Electricity Demand Forecasting, Coverage Estimation, and Distribution Planning using Mobile phone Call Detail Record (CDR)

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Abstract

Electricity serves as a nation's development engine. Energy is a finite resource, and worldwide energy use is rising at a 1.6% yearly rate. The difficulties associated with power storage, generation, and distribution are growing as a result. Understanding and regulating urban energy use is crucial for assisting climate change activities and creating more durable and sustainable cities. This study aims to investigate the potential applications of Call Detail Records (CDR) in forecasting, coverage estimation, and distribution planning. By putting the numerous factors that affect how much electricity is consumed in context and demonstrating how Call Detail Records might be used, we investigated how it might be used in Nigeria.

1 Introduction

The annual global energy consumption is increasing by 1.6% [2] due to rapid urbanization. Urban areas are experiencing a surge in electricity demand, leading to challenges in power storage, production, and distribution [10]. Consequently, this higher energy demand results in increased greenhouse gas (GHG) emissions [27]. To support climate change initiatives and promote resilient and sustainable cities, it becomes crucial to comprehend and regulate urban energy usage [6]. A comprehensive understanding of current urban energy profiles can significantly contribute to this goal. Evaluating energy efficiency programs can facilitate early-stage planning, design, and optimization of energy systems, especially in developing countries like Nigeria, which has twenty-three power generating facilities connected to the national grid, producing 5,301.32 MW of energy [1]. However, this capacity falls short of meeting the needs of Nigeria's 206.1 million population, leading to inconsistent electricity supply [34]. To address this issue, it is imperative to allocate limited electricity resources to areas where they are genuinely required, thereby improving the quality of life for residents and fostering overall state development.

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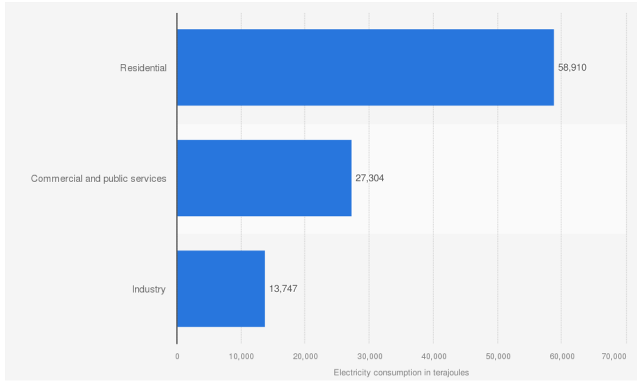

Figure 1: Amount of electricity consumed in Nigeria ad of 2020, by sector (in terajoules)

Mobile phones have achieved widespread adoption across various sectors, with a global penetration rate of approximately 78.05% [18]. In Nigeria, the rate of mobile phone adoption is about 52% according. This means that about 120 million people in Nigeria have mobile phones.[31]. This can be attributed to the growing affordability of airtime and mobile devices [24]. This study explores the use of Call Detail Records which already has a wide adoption rate as a dependable indicator of electricity consumption in the country.

2 Literature Review

2.1 Nigeria

The data collected by Mobile Network Operators (MNOs), known as Call Detail Records, contains information about all calls made within a specific area. According to a study by the National Identity Management Commission (NIMC) [11], approximately 85,591,398 individuals possess National Identification Numbers (NIN), while reports from the Nigerian Communications Commission (NCC) [25] suggest around 220,931,688 active mobile lines in Nigeria. Recently, the Nigerian government made it mandatory to link phones with individuals' NINs, highlighting the widespread use of multiple mobile phones in the country.

According to a report by Statista [30], based on data from the International Energy Agency (IEA), the majority of electricity consumed in Nigeria is attributed to residential areas. The plot is shown in Figure 1. This trend can be attributed to the insufficient power supply, as explained by Ekpo et al. [15], which has compelled manufacturers to rely on privately generated electricity to power their production processes. This establishes the fact that electricity consumption in Nigeria is mostly done by the people in their houses.

2.2 Electricity Consumption Prediciton

Extensive research has explored diverse approaches to estimating energy consumption across various sectors of the economy. For instance, Le et al. employed CNN and Bi-LSTM-based models to predict energy consumption based on previous years' electricity data. The emergence of data mining has brought a revolutionary shift in electricity consumption analysis, opening up new avenues of exploration. Researchers have utilized multiple datasets for this purpose, including Wi-Fi connection data to estimate building consumption rates [39], weather forecasts [21], calendar data, household appliance usage data, and the number of occupants in a house [34], along with building occupancy information [23].

Ezennaya et al. [16] and Abdullah [3] have utilized past energy usage data to make predictions about energy consumption in Nigeria. The Nigerian government has taken steps in this direction as well, establishing a dashboard through the SEforall program to plan future energy consumption in the country. However, these methods lack the consideration of real-time movement patterns of people in the community. Moreover, they often come with accessibility challenges, require significant resources for data collection, and can be expensive. Consequently, there is a need to explore more cost-effective methods to gather this type of information.

2.3 Factors affecting Electricity in Nigeria

Several studies, such as those conducted by Dokas et al. [12], Ippolito et al. [20], and Agyei-Sakyi et al. [4], have emphasized the pivotal role of Gross Domestic Product per capita (GDPC) in influencing electricity consumption in developing countries. In the context of Nigeria, Ekpo et al. [15] unveiled that electricity consumption exhibits positive and significant correlations with income, population, and the industrial sector's output. Additionally, Ubani [35] identified six key factors contributing to changes in the electricity consumption rate in Nigeria. These factors include the degree of urbanization, population density, number of manufacturing industries, number of households with electricity, employment rate, and distance to the nearest power generating station. Moreover, Onisanwa and Adaji [26] further emphasized that income per capita, electricity distribution shortages, the number of electricity customers, and population density are the primary determinants shaping electricity consumption patterns in Nigeria.

2.4 Call Details Records

Anonymous mobile phone records, also known as CDRs (Call Detail Records), have shown their ability to provide insights into human behavior across different domains. These records have been employed in crime prediction [9], population modeling for disaster response during earthquakes and floods [7, 28], epidemic outbreak modeling Wesolowski et al. [36], inferring local socio-economic statistics in both developed and developing countries Eagle et al. [14], Smith et al. [29], identification of urban functional areas Yuan et al. [38], crowd estimation at social events using call data records Sumathi et al. [32], track unemployment Toole et al. [33], measure economic activities Dong et al. [13], Arhipova et al. [5], poverty Hernandez et al. [19] and urban transportation system development Berlingerio et al. [8]. Gilbert et al. [17] used Call Detail Records (CDR) to plan the Nigerian government's response to the outbreak of the COVID-19 Virus.

In various parts of the world, Call Detail Records have already been used to predict Electricity Consumption. Wheatman et al. [37] used Call Detail Records (CDRs) and historical energy records from a small European country. He trained a simple support vector machine (SVM) auto-regressive models are capable of baseline energy demand predictions with accuracies below 3% percentage error and active population predictions below 10% percentage error. In Africa, Martinez-Cesena et al. provided a methodology for planning electricity consumption in certain local regions in Senegal using the D4D–Senegal challenge data set. The author correlated the data set with the countrywide aggregated electricity load curve and used his insight to look for the areas that need electricity based on their electricity demand.

3 Methodology

We were not able to get Call Detail Records (CDR) from Mobile Network Operators. So a study was done on a lot of research works and found the factors affecting electricity in various countries and we looked into well-established literature on how these factors have been extracted from Call Detail records. From the review of various literature highlighted above the Gross Domestic Product per capita (GDPC), which brings together the Population and GDP which is a measure of income proves to be the most common determinant of electricity consumption. It is a measure of the economic output of a country divided by its population. GDPC is often used to compare the economic performance According to a report by Statista [30], based on data from the International Energy Agency (IEA), the majority of electricity is in different countries.

The formula for GDPC is:

$$GDPC = \frac{GDP}{Population}$$

We examine how all these features can be generated from Call Detail Records. The typical features found are

1. A special ID for the call

2. If the call is outgoing or incoming
3. The date the call was made
4. The duration of the call
5. The Mobile Station International Subscriber Directory Number (msisdn) of the caller.
6. The Mobile Station International Subscriber Directory Number (msisdn) of the call receiver
7. The location of the cell towers that were made

3.1 Determining GDP from Call Detail Records in Nigeria

For this, we perform our analysis based on the analysis performed by Dong et al. [13] which involved calculating the area where calls were made during work hours 9:00 a.m. to around 6:00 p.m., and outside work hours activities that occur outside these hours. Then clustering the found location using DBSCAN. A density-based clustering technique. This can then be used as a number of places where economic activities occur. We can then calculate the number of commercial activities using the number of calls that occur in that area for more than 10 minutes to avoid noise.

3.2 Determining Population from Call Detail Records in Nigeria

To tackle this issue, depending solely on individual phone numbers is insufficient. Instead, we adopt a method already well-documented in existing literature, which proves especially pertinent in our local context. By scrutinizing the volume of active users within a specific geographical area, we can extract valuable information regarding the distribution of the population in that region. This can be achieved by aggregating the count of calls made by a single user across different time frames. If this count surpasses a defined threshold, it signifies the continued activity of that particular line.

4 Conclusion

In conclusion, this research paper delved into the potential utility of Call Detail Records as an indicator for gauging electricity consumption in Nigeria. Our investigation unveiled that Gross Domestic Product per capita (GDPC) stands out as the predominant influencing factor on electricity consumption, particularly within our local context. Subsequently, we probed how the two primary components of GDPC could be inferred from Call Detail Records, suggesting the feasibility of utilizing this data source to estimate electricity consumption in these regions.

It is imperative to underscore that this study represents just one of the distinctive applications of Call Detail Records. Furthermore, it serves as a call to action for Mobile Network Operators (MNOs) and government bodies to consider releasing this data to the public in an anonymized format, thus opening doors for exploration and valuable insights for society. This could pave the way for further empirical research, albeit our most significant constraint was the unavailability of actual data for analysis. Instead, we relied on adapting concepts from prior research conducted in other countries to the Nigerian context.

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