How Many Smartphones Does It Take To Detect A Power Outage?

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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 (relative to customers). 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 analyze the size of deployment needed for outage detection via the GridWatch system, a novel crowdsourcing mobile application for measuring outages. Using outage data from Kenya Power and user mobility data, we consider different deployment sizes and varying levels of detection accuracy of the GridWatch app. Our results show that differences in neighborhood infrastructure and dynamics can necessitate a more than 3x difference in GridWatch deployment size to achieve the same outage detection performance, stressing the importance of deployment planning for a crowdsourced infrastructure monitoring system.

1 INTRODUCTION

Electricity reliability varies by orders of magnitude around the world. Where typical utilities in the United States have roughly 1.5 hours of outage per customer annually [2], utilities in low- and middle-income countries often have over 100 [13]. In these settings, electricity reliability remains a serious challenge, negatively affecting economic growth and livelihoods.

Before electricity reliability can be improved, it must 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 transmission system, distribution lines are often unmonitored, and outages remain unreported until unhappy customers directly contact the utility. To characterize the scale of this challenge, we compare responses from two global surveys conducted by the World Bank, one which asks customers (businesses) and another which asks utilities [13, 14]. The surveys report annual hours of outage duration per customer, a common measure of electricity reliability. Figure 1 compares the responses for the 109 countries common to both surveys. The difference between the two measurements, expected to be equal, is striking; on average, utilities report 15% of the outage durations that customers report. Part of this discrepancy likely arises due to flawed incentives from utilities self-reporting their performance. However, this finding, taken over a large sample across the globe, underscores the challenge that utilities in low- and middle-income countries face in properly measuring reliability performance.

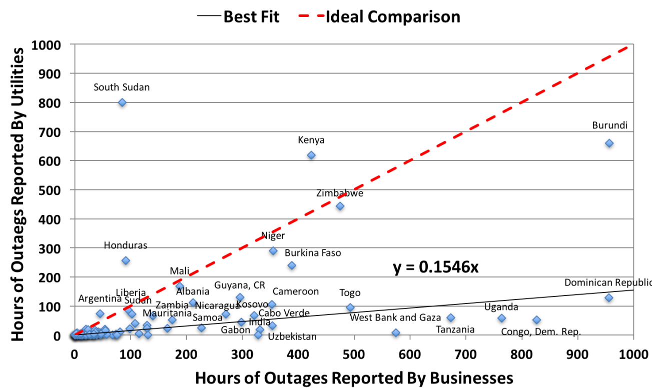

Figure 1: Comparison of national reliability measurements from two World Bank survey programs. Utilities observe only 15% of outage duration as compared to businesses.

Smart grids, built from instrumentation and analytics for monitoring grid systems, have shown innovative methods for measuring electricity reliability. However, smart meters have been adopted unevenly; only a handful of countries enjoy near universal deployment. At present, smart meter penetration in the U.S. is roughly 44% with slowing growth, indicating that many localities in the U.S. will be without smart meters for the foreseeable future [4]. 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 (for over 6 million customers) [7], and few other utilities in sub-Saharan Africa (beyond South Africa) have any smart meters whatsoever.

Two recent initiatives present alternatives to smart meters for collecting reliability data. The Electricity Supply Monitoring Initiative (ESMI) [1] gathers reliability information using custom-built electricity monitoring equipment, acting as an independent monitor of electricity supplies. At present, ESMI has 352 monitoring stations deployed throughout India, along with small or planned deployments in Tajikistan, Indonesia, Kenya, and Tanzania. Unfortunately,

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the high cost of equipment ($150 per device) and technical effort required to maintain the system are challenges for reaching scale.

The GridWatch project [9] takes a different approach, using mobile applications on commodity smartphones to automatically detect electricity outages. The "app" works by identifying correlated changes in side-channel readings from relevant sensors, observing charge state, WiFi, and ambient light, among others. GridWatch enables crowdsourcing of outage data by leveraging the broad deployment of smartphones among electricity consumers, enabling electricity grids with limited low-voltage sensing to achieve many of the same outage detection benefits bestowed by smart meters.

However, GridWatch has not been deployed widely, and a key question remains about its viability at scale: *how many observation points (phones) are needed to ensure coverage of outages?* In this work, we address this question for an urban environment by building an analytical model driven by empirical outage data provided by the national utility of Kenya. Our model considers the ramifications of heterogeneous underlying patterns of outages, user mobility patterns, and varying levels of accuracy of the sensing method. While this is work-in-progress, understanding the deployment considerations for a crowdsourced system like GridWatch will help to focus system design, direct marketing efforts to encourage app installation, and allow comparisons across different areas.

2 RELATED WORK

The growing ubiquity of mobile devices and sensors creates innumerable opportunities to modernize electricity infrastructure. There have been many demonstrations using mobile devices to crowdsource profile analytics, user-assisted predictions, and demand-side management to enable utilities to innovate towards smart grids [6]. However, most visions of smart grids center on continuous, high-resolution data originating from smart meters, which are typically not deployed in developing country settings.

In the absence of smart meters, much of the research involving sensing of electricity outages using crowdsourcing techniques uses information collected from social media to locate and detect power outages [3, 8, 11]. Even though these initiatives use probabilistic frameworks and machine learning techniques to obtain spatial and temporal detection, they still require active user participation to report incidents on social networks and often include only coarse localization (*e.g.*, at the neighborhood level).

Another important aspect of our work is the deployment strategy of sensors in order to maximize the performance of outage detection. In order to monitor a specific geographic area, it is required to have a collaborative detection using multiple sensors. The number of sensors not only impacts the robustness of the detection but also the cost associated with the deployment. Clouqueur, *et al.* [5] address these problems for sensors that are placed to detect a target moving through a region using signal and path exposure measurements.

3 METHODOLOGY

3.1 Datasets

We construct a coverage model for a theoretical GridWatch deployment based on historic outage data collected by Kenya Power (October 2014 through September 2015). Because Kenya Power's grid does not contain low-voltage sensors, these data are comprised solely of customer-reported faults. Kenya Power allows customers to call, visit, post Facebook messages, and tweet to their national call center. We further classify each Kenya Power outage into one of four grid tiers: "circuit", "transformer", "feeder", or "phase across feeder". A "phase across feeder" outage affects multiple feeders (μ = 3220 customers affected), a "feeder" outage affects multiple transformers (μ = 3127 customers affected), a "transformer" outage affects multiple circuits (μ = 297 customers affected), and a "circuit" outage affects multiple households (μ = 120 customers affected). Figure 2 shows the average number of customer fault reports for each hour of the day for each tier across the dataset.

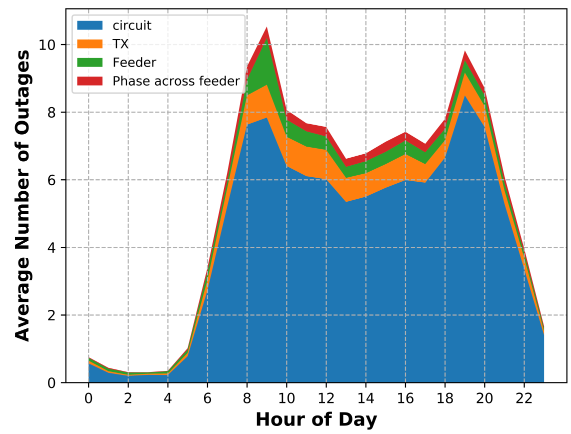

Figure 2: Average number of outages at different levels of the distribution grid in Nairobi, Kenya as reported by consumers to Kenya Power from October 2014 through September 2015. Outages could be occuring during the times of peak demand in the morning and evening, or these could be times where consumers are most likely to report outages.

To model the conditions GridWatch requires to sense power outages, we incorporate the publicly-available StudentLife Dataset [12], which has records of phone charge events of 50 college students during approximately two months. This dataset allows us to identify smartphone users' charging patterns and obtain the proportion of users that are plugged in to the wall over the course of a day. Charging patterns are shown in Figure 3. These proportions serve as proxies for the availability of GridWatch to report an outage at any given time when it is monitoring changes in the charge state sensor of the phone. While we recognize that the smartphone usage behavior of U.S. college students is likely to differ from urban dwellers in Nairobi, such data are not publicly available, and could be trivially incorporated into our model upon collection.

3.2 Coverage Model

We propose a stochastic model to approximate the number of GridWatch devices required to detect a fixed percentage of outages. Our first step is to analytically obtain the probability of detecting an outage (P_d). In order to do so, we define the following random variables (herein, abbreviated r.v.) and probabilities:

- The r.v. N is the number of customers (households) affected when an outage occurs. Its probability mass function (PMF) is obtained from the utility data:

$$N \sim P_N(n) \tag{1}$$

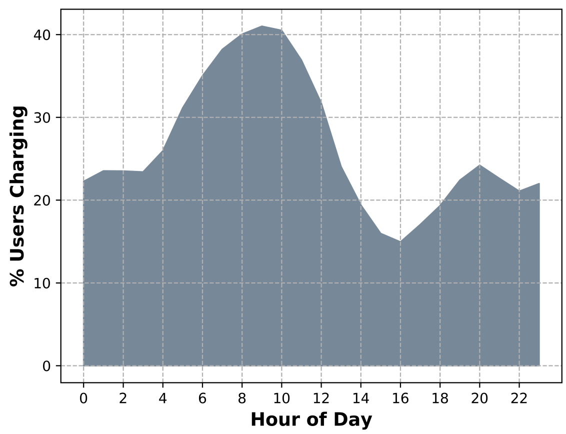

Figure 3: Percentage of users charging their phones by hour of the day, from the StudentLife Dataset [12]. People are less likely to be charging in the middle of the day.

- The probability that a customer reports an outage given that (a.) they were affected and (b.) they are a GridWatch user is denoted as p. The ability of GridWatch to detect an outage depends on the probability of two events: either changes in the charging state when smartphones are plugged into the wall (p_c) or the detection of changes in available WiFi networks for a phone that is not moving (p_w). These two events are independent and not disjoint, so p is given by:

$$p = p_c + p_w - p_c p_w \tag{2}$$

- The proportion of households with GridWatch installed on a smartphone that are available at the time of the event, q.
- The r.v. representing the number of customers that can report an outage (n_1) given that they (a.) were affected and (b.) are GridWatch users follows a binomial distribution:

$$N_1|N = n \sim Binomial(n, q) \tag{3}$$

- We also define A as the event of an unreported outage. If we calculate this probability, finding P_d is equivalent to $1 - P(A)$.

Given the definitions above, we can express the probability of missing an outage given that it could have been detected by a group of GridWatch users as:

$$P(A|N_1 = n_1) = (1 - p)^{n_1} \tag{4}$$

However, the definition in 4 holds only for a specific value of n_1. We generalize this probability using the Law of Total Probability:

$$P(A) = \sum_{n_1} P(A|N_1 = n_1) * P_{N_1}(n_1) \tag{5}$$

Which corresponds to the definition of expectation:

$$P(A) = E[(1 - p)^{N_1}] \tag{6}$$

We use the Law of Iterated Expectation [10] and obtain:

$$P(A) = E[E[(1 - p)^{N_1}|N]] \tag{7}$$

Given that $N_1 \sim Binomial(N, q)$ and using its Moment-Generating Function, we can simplify the expression to:

$$E[(1 - p)^{N_1}|N] = (1 - q + q * (1 - p))^N \tag{8}$$

Replacing 8 in 7 we can obtain:

$$P(A) = E[(1 - qp)^N] \tag{9}$$

Finally, applying the definition of expectation we conclude that:

$$P(A) = \sum_{N} (1 - qp)^n * P_N(N = n) \tag{10}$$

It is worth noting that Equation 10 represents only the probability of detection when the event occurs. However, power outages are a stochastic process that occur over time and at a certain rate. According to our dataset, during peak hours Nairobi experiences larger rates of outages compared to other times of day. This phenomenon can be modeled as a non-homogeneous Poisson process $(N(t) : t \geq 0)$, where the number occurrences in any time interval is a Poisson r.v. but its intensity function λ depends on the time interval $(\lambda(t))$ [10]. Assuming that each occurrence of an outage is independent, the non-homogeneous Poisson process can be split into two events, undetected and detected outages, so that the counting process is bounded by their individual probability. For detection we can express the process as:

$$N(t + s) - N(t) \sim Poisson\left(\int_t^{t+s} \lambda(\alpha) P_d \, d\alpha\right) \tag{11}$$

Where s is any given interval and the Poisson r.v. is defined as $X \sim Poisson(\lambda)$:

$$P_X(k) = \frac{e^{-\lambda}\lambda^k}{k!} \text{ For } k = 0, 1, 2, ... \tag{12}$$

4 RESULTS

In this section, we examine how our model responds to variation in parameters such as the proportion of customers with GridWatch installed on their smartphone, the ability of GridWatch to identify outages through changes in available WiFi networks, and the neighborhoods in which the system would be deployed. We begin with a simplified model and progressively add the complexity that arises from a widely-distributed, crowdsourced system.

4.1 Detection with varying app accuracy

We begin with a simple model where GridWatch devices are always plugged in and not moving around. As mentioned in Section 3.2, Equation 10 represents the probability of an undetected outage ($1 - P_d$) given that the event occurred. Figure 4 shows the probability of detection (P_d) at different levels of the distribution grid in the entire city of Nairobi. In this simple formulation, the model considers a low-accuracy GridWatch app (Figure 4(a.), 10% accurate) and a high-accuracy GridWatch app (Figure 4(b.), 100% accurate). Taken together, these show the envelope of deployment density needed to detect different types of electricity outages throughout Nairobi, showing the dramatic effects of app accuracy and deployment size on the probability of outage detection.

4.2 Detection using changes in available WiFi

To better understand the interplay between customers, their phones, and power outages, it is important to add complexity to our model. We begin by taking into account the time-varying occurrence of outages – to do this, we incorporate a Poisson process as described in Equation 11. We also incorporate time-varying customer charging patterns from the StudentLife dataset, seen in Figure 3, as our parameter p_c. With this addition, a GridWatch app that solely leverages the charge state sensor to detect outages becomes substantially less effective. However, the GridWatch app is not limited to detecting outages only when the phone is charging; it can also monitor

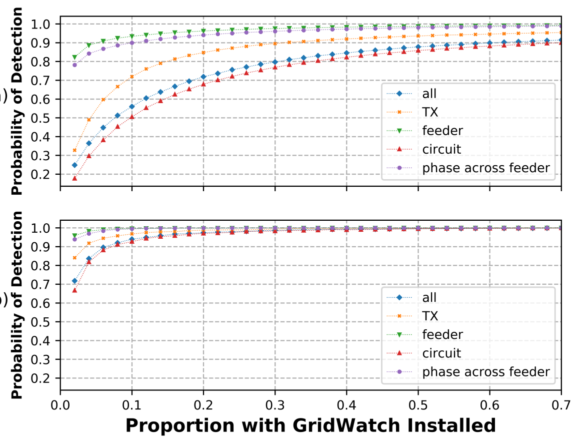

Figure 4: Probability of detecting outages at different tiers of the power distribution grid at different proportions of customers with GridWatch. Detection when the application accuracy is (a.) 10% and (b.) 100% given that the users were affected and have GridWatch installed.

changes in available wireless networks to detect outages, though this detection may have lower accuracy.

With a more realistic and complex model, we seek to quantify the implications of the lower accuracy of detecting outages when phones are not charging (i.e., detection via changes in WiFi networks). Time-varying outage arrivals also enable setting an intermediate target; for the remainder of our experiments, we set a goal of detecting 80% of electricity outages. Figure 5 shows results of this analysis for a particular neighborhood of Nairobi, Embakasi South. As expected, increasing the number of GridWatch users as well as improving the accuracy of the WiFi detection method each improve the probability of detection. Larger incremental gains in probability are observed at low penetrations of the GridWatch app and at low accuracy of the WiFi detection method. Thus, for a typical operating regime prior to wide deployment, improvements in engineering and app adoption have relatively larger returns to system performance.

4.3 Detection in different neighborhoods

To get a sense for the effects of underlying grid topology and neighborhood characteristics, we evaluated our model in two neighborhoods of Nairobi with different density and income levels: Westlands (sparser and higher income) and Embakasi South (denser and lower income). Westlands reports faults four times more often than Embakasi South and the average fault in Westlands lasts 15% longer. In contrast, Embakasi South reports on average twice as many households affected per outage. Figure 6 compares the probability of meeting our detection target (detecting 80% of outages) between the two neighborhoods. For this experiment, the WiFi detection accuracy was set to a conservative 50%. As a result, even though Westlands has a higher frequency of outages, only 20% of the households affected must have GridWatch installed to meet our detection target. In contrast, for the same target, Embakasi South would require 70% of affected households to have GridWatch installed. This demonstrates that neighborhood infrastructure and characteristics can have a significant effect on the number of observation points needed – a more than 3x difference in deployment penetration!

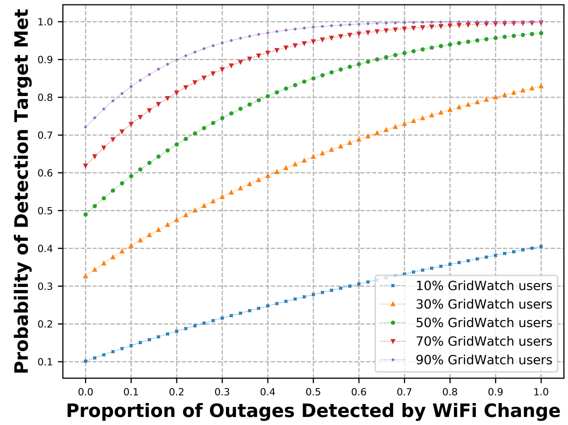

Figure 5: Probability of detecting 80% of the outages in Embakasi South, Nairobi, using different accuracy levels for outage detection via changes in available WiFi networks.

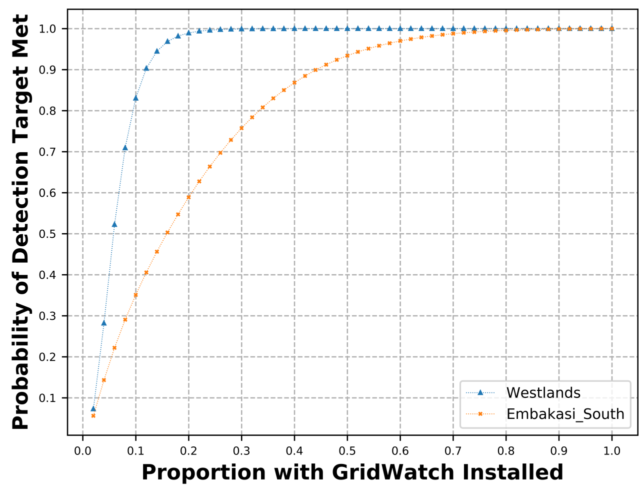

Figure 6: Comparison of the proportions of customers needed to install the GridWatch app to detect at least 80% of outages with 50% accuracy of outage detection via WiFi.

5 CONCLUSIONS AND FUTURE WORK

In this work, we showed that utilities worldwide struggle with measuring electricity reliability on par with the experience of their customers. We explored the potential of a novel system, GridWatch, for automatically detecting electricity outages using customer smartphones and analyzed the question of how many observation points are needed in different neighborhoods and with varying levels of detection accuracy considering user charging patterns. As we continue this work, we will aim to collect better data about smartphone usage, the availability of WiFi networks, and the accuracy of GridWatch in a real deployment in our target setting. We believe that this crowdsourcing approach and others like it have enormous potential for impact, and that our work can help to guide deployment efforts and improve the reliability of electricity grids in challenging environments.

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