Measuring Electricity Reliability in Kenya

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***Abstract*—Utilities across the world struggle to accurately measure electricity reliability on their grids; the average utility in a 109-country sample underestimates outages by a factor of 7. While some utilities are addressing this challenge by installing smart meters, many utilities in emerging economies do not have the technical or budget capacity to deploy smart meters widely. In this paper, we present reliability data for one such utility, Kenya Power, documenting the collection, analytics, and summary metrics used by the utility to monitor and manage electricity outages. We show that using a simple metric obscures the primary contributor to electricity outages on the grid, and discuss the implications and potential solutions for Kenya Power to vastly improve electric reliability using data analytics and intelligent deployment of technology.**

I. Introduction

Electricity reliability varies by orders of magnitude around the world. Where typical utilities in the United States have roughly 1 hour of outage per customer annually, utilities in low- and middle-income countries may have over 100. Smart grids, built from more and better instrumentation and analytics for monitoring grid systems, have shown innovative methods for measuring and managing electricity reliability. However, smart meters are being deployed unevenly; while some countries enjoy near universal deployment, most developing countries have few if any smart meters. In these settings, electricity reliability remains a serious challenge, negatively affecting economic growth and livelihoods.

Before electricity reliability can be improved, it needs to be accurately measured. Many utilities in low- and middle-income countries have limited instrumentation for measuring electricity reliability events, such as blackouts and brownouts. While there may be sensing at higher tiers of the electricity grid for monitoring the condition of transmission lines, distribution lines often go unmonitored, and outages go unreported until unhappy customers contact the utility directly. In this work, we perform a deep case study of one such utility, examining the collection, analysis, and implications of electricity reliability data for the electricity grid of the Republic of Kenya. While Kenya Power, the sole electricity distribution utility in the country, has made enormous strides in improving electricity access, we show that consistent reliability of electricity remains a problem. We perform custom analytics on a year of outage data from Kenya Power, showing differences in outages by duration, cause, and location. We document our methodology for determining revenue loss from outage information with limited location data and compare different metrics for measuring reliability, showing that using a simple metric can provide incorrect guidance to utility personnel. This work exhibits the potential to improve measurement of electricity reliability in low-resourced and limited-infrastructure electricity grids by using data analytics, and highlights opportunities for deploying smart grid technology in a still-growing electricity grid typical of much of the developing world.

II. Background and Related Work

A. Background

While smart meters have substantially improved visibility of reliability events on grids, most grids globally still do not have a large proportion of smart meters; these grids persist with non-communicating analog and digital electric meters, with a combination of postpaid and prepaid billing arrangements. Smart meters present many benefits to utilities, including eliminating the need for periodic meter reading, automatic notification of electricity outages, remote management of electricity connections and disconnections, and efficiency gains that reduce future generation, transmission, and distribution investments. Still, due to the technical capacity and high costs of meters, installation, and the analytic packages required to derive value from the investment, many utilities in the developing world have few if any plans to install smart meters in the near future. In the absence of smart meters, measuring reliability of electric grids is difficult.

To characterize the scale of this challenge, we compare datasets from two different global surveys conducted by the World Bank; both datasets provide measurements of annual hours of outage duration per customer in a country, a common measure of electricity reliability. This metric is called the System Average Interruption Duration Index (SAIDI), and is explained further in Section IV-B. The two data sources are:

- Enterprise Surveys [1] are conducted with hundreds of business owners in each of 139 countries every three to five years. One particular question focuses on the number of hours of outages experienced over the previous month. Using the average response from the most recent survey available for each country, we derive an annual measure of hours of outages.
- Doing Business Surveys [2] annually collect an array of metrics of policy and process relevant to starting and operating small and medium enterprises in 190 countries. As part of each country analysis, the utility of the largest business city provides data, including a self-reported SAIDI measurement. We use data from the 2016 surveys.

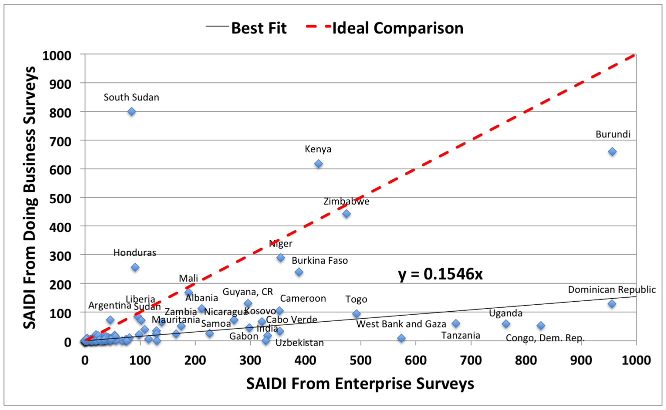


Fig. 1: Comparison of national reliability measurements from two different World Bank-administered surveys.

Figure 1 compares the measurements of annual outage hours for the 109 countries with data reported in both surveys. Since both surveys attempt to measure the same quantity, we would ideally expect all points to lie along the dashed line that represents equality of the two measurements. However, what we see is that the hours of outage from the Enterprise Surveys, as reported by customers, differs vastly from the hours of outage from the Doing Business Surveys, as reported by utilities. While part of this discrepancy likely results from the flawed incentives of utilities self-reporting their performance, the pattern is striking; on average, according to the line of best fit also plotted, utilities report 15% of the outage durations that customers report. However, since this is a global finding that includes primarily low- and middle-income countries, we believe this underscores the challenge utilities in these countries face in properly measuring reliability performance.

From the IEEE 1366 standard, which governs metrics for electricity distribution reliability, the typical number and hours of outages experienced by a customer on U.S. utilities each year is 1.1 and 1.5, respectively [3]. This is a substantial difference from those seen in Figure 1, though outages on electricity grids in higher-income countries are relatively far more costly to the utility. At present, smart meter penetration in the U.S. is roughly 44%, and growth has slowed in recent years [4]. This slowing growth indicates that many localities in the U.S. will be without smart meters for the foreseeable future. In the developing world, few utilities have substantial smart meter deployments; for example, Kenya Power is presently piloting an initial deployment of approximately 5000 smart meters [5], and few other utilities in sub-Saharan Africa (beyond South Africa) have any smart meters whatsoever.

B. Related Work

There have been many demonstrations of how smart grids can be used to better measure and manage reliability [6]. These tests use a wide array of new technologies (smart meters and Fault Detection, Isolation, and Restoration (FDIR) systems chief among them), and are at various levels of scale.

Much of the research involving electricity reliability in the developing world is in impact evaluation studies. Chakravorty, *et al.* [7] find that improved electricity quality increased non-agricultural incomes by 28.6% over their study period. However, this study measures reliability purely from household surveys, limiting accuracy and resolution of the data. Carranza, *et al.* [8], despite having a strong relationship with the electric utility in Kyrgyzstan for their study of an intervention of compact fluorescent light bulbs (CFLs), also use household surveys to measure reliability. They report that the utility did not collect distribution-level reliability data. Other work, from Allcott, *et al.* [9], uses a combination of facility data from textile mills and utility data for measuring reliability. The utility data, which stretches back 25 years, is provided at yearly intervals at the resolution of entire states, providing additional, yet limited, insight.

The Electricity Supply Monitoring Initiative (ESMI) [10] is an NGO-led initiative for collecting reliability information using custom-built electricity monitoring equipment. The project aims to be an independent monitor of electricity supplies, measuring both the reliability and quality of electricity via voltage and frequency measurements. At present, ESMI has 352 monitoring stations deployed throughout India, along with small deployments in Tajikistan and Indonesia. While the volume of publicly available data on electricity reliability collected is unprecedented in the developing world, the high cost of equipment ($150 per device) and customer initiative needed to maintain the system are challenges for scaling this approach of monitoring reliability. Another team has extended the ESMI deployment by combining the meter data with night lights imagery from satellites [11]. This approach at present does not provide the resolution in time or space to measure individual outages, but will improve with the quality of imagery. However, it still bears the requirement of high-resolution electricity sensing.

III. Methodology

A. Metrics for Reliability

The IEEE 1366 standard describes a number of indices for use in quantifying the reliability of an electricity grid [3]. Some of these metrics describe overall service availability and others describe particular types of outages (*i.e.*, momentary or catastrophic). In this section, we describe four different metrics used by utilities for monitoring grid reliability.

1) Number of Outages: A simple way for a utility to keep track of electricity outages is by simply counting the number of outages reported by customers. In the absence of smart meters or other sensing embedded in the grid, these data are often collected by a combination of call centers and social media feeds operated by the utility. One benefit of this approach is that every outage is handled equitably – outages in lower-income areas can theoretically be treated with the same urgency as those in higher-income areas. This has a corresponding downside of providing little guidance to repair teams about which outages may be a priority from a revenue or scale perspective. When this study began, number of outages was the key performance indicator for Kenya Power.

2) SAIFI: As the quality of utility data improves, a number of common metrics emerge. One of those is the System Average Interruption Frequency Index (SAIFI), which measures the average number of outages experienced by a customer on the grid. Though the temporal and spatial extents can vary, SAIFI is typically measured over a year and can be provided for a city, region, or entire national grid, and is provided in units of outages per year per customer. To calculate SAIFI, the following equation is used:

$$SAIFI = \sum_{outages} \frac{N_i}{N_T} \tag{1}$$

where N_i is the number of customers affected by outage i and N_T is the total number of customers served in the region of interest. An advantage of SAIFI is that larger outages – those affecting more customers – contribute more to its calculation. To calculate SAIFI, the utility must also record how many customers are affected by each outage. For grids with limited monitoring capability and especially grids without mapping from customer to electricity infrastructure, measuring the scope of an electricity outage is not straightforward. At present, SAIFI is a key performance indicator that Kenya Power uses to monitor and manage electricity outages.

3) SAIDI: Another common metric is the System Average Interruption Duration Index (SAIDI), which measures the average time of outages experienced by a customer on the grid. SAIDI is typically measured over a year, can be provided for a city, region, or entire national grid, and is provided in units of minutes or hours of outages per year per customer. To calculate SAIDI, the following equation is used:

$$SAIDI = \sum_{outages} \frac{N_i * D_i}{N_T} \tag{2}$$

where N_i is the number of customers affected by outage i, D_i is the duration of outage i, and N_T is the total number of customers served in the region of interest. SAIDI has similar advantages and challenges to SAIFI, with the additional consideration that outage durations must be collected as well. The extra information improves the perspective of the utility of the typical reliability experienced by a customer. At present, SAIDI is a key performance indicator that Kenya Power uses to monitor and manage electricity outages. SAIDI is also very popular for comparing among utilities; for example, along with SAIFI. it is the main comparison of utility reliability used in the World Bank-administered Doing Business surveys [2], whose results were shown in Section II-A.

4) Revenue Loss: Beyond the customer service benefits of fewer and shorter outages, a key motivation for reducing outages is collecting revenue from additional electricity sales. This additional revenue allows for a direct comparison against the cost of mitigating particular types of outages. The revenue loss, expressed in a currency unit, is calculated as follows:

$$RevenueLoss = \sum_{outages} (N_i * D_i * \sum_{customers} C_{i_j}) \tag{3}$$

where C_{i_j} represents the expected hourly consumption of customer j during outage i. A distinct challenge in measuring revenue loss is calculating the expected hourly consumption of affected customers. With extensive historical usage data, as would be provided by smart meters, it may be possible to build models that accurately predict lost consumption; additionally, as customer consumption varies, an ideal model would consider hour of day, day of week and month, seasonal patterns, and more context in calculating lost consumption. However, even calculating this large number of potentially complex predictive models may suffer from the effects of difficult-to-quantify shifts in customer behavior that can arise from repeated reliability events. Further, for utilities with minimal metering infrastructure, it may not be possible to understand consumption variability on a per customer basis. Presently, Kenya Power does not use any calculation of revenue loss in making any decisions related to improving reliability.

B. Outage Data Collection

In this work, we leverage a range of utility data from Kenya Power in order to analyze outage performance by the utility. Data used in this study include one year of complaint and incidence information (from October, 2014, through September, 2015), customer to transformer mapping data, and average consumption levels calculated from monthly bills for customers, all in Nairobi. Complaints are records of individual customer phone calls, Facebook messages, and Twitter messages, reporting electricity outages. Incidences represent grouped complaints that are associated on the basis of the electricity distribution tree; for each incidence, a repair team is sent in response. In this work, we focus on low-voltage electricity outages, below the lowest level of sensing available on the grid. In practice, Kenya Power has some substations monitored in the medium-voltage tier (to 66 kV) and every substation monitored above that in the high-voltage tier; these substations are monitored with a SCADA system, with real-time status updates and any faults immediately reported to a national control center. This infrastructure and other steps the utility has taken result in very few high-voltage outages on the Kenya Power grid. In this work, we are concerned with data about outages that occur below this sensing in the grid hierarchy. To understand the validity of this data, we document the process by which it was created:

1) A customer initially reports an outage to Kenya Power via a phone call to the national call center, by a Twitter message to the @KenyaPower_CARE account, or by a post to the KenyaPowerLtd Facebook page.
2) Operators collect important details about the customer, including an account number and the purported cause of the fault, if possible. Each call or message is entered into a database as a ”complaint” with a timestamp.
3) Other operators in the Emergency section then group complaints on the distribution tree together as an ”incidence.” Each incidence aggregates any unattached complaints that occur on the same transformer sub-tree. A database entry is created for an incidence with the timestamp of the earliest grouped complaint.

4) The same operator then dispatches an appropriate repair team (based on region) with details about the incidence.
5) Repair teams respond to and service outages. If the team determines that fixing the outage is beyond the capabilities of their equipment, the repair team can call in a "breakdown" team, which is responsible for fixing more serious faults.
6) When an outage is repaired, the cause of the fault is relayed to the Emergency dispatch operator for recording in the database and the outage is marked as resolved.
7) Outage reports are compiled weekly for review by Kenya Power management.

In particular, the quality of location data used by Kenya Power has improved dramatically since the study data were collected. Initially, mappings between customers and their transformer were often either missing or inaccurate, and locations of transformers were provided by street at best, but at worst only by neighborhood. Geocoding of streets and neighborhoods remains only approximate in Nairobi, and specific addresses are strikingly few, with specific locations usually identified by nearby landmarks, as is common practice in much of the developing world. To address this state of affairs, Kenya Power conducted a yearlong set of campaigns around GIS data collection in order to improve the quality of their Facilities Database ("FDB") [5]. By collecting geospatial locations of each piece of infrastructure in their network, Kenya Power will improve service delivery processes throughout their network. In this work, we employ the older, coarser location data previously available to Kenya Power.

IV. Results

In this section, we examine the patterns inherent in low-voltage electricity outages in the city of Nairobi. We look at where, when, and how many outages there are, as well as the causes of electricity outages. We then calculate the four metrics for electricity reliability introduced in Section IV-B.

A. Outage Patterns

Kenya Power arranges its national electricity grid into ten regions, three of which are constituted by portions of Nairobi (Nairobi North, Nairobi South, and Nairobi West). As Nairobi is the capital city and the center of business for the country, these three regions account for 49% of total electricity consumption on the Kenya Power grid [5]. The results in this work all deal with aggregations of the three regions.

First, we examine the time of day of electricity outages. Figure 2a shows two probability density functions of the hour of day of outage detection and outage resolution across the entire year. We see that for Nairobi as a whole, there is a bimodal distribution, with peaks in outage detection during the 9am and 7pm hours. As the Kenyan grid is generally not constrained by supply (unlike most grids in sub-Saharan Africa), we believe that substantial numbers of outages are driven by peak user demand, which anecdotally occurs during these hours, causing local overloading events that result in low-voltage outages. Nonetheless, we note that the timestamps of outages are as recorded by the times of initial phone calls or messages to the call center; these are delayed from the actual onset of the outage, though it is unclear by how much they are delayed. Looking more closely at the PDF of outage resolution, we also see a bimodal distribution, with peaks 1-2 hours after the peaks from the detection PDF. During our study, the median outage resolution time was 1.63 hours ($\mu \approx 7.87$ hours). However, we note that resolution times are manually recorded by Emergency dispatch personnel. From our experience in observing this process, the validity of outage resolution timestamp data may be doubtful.

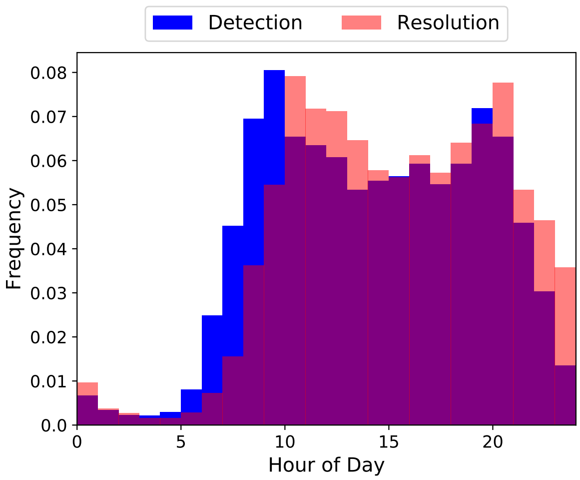
Figure 2b shows the same PDFs, one for each of outage detection and outage resolution, for each of the 9 largest "branches" in Nairobi, as defined by Kenya Power. These branches represent areas that are larger than individual neighborhoods, but do not exactly align with any administrative boundaries. Nonetheless, we can see some distinct patterns. While every branch is bound to include some proportion of residential, commercial, and industrial customers, there are relative differences in these proportions. For areas that contain relatively more commercial and industrial activity, such as the Industrial Area + Embakasi branch and the City Centre branch, we see a unimodal distribution, driven by outages during the 9am hour. For more traditionally residential branches, such as Karen and Dandora-Kariobangi-Githurai, the bimodal distribution from Figure 2a dominates. We believe that this indicates that evening outages are generally due more to residential customers than business customers.

To support our intuition of the causes of the outage patterns, we next examine the metadata recorded by the repair teams for each outage. From Figure 3, we can see that the foremost cause of electricity outages in Nairobi is fuses; these faults occur when there is a local overload on a transformer, causing one phase to blow its fuse and lose power until the fuse is replaced. Another primary cause of faults, happening for nearly 1 in 5 incidences, is labeled as "back on supply" – our understanding is that this category of faults represents when a repair team visits the purported location of a fault and discovers that the power is working. This can arise due to a momentary interruption, a circuit breaker auto-reclosure, another fault repair and a mis-identified fault scope, or an incorrect location, among other reasons. Improving analytics around outage management should help to greatly reduce these events, saving the valuable time of repair teams.

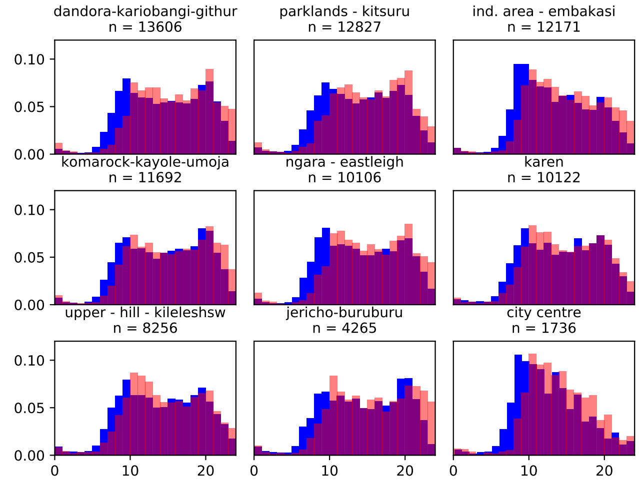
B. Outage Metrics

To understand the implications of these outages, we compiled four metrics of reliability, as introduced in Section IV-B: (1) Number of Incidences, (2) SAIFI, (3) SAIDI, and (4) Revenue Loss. Results of our analysis are in Figure 4.

We note that our estimate of SAIDI, 216.3 hours per customer per year, is far below the estimate for Kenya from the Doing Business Surveys, as shown in Figure 1. However, the process by which Kenya Power derived those estimates has substantial inconsistencies, rendering it nearly unusable. That our estimate falls short of the reported outages seen by firms



(a) Time of day of electricity outages over a year in Kenya.



(b) Time of day of electricity outages over a year in Kenya, separated by neighborhood.

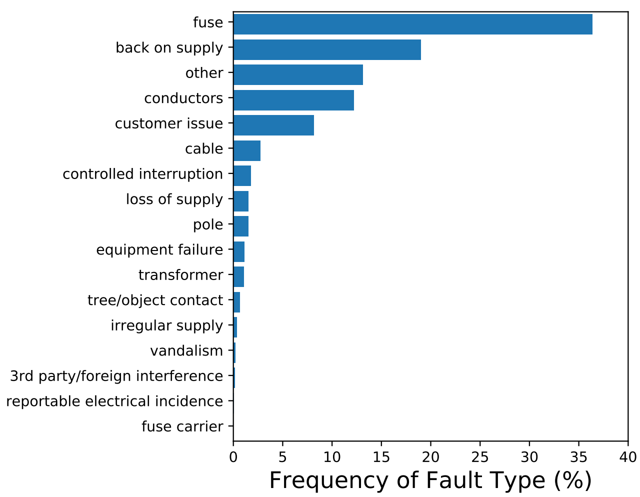


Fig. 3: Reported causes of outages over one year in Kenya.

Total Incidences	SAIFI	SAIDI	Revenue Loss
89464	22.5	216.3	2.2bn Ksh

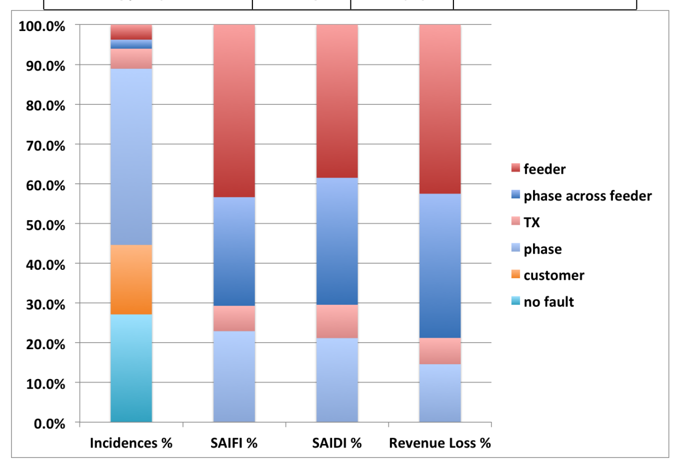


Fig. 4: Four different metrics of reliability calculated for the Kenya Power grid for one year.

in Kenya underscores the challenge of accurately measuring reliability from the perspective of a utility.

For deeper analysis of which types of faults contribute to these calculated metrics, we classify each of the 53 different cause types as reported in the Kenya Power database of incidences into one of six different categories:

- Feeder – These faults represent large-scale outages, often as a result of maintenance activity (including planned outages) or other major events.
- Phase Across Feeder – Medium-voltage conductor faults can affect customers on the same phase of all transformers on a feeder.
- TX – These faults occur when an entire transformer has a failure, sometimes due to issues with poles and wires.
- Phase – These faults are the result of individual phases being knocked out, and include issues with fuses.
- Customer – These faults are limited to individual customers, such as issues with meters.
- No Fault – These faults represent those incidences where no additional downtime was recorded, such as when a fault is already restored when a repair team arrives.

We compare the proportions of these categories of faults within each metric in Figure 4. We can immediately see the disparity in the results – looking only at the proportions of incidences, we notice that Phase faults constitute nearly half of all faults. We also see that more than a quarter of incidences are in our category of "No Fault," meaning that they do not affect downtime, further bolstering the overwhelming proportion of Phase faults. As we increase the complexity of our outage metrics, we see that SAIFI and SAIDI are relatively similar by proportion. Faults with minimal effects on overall downtime – those classified as "Customer" or "No Fault" – have negligible contributions to these metrics, and faults with wider scopes – such as Feeder and Phase Across Feeder faults – have a larger impact on the metrics. Last, as we examine Revenue Loss (labeled as Ksh Loss, to reflect the Kenya Shilling currency), we see that Feeder faults and Phase Across Feeder faults dominate, accounting for nearly 80% of the overall revenue not realized due to low-voltage electricity outages. This emphasizes the importance of attentiveness to large outages – both in taking care when scheduling maintenance as well as in accelerating response to unexpected large faults. Though this is an intuitive finding, a utility operator might choose a different strategy if presented only with data on the Number of Incidences. This is because the effect of Feeder outages can vary in relative importance by 11x, depending on the reliability metric used.

For further context, we now consider the total revenue loss from low-voltage outages as calculated by our bottom-up metric, which estimates the number of customers affected by each outage using the best available data that Kenya Power has. We calculated total losses of ≈2.2 billion Ksh (≈$23 million USD[1]). We compare this to the top-down estimate that Kenya Power uses for losses in their annual report, which is 17.5% of total sales [5]. This loss is comprised of transmission loss (measured to be around 4%), commercial/non-technical loss (estimated to be around 6%, and distribution loss as the remainder, roughly 7.5%. Since Kenya Power's revenue for the fiscal year ending in 2015 was 106.8 billion Ksh [5], distribution losses account for roughly 8 billion Ksh (≈$83.2 million USD). Considering that Nairobi accounts for 49% of total consumption on the Kenya Power grid, our estimate would be 4.5 billion Ksh over the entire country, only accounting for about 56% of total distribution losses. There are many potential explanations for this disparity: (1) outages in rural areas tend to last longer than those in urban areas; (2) outage durations, used to create our metric, may be systematically underreported, as explained in Section IV-A; and (3) estimates for commercial/non-technical losses can vary substantially.

Nonetheless, we know of no more thorough accounting of revenue loss due to individual electricity outages on grids without smart meters in the literature. As consumption grows on these grids (at 5-6% annually in Kenya, for example), better monitoring and management of these types of electricity outages is critical for delivery of reliable and plentiful electricity.

V. Discussion

Many strategies can improve the reliability of electricity on grids without smart meters. Here, we document some of those strategies, many of which Kenya Power is already undertaking.

One key approach is to better plan outages for maintenance. In our dataset, though planned outages only account for 0.5% of total incidences, they account for 5.6% of total revenue loss. Limiting the number of planned outages by grouping together maintenance activities whenever possible can help to alleviate some of this revenue loss. Another strategy that Kenya Power is undertaking is to train maintenance teams to be able to conduct operations on live wires whenever possible; this can replace downtime with continued service.

Another set of strategies involve improving outage measurement and repair. By more quickly identifying and remotely diagnosing electricity outages and providing this information to repair teams, outage durations can be shortened. An approach that Kenya Power is developing is to establish heterogeneous repair teams; since the single largest category of faults are simple fuse replacements, having "Rapid Response Teams" of fast-moving motorbikes that can quickly pass through slow Nairobi traffic should also improve repair times. In the future, Kenya Power wants to outfit these teams with digital tools for accelerating information flow. Further, estimations of outage scope or revenue loss can help utilities continuously prioritize outage responses to either restore power to the most customers or to minimize losses due to outages.

Other approaches are longer term, and represent proactive strategies. If particular areas of the grid tend to have more events, it may be possible to prevent those outages with intelligent rebalancing of phases, moving customers from phases with heavier loads to phases with lighter loads. Though phases were likely initially balanced, unequal evolution in customer demand is likely to create imbalances over time. Further, if certain transformers are undersized, using analytics to identify those transformers and then replacing them can yield benefits, though it may be important to prioritize improvements from a revenue loss perspective, as small changes to procedures for managing feeder outages may have outsize impact.

VI. Conclusions

In this work, we showed that utilities around the world struggle with measuring electricity reliability on par with the experience of their customers, and performed a deep analysis of the process and techniques used to measure electricity reliability in Kenya. Our analysis of outages uncovers temporal patterns, primary causes, and variability among reliability metrics, highlighting the heavy cost burden of poorly-measured low-voltage grid reliability. We know of no other work that presents as deep an analysis of reliability patterns of electricity grid operations in the developing world, providing unprecedented insight into systems that are the next frontier for smart grid development. Understanding these grids and building technologies and systems for applying smart grid principles to them will be an enormous challenge.

[1]During our study, the average exchange rate was 96.3 Ksh / 1 USD.

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