costs difference at higher proportions are almost zero since fewer passive nodes are available to network. Bottom: Difference in cable length (meters) for each strategy. MST is more efficient in terms of wire length required; however, cable costs are minor.

demand reduce the electrification rate which seems to have more relevance between a 30 to 50% proportion of SHSs. In this range, we can observe electrification reductions of up to 10%. As the SHS proportion approaches 100%, fewer passive nodes are available to interconnect so the impact of different factors in electrification shrinks. For the opposite case, few initial SHS nodes do not make an impact on the overall electrification. This suggests an opportunity to increase electrification using passive nodes, with an especially pronounced potential in a particular range of electrification.

Another important result is the status of the storage devices after the networking strategy. Figure 9 shows the average state of charge of batteries by hour of day. Different bar color represents two different scale factors of the consumption profile. As a result, batteries are more depleted during the morning due to the impact of two consecutive peaks of demand: one from the evening prior and one in the morning. Low consumption during the middle of the day allows the batteries to recharge using the available solar generation and nodes with higher scale factors deplete their batteries more, with an average difference of 6.5% in SoC between 1.5x and 3x.

4.2.3 Varying Passive Nodes with Storage. Passive nodes with storage certainly affect the overall cost of electrification since batteries account for almost 30% of the total infrastructure cost per household. We evaluate the average connection cost of all connected

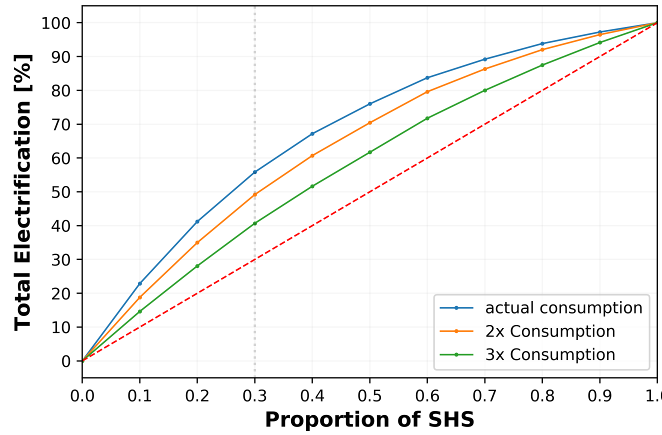

Figure 8: Impact of energy consumption profiles. Each line represents a demand increment by a given factor. The vertical line represents an approximation of today's proportion of off-grid households in Kenya that have a solar product [3]. The red line illustrates electrification using the all-SHS strategy.

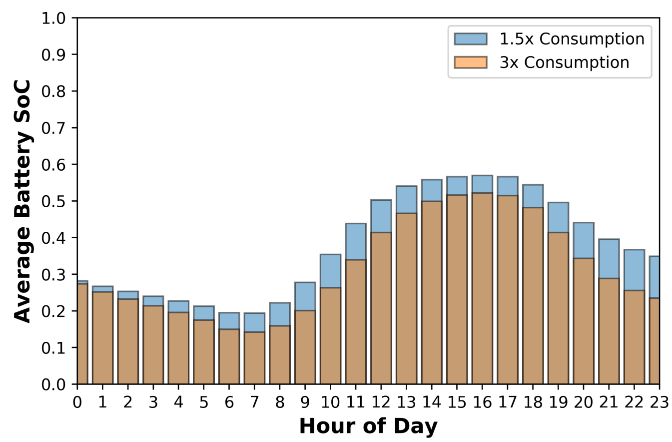

Figure 9: Average percentage of SoC by Hour of Day. Batteries are more depleted in the morning due to the two consecutive demand peaks without additional supply. SoC increases with the available solar generation and as scale factors of consumption profiles increase, the average SoC decreases.

households with different proportions of passive nodes with storage. These nodes are significantly more expensive but alleviate the possible overload of SHS batteries. Figure 10 presents the results of changing this proportion of devices. We fix the proportion of SHSs deployed to 30% [3] and the red line illustrates the connection cost per electrified household if only SHS devices were used to increase electrification, which in this case is the approximate cost of a 50W SHS (≈USD 485). As a result, increasing access through connecting neighbors with different proportions of battery nodes is less expensive than using an all-SHS strategy. Even for high proportions of battery nodes (70%), the connection cost per connected household is reduced at least 12% (from USD 485 to USD 432). Further, for the opposite case with 0% of nodes with batteries, the connection cost is reduced 30% (a cost reduction of ≈USD 145 per connected household on average) and could increase electrification to ≈57%. We can

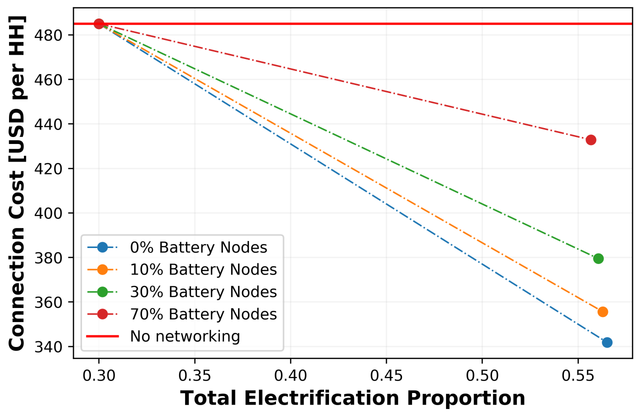

Figure 10: Impact of passive nodes with battery to the connection cost per household electrified. Each line represents a different proportion of battery nodes. The red line illustrates the connection cost per electrified household if only SHS devices were used to increase electrification.

also observe that adding storage to the passive nodes does not have a significant effect on increasing electrification. We believe that this behavior is due to distribution losses and distance limitations from the SHSs to neighboring nodes, as we limit the connections to a SHS only with nodes within 40 meters distance to avoid large voltage drops. Even though nodes with batteries have the capacity to add more load, there are not additional nodes that meet these constraints. We also believe that these results show that there is ample PV generation to continue to augment electrification via only increased connectivity, presenting a significant opportunity.

5 FUTURE WORK AND CONCLUSIONS

In this work we developed a framework to evaluate the viability of connecting neighboring households to existing SHS infrastructure. We observed an opportunity to utilize the excess generation from standalone SHSs to share electricity with underserved users at a fraction of the cost of electrifying the households otherwise. We also show that an all-SHS electrification strategy, which is what is effectively happening in many communities, is relatively more expensive than our hybrid approach, and will likely lead to lower electrification on its own.

By creating interconnections of households with complementary consumption patterns, we show that it is possible to cost-effectively achieve a middle ground between a fully-centralized electricity grid and a fully-decentralized array of standalone SHSs. Our results show the sensitivity of this framework to the variation of different parameters such as topology of networking, changes in consumption patterns and infrastructure cost. It is possible to observe cost reductions of up to 30% per connection and increase in electrification by almost 2x using today's proportion of off-grid households in Kenya that have a solar product.

Further exploration of this nascent space can enable faster and more equitable expansion of electricity access, accelerating progress towards universal electrification and UN Sustainable Development Goal 7.

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