Electricity Outages in Uganda: Causes, Trends and Regional Disparities

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***Abstract*—Uganda's unreliable electricity grid is a significant hurdle to its development. This paper analyzes the country's electricity situation using data from the national electricity regulator, focusing on Umeme, which supplies electricity to over 90% of the country. Our study reveals that while the median outage duration has decreased in all regions, the frequency of the outages has remained largely unchanged, except in Kampala West. Outages are now more frequent during the day rather than the evening peak demand hours, suggesting that supply constraints are not the primary cause of these outages. We identified failure of overhead equipment accessories as the most common cause of outages, with vandalism-related outages taking the longest to resolve. Additionally, our analysis reveals a connection between rainfall and increased outage intensity, underscoring the electricity grid's vulnerability to climate conditions.**

***Index Terms*—Power Outages, Uganda, Umeme, Rainfall, Reliability**

I. Introduction

In Uganda, utilities face persistent challenges in delivering consistent and high-quality electricity to their customers [1], [2]. A crucial tool for evaluating the quality of electricity supply is the Supervisory Control and Data Acquisition (SCADA) system. However, current SCADA systems often lack the capability to capture detailed, localized data on power quality [3]. Monitoring instrumentation is often confined to substations and tee-off points[1] along medium voltage feeder lines, limiting its ability to identify disturbances at specific low voltage locations.

Despite these limitations, medium voltage level outage measurements offer crucial insights into the grid's condition, guiding utility investment decisions related to service quality and grid expansion. This paper describes the state of reliability in the country by leveraging proprietary raw outage data spanning eight years, obtained from Umeme Limited, the primary distribution utility in Uganda, through the Electricity Regulatory Authority(ERA). We employ custom analytics to illustrate the temporal evolution of electricity outages and the regional differences. Our analysis reveals the spatial disparities in outages across the country and underscores the grid's susceptibility to disruptions due to factors such as weather events, vandalism, and inadequate maintenance.

[1]The term "tee-off" is employed in a context suggesting a resemblance to the letter "T." This point marks the juncture where the bus bar extends from the source in one direction and further connects to other loads in an alternative direction.

II. Data

A. Feeder infrastructure and outage dataset

The Umeme electricity distribution grid is geographically divided into four regions, encompassing most of Uganda. Each of these regions are further subdivided into districts.

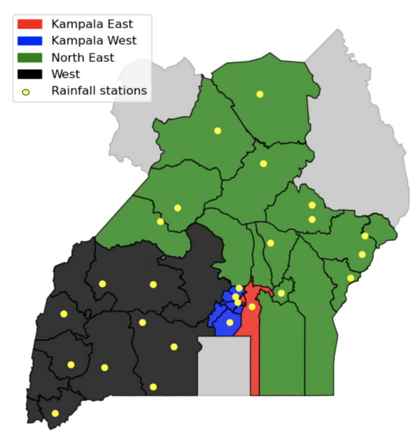

Fig. 1. Umeme Grid Coverage

Figure 1 illustrates the spatial coverage of each Umeme region, and Table I presents the distribution of districts and customer counts by region. The gray regions in Figure 1 denote areas that fall outside the operational coverage of Umeme.

Our dataset identifies a total of 319 unique feeders spread across Umeme's service territory as of 2021. The aggregate customer count across all feeders stands at 1,007,118, marginally lower than the 1.6 million reported by Umeme [4]. We attribute this variance to potential gaps in our dataset.

The dataset includes records of daily outages, including the start and resolution times, covering eight years from January 2015 to October 2022. Each outage is accompanied by a cause description, such as 'tree fell on overhead wires.' Furthermore, the utility provides monthly Energy Not Served (ENS) data in GWh for each feeder. Although we have ENS data for 2021 and 2022, our analysis focuses on the comprehensive 2021 dataset, which offers data for every month, unlike the 2022

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dataset, where the final quarter is unavailable. Only 258 of the 319 feeders for 2021 have reported ENS data.

TABLE I
Electricity infrastructure and customer distribution

Regions	North East	West	KLA East	KLA West
No of feeders	65	49	119	86
No. of Districts	11	9	8	7
No. of Customers	126,102	196,488	412,500	272,028
No. of transformer(tx)	3241	3986	4330	2916
Median tx size (kVA)	50	50	100	200

Our data set covers 14,425 transformers; however, as of 2022, the Umeme network is reported to host just under 15,000 transformers [5].

B. Rainfall Monitoring

The dataset utilized in this study was procured from the Uganda National Meteorological Authority [6]. Our analysis encompasses daily rainfall levels collected from 29 meteorological stations dispersed across the nation, with 26 of these stations situated within Umeme's grid territory. Figure 1 depicts the geographical distribution of these rainfall stations falling within Umeme's service territory. This dataset spans three years (2019-2021), providing a wealth of daily rainfall measurements in millimeters.

III. Methodology

A. Qualitative analysis

In this section, we analyze power outages in Uganda at both regional and district levels from 2015 to 2021 to understand patterns in grid reliability. We calculate the average duration and frequency of outages each month for each region using a thirty-day moving average. We also look at when these outages occur during different times of the day.

We concentrate on the most recent complete year, 2021, for the spatial analysis. We calculate the average outage duration and frequency for each feeder by district. Additionally, the ENS values, reported by the utility at the feeder level, are aggregated at the district level and converted from Gigawatt-hours to a monetary value in United States dollars using the effective tariff rate[2] and an exchange rate of 1 USD to 3586 Ugandan Shilling [8]. The resulting insights provide a detailed understanding of grid reliability dynamics in Uganda.

B. Outage Cause Classification: Automated Labeling

Each outage is accompanied by a descriptive account of its cause. The granularity of these descriptions varies, ranging from detailed explanations to brief and sometimes ambiguous mentions, occasionally omitting the underlying cause altogether. To streamline the categorization process, the utility employs a set of predefined labels for outage causes, utilizing occasional manual processing to assign these labels. We introduce an "unknown" label category for descriptions that lack information about the root cause(s) of the outage, in addition to the utility-defined labels.

To automate this classification process, we employ a supervised learning approach. A representative subset of our dataset is manually labeled, ensuring diversity across label categories. A total of 2452 cases are labeled for training and testing, with an 80:20 split ratio. For the label prediction task, we utilize SetFit [9], a framework designed for few-shot fine-tuning of sentence transformers. SetFit fine-tunes a pre-trained sentence transformer on a limited set of text pairs, leveraging few-shot learning to effectively address specific categorization tasks.

C. Wavelet Coherence analysis

This section investigates whether a relationship exists between climate factors, specifically daily rainfall, and daily power outages.

Wavelet analysis serves as a powerful method for analyzing time-series data by delineating its structure in time-frequency space, facilitating the identification of dominant modes of variability and their temporal evolution [10]. Solely relying on frequency domain analysis proves inadequate when investigating the temporal occurrence of events in a time-series. Wavelets offer the unique capability to adaptably stretch and translate in both time and frequency [11]. In this study, we employ wavelet coherence, a localized correlation coefficient in time-frequency space, to examine the relationship between two time-series at various scales and time intervals [12].

IV. Results

A. Qualitative analysis

As stated in the methodology section, we delve into a qualitative exploration of the outage data, aiming to uncover patterns of variation over time and space and the immediate financial repercussions of outages for the utility company.

1) Temporal Variations in Outages: Our analysis starts with a graphical representation in Figure 2, which shows the median outage duration per month, broken down by region. The Kampala West region, encompassing the capital and its suburbs, experiences the shortest outage durations. The Western region has a significant reduction in median outage duration over time, marking a drastic improvement from being the worst-performing in 2016 to rivaling Kampala West, historically best performer, by the end of 2022. The Northeast region exhibits a notable peak in outage hours in 2019, yet aligns with the overall downward trend by early 2020.

Interestingly, Figure 3 reveals that the stagnant trend in outage frequency does not parallel the downward trend in outage duration. While Kampala West shows a declining trend in outage frequency, signaling enhanced reliability, other regions do not consistently follow this pattern.

Time of Use (TOU) pricing, a method to modulate electricity rates based on the time of day, is utilized in Uganda for non-residential customers. This system aims to reduce electricity consumption during peak demand hours, thus averting potential supply and demand imbalances. The TOU periods

[2]Effective tariff is the weighted mean tariff across all tariff categories. We use the tariff scheme used by the ERA at the start of 2021 [7].

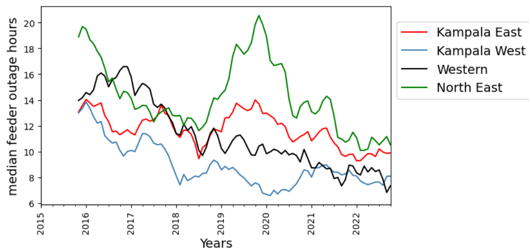

Fig. 2. median feeder outage duration

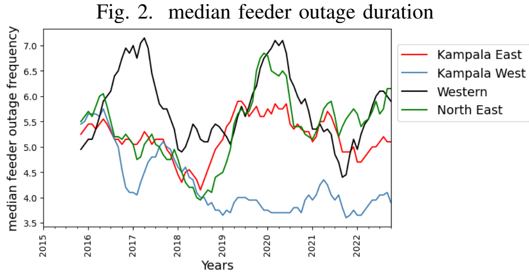

Fig. 3. median feeder outage frequency

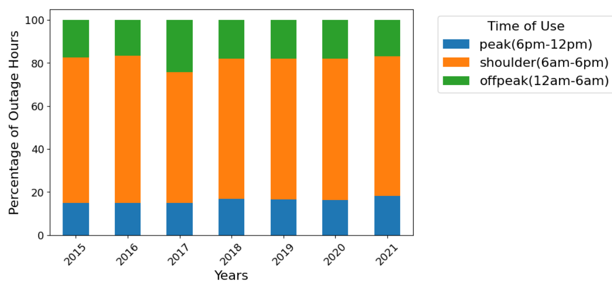

Fig. 4. Percentage of outage hours by time of use period

in Uganda are defined as peak (6pm-12pm), off-peak (12am-6am), and shoulder (6am-6pm) [13].

Figure 4 illustrates that the shoulder period accounts for over 60% of outage duration within our dataset's timeframe. This suggests that supply shortages which typically occur during peak hours, are not the predominant cause of outages. This marks a shift from the 2005-2012 era, when outages were primarily caused by demand exceeding supply [14], indicating recent improvements in supply stability.

2) Spatial Variations in Outages: Figure 5 explores district-level variations, using yellow vertical lines to demarcate districts within the same region. The visualization presents a cumulative count of outages and outage hours per feeder in 2021, with the districts and the number of feeders per district noted on the x-axis. The number of feeders in each district is enclosed in brackets (e.g., Jinja [30] signifies 30 separate feeders in Jinja district). The outage duration boxplots are depicted in blue, and the outage frequency boxplots are illustrated in red.

A critical observation is that Kampala West, despite having the highest customer density per kilometer of feeder line, showcases superior reliability. In contrast, regions with sparse customer densities, such as the Northeast, tend to exhibit lower

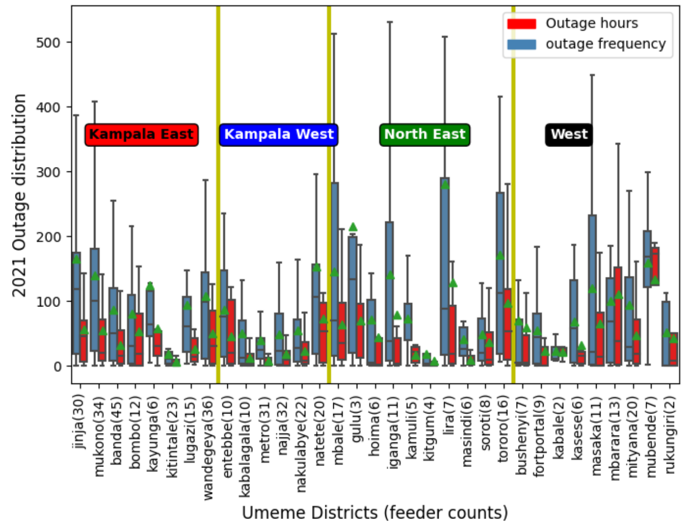

Fig. 5. Outage distribution by district

reliability metrics.

3) Energy Not Served: The top ten districts with the highest energy deficits are highlighted in yellow in Figure 6. We learn from the figure that four of the districts namely Wandegeya, Natete, Banda and Najja (Najjanankumbi) are suburbs of the capital city Kampala. We also observe large energy deficits in historical industrial bases [15] in east and central districts of the country, such as Jinja, Iganga, Mukono, and Kamuli.

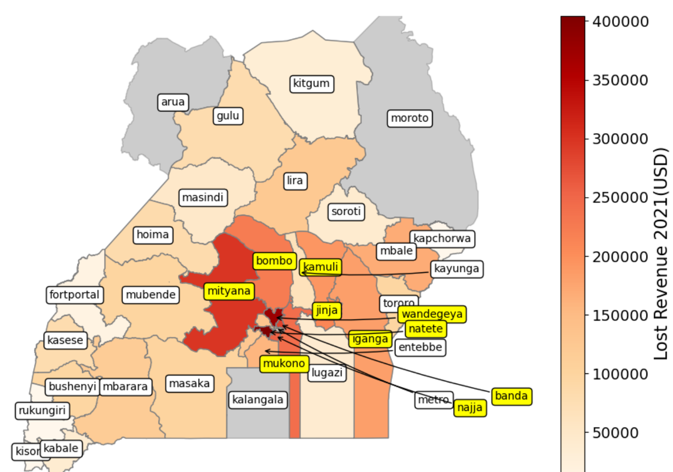

Fig. 6. Lost revenue resulting from energy not served

B. Outage Cause Classification: Automated Labeling

As explained in the methodology section, we created a model to categorize outage descriptions into 18 different categories. These categories fall into three main classifications. Firstly, equipment failure; this encompasses issues related to infrastructure, including aerial earth wires, conductors, cables, meters, poles, overhead accessories, SCADA systems, sectionalizers, and transformers. Such failures directly impact the physical delivery of electricity and are often due to wear and tear or technical malfunctions. Secondly, external disturbances; these are faults induced by external factors, including environmental influences like vegetation growth and adverse weather conditions, vandalism, animal interactions, and fires. These causes reflect the vulnerability of power infrastructure to its surroundings and external human actions. Lastly, system related issues; this category addresses faults stemming from systemic operational challenges, such as those caused by third-party utilities, sections of the grid (e.g., T-off sections), and issues related to power quality. These faults can arise from complex interactions within the power delivery system itself, including coordination with other utility services or inherent problems within the grid's design or operation.

From a starting pool of 215,387 outage descriptions, filtering out those without corresponding feeder identification codes reduces the dataset to 184,134 entries. A significant portion, 60%, of these descriptions are tagged as "unknown" by the model. This category includes vague descriptions like *'Fault; Reclosure Successful.'*, which provide little insight into the underlying causes of the outage. This ambiguity may suggest difficulties technicians face in pinpointing exact outage causes.

Concentrating on the remaining 40% of the data allows for the application of labels that clarify the root causes of outages. This refined dataset offers a solid base for deeper analysis, giving a clearer view of the reasons behind power outages. The classification model boasts a commendable weighted average F1-score of 0.98 on the training dataset and an F1-score of 0.93 on the test dataset.

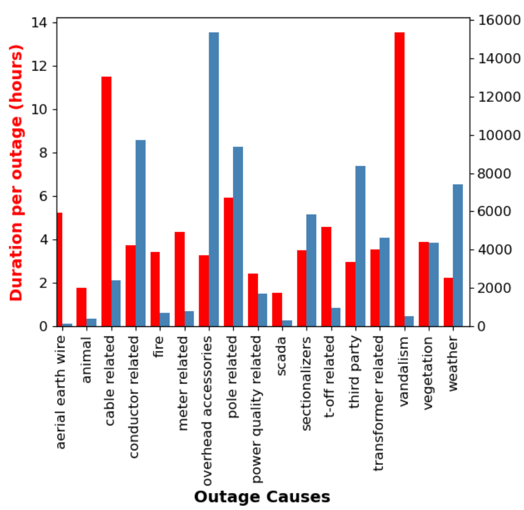

Fig. 7. Average duration per outage and outage counts

Figure 7 analyzes these classified outage labels, highlighting the average duration and frequency of outages per category. Equipment failures, primarily overhead accessories failures, emerge as predominant and are typically resolved within six hours. Conversely, vandalism and cable failures, though less frequent, demand considerably longer resolution times; 14 and 12 hours on average, respectively. Despite its rarity, vandalism has a substantial impact due to high replacement costs and procurement delays for new equipment [16].

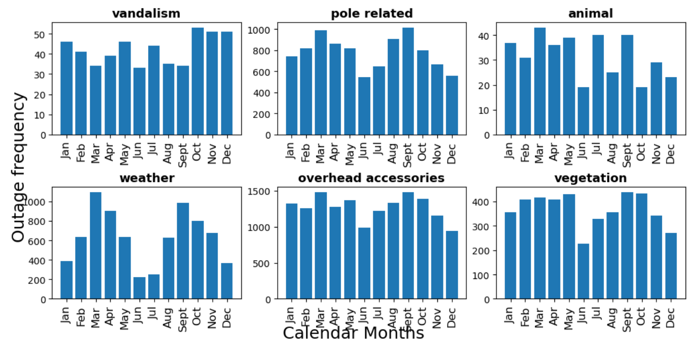

Fig. 8. Barchart showing duration per outage and outage counts

We also explore seasonal patterns in the recorded outages, focusing on six categories commonly cited as leading causes of outages: vandalism, pole-related issues, animal interference, weather damage, damaged overhead accessories, and vegetation [14]. Specifically, we investigate the correlation with weather events, a situation expected to worsen with the impacts of global warming [17]. Figure 8 displays the monthly distribution of outages by selected categories from 2015 to 2021. June consistently sees the lowest number of reported outages across all categories. Additionally, outages due to weather and vegetation peak during Uganda's wet seasons, March to May and September to December [18]. Vandalism and animal related outages do not appear to show any seasonality.

C. Wavelet Coherence

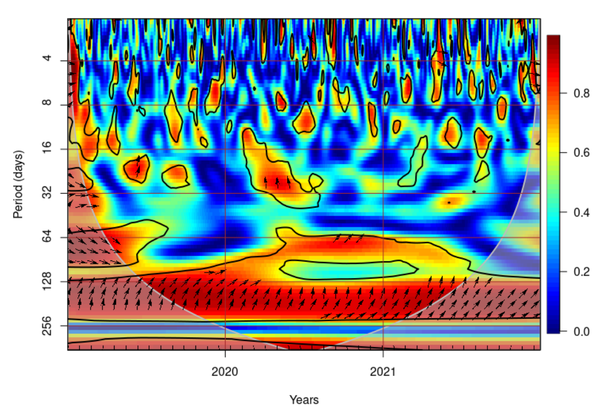

Fig. 9. Wavelet Coherence

This section uses wavelet analysis to further explore the relationship between electricity outages and weather, specifically daily rainfall data. Figure 9, shows a wavelet coherence plot comparing two time-series: 1) the country wide average daily number of outages from 2019 to 2021, and 2) the average daily rainfall across all stations within Umeme's coverage area during the same period.

In the plot, the x-axis represents time in years, and the y-axis represents frequency converted to periods (days) to make the results easier to understand (period = 1/frequency). The colorbar on the right side of the plot shows the coherence between the two time-series. Warm colors indicate high coherence, while cool colors indicate low coherence. The intensity of the color at each point on the plot shows the strength of the coherence between the two time-series at that specific time and frequency.

The plot shows short bursts of high coherence between 4 and 32 days on the y-axis throughout the x-axis range. This suggests that these are extreme rainfall events that immediately lead to power outages.

We also observe high coherence between the rainfall and outage frequency time-series at periodicities between 128 and 256 days, which corresponds to 4-6 months. This indicates a strong correlation between the rainy seasons and increased power outages.

Furthermore, the plot shows a phase lag of about 45 degrees between the outage frequency and rainfall time-series. This suggests that the effects of rainfall on outages are not immediate but delayed. We can speculate that prolonged rainfall can impede movement on non-asphalt roads, hindering maintenance work. Given that most of the grid is overhead, we can expect damage to overhead poles and interference from vegetation. Figure 8 also shows an increase in pole-related outages and vegetation-related outages during the rainy seasons.

V. Conclusion

Our study examined electricity outages in Uganda, focusing on their frequency, duration, and financial impact on the utility company. We found that while the duration of outages has decreased across all regions, their frequency remains unchanged except in Kampala West. Here, both the frequency and response times have improved, showing effective management by the utility. Notably, outages are now more common during the day (6 am to 6 pm) rather than peak hours (evening time), suggesting that supply shortages are less of an issue than before.

The data showed that equipment failure, particularly of overhead accessories, is the most frequent outage cause but is typically resolved within six hours. Vandalism, although rarer, takes longer to resolve, averaging 14 hours.

Our wavelet coherence analysis also linked rainfall to outages, particularly during rainy seasons, with a recurring pattern every 4 to 6 months. There appears to be a delayed impact of rainfall on outages, likely due to its effect on maintenance activities and gradual damage to the overhead grid through factors like vegetation encroachment.

These insights underline the challenges on Uganda's power infrastructure and emphasize the need for robust maintenance strategies and enhanced infrastructure resilience to reduce weather-related outages.

VI. Acknowledgement

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