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Guidelines for Demand Data Collection for Rural Access to Electricity Projects

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***Abstract*—Accurate data collection is a key element for scientifically solid and efficient off-grid energy system planning. In particular, this contribution focuses on the process of demand side data collection for supporting access to electricity projects. With the support of a field survey campaign conducted in early 2023, this paper outlines the main steps to be followed from preparation of the data collection, performing the data collection, and preliminary data pre-processing for future analysis.**

***Index Terms*—Electricity access, data collection, mini-grids, load estimation, energy planning**

I. Introduction

Dimensioning rural off-grid energy systems through mathematical models [1] is an action double tied with data availability and data quality. Data availability and quality are, among others, major obstacles in energy planning in developing countries [2]. In energy modelling, data is both an input and an output of the modelling process, therefore the quality and the accuracy of input data will affect the output. The high variability of demand, combined with lack of available and reliable data, may lead to wrong predictions of the electricity demand that negatively impact the local socio-economic development, and cause an inappropriate sizing of local energy solutions [3]. In many cases, data on electricity demand are not available or not reliable since they are rarely collected, and not reported systematically [4]. The lack of databases with high-resolution data on energy usage from rural areas results in limited historical data to draw from [5]. The most common method for estimating electricity usage currently adopted is through appliance ownership and use data collected via interviews [6]. Actual electricity consumption data are rarely available at a high level of spatial resolution, hence an ongoing debate is centered on how to best deliver good quality data to track energy access objectives and to lower its collection and processing costs, as well as to make sound decisions under data scarcity [7]. For under-served communities that do not yet have access to energy, the current methods to estimate a first load demand are:

- Top-Down assignation of load demand: consisting in assigning pre-defined consumption tiers to different areas or users, adopting econometric approaches or relying on existing datasets [8].
- Load Archetypes: definition of load demand archetypes for different categories of users to be then used to simulate the load of a community. An example is applied in Kenya in [9] where the developed archetypes, for residential users, primary schools and rural health facilities, consider seasonal variations of the load and the relative wealth tier of the users.
- Relying on observed data from neighboring or similar communities: it is possible to assume that communities that share similar socio-economic and geographical traits will share similar energy related behaviors [10].
- Using a survey-based approach: this is currently the most used methodology and represents a cost-effective way to gather information about energy use patterns and factors affecting energy demand

Performing a high-quality data collection to reach an accurate characterization of energy demand for energy modeling is a crucial step in order to ensure the formulation of energy strategies that can maximize the outcome of the intervention, and guarantee cost-optimal solutions [11]. This paper represents a collection of guidelines based on literature and relevant past experience of the authors in the field to support the creation of best practices in data collection for access to electricity in developing countries. A case study in Faza, Kenya, will be used throughout the paper as proof of concept of the described guidelines.

II. Case Study - Faza Island

Faza Island is a town on Pate Island within the North Coast region of Kenya. The island has 17,540 inhabitants with seven villages, i.e., Mpate, Faza, Siyu, Tchungwa, Kizingitini, Mbwujumwali (Myabogi), and Ndau. Excluding Ndau, all the villages are electrified through the Faza off-grid mini-grid (MG) station, which serves a total of around 3500

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connection points. The MG has an installed capacity of 0.9 MVA and is comprised of two diesel generators rated 650 kVA and 500 kVA, respectively. The Faza MG is publicly owned, it was constructed in 2016 by Rural Electrification and Renewable Energy Corporation (REREC) and commissioned in 2017. It operates under Kenyan's main utility provider, Kenya Power and Lighting Company (KPLC). The villages are located up to 26 kilometers from the MG. The data collected from the households during the campaign was relative to the socio-demographic characteristics of the households, appliance ownership, and energy consumption. Technical data of the MG was collected from the MG operator.

III. Preparing the Data Collection

To carry out a data collection campaign to study energy demand or load profiling of a sample population, building a clear and reliable plan that involves allocating sufficient time for each stage of the campaign is essential [12]. In addition, it is crucial to take into consideration how consumer behavior, socio-economic, time, environmental, and technological factors differ from one area to another and the impact they have on how energy is consumed and, consequently, the load profile. When planning for an energy data collection campaign, the following steps should be taken into consideration during the pre-planning phase:

A. Definition of the research problem and literature review

By clearly understanding the research problem, one can determine the appropriate research approach to implement and achieve the study objective. The problem must be defined unambiguously, as that will help to discriminate and filter out relevant data from irrelevant ones [13]. This then allows for research questions to be structured in alignment with the study objective. For the Faza data collection study, the project aims to study MG impacts on under-served community livelihood improvement in the African context using technology, digitalization, and socio-economic models. In the initial research phase, it's important to address key questions: Which data aspects are vital for understanding community energy? Who to interview among stakeholders? What are the local economic activities? Obtaining these answers in the pre-planning phase is crucial in defining the research problem.

Searching for data that already has been developed in the research area under interest allows one to find the similarities and avoid repetition while also learning about the previous obstacles encountered in similar exercises. Knowing what data is available often serves to narrow down the research problem further, uncover certain gaps in existing theories and highlight whether previous findings follow a consistent or inconsistent pattern with theoretical expectations [13]. For the Faza MG project, the literature review was very limited, especially on the energy-specific data. Hence this set a requirement that the technical and socio-economic questionnaires need to be very detailed to capture this information.

B. Scope definition and pre-assessment of the population

To define the boundaries and parameters of the research study, the following factors are needed:

- Triangulation: Data, methods, investigators, and theory can be triangulated to boost reliability. This study uses data triangulation, integrating diverse sources like customers from various villages and MG operators' data, and investigator triangulation, engaging different researchers in data collection, processing, and analysis.
- Sampling: Selection of a representative part of a population to determine the parameters or characteristics of the whole population. When dealing with a large population, the sampling technique should be adopted.
- Timeframe: A specific time period for the data collection should be defined. One should take into consideration the timelines for getting necessary approvals. In the Faza case, the timeline to get the necessary approvals took four months. Additionally, road conditions should be factored in when estimating travel time.
- Data collection methods: The methods that are used for data collection, for instance, whether to use surveys, interviews, or focus groups. The method is constrained by available resources and research questions.

The environment of the targeted area, the energy demand patterns related to religion or cultural behavior, and the socio-economic aspects are crucial factors to be considered before embarking on the data collection campaign. Furthermore, the probability of community engagement and cooperation as well as the appropriate time for approaching people for interviews should be considered. These factors have been taken into account with the assistance of the Faza MG operator.

C. Preparation of the questionnaire

A questionnaire is a research instrument consisting of a series of questions and other prompts to gather information from respondents. It is good practice to keep the wording of questions simple, with clearly defined terms, and avoid both leading questions and making assumptions about the respondent [14]. If the questionnaire is to be submitted in physical form, then the questionnaires should be translated into the local language used. It is then necessary to decide if the questionnaires will be split into different categories of stakeholders, depending on the objective of the project. Once the questionnaire is ready, the appropriate tool for data collection should be selected. For the Faza study, the questionnaires for the operator and local chiefs were administered through the Kobo toolbox app, which is an open-source data collection, management, and visualization tool [15]. To determine the user profile, a set of questions was prepared and administered through a physical paper questionnaire, conceptualized, prepared, and delivered by the research team through face-to-face interviews. The research team developed the questionnaires based on the specific use that the data were meant for. Specifically, since the goal of the study was to estimate the existing energy demand and the current unsatisfied and future predictable energy needs, the questionnaires focused on obtaining appliance ownership and use patterns and desired services to improve quality of life or expand business opportunities, to be then translated into present and future load curves with specific instruments. As a point of reference, questions from surveys identified in the literature [16]–[18] were employed, and additional inquiries were subsequently integrated to align with our research objectives.

D. Budgeting and training enumerators

With all the above points taken into consideration, a budget should be drafted to determine the available resources for the study. Budgetary considerations suggest that some trade-off is needed between the ideal data collection study and what the budget permits [13]. The budget should take into consideration the travel, accommodation, and meal costs of the enumerators, the cost of hiring the local guides, the cost of obtaining a permit from the local chief (as was applicable in Faza), printing or data costs, etc. The enumerators, either internal project team members or external team hired for doing the data collection should be trained on the chosen data collection methodology as well as the variables of the study well-articulated. For the Faza data collection study, four enumerators; project team members were trained on the structure of the questionnaires.

IV. Collecting the Data

To evaluate the energy demand of the island, a data collection was conducted on a sample of 261 respondents. The sample size was determined using the Bukhari sample size calculator, as shown in Eq. 1, which is employed to establish sample sizes for known populations. By adjusting the confidence level, margin of error, and sample proportion, it's possible to compute sample sizes for various z-scores. Another frequently utilized sampling technique is the Krejcie and Morgan method. While the Bukhari method relies on the z-score for sample determination, the Krejcie and Morgan approach employs the chi-square (x^2) value. We selected the Bukhari sampling formula for this study due to its ability to optimize sampling effort while adhering to project budget and timeline constraints.

$$Sample\ Size = \frac{\frac{p(1-p)z^2}{e^2}}{1+\frac{p(1-p)z^2}{Ne^2}}, \tag{1}$$

Where p is standard deviation, z is z-score, e is confidence-interval, and N represents population size. Using N as 3500, for the connection points to the MG, a conservative estimate of the energy consumption of the island, and p as 0.5, the sample size was calculated with a 90% confidence level, and the resulting z-score was 1.65 with a margin error of 5%. The sample includes MG customers, consisting of households (192), health centers (3), schools (7), and commercial and productive businesses (27), and a second group with potential customers, who did not yet have electricity access, including households (29) and businesses (3). Utilizing sample size calculations, a defined participant count was set for diverse village and area categories. Residential participants, hospitals, and schools were included based on their expressed willingness to engage, fostering a participant-oriented approach. In contrast, commercial users were randomly selected, ensuring a diverse representation of various business types. Data collection pre-planning was done by the enumerators with the assistance of the local MG operator through phone calls and virtual meetings to understand the island's landscape.

The data collection took a week, and was executed as follows:

- Day 1: Site mapping with the MG operator.
- Day 2: Surveys to schools, health centers, and businesses.
- Days 3-5: Household surveys.
- Days 6-7: Consolidation and data quality check.

The exact locations were site mapped with the targeted number of consumers in each village with the assistance of the MG operators and local guides. Before taking the respondents through the questionnaires, consent was sought from all respondents. Termination of the interview was done immediately for respondents who were unwilling to participate in the interview. Below are described some of the challenges that were encountered during the data collection exercise.

- The Swahili dialect was heavier than anticipated; hence it took a while for interviewees to comprehend what question the respondents were expected to answer.
- Trust issues among some interviewees. In some cases, it was quite difficult to get honest feedback, especially on income-related questions. However, the presence of local guides significantly facilitated the interview process, bridging cultural gaps and clarifying the good deeds behind the campaign.
- Asking proxy questions to be able to build a profile with the language barrier and illiteracy levels led to questionnaire fatigue.
- Group interview results were less effective than expected. It was time-consuming and decreased the interviewee's attention span. The one-to-one interview proved to be more practical and provided a higher level of accuracy to the collected data.

V. Pre-Processing the Data

Data pre-processing is essential for reliable data analysis, the aim is to improve data quality and accuracy by addressing issues with completeness [19], and to prepare for the posterior data analysis [20]. The techniques for building operational data can be summarized in five main tasks, which include: data cleaning, reduction, scaling, transformation, and partitioning [19]. In addition, we incorporate the tasks of new information generation, as outlined in [20], and the task of data digitization. The following subsections are chronologically organized.

A. Data digitization and data cleaning

Since the method chosen to collect the data was a paper-based questionnaire, the first step was digitizing the data through data input to Excel. Afterward, data usually need to be cleaned as those may be incomplete and noisy. Cleaning involves deleting useless data and detecting outliers and wrong or missing values. Missing information can be either taken from literature or from the local guides directly, when in contact with them. During the digitization process data were partially cleaned. Subsequently, a second cleaning was carried out to fill out the missing data, in our case, related to the average daily use and the nominal power of the appliances. For each category of respondents, the former was replaced by the mean average daily use of each appliance. The latter has been filled with data taken from literature or from pictures taken during the field visit. Furthermore, income and energy expenditure values were compared, leading to their exclusion when energy expenditure exceeded income. Properly managing unfilled data gaps is essential. In certain cases, missing values are set as zeros, and these should be substituted with a designated missing value code like "." in Stata. This process is known as missing value recoding.

B. Data scaling and data transformation

The next step is data scaling aiming to normalize data into comparable ranges for predictive modeling. Examples of these techniques include max-min normalization, z-score standardization, and logarithmic functions [19]. The logarithmic transformation is commonly used to deal with skewed data or minimize variation between variables, such as income. Data transformation involves reformatting the original data to fit the posterior data analysis needs. For example, transforming numerical data to categorical data or transforming categorical data to numerical data [19]. It can also involve coding of data [21], which is the process of transforming qualitative or text data into dummy variables, numerical or categorical codes for easier analysis. The researcher should determine the data transformation needs based on the statistical models employed. In our case, text inputs like gender or ownership of specific appliances were transformed into dummy variables, while the household location was categorized. Similarly, age, initially a continuous variable, was redefined as categorical.

C. Generation of new information

Besides the above-mentioned techniques, sometimes it is needed to generate new information with the goal of uncovering valuable insights that may be present within the data. This is useful to conduct in-depth analysis [20]. For example, if the data contains individual events or records, it may not capture temporal trends effectively. The data could be transformed to represent trends so that the analysis results would be more meaningful [20]. We have used this technique to transform the year of purchase of an appliance into a numeric value that denotes the duration of electricity access by subtracting the year of connection to the MG from the year of purchase. This procedure permits the representation of the uptake trends of appliances relative to the year of electricity access. For instance, if a participant has had access to electricity since 2018 and purchased a TV in 2020, the transformed value of the variable "year bought" would be 2, indicating that the appliance was acquired two years after the onset of electricity access. Other forms of data pre-processing for in-depth analysis employed in this study include the addition of new features and data fusion. The addition of new features, derived from existing ones, involved the creation of a new variable named "appliances tier", which takes values from 1 to 5 and accounts for the number and types of appliances present in each household. The rules to create the new variable were formulated as "If-Then statements". The second technique; data fusion, usually involves combining information from various sources of data. In this study, the source of data is the same, however, two datasets, one with information about appliances and another with socio-demographic data from each household, needed to be linked. Socio-demographic data was organized in a wide format, while information about appliance ownership was organized in a long format, therefore, for each observation in the socio-demographic dataset, there are multiple observations in the appliances data set. Data fusion is used to merge both datasets into a single one, several data analysis software incorporate the merge function for this purpose. More information about generation of new information can be found in [20].

D. Data partitioning

Data partitioning is used to divide the entire data set into different groups based on defined characteristics to improve the sensitivity and reliability of subsequent analyses [19]. An example of data partitioning is clustering. Before applying clustering methods, data have been grouped into the four categories interviewed: households, businesses, schools, and hospitals. Four different clustering methods have been applied in order to find the best fit to simulate demand curves provided by the MG operator. The 1st method uses the Multi-Tier Framework (MTF). MTF is used to measure access to electricity in rural villages, based on the combination of seven attributes with minimum requirements by tier of electricity access [22]. In this regard, the daily energy consumption for each of the five tiers has been taken into consideration. The 2nd clustering method is based on the appliance ownership, whether a household belongs to one category rather than another depends on the appliances owned. The 3rd clustering approach involved manually dividing the households into five groups, based on similar consumption patterns and a similar collection of owned appliances. Lastly, the 4th method used follows a quintiles-based division, where 20% of total households are concentrated within each consumption tier. Tabl I shows the clustering rules for each method. From a preliminary analysis made of households' income and energy expenditure, we came to the conclusion that these data are not reliable and therefore they have not been used during the analysis.

In the commercial category, users were divided according to the type of activity. Businesses of the same type are more likely to own the same or similar appliances. For some types of business more than one "user type" has been introduced to better capture the differences. In particular, businesses in Faza vary among shops, carpentry activities, pharmacies,

TABLE I
CLUSTERING METHODS.

Tier	Daily electricity consumption (Ec) (Wh)	Appliance ownership	Manual	Quintiles
0	Ec<12	No appliances	-	-
1	$12 \leq Ec<200$	Bulbs and mobile phone chargers	98$\leq Ec \leq 736$	98$\leq Ec \leq 637,6$
2	$200 \leq Ec<1000$	Fan, TV, speakers, MP3 and radio	737$\leq Ec \leq 1700$	637,7$\leq Ec \leq 1585,6$
3	$1000 \leq Ec<3400$	Owning maximum 2 types among blender, iron box, electric kettle, pressure cooker, donuts maker, microwave, PC, printer, Wi-Fi router	1701$\leq Ec \leq 3000$	1585,7$\leq Ec \leq 2946,1$
4	$34000 \leq Ec<8200$	Owning 3 appliances from Tier 3 or any among water pump, oven, heating, fridge	3001$\leq Ec \leq 6000$	2946,2$\leq Ec \leq 4692,3$
5	Ec $\geq$ 8200	Owning at least 2 appliances Tier 4 or having 4 appliances from tier 3 and 4	6001$\leq Ec \leq 29000$	4692,4$\leq Ec \leq 29000$

restaurants, hotels, and other small businesses. Schools and hospitals are divided according to their size and characteristics. The schools are grouped both according to the number of students and classrooms, but, above all, according to the appliances owned. Similarly, hospitals were divided according to the presence and number of beds and the types of appliances in the facility. Three typologies were defined based on the sample collected: dispensary, health center, and hospital.

VI. CONCLUSIONS

This paper presented an overview of the entire process behind data collection for access to electricity planning projects, from the preparation phase to preliminary data pre-processing, accompanying the described methodologies with references from a recently conducted data collection campaign to support the conceptual part. The purpose of the paper is that of representing a practical guide to researchers and practitioners in the field that intend to conduct data collection campaigns, aiming to build a body of shared knowledge on the subject. The practical insights gained from our hands-on field experience underscore the importance of meticulous pre-planning and a realistic evaluation of project timelines. Reluctance to disclose personal information during data collection, particularly regarding financial matters, can hinder accurate feedback. To address this, we suggest including alternative questions that can serve as socio-economic indicators, such as the number of rooms in the house. Furthermore, paper-based questionnaires have shown increased efficiency compared to digital ones, especially when integrating qualitative inquiries and addressing users with limited literacy levels. Lastly, close collaboration with local operators and guides enhances data collection efforts, aiding in pre-planning and offering valuable insights into environmental and cultural behaviors.

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