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A longitudinal study of electricity consumption growth in Kenya

Simone Fobi[a], Varun Deshpande[b], Samson Ondiek[c], Vijay Modi[a], Jay Taneja[b,*]

[a] QSEL Lab – Department of Mechanical Engineering, Columbia University, New York, United States
[b] STIMA Lab – Department of Electrical and Computer Engineering, University of Massachusetts, Amherst, United States
[c] Business Strategy, Kenya Power, Nairobi, Kenya

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ABSTRACT

During the past 5 years, electrification in Kenya has grown by more than 30% due primarily to increases in grid penetration and solar home systems. This represents a way forward for governments, international finance institutions, and entrepreneurs to address some of the challenges of energy access. However, little is understood about how consumption has evolved among these newly-electrified customers. In this paper, we address this by conducting a longitudinal analysis for 136k utility customers across Kenya over six years of electricity bills, uncovering critical trends in spatio-temporal evolution of electricity consumption. Our analysis reveals that recently-electrified customers are reaching their steady-state consumption more quickly than previous customers, that the steady-state is increasingly less, and that typical urban and peri-urban customers tend to consume 50% more electricity than rural customers. In addition we present implications for policymakers and electricity planners considering grid extension and distributed systems for improving electrification.

1. Introduction

Developing countries regularly make critical decisions on how to allocate precious public-sector resources to increase electricity access, often with little evidence. Governments, finance institutions, and entrepreneurs are exploring new pathways for electrification such as solar home systems and mini-grids, as well as redoubling investments in traditional grid extension, all in an effort to build sustainable institutions for delivering electricity services.

Grid extension efforts in Kenya have led to an up-tick in the percentage of population that has access to electricity at home; however, a less well-understood change is the evolution of consumption among these newly-electrified customers. Projecting future electricity consumption is difficult, underscored by the observation that projections tend to understate growth in electricity demand in the developing world (Wolfram et al., 2012). Plausible electrification strategies depend on analyzing existing customer data to predict the behavior of newly-connected customers.

Kenya is an example of a country that has vastly expanded its electrification – from 2010 to 2015, grid penetration has increased by 27%, more than doubling the number of customers on the centralized grid – see Fig. 1 (Kenya, 2016). In addition to the centralized grid, there are now upwards of 600,000 solar home systems deployed, which contribute another 5–6% in electrification (estimated using census figures (Kenya National Bureau of Statistics, 2009) and current population estimates (AfriPop, 2010)). Most of the grid connections from 2010 to 2016 were residential, and nationwide residential electricity consumption has increased at roughly 9% annually over the period. Despite these large gains, little is understood about how much electricity these new customers consume, and even less is known about how their consumption will change with time. This study seeks to address this question: *how much electricity do newly-connected electricity customers use, and how will that consumption evolve?*

To that end, we present a longitudinal study of electricity consumption growth in Kenya. This study is built upon a dataset of billing records from Kenya Power, the sole distribution utility in Kenya. The dataset includes monthly billing records over a six-year period, from 2010 through 2015, for a random sample from Kenya Power's customer database at the end of 2015. After cleaning and meta-data verification, the random sample amounts to roughly 136k residential customers. The scale and extent of the longitudinal dataset is heretofore unseen in the literature on electricity consumption for an African country. Further description of this dataset is provided in Section 3. To identify which customers in our randomly-sampled dataset are rural, we developed an algorithm for determining which areas of the country are urban, peri-urban, and rural based on a constrained clustering method – we describe this method and its relevance in Section 4 and Appendix A. Subsequently we show results for urban and rural consumption, where

* Corresponding author.
E-mail address: jtaneja@umass.edu (J. Taneja).

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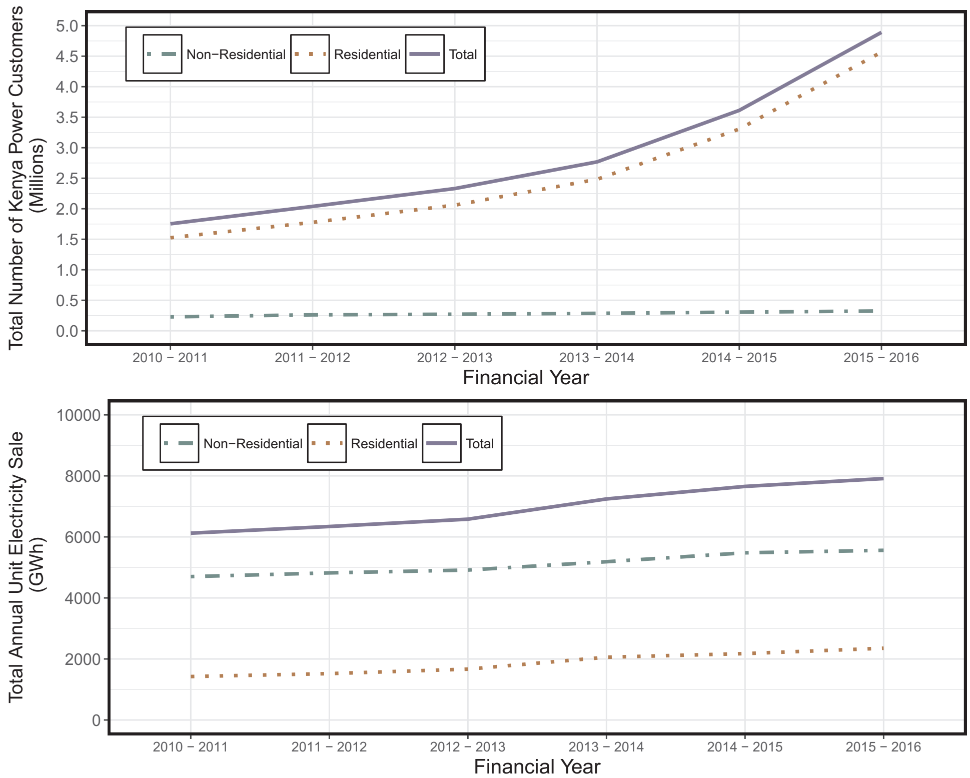

Fig. 1. Total number of customers and total electricity sales for Kenya Power between 2010 and 2016. Non-residential includes industrial, commercial, street lighting, and off-peak loads. Customer additions were mainly to the residential sector. Data are from Kenya Power annual reports (Kenya, 2016).

the urban results are a straightforward combination of both urban and peri-urban customers. In Section 5, we use the results of this method as well as other customer meta-data in order to segment our sample of customers and identify patterns of consumption growth among various groups. We conclude with implications of this study for policymakers and electricity planners, discussion of the limitations of our work, and next steps for research in the area.

2. Related work

Accurate electricity consumption estimates are important in designing electrical generation and delivery systems and meeting reliability requirements. A study in Malawi (Louie and Dauenhauer, 2016) uses off-grid data from 7 PV and battery systems to show the impact of incorrect load estimation on system cost and reliability. They found that system cost scaled proportionally with errors in consumption estimates, where over estimation led to significant increases in system cost of between USD 1.82 to USD 6.02 per watt-hour, while underestimating consumption eroded system reliability. This dichotomy between system cost and reliability emphasizes the need for data-driven approaches to understanding and predicting consumption, which can in turn yield more optimal system design.

In the case of residential electricity consumption, predictions are typically made by using multiple variables including socio-economic characteristics, appliance ownership, and living conditions. A literature review on the topic suggests that at least 62 variables potentially affect residential electricity usage (Jones et al., 2015). Other authors conclude that some important explanatory variables for household electricity consumption include appliance ownership, electricity tariffs, available income, and number of residents in the household (Villareal et al., 2016; Mensah et al., 2016; Esmaeilimoakher et al., 2016). While these analyses offer a deep-dive into electricity consumption patterns, they depend on expensive and time-consuming household surveys, rendering them difficult to scale with similar resolution to larger areas such as countries or regions.

Spatio-temporal analysis can provide insights to electricity consumption over large areas. Socio-economic and demographic variables such as population and income levels can be folded into such methods when studying electricity demand. For example, Amarala et al. (2005), Xie and Weng (2016), and Elvidge et al. (1997) demonstrate spatio-temporal analyses using satellite imagery to study population and energy dynamics in various regions. Results from these papers show a relationship between spatial dynamics, electricity consumption, and population. To explore the differences in electricity consumption due to urbanization, Xie and Weng (2016) use a pixel-based method to delineate urban, suburban and rural regions in China. A universal definition for urban regions was difficult to obtain and the Chinese administrative units “prefectural city” are a mix of both urban districts and rural counties. The authors use population adjusted nighttime lights to delineate urban areas. Land cover was then used to determine the optimal nighttime lights threshold for highly dense built-up areas in China. The obtained highly dense regions are labeled as the urban core while the difference between urban regions and urban core gives the suburban region. This definition of urbanization allows them to study differences in electricity patterns by urbanization levels.

Chévez et al. (2017) propose another approach for obtaining spatially homogeneous areas using k-means clustering algorithm. In this case, rather than using urban, suburban and rural as homogeneous areas, they define k clusters, where each cluster is a spatially homogeneous region. Homogeneity is defined by the authors as regions with similar electricity consumption. The algorithm classifies n users with M features into the k clusters. Given the number of clusters (k) defined a priori, the algorithm finds k clusters which minimize the euclidean distance as defined by sum of least squares. Initially, $k \times M$ values are chosen to represent cluster centroids. The authors compute the euclidean distance of each user from the initial centroids of the clusters and then assign the user to the cluster which yielded the smallest distance from the user. The process is repeated until users do not change

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