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Rural electrification subsidy estimation: a spatial model development and case study

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Abstract

A global push to achieve universal electricity access, paired with drastic reductions in the cost of decentralized electricity technologies, has led to significant research on how best to roll out access to rural communities in sub-Saharan Africa. Various geospatial electrification models have been developed to aid the decision-making process considering decentralized grid alternatives such as mini-grids and solar home systems. Despite these tools suggesting that in many cases, decentralized systems are a more cost-effective electricity access pathway, grid extension still predominates in practice. This is due, at least in part, to institutional structures in most countries that provide significant direct and indirect subsidies to grid extension projects, commonly through publicly-owned utilities. These sources of finance are generally not available to primarily privately operated off-grid energy service providers. However, the subsidy provided for grid extension projects is not well understood. In this paper, we employ utility grid extension costs and revenue data, and geospatial grid infrastructure data to estimate the size and distribution of subsidy implicitly provided to rural grid extension projects for 129 communities in Mombasa County, Kenya. We also estimate subsidies for hypothetical off-grid electricity systems in the same communities that would deliver equivalent services to the grid. We allocate the cost of shared medium voltage (MV) distribution infrastructure using a marginal and an average cost method for grid extension and compare these with subsidies for off-grid systems. We find that the average of average subsidy per customer across communities for grid extension is US$5,118 and US$5,330 for the two MV cost allocation methods respectively, while for the off-grid systems the corresponding average of average subsidies are US$3,380, using a real discount rate of 1.3% evaluated from a nominal discount rate of 8% and inflation rate of 6.7%. Our results show that in the communities in our case study, 40% and 37% of the communities would command less subsidy while served by minigrids over the grid, and the switch would save 50% and 54% of the total cost for average and marginal cost allocation methods respectively. We also show that by using a multi-model approach to electrification and by reallocation of implicit subsidies that have been exclusive to grid extension to other technology options utilities can cast the net wider, without an increase in budgets.

1. Introduction

According to the World Bank, only 47.7% of the population in sub-Saharan Africa (SSA) has access to electricity. This translates to about 580 million people still left without electricity access, the majority of whom live in rural areas. With a population growth rate of 2.7%, the absolute number of people without access is expected to grow despite an overall improvement in the rate of access [3]. The United Nations (UN), through sustainable development goal 7 (SDG7), aims to ensure access to affordable, reliable, sustainable and modern

energy for all by the year 2030 [18]. To bridge the energy access gap on this timeline, governments must adopt and implement aggressive electrification programs. Rosnes and Vennemo [43] note that 'national authorities and international organizations have drawn up plans to increase access, but key policy choices underpin these plans'. For perspective, historically the annual average electrification growth rate in SSA has been 1.7%, a number dwarfed by the 13% required to achieve SDG7 by 2030 [6]. To keep up with the 2030s universal electricity access goals, governments must consider two complementary tracks of electrification: grid extension and off-grid development to serve different populations based on their demand for electricity, connection density, and distance from existing grid infrastructure. Research has shown that most utilities in SSA incur massive financial losses which challenge their ability to provide reliable service [45], a situation exacerbated by extending the grid to low-revenue, high-cost locales, many of which are rural. According to Trimble *et al* [45], as of 2014 the only two out of 39 utilities, the primary utilities in Uganda and Seychelles, recovered their capital and operating costs through the sale of electricity.

The question of how best to provide access to electricity to rural dwellers has drawn a great deal of interest among policymakers and academics alike, with the goal of seeking cost-effective pathways to universal electricity access. Thus, various tools have been developed to support governments, utilities, and project developers to address this challenge. These tools include open source spatial electrification tool (OnSSET), the reference electrification model (REM), network planner, renewables for the rural electrification of Kenya (RE_RU_RE) and numerous others. Among these tools, OnSSET and RE_RU_RE use spatially explicit characteristics to design a least cost electrification strategy [28, 31]. REM utilizes regional information to identify areas that are appropriate for grid electrification and off-grid electrification [11]. Network planner determines the technology to use to connect population centres between grid extension and off-grid systems [36]. What all these tools have in common is that they are optimization models with cost minimization as their objective. Despite studies conducted using these tools that suggest the least-cost way to electrify many rural communities is through decentralized renewable energy systems [5, 24, 49] in the form of community-scale mini-grids, there remain few deployed mini-grids, and grid extension remains the dominant mode of electrification expansion. This is due in part to the institutional structure of the power sector in most African countries and how electrification projects are typically financed. The cost and source of finance have direct impacts on tariffs and financial feasibility. The majority of national electricity utilities on the continent are wholly or partially state owned [30]. Most African utilities enjoy several forms of subsidy and government support to limit the cost of energy to consumers and buttress otherwise financially unsustainable projects in the name of social benefits [40]. On the other hand, barring Senegal which has undertaken large scale mini-grid deployment under the national utility, the mini-grid sector is largely driven by the private sector [4] and does not enjoy similar financial support. Grid subsidies take many forms, including concessional loans, grants from international donor organisations, transfer of public funds from national treasury to the utilities and internal cross subsidies from high consuming, high density population centres to low consuming, sparsely populated rural communities. These funding mechanisms are not accessible to the mini-grid sector. This is despite the fact that mini-grid costs have over time decreased significantly and thus could prove a more efficient allocation of scarce subsidies in some settings. This sort of institutional structure, combined with insufficient attention to newly emerging alternatives has, albeit not formally, cemented grid extension as a de facto electrification mode. In particular, rural households and businesses, mainly because they are low consuming and thus utilities have no tangible incentives to connect them, bear the brunt of the current electrification policy, receiving adequate electricity access more slowly. For the status quo to change, major policy changes are a necessity. An efficient allocation of subsidies that cuts across all electrification alternatives not only helps improve the operations of utilities, but can also help electricity providers focus their efforts where their business model is most sustainable and their competencies are most exercised.

This lack of subsidy support for mini-grid deployment necessitates mini-grid operators to charge customers cost-reflective tariffs to maintain financial sustainability, often resulting in tariffs that are an order of magnitude higher than the grid [41]. There is growing recognition that subsidies are required in the off-grid sector both to ensure financial viability of off-grid providers as well as to support equitable access between grid and off-grid customers. It is widely discussed in the academic literature that electricity is one of the utility services for which subsidies are widespread and, in developing nations, often necessary [22, 26, 27]. However, this is not only the case for developing countries, as the history of rural electrification of the United States and Europe shows that connection subsidies played a prominent role for extending the electricity grid. The establishment of initiatives like the rural electrification agency in the United States and power cost equalization (PCE) in Alaska [19] channelled huge connection and operational subsidies to lower electricity prices for consumers. In SSA, pretax electricity connection and operational subsidies accounted for over 70 percent of total pretax energy subsidies in 2011.[4] Despite the fact that 'discovering and quantifying the extent of subsidies to energy firms has

[4] Clements, Benedict *et al*. Energy subsidy reform: lessons and implications, International Monetary Fund, 2013.

proven to be extremely difficult' [26], it is still important to make efforts to estimate them. Subsidy estimates afford governments an opportunity to make better investment decisions and allocate scarce resources more efficiently. The energy sector management assistance programme reported that in SSA, the on-grid upfront connection subsidies range from 40 to 81 percent of total connection costs [12]. It also notes that performance based grants for the mini-grids are often below the upfront subsidy level on the grid, thus making mini-grids a more attractive option for rural electrification from a financial standpoint.

The two most widely used methods of measuring subsidies are the price gap approach and producer support estimate–consumer support estimate (PCE–CSE) framework. The price gap approach measures the difference between the subsidized price and a reference price had there not been governmental intervention [21, 38]. The PCE–CSE framework on the other hand 'measures the annual monetary value of gross transfers from consumers and taxpayers to producers, measured at the producer property, arising from policy measures that support producers by creating a gap between domestic market prices and border prices of the specific commodities [38]'. In a study that cuts across seven countries, Phillips *et al* [39] reported an average rural connection cost of US$1,500 and an average connection fee of US$210, resulting in a mean connection subsidy of US$1,290. To evaluate the connection cost, they simply took the reported invoice value of rural electrification projects, added them together and divided the sum by the total number of connected customers. This value can be misleading, as it is an average of costs from different countries with different geographical landscapes. For Brazil, upfront subsidy per connection amounted to over US$4000, while on the low end less than US$500 was reported for Thailand [39]. This variation suggests that more than just an average value is necessary to inform decisions at a planning stage for electricity systems. Blimpo and Cosgrove-Davies [7] highlight that connection cost varies not only across countries, but even at a household level. As a case study on Niger, they further showed that this cost can be as low as US$108 for a *simple connection*[5] and get as high as US$9000 for connection with *extension*[6]. Parshall *et al* [36] estimated an average connection cost of US$1,900 per household (both rural and urban) in Kenya. In their calculations, Parshall *et al* estimated the sum of medium voltage (MV) infrastructure cost and low voltage (LV) infrastructure cost to be incurred to connect all customers, and divided it by the number of customers. In both Niger and Kenya, these connection costs are too high for the majority of households to afford, and as a result high upfront connection subsidies make the connections possible.

While these studies provide a high level understanding of how costly grid extension is as an endeavor, they tell only a part of the story. First, these studies only report connection costs and revenues generated from making such connections. From this, we are able to calculate upfront/connection subsidies. A connection subsidy is the difference between the actual cost of making a connection and what the customer pays to get connected to electricity grid. Throughout this paper, the terms subsidy and implied subsidy used on their own refers to the difference in cost of providing electricity service to a customer and the amount the customer pays for such a service over the electricity system lifetime. While it is important to understand the connection subsidies, they do not account for all of the costs and revenues in the life cycle of a connection. Due to the high initial cost of electricity transmission and distribution infrastructure, utilities can only realistically expect to recover the costs over time. Therefore, it is important to also understand operating and generation costs, and expected revenues in order to better understand the amount of subsidy that goes into providing electricity access. Second, the subsidies in literature have been evaluated in such a manner that implies that the infrastructure cost is shared evenly among the customers. This subsidy modeling approach ignores the differences in costs and revenues that arise as a consequence of the spatial distribution of customers and differing economic conditions which affect consumption of electricity. The objective of this research is to develop a method to make spatially resolved electrification subsidy estimates at the level of the distribution transformer (DT). We then apply this method to a case study in Mombasa County, Kenya using grid infrastructure cost and geospatial infrastructure data, and historical metering data to estimate revenues. We use the results to understand how information about the distribution of subsidies among rural DTs could inform more efficient allocations of resources to electrification activities given decentralized alternatives to grid extension. We consider the spatial distribution of the customers in our cost allocation models and also include revenues generated and expenses incurred serving the customers, and instead of reporting averages, we show distributions of the subsidies across transformer communities. A transformer community is constituted by a cluster of households and or businesses that are served by a single DT. The key difference is that we evaluate average subsidy per customer at a transformer community level instead of across all customers. This new approach enables us to (i) recognize the set of communities that require substantially higher shares of the grid subsidy, (ii) compare the grid extension and mini-grid deployment as alternatives at a community level and (iii) make targeted recommendations for future electrification projects.

[5] A connection which does not need poles to be made.

[6] A connection needing additional poles to make.

In this research, the key questions we answer are: (i) what is the implicit subsidy that go toward providing grid electricity to rural customers, (ii) how do these subsidies compare against the subsidies required for decentralized alternatives, and (iii) what are efficient ways of subsidy allocation considering mini-grids as a technological option to reach more rural customers? An example of an implicit subsidy is a cross subsidy, whereby profits realized from a subset of customers are used to cover costs of the other customers in order to keep prices low in areas that are expensive to serve. By uncovering the 'hidden' subsidies that drive grid extension models, we aim for this work to begin a conversation on how best to enable increased electricity access while enabling financial success for both grid electricity service providers as well as off-grid electricity service providers.

Core contributions of this research can be summarized as follows: (i) we present novel electricity infrastructure costing methods and cost allocation methods to the level of a DT, (ii) we estimate implicit subsidy for a case study in rural Mombasa County, Kenya, resolved at the DT level, (iii) we present an implicit subsidy-based classification criteria of communities into grid space and off-grid space, and (iv) using the least subsidy classification criteria, we estimate how a reallocation of resources between different electrification modes could reach more customers at the same cost if electrification strategies follow a technology-agnostic approach.

2. Methods & data

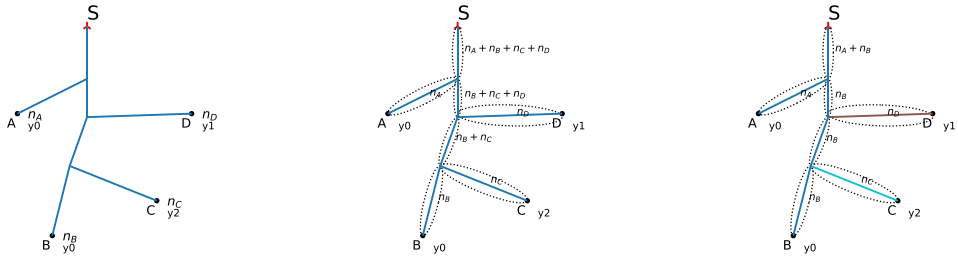
We define a subsidy provided to a community as a positive difference between the net present values (PVs) of the cost of the delivered energy and related infrastructure and the revenue generated from customers in that community. This is expressed in 1 below, where C_{NPV} is the net present value of costs and R_{NPV} is the net PV of revenues generated by a connection of set of connections. equations (2) and (3) provide mathematical models to bring the values to PV

$$\text{subsidy} = \begin{cases} C_{\mathrm{NPV}} - R_{\mathrm{NPV}}, & \text{if} \quad C_{\mathrm{NPV}} \geqslant R_{\mathrm{NPV}} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

$$C_{\mathrm{NPV}} = \sum_{k=0}^{N} \frac{G_k + T_k + D_k + O_k}{(1+i_r)^k} \tag{2}$$

$$R_{\mathrm{NPV}} = \sum_{k=0}^{N} \frac{R_k}{(1+i_r)^k}. \tag{3}$$

In equations (2) and (3) G_k is energy generation cost, T_k is transmission cost, D_k is distribution cost, O_k is the operations and management (O & M) cost, k a time index, p is the number of discounting periods in one year, R_k is revenue, i_r is the real discount rate and N is the number of periods in the project lifetime. In the ideal case, estimating the cost of delivering energy is a straightforward process: compute capital costs of infrastructure, allocate costs of shared infrastructure to consumers, and add the discounted cost of operations, maintenance and energy generation, and sum them up. However, such detailed data are seldom available which requires estimates to be made based upon data that are accessible. Thus, we rely heavily on existing utility grid infrastructure data that are often incomplete, their related costs and historical electricity consumption data to estimate the size of subsidy and its distribution across communities, defined as a set of connections served by a single DT. For the same communities, using local historical climate data and historical consumption data, we size and cost the hybrid solar photo-voltaic (solar PV)—battery storage—diesel generator mini-grids capable of providing electricity of same power quality and reliability as the grid. An assumption that the grid provides service of the same level as the offgrid systems in SSA paints a better picture of the grid than is deserved, as research has shown that most utility grids in SSA face massive reliability issues [8, 15, 33, 46] that are often mitigated by offgrid backup systems. However, because the goal is to be conservative in our subsidy estimates (i.e. estimate the lower bound), this assumption is reasonable. This type of mini-grid configuration is the most common in SSA [4, 42], primarily designed to meet the bulk of the daytime demand using solar PV, with the battery bank absorbing the shortfalls introduced by the intermittency of the solar power and night demand. The diesel generator is dispatched as a last resort when neither solar PV nor battery power are available. We then estimate the minigrid subsidy and show the distribution across transformer communities. We compare grid subsidies and mini-grid subsidies to make a determination of what is the best electricity access provision technology suitable for each community. The exercises of evaluating electricity subsidies and determining suitable electricity access pathway for rural customers are not new, however we present unique methods of doing both. In the following sections, we detail these methods and apply them to a case study.



(a) Typical MV network showing demand nodes A through D, with the number of served customers n and corresponding years of connection y.

(b) A typical MV network showing how the cost is allocated to customers under average cost allocation model. The number of downstream customers allocated to each network segment is shown alongside each segment.

(c) Typical MV network showing the marginal cost allocation model. The number of downstream customers allocated to each network segment is shown alongside the segments.

Figure 1. Graphical representation of MV network infrastructure and how it is shared among customers under the two cost allocation models, the average method and the marginal method.

2.1. Evaluating costs

We use geospatial grid network data and associated cost data to estimate grid extension costs that include high voltage (HV), MV and LV components of the power system. We also estimate generation costs and mini-grids components cost. In this section we explain how, given detailed and well documented network and cost data, we evaluate and allocate the costs for these individual components of the power system to transformer communities.

2.1.1. Grid costs

HV costs are estimated by assuming that the HV infrastructure cost is shared evenly among all customers. The MV cost for each community consists of substation costs and all associated infrastructure necessary to connect the substation to the DT using MV lines (including poles, wires, stays etc). In literature [36, 39], the costs are computed as simple arithmetic averages across all customers without regard to the grid network topology and location of customers relative to the grid and their time of connection. This method of evaluating MV infrastructure cost introduces two problems; (i) it ignores the spatial distribution of the customers, hence it artificially lowers the cost for customers that are located far from the distribution centres and (ii) it ignores the fact that a decision to electrify hinges not on individual customers, but on the proximity of the community as a whole to the MV backbone.

Thus, to address these problems, we propose two MV cost allocation models that evaluate cost at a transformer community level: (1) a weighted average cost method (hereafter called *average*) and (2) a marginal cost method. Under the average cost approach, we allocate the cost by weighting the shared infrastructure by the number of downstream customers served. The marginal cost approach on the other hand not only weights shared infrastructure by the number of downstream customers served, but also considers the year in which each DT was installed. However, for any DTs that have been connected in the same year and share portions of the MV infrastructure, the cost is distributed in the same manner under marginal method as in the average method. Thus, under marginal cost approach, the cost of already existing infrastructure constructed in prior years is not allocated to new transformer communities when the grid is expanded. This is because decisions about extending the grid do not consider sunk costs in existing infrastructure. Because of this, for the customers that are further upstream in communities that get connected earlier the marginal cost is higher than that average cost. However, the grid is built with a philosophy that it will expand in the future and the cost per connection will be lowered by the fact that infrastructure will be shared by a large number of customers. It is this philosophy that has inspired the average cost allocation model. We show graphically how these two cost allocation models work in figure 1. In figure 1(a), a typical MV network is shown with substation location S, transformer communities A through D, number of customers n_A through n_D served by those transformer communities and their corresponding years of connection. In figures 1(b) and (c), the same network is shown with corresponding number of customers assigned to network segments for average and marginal cost allocation models respectively.

From graphical representations in figure 1, the derivation of equations (4) and (5) below describing models for the two cost allocation methods, weighted and marginal respectively are shown

$$C_t^a = N_t \frac{C_s}{N_s} + N_t C_f \sum_{j=s}^{t} \frac{L_j}{N_j} \Bigg| \; j \in \text{Path}(s \mapsto t) \tag{4}$$

$$C_t^m = N_t \frac{C_s}{N_s} + N_t C_f \sum_{j=\alpha}^{t} \frac{L_j}{N_j} \Bigg| \; j \in \text{Path}(\alpha \mapsto t, \alpha : y_0 \leqslant y_t). \tag{5}$$

In equations (4) and (5), the variables are summarized below.

s	Substation ID
t	Transformer ID
y_0	Substation construction year
y_t	Transformer connection year
C_t^a	Weighted MV cost of transformer community
C_t^m	Marginal MV cost of transformer community
N_t	The number of customers in the transformer community
C_s	The substation cost
N_s	The number of customers serviced by the substation
C_f	The fixed cost per metre of MV line
L_j	The length of MV line segment
N_j	The number of customers downstream of line segment

The MV line segments L_j and downstream customers N_j must be on the path from the substation to the DT. For the marginal model, the MV line segments L_j and N_j have to start at a point α which, depending on when the infrastructure was built, may be at the substation point, or at some point between the substation and the DT, and terminate at the DT.

The LV infrastructure costs consist of DT costs and LV cabling costs (including poles, wires, insulators, and other associated components). We have argued that electrification decisions are made not based on individual customers but clusters of customers who spatially are in close proximity to each other. Therefore, we lump together a group of customers connected to a single DT to form a unit. For each DT community, the LV cabling costs are distributed evenly among the customers. Generation cost is evaluated by multiplying demand and cost per kWh of electricity generation, inclusive of losses in transmission and distribution.

2.1.2. Minigrid costs

We estimate hybrid solar PV, battery storage and diesel generator minigrid capital costs for each of the transformer communities. We assume the distribution network for the mini-grid is the same as the LV network for grid electricity. The mini-grids are sized to provide power of same quality as the grid. Using monthly global horizontal insolation data from the European Commission's PVGIS web tool[7] spanning 12 years from 2005 to 2016, we size the mini-grid power systems using the month with the lowest insolation. We disaggregate the monthly consumption into hourly consumption by assuming a 30 days month, dividing it by 30 and then multiplying by a normalized load profile constructed from a rural mini-grid consumption data from Kenya and Tanzania reported by Williams *et al* [48]. We use cost data from Reber *et al* [42], specifically taking the higher costs in order to estimate the lower bound threshold which is a tipping point between grid extension and minigrids. An indepth description of this can be found in the accompanying supplemental information.

2.2. Revenues

For revenues, two streams—electricity sales and connection fees—are considered. Revenue collected from connection fees is assumed to be standard for each customer. To estimate electricity sales revenues, forecast demand over the system life cycle is multiplied by a volumetric (per kWh) tariff. Historical consumption data from Kenya power are used to build demand forecasting models [14]. We make the assumption that the tariff levels are the same for grid connected customers and for minigrid connected customers.

2.3. Grid vs minigrid decision boundary

Making a decision of which communities have to be electrified via grid extension as opposed to through mini-grids is complex. This is due to that while electrifying via decentralized mini-grids the communities are assessed

[7] https://re.jrc.ec.europa.eu/pvgtools/en/MR.

as independent entities, the interconnectedness of the communities on the grid means that a change in one community affects other communities as well. To define the decision boundary of grid and off-grid, we formulate an 0–1 interger programing problem whose objective is minimization of the total implied subsidy across all communities. This problem is expressed formally in equation (6), where U_{st} is a binary variable indicating whether a transformer community is connected to the grid, V_{st} is a binary variable indicating whether a transformer community is connected through a minigrid, G_{st} is the implied subsidy for a grid connected transformer community, and O_{st} is the implied subsidy for a minigrid electrified community

$$\begin{aligned} \min_{U,V} \quad & \sum_{s=1}^{S}\sum_{t=1}^{T} U_{st}\cdot G_{st} + V_{st}\cdot O_{st} \\ \text{s.t.} \quad & U_{st} + V_{st} = 1 \\ & U_{st}, V_{st} \in \{0,1\} \end{aligned} . \tag{6}$$

For a system with S substations and T_s transformers communities per substation, there exists $2^{\sum_{s=1}^{S} T_s}$ grid network states. These range from none of the communities connecting to the grid ($\mathbf{U} = \mathbf{0}$) to all of them connected to the grid ($\mathbf{U} = \mathbf{1}$). To search the entire solution space, the algorithm follows an exponential running time. In this paper, we consider only one of these possible states of the grid network. We do this by estimating the subsidy for grid extension and subsidy for minigrid for each community. In a community *st*, when the grid subsidy is less than the offgrid subsidy, $U_{st} = 1$ and $V_{st} = 0$, and when the grid subsidy is greater than the off-grid subsidy, $U_{st} = 0$ and $V_{st} = 1$. We acknowledge that by considering a single possible state of the network, we may end up with a feasible solution which is not necessarily a global optimal result.

3. Case study

As a case study, we apply the methods we have described in the previous section to make a comparative analysis of grid and off-grid subsidies for rural parts of Mombasa County, Kenya. In the following subsections, we describe the data and how they are used to estimate subsidies. These data include geospatial grid network data, historical consumption data for rural residential Kenya power customers and cost and infrastructure data for fill-in grid extension connections in rural areas of the country. The description of the data includes the missing values found in the data and techniques applied to fill those missing values are explained. For this case study, we discount cash flows to NPV in real terms. In our analysis, we estimate costs and revenues on a monthly basis over a 30 years time horizon for each customer, using the number of customers from 2015. Using a nominal discount rate of 8% that is normally applied for electrification projects in developing countries [28, 32] and an average inflation rate of 6.7% evaluated from the world bank inflation database [17], using the rates for 12 years after the great recession of 2008, we found a real discount rate of 1.3%. In reality, a nominal discount rate is dependent on various factors such as electrification mode, inflation rate, financier, location, borrowing currency, etc, thus we acknowledge the uncertainty around the 8% used in the analyses, and therefore we test the sensitivity of the subsidy to changing discount rate (see figure 16). We evaluate subsidy in 2015 US$. Because the cost data comes from different sources reporting in different years, we adjust all the costs to 2015 US$. Table 1 provides a summary of key inputs used to evaluate both grid and minigrid subsidies.

3.1. Geospatial grid network data

We use geospatial grid network data provided by Kenya power, the primary electricity distribution utility in Kenya. The grid network data are in the form of shapefiles and contain HV transmission lines, MV distribution lines, MV poles, LV distribution lines, LV poles, customer locations, DT locations and substation locations. Figure 2 shows how these data map to each other. A pointed arrow indicates a mapping between two data types through unique identifiers (i.e. an arrow from customers to transformers means we know the transformer IDs to which customers are connected).

HV lines, transformers and customers span the whole country of Kenya, while the MV and LV networks span Mombasa county and parts of Kilifi and Kwale counties. For this reason, the analysis focuses on rural regions of Mombasa, Kilifi and Kwale. The network covers both urban and rural areas. We define the rural extent of the grid network coverage using methods developed by Fobi *et al* [14], in which they used a k-means clustering algorithm making use of data on population density, land use classification and satellite nighttime light intensity to classify locations in Kenya as urban, peri-urban and rural. In the service area contained in our dataset, we found 180 independent rural LV networks. Each of these networks are associated with a single DT which connects the LV network to the MV system (figure 3).

Table 1. Key inputs for evaluating subsidy.

Parameter name	Value	Source
HV transmission cost	US$79/connection	Evaluated using [2, 16]
Substation cost	US$2.23 million	Evaluated from [16]
MV distribution cost	US$25/m	[14]
Transformer cost	Varies	Evaluated from GE[a]
LV cost	Varies	Evaluated from [29]
Solar PV cost	1200 US$ kWp^{-1}	[42]
Charge controller cost	400 US$ kW^{-1}	[42]
Inverter cost	800 US$ kW^{-1}	[42]
MG powerhouse cost	600 US$ kW^{-1}	[42]
Diesel genset cost	400 US$ kW^{-1}	[42]
Battery storage cost	500 US$ kWh^{-1}	[42]
MG auxiliary costs	400 US$ kW^{-1}	[42]
Grid O & M cost	2.5% capital yr^{-1}	[13]
Offgrid O & M cost	2% capital yr^{-1}	[42]
Tariff	15.8 KES kWh^{-1} (0.158 US$ kWh^{-1})	[1]
Generation cost	10.2 KES kWh^{-1} (0.102 US$ kWh^{-1})	Evaluated from [34]
Exchange rate	100 KES $US\$^{-1}$	World bank data (mean of 7 years from 2014 to 2020)
Connection fee	35 000 KES $cust^{-1}$ (350 US$ $cust^{-1}$)	[29]
Modeling horizon	30 years	
Nominal discount rate	8%	[28, 32]
Inflation	6.7%	[17]

[a]http://dstar.org/uploads/public/DSTAR_Transformer_Cost_Analysis_Application.pdf.

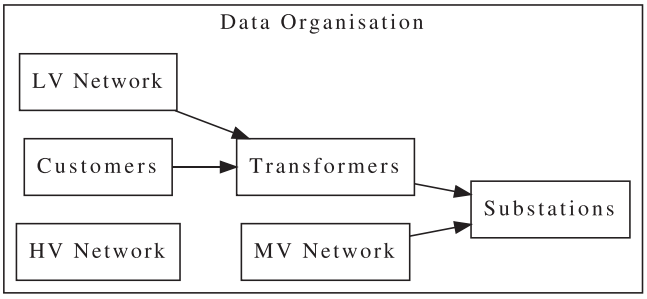


Figure 2. Geospatial grid network data. Arrows indicate associations between network components.

3.2. Demand estimation

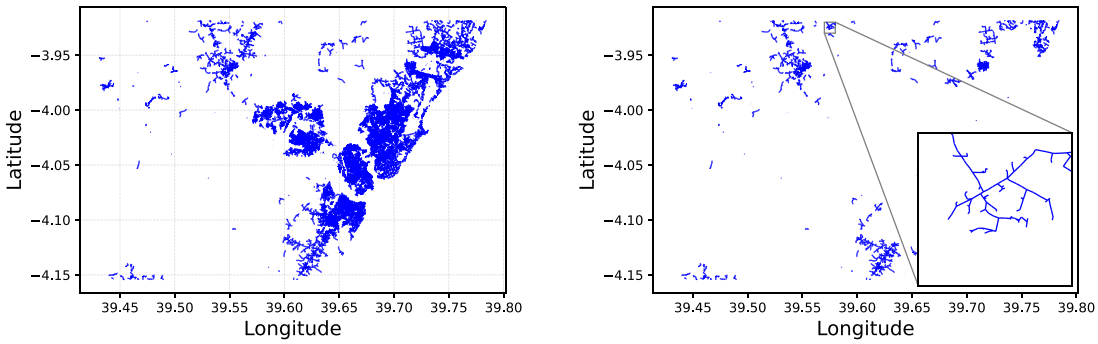
We use historical electricity consumption data from customers in rural Kenya as described in Fobi *et al* [14] to construct a demand forecasting model. Figure 4 shows the scatter plots of average monthly consumption for rural Kenya power customers connected to the grid between 2009 and 2013, and the lines of best fit.

We assume the mean consumption levels are representative of how a typical customer's use of electricity would evolve over time. Demand for electricity is estimated by a model in (7) below

$$D_{kj} = D_{ss}\dot{(}1 - \mathrm{e}^{-\alpha_j(\beta_{0j}+k\beta_{1j})}). \tag{7}$$

In equation (7), D_{kj} is demand in month k since connection for a customer connected to the grid in year j, D_{ss} is steady state demand achieved after a period of exposure to electricity, α_j is a constant representing the consumption growth rate, β_{0j} and β_{1j} are linear regression parameters for customer connected in year j. D_{ss}, α_j, β_{0j} and β_{1j} for each year are chosen to minimize the mean square error. These parameters are summarized in table 2.

These models reflect a trend where customers connected in earlier years tend to consume more while those in latter years consume less, with the exception of 2011 and 2012 which have quite similar profiles. While the general shapes of the profiles are similar, the underlying models cannot be generalized to years for which the training data is either not available or are available for a period of less than 36 months, a typical time for which consumption patterns have stabilized. Consequentially, for all customers connected prior to 2009, we assume that their consumption level is similar to those connected in 2009. Also, we assume that customers connected after 2013 have consumption level similar to that of 2013 customers.



(a) LV distribution networks (b) Rural LV distribution networks

Figure 3. LV distribution network lines. (a) Is a complete LV network for both rural and urban Mombasa, while (b) shows LV network in rural Mombasa.

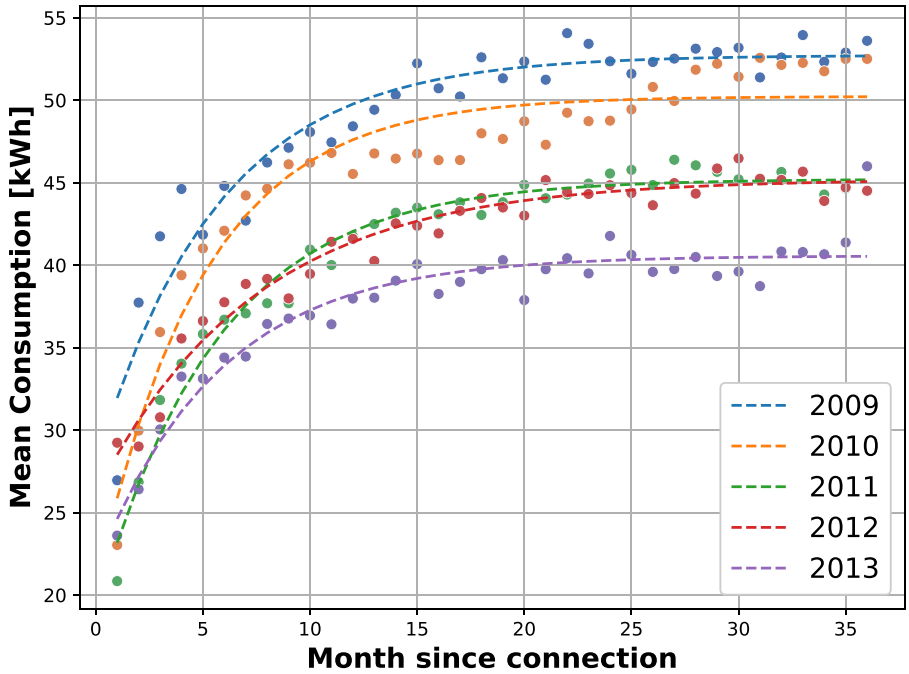


Figure 4. Scatter plot of mean consumption over first 36 months after first day of connection and plot of lines of best fit for different years.

3.3. Costs

We estimate grid extension costs that include HV, MV and LV portions of the power system. We also estimate generation costs and mini-grids components cost. In reality the grid network evolves over time, generally starting in densely populated urban centres and spreading out to reach far deep into rural areas. However, detailed longitudinal data on specific grid extension projects are not available. For this reason, and for the fact that we are doing a comparative study with mini-grids which can take a few months to construct, we model the grid network as if it was built overnight. HV costs are estimated by analyzing a power transmission improvement project appraisal report from 2010 [16] to get a cost per km of HV line. A per connection HV cost is evaluated from a knowledge of the total HV lines length and total number of connections served. We estimate the substation cost by analyzing a power transmission improvement project appraisal report of 2010 [16]. Unfortunately, the LV cost data and LV network data do not overlap spatially. We therefore develop empirical models to relate costs of LV infrastructure to geospatial network data which we can use to estimate costs in regions where complete LV network data are not available. We use fill-in connection cost data as described in Lee *et al* [29] from 62 transformer communities in Busia and Siaya counties in rural Kenya to build cost estimation models for LV network costs. Per electrification policy in Kenya, customers that are within a 600 m radius

Table 2. Demand model parameters for customers connected in different years.

Connection year	D_{ss}	α	β_0	β_1	R^2	MSE
2009	52.72	−0.98	−0.77	−0.18	0.92	2.54
2010	50.23	0.47	1.11	0.43	0.92	2.95
2011	45.22	−1.18	−0.46	−0.14	0.97	0.92
2012	45.21	−1.03	−0.83	−0.13	0.96	0.81
2013	40.57	0.15	5.03	1.16	0.91	1.58

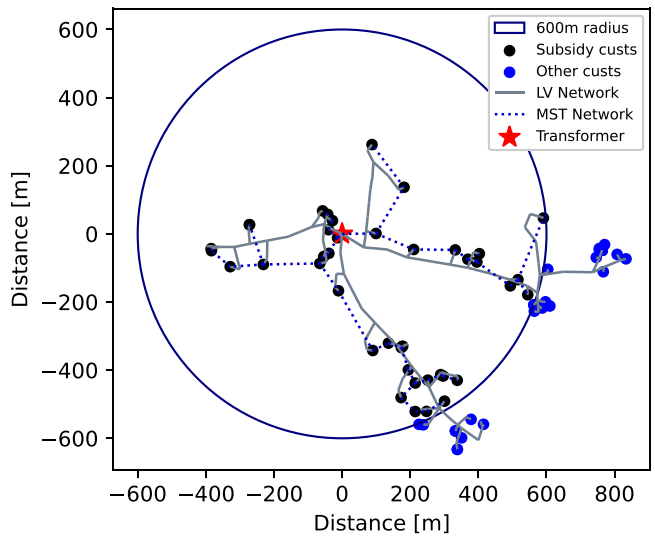


Figure 5. Transformer community showing positioning of the transformer, the LV network and the customers. The circle marks the 600 m borderline, beyond which protruding network segments and customers are ignored for regression models.

from a DT are eligible for a subsidized connection fee of 35 000 KES [23]. Using data on the geospatial location of all Kenya power customers, we use a radius of 600 m around each DT to define the set of all customers in each transformer community that are eligible for a connection subsidy, as can be seen in figure 5.

The LV cost data only provide information on the number of poles and number of new customers associated with fill-in connections. Transformer cost (T_c) is estimated through a regression model that relates the transformer cost with the kVA rating. This regression model is constructed with data from a general electric (GE) transformer cost analysis study [47]. Equation (8) illustrates this model, whereby τ_0 and τ_1 are regression parameters (refer to SI) and T_s is transformer rating

$$T_c = \tau_0 + \tau_1 T_s. \tag{8}$$

Because the LV network data are incomplete (i.e. a customer belonging to the same DT as a LV network but with connecting LV lines missing), the LV network cost is evaluated by using simple regression models that relate minimum spanning tree (MST) LV network, the number of poles required to support LV wires and cost of fill-in connections. For all complete LV networks (see figure 5), MSTs are built to connect all customers within 600 m radius of each DT. Then, the number of poles that support the actual LV network that connects these customers within the 600 m radius are correlated with the lengths of associated MSTs. The number of LV poles (N_p) is then estimated by equation (9),

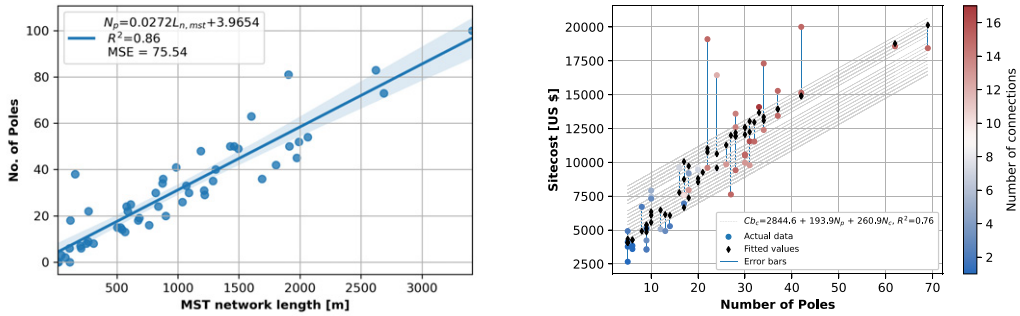
$$N_p = \gamma_0 + \gamma_1 L_{n,mst}, \tag{9}$$

where $\hat{\gamma}_0$ is the intercept, $\hat{\gamma}_1$ is the estimate of number of poles per metre of cabling and $L_{n,mst}$ is the MST network length. The LV line cost is estimated by equation (10),

$$Cb_c = \eta_0 + \eta_1 N_p + \eta_2 N_c \tag{10}$$

where η_0 is base cost, η_1 is the marginal cost of adding a pole to the network, N_p is the number of poles, η_2 is the marginal cost of adding a customer to the network and N_c represents the number of customers. The figures 6(a) and (b) below show the regression models.

We estimate the per kWh generation cost by analyzing the most recent financial statements from Kenya power which does not generate its own electricity. In their 2018 financial statements, Kenya power reports



(a) Scatter plot of the MST network and the number of poles. Distribution of the points exhibit a strong linear relationship. The solid line is the least squares regression best fit line.

(b) Plot of fill-in project cost against the number of poles installed. The scattered points represent actual cost for different projects, while the black diamond points represent estimated costs using a least squares regression of the cost of the network on the number of poles and customers. The slanting lines show slices of the plane represented by the Equation 10 for different number of customers.

Figure 6. Simple regression models relating cost of LV distribution network to minimum spanning network.

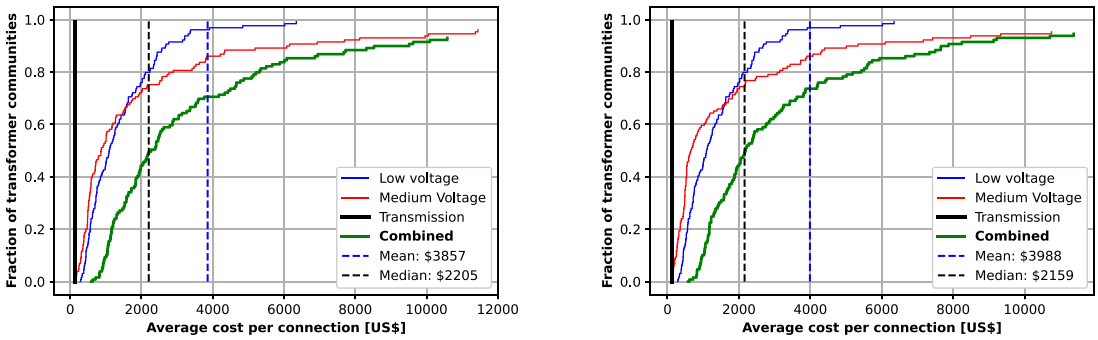
spending US$841 million (84.1 billion KES) on power purchases and sold 8,486 GWh in the same period [34]. This equates to 0.102 US$ kWh^{-1}. Because we are dividing by electricity sales rather than purchases of electricity, this number also factors in an average cost of losses. This approach implicitly assumes that this cost of electricity generation is unsubsidized. In reality, large scale power generation projects in Kenya likely benefit from concessional finance and other external support which amounts to a subsidy, making actual costs of generating electricity even higher. Furthermore, losses are likely relatively higher in rural areas as compared to urban areas due to longer transmission and distribution distances. For all of these reasons, our generation cost estimates are therefore prone to underestimation.

3.4. Revenues

These are customers who are within a radius of 600 m from the transformer, who, as per electrification policy in Kenya, qualify for a connection subsidy, and pay a uniform discounted connection fee [23]. A flat tariff of 15.80 KES kWh^{-1} [1] (0.158 US$ kWh^{-1}) is applied to evaluate energy sales revenue. This tariff is applicable to domestic customers who consume between 10 and 15 000 units of electricity per post paid billing period or prepaid unit purchase period. For connection fees, we apply a flat rate of 35 000 KES [29] (350 US$) fee per connection which is designed for customers who need single-phase supply. This value is conservative as the vast majority of recent connections are highly subsidized by grant programs like last mile connectivity under which customers pay 15 000 KES [44] (150 US$).

4. Results and discussions

We use transformer communities as units of analysis for estimating subsidies. For each transformer community, we evaluate the LV connection costs, MV distribution costs, HV transmission costs, revenue from connection fees, revenue from energy sales, and generation costs. Using these, we evaluate the per connection subsidy at each transformer community. Throughout the rest of this paper, we use the term average subsidy to refer to the mean across all transformer communities of the average subsidy per customer in each individual transformer community. Note that this does not correspond to the overall average subsidy per customer across all transformer communities because the population of customers connected to each transformer is non-uniform. We assume a static grid network, frozen to the state of the grid network of 2015 over this horizon, with no further expansion and no additional connections. This assumption is a consequence of data availability limitations, with the grid network data at our disposal updated to 2015. From a perspective of the first rural connection date of 1995, freezing the grid network to a later state effectively result in a lower bound in the estimation of the costs, and hence subsidies associated with grid extension because the number of customers grew, thus the costs are shared among a larger customer base. A different approach would consider the fact that the network grows over time as more customers get connected. This would result in higher



(a) Average method (b) Marginal method

Figure 7. Distribution of expected connection cost per customer in different transformer communities.

subsidy at the beginning, gradually decreasing over time as more customers get added to the network. While this approach would help us understand the incremental costs of grid extension, and perhaps would justify the need to expand the grid further to distribute the costs over many customers to drive the average down, we instead follow the static grid approach because we understand that allowing the grid to evolve would also require evolving minigrids for apples-to-apples comparison. However, since we are performing a comparative analysis, doing this will not change the comparative results because subsidy per connection decreases for minigrids as more connections are added, just as the subsidy decreases for grid extension. We also assume that there is no long term growth of electricity demand per connection over the modeling horizon, as observed in historical consumption data over around 10 years. While we make assumptions that lead to a lower bound in subsidy, this particular assumption runs counter to this practice. A counter approach which assumes long term growth in demand would result in increased expected revenues and generation costs. However, because user tariff is greater than generation cost on a per kWh basis, an increase in demand results in higher net income, hence would lead to lower subsidy overall, for both grid extension and minigrids.

4.1. Grid connection costs and subsidy

The distribution of transmission and distribution costs per connection across the transformer communities are shown in figure 7. The average LV connection cost is 1360 US$, in line with values estimated by other researchers [10, 36]. When adding transmission and MV cost, the average per customer across all communities is increased to 3857 US$ and 3988 US$ for the average and marginal cost methods for allocating MV costs respectively, which are in line with what other researchers also found [45]. It is important to note that costs reported by other researchers include both rural and urban settings. Urban areas are more densely populated, hence it requires shorter MV and LV lines per customer to connect entire communities. Presumably, including the urban communities in the analyses would lower the overall average cost.

Generation costs and energy sales revenues are assumed to be incurred monthly. We apply a real annual discount rate of 1.3% to bring the generation costs and energy sales revenue to PV. Figure 8 shows the distribution of subsidy over the 129 rural transformer communities in the service area. We wish to point out here that this distribution is of the mean subsidy per customer in a transformer community across the 129 transformers. We report the average per community subsidy instead of per customer subsidy because the decision to electrify is made based on units of communities rather than individual customers. A per customer subsidy across all customers masks the spatial distributional effects of communities/customers.

We find a mean subsidy of 5118 US$ and 5330 US$, as reported in the figure 8, for the average and marginal cost approaches, respectively. These mean values are considerably higher compared to the corresponding median values, and are highly influenced by a few outlier communities that have relatively high average per customer subsidy. However, as the grid extends further into rural areas, these outliers may become the norm. For context, the average subsidy per connection without clustering by transformer communities is US$1585 and US$1608 for the average and marginal approaches respectively. These values are small compared to the average of averages at transformer communities due to the lower average subsidy in communities with larger number of connections, and are also lower than the average minigrid subsidy (see figure 11). This is because while evaluating average without clustering customers, the differences in cost driven by spatial distribution of communities relative to grid infrastructure are not captured, hence a failure to capture the fact that in some communities, the average grid subsidy is higher than the average minigrid subsidy. This can lead a poor decision of extending the grid to communities in which it would make a better investment decision to electrify via the minigrids.

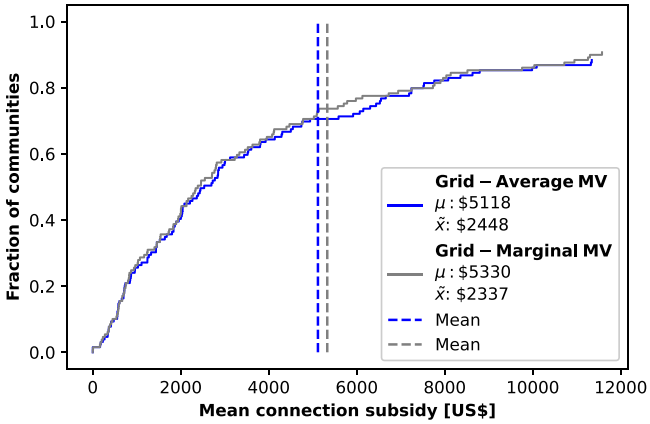


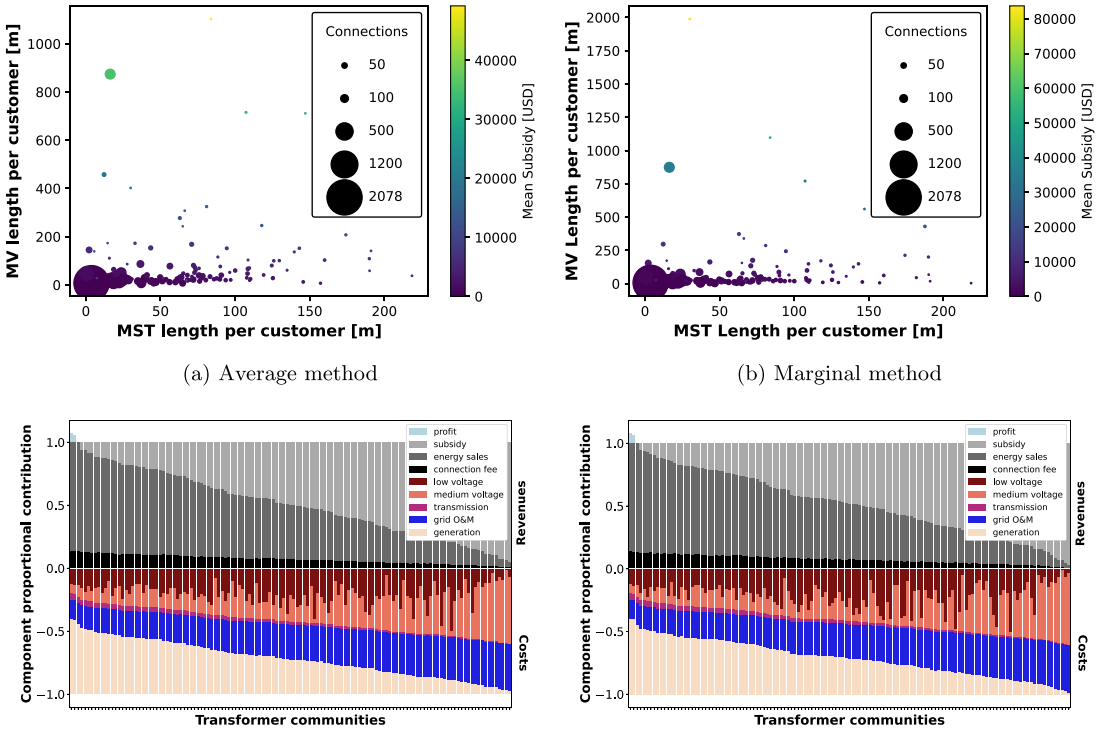
Figure 8. Distribution of subsidies at 1.3% discount rate.

With the goal of being conservative, when imputing missing data or choosing model inputs that are subject to uncertainty, we make assumptions that would result in lower subsidy estimates. Thus, the subsidy estimates provided represent a lower bound. In general, the costs of providing electricity to rural communities are dominated by the MV and LV distribution network costs, as evidenced by the large gap between the average per customer LV network cost and the generation costs. Figure 9 shows how different cost and revenue components contribute toward the level of subsidy. In figures 9(a) and (b), we show the scatter plot of dispersion (described as average MST network length per customer in a community) and the weighted proximity of the community from the supply point. In general, lower dispersion and closeness to the supply point, mainly driven by a higher number of connections, results in a lower subsidy. In figures 9(c) and (d), we show the distribution of the normalized contributions of different cost components and normalized revenue components across all transformer communities. For a small fraction of the communities, the utility actually realizes profits. In regions of high energy consumption and many connections, the energy generation cost far dominates the total costs, resulting in low subsidy levels. This is because higher consumption and many connections imply higher revenue levels, and because tariff is higher than generation cost, the marginal revenues exceed marginal costs. In communities of low energy consumption and few connections, the revenue is small and the distribution costs, mainly the MV distribution and the O & M costs comprise most of the cost and result in a high subsidy level for those communities.

For a transformer community, the difference between the subsidy evaluated using the average cost and marginal cost allocation methods is driven by the share of MV cost. Thus in figures 9(c) and (d), because the communities have been sorted in ascending order of the subsidy, the position of any particular community is not the same. We explore these differences in figure 10. Figure 10(a) is a scatter plot of MV cost proportion, with the two allocation methods plotted against each other. If for all substations the corresponding transformers were connected in the same year, all the points would lie on the line of parity. A transformer community that lies above the parity line is an indication that the transformer was installed earlier relative to others with which it shares portions of the MV network infrastructure. Conversely, a community that lies below the parity line signals that the transformer was installed later relative to others with which it shares infrastructure. In figure 10(b), we show a scatter plot of subsidy proportion of the revenues for the two MV cost allocation methods compared against each other. Similar to the MV costs plot in figure 10(a), the position of a transformer community relative to the parity line tells us when it was installed relative to others that share the infrastructure.

4.2. Average method vs marginal method

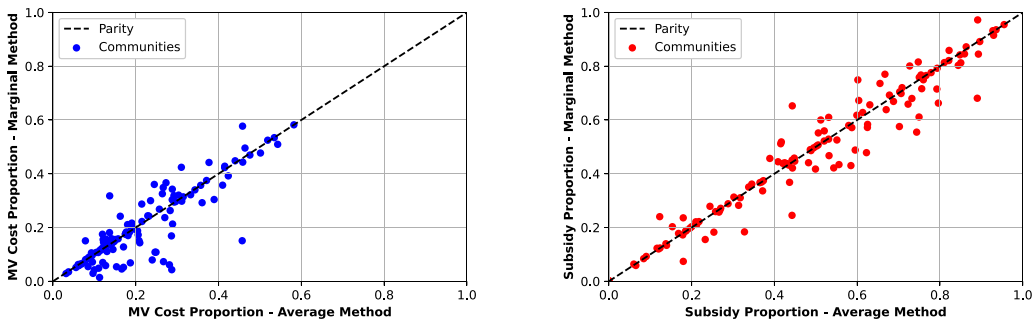
We have been comparing these two methods of allocating the MV costs which yield different results that must be interpreted differently and with great care. Both methods are useful to evaluate and make decisions pertaining electrification, and each is more suited to being applied at particular stages of the grid network evolution. In a case where a new central distribution point (substation) is to be constructed to feed a set of communities, the average method presents a better model to evaluate and make decisions because it gives the ability to assess the electrifying all the communities holistically as if they are a unit. On the other hand, where there already exists a substation with some communities already connected via MV lines, the rollout of electricity to new communities is better assessed through the marginal method of MV cost allocation. From the utility's perspective, the average cost gives a good estimate of what the cost will be to electrify communities at the planning



(a) Average method (b) Marginal method

(c) Average method (d) Marginal method

Figure 9. Subsidy drivers. In (a) and (b), the distributional effects are captured. On the horizontal axis a measure of the dispersion of customers within a community is shown, on the vertical axis a measure of how far from the feeder point (substation for average, either substation or MV backbone for marginal) is shown. Each point is sized to reflect the number of customers, while the colour coding indicates the subsidy level. In (c) and (d), we show the distribution of costs and revenues across transformer communities, in ascending order of subsidy level. On the positive vertical axis are proportional contributions of revenue streams that level out the negative y-axis values, which are costs. The horizontal axis represents different transformer communities.



(a) Scatter plot of MV cost as proportion of total costs for weighted method cost allocation vs marginal cost allocation method.

(b) Scatter plot of subsidy as proportion of total costs for weighted method cost allocation vs marginal cost allocation method.

Figure 10. Direct comparison of MV costs and subsidy for weighted and marginal cost allocation methods per transformer community. Each dot represents a unique transformer community.

stage, thus affording them an ability to do long term planning. In truth, electricity rollout is done in increments, starting with communities that are closer to the distribution point and growing radially as more and more remote communities get connected. Because of this, when it comes to continuing electrification projects, the marginal method presents itself as a better assessment tool, allowing short term planning which is often imposed by budget constraints.

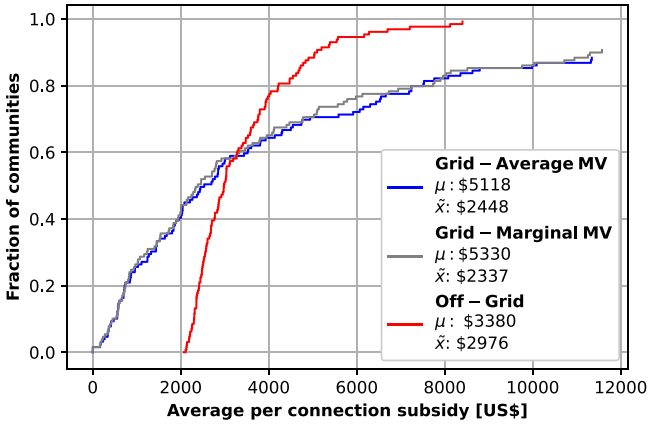
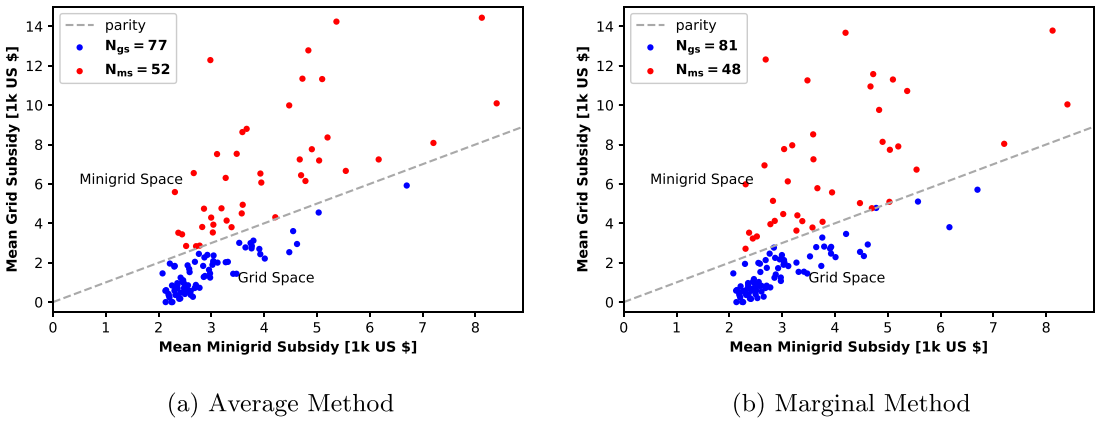


Figure 11. CDFs of grid subsidy and off-grid subsidy. The mean subsidy is lower for off-grid subsidy, and the off-grid subsidy distribution has less variance.



(a) Average Method (b) Marginal Method

Figure 12. Direct per transformer community average per customer subsidy comparisons for grid electrification and off-grid electrification. Each dot is representative of an average customer in a transformer community.

4.3. Grid subsidy vs mini-grid subsidy

We also evaluated a hypothetical minigrid subsidy in these communities by sizing and costing minigrids to supply the same amount of electricity as in the grid extension case. We assume that both technologies provide a similar level of service in terms of power quality and reliability but note that in some settings, privately operated minigrids may provide better service in both regards. The minigrid distribution network is taken to be the same as the grid LV network, but without the DT. Also, connection fee, tariff, generation cost and energy consumption were retained to be the same as those for grid. We then compare these subsidies to the grid subsidies. The figure 11 shows these benchmarks. As has already been discussed, the grid subsidy distribution is left skewed, with more communities requiring average subsidy level that is below the mean. In contrast, the off-grid subsidy distribution is less spread out, has a median that is close to the mean and approximates a Gaussian distribution as can be seen on figure 11 below.

These distributions show that there are communities that are heavily subsidized, with their levels of grid subsidy exceeding the levels that would be necessary if they were serviced by the mini-grids. Conversely, figure 12 shows the direct comparison of mean per customer subsidy for grid electrification and off-grid electrification for each transformer community. We define a borderline between grid space and mini-grid space as points of equivalence of the subsidy for grid electrification and off-grid electrification. A transformer community falls in grid space if it requires grid subsidy that is less than that of off-grid subsidy, and the converse is also true. For the transformer communities in our service area, 40% of them fall in the mini-grid space using the average MV cost allocation method while 37% fall in the mini-grid space under the marginal MV cost allocation method, as seen in figures 12(a) and (b). This means that, assuming these communities were electrified in the early 2010s, 37%–40% of the communities could have been connected at lower cost if alternatives to grid extension were considered.

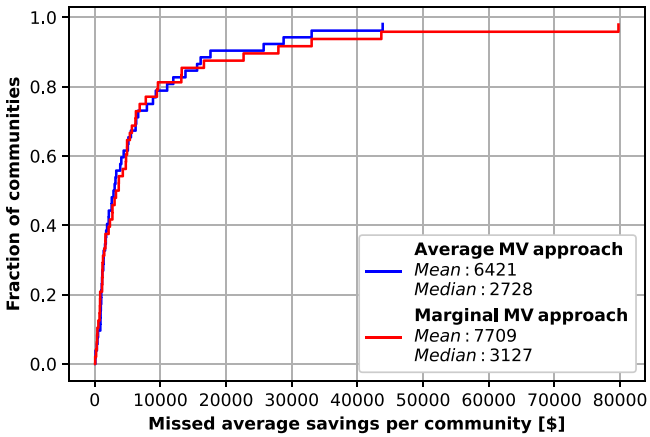
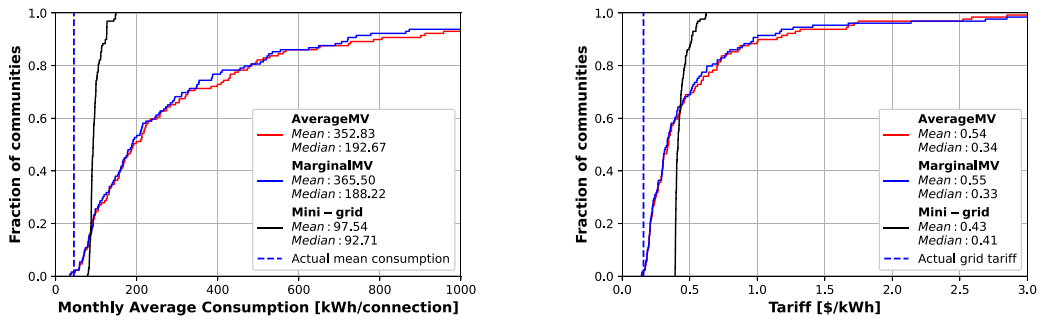


Figure 13. Missed potential savings the utility could have made per customer had it correctly electrified the regions falling under the mini-grid space with mini-grids.

We evaluated the savings that could have been made for the transformer communities that fall in the mini-grid space. A saving is the amount of subsidy that could have been saved by installing a minigrid in a community that falls in minigrid space. It is characterized by a positive difference between grid subsidy and off-grid subsidy (i.e. grid subsidy exceeds off-grid subsidy). The cumulative distribution function (CDF) shown in figure 13 quantifies these lost savings for both the weighted and marginal approaches.

From figure 13, we see that on average over a 30 years period, the utility spends 6421 US$ and 7709 US$ more per customer by extending the grid to locales for which it would be cheaper to service via off-grid electrification, under average and marginal cost allocation methods respectively. The difference of 1288 US$ is driven by an outlier in the distribution of lost potential savings for marginal cost approach. These lost potential savings averages have been computed from differing number of communities (see figures 10 and 12). From a utility's perspective, it is better to use the lost potential saving under the average MV cost allocation method because the grid is built with a philosophy of growth over time in mind so that costs could be lowered by being shared among as many customers as possible. Using the fact that these communities comprise 40% and 37% of all communities, we find that these savings would result in 50% system wide savings for the average approach and 54% for the marginal approach. Using a median 22 customers per transformer community (representative of a typical number of connections per transformer) and multiplying by number of communities and average subsidy, this results in total grid extension and service expenditure of US$14.54 million for the average method and US$15.13 million for the marginal approach for this fraction of communities it would have been least costly to electrify via minigrids. In absolute terms, this translates into savings of US$7.27 million and US$8.17 million for average and marginal approaches respectively. These show further evidence that extending the grid to these remote communities requires an enormous share of the overall subsidy. At an average per connection subsidy of US$3380 for the mini-grids, this suggests that the use of mini-grids in lieu of grid extension for these communities could have facilitated funding for a further 97 communities at the same overall cost considering average method, or 109 under the marginal approach. These represent staggering 75% and 84% increases in the rural electrification penetration rate for the average and marginal approaches, respectively. If we assume that these communities we have analysed are representative of the whole rural Kenya landscape, with a total of 44 471 grid-connected rural transformers, this number implies that about 33 353 and 37 355 more communities or, assuming the median of 22 connections per community, 733 766 and 821 810 more customers could have been electrified under average and marginal approaches respectively. With about 8 million total connections nationwide, these would result in a 9.2% or 10.2% increase in national electrification rate over the 20 years between 1995 and 2015 for average and marginal approaches respectively. This is an important finding that must be treated with caution, we cannot make a solid claim that this would hold for the reasons that follow. The statistical analysis made in this study covers a small subset of rural transformer communities in Kenya with little heterogeneity, covering a specific geographic area which we cannot make a substantive case that it is representative of all of rural Kenya. Mombasa County is a fairly urbanized county, and one can imagine that the fact that some communities in Mombasa County require subsidies, then rural communities in other more sparsely populated counties require even more. The most important aspect of the results obtained here is that they provide an important lower bound for the case study, and the methods are scalable. We wish to state at this point that these results are based off mini-grid costs of the mid-2010s. By that time, the majority of the customers in our analyses were already connected to the Kenya power grid. It is also worth considering that



(a) Distribution of monthly consumption across the transformer communities needed over 30 years for the utility to break even under the current tariff.

(b) Distribution of tariff levels across the transformer communities to ensure break even over the 30 year horizon, on the current consumption level

Figure 14. CDFs of consumption and tariff levels that would guarantee that the utility breaks even serving these rural communities.

Table 3. Consumption and tariff levels for simple payback.

	Consumption (kWh month^{-1})		Tariff ($ kWh^{-1})	
	Mean	Median	Mean	Median
Average MV	292	159	0.46	0.30
Marginal MV	302	155	0.47	0.30
Mini-grid	81	76	0.37	0.36

mini-grid costs have been falling rapidly over the last decade, thus introducing another element of uncertainty in the results. Despite this, the results provide an estimate of the magnitude of expansion of rural electrification that a more data driven reallocation of implicit subsidies could achieve.

4.4. Breakeven analysis

We evaluated the amount of electricity customers would need to use over the model horizon for the utility to break even 30 years after the connection. Figure 14(a) shows the distribution of the average per customer monthly consumption across the transformer communities necessary to ensure breakeven. On the current tariff level and cost of generation, each customer would have to use at least 353 kWh month^{-1} under the average approach and 365 kWh month^{-1} for the marginal cost approach. These are more than triple what a customer needs to use if served by mini-grid, which is 98 kWh month^{-1}. For perspective, the median monthly consumption for highest consuming rural customers is 34 kWh month^{-1} [14]. We further evaluated the tariff level that would ensure that the utility would recover costs fully over the modeling horizon, at the current consumption level and unchanging generation cost. Figure 14(b) shows distributions of tariff in $/kWh across the transformer communities. For the average cost allocation method, the average tariff is 0.54 $ kWh^{-1}, while it is 0.55 $ kWh^{-1} for the marginal method. In comparison to the mini-grid level tariff, these represent close to 20% and 22% more, with the mini-grid mean tariff at 0.43 $ kWh^{-1}. These findings are consistent with those of Levin and Thomas [24], Zeyringer *et al* [49] and Ohiare [35], who have shown that most rural customers are better off serviced via off-grid electricity systems from a financial perspective.

These consumption levels and tariff levels are prohibitively high, especially for rural consumers, whom we have shown in figure 4 do not use a lot of electricity. We acknowledge that these values are driven by the discount rate and modeling horizon, which can vary based on many factors (like borrowing currency, country, perceived risk etc). Thus, to find the minimal levels, we evaluated the simple payback (0% discount rate) consumption and tariff levels over the modeling horizon. Table 3 shows the summary of the simple payback analysis. For both grid extension costing methods and mini-grid, discounted break even consumption and tariffs are significantly higher than in the simple payback case. Thus, the higher cost of capital in most developing countries represents a huge financial burden to the utilities, which at the end of the day are unlikely to recover the cost from selling electricity services to low consuming customers.

4.5. Model consistency & accuracy

For any computational model to be practically useable, it is crucial to ensure that the results it produces are correct. We use two metrics to measure the correctness of our computational model; (1) model consistency,

Table 4. Model consistency between average and marginal MV cost allocation methods.

Condition	Consistency
$P(\text{average} = \text{grid}\|\text{marginal} = \text{grid})$	0.901
$P(\text{average} = \text{minigrid}\|\text{marginal} = \text{minigrid})$	0.917
$P(\text{marginal} = \text{grid}\|\text{average} = \text{grid})$	0.948
$P(\text{marginal} = \text{minigrid}\|\text{average} = \text{minigrid})$	0.846

Table 5. Accuracy of MV cost allocation methods in classifying communities into grid and offgrid space.

Cost allocation method	No. of minigrids	No. of upstream minigrids	Accuracy (%)
Average	52	2	96.15
Marginal	48	4	91.67

defined as the probability of the model classifying a sample (community in this case) into a particular class (e.g. grid space) using one cost allocation method given that the other cost allocation method has classified that sample into the same class and (2) model accuracy, which we define as the percentage of communities that have been classified as falling into minigrid space that do not have grid classified communities downstream on the network. Consistency $C(A, B)$ is evaluated using equation (11), where $P(A|B)$ refers to probability of event A occurring given that event B has occurred. Model accuracy A_m is evaluated using equation (12), where $n_{m,up}$ and n_m refer to number of communities classified as falling in minigrid space but have grid classified communities downstream of them on the MV network and the total number of communities classified as falling under minigrid space respectively

$$C(A, B) = P(A|B). \tag{11}$$

$$A_m = \frac{n_{m,up}}{n_m}. \tag{12}$$

Table 4 shows the model consistency results. From table 4, we see that $C(Av = g, Mg = g)$ is less than $C(Mg = g, Av = g)$. This means that the number of communities classified as falling under the grid space under the marginal MV cost allocation method exceed the number of communities classified as falling under the grid under the average MV cost allocation method. Further, this means that there is a higher likelihood that a community that is classified as falling under grid space under average MV cost allocation is also under grid space under marginal MV cost allocation method. Ideally, the consistency $C(Av = g, Mg = g) = C(Mg = g, Av = g) = 1$.

The table 5 shows the model accuracy for the two MV cost allocation methods. At accuracy scores of 96.15% and 91.67% for the average and marginal MV cost allocation methods respectively, it is shown that it is rare for the model to classify transformer communities into minigrid space while in actual fact they belong to grid space.

The model consistency and accuracy results show that if it is determined using the average MV cost allocation method that a community falls under grid space, there is an even higher probability that under the marginal MV cost allocation method that community shall also fall under grid space. This result suggests that in the planning stages of electrification, average method should precede the marginal method. This is in alignment with the grid expansion philosophy of spreading costs as the grid expands to reach more customers.

4.6. Sensitivity analysis

We evaluated the sensitivity of the percentage of communities for which grid service is a lower cost option and the savings as a percentage of total grid costs that would have been realized if communities for which mini-grids are a cheaper alternative could be serviced via them. We explored sensitivity to MV cost per metre, grid electricity generation cost and mini-grid cost by decreasing and increasing their base values by 10% and 20% to see how they affect the grid share of communities and savings. Figure 15 shows a summary of these analyses.

Savings are most sensitive to the MV cost, while the grid share of communities is most sensitive to the minigrid cost. A 10% change in MV cost for both costing methods results in close to 4% change in savings percentage. In both cases, lowering the minigrid cost by 10% also drastically lowers the grid share of the communities. Using the marginal method, a 10% decrease in minigrid cost yields 8.53% decrease in grid share of communities which is almost double the decrease realized with the average method for which the decrement value is 4.65%. Changing the MV cost by 20% changes the savings percentage by close to 8%, a suggestive of a

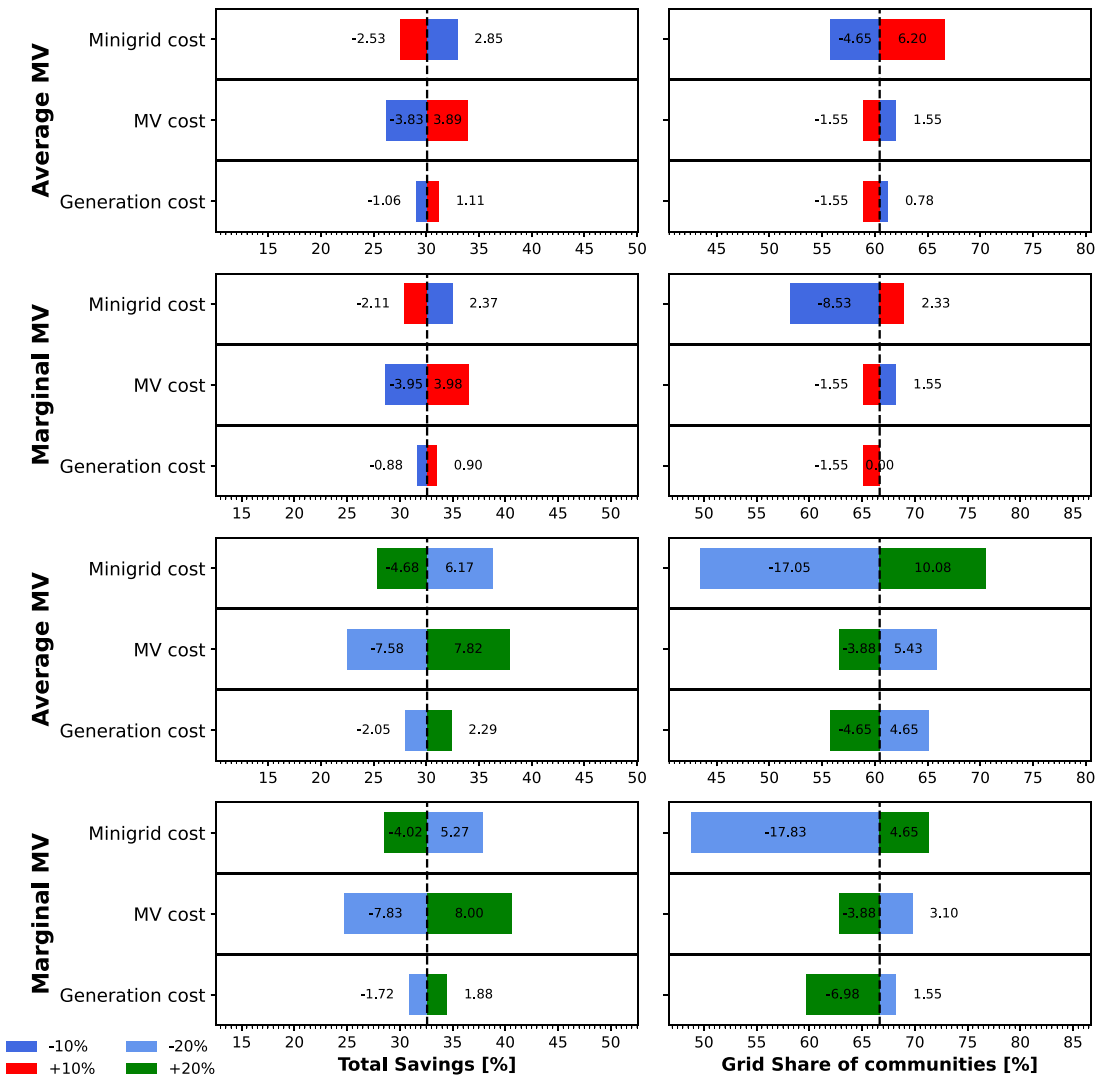


Figure 15. Sensitivity on key parameters MV cost per metre, generation cost and end mini-grid costs. These parameters are increased and decreased by 10% and 20% to see how they impact the grid share of communities and savings as a percentage of total cost. Black, dashed vertical lines mark the baseline savings and grid share.

direct proportionality of 0.4 (a 1% change in MV cost results in savings percentage cost of 0.4%). While there is a difference of almost 4% in grid share of communities when the minigrid cost is decreased by 10% for the two MV cost allocation methods, an interesting result is realized when the minigrid cost is decreased by 20%—the difference shrinks rapidly to less than 1%. This result suggests that as minigrid cost falls, it will reach a level where neither of grid expansion models shall matter because it would not make economic sense to pursue grid expansion. Minigrid costs are projected to fall significantly, therefore it is expected that the grid share will shrink further. The central grid is built with the philosophy that it must connect as many communities as possible so that costs could be shared by a large number of customers. Thus, even though falling minigrid costs result in the decreasing grid share of communities, this can only be the case until a particular threshold that is dependent on factors such as population density and consumption pattern. In this study, we acknowledge such a threshold, but only conceptualize it (i.e., we do not evaluate it). We also explored the sensitivity of the average subsidy and the fraction of the communities for which grid service is a lower cost option in figure 16. Increasing the discount rate results in an increase in both the average and median subsidy. However, the rate of growth of the subsidy decreases with increasing discount rate, hence at some point a steady state is reached. This is because an increase in the discount rate shrinks the net PV of costs and revenues, hence the subsidy. Further, increasing the discount rate results in some communities shifting out of the grid zone into the minigrid zone. This is because the mean marginal subsidy of grid extension compared to mean minigrid subsidy, evaluated as grid subsidy *minus* minigrid subsidy, grows with increasing discount rate. For the communities in our case study, the percentage of communities for which it is a least cost option to electrify via the grid is higher for the marginal MV cost allocation method than for average MV cost allocation method. This implies that there

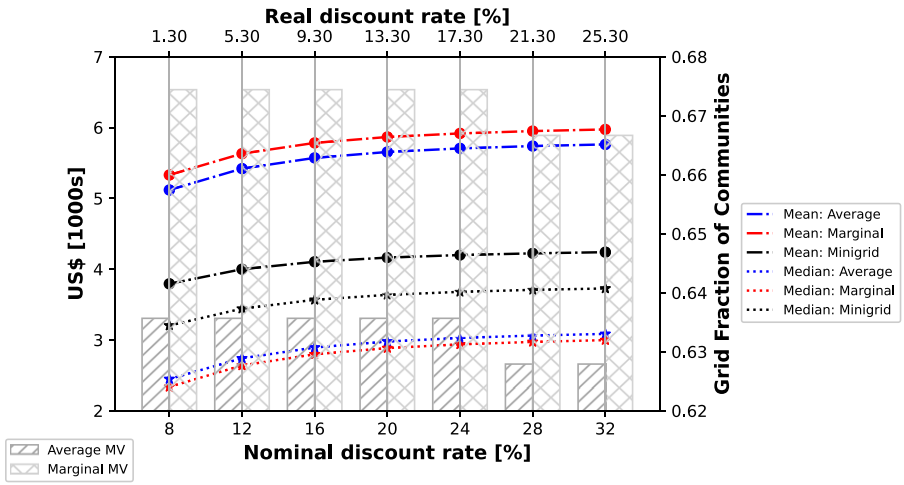


Figure 16. Sensitivity of subsidy and fraction of communities for which grid service is a lower cost option to discount rate. Line plots are for average of average subsidy across communities and median of averages across communities, while bar plots are for fraction of communities for which grid is lower cost option.

are communities which are downstream on the grid network which were connected earlier than communities upstream on the grid network, and thus get allocated disproportionately higher MV infrastructure costs.

4.7. Policy implications

The results we have presented show that by not taking advantage of using a multi model approach while extending electricity access to rural communities, instead electrifying rural communities via grid extension, utilities make huge losses. This is mainly due to low consumption levels realized from the set of customers in these communities. On the other hand, charging cost reflective tariffs is not a viable option, as these communities are low-income areas and electricity provision is often rightly considered as a social imperative by governments. In the context of the communities we studied, the benefits of taking a multi model approach to expanding electricity access are shown, as there is no *one-size-fits-all* solution. Our results further show that even the minimum consumption levels that would make the mini-grid model financially sustainable without subsidies are still too high for rural SSA dwellers. Most importantly though, the results help us to think about electricity access provision from a unique holistic perspective. We have identified that rural electrification is an expensive endeavour, an expense that is financed primarily through subsidy programs. Through careful evaluation of rural electrification of the past in Mombasa, Kenya, we show that there is an alternative way of planning electrification that depends on smart allocation of implicit subsidies which considers additional context specific factors that enable both faster and cheaper electrification mode. We show why it is crucial to consider the distribution of subsidies at community clusters rather than take averages over the entire population and document how policy makers could use the information about subsidy distributions advantageously to make electricity access expansion decisions under constrained budgets.

To reach a wider customer base at a faster rate, utilities must move on from grid-only expansion models to a larger portfolio of options that provide the same level of service. While expanding electricity access, it would be worthwhile for the utilities to consider not only the spatial distribution of the communities and their locations relative to the existing electricity infrastructure, but also factors such as the opportunities to stimulate demand for electricity and improving local economies to improve their financial sustainability. Ways of stimulating demand include but are not limited to providing electricity connection recipients with appliances that they could pay for over an extended period of time [25], and promoting productive use of electricity for the local industry.

We have argued on how to give access to electricity through which mode from a financial perspective. We acknowledge that there are other indirect and dynamic impacts that come with the choice of electrification mode which can result in unintended long term equity concerns among different communities. These include but are not limited to implications on things such as economic activity, job creation and urbanization. This is because investment toward heavy industry is more likely to go to areas with reliable electricity. However, there is no evidence that point toward access to electricity spurring rural industrialization [9, 20], and in an African context 'impact on income, education and health should be discounted considerably' [37]. In fact, according to Peters *et al* [37], because the rural African electricity users consume little electricity, they can be served adequately by low-cost solar solutions. Thus, the manner in which we map out how communities have to be connected to electricity systems promotes equity because we suggest a methodical process that ensures

that the scarce financial resources can be invested in a way that maximizes the intended output of reaching the most customers.

5. Conclusions

The objectives of this research were to (i) estimate the levels of implied subsidies that go into rural grid extension, (ii) to benchmark the grid extension subsidies against off-grid minigrids subsidies and (iii) explore opportunities to improve investment efficiency by considering allocating grid subsidies to minigrids to reach more customers. Here, we layout specific conclusions reached pertaining these objectives. The results of our analyses show that at current energy consumption rates, rural grid connected Kenyans generate far less revenue than the cost of their connections. Assuming annual real discount rate of 1.3% (8% nominal), we find the mean average per customer implicit subsidy in different communities in our sample over a 30 years time horizon to be about $5,118 and $5,330 for grid electrification depending on the chosen MV costing method, while it is $3,380 for off-grid electrification. The subsidy estimates that we calculate most likely underestimate total subsidies to both rural grid and off-grid connections. In this analysis, we have not considered soft costs, subsidies in the form of concessional finance and subsidization of grid based electricity generation. For these reasons, our results provide an important lower bound on the real cost of extending grid-based electrification in Kenya. We have also shown that utilities spend an average of $6,421 and $7,709 more per customer for weighted and marginal MV respectively by extending the grid to areas that could have been better off serviced via off-grid solutions. This translates to close to 50% and 54% of the total grid subsidy. These values will only grow if utilities continue to extend the grid to more far-flung communities. While electrification via grid extension has always required substantial upfront subsidies, sluggish growth of electricity consumption in rural SSA and the emergence of potentially less costly decentralized electrification alternatives urge an evidence-driven reevaluation of electricity access financing policies in this area. There is potential to improve the investment efficiency of rural electrification projects. Our results have shown that by servicing communities with the least cost option, 55% and 60% more rural communities could have been electrified under average MV cost algorithm and marginal MV cost algorithm respectively. Further, the results show that there could have been a 9.2% and 10.2% increase in national electrification rate over the past 25 years for weighted and marginal approaches respectively, at no additional subsidy cost.

Only a fraction of the communities in this study would have been connected at lower cost with minigrids, however the cost of subsidizing this subset is extremely high. The scarce resources that are available for electrification programs could be allocated much more efficiently if they were to be distributed in a more technology-agnostic manner. Therefore, National Electrification Plans need to look beyond least cost geospatial plans and reform electricity sector institutions to support off-grid technologies.

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Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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