CALIBRATION AND EXTRAPOLATION OF A STOCHASTIC MODEL FOR ELECTRICITY DEMAND FORECASTING IN RURAL COMMUNITIES: THE CASE OF SAMIONTA, BENIN

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ABSTRACT

To achieve sustainable rural electrification in sub-Saharan Africa, innovative approaches are required to address technical inefficiencies, high electricity costs and socio-economic disparities. In this context, accurate electricity demand forecasting is a fundamental prerequisite for efficient design and operation of solar microgrids in rural areas where consumption profiles are highly variable, which highlights the need for robust predictive tools. Therefore, this paper aims to calibrate and extrapolate the Remote-Areas Multi-energy systems load profiles (RAMP) model to anticipate future electricity demand in order to plan the increase in the capacity of the solar microgrid of Samionta, a rural community in southern Benin. Using data from smart meters and socioeconomic surveys, the calibration process integrates key variables such as socio-economic conditions, appliance adoption and usage patterns, and external conditions such as climatic conditions. The resulting improvements allow the model to accurately forecast the community's energy demand over time. With this calibrated model, the study extrapolates demand trajectories with different scenarios highly influenced by PUE, offering reliable forecasts for system upgrades over several years. Furthermore, the calibrated model has potential for application in other rural communities with similar conditions. This paper underscores the importance of adaptable demand prediction tools in solar microgrid projects. It establishes a replicable with the potential to minimize costs, improve energy access, and foster socioeconomic development. Such advancements highlight the broader relevance of this approach in accelerating sustainable rural electrification in Sub-Saharan Africa.

Keywords: Solar microgrids, energy demand forecasting, rural electrification, productive uses of electricity.

1 INTRODUCTION

Access to reliable electricity is a cornerstone of economic and social development, particularly in rural areas of Sub-Saharan Africa, where electrification rates remain critically low (Yang & Yang, 2018). Despite significant efforts to expand grid coverage, there are several rural localities for which connection to the national grid is not financially viable. The good news is that these isolated communities can rely on decentralized energy solutions, such as solar microgrids, to meet their electricity needs (Come Zebra et al., 2021). However, a key challenge in the sustainable operation of these microgrids lies in the accurate forecasting of electricity demand, as rural consumption profiles are highly variable due to socio-economic dynamics, seasonal effects, and the integration of productive uses of electricity (PUE) as stated by Hartvigsson et al. (2021).

Ovie Vincent Erhueh et al. (2024) showed that electricity demand forecasting is essential for optimizing energy infrastructure investments, ensuring system reliability, and minimizing costs. Traditional deterministic models often fail to capture the stochastic nature of rural electricity consumption, making them less suitable for such environments (Herraiz-Cañete et al., 2022). To address this gap, stochastic modeling approaches like the Remote-Areas Multi-energy systems load Profiles (RAMP) model developed by Lombardi et al. (2024) have gained attention. However, tts accuracy and applicability depend heavily on proper calibration with local conditions Sanchez-Solis et al., 2023.

This study focuses on the calibration and extrapolation of the RAMP model to improve electricity demand forecasting for the solar microgrid of Samionta, a rural community in southern Benin. By leveraging data from smart meters, field surveys, and seasonal consumption trends, the model is refined to align with real demand patterns. Once calibrated, the model is used to simulate future demand trajectories under different scenarios, particularly considering the increasing impact of PUE-driven growth. These forecasts provide critical insights for system upgrades and long-term energy planning. Beyond the case of Samionta, the proposed methodology is designed to be replicable in other rural communities with similar socio-economic and environmental conditions. By offering a scalable and data-driven approach, this research contributes to the broader goal of accelerating sustainable rural electrification in Sub-Saharan Africa.

2 METHODOLOGY

This section describes the methodological approach adopted for analyzing and forecasting the electricity demand in the rural community of Samionta. The process, described on Figure 1, is divided into four main steps: data collection and processing, development of proxy data for calibrating the RAMP model, calibration and simulation, and finally, forecasting future consumption under different scenarios. In the first step, an analysis is conducted based on historical electricity consumption data from the Samionta community. The data are collected through smart meters on a 15 minutes time resolution, stored on a cloud platform and retrieved daily via API requests. Through the data analysis, significant variables affecting the community electricity consumption are identified. The residential consumers, SMEs and community institutions are grouped according to their load profiles and energy consumption habits to determine typical consumption ranges. The second step consists in developing input parameters for the model based on the characteristics of the Samionta community, the characteristics of customer appliances, and their daily usage patterns. The RAMP model is then calibrated using the parameters developed in the previous step. The calibrated model is simulated and validated against actual consumption data. Once the model is validated, the final step is to develop different future demand scenarios and predict the corresponding consumption for each scenario. The objective is to understand how various conditions might influence load demand that will lead to resizing the capacity of the microgrid to ensure a reliable and sustainable energy supply.

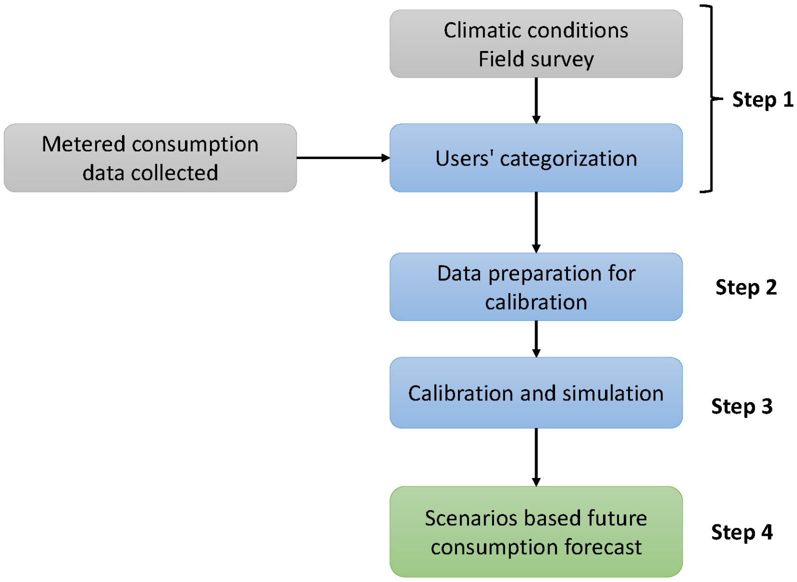

Figure 1: Global methodology for the demand forecasting

2.1 Users categorization

There are three main categories of connections generally adopted:

- **SMEs**: Income-generating activities. Typically, this includes Small and Medium Enterprises (SMEs) such as bars, hair salons, frozen food shops, mechanical workshops, welding workshops, etc.
- **Households**: Homes using electricity generally for domestic needs.

- **Community services**: Churches, private and public schools, and clinics.

Households are further categorized according to their daily average consumption over the study period. Subsequently, the k-means clustering method (Hastie et al., 2009) is used to identify and group them in different consumption categories.

The K-means Algorithm

The k-means algorithm as described by Hartigan and Wong (1979) is a popular choice for clustering, involving the partitioning of a dataset into K clusters. Each data point is assigned to the cluster whose center (or centroid) is nearest, as determined by Euclidean distance. The algorithm operates iteratively, seeking to minimize intra-cluster variance by reducing the sum of squared distances between data points and their respective cluster's centroid. Formally, given a set of observations $(X_1, X_2, X_3, \ldots, X_n)$, the objective is to partition these n observations into k groups $\{\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3, \ldots, \mathcal{S}_k\}$ so as to minimize the sum of squared distances between the points in each group and their respective centroid as described by Equation 1.

$$\text{Minimize } I = \sum_{i=1}^{k} \sum_{x_i \in S_i} \|x_i - \mu_i\|^2 \tag{1}$$

where μ_i is the mean (also called the centroid) of the points in S_i, that is:

$$\mu_i = \frac{1}{|S_i|} \sum_{x_i \in S_i} x_i \tag{2}$$

$|S_i|$ represents the cardinality of S_i

The k-means algorithm requires a pre-determined number of clusters, K, which is typically an input parameter. However, K can also be determined using the elbow method. The elbow method is a heuristic approach used to determine the optimal number of clusters in k-means clustering (and other clustering algorithms) (Hastie et al., 2009). It involves calculating the within-cluster sum of squares (WCSS) for a range of K values. The WCSS is defined as the sum of the squared distances between each point in a cluster and the centroid of that cluster. A plot of WCSS against K is then examined. The "elbow" point on this plot, where the rate of decrease in WCSS starts to slow down significantly, is considered the optimal K. This point represents a balance between minimizing the WCSS and avoiding overfitting by using too many clusters. While other methods exist for determining the optimal K, such as the silhouette score (Rousseeuw, 1987), the elbow method is widely used and well-suited to the exploratory analysis of consumption patterns.

2.2 The RAMP model

RAMP, as described by Lombardi et al. (2024), is based on a bottom-up forecasting approach, making it particularly well-suited for rural electrification planning. This approach is especially advantageous in situations, where historical consumption data is scarce or unavailable. Among the electricity demand forecasting models identified in the literature, RAMP distinguishes itself through two key characteristics. First, its stochastic nature enables the accurate reproduction of load curves. Second, its open-source nature is a significant advantage that allows researchers and practitioners to adapt the model to the specific characteristics of the study area, such as local climate conditions, appliance ownership rates, and cultural practices.

2.3 Validation Criteria for the Calibrated Model

For the validation of the calibrated model, a set of indicators is defined to assess the extent to which the RAMP-generated load profiles adhere to the metered profiles. The accuracy of the shape of the aggregated average daily load profile is evaluated using the relative error described by Equation 3 and the normalized root mean square error (NRMSE) defined by Equation 4.

$$\text{Error}[\%] = \left| \frac{P_{\text{model}} - P_{\text{measured}}}{P_{\text{measured}}} \right| \tag{3}$$

$$\text{NRMSE} = \frac{\sqrt{\frac{\sum_{X=1}^{N_t}(P_{\text{measured}}(X) - P_{\text{model}}(X))^2}{N_t}}}{P_{\text{measured,mean}}} \tag{4}$$

where P_{measured} [W] is the value of the measured real load, P_{model} [W] is the load modeled via RAMP , N_t the total number of time steps (for example, 1440 for a 1-minute resolution) and $P_{\text{measured,mean}}$ the average value of the measured average daily load profile.
Other parameters that are widely used to validate load profile models against measured data and that are also critical with regard to the sizing of electric power generation plants are the load factor (LF) which we will focus on, the peak load value, and the aggregated demand value (Widén & Wäckelgård, 2010). The formula for the load factor is given by Equation 5

$$\text{LF} = \frac{P_{L,\text{mean}}}{P_{L,\text{peak}}} \tag{5}$$

Where, $P_{\text{L,mean}}$ [W] and P_L, peak[W] are respectively the daily average values and the maximum (or peak) values of the average profile resulting from the measured or modeled loads.

Data availability statement

The data and scripts used in this work are available in the following GitHub repository: https://github.com/ssossou-liege/SAMIONTA_RAMP_CALIBRATION.git

3 THE CASE STUDY

3.1 The Samionta solar microgrid

The Samionta photovoltaic solar microgrid is constructed in the rural community of Samionta, a locality of the Koussoukpa district in the Zogbodomey municipality of the Zou department of Benin. It is the first microgrid installed by 1PWR (OnePower, 2024) in Benin and is to serve as a pilot site prior to the deployment of additional planned sites for other communities across Benin.
According to the INSAE (2016), Samionta comprises 537 households, of which 238 located in the concession perimeter of 1PWR are potentially connectable to the microgrid based on the field study conducted by 1PWR. The community also includes a public primary school and two churches. As shown on Figure 2, the generation system consists of a photovoltaic panel array, a lithium battery bank, a diesel generator and a low voltage distribution board all wired to three hybrid inverters connected in parallel. The diesel generator is installed as a backup solution to support the battery during unfavorable and unpredictable conditions. The technical specifications of the equipment are detailed in Table 1.

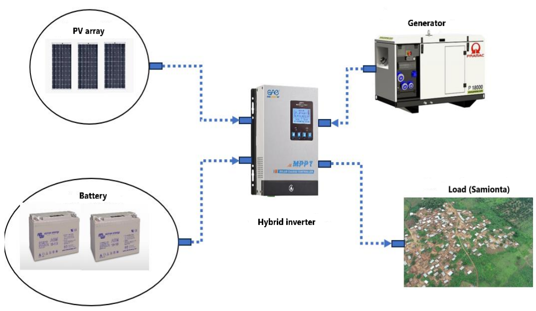

Figure 2: Diagram of the Samionta microgrid generation system

3.2 OnePower Benin's smart metering solution

To provide a reliable and user-friendly service to the community, 1PWR use class 1 single-phase and three-phase smart meters that synchronize data every 15 minutes with a cloud platform dedicated to customer management. The platform has an API that allows queries for collecting the consumption data. Production data, on the other

Table 1: Technical specification of the Samionta microgrid generation system

Equipment	Total capacity	Brand	Model
PV	17.4 kW	JA Solar	JAM72S20
Battery	50 kWh	BYD	Battery-box LV Flex
Inverter	36 kW	Deye	SUN-12K-SG04LP3-EU
Diesel Generator	20 kVA	CGM	20P

hand, are collected via the Solarman platform that is a solar energy monitoring and management platform that enables real-time tracking of the microgrid's electricity production.
The microgrid was officially commissioned on February 1, 2024. As of July 31, 2024, 30 connections had been made, representing 12.6% of the potential connections. The connections include 26 households, 2 SMEs, and 2 churches. In Samionta, although a public primary school is present, it is not yet connected to the grid. The consumption data of these connections were collected for analysis to develop an accurate model for forecasting electricity demand in this locality.

3.3 The RAMP model validation with Samionta's historical data

This section describes the validation of the RAMP model using Samionta's real data by comparing the RAMP generated energy demand profile with the metered load profile to verify that the model accurately reflects the community's energy consumption patterns.

RAMP model parameters
The Samionta microgrid load is divided into three main categories: households, SMEs and community services. Regarding community services, in addition to the two connected churches and the primary school (not yet connected), the locality has a public lighting system consisting of 8 LED lamps of 60 W each. For the model calibration, the powerhouse self-consumption is also added to the community services category.
Although agriculture is the main economic activity in Samionta, there is no local processing facility. Most agricultural products are transported and sold in Bohicon (the closest city). Indeed, whether from a financial perspective (operator's interest) or socioeconomic (general interest), the presence of productive activities is crucial for the long-term viability of rural electrification projects. This means not only enabling PUE connections but also implementing projects to incite the creation of new electricity-consuming activities. With that awareness, 1PWR is implementing a parallel project to promote the productive use of electricity. This project is aimed at the entire rural population, especially women and young people, who are the most vulnerable by providing them with electric production and processing equipment, thus enabling them to engage in income-generating activities. However, there are currently two SME connections: an ice-sales shop and a small fish shop coupled with a mini-bar.

Inventory of customer appliances and their characteristics
Generating load profile with the RAMP model requires linking user types (category) to the different appliances they use and their characteristics. It is also essential to take into account the usage habits of these appliances. To collect these information, a survey was conducted within the community, whose results are summarized in Table 2.

Table 2: Summary of average appliances owned by each user of the different user categories

Appliance	Power (W)	Quantity per user type					
		LC	MC	HC	SME	Church	PL
Lamp	5	3	4	4	2	8	0
Street lamp	60	0	0	0	0	0	8
Television	50	0	0	1	0	0	0
Decoder	10	0	0	1	0	0	0
DVD Player	10	0	0	1	0	0	0
Phone charger	5	1	2	2	3	0	0
Radio	7	0	1	0	0	0	0
Woofer	60	0	0	1	1	0	0
Fridge	100	0	0	0	1	0	0
Loudspeaker	100	0	0	0	0	1	0

Duty cycle modulation of thermal devices

The duty cycle of thermal devices, such as fridges and air conditioners is strongly influenced by seasons and external climatic conditions. Although these devices are designed to maintain a stable internal temperature, their performance and operating frequency vary depending on the ambient temperature, and the intensity of their use.
All these information, namely the categories, the types of user by category, the appliances used by each type of user, the usage habits of the appliances (such as the total daily usage duration, the usage time slots, the frequency of use whether it is occasional or daily, or even the specific use on weekends), as well as the seasonality of each month, contribute to the calibration of the model.

3.4 Future demand scenarios

With 228 potential connections identified, the microgrid experienced only 20 connections at commissioning on February 1st, 2024, and 10 new connections within 6 months. Figure 3 shows the evolution of the number of connected customers over the months.

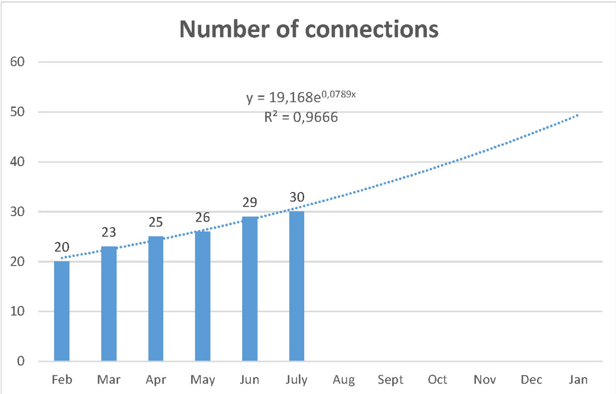

Figure 3: Monthly evolution of connections in Samionta

Given the limited six-month dataset, a linear trend is initially apparent in the growth curve. However, in accordance with the research of Hattam and Greetham (2018), the growth pattern is more accurately characterized by a logistic trend, where the initiation and rapid growth phases exhibit exponential characteristics with a coefficient of determination R^2 of 0.9666. Based on the equation associated with this curve, approximately 50 connections are estimated in total within a year.
The electricity demand forecast analysis of Samionta residents is not established solely on this trend but also on the assumption that the support measures implemented by 1PWR allow: (i) all connections categories to be eligible for a connection in order to reach 70% of connections within 5 years and (ii) the emergence of productive uses of electricity for which 1PWR plans to deploy 3 freezers of 100 W, 2 grain mills of 2.5 kW and 1 incubator of 600 W. The connection of the primary school is also planned. A primary school in rural Benin usually has the following loads: 2 outdoor lamps of 5 W and for the director's office, 1 indoor lamp of 5 W, a radio of 7 W, a mobile phone charging of 5 W, a printer of 27 W and a computer of 65 W. Currently, Samionta does not yet have a health center, but one is planned with the following loads: 1 refrigerator of 100 W, charging of 2 to 3 telephones with 5 W charger, a fan of 50 W, 6 lamps of 5 W including 4 indoor and 2 outdoor. To these different loads are added those of the generation site composed of an air conditioner of 1.2 kW, a surveillance camera of 7 W, a WiFi router of 10 W and a lamp of 5 W. Table 3 presents various scenarios of demand forecasts.

4 RESULTS AND DISCUSSION

4.1 Analysis of overall consumption trends over the months

The Figure 4 shows the overall consumption trends over the months. Analyzing the data reveals several observations and interpretations. February shows the highest consumption, with a value of around 440 kWh, followed by March with a consumption of 357.84 kWh. Consumption decreases until June, reaching 262 kWh, before stabilizing in July at around 270 kWh. This consumption trend suggests two interwoven hypotheses: first, initial overconsumption driven by novelty, followed by a reduction due to financial awareness; and second, climatic influences tied to seasonal temperature shifts. Field surveys validated both. Customers acknowledged implementing energy-saving practices due to cost concerns, and agricultural activity during the rainy season reducing overall consumption,

Table 3: Demand forecasts scenarios

Scenario	Nb. of connections	PUE deployed	Primary school	Health center
1-year horizon				
1	50	No	No	No
2	50	Yes	No	No
5-year horizon				
1	160	Yes	No	No
2	160	Yes	Yes	No
3	160	Yes	Yes	Yes

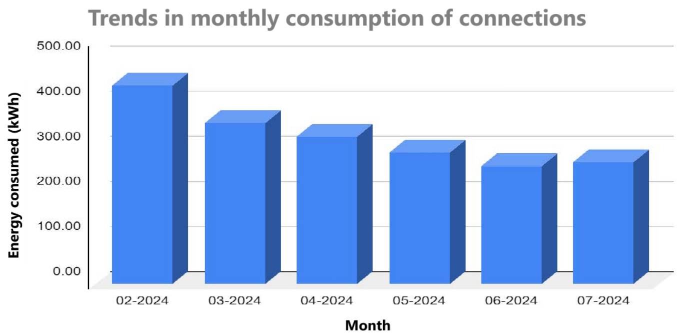

Figure 4: Overall consumption trends over the months

especially for refrigeration-based businesses. Thus, the observed pattern likely results from both behavioral adjustments and seasonal energy demand variations.

4.2 Households connections clustering

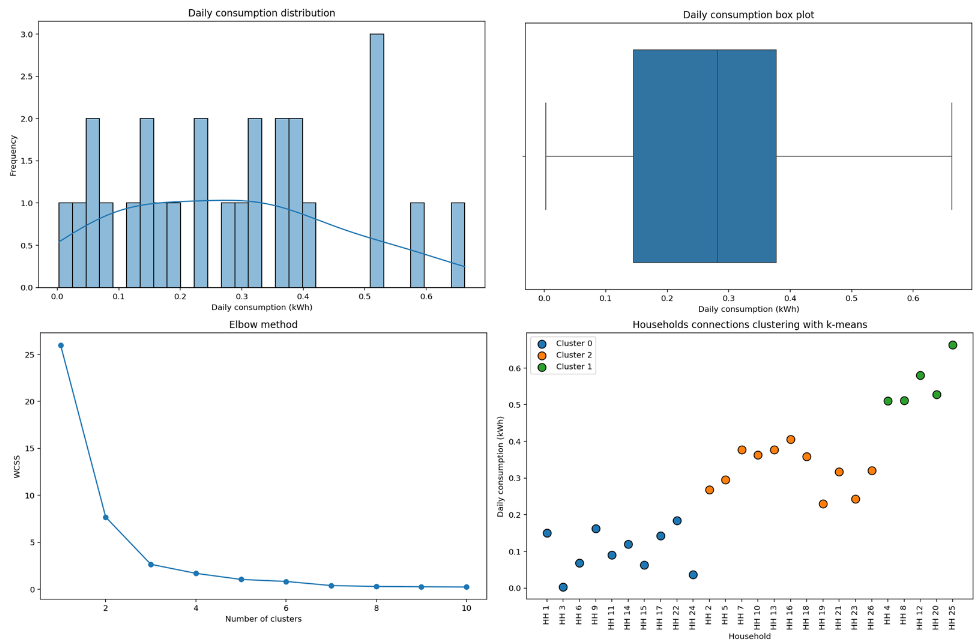

Figure 5: Households consumption distribution. Top left: Frequency histogram. Relatively uniform distribution but with distinct consumption groups: a low-consumption group (0.0–0.2), a medium-consumption group (0.2–0.4), and a high-consumption group (0.5–0.7). Top right: Distribution box. Slight right-skewness with relatively dispersed values. Down left: WCSS elbow plot. Identified elbow in 3. Down right: Clusters with k-means. Identified 3 groups of consumers

Figure 5 shows the result obtained after clustering residential connections. It is observed that customers are divided into three distinct categories:

- Cluster 0 (blue points): This group includes customers with a lower typical daily consumption, less than 0.2 kWh/day. These customers primarily use electricity for lighting needs. We will rename this category ”low consumption households.” There are 10 customers in this category.
- Cluster 2 (orange points): This group comprises customers with a higher daily consumption between 0.2 kWh/day and 0.4 kWh/day. In addition to lighting, these customers likely use a small radio. We will rename this category ”medium consumption households.” There are also 11 customers in this category.
- Cluster 1 (green points): This group includes customers with a typical daily consumption greater than or equal to 0.5 kWh/day. In addition to lamps and a radio, these customers likely use televisions and fans. We will rename this category ”high consumption households.” There are 5 customers in this category.

Table 4 summarizes the categorization of microgrid connections and the consumption share of each category.

Table 4: Monthly unit consumption by subscriber category

Customer category		% of the number of connections	Consumption ($kW\,h\,d^{-1}$)
	Low consumption	33 %	0–0.2
Households	Medium consumption	36 %	0.2–0.4
	High consumption	17 %	> 0.5
SME		7 %	> 1.0
Church		7%	0.6–1.0

Typical daily average consumption ranges for SMEs and churches are derived from the collected data.

4.3 Comparison of load profile derived from real data and the calibrated RAMP model

The comparison between the measured data load profile and the synthetic profile generated with the calibrated model is presented in Figure 6. The green curve represents the average daily consumption of customers, calculated

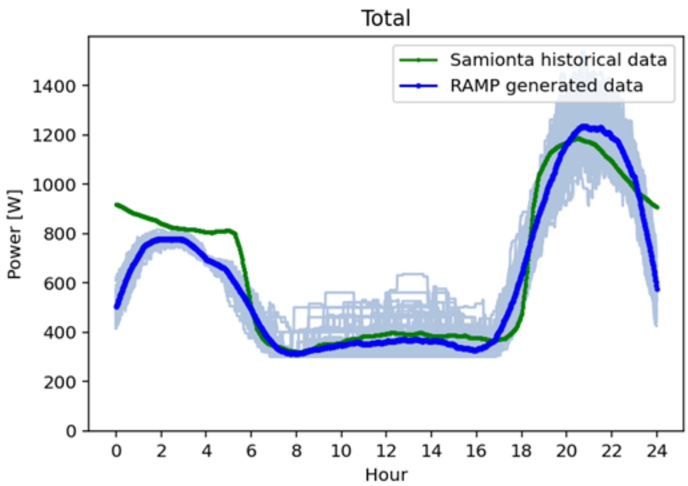

Figure 6: Load profile matching from metered data and RAMP-generated data with 3 line types representing the average of historical consumption (green line), the average of the RAMP-generated time series (blue line) and a set of synthetic load profiles generated by the RAMP model (light steel blue line).

from real data collected over the study period. The blue curve illustrates the average daily load curve of the same customers, simulated using the model over the study period.
Correspondence of general trends:
Both curves show similar trends, with consumption peaks in the evening and at night. This indicates that the model accurately captures the key times of day when electricity demand is high.

Difference observed from 00h:
The blue curve exhibits a more gradual increase from midnight compared to that of the real data. This difference is due to a limitation of RAMP, which is structured to generate load profile one day at time for every appliance with discontinuity at 24:00, unlike traditional time series. Each day is therefore modeled independently. Consequently, for appliances that operate beyond midnight, such as lighting that operates from 6 PM to 6 AM, the model divides this time range into two segments: [6 PM to 11:59 PM] and [12 AM to 6 AM]. At 11:59 PM, the appliances turn off before being turned on again at midnight, resulting in a gradual decrease in power near midnight and a gradual increase immediately after midnight.
The results presented in Table 5 reveal that the model achieved a relative error of 6.34 % in estimating the peak load and a NRMSE of 14.33 %.

Table 5: Quantitative comparison of measured data with data generated by the calibrated model

	Real data	RAMP data	Error [%]
Peak load [kW]	1.18	1.26	6.34
Load Factor	0.55	0.49	10.9
Daily average demand [kWh]	12.06	14.86	23.12
NRMSE [%]	-	14.33	-

A comparison can be done with other studies, which have also performed load forecasting for rural areas in low or middle income countries. The original study by Lombardi et al. (2019) introducing the RAMP model and applying it to the village of El Espino in Bolivia shows a peak load error of 2.9%, a load factor error of 1.2% and an NRMSE of 9.6% for the month of November. For the other months of the year the load factor error varies between 0.4% and 9% while NRMSE varies between 8.1% and 14.3%. A different study done by Yuan et al. (2023) proposes another buttom-up stochastic model for electricity consumption in Chinese rural residencies. Similarly as for Samionta lack of historical data often does not allow for the use of models based on machine learning. Even though the electrical consumption profile in the study is different from the one in Samionta, the problem contexts are similar and both RAMP and the presented model have the same purpose of predicting load consumption based on surveys without any historical data. The model in the study performed with a relative peak load error of 15.03% and 12.96% in non-heating and heating seasons respectively while the average load errors in both seasons were 5.65% and 5.25% respectively.
While the results of the calibrated RAMP model show higher prediction errors than in the study done in El Espino by Lombardi et al. (2019) the peak load errors are significantly lower than in the study done by Yuan et al. (2023). Additionally, if the RAMP software is improved by considering the days as a connected time series instead of considering them independently the average demand error of 23.12 % will likely decrease as well.
It is important to note, however, that the impact of different error ratings vary from case to case. If load forecasts are used as an input for the microgrid sizing or dispatch the magnitudes of different error metrics will have a varying impact in the final price for different projects. For example, Antoniadou-Plytaria et al. (2022) has shown that higher values of MAPE (Mean absolute percentage error) have a noticeable effect on the peak power cost (12 % of MAPE resulted in 20 % of increase in peak power cost) while the operation cost remains unchanged for different accuracies of forecasts and the total cost stays within 1 % of the optimal one. The study examines a grid-connected microgrid consisting of solar panels and a battery. Another study done by Sanfilippo et al. (2023) analyzes isolated microgrid in Benin consisting of solar panel array, a battery energy storage and a diesel generator. It is shown that an overestimation or underestimation of the average load by 15 % could change the share of diesel engine electricity by up to 8 %, which consequently led to change in the LCOE of 4 %. The comparison of the two studies illustrates the fact that load forecast can have vastly different impact on the final cost of the project depending from case to case.
In summary, all these indicators show that the calibrated model offers a globally satisfactory performance and is capable of providing useful forecasts for our case study.

4.4 Model simulation for established scenarios

1-year horizon

In both scenarios, households and community loads remain constant, including public lighting. However, in scenario 2, the integration of productive uses of energy in the SME sector leads to a significant increase in total annual consumption, from 10.33 MWh to 26.90 MWh. This increase is explained by the PUEs demand. The analyze of the two load profiles shows that the average daily consumption has almost tripled in the second scenario

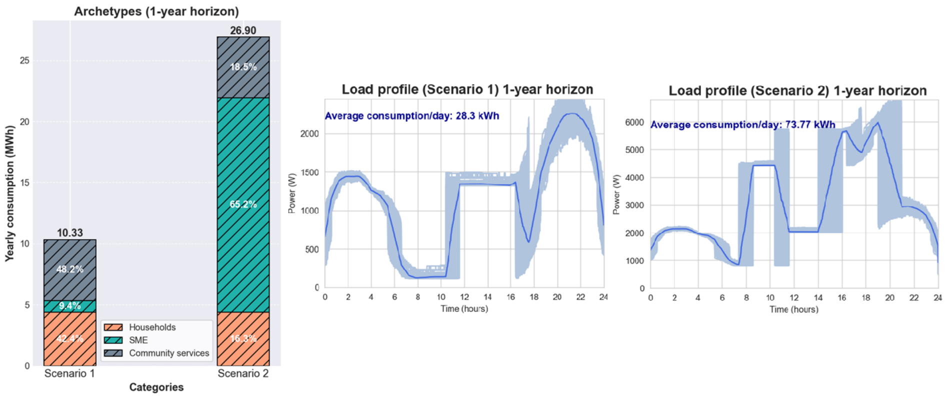

Figure 7: Demand estimation at 1-year horizon

compared to the first one. The scenario 1 load profile displays an increase in daytime consumption from 11AM to 5PM that corresponds to the working window set by 1PWR for the powerhouse air conditioner. For scenario 2, a significant demand is observed from 8 AM to 12 PM and 2 PM to 8 PM, periods that correspond to the operating hours of the mills authorized by a decree of Benin Government (2022). The integration of productive uses of energy therefore represents a considerable additional load, especially the grain mills.

5-year horizon

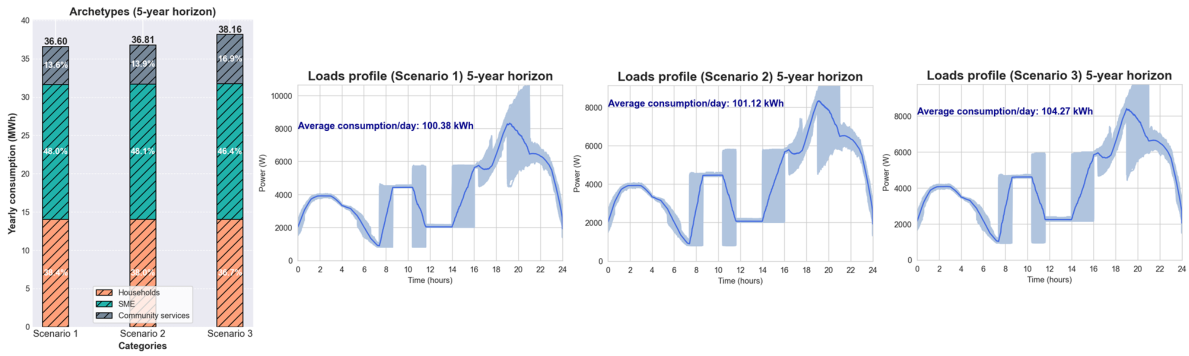

Figure 8: Demand estimation at 5-year horizon

At the 5-year horizon, with 160 household connections and all the PUEs deployed, the main variation is observed at the community services level, with the eventual connection of the primary school and a health center in scenario 3 which increase the annual demand by 1.56 MWh. The shape of the load profile does not change by scenario and not much compared to scenario 2 of the 1-year horizon since the PUEs remain the largest consumers.

Possible improvements for demand growth modeling

The study has shown an implementation of possible scenarios over 1-year and 5-year horizons, however, this approach gives limited capabilities of modeling details of the demand growth. For example, only the number of new connections and change in large loads has been modeled. In reality, the number of appliances, types of appliances and the usage windows could potentially change over time. These dynamics could be modeled by making adjustments in the RAMP software that would allow the user to define the introduction of new appliances together with the expected year when such an appliance would be added. The growth of the number of appliances per user category could be implemented similarly as has already been done by Stevanato et al. (2020). However, instead of increasing the number of appliances randomly, they should be based on socio-demographic studies, to make it more accurate. Additionally, the operating windows of certain appliances could be randomized over the time to model change in user behavior. Ultimately, the demand growth should be modeled using probabilistic methods instead of deterministic ones if it is desired to obtain more accurate picture of the necessary electric generation.

5 CONCLUSION

Accurate forecasting of electricity demand in microgrid projects is crucial to optimize financial and energy resource management while ensuring a sustainable and reliable energy supply to end users. This study focuses on the analysis and modeling of electricity demand on the Samionta microgrid, aiming to anticipate future consumption trends leading to appropriately size the generation capacity.
Consumption data collected over a 6-month period allowed the categorization of users based on their usage patterns. Leveraging this dataset, along with insights from user surveys on appliance ownership and consumption behaviors, a high time-resolution stochastic model was developed to generate a demand forecast tailored to this rural community. The validation of the model against the data of real consumption yielded a NRMSE of 14.33%, demonstrating good predictive accuracy.
Using the validated model, demand projections were conducted for 1-year and 5-year horizons to assess future electricity consumption trends. The analysis underscores the increasing significance of PUE, which constitute a growing share of total demand.The stochastic time series generated for each future period considered constitutes a solid input data set for microgrid sizing tools under uncertainty.
Nevertheless, the presented scenarios present only a fraction of the possible future demand growth outlooks. Improvement in the RAMP model is necessary to model the future demand growth probabilistically instead of deterministically. These findings highlight the critical need for strategic planning before the large-scale integration of productive loads to prevent capacity constraints and supply inadequacies.

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NOMENCLATURE

1PWR	OnePower Benin
HC	High Consumption
LC	Low Consumption
HC	High Consumption

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