Investigating the Necessity of Demand Characterization and Stimulation for Geospatial Electrification Planning in Developing Countries

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Abstract

Despite substantial progress in recent years, the global community is projected to fall short in its goal to achieve universal electricity access by 2030. State-of-the-art electrification planning models enable planners to outline pathways towards improving the economic feasibility of extending access. The studies presented in this paper employ the Reference Electrification Model (REM) to investigate the value of accurately modeling detailed demand characteristics for electrification planning endeavors. Additionally, the benefits of demand stimulation are explored. REM uses information about consumer demand, existing grid topology, network and generation components, and other features to produce detailed engineering designs of recommended systems for every consumer in an area of interest. These designs may comprise different supply technologies including grid extension, mini-grid, and stand-alone systems. In our case study, the model determines the cost-optimal technology mix to provide full electrification for a 10,914 km^2 area of Uganda with 366,946 individual consumers. These consumers are categorized into 20 consumer types. The studies presented are unique from those previously reported due to the high (consumer-level) spatial granularity, technical detail in system designs, and large areal extent of analysis. A number of contributions are made. First, the criticality of adequately estimating demand and its evolution is demonstrated for large-scale planning; notable cost and supply technology sensitivities are observed as a function of anticipated demand levels. Second, the importance of representing demand heterogeneity is elucidated via modeling a diversity of consumer types. In the "central demand case" presented, modeling demand heterogeneity results in least-cost plans that are 9% less costly than modeling assuming one single customer type. Modeling heterogeneity also decreases prescribed grid extension shares from 89% to 77%, increasing the prevalence of mini-grid and stand-alone systems. Lastly, the potential economic benefits of demand stimulation are characterized. We show how stimulating demand can lead to positive feedback loops: increasing electricity demand can lower electricity unit-costs through the realization of economies of scale and improved network utilization, which can improve the viability of additional electric loads, continuing the cycle. Specific studies comparing the economics of clean cooking via electric and liquefied petroleum gas (LPG) cookstoves show how these feedback loops can jointly benefit progress towards universal access to clean cooking and electricity. The demand assumptions modeled show that coordinated planning can reduce electricity costs by 34% and increase electric cookstove viabilities from 42% to 82%.

Keywords:
demand characterization, demand stimulation, demand forecasting, productive use of energy, energy for growth, electrification planning, clean cooking, electric cooking, universal energy access, reference electrification model

1. Introduction

The International Energy Agency (IEA) recently estimated that roughly 860 million people live without elec-

⋆This paper documents spotlights presented in IEA's World Energy Outlook 2018 [1]. Descriptions have also appeared in [2, 3].

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tricity today [4]. While this figure represents noteworthy progress from the 2016 figure of roughly 1 billion without access, there is still significant room for improvement. The IEA projects that, unless progress is accelerated, 650 million will still be left without access to electricity in 2030 [4]. While complex sociotechnical factors can hinder progress towards universal electricity access [5, 6], economic constraints predominate for the majority of cases. In 2018, the IEA estimated that achieving universal energy access by 2030 would require roughly $55 billion of investment per year, with the majority being apportioned for electricity access [1]. These expenditures are almost double the amount of investment expected [1].

"Geospatial electrification plans"[1] aim to prescribe cost-optimal and practicable mixes of grid extension, mini-grid, and stand-alone system solutions to power areas without electricity services. They can additionally guide the rollout of infrastructure over time, improve coordination among stakeholders, and provide transparency to investors [1, 7]. Because of the financial constraints mentioned previously, geospatial electrification plans are essential instruments for achieving universal electricity access in a timely manner.

The use of electrification planning models to assist in the production of geospatial electrification plans has popularized in recent years. These computer-based models employ optimization algorithms that automate parts of the engineering design process. They have shown to be particularly effective in supporting electrification planning because of the significant technical complexity associated with designing systems that can employ a diversity of supply technologies in different places with unique demand, geography, and resource characteristics. Traditional and manual approaches to engineering design generally do not scale as well as computer-based methods. While numerous electrification planning models are available [10, 11, 12], many of them have different characteristics and occupy unique niches, as elucidated by Ciller et al. [12].

Users of some of the more detailed electrification planning models are benefiting from improving data availabilities, remote sensing capabilities, and machine learning-powered inference to produce high-resolution country-scale plans. While these methods were previously limited to areas with detailed geospatial data collected via extensive surveys, they are now able to extend to larger areas as massive data sets of building locations, electrification status, productive uses, existing grid topology, and inferred demand are becoming available [13, 14, 15, 16]. Previously, only more coarse (region-level) electrification planning modeling was feasible for planning over large spatial extents due to input data limitations.

The goal of this paper is to explore the value of demand characterization and stimulation for electrification planning. Numerous accounts in the literature describe how characterizing demand is critical to electrification planning [17, 18, 19, 20, 21]; however, to our best knowledge, these accounts miss key insights that can only be appreciated when modeling at very high levels of granularity and large spatial extents.

The studies presented in this paper employ the Reference Electrification Model (REM) [12, 22] to analyze sensitivities for a 10,914 km^2 area of Uganda with 366,946 individual consumers, representing 20 consumer types. REM uses information about areas with poor electricity access to determine cost-optimal electrification modes (e.g., grid-connected, mini-grid, or stand-alone system) for each consumer, estimate costs of electrification, and produce detailed engineering designs of recommended systems. The model takes account of highly granular economic and technical detail: it considers multiple customer types with different demand profiles, individual lines, transformers, and generation assets, medium and low voltage network codes, voltage drops, solar resource availability, and even topographical and streetmap-level information if desirable [12, 22].

The studies presented are unique from those previously reported due to the high (individual consumer-level) spatial granularity, engineering design detail, and large areal extent of analysis. A number of contributions are made:

1. The criticality of adequately estimating demand and its evolution is demonstrated for large-scale planning; significant cost and supply technology sensitivities are observed as a function of anticipated demand levels. Efforts to improve methods

[1]The specific vocabulary describing a "geospatial electrification plan" is not well-defined in the planning literature. The types of individual consumer-level and large-area electrification plans modeled in this study are sometimes referred to as "comprehensive geospatial plans," and also "nationwide geospatial coverage least-cost plan[s] for implementation" and "national electrification rollout plan[s]" when extended to the country-scale [7]. They are sometimes equated to "electrification master plans," which may also go by variants including "rural electrification master plan," "national electrification master plan," "low cost rural electrification master plan," "rural electrification strategy and plan," and "national electrification plan" [8, 9]. Nevertheless, some sources differentiate between the two groups due to the level of granularity employed. "Electrification master plans" may not necessarily encompass detailed system designs in the way "comprehensive geospatial plans" do [7].

for demand forecasting are essential to prospects for right-sizing system designs. Over the domain of aggregate demand values modeled, the average cost of service provision range from \$0.13/kWh to \$0.37/kWh: a nearly three-fold difference.

2. The importance of consumer-level modeling and representing a diversity of consumer types is elucidated; using homogeneous consumer type assumptions can significantly distort costs and prescribed designs over heterogeneous representations. Improved characterizations of consumer types are shown to decrease costs and yield plans that more efficiently serve populations of interest. For the "central demand case" modeled, modeling demand heterogeneity results in least-cost plans that are 9% less costly than modeling assuming homogeneous demand. When comparing supply technology shares for cost-optimal designs, modeling heterogeneous demand decreases prescribed grid extension shares from 89% to 77%.
3. The potential economic benefits of demand stimulation are demonstrated. Mechanisms are elucidated showing how stimulating demand can lead to positive feedback loops: increasing demand can lower electricity unit-costs through realized economies of scale and improved network utilization, improve the viability of additional electric loads, and further increase demand, continuing the cycle. Specific studies comparing the economics of clean cooking via electric and LPG cookstoves demonstrate how these feedback loops can jointly benefit progress towards universal access to clean cooking and electricity through coordinated planning. The demand assumptions modeled show that coordinated planning can reduce electricity costs by 34% and increase electric cookstove viabilities from 42% to 82%.

2. Case Study: the South Service Territory in Uganda

According to the World Bank, Uganda had a 22% electrification rate in 2017 [23]. As a result, universal electricity access in Uganda is seen as a major national priority. The country split into 13 electric service territories. The study region modeled in REM comprises the majority of current and potential consumers across one of them: the South Service Territory (SST). The SST covers the districts of Masaka, Rakai, Isingiro, and Ntungamo, with electrification rates of 37%, 15%, 11%, and 12%, respectively, according to the Uganda 2014 Census [24]. The case study that the following analyses are based on was originally produced and compiled by the MIT-Comillas Universal Energy Access Lab in partnership with German Corporation for International Cooperation GmbH (GIZ) in support of master electrification planning and mini-grid project evaluation across the territory.

3. Methods

The studies that will be presented employ REM and make a number of general assumptions when analyzing cost-optimal plans for the SST. Detailed accounts of the methods employed in REM are provided by Ciller et al. and the MIT-Comillas Universal Energy Access Lab in [12] and [22], respectively. Although REM has the ability to account for topography when designing electrification plans, it is omitted in these analyses because this region is mostly flat, it does not affect the conclusions of this study, and disabling this feature improves computation times. Lastly, diesel generation is not employed as an option in these studies; mini-grids and stand-alone systems are powered exclusively using solar generation and battery storage options. This modeling decision conforms to specifications of the original SST study in REM and relates to area-specific ambitions for low-carbon electrification.

The buildings across the SST were identified using satellite imagery from the Google Maps API and a convolutional neural network for semantic segmentation

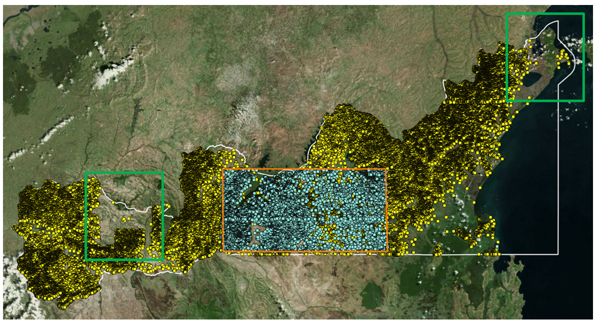


Figure 1: Buildings identified in the Uganda South Service Territory (SST). An image showing a basemap with the SST border (white outline), building locations from deep learning-based building extraction (yellow points), a sub-area with manual corrections (orange outline), and building locations from German Corporation for International Cooperation GmbH (GIZ)-led manual building identification efforts (blue points). Note that building points are fully missing in regions where high quality satellite imagery was not available (green outlines).

with human-based manual corrections. 366,946 individual consumers were identified, as shown in Fig. 1. Some consumers were not accounted for due to incomplete satellite image coverage for the service territory. The supplement for this working paper enumerates the assumptions that were used in the base model, including the network and generation component catalogs that were employed in REM, financial modeling assumptions, and other key parameters.[2]

While some parts of the SST are already electrified, it is assumed that all buildings are non-electrified in the following experiments in order to observe the full effects of the demand assumptions made on cost-optimal plans. Georeferenced data representing the existing medium-voltage (MV) grid was shared by partners at the Rural Electrification Agency of Uganda (REA).

Solar irradiance data is estimated using the National Renewable Energy Laboratory's PVWatts tool [26, 27] in order to describe the generation potential of solar resources in the territory. Because PVWatts data was not available in the SST, historical PV performance data is used for Mombasa, Kenya, which is assumed to have adequately similar solar irradiance characteristics for modeling purposes.

4. Why estimating demand and its evolution deserves more attention

Demand forecasting is the process of projecting how a population's explicit and latent demand will evolve into the future. Calculating demand functions is a non-trivial task and forecasting their evolution can be even more difficult. A recent review paper by Riva et al. categorizes 85 studies that pertain to long-term electricity and thermal energy planning [28]. The authors classify demand forecasting methods for developing countries as belonging to one of five categories: "fixed demand," "arbitrary trends," "extrapolation," "input/output," and "system dynamics" [28]. Each has drawbacks for use in support of high-resolution and large scale electrification planning. Additionally, since data constraints are ubiquitous for electricity demand forecasting in developing countries, it is often common to rely on non-local data to construct plausible demand scenarios. In this section, we argue that this problem deserves more consideration by showing how forecasting demand may be critical to efforts for right-sizing infrastructure development programs. Section 5 investigates a related but different dimension of the problem: the importance of modeling demand heterogeneity.

The demand scenarios employed in this section and Section 5 should be contrasted up-front. For this purposes of paper, we define demand heterogeneity as variability in the demand profiles modeled for the consumers of interest. In contrast, demand homogeneity assumes that there is only one consumer type: all consumers are assumed to have the same demand profile. In this section, we assume heterogeneous demand types for all the cases modeled. In Section 5, these cases are contrasted with those assuming homogeneous demand.

4.1. Modeling Assumptions

While electricity demand for any one consumer is theoretically a function of price, reliability, individual preferences, available productive uses of energy, historical consumption, precise time and day of the year, and other factors, we make a number of simplifications in order to make electrification modeling straightforward and tractable. For every consumer and for every hour of a full year, two types of demand are modeled in REM: critical and regular demand. Each type of demand is assumed to have a different cost of non-served energy (CNSE), with the CNSE of critical demand set to a per-kWh value higher than that of regular demand. REM then takes account of the specified demand profiles and CNSE values in order to prescribe designs for supply infrastructure that minimize the sum of these social costs with the explicit costs of service provision.

Consumer type	Number of consumers modeled in region	Demand multiplier for low case	Demand multiplier for central case	Demand multiplier for high case
Cell office	271	8.98	32.08	79.55
Coffee washing station	29	6.74	24.06	59.66
Health center	91	8.08	28.87	71.60
Health post	11	4.49	16.04	39.78
Large market	10	58.38	208.50	517.08
Small market	65	35.93	128.31	318.20
Irrigation pumping	5	13,472.53	48,115.44	119,325.86
Milk collection center	10	6.29	22.45	55.69
Mining	16	112.27	400.96	994.38
Preprimary school	96	1.80	6.42	15.91
Primary school	259	1.80	6.42	15.91
Secondary school	213	5.84	20.85	51.71
Sector Office	67	6.29	22.45	55.69
Tea Factory	2	17,065.21	60,946.23	151,146.10
Technical Schools	7	116.76	417.00	1,034.16
Telecom Tower Type 1	45	1,257.44	4,490.77	11,137.08
Telecom Tower Type 2	47	1,257.44	4,490.77	11,137.08
Universities and Institutes	18	583.81	2,085.00	5,170.79
Water pumping stations	16	179.63	641.54	1,591.01
Residential	365,668	0.28	1.00	2.48

Table 1: Heterogeneous consumer type information. For each of the 20 consumer types modeled, this table shows the number of consumers modeled in the SST and corresponding demand multipliers over the basic demand profile shown in Fig. 2 for the low, central, and high demand cases.

[2]This work was published in [25]; however, document is not publicly available as of the time of writing

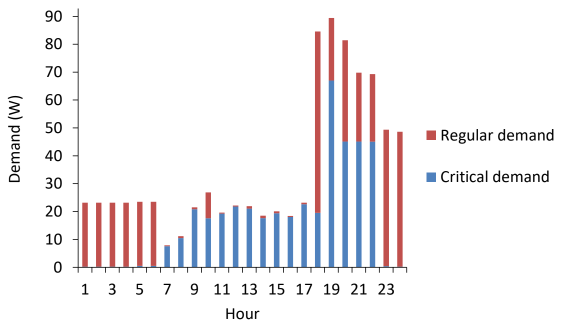


Figure 2: The base demand profile. The base demand profile shown corresponds to a residential consumer in the heterogeneous central demand case. Note that critical and regular demand is differentiated.

There are two steps required to define demand profiles for the consumers considered in REM. The first is to specify a basic hourly demand profile or pattern spanning a full year, and the second is to optionally specify a nonnegative scalar multiplier to be applied to this basic profile to proportionally increase or decrease demand values at every hour of the year.

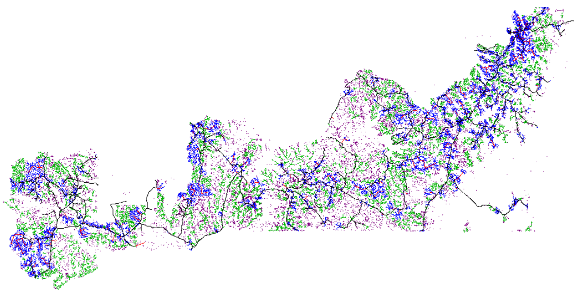
In the experiments described in this section, one base demand profile was specified for all of the consumers modeled, shown in Fig. 2. This base pattern was computed by taking time series data of hourly aggregate consumption for the agricultural village of Karambi in Rwanda and scaled to match the total energy demanded annually by a typical residential consumer in the "central case with heterogeneous demand," which will be described shortly. Because Karambi has residential loads, a school, health center, bank, government buildings and shops, using its demand profile may be considered a reasonable composite for the types of profiles found in other rural parts of East Africa. Additional information about the base demand profile can be found in [29, 30]. Because appropriate data on the effects of seasonality on basic demand profiles was not available, the basic profile described was used for every day of the year modeled in REM.

Critical and non-critical shares for this base demand profile were differentiated by applying expert-validated logic for determining which hours are critical and not critical for individual consumer types. For instance, every hour of health center demand is considered critical; residential demand is only considered to be critical in the evening hours; and school, government building, and shop-related demand is considered critical during the day. Differentiated critical and non-critical demand values are summed across all consumer types. For each hour, critical shares are computed as the fraction of aggregated critical demand in Karambi over the village's total demand.

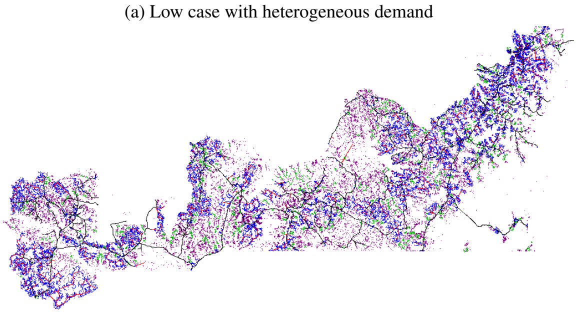
Demand heterogeneity is modeled using 20 multipliers, one for each consumer type analyzed, as reflected in Table 1. The same base demand profile is applied to each consumer type before accounting for the multiplier. Though it is certain that the various consumer types modeled have different relative demand patterns from the base profile chosen, constraints on data availability and the fact that the base pattern reflects a composite of residential and non-residential East African consumers justified the modeling decision. The multipliers and the number of consumers for the consumer types shown are derived from a data set shared by Rwanda Energy Group Limited (REG) Energy Development Corporation Limited (EDCL) across the country of Rwanda [31]. The data set provides frequencies of these various consumer types and peak demand values for each type. Relative multipliers for the different consumer types in the SST case study are computed in accordance with relative levels of peak demand from the Rwanda data set. The implicit assumption that all consumer types have the same load factor may be reasonable since likely load factor variations would only cause minor distortions. Additionally, while data sets on Rwandan consumers are certainly different from those that would be most appropriate to our Uganda SST case study, they are assumed to be acceptable proxies in the absence of better information. Each of the 20 consumer types are spatially distributed across the Ugandan SST in a random manner following a multinoulli distribution. The parameters of the distribution specifying the probabilities of each of the 20 possible consumer types were simply set to the empirical share of the consumer types from the Rwanda data set. In essence, the multinoulli distribution reflects a 20-sided die, each side of which is weighted and represents a single consumer type; this die is rolled once for each consumer, dictating its type. Although the Uganda SST and Rwanda have different characteristics in reality, it is assumed that their respective distributions of consumer sizes and frequencies of occurrence are similar enough to provide these experiments with an adequate level of realism.

4.2. Analysis

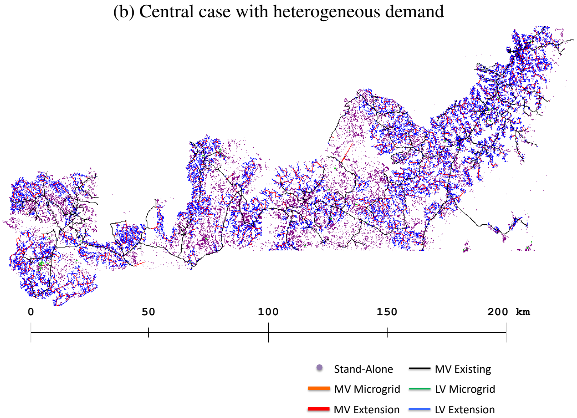
Demand growth in the real world is a phenomenon with intrinsic uncertainty. Forecasting demand for any population at any future date with very high accuracy is typically infeasible, though on-going research in the planning community is aimed at making improvements to current forecasting methods. Because of this uncertainty, we try to appreciate the value of demand forecasting improvements by modeling three cases that are designed to target aggregate demand levels within a reasonable range of what a planner may consider. We show sensitivities to aggregate demand in cost-optimal planning under heterogeneous demand assumptions by modeling a "low case," "central case," and "high case" with annual aggregate demand levels of 103 GWh, 369 GWh, and 915 GWh respectively. Demand multipliers for various consumer types across these cases are summarized in Table 1; it can be noted that multipliers across customer types are higher for demand cases with higher



(a) Low case with heterogeneous demand



(b) Central case with heterogeneous demand



(c) High case with heterogeneous demand

Figure 3: Prescribed system designs featuring grid extension, mini-grid, and stand-alone systems. These cases use the heterogeneous consumer type assumptions reflected in Table 1. Key metrics for these different runs are provided in Fig 5

aggregate demand.

Demand multipliers for residential and commercial & industrial (C&I) consumer types were computed differently from one another. Residential demand values were scaled in accordance with empirical consumption data for newly electrified consumers in Kenya. Monthly demand for a residential consumer under the "low case," "central case," and "high case" are 7.1, 25.3, and 62.8 kWh, respectively. These values roughly match median consumption values observed by grid-connected consumers in Kenya at 0.25, 1, and 10 year time spans from initial connections as presented by Fobi et al. [32]. Assuming demand growth in Uganda may progress similarly to how consumption growth has proceeded in Kenya, the 0.25 to 10 year time horizons chosen may be considered to be reasonable bounds on the domain of residential demand values modeled.

Demand multipliers for C&I consumer types are calculated differently than those for residential consumers in these three cases. A linear relationship between residential and C&I consumption per capita for all of Kenya was discerned using country-level data from the IEA's World Energy Statistics database [33] and the World Bank's World Development Indicators data set [23] between 1971-2012 as shown in Fig. 4. Per capita values are used instead of aggregate ones to mitigate the effects of potential nonstationarities from population growth.

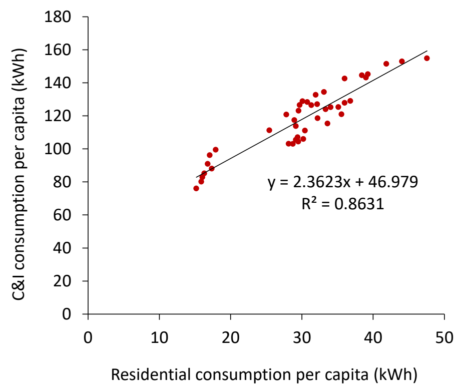


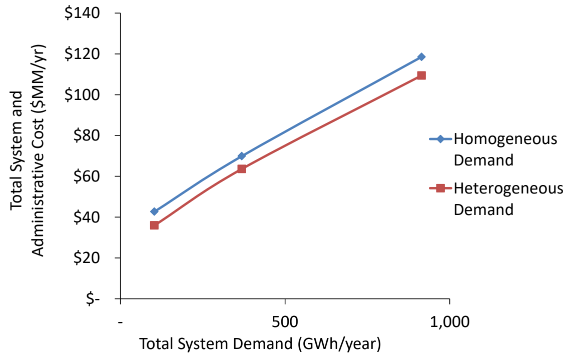
Figure 4: Historical relationship between residential and commercial and industrial (C&I) consumption in Kenya. Aggregate country-level statistics from the IEA's World Energy Statistics database [33] and population data from the World Bank's World Development Indicators data set [23] are used to understand the relationship between residential and commercial consumption in Kenya. Each point on the scatterplot represents residential and C&I consumption per capita for a single year between 1971-2012. This relationship is used as a proxy for how C&I demand could reasonably develop in the Uganda SST for the three demand cases defined.

Given aggregate levels of residential demand for the three cases as defined in the preceding paragraph, aggregate C&I demand figures are determined following this learned function. It is assumed that the historical relationship between residential and C&I consumption in Kenya can serve as an adequate proxy for that between residential and C&I demand in the Uganda SST.

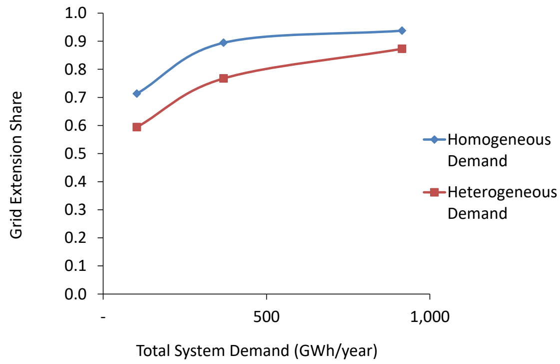
4.3. Results and Discussion

Independent consumer-level electrification plans were designed using REM for the low, central, and high cases described. Geospatial maps of the different runs are shown in Fig. 3 showing qualitative changes to the prescribed designs as demand increases. Fig. 5 communicates key metrics from these plans more concretely. For this section, we will only discuss general trends for the heterogeneous cases (the red curves in the figures). Fig. 5a depicts how total system and administrative costs increase with increasing total system demand and follow a nearly linear relationship. While this should be expected, understanding the general shape of this relationship is critical to right-sizing planning. Underestimating demand leads to more non-served energy and lower reliability levels, undermining potentials for economic growth. Over-estimating demand can lead to unnecessary expenditures and underutilized infrastructure. Fig 5b reinforces this finding, as it shows how the ratio of grid-extensions to mini-grids and stand-alone systems can change by tens of percentage points over the modeled range of demand cases. Large demand forecasting errors can change the supply technology pathways planned for large shares of a population. Although planners may have the ability to make adjustments, such forecasting errors are likely to precipitate the need for costly reactive measures.

Fig 5c reflects the economies of scale that impact per-kWh system costs. The explicit costs of service provision decrease significantly as demand grows: the average cost in the central case is half that in the low demand case at \$0.18/kWh and \$0.37/kWh, respectively. These effects weaken, however, as demand continues to increase. The average cost of the high demand case only falls to \$0.13/kWh. These trends reveal part of how beneficial it can be to stimulate demand for electricity, especially if demand is initially very small. Increasing demand can improve the affordability of electricity services for the system as a whole. Section 6 investigates the benefits of stimulating demand further. Furthermore, lower per-unit electricity costs can help accelerate development. Adequately characterizing the economies of scale associated with increasing demand



(a)



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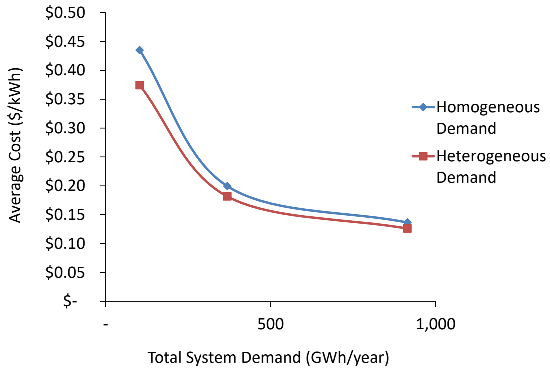


(c)

Figure 5: Cost and grid share sensitivities for various demand cases across heterogeneous and homogeneous consumer type assumptions. The analyses presented in Section 4 only discuss the general trends shown in the heterogeneous cases. Section 5 contrasts both heterogeneous and homogeneous cases. (a) As demand increases, total system and administrative costs increase nearly linearly. (b) As demand increases, the share of consumers prescribed grid extension-based supply increases as well. Homogeneous demand assumptions bias plans towards higher costs and high grid extension shares. (c) Finally, average costs per kWh of electricity served show significant economies of scale.

can be instrumental to endeavors around planning for infrastructure and development.

5. Why consumer-level modeling and characterizing demand heterogeneity is needed

Many of the published approaches to large-area electrification planning aggregate consumers spatially when performing analyses at the region-level. As a result, they ignore consumer-level characteristics. While aggregate analyses can provide value and have numerous advantages in terms of improved input data availability, the simplifications they make inhibit their utility for detailed system design. Furthermore, even when consumer-level electrification planning models are used, they are sometimes employed to assume that all consumers are of the same "type," with one single demand profile and level of annual demand[3]. When these assumptions are made, it is likely because more granular demand data is unavailable at high spatial resolutions. A review of planning models and the methods they employ is provided in [12].

5.1. Analysis

The importance of characterizing demand heterogeneity is demonstrated by contrasting the difference in key metrics of cost-optimal plans for the Uganda SST designed when modeling with homogeneous and heterogeneous demand assumptions. The same low, central, and high demand cases are used as those described in Section 4.2, demonstrating the sensitivities of cost-optimal designs to total system demand. The three cases previously discussed employ multipliers for 20 consumer types as described in Table. 1. These cases will now be designated the "low case with heterogeneous demand," "central case with heterogeneous demand," and "high case with heterogeneous demand." These cases are contrasted with three new homogeneous demand cases, each of which are constrained to have the same total system demand as one of the previous three, but only have one composite consumer type modeled. We refer to these cases as the "low case with homogeneous demand," "central case with homogeneous demand," and "high case with homogeneous demand," and their demand profile multipliers are provided in Table 2. As with the heterogeneous cases, the homogeneous cases reflect annual aggregate demand levels of 103 GWh, 369 GWh, and 915 GWh respectively.

[3]To the authors' best knowledge, REM is the only consumer-level electrification planning model that can be employed at large scales [12, 22]

Consumer type	**Number of consumers modeled in region**	**Demand multiplier for low case**	**Demand multiplier for central case**	**Demand multiplier for high case**
Aggregated	366,946	0.94	3.35	8.31

Table 2: Homogeneous consumer type information. In the homogeneous case, only one aggregated consumer type is modeled per case. Demand multipliers are based on the basic demand profile shown in Fig. 2.

5.2. Results and Discussion

As in Section 4, the key metrics evaluated for the case studies presented include total system and administrative cost, grid extension share, and average cost per kWh of demand, as shown in Figs. 5a, 5b, and 5c, respectively. In this section, the comparison of interest pertains to the blue and red trend lines, contrasting homogeneous and heterogeneous demand assumptions. It should be noted that while the general trends for each series are similar, systematic shifts in these key metrics are observed. When comparing the total and average costs, as in Fig. 5a and Fig. 5c, modeling more granular types of demand decreases costs relative to cases under the homogeneous demand assumption. For the central demand cases in particular, modeling demand heterogeneity results in least-cost plans that are 9% less costly than modeling assuming homogeneous demand. When comparing the supply technology shares of these cost-optimal designs for the central case as in Fig. 5b, heterogeneous demand types decrease prescribed grid extension shares from 89% to 77%.

Our analyses demonstrate that failing to account for demand heterogeneity at the consumer-level for large-scale and cost-optimal plans can potentially distort plans in significant ways. The homogeneous demand assumption biases designs towards higher grid shares and costs. This results in large part from the fact that such an assumption effectively blends C&I and residential consumers into a single composite consumer type. While this assumption keeps demand distributed in ways consistent with average demand across the homogeneous and heterogeneous demand cases and in both urban and rural areas, the assumption contrasts significantly with the power law-distributed demand types (reflecting few consumers with very high demand, many consumers with low demand, and some in between) represented by the heterogeneous cases, as reflected in Table 1.

To understand the distortive effects of modeling homogeneous demand, consider a hypothetical example with a number of non-electrified rural villages. Each of these villages has equal land areas, consumer densities, and distances to the existing grid. In the heterogeneous case, most of these hypothetical villages will only have consumers with very low latent demand: the consumers may be mostly residential with perhaps a school and a health center. The small remainder of these villages may have very high demand, with the vast majority coming from one or a few massive-demand consumers: a tea factory, telecom tower, or farm employing large-scale irrigation. The many low-demand villages are much more likely to be cost-optimally supplied with mini-grids and stand-alone systems while the few high demand villages are much more likely to be supplied by extensions to the main grid. Because there are many fewer high-demand villages than low-demand villages, the overall grid-extension share will be low. Now, consider the homogeneous demand case where we assume that all consumers in each of these villages have the same medium-level of demand. Since we are now effectively distributing demand from the few massively-demanding tea factories, telecom towers, and commercial farms across all villages in our example, demand will rise significantly for villages that were low-demanding in the heterogeneous case. Such a large increase can change the cost-optimal mode of supply from mini-grid and standalone-systems to grid-extensions, necessitating higher infrastructure costs. As a result, the share of grid-extensions and total and average costs in cost-optimal planning can be inferred to rise. The phenomena described by this thought-experiment is directly observed when analyzing results for the consumer-level designs produced by REM. While other complexities may also affect the designs ultimately produced, the underlying observation is that cost-optimal plans can demonstrate significant sensitivities to spatial characterizations of demand heterogeneity.

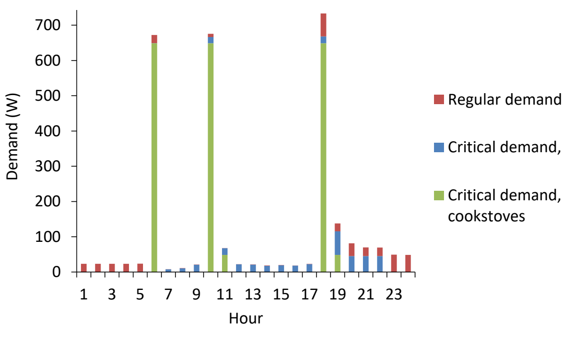


Figure 6: The demand profile for residential consumers with electric cooking. This alternative demand profile corresponds to a residential consumer that has adopted electric cooking. Critical demand increases significantly for three hours out of the day

6. How coordinated clean cooking and electrification planning can yield significant co-benefits and why demand stimulation pays dividends

In this section, demand stimulation using electric cookstoves is explored to investigate techno-economic pathways towards the joint achievement of universal electricity access and universal access to clean cooking solutions. Although the topic of clean cooking is complex and involves cultural and behavioral challenges (e.g., it may be difficult to prepare some traditional foods with electric cookstoves, etc.) [34, 35], techno-economic dimensions to the problem are still important to explore. This is especially true considering that there are 2.7 billion people without access to clean cooking solutions. Furthermore, under current and planned policies, the number of people without access is expected to be 2.2 billion in 2030, with significant impacts on health, environment, and gender equality [4]. There is much to be said about the potential for electric stoves to displace solid fuels and compete with LPG-powered options. In 2018, the IEA reported that around 1.7 billion of those without access to clean cooking have some sort of electricity connection [1]. Urban markets in some countries, including India, already have a mature market for electric induction stoves. Furthermore, electric-powered appliances including pressure cookers, rice cookers, and insulated pots may be preferable for more specialized cooking-related loads [1, 36].

The studies presented in this section aim to isolate just the techno-economic dimensions of choosing between alternatives for clean cooking fuels and technologies. To demonstrate the synergistic effects of clean cooking and electrification goals, the Uganda SST REM base case is used. A new demand profile is introduced for residential consumers who cook meals exclusively with electric cookstoves, and REM sensitivities are analyzed showing the effects of demand from different penetrations of electric cookstoves on cost-optimal electrification designs. Analyses are subsequently presented that characterize the economic viability of clean cooking solutions assuming that each residential consumer is constrained to choose between adopting electric- or LPG-powered cookstoves.

Although the benefits of cooking with electric stoves are central to the analyses presented [37], more general effects are demonstrated concerning electricity demand stimulation and how notable positive feedback effects can result from it.

6.1. Analysis

The analyses in this section build off of the "central case with heterogeneous demand," initially described in Section 4. In this case, 20 consumer types are distributed throughout the Uganda SST as shown in Table 1. The key difference between runs for this section and the "central case with heterogeneous demand," is the modeling and implementation of one additional consumer type: residential households that have adopted electric cookstoves. The demand profile for this consumer type is shown in Fig. 6, representing the same basic demand profile shown in Fig. 2, but with additional critical demand from electric cooking for five hours of the day. These modeling assumptions reflect a conservative level of demand from electric cooking, as expounded upon in the supplement.

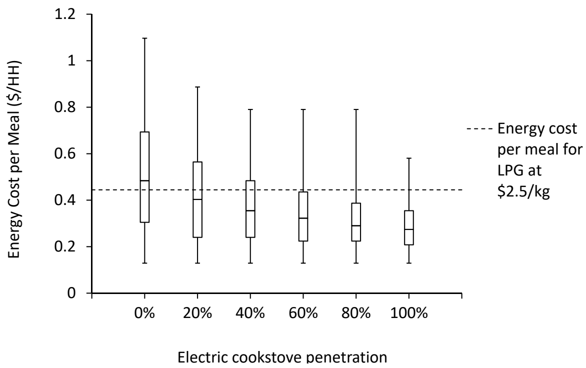
Five additional REM cases are modeled for these cooking analyses. The "central case with heterogeneous demand," reflects electrification planning assuming there is 0% electric cookstove penetration; additional cases with 20%, 40%, 60%, 80%, and 100% electric cookstove penetration are modeled, assuming that electric cookstoves are distributed randomly across the residential population of interest.

After modeling REM cases with a full range of electric cookstove penetrations, analyses are performed to investigate the economic viability of electric cookstoves assuming universal access to clean cooking solutions is achieved in addition to universal electricity access. The most salient assumption in these analyses is that clean cooking can only be brought about using electric or LPG-powered cookstoves and that LPG prices are \$2.5/kg across the study region. Since the fixed costs of these two different cookstove options are similar, only the energy costs are compared in these analyses. While numerous clean cooking technologies have been developed including solar and biogas stoves, the analyses were constrained to LPG and electric cooking solutions as these technologies have the greatest potential to scale and serve the majority of consumers.

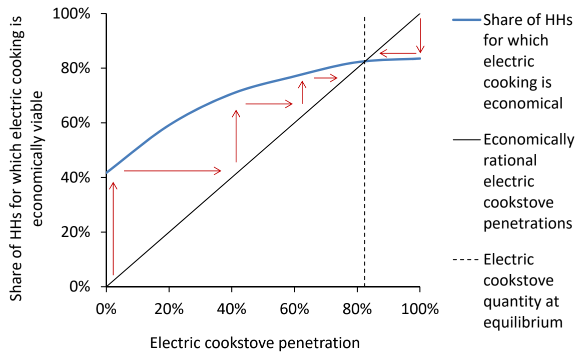
6.2. Results and Discussion

The results of analyzing REM cases with various levels of electric cookstove penetration are summarized in Fig. 7. Fig. 7a shows a boxplot depicting the distribution of energy costs per meal using electric cookstoves as a function of electric cookstove penetration. The figure shows that as electric cookstove penetrations increase, the distributions of energy costs per meal for electric cooking shift downward due to economies of scale and economies stemming from increased utilization of discrete network investments. As the distribution shifts with each subsequent increase in electric cookstove penetration, it can be observed that greater and greater shares of households are more economically served with electric-powered cookstoves than by LPG-powered ones.

The comparisons of energy costs per meal from electric- and LPG-powered cookstoves enable calculation of the share of residential households for which



(a)



(b)

Figure 7: Positive feedback from demand stimulation via electric cooking showing the benefits of coordinated planning. (a) As electric cookstove penetrations increase, the distributions of energy costs per meal for electric cooking shift downward due to economies of scale and economies stemming from increased utilization of discrete network investments. The boxplots depict the minimum, first quartile, median, third quartile, and maximum energy costs per meal using electric cookstoves, and the dotted line reflects the energy cost per meal assuming LPG is employed with a market price of \$2.5/kg. (b) Assuming that LPG costs are a constant \$2.5/kg, the share of households for which electric cooking is economically viable over LPG-powered cooking is calculated. As more electric cookstoves are adopted, electricity prices for cost-optimal plans fall and electric cooking becomes viable for more households.

electric cooking is economically viable. Energy costs per meal from electric-cooking are calculated for every consumer modeled in REM given costs for electricity, the efficiency of electric cookstoves, and the energy required to cook two and a half meals each day, as described in the supplement. It is reasoned that electric cooking is viable if the energy costs per meal from electric cooking are lower than those for LPG-powered cooking. Using these energy cost-based comparisons, the shares of residential households for which electric cooking is economically viable over LPG-powered cooking is computed as a function of electric cookstove penetration and displayed by the blue line in Fig. 7b. An interesting comparison can be made between the blue line and the reference line in black, the latter of which shows economically rational electric cookstove penetrations. The assumption of rationality reflects the fact that electric cookstove penetrations should be equal to the share of households for which electric cooking is economically viable. If electric cookstove penetrations are lower than this share, then some consumers that are recommended LPG-powered cooking could cook more cost-effectively with electric solutions, and costs could be decreased by increasing electric cookstove penetrations. The reverse is also true: if electric cookstove penetrations are higher than the share of households for which electric cooking is economically viable, some consumers recommended electric cooking solutions would save by switching to LPG-powered solutions. Costs could be decreased by decreasing electric cookstove penetrations. Because of the characteristic shape of the blue curve in Fig. 7b, positive feedback effects may be discerned. At 0% electric cookstove penetration, electric cooking is economically viable in 42% of residential households. A Pareto improvement can be made by naively increasing electric cookstove penetrations to the 42% of households for which electric cooking is less expensive than LPG-powered options. When this is done, however, demand for electricity increases, the economies of scale in electricity provision and economies stemming from increased utilization of discrete network investments cause electricity prices to fall, and the share of households for which electric cooking is economically viable actually increases. This effect reflects a positive feedback loop of increasing electric cookstove penetrations, falling electricity costs, and greater demand for electric cookstoves. Fig. 7b shows that this positive feedback loop can continue until Pareto optimality with an equilibrium share of 82% electric cookstove penetrations.

The analysis presented demonstrates how there is promise for coordinating planning endeavors around universal electricity access and clean cooking goals. Without coordinated planning, it is conceivable that systems for universal electricity access are planned assuming that no additional demand for electric cooking persists; a planner may assume that clean cooking might not be achieved in a reasonable time frame or that LPG stoves would predominate. Such independent or uncoordinated planning around clean cooking and universal electricity access results in cost-optimal plans reflecting 42% electric cookstove viability and \$0.51 average electricity costs per household meal. On the other hand, coordinated planning accounts for positive feedback effects from electric cooking-related demand stimulation, and results in plans with 82% electric cookstove viability and \$0.33 average electricity costs per household meal.

While the results presented demonstrate how coordinated clean cooking and electrification planning can yield significant co-benefits, it more generally reflects how demand stimulation can have profound effects on prospects for the provision of affordable electricity.

7. Conclusions

This paper uses large-scale, high-resolution electrification modeling to demonstrate "why estimating demand and its evolution deserves more attention" in Section 4, "why consumer-level modeling and characterizing demand heterogeneity is needed" in Section 5, and "how coordinated clean cooking and electrification planning can yield significant co-benefits and why demand stimulation pays dividends" in Section 6. Changes to aggregate demand assumptions and the characterization of how these demands are distributed geospatially can have outsized effects on both the contents of electrification plans and projected costs for achieving universal energy access. Improving georeferenced demand forecasts can help planners to 'right-size' infrastructure designs and lower risks associated with under- or overbuilding energy systems. Average per-kWh costs under the central demand case with heterogeneous consumer types were 51% lower than those under the corresponding low demand case. Additionally, plans considering demand heterogeneity resulted in 9% lower costs than those employing a single, homogeneous consumer type. Section 6 goes further to show that coordinated clean cooking and electrification planning can yield significant co-benefits. Positive feedback loops of increasing electric cookstove penetrations, lower electricity costs through economies of scale and economies stemming from increased utilization of discrete network investments, and increasing electric cooking viabilities can have significant effects on lowering per-unit costs and expanding access to clean cooking solutions. The demand assumptions modeled show that coordinated planning can reduce electricity costs by 34% and increase electric cookstove viabilities from 42% to 82%. These same effects are characteristic of demand stimulation more generally, and demonstrate the significant potential benefits of electrifying other economic sectors including agriculture and transportation. As better data becomes available, more attention should be paid to improving methods for demand forecasting. While the geospatial electrification modeling community has recently made significant advances in large-scale and highly granular planning [12, 22], sensitivity analyses demonstrate that much of the potential benefit from such methodologies can only be realized provided better capabilities around characterizing demand, forecasting its evolution, and determining ways to stimulate its growth.

8. Ongoing and Future Work

While the version of REM used in this work can be considered state-of-the-art for large-scale and high-resolution electrification planning models, ongoing and future work is aimed at improving modeling methodologies relevant for this research. The most important methodological improvement pertains to how REM is currently treating aggregated 'cluster-level' demand as the sum of corresponding individual demands. This implies that coincident factors are not properly applied when designing distribution networks. Ongoing work is directed towards better modeling the aggregation of individual demand profiles.

Additional improvements are planned around developing metrics for the total costs of over- and underplanning system designs, improving representations of the spatial distributions of consumer types, and increasing the number of basic demand profiles modeled in order to improve the realism of modeling a variety of consumer types.

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