# Like a Good Neighbor, Solar is There

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## ABSTRACT

The deployment of solar home systems – consisting of a photo-voltaic panel, battery, and a few appliances – is increasing rapidly in low- and middle-income economies. The simplicity of these systems has made them easy to deploy for customers without access to electricity who are far from centralized grids. However, sizing of solar PVs and storage capacity is challenging and error-prone, which in practical terms manifests as a fully-charged battery by midday - resulting in a curtailment of more than 30% of potential electricity. This represents a loss of valuable energy that could have been supplied to nearby homes without solar home systems. Prior work has proposed interconnecting existing solar home systems to increase electricity access. In this work, we analyze the problem of connecting a solar home system with other passive nodes, considering excess energy, the cost of connection, and the payback period. Using datasets of actual consumption, generation, and structure locations from Western Kenya, we show that electricity access in some communities can be increased by more than 3x.

## CCS CONCEPTS

• **Hardware → Renewable energy**; *Power networks*;

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## 1 INTRODUCTION

Energy access plays a fundamental role in the socioeconomic development of communities in rural areas of low- and middle-income economies [15]. Today, one billion people have no access to electricity and even though the UN Sustainable Development Goal 7 has redefined the way we ensure universal access, affordability and policy remain the key challenges to keep the pace required to meet the 2030 target [3, 7]. Figure 1 shows the trend of renewable generation in different regions of the world, excluding high-income economies in America, Europe, and Asia, and hydroelectric generation [13]. All the regions have experienced more than a 3x increase in renewable sources primarily driven by the large adoption of distributed

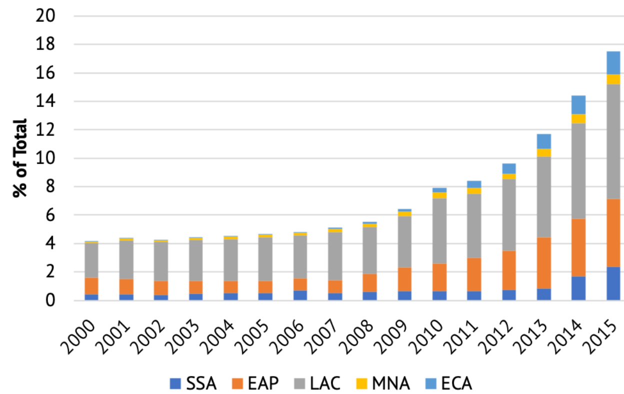


**Figure 1: Electricity production from non-hydro renewable sources [2]. SSA: Sub-Saharan Africa; EAP: East Asia and Pacific; LAC: Latin America and Caribbean; MNA: Middle East and North Africa; ECA: Europe and Central Asia.**

solar systems since 2012. It is estimated that solar photo-voltaic (PV) decentralized systems, which range from stand-alone off-grid solar (OGS) devices to solar mini-grids, will provide energy access to about 60% of non-electrified rural areas by 2030 [3].

Even though OGS and mini-grids offer higher Levelized Cost of Electricity (LCOE) in comparison to access through centralized grid extension, for remote rural areas they represent a cost-effective and eco-friendly solution. Since 2010, OGS devices have shown a compound annual growth rate near 60% with cumulative sales of more than 130 million devices, consisting of pico solar (solar lights of less than 11Wp), plug-and-play Solar Home Systems (SHS), and component-based systems (SHS with components compiled independently) [5]. This emerging sector is predominantly located in East Africa (86%) and mainly incentivized by business models such as Pay as You Go (PAYGO) which allows a household to make a downpayment followed by periodic partial payments to lease or purchase the device. However, remote communities in general have very low incomes and so a downpayment may still be unaffordable [1]. This represents a critical barrier to reaching universal access throughout these communities where electrification needs to advance four times faster to meet the 2030 goal.

The *SHS*, consisting of small PV panels and a battery, have been widely deployed in East Africa. Their simplicity has made them affordable even for households in middle or lower income classes. However, sizing of solar PVs and storage capacity is a challenging and error-prone activity [16], which in practical terms manifests as a full battery by midday - resulting in a curtailment of ~30% [18]. There has been prior work on bottom-up approaches that connect already available SHSes to increase electricity access. In this work, we analyze different factors that could govern the decision to connect two homes and evaluate how much improvements in


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electrification can be made using only existing SHS systems. In doing so, we make the following contributions:

**SHS Data Analysis:** We analyze empirical data on solar generation, electricity consumption, and structure locations from 1000 sites over a 23-month period in Homa Bay County in Western Kenya. Our analysis results in probability distributions over both solar generation and energy consumption.

**Decision Problem for Connecting** We present a basic decision problem for connecting a SHS node with a passive node with or without a battery. We consider excess energy, levelized cost of electricity, and payback period while formulating this problem.

**Implementation and Evaluation** We leverage our probability distributions for connecting SHSes with neighbouring nodes. We show that by sharing the excess of energy , the electrification can be increased by more than 3x in many clusters of structures.

## 2 RELATED WORK

Central grids have failed to bring electricity to 27% of rural communities worldwide [1]. Traditional grid extensions typically take years to construct, incur large expenses to the electrical utility, and are difficult to realize in many remote areas (e.g. those with difficult terrain). For these reasons, it is expected that only 30% of rural areas could be added to the grid [1, 21].

There is a large number of different approaches for rural electrification [20], out of which, three of them are either widely used or seem to be gaining significant attention, namely: i) **SHS**: this type of system consists of PV panels and a battery. Their simplicity and mobile money-based payment schemes have made them affordable even for households in middle or lower income classes; ii) **Micro-grids**: they are specifically designed to meet the community demand, but require professional planning and a large upfront capital investment; and iii) **Swarm (or peer-to-peer) grids**: this is a bottom-up approach that consists of connecting already available power supply units (e.g., SHS). Advocates of this solution [19, 24] see them as an alternative for social development, since it allows each household to decide when and how much to invest and supply to the community grid [22, 23]. In [4] the authors evaluate the process of forming coalitions to share energy. Modelling the social efficiency of these systems, they assess cost-sharing principles using hedonic coalition formation games.

This paper describes a solution that is midway between a swarm and a micro-grid. It is different from micro-grids in that it does not require significant capital investment, but also different from swarm grids in that we do not propose to have a completely uncontrolled and organic interconnection between houses – as described by most researchers in the area, e.g., [8, 18, 25]-. This work proposes that before connecting two households, grid operators should consider the daily consumption data from existing SHS, the distance to the neighboring house, the ability to supply the load of that node, and the ability to pay back the cost of the connection. Even though we are not proposing an explicit shared energy storage investment algorithm [17] which uses cooperative game theory, our collaborative consumption approach can help households to reduce the financial barrier to access electricity infrastructure in rural communities.

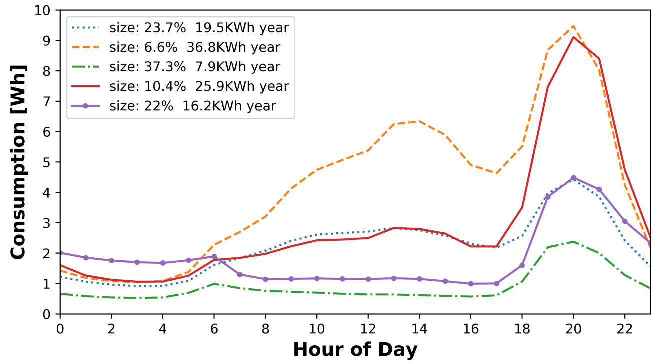


**Figure 2: Clusters of average daily consumption. The legend provides cluster size (in %) and average yearly consumption.**

## 3 METHODOLOGY

Our work addresses the problem of determining when to connect a passive (non-generating) node, with and without a battery, to an existing SHS. We use the location, energy consumption, and generation data to compute probability distribution for energy consumption and solar generation. We next create a model for estimating the solar generation potential, which is used to calculate the excess energy available. We next model the distribution costs for connecting different homes. Finally, we present the algorithm for connecting SHS with passive nodes that leverages the above distributions and cost model.

### 3.1 SHS Energy Data Analysis

Figure 2 illustrates the average daily consumption of five consumption profiles that were found using agglomerative hierarchical clustering techniques [26]. The largest proportion of SHS users (37.3%) consume on average only 7.9 kWh/year whereas only 6.6% consume 36.8 kWh. Besides the high disparity in aggregated consumption, we observe a common spike in consumption across all the clusters during the evening and a substantial difference in the consumption patterns during the day. High consumers are more active in off-peak hours possibly due to the use of additional appliances such as fans, TVs, and radios. To model the spatial distribution of households for our experiments, we use geographic location of more than 360K structures in Homa Bay County obtained from satellite imagery. We assume that each location corresponds to the location of one household and found $k = 20$ as the optimal number of independent clusters using yhr $k$-Means algorithm and "the elbow method".

One of the key insights of our approach is that the SHS are not generating the maximum amount of energy, which our data analysis shows can be 4x less than expected. As the energy consumption for the homes is very low, the solar panels produce only the amount of energy needed to fully recharge batteries after nightly use. Figure 3 illustrates this behavior, where the solar panel starts charging the depleted battery at the start of the day and generation reduces as the day progresses and battery becomes fully charged. If the battery was depleted significantly or there was more demand, the solar panel will potentially produce throughout the day.

### 3.2 Estimating Solar Generation Potential

In order to tap into the extra solar generation potential, we need to estimate the maximum solar generation potential for an SHS.

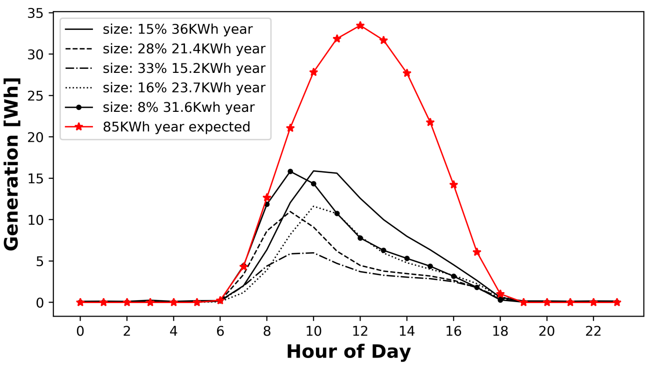


**Figure 3: Clusters of Average Daily Generation. Black lines show clusters of daily average generation in a thousand SHS. The red line shows the average solar generation potential for a 50W PV solar site obtained from PVWatts.**

One option is to use physical models for solar performance that give an estimate of solar generation potential based on location, weather, and sites' physical characteristics. However, this is a very complex process and outside the scope of this paper. Instead, we use a solar PV generation model, PVWatts, that gives hourly generation estimates for any location on earth for a typical meteorological year (TMY) with a reported accuracy of 20% [6]. It works well for our approach as it only requires an estimate of annual solar generation potential rather than real-time generation values.

The PVWatts model takes latitude, longitude, system capacity, tilt, orientation, and system losses as the input. We specify the solar site location from structure location data, system capacity to be 50W, and system losses to be 10%, a typical value for solar systems [14]. As the SHS are adopted and deployed in an organic manner, the tilt and orientation angles for solar panels can be arbitrary and are unknown. A prior study suggests the ideal tilt and orientation for modules in Kenya to be 4°and south-facing, respectively [14]. However, to capture the randomness in deployment characteristics, we generate the tilt using a normal distribution ($\mu$=4, $\sigma$=2) giving us a range of (0-14°) and set the orientation to be south-facing.

## 3.3 Distribution Costs

To construct a peer-to-peer solar energy network, we consider three types of households: active nodes, passive nodes with storage, and passive nodes without storage. Active nodes correspond to households that own the 50W SHS. Passive nodes with storage only have a 17Ah 12V lead-acid battery that connects directly to the solar panel of neighboring SHS and stores energy on-site. Passive nodes without storage tap to the neighboring SHS battery instead of the solar PV panel which eliminates the cost of battery and charge controller but limits consumption, due to the maximum depth of discharge limit of 50% for these batteries.

The cost of a new connection depends on the type of passive node being connected. Non-battery nodes need only the power line and a ready board; nodes with storage require additionally a battery and charge controller. Even though batteries account for a large proportion of the system cost, both scenarios reduce the cost in terms of the solar PV panel and the high upfront payment. In addition, a reasonable option for distribution cables is a 14 AWG aluminum cable which costs approximately $0.0578 per meter [11].

**Algorithm 1** SHS Connection Algorithm

**Require:** *structure locations, no. of SHS, payback threshold* $T_{th}$
1: *create clusters of structures based on location*
2: *pick all structures in a random cluster*
3: *compute distance matrix,* $\forall$ *homes* $\in$ *structures*
4: *randomly assign available SHS to structures*
5: *randomly assign passive nodes to remaining homes*
6: **for** (each SHS) **do**
7:     *randomly assign consumption and generation profiles*
8:     *compute excess generation for each home*
9:     *get closest unconnected node and assign consumption*
10:     *calculate the monthly energy payment and wire losses*
11:     *calculate payback time* $T_{payback}$
12:     **if** ($T_{payback} < T_{th}$ & $excess > 0$) **then**
13:         *connect the node, set distance to infinity*
14:         *compute excess energy after connecting the node*
15:         *go back to Step* 9
16:     *go back to Step* 9
17: *calculate total no. of connections*

## 3.4 SHS Connection Algorithm

Algorithm 1 illustrates the sequence of steps to determine the ability of a SHS to connect and share electricity with other passive nodes. Given the non-overlapping clusters of structure locations, we randomly select a cluster and locations for SHS based on the proportion of active nodes. The remaining structures within the selected cluster are randomly assigned and split into passive nodes with and without batteries. We give consumption profiles to each node according to the distribution shown in figure 2. For each SHS, we evaluate if the nearest node can be networked taking into account excess of generation available, wire losses, and payback time in an iterative manner which produces a star topology. Even though this might be prone to wastage of extra energy and reliability issues, the simplicity of this network topology is a common choice in real swarm electrification scenarios. We run experiments with this algorithm 1000 times using random assignments of nodes, clusters, and consumption profiles. This approach allows us to reduce bias to a specific scenario and generalize our results. The impact of the battery's state of health, the decreasing cost of solar PVs, and the reliability of connections under accidents or natural disasters are out of the scope of this paper and may be future work.

# 4 RESULTS

In this section, we vary simulation parameters such as payback time, proportion of passive nodes without storage, and cluster density. We examine the impact of these parameters in electrification and evaluate the opportunities to use this approach in real settings.

## 4.1 Electrification with varying payback time

We compute electrification rate with varying number of months to pay back the distribution costs. We assume that passive nodes would spend around 50 USD per year for lighting [10] and an additional cost for the electricity consumed. Since passive nodes with storage have similar behavior and a comparable infrastructure cost, we assume that the electricity cost is similar to the solar PV off-grid LCOE of $0.37/kWh approximately [1]. In contrast, we assume non-battery nodes are charged $0.685/kWh, which is calculated using 500 USD average cost of 50W SHS [12], 8 hours of daily solar

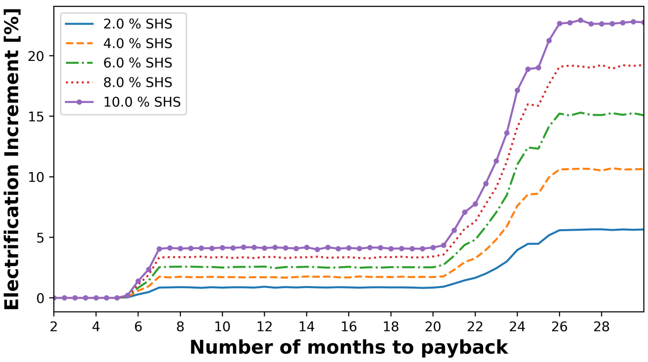


**Figure 4: Percentage of Improvement in electrification as payback time increases. Improvements of more than 3.5x are observed as payback time exceeds 26 months. Increments in electrification are driven by consumption profiles.**

generation, and five years of operation due to lead-acid battery life [9]. Figure 4 illustrates the results of the simulation where each line represents a different proportion of SHS in the region of analysis. We observe that after 26 months of payback time, the electrification rate reaches the maximum possible and shows an increment of approximately 3.5x in comparison to the initial rate. We also observe two dramatic increases in electrification, one around the 6th and 20th month. We believe that the first conservative increment is driven by the small percentage of high consumers that we found in the consumption profiles. These consumers have a higher monthly electricity bill which allows them to pay back the distribution costs in a shorter period. However, given the small proportion of these users, the increment of electrification is also small. Similarly, the second increment shows that the bulk of nodes have a consumption profile that allows them to start paying the costs after the 20th month and the electrification is maximized after the 26th.

## 4.2 Varying nodes without storage

To better understand the impact of the of the two different kinds of passive nodes, we evaluate the possible electrification rate at different proportions of non-battery households. Even though these nodes are significantly less expensive than the ones with storage, they present limitations due to the depth of discharge allowed in the battery which constrains the number of nodes to which the active node can supply electricity. Figure 5 shows the results of varying this parameter, where each line shows a different proportion of SHS and the x-axis is the variation in the proportion of non-battery nodes. As a result, higher proportions of these nodes significantly reduce the electrification rate and seem to have more relevance at higher percentage of SHS. We also observe that with a proportion of nodes between 15 to 50% we have a better electrification rate.

## 4.3 Electrification change by density

Distance between households affects the cost of low-voltage DC lines and hence the change in electricity access in our scenarios. In this experiment, we evaluated changes in electrification as we consider settings with different structure densities. We randomly select clusters of structures with large, average, and small numbers of households within 200 meters and calculate the distance matrix with the 1000 closest structures. Using this distance matrix and the

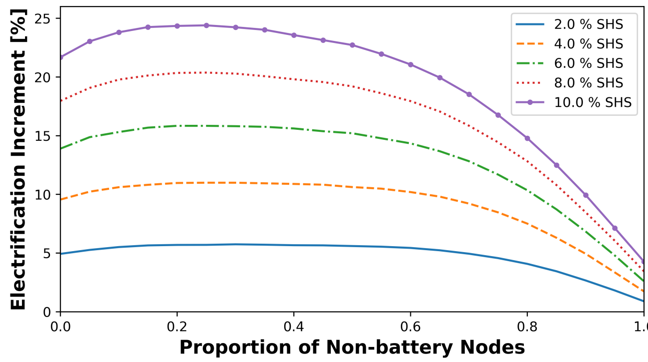


**Figure 5: Impact of passive nodes without batteries. Each line represents a different proportion of SHS. Non-battery nodes share the battery with SHS and the ability to connect more nodes is limited by the storage capacity and depth of discharge, reducing electrification.**

observation that Homa Bay has approximately 15k SHS, accounting for approximately 1.5% of all households, we present the results in Table 1. As expected, in dense clusters, it is easier to connect nearby nodes more cost-effectively as opposed to sparse settings where the cost of distribution and wire losses may be unaffordable. We observe that dense communities would experience an increase in electrified households of 4.1x as compared to sparse communities that would realize an increase of only 2.7x.

**Table 1: Comparison of electrification at different geographic densities. These experiments begin with 1.5% of households with electricity.**

| Structure Distribution | Electrification Increase [%] |
|---|---|
| Dense | 4.67 (4.1x) |
| Average | 4.30 (3.8x) |
| Sparse | 2.59 (2.7x) |

## 5 CONCLUSIONS AND FUTURE WORK

In this work, we showed that using the excess of generation in standalone solar home systems efficiently, access to electricity could be expanded in rural areas where traditional grid connections are nonviable. We explored the potential of this energy sharing mechanism considering the ability to supply the load of nearby households, payback period for the distribution costs, and the geographic density of these settings. However, we believe that our approach can be improved if we include additional physical characteristics of the system components, external weather factors, reliability constraints based on time of usage, and more efficient connection algorithms.

As we continue this work, we will aim to incorporate battery storage models to evaluate the state of charge at different hours of the day and more sophisticated connection algorithms based on graph theory. These new features will allow us to better assess energy access using the World Bank Multi-Tier Framework [7]. We also plan to collect data with a higher granularity to evaluate the implementation of more intelligent techniques such as demand response, energy trading, and real-time forecasting that increase the efficiency of these systems and can ultimately improve access in rural communities.

## REFERENCES


[1] International Energy Agency. 2017. *Energy Access Outlook 2017*. 140 pages. https://doi.org/https://doi.org/10.1787/9789264285569-en

[2] The World Bank. 2015. Electricity Production from Renewable Resources. (2015). Retrieved January, 2019 from https://data.worldbank.org/indicator/EG.ELC.RNWX.ZS Data retrieved from World Development Indicators.

[3] The World Bank. 2018. *Tracking SDG7: The Energy Progress Report*. Technical Report. Washington DC 20433.

[4] Sid Chi-Kin Chau, Jiajia Xu, Wilson Bow, and Khaled Elbassioni. 2019. Peer-to-Peer Energy Sharing: Effective Cost-Sharing Mechanisms and Social Efficiency. In *ACM e-Energy'19*.

[5] International Finance Corporation. 2018. *Off-Grid Solar Market Trends Report 2018*. Technical Report. 2121 Pennsylvania Avenue, N.W. Washington, D.C. 20433.

[6] A. Dobos. 2014. PVWatts Version 5 Manual. (2014). Retrieved May 2019 from https://www.nrel.gov/docs/fy14osti/62641.pdf

[7] ESMAP. 2015. *Beyond Connections: Energy Access Redefined*. Technical Report. Energy Sector Management Assistance Program (ESMAP), World Bank, Washington, DC.

[8] Sebastian Groh, Daniel Philipp, Brian Edlefsen Lasch, and Hannes Kirchhoff. 2015. *Swarm Electrification: Investigating a Paradigm Shift Through the Building of Microgrids Bottom-up*. 3–22. https://doi.org/10.1007/978-3-319-15964-5_1

[9] Battery University Group. [n. d.]. Can the Lead-acid Battery Compete in Modern Times? ([n. d.]). Retrieved May 2, 2019 from https://batteryuniversity.com/learn/archive/can_the_lead_acid_battery_compete_in_modern_times

[10] Kat Harrison, Andrew Scott, and Ryan Hogarth. 2016. *Accelerating access to electricity in Africa with off-grid solar. The impact of solar household solutions*. Technical Report. 203 Blackfriars RoadLondon SE1 8NJ.

[11] Wardah Inam, Daniel Strawser, Khurram K. Afridi, Rajeev J. Ram, and David J. Perreault. 2015. Architecture and System Analysis of Microgrids with Peer-to-Peer Electricity Sharing to Create a Marketplace which Enables Energy Access. In *Proceedings of the 9th International Conference on Power Electronics and ECCE Asia (ICPE-ECCE Asia)*. IEEE, Seul, Korea.

[12] IRENA. 2016. *Solar PV in Africa: Costs and Markets*. Technical Report. International Renewable Energy Agency (IRENA), Abu Dhabi.

[13] IRENA. 2018. *Measurement and estimation of off-grid solar, hydro and biogas energy*. Technical Report. International Renewable Energy Agency (IRENA), Abu Dhabi.

[14] M. Jacobson and V. Jadhav. 2018. World Estimates of PV Optimal Tilt Angles and Ratios of Sunlight Incident upon Tilted and Tracked PV Panels Relative to Horizontal Panels. *Solar Energy* 169 (2018), 55–66.

[15] Makoto Kanagawa and Toshihiko Nakata. 2008. Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries. *Energy Policy* 36, 6 (2008).

[16] Fiodar Kazhamiaka, Yashar Ghiassi-Farrokhfal, Srinivasan Keshav, and Catherine Rosenberg. 2018. Robust and Practical Approaches for Solar PV and Storage Sizing. In *Proceedings of the Ninth International Conference on Future Energy Systems (e-Energy '18)*. ACM, New York, NY, USA, 146–156. https://doi.org/10.1145/3208903.3208935

[17] Diego Kiedanski, Ariel Orda, and Daniel Kofman. 2019. The effect of ramp constraints on coalitional storage games. In *ACM e-Energy'19*.

[18] Hannes Kirchhoff. 2014. Identifying Hidden Resources in Solar Home Systems as the Basis for Bottom-Up Grids. In *Proceedings of the International Conference on Innovating Energy Access for Remote Areas: Discovering untapped resources*. https://doi.org/10.1007/978-3-319-15964-5_2

[19] ME SOLshare Ltd. 2017. Create a Network. Share Electricity. Brighten the Future. https://www.me-solshare.com. (2017). Accessed: 2019-01-31.

[20] Stefano Mandelli, Jacopo Barbieri, Riccardo Mereu, and Emanuela Colombo. 2016. Off-grid systems for rural electrification in Developing Countries: definitions, classification and a comprehensive literature review. *Renewable and Sustainable Energy Reviews* 58 (05 2016), 1621âĂŞ1646. https://doi.org/10.1016/j.rser.2015.12.338

[21] Kazi Rahman, Rahman Saidur, Wooi Hew, and K.R. Ullah. 2013. Comparative study of stand-alone and hybrid solar energy systems suitable for off-grid rural electrification: A review. *Renewable and Sustainable Energy Reviews* 27 (11 2013), 738–752. https://doi.org/10.1016/j.rser.2013.06.043

[22] George Ritzer and Nathan Jurgenson. 2010. Production, Consumption, Prosumption: The nature of capitalism in the age of the digital âĂŸprosumerâĂŹ. *Journal of Consumer Culture* 10, 1 (2010), 13–36. https://doi.org/10.1177/1469540509354673

[23] Wolf-Peter Schill, Alexander Zerrahn, and Friedrich Kunz. 2017. Prosumage of solar electricity: Pros, cons, and the system perspective. *Economics of Energy and Environmental Policy* 6 (02 2017), 7–31. https://doi.org/10.5547/2160-5890.6.1.wsch

[24] Okra Solar. 2017. Empowering People Through Energy Access. https://www.okrasolar.com. (2017). Accessed: 2019-01-31.

[25] Kurtis Unger and Mehrdad Kazerani. 2012. Organically grown microgrids: Development of a solar neighborhood microgrid concept for off-grid communities. 5663–5668. https://doi.org/10.1109/IECON.2012.6389060

[26] T. Warren Liao. 2005. Clustering of time series data - a survey. *Pattern Recognition* 38, 5 (November 2005), 1857–1874. https://doi.org/10.1016/j.patcog.2005.01.025