BEYOND ACCESS: MEASURING POWER QUALITY ISSUES AT 27 HEALTHCARE FACILITIES IN THE DRC

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ABSTRACT

In many low and middle income countries (LMICs), energy access is expanding rapidly, supported by the deployment of diverse power system types, varied in scale — microgrids, bulk systems, individual backups — and energy source — solar, diesel, hydro. However, especially when it is targeted at critical infrastructure such as healthcare facilities, electricity access without a reasonable level of power quality (PQ) is a broken promise. Poor PQ, encompassing interruptions, voltage spikes and sags, and other power artifacts, can cause sensitive and costly equipment such as X-ray machines to fail, significantly reduce device lifespans, and lead to costly inefficiencies when, e.g., lab tests are lost due to power outages. Measuring, evaluating, and developing standards for PQ in electricity access projects across the developing world is critical to realizing the promise of powering critical infrastructure. In this work, we collect continuous data from a deployment of outlet-level power supply monitors at 27 health facilities in Eastern Democratic Republic of Congo, each powered by a distinct combination of grid-based and decentralized energy systems. These data reveal the near universal presence of serious power quality issues, but great variety in the specific nature and scale of the issues across sites. Quantitative results are accompanied by anecdotal evidence of frequent medical equipment failure due to PQ problems, and associated degraded ability to deliver medical services, including avoidable deaths. These results demonstrate the dire need to collect localized PQ data for electricity access projects in the Congo, suggestive of a broader need across the developing world, and underscore the importance of considering the specific power quality features of local supply sources when designing electricity solutions for healthcare.

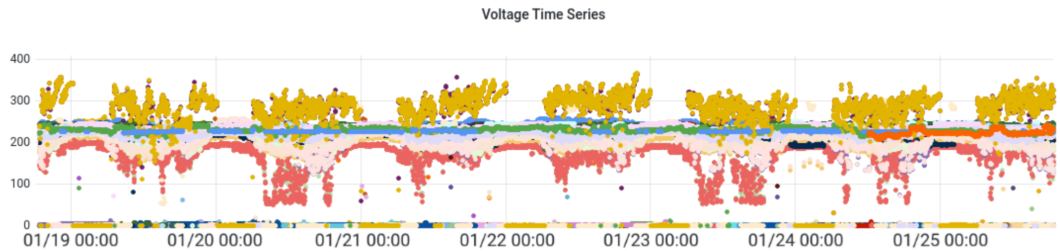

Figure 1: **One week of voltage data collected by PowerWatch sensors at 27 healthcare facilities in eastern Democratic Republic of Congo.** Each PowerWatch takes a measurement every two minutes of voltage magnitude, frequency and power state. Nominal voltage is 220 VRMS in the DRC. Outages and frequent voltage excursions from the nominal range, like those seen here, take a toll on sensitive equipment such as those in healthcare facilities.

1 Introduction

According to national surveys collected between 2000 and 2013, one in four healthcare facilities (HFs) in Sub-Saharan Africa lacked any source of electricity (Adair-Rohani et al. (2013)). In the decades since, many grid access projects were executed with the goal of electrifying critical infrastructure, often starting with HFs (e.g. WHO et al. (2023); USAID Power Africa: Nigeria (2022)). These access projects provide connections to a multitude of supply sources, including traditional large-scale distribution grids, community-scale hydro-powered mirco-grids, and clinic-scale solar stand-alone systems. Deploying new and traditional energy solutions to electrify critical infrastructure raises an important question: *is the quality of power supplied by diverse access projects sufficient to support the needs of the people and infrastructure it's meant to serve?*

The power quality (PQ) of an electrical generation source captures the utility of the electricity provided after access, and includes the duration and frequency of outages, voltage quality, and other power artifacts (Dougherty & Stebbins (1997)). A detailed understanding of PQ is important for the design, implementation, and evaluation of energy solutions for critical infrastructure and sensitive loads. This is especially the case for HFs, where the quality of power delivered has a huge impact on the operation and longevity of health equipment and the success of many medical procedures. Indeed, power challenges are the single most common cause of medical equipment failure in low- and middle-income countries (LMICs), where up to 70% of devices are broken or remain unused WHO (2010).

Despite the important implications of PQ for the operation of critical infrastructure, empirical and longitudinal data on power quality for diverse energy access solutions in LMICs is extremely limited. What power quality information exists is collected through recall-based surveys, such as the binary question: "In the previous week, have you experienced any outages exceeding two hours?" Adair-Rohani et al. (2013); WHO et al. (2023). Such coarse, survey-based measurements are insufficient for effectively targeting corrective interventions in the design and deployment of (a) medical equipment to HFs and (b) the energy systems that power them. For example, HFs acquire and use sensitive medical equipment without investing in additional protection such as stabilizers or regulators. This equipment is largely designed based on PQ expectations in very different contexts, such as the United States, where power quality is far higher and more stable (Melhorn et al. (2005)). Therefore, when the PQ in LMICs fails to meet these standards, equipment often fails to function or is quickly rendered inoperable, with tragic human costs.

There are few geographies in the world where the implications of the variability in supply PQ on critical infrastructure are as fraught as in the Democratic Republic of the Congo (DRC). Despite the fact that the DRC hosts the largest unelectrified urban and rural populations in the world as a share of national total (McCallum et al. (2022)), little empirical literature has catalogued the Congolese energy experience (Trotter et al. (2017)). In contrast to other countries with large unelectrified populations, no single integrated grid system connects the various generation plants and demand loads across the DRC. SNEL, the national utility, operates several, disconnected grid networks across the country. Hundreds of "second generation" mini-grids (ESMAP (2022)), principally hydro-installations financed by local communities, councils, and faith-based institutions, supply smaller towns and cities. A number of private-sector electricity providers have emerged in recent years.

Our study is primarily based in the Eastern DRC Province of North Kivu, one of the most active and dynamic sectors for expanding grid access, and spans 27 healthcare facilities that are supplied by SNEL, three commercial electricity providers, local hydro-power, off-grid solar power, stand-alone generators and combinations of these local supply options. Two of the 27 facilities lie outside of North Kivu: one in South Kivu, and one in Haut-Uélé.

In this paper, we demonstrate a methodology for measuring and evaluating the power quality of electricity access projects in the DRC and argue that developing data-based PQ standards for access projects in LMICs is critical to realizing the promise of powering critical infrastructure. Our study area reveals high variability in PQ across different energy supplies that, anecdotally, has a significant impact on the operation of the healthcare facilities they power. The data show broadly low PQ, but great variation in the nature of the PQ issues, underscoring the importance of designing hyper-local power supply solutions for healthcare facilities. Critical choices, such as whether to install backup generation, voltage stabilization, supply switching, and what an appropriate tolerance for sensitive equipment is must be informed by the PQ of the local supply, as revealed by longitudinal and continuous data collection. Foundational PQ data is critical for the ultimate success of grid expansion projects that target healthcare and other sensitive and critical loads.

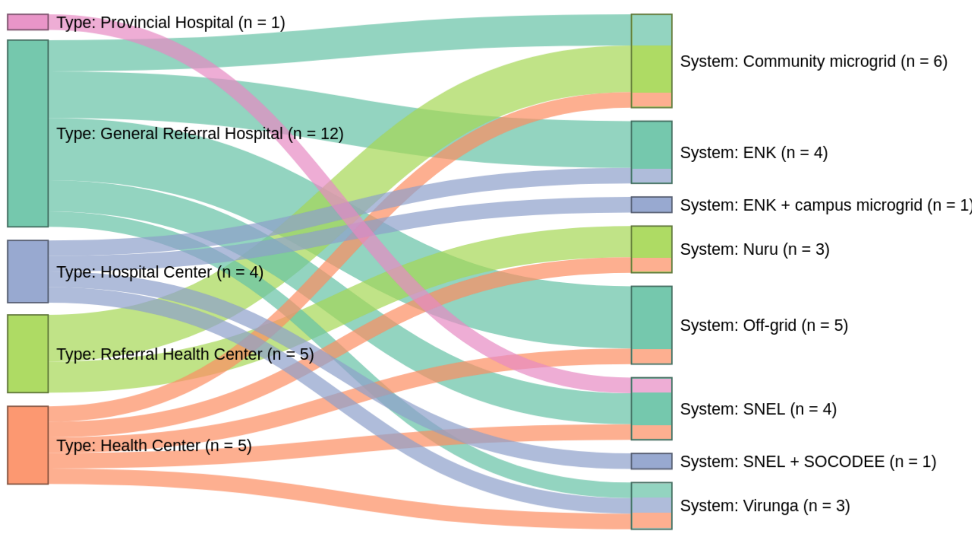

Figure 2: **The sample of healthcare facilities and supply connections.** On the left, we show HF types, in order of how many people the facility serves. Provincial hospitals are the top of the referral pyramid —- there is just one of these in all of North Kivu, which we instrumented — and at the bottom of the pyramid are health centers, of which there are 598 in North Kivu, each with 28 beds on average. These HFs are map to electrical supplies on the right. Facilities will often have more than one power source (at least a diesel generator as backup). This figure illustrates the diversity of enregy solutions used to power HFs in the study area.

2 Methods

In May 2022, through a formal partnership with the Provincial Health Department (DPS), we deployed PowerWatch sensors (Klugman et al. (2021)) — outlet-level power supply monitors — to measure the real-time power quality of 25 hospitals and health centers across North Kivu, an eastern province of the DRC, as well as one health center in Haut-Uélé province and one hospital in South Kivu. The selected facilities included 20 HFs powered by 13 distinct grids of various sizes built by the private sector, national government, local town councils, communities and churches, and 5 off-grid facilities powered by solar and diesel generators (see Figure 2 for a mapping of facility type to supply connection). When we refer to facilities heretofore, we will use the French acronyms:

HGR = General Referral Hospital; CH = Hospital Center; CSR = Referral Health Center; CS = Health Center. Hôpital Provincial du Nord-Kivu (HPNK) is the one provincial hospital in our sample. Figure 3 shows the selected health facilities, distributed along the major Goma-Butembo-Beni population axis, along with some facilities in more remote and isolated geographies.

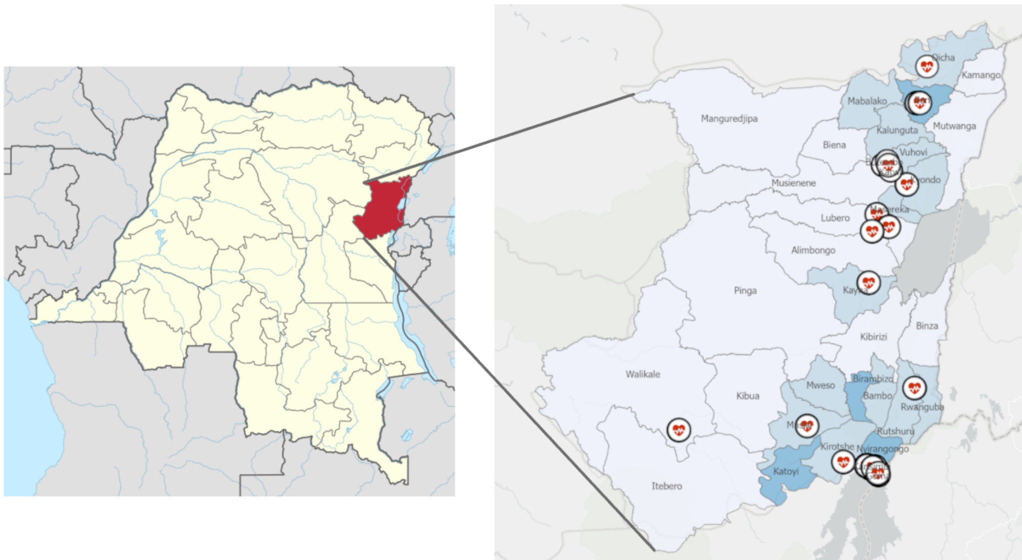

Figure 3: **Map of facilities instrumented with PowerWatch sensors in the North Kivu province of the DRC.** (Left) DRC, with North Kivu in red. (Right) Instrumented facilities. Darker blue indicates regions with higher population density. *Map credit: Esri, © OpenStreetMap contributors, HERE, Garmin, FAO, NOAA, USGS*

The PowerWatch sensors measure the voltage magnitude, AC frequency, and power state (energized or not-energized) at the outlet they are installed in. Integrated SIM cards provide data at two-minute intervals over the cellular network; this data is stored in a backend database for further analysis. To detect outages and evaluate outage extent from sensors installed at individual clinics, further analysis is performed to identify simultaneous reports of individual sensors losing power nearby in space and time (see Figure 5). This algorithm is discussed in depth in Section 2.1. Finally, data are aggregated to produce key performance indicators (KPIs) for power quality, grouped in time and space (Section 2.2). We compute a set of standard KPIs at the facility level, as well by the type of grid connections in Table 1. The final KPIs are visualized using a web-based Grafana dashboard for near-real-time insight into hyper-local PQ conditions in each HF.

Grid connection	Generation Capacity	No. connections	Generation source
SNEL (state-run utility)	∼2MW	∼10k	Hydro
SOCODEE	*	**	Hydro
ENK	1.8 MW	1.5k	Hydro
Virunga SARL	∼15 MW	∼7k+	Hydro
Nuru	1.3 MW	∼1k	Solar
Community microgrid	8kW - 600 kW	50 or fewer	Hydro
Campus microgrid	50 kW	University	Hydro
Off-grid	1kWp - 65kVA	N/A	PV-only, generator-only, and PV-gen hybrids

Table 1: **Supply Characteristics**: For the different generation supplies in the study region, we show the output capacity, typical or actual number of connections, and the nature of the generation source. * SOCODEE is a retailer of power from Virunga SARL's 13.1 MW Matebe hydro plant (World Bank (2020)). ** The number of connections is uncertain, but SOCODEE only operates in the city of Goma.

Figure 4: **The entry to the "Cliniques Universitaires du Graben" (CUG) in Butembo, North Kivu.** CUG Butembo is a teaching hospital with two grid connections: ENK and a campus minigrid that serves just the facility and the university.

2.1 Identifying Outages from Sensor Data using Clustering

To detect power outages, we deploy two PowerWatch sensors in each health clinic in the study. PowerWatch sensors are plugged into a power outlet in a secure location in the clinic, such as in the hospital director's office. The sensor records an outage report each time it detects a loss of power at the outlet. However, these losses of power are not always caused by grid outages. The sensor may have been unplugged or locally experienced a loose or poor connection. To accurately estimate grid reliability from this dataset of outage reports, it is critical that we identify true grid outages and remove the "false" outage reports caused by unplugs or loose connections. We also need to group the true individual sensor outage reports into coherent, localized outages that indicate longitudinal grid reliability. We will leverage spatio-temporal clustering to transform noisy, individual outage reports into coherent outage events to serve both of these needs.

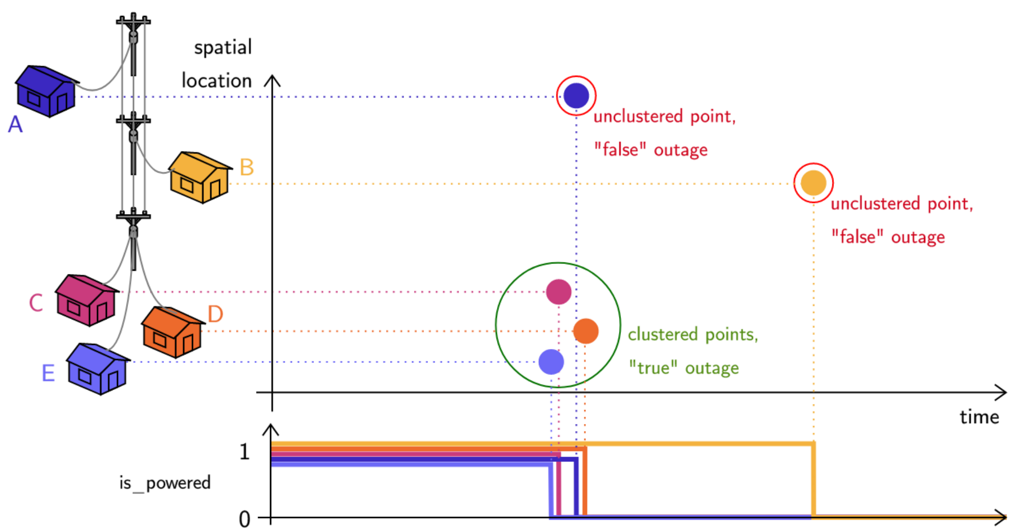

Figure 5: **Space and time thresholds for clustering.** When at least two sensors lose power nearby in space and time, we treat that as a true outage. Here, five facilities lost power. The PowerWatch sensors at facilities C, D and E lost power within a few seconds of each other, and they are close together in space, so we record an outage. Facility A also lost power around the same time, but it was too far away for its interruption to have been caused by the same failure, and no one else lost power near A, so we consider that interruption a false report and don't record that as an outage. Facility B lost power too long after C, D and E for that interruption to have been caused by the same failure that interrupted the power at C, D and E, so B too does not get clustered.

The core intuition behind the proposed outage detection algorithm, visualized in Figure 5, is that sensors on the same electrical infrastructure will be located close to each other in space and will experience a loss of power at nearly the same time. This is not a perfect rule: nearness in space does not always signify electrical connectivity; the sensors often don't have a GPS lock for clock synchronization and their local time can drift; and rolling outages can cause a delay in when outages are experienced in different parts of the grid. However, the closer in space and time an outage report occurs, the more likely it is to be caused by common electrical infrastructure. A secondary complication is that we do not know *a priori* how many outages occur in a given time window. To identify an unknown number of true, coherent grid outages based on nearness in time and space, we will perform non-parametric, density-based clustering space and time with the ST-DBSCAN clustering algorithm (Birant & Kut (2007)).

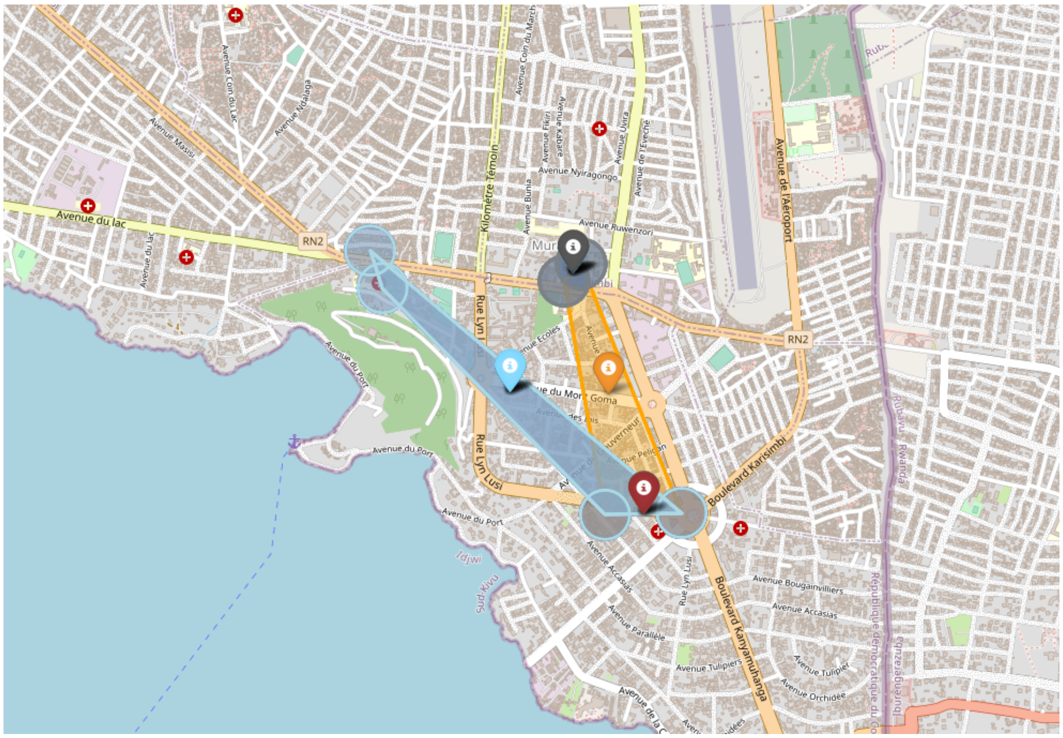

Figure 6: **An example of granular outage data collected by PowerWatch.** There were four outages that occurred in the span of two days in September, 2022, in Goma, DRC. Each outage is shown with a colored marker and the convex hull of the sensors involved in the outage; sensors are shown with colored circles; and two sensors are deployed at each facility. The black outage, at Health Center Murara, was the longest: it began at 7:02AM on September 29 and lasted for about six hours at one sensor deployed in the pharmacy and over nine at the other sensor deployed in the lab. The pharmacy had power restored sooner because that part of the facility had another grid, SOCODEE, that it could switch to; the lab had no backup. The blue outage began at 9:12AM, affected two facilities, and lasted just under two minutes. The red outage affected one facility, HEAL Africa, and lasted one minute before the facility was switched manually to a backup generator. The orange outage affected two facilities; power was restored sooner at HEAL (just under two minutes) then at Murara (21 minutes), because HEAL was able to switch to backup power. All these facilities are on the SNEL grid. *Map data copyrighted OpenStreetMap contributors (2017).*

Our implementation of ST-DBSCAN (Klugman et al. (2021)) has three input parameters: ϵ_s (a space threshold), ϵ_t (a time threshold), and n_{min}, the minimum number of points necessary to define a cluster. ST-DBSCAN is initialized with a stack containing the full dataset of outage reports and iterates through each point incrementally, popping it from the stack. In the following, a point p is a *space-time neighbor* of a point q if p is within ϵ_s of q in spatial distance **and** ϵ_t of q in temporal distance, where distance is measured using a Euclidean distance function.

We start by popping point p from the stack and initializing an initially empty set of discovered clusters $C = \{\}$. We then retrieve p's space-time neighbors. If any of p's space-time neighbors are in an existing cluster, we add p to that cluster (if multiple clusters are possible, we choose the first of these) and push p back to the stack. If not, we evaluate whether p has n_{min} space-time neighbors; if so, we add a new cluster c to C, include p and all space-time neighbors of p to that cluster, and add these newly clustered points to the stack. Otherwise, if neither of the above apply, p is marked as a noise point and removed from the stack. This process continues until the stack is empty, at which point the set of discovered clusters C and all points marked as noise-points are returned. The outage durations and frequencies from the resulting set of clusters C are used to evaluate grid reliability, while the set of outage reports corresponding to the noise cluster are dropped as false reports. This ST-DBSCAN algorithm runs in $\mathcal{O}(n \log(n))$ time (Birant & Kut (2007)).

Figure 6 shows a real example of an application of the clustering algorithm to detect power outages in Goma. In 48 hours, there were four outages that affected four different sets of facilities in Goma. In one case, within one facility, one sensor had its power restored before the other. It is often the case that only certain rooms or wings in a HF will have a backup power source. In this case, at CS Murara, the outage lasted nine hours in the lab, but six hours in the pharmacy, where they had the option of switching to SOCODEE.

2.2 SAIDI AND SAIFI ESTIMATION

Although the sensors have fairly high uptime — time in which the sensor is powered and reporting data over the cellular network — as seen in Figure 7, this real-world deployment is subject to occasional gaps in the dataset, e.g., when a sensor loses cellular reception or otherwise fails. To estimate key performance indicators such as SAIDI and SAIFI, we must build estimators that are robust to these data gaps. We estimate SAIDI and SAIFI for time period T and spatial area S from the PowerWatch data using the following formula:

$$SAIDI_{n\text{Line}}(S,T) = \frac{\sum_{i=1}^{n} O_{i,T}}{\sum_{i=1}^{n} R_{i,T}} \times \text{dur}(T), \tag{1}$$

where $O_{i,T}$ is the total duration or number of outages (for SAIDI and SAIFI respectively) sensed by PowerWatch sensor i (of n total deployed in region S) during period T, and $R_{i,T}$ is the total uptime of PowerWatch sensor i during period T. This estimator can be shown to be unbiased and consistent; see Bariya et al. (2023) for a more detailed derivation of *n*Line's estimator.

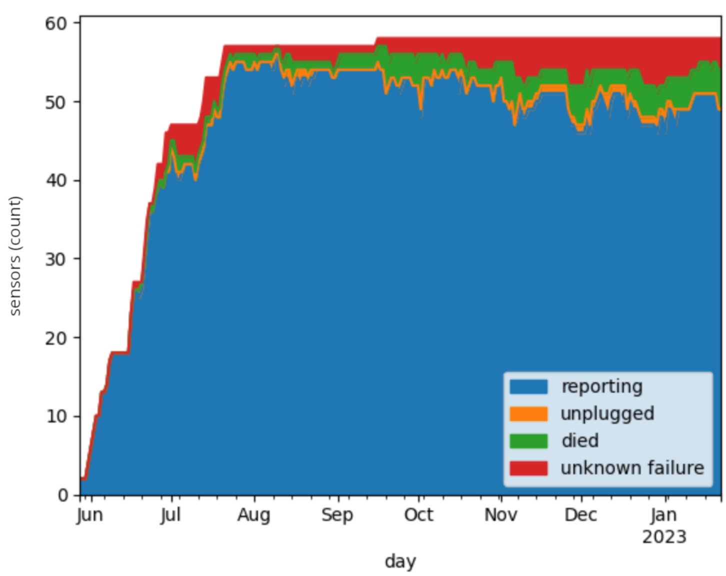

Figure 7: **PowerWatch sensor uptime at the healthcare facilities.** Stacked bar graph shows counts of sensors reporting (blue) and those that failed to report for any reason (dead, unplugged, or failure unknown), since the deployment began in late May 2022. Average daily uptime over the whole course of the deployment has been about 90%, but has dipped down to 79% on some days. sensor unplugs are detected using an accelerometer. Sensors die if they have been unpowered for a prolonged period of time (over 48 hours, usually), and resume reporting when power is restored.

3 Results

In this section we present features of power quality observed across (a) individual health facilities and (b) power supply categories. These data demonstrate how different electricity supplies manifest different PQ issues requiring different intervention/mitigation strategies and offer a variety of insights; for example:

- Informal, town-level hydro grids show the largest deviations from nominal voltage, which can degrade medical equipment.
- Of the large grid operators, the state-run SNEL has the most interruptions, but provides fairly stable voltage close to nominal, especially in recent months, compared to ENK and Virunga.
- HGR Walikale, where Doctors Without Borders installed a 30 kWp solar system just before our study began, is a strong success story. We recorded no interruptions at HGR Walikale and this HF has the most stable voltage of the facilities in our sample.

The following sections summarize the quantitative and qualitative results of the study for two aspects of PQ: voltage stability and power outages.

3.1 Power Quality: Voltage

Figure 8 shows a violin plot for each of the instrumented facilities over six months. Figure 9 shows daily hours undervoltage for four groups of facilities: the town-level microgrids, state-run utility SNEL, ENK, Virunga, and the off-grid facilities with only generator power. The town-level microgrids, which are all hydro powered, exhibit the largest voltage deviations both above and below nominal and prolonged voltage excursions below 10% of nominal (198V). Facilities served by ENK and Virunga – large hydro operators with seven thousand and over 1.5k connections respectively – also saw poor voltage quality, which varied greatly by week: for Virunga, some weeks had more than six hours undervoltage in a day, while others no more than three hours. For the facilities we observed, power quality from SNEL improved over the course of the study: before October, there was often more than an hour of below-nominal voltage in a day, but since October there have been almost no days with more than a few minutes undervoltage.

These power quality issues have important, anecdotal impacts on the clinics studied. One clinic reported a malfunctioning X-ray machine. There, the voltage in radiology and the voltage in another room exhibit a suggestive anti-symmetry, seen in Figure 10. Undervoltage affects the longevity of sensitive medical equipment, and is especially damaging to motor-driven equipment such as fridges. At HGR Kyondo, like at many facilities, oxygen concentrators often break because of voltage surges. Kyondo is another town-level microgrid and is the largest consumer of electricity from its local hydro plant. A technician relayed that when there are heavy rains, or a tree gets stuck in the dam, the power at the HF often goes out; data around such seasonal power quality variation could provide valuable insight for hospital operations, such as the scheduling of procedures requiring reliable power.

3.2 Power Quality: Outages

Many of the instrumented facilities experienced between 0.3 and 1.2 power interruptions per day, on average, over the six months observed, and sometimes eight or more interruptions in a day. Interruptions occur for a variety of reasons. Some facilities have regularly scheduled outages. HGR Oicha, with 305 beds, relies solely on a diesel generator for power which is turned on daily from 9AM-12PM and 6-11:30PM to save on fuel costs. In constrast, HGR Virunga, also a large, off-grid referral hospital, is able to run their generator 24/7 under the auspices of the Catholic Church.

Figure 11 shows the full range of weekly interruption frequencies, which vary widely by facility and week. One week at HGR Kyondo, on a community-level hydro grid with PV backup, stands out with 36 interruptions. On the Tuesday of that week, the facility experienced 14 interruptions, lasting an average of 2.3 minutes each.

While outage duration is clearly important (e.g. long outages mean the loss of vaccines, blood, and reagents that need refrigeration) outage frequency also tells an important story. Every interruption,

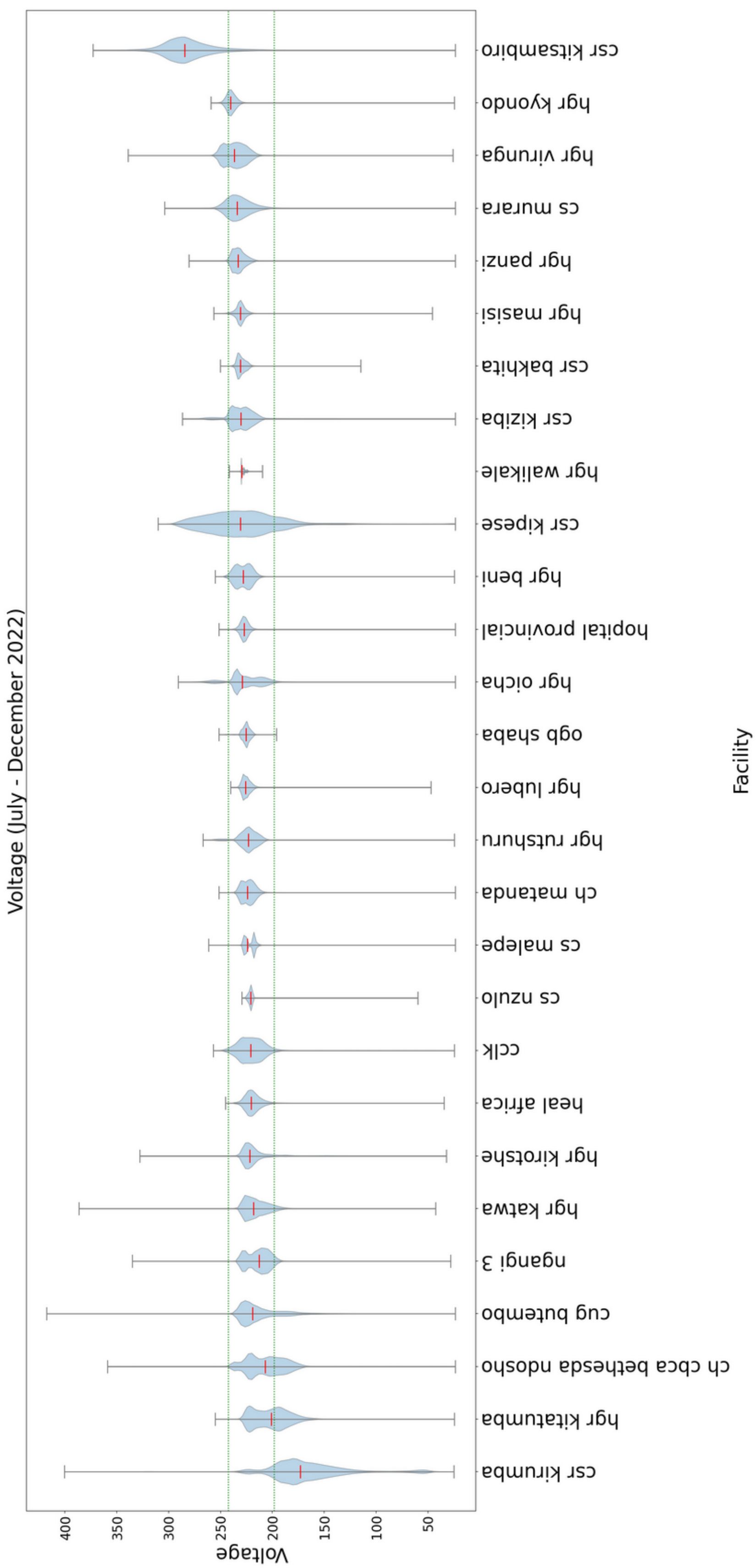

Figure 8: **Voltage stability**. Voltage profiles vary dramatically between facilities in the study. One of the facilities on a town-level microgrid, CSR Kitsambiro, almost always has overvoltage, whereas another town-level microgrid, CRS Kirumba, is chronically undervoltage. HGR Walikale is the only facility where voltage never strayed outside of nominal (+/- 10% from 220 V, indicated by dashed lines).

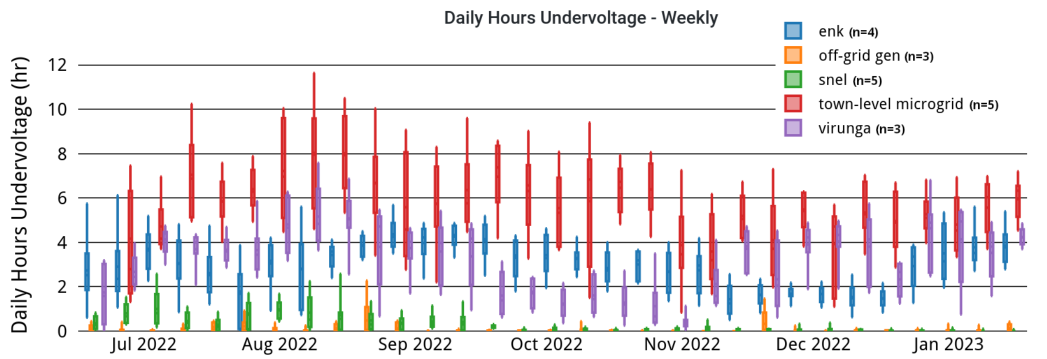

Figure 9: **IQR daily hours undervoltage over the past three months.** Town-level microgrids exhibit the most daily hours undervoltage of all the groups, typically, and the most variation. ENK and Virunga (both large, hydro operators) are also fairly unreliable, with sometimes more than four daily hours undervoltage. We define "under-voltage" as more than 10% below nominal, i.e. 198 V.

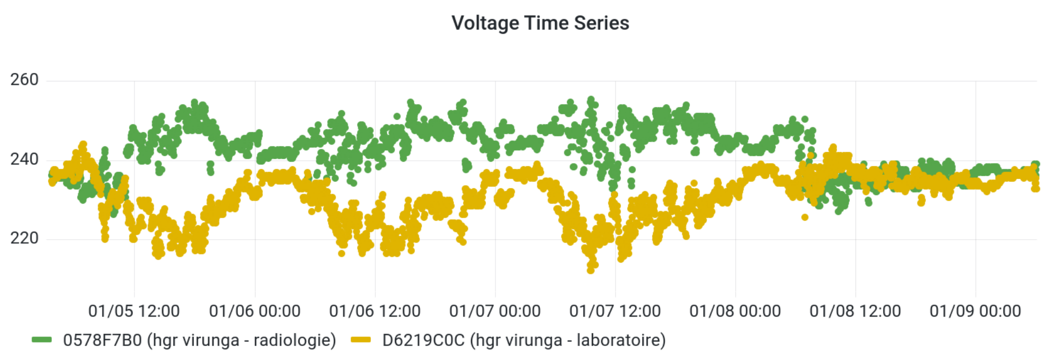

Figure 10: **Voltage recorded at two-minute intervals by the two sensors at HGR Virunga, one in the radiology room, and one in the lab, over the course of a few days in January 2023.** This anti-symmetry is persistent from when the facility was first instrumented. The X-ray technician told us the X-ray machine malfunctions, which could be caused by these large voltage deviations (frequently above 250 V).

however short, disrupts operations at a HF. A lab technician at HEAL Africa — one of the best-equipped HFs, but with among the most interruptions — informed us that power outages mean the loss of blood samples, which have to be re-prepared. Even short outages can have terrible consequences when electricity is needed for oxygen concentrators and baby incubators.

3.3 Two off-grid solar stories

Figure 12 shows voltage measurements at CSR Kiziba, which was powered by its own small solar system before being connected to a solar minigrid operated by Nuru in mid-July 2022. Prior to the Nuru connection, voltage climbed and fell daily, more often outside than within the nominal range. There were nightly outages when the battery was depleted. After the Nuru connection, we see dramatically improved voltage quality. There are still nightly outages, but they are shorter than before the supply change.

Contrast CSR Kiziba with HGR Walikale, which is equipped with a 30 kWp system that Doctors Without Borders installed just before our study began. HGR Walikale is the only facility in our study where voltage has never deviated from $\pm 10\%$ of nominal and where there were no sensed interruptions in over six months of data collection.

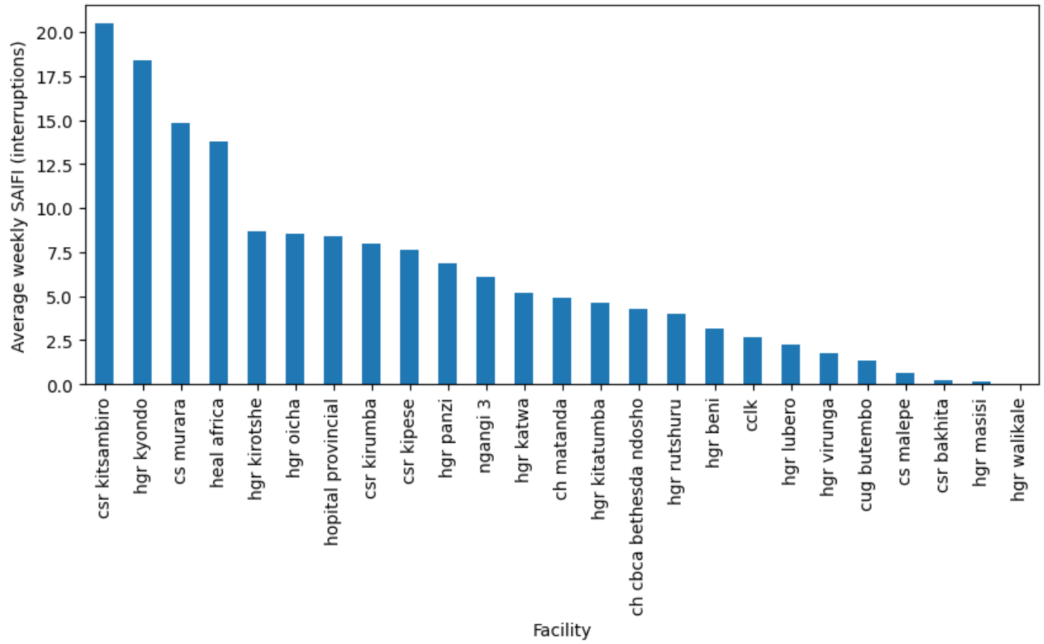

Figure 11: **SAIFI: Average Weekly Grid Interruptions.** Interruption frequency varies widely, from 20.5 interruptions per week, on average, at CSR Kitsambiro, to none at HGR Walikale, the off-grid facility on its own, new solar system.

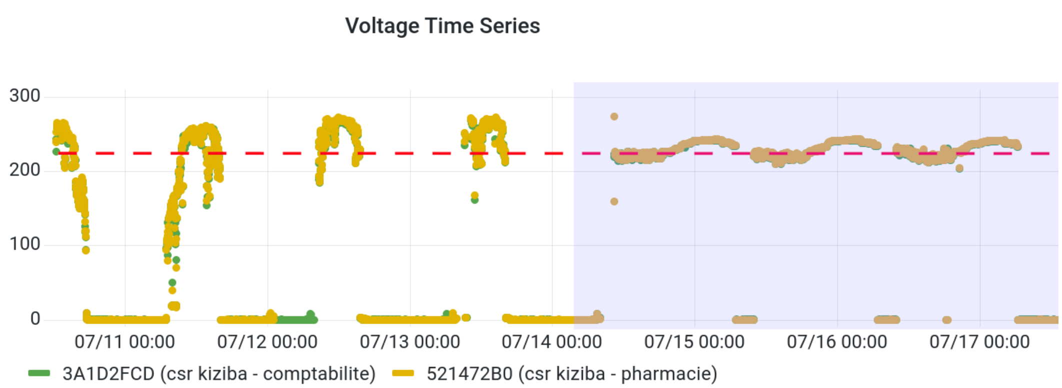

Figure 12: **Voltage before and after supply switch.** This high resolution voltage magnitude time series clearly shows the point where the CSR Kiziba HF transitioned from its own PV system to the solar minigrid provider Nuru on July 14, 2022 (shown with the shaded box). Voltage fluctuations improved after the connection and, although there continued to be nightly outages, these outages were shorter.

4 Discussion

The results presented in this paper provide initial insights into the value of continuous, longitudinal data on grid power quality for critical infrastructure. Longitudinal data is important: the PQ situation changes from week to week (e.g. in the case of the hydro grids where heavy rains have a huge impact on reliability) and month to month (e.g. in the case of SNEL where PQ changed dramatically before and after October, as detailed in Section 3.2). Continuous data is also important: even short outages have a large impact on hospital operations and require high-resolution data to be captured.

Longitudinal, continuous monitoring, such as we demonstrate in this work, should be the norm for expanding electrification. Binary reliability indicators from recall-based surveys are not sufficient to capture the variety of ways that PQ affects critical infrastructure. Our data show a variety of important consequences of poor PQ that would be missed by these surveys: like when voltage frequently deviates far from nominal—like at the chronically undervoltage CSR Kirumba HF (as seen in Figure 8)—or when there are frequent, short outages—like at HEAL Africa in Goma.

Empirical data on power quality have value beyond monitoring and evaluation of existing systems, and can inform the design and expansion of future grid access projects. PQ data, such as we present here, can help improve sizing decisions for different kinds of energy uses and systems, as well as inform what equipment a HF should be equipped with to mitigate their local PQ problems. Protection strategies for individual facilities or regional health systems with poor PQ could include integrated UPS systems capable of keeping entire wards (5-15 kWp) or even facilities (15-150 kWp) energized during grid interruptions, and smart power control systems that decide how to allocate multiple energy resources (PV, battery, grid(s), generators) across the different health facility wards/biomedical/patient needs.

On longer time scales, we believe that measuring and developing PQ standards for electrification can inform the design of key electricity policy and market-design considerations, like performance-based regulation and incentives for health facility electrification based on indicators of quality and reliability. It is easy to imagine program designs that hinge on basic metrics of reliability will more effectively increase reliability. Results-Based Financing (RBF) mechanisms have recently been announced for the DRC[1] through SEforALL's Universal Electrification Facility and the DRC's new Rural and Peri-Urban electrification financing agency, ANSER[2], with an interest in big-data approaches to developing electrification policy.

5 Conclusion

In this paper, we argue that empirical data-driven indicators of power quality should feature prominently in the discussion around energy access for critical infrastructure. When powering sensitive equipment in a healthcare facility, for example, we must go beyond simple binaries of connected or not connected, and towards a more nuanced understanding of the salient dimensions of power quality offered by diverse energy access solutions. The lack of data to evaluate power quality in energy access projects has real and serious implications: the sample considered in this study featured faulty X-ray machines, failed laboratory tests, and unpowered oxygen concentrators and incubators. The detailed, quantitative PQ data enabled by remote outlet-level sensors at individual healthcare facilities provided unprecedented insight into the existing spectrum of PQ problems faced in the Goma region of the DRC and are suggestive of broader trends in LMICs. These data form the basis of potential data-driven answers to the dual questions of how energy access solutions should be designed to support critical infrastructure and of how critical infrastructure should adapt to the reality of existing energy solutions.

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