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Methodological Framework for Estimating Load Curves in Isolated Communities: Addressing Electrification Challenges in Data-Scarce Contexts

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ABSTRACT

Access to electricity remains limited for nearly 655 million people worldwide, primarily in rural and isolated communities. This study addresses the persistent challenge of planning electricity access in off-grid, data-scarce contexts, where the absence of historical consumption data hinders effective energy system design. A literature review was conducted to identify, classify, and analyse existing methods for estimating electricity demand based on six criteria: hierarchy, source of information, scale, modelling approach, temporal resolution, and time frame. Based on this analysis, a structured framework was proposed, integrating common insights and practices from previous studies and the authors' experience. The framework outlines key steps, including community diagnosis, methodological selection, data collection, data processing and modelling, and result assessment. It provides guidance for selecting and applying appropriate methods and supports the comparison and evaluation of different approaches. The practical application of the proposed framework is illustrated through a case study in a rural electrification context. The framework assists in informing decisions in electrification projects and contributes to the design of cost-effective and context-appropriate energy systems. This contribution addresses a critical gap in rural electrification research and practice, particularly under conditions of limited data availability.

KEYWORDS

Electricity access, Load curve estimation, Off-grid communities, Data-scarce contexts, Methodological framework.

INTRODUCTION

Ensuring affordable and clean energy for all has become a fundamental pillar of contemporary society, as it is crucial for advancing health, education, economic development, and climate change mitigation. The International Energy Agency (IEA) highlights the role of energy access in achieving SDG 7 and net-zero emissions [1], while the Tracking SDG 7 report assesses global progress and remaining challenges toward universal access [2]. Yet, despite its significance, more than 655 million people—primarily in rural and marginalised communities—still lack access to electricity [3]. Electrification strategies based on off-grid or

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autonomous systems, such as mini-grids and micro-grids, are increasingly considered viable solutions for communities located far from the main grid, in sparsely populated or difficult-to-access areas, and with limited financial resources. The Energy Sector Management Assistance Program (ESMAP) highlights the growing role of decentralised energy solutions in achieving universal electricity access [4]. From a technological and sustainability perspective, Ortega-Arriaga *et al.* (2021) reviewed grid and off-grid electrification options and demonstrated that off-grid systems can provide economically and environmentally viable alternatives under specific geographical and socioeconomic conditions [5].

Within this context, accurate assessment of local electricity demand—commonly expressed as load profiles or load curves—is critical for the technical, economic, environmental, and social viability of electricity access projects. Mandelli *et al.* (2016) developed a procedure to formulate representative load profiles for off-grid rural areas, highlighting the importance of demand characterisation for appropriate system design [6]. Louie *et al.* (2016) demonstrated that load estimation errors can significantly affect system sizing, investment costs, and reliability performance in isolated systems [7]. Mandelli (2015) further emphasised that demand estimation is a key component in the planning process of off-grid power systems, influencing technology selection and system optimisation [8]. In a broader literature review, Mandelli *et al.* (2016) analysed rural electrification systems and identified load estimation as one of the main challenges affecting sustainable energy access planning [9].

Furthermore, Yadav *et al.* (2019) found that while mini-grids can have an affordable operational expense (OpEx), the challenge of raising financial capital expenditure (CapEx) remains [10]. Therefore, the solution needs to be tailor-designed and cost-effective. Oversizing increases CapEx and OpEx and jeopardises economic viability, as demonstrated in multiple case studies by Robert *et al.* (2018) [11]. Undersized systems result in a lack of reliable and continued electricity supply, generating discontent among the customers and forcing the components' operation and thus decreasing their duration. Both scenarios can lead to the least desirable outcome, 'User Disconnection.' This, in turn, may exacerbate poverty and inequality beyond their original state, as reflected by Louie (2018) [12].

In many off-grid electrification contexts, historical consumption data are unavailable, creating significant challenges for energy system design. Blodgett *et al.* (2017) analysed the accuracy of energy-use surveys for predicting rural mini-grid consumption and highlighted the uncertainty associated with estimating demand before electrification [13]. Lombardi *et al.* (2019) addressed this limitation by developing a stochastic model capable of generating high-resolution multi-energy load profiles for remote areas without historical measurements [14]. Together, these studies demonstrate that accurate load estimation is not only a technical requirement for system sizing but also a critical factor influencing the long-term sustainability and reliability of rural electrification projects.

To address this, the literature proposes a range of methods for estimating load profiles in data-scarce settings. Bottom-up approaches aggregate appliance- or household-level consumption data, while top-down approaches disaggregate regional or national statistics to local contexts. Hybrid methods combine top-down and bottom-up information to leverage the strengths of both. Deterministic and stochastic models represent consumption patterns as either fixed or probabilistic, and data-driven or expert-based strategies rely on surveys, proxies, or local knowledge to approximate demand in the absence of historical measurements [15]. Existing guidelines from organisations such as NREL, IRENA, GIZ, and the World Bank provide practical recommendations for load estimation. However, they generally focus on specific regions, technologies, or operational contexts and do not systematically guide the selection of methods in data-scarce communities.

Despite the variety of approaches, the literature remains fragmented. Most studies focus on developing individual estimation methods, comparing a limited number of approaches, or addressing specific applications rather than providing a structured synthesis across key methodological dimensions, including hierarchy level, information sources, scale, modelling approach, temporal resolution, and planning horizon. Consequently, existing guidelines provide limited support for selecting the most appropriate method according to project objectives, data availability, and user expertise. In contrast, this work integrates these approaches into a unified, decision-oriented framework that supports context-specific method selection.

Building on the existing body of knowledge, this study proposes a flexible, decision-oriented framework that organises, synthesises and integrates existing methods, offering several key contributions. First, it provides a comprehensive analysis across multiple dimensions, including hierarchy, scale, modelling approach, temporal resolution, and time frame. Second, it presents flexible methodological pathways, allowing users at each step to select approaches based on project objectives, available resources, and familiarity with tools, thereby supporting more informed method selection under different planning conditions.

Thus, the central research question of this work is: *Which methodological approaches and tools are most effective for estimating context-specific load curves in off-grid communities with no prior electricity access?* The working hypothesis is that a structured, decision-oriented framework that organises, synthesises and integrates diverse methodological approaches can improve the consistency, transparency, reproducibility, and practical applicability of load curve estimation by supporting context-appropriate method selection in off-grid, data-scarce communities.

This hypothesis is based on the premise that a systematic pathway for method selection, informed by explicit criteria, improves planning effectiveness by promoting greater consistency, transparency, and reproducibility in the communication of load estimation procedures. To evaluate this hypothesis, the study conducts a structured narrative literature review, systematically classifies existing approaches according to six methodological dimensions, and develops a decision-oriented framework based on this synthesis. The resulting framework organises the existing methodologies into five interconnected phases and provides practical guidance for selecting appropriate load estimation approaches according to project objectives, available data, and implementation constraints.

This study aims to support a wide range of stakeholders (including energy planners, utility operators, project developers, local authorities, NGOs, researchers, policymakers, and community energy committees) in making informed decisions regarding the design of off-grid energy systems and providing practical recommendations for implementation. By improving the selection of load estimation methods, the framework aims to contribute to more effective energy planning, optimised resource allocation, and measurable progress toward broader sustainability goals.

This paper is organised as follows. **MATERIALS AND METHODS** outline the methodological procedure adopted in this study in a step-by-step manner. **RESULTS AND DISCUSSION** present the outcomes of each stage of the proposed method and illustrate the applicability of the framework through a real case study. **CONCLUSION** summarise the main findings, discusses the study's limitations, and suggests directions for future research.

MATERIALS AND METHODS

The flowchart to conduct this study is outlined in **Figure 1** and comprises four work packages. First, approaches for load curve estimation were identified and classified. Second, these approaches were analysed to evaluate their strengths, limitations, and suitability for data-scarce contexts. Third, a guideline framework was developed, integrating insights from previous studies. Finally, the framework's applicability was assessed to support practical decision-making in off-grid electricity access projects. Each step is explained in more detail below.

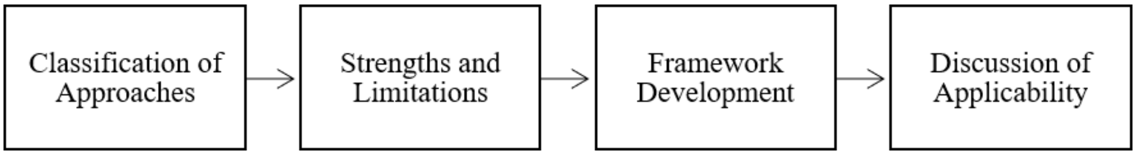

Figure 1. Workflow

Classification of approaches was based on a structured narrative literature review following the approach proposed by Snyder (2019) [16]. The review focused specifically on rural, isolated, remote, last-mile communities in developing countries, while excluding studies related to urban areas or grid-connected areas. The primary database used was Scopus. A combination of general and specific keywords was applied using boolean operators (AND, OR, NOT). The search was limited to English-language documents published within the past 15 years in the fields of energy and engineering. Priority was given to peer-reviewed journal articles, books, and book chapters, though relevant reports and case studies were also considered. The review acknowledges its limitations, as the use of a single database and English-only publications could introduce selection bias, potentially excluding relevant studies from other databases, regional journals, or non-English publications, and biasing the evidence toward certain regions or authors.

The retrieved documents were screened for relevance to rural, off-grid, and data-scarce contexts, prioritising studies that addressed load estimation methods applicable to isolated communities. The literature review was complemented by desk research, as suggested by Moore (2006) [17], incorporating additional sources, such as technical reports and other relevant references that were not captured during the database search. The desk research component was conducted using predefined inclusion and exclusion criteria to enhance transparency and reduce potential selection bias.

Studies were considered eligible if they: i) addressed load estimation, load-curve reconstruction, or electricity demand modelling; ii) focused on isolated, off-grid, rural, or data-scarce contexts; and iii) provided sufficient methodological detail to enable systematic classification.

Both peer-reviewed journal articles and technical reports from internationally recognised institutions (e.g., NREL, IRENA, GIZ, World Bank) were included, given their relevance in rural electrification practice. Conference proceedings were considered when methodological transparency was adequate.

Studies were excluded if they: i) focused exclusively on national or regional capacity-expansion modelling without explicit load-profile characterisation at community or system level; ii) addressed energy-transition scenarios without methodological specification of demand estimation; or iii) lacked sufficient methodological description.

The search strategy combined keyword-based queries with backward and forward citation tracking to ensure broad coverage across methodological families and geographic contexts. Although this work does not constitute a fully systematic literature review, structured screening criteria were applied consistently throughout the selection process to improve transparency and reproducibility.

The classification of approaches focused on systematically organising the identified load estimation methods according to six predefined criteria: hierarchy of data aggregation, source of information, system scale, modelling approach, time resolution, and time frame. This classification allowed for a structured and consistent comparison of the methods. A flow diagram summarising the literature search, screening, eligibility, and study selection process is provided in APPENDIX A, providing a visual summary of study identification, screening, eligibility, and inclusion.

The analysis of strengths and limitations uses these six criteria, drawing on insights from previous case studies, aimed at identifying successful practices, failures, challenges, and lessons learned. Key issues highlighted included data availability constraints, inconsistencies in data collection processes, methodological limitations, limited resources, and difficulties in adapting methods to specific off-grid contexts. This analysis provided valuable lessons that offered a realistic understanding of how different approaches perform in practice.

The framework development followed an inductive–deductive logic. First, an inductive review of the selected literature was conducted to identify recurring methodological dimensions used in load curve estimation. These dimensions were then deductively organised into a decision-oriented framework, aligned with electrification planning objectives, data availability, and resource constraints.

The discussion of applicability examined the framework through benchmarking and contextual validation. Estimated household electricity consumption was compared with reference ranges from international frameworks (MTF, IEA, World Bank) and with values reported in the literature for off-grid and rural communities to identify potential over- or underestimation. Total demand was also disaggregated to distinguish household from productive, commercial, and communal uses, given their high variability across contexts. In addition, further recommendations were incorporated based on the literature review and the methodological considerations proposed by multiple authors. The step concluded by consolidating the main findings and outlining the conditions under which the framework can support future research and practical electrification planning.

RESULTS AND DISCUSSION

The results are presented and discussed according to the work packages of the research method introduced in section Materials and Methods, **Figure 1**.

Classification of Approaches

After screening for relevance and alignment with the objectives of this study, 39 peer-reviewed articles were selected for inclusion, which was deemed adequate to support the aims of the research. Additionally, via a desk research process, relevant technical reports from organisations with extensive involvement in off-grid electrification—including the National Renewable Energy Laboratory (NREL), International Renewable Energy Agency (IRENA), Africa-EU Renewable Energy Cooperation Programme (RECP), National Rural Electric Cooperative Association (NRECA), and Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)— were consulted to complement the peer-reviewed literature **[18]**, **[23]**. To complement and streamline the synthesis, a small number of prior literature reviews were also included **[9]**, **[12]**, **[24]**. We acknowledge that this selection represents only a portion of the available literature and that future studies could expand upon this work.

The studies provided diverse approaches to address the load curves in data-scarce areas. For instance, several studies consider a simple assumption that one community will behave like another, already with a supply, by scaling the number of households **[25]**, **[27]**. Other studies base the assessment on expert knowledge in similar installations **[12]**. Some studies rely on deterministic models, which predict a single outcome based on fixed inputs and assumptions, assuming no variability, resulting in an averaged daily constant load curve **[28]**, **[31]**. In contrast, other studies implemented stochastic models to incorporate random variability to account for uncertainty and potential variations in demand **[32]**, **[34]**. These models combine expert knowledge with mathematical techniques based on statistical methods. For a comprehensive comparison between deterministic and stochastic approaches, see **[15]**.

These models are as accurate as the inputs used, and the lack of data in isolated off-grid communities remains the norm. Different correlations between communities were done by using data-driven approaches; however, they found that communities vary significantly in various aspects, including household usage, communal, social and productive applications of electricity, emphasising the importance of tailoring energy solutions to community-specific conditions to better predict and manage the energy in isolated settings [35], [36]. These approaches may overlook cultural, social, economic, climatic, geographic, demographic, local resources, infrastructure and consumption habits. These differences, indeed, make each community unique.

As advanced, the approaches found were categorised according to the following criteria: hierarchy, sources of information, scale, modelling, time resolution and time frame (see Table 1). Each category is described in more detail below, with reference to the supporting evidence from the reviewed studies.

Table 1. Approaches for estimating load curves in off-grid electricity access projects.

Hierarchy	**Source of Information**	**Scale**	**Modelling**	**Time Resolution**	**Time Frame**
Bottom-Up:	Primary:	Microscopic:	Stochastic:	High:	Long:
From disaggregated data	Fieldwork, Surveys, Interviews	By appliance and person	Probabilistic, Markov Chain, Monte Carlo	Minutes, Seconds	More than 10 years
Hybrid:	Secondary:	Mesoscopic:	Hybrid:	Medium:	Medium:
Combination of Bottom-Up and Top-Down	Private and Public Statistics and Reports, Literature	By households	A combination of stochastic and deterministic	15 to 30 minutes	From 5 to 10 years
Top-Down:	Data-Driven:	Macroscopic:	Deterministic:	Low:	Short:
From aggregated data	Meters, Sensors, Databases	Archetypal Clusters, Community	Regression, Neural networks, Simple estimation	Hourly	Less than 5 years

Hierarchy. The first analysis involves the hierarchical position of data inputs in relation to the community as a whole [37]. The bottom-up approach consists of collecting a large quantity of detailed data at the individual or household level and then scaling up to the community level. For example, the RAMP model used input data from interviews [14]. Other examples can be found in [38], [39]. This method provides detailed insights but requires substantial data collection efforts. Furthermore, the authors' experience shows that potential beneficiaries may find it difficult to estimate their future demand if they have never used electricity before. In contrast, top-down approaches begin with aggregated data at the community or regional level and analyse it to infer individual or household-level patterns [40]. This approach may produce biased results if the data does not align with the actual needs of the community [14], [33]. The hybrid approach combines elements of both bottom-up and top-down methods. It can offer a more comprehensive understanding of energy consumption when both detailed data and reliable statistical data are available [41]. On the contrary, if neither detailed data nor reliable statistical data are available, both can be combined for completeness.

Sources of Information. The second analysis considers the proposed sources of information according to the book *Off-Grid Electrical Systems in Developing Countries* by Louie (2018) [12]. Primary data is collected directly from beneficiaries through fieldwork, surveys, and interviews. This approach allows for obtaining tailored and site-specific information. Some of the most relevant studies employing primary data collection are [18], [22], [42]. However, this approach may be time-consuming and require specialised expertise. It may not always provide accurate or reliable data.

Secondary data refers to pre-existing information from sources other than the beneficiaries. These include statistics, reports, and literature. Secondary data often comes from government agencies and international organisations, such as the World Bank [42], [45], the International Energy Agency [2], [46], [48], or the International Renewable Energy Agency [49]. However, it may lack specificity in understanding unique consumer needs within a community. The data-driven approach utilises secondary data derived from primary data using technology, such as meters, sensors, and other databases from similar communities. This approach is commonly led by private companies with access to both the technology and the customers needed for analysis [50], [51].

The accuracy of the data-driven approach to determine the load curves in off-grid communities depends on the available data, similar to that of the specific site location. These databases encompass monitored consumption data (over many years), climate files, house type data and energy certificates, among others, which usually do not exist for communities taking their first steps in the use of electricity.

Scale. The third analysis is the different sample scale in data collection. At the microscopic scale, the load curve is constructed by focusing on the interaction between individual electrical appliances. This approach provides detailed insights into specific devices [52]. Although providing deep insights, the microscopic scale is limited in its ability to offer a holistic view of broader energy usage trends.

The mesoscopic scale shifts the focus to the household level. This scale provides a balance between granularity and broader applicability [53], [54]. This scale provides more contextualised insights while still being more manageable in terms of data collection and analysis than the microscopic scale.

At the macroscopic level, the analysis expands to the entire off-grid community. This scale provides a holistic view of overall energy needs and trends within the community [55], [56]. This approach provides valuable insights into larger-scale energy needs but may overlook segregated demand patterns, such as household-level social and productive uses.

Modelling. The fourth analysis refers to the process of creating mathematical or computational representations of real-world systems to analyse and predict load curves. Different models are discussed in [15]. Deterministic modelling provides straightforward, predictable results based on historical data or predefined parameters. It is often easier to interpret and communicate, requiring less computational effort [57]. Some techniques implemented in previous studies are Linear, Multiple Linear Regression or LASSO [28], [31].

While useful for simpler predictions, deterministic models may not fully capture the unpredictability and variability inherent in load curves. Stochastic modelling, in contrast, is more realistic as it accounts for random variations and uncertainties in energy usage patterns [24], [58]. Common techniques implemented in previous studies are Markov Chain and Monte Carlo methods [59], Neural Networks and Genetic Algorithms [60], [62] or ARIMA and SARIMA [14], [28]. Although more realistic, stochastic models require more computational resources and are often limited to specialised software that includes these functions.

Hybrid modelling combines both alternatives. This model can better reflect real-world conditions, making the load curves adaptable to unforeseen changes [63]. This process may require fine-tuning to prevent overcomplicating the model.

Time Resolution. The fifth analysis is the temporal resolution. It determines how finely the data is broken down over time. Low resolution simplifies the model by aggregating data over a longer period (generally hourly), making it easier to handle. This approach allows for the comparison of results across a larger number of cases and is widely used in many studies, including Genetic Algorithms [60], Particle Swarm [64] or Hybrid Optimisation of Multiple

Energy Resources [65]. However, it may smooth out short-term demand spikes and considerable consumption patterns.

Medium resolution typically provides data at intervals such as 15 or 30 minutes (smart-meters). An example justifies this choice by having data from previous studies consulted in the literature [64]. While more manageable than high-resolution data, it can still introduce complexity. High-resolution models provide detailed insights, breaking data into very short intervals (minutes or even seconds). Their use in off-grid load curve estimation is rare, as most case studies focus on power electronics design rather than general demand assessment.

The choice of temporal resolution should reflect the purpose of the assessment: for sizing mini-grid systems in communities without major peaks, hourly resolution may be sufficient, while finer intervals are needed when designing systems to handle short, intense peaks. High-resolution models require substantial computational resources and detailed data, which are often unavailable in data-scarce contexts.

<u>Time Frame</u>. The sixth analysis focuses on the time frames and addresses how different periods are considered in energy planning. Each requires distinct strategies based on the evolving needs of off-grid communities. The short-term addresses immediate energy demand over five years or less. These models are particularly helpful for rapid adjustments to meet demand [66]. This focus on immediate solutions may compromise long-term sustainability.

In contrast, studies with a medium time frame (between 5 and 10 years) focus on addressing the evolving needs of off-grid communities, accounting for factors like population shifts, economic changes, and other uncertainties [67], [68]. This approach requires careful consideration of evolving dynamics and may still be subject to considerable uncertainty as time progresses.

Studies with a long-term frame align well with the expected lifespan of energy projects (from 10 to 20 years or, in some cases, even 30 years) [69]. This approach increases complexity and data requirements, with more uncertainty as the time frame extends.

Table 2 presents relevant studies consulted in this review according to the classification criteria previously introduced in **Table 1**. The distribution highlights the prevalence of bottom-up approaches, often relying on field surveys and appliance-level data, and making use of either deterministic, stochastic or hybrid modelling depending on the objectives of each study. This predominance can be explained by the ability of bottom-up methods to provide granular, context-specific estimates, capturing household-level variability, appliance usage patterns, and local behaviour, which is particularly valuable in off-grid, data-scarce communities. Top-down studies, while fewer, contribute valuable insights at regional or aggregated scales, particularly when local primary data are unavailable. Together, these methodological variations illustrate the range of strategies used in the literature to address the challenge of load curve determination in data-scarce contexts. However, apparently, no single approach fits all contexts for estimating load curves in off-grid, data-scarce communities. Thus, this study aims to explore in greater detail the advantages and limitations of each method, identify the conditions under which they are most suitable, describe the tools required for their implementation, and support decision-making in selecting the most appropriate approach for specific cases.

Table 2. Methodological approaches for estimating load curves in off-grid electricity access projects. Evidence from the literature

Ref	Hierarchy	Source of Information	Scale	Modelling	Time Resolution	Time Frame
[6], [8]	Bottom-Up	Primary (field surveys)	Micro (appliances)	Stochastic	Low (hourly)	Long
[13]	Bottom-Up	Primary (field surveys)	Micro (appliances)	Deterministic	Low (hourly)	Medium
[14]	Bottom-Up	Secondary (statistical data)	Micro (appliances)	Stochastic	Low (hourly)	Medium
[34]	Bottom-Up	Primary (field surveys)	Meso (households)	Stochastic	Low (hourly)	Medium
[41]	Bottom-Up	Primary (field surveys)	Macro (community)	Stochastic	Low (hourly)	Medium
[11]	Bottom-Up	Data-driven (meters)	Macro (community)	Deterministic	Medium (15′)	Medium
[70]	Bottom-Up	Data-driven (meters)	Meso (households)	Deterministic	Medium (15′)	Medium
[10]	Bottom-Up	Data-driven (meters)	Meso (households)	Deterministic	Medium (15′)	Medium
[68]	Hybrid	Primary + Secondary (surveys/statistics)	Meso (households)	Hybrid	Medium (15′)	Medium
[71]	Hybrid	Primary + Tertiary (surveys/meters)	Macro (community)	Stochastic	Medium (15′)	Medium
[7], [12]	Top-Down	Secondary (statistics)	Macro (regional)	Deterministic	Low (hourly)	Short
[36]	Top-Down	Data-driven (meters)	Meso (households)	Stochastic	Medium (15′)	Medium
[33]	Top-Down	Data-driven (meters)	Macro (community)	Deterministic	Medium (15′)	Short

Recent studies have further advanced the modelling of electricity demand in rural off-grid communities by moving beyond static load assumptions towards dynamic, data-driven, and stochastic approaches capable of representing demand evolution after electrification. Tomas Fillol *et al.* (2025) introduced a bottom-up modelling framework to improve long-term electricity demand estimation in rural mini-grids by explicitly considering appliance diffusion dynamics [72]. Using empirical data from a Kenyan rural mini-grid, the authors combined appliance adoption trends, clustering techniques, logistic diffusion functions, and optimisation methods to estimate future changes in household electricity consumption. Their findings demonstrate that newly electrified households do not follow homogeneous consumption trajectories; instead, different customer groups exhibit distinct appliance adoption pathways and demand growth patterns. This highlights the limitations of conventional approaches based on fixed customer categories and emphasises the importance of dynamic load modelling for multi-year mini-grid planning and expansion strategies.

Complementing this demand-growth perspective, Wassie and Ahlgren (2024) provided an empirical assessment of electricity consumption patterns in rural photovoltaic mini-grids in East Africa using high-resolution metered data collected over 20 months from two remote Ethiopian communities [36]. Their study demonstrated significant variability in load profiles between locations and customer categories, showing that productive users can consume substantially more electricity than residential users. The authors also identified temporal increases in electricity consumption after grid connection, confirming that demand evolves as communities gain access to electricity services and adopt new appliances and productive activities. These findings reinforce the need for demand assessment methodologies based on both measured and estimated consumption behaviour rather than initial connection estimates.

Similarly, Ashetehe *et al.* (2024) proposed a stochastic bottom-up methodology for generating synthetic load profiles for rural communities [73]. The approach integrates field surveys, appliance ownership information, usage schedules, and probabilistic variations to represent the uncertainty associated with rural electricity consumption. By considering different consumer groups, including households, public institutions, businesses, and small industries, the model provides a more comprehensive representation of community-level demand patterns. The study further demonstrates the value of synthetic load generation approaches for renewable energy system sizing, particularly where long-term monitoring data are unavailable.

Recent research has also increasingly linked load profile characteristics with mini-grid technical and economic performance. Wu *et al.* (2025) analysed electricity demand data from 25 rural mini-grids in Uganda, including more than 2000 households and productive users, to investigate the influence of demand characteristics on system economics [74]. The study showed that peak demand variability and the proportion of daytime electricity consumption strongly influence generation costs, with productive-use loads improving load factors and reducing the levelised cost of electricity. These results highlight the importance of incorporating demand-side characteristics, load flexibility, and productive-use electricity patterns into mini-grid design approaches.

Strengths and Limitations

Table 3 summarises the strengths and limitations of the approaches defined in **Table 1**. Understanding these aspects provides valuable guidance for selecting appropriate strategies to determine load curves in the context of diverse communities and projects. The analysis indicates that hybrid approaches—across hierarchy, modelling, or data sources—offer a balanced perspective by combining the contextual accuracy of bottom-up or primary methods with the efficiency and broader coverage of top-down or secondary approaches.

This advantage, however, comes with increased complexity and the need for expertise to integrate both approaches effectively for completeness. Similarly, microscale and high-resolution analyses provide detailed insights for household-level planning but may be impractical for larger-scale studies, where mesoscale or low-resolution approaches offer a feasible compromise at the community level and facilitate comparison with a wider body of studies.

From a temporal perspective, medium- to long-term analyses support more robust policy and system design but require high-quality data and careful management of associated uncertainties. Overall, these findings emphasise the need to align methodological choices with the objectives, scope, and available resources of each study.

Table 3. Strengths and limitations of approaches for estimating load curves in

Approach		Strengths	Limitations
Hierarchy	Bottom-up	+ Provides granular insights into specific energy usage patterns and behaviours within households. Adapts well to specific regions or communities.	- Requires significant work to gather information and risks errors if data is not well-tuned or sources are unreliable. Comparisons to top-down data are needed to verify results.
	Top-down	+ Efficient for larger-scale analysis, especially useful for broader regional or national applications.	- Lacks detailed insights into the specific energy demands of beneficiaries. Highly dependent on accurate data to avoid biases.
	Hybrid	+ Combines detailed insights from bottom-up with broader coverage of top-down, providing a balanced view.	- Coordination and integration between methods can be challenging and resource-intensive.
Source of Information	Primary	+ Provides specific, community-level insights and can raise awareness about responsible consumption.	- Time-consuming and requires specialised expertise. It may not always provide accurate or reliable data.
	Secondary	+ Efficient if accurate, providing quick access to data for broader analysis.	- Lacks specificity in understanding unique consumer needs within a community.
	Data-driven	+ Combines the strengths of primary information without requiring first-hand data collection efforts.	- Monitoring off-grid systems can be difficult, and each community is unique, making standardisation challenging.
Scale	Microscale	+ Offers detailed insights into individual energy demands and appliances, facilitating better energy planning and demand management.	- Requires more time, work, and computational power to generate full-period load curves for entire communities.
	Mesoscale	+ Generates comparable results across different communities, which requires fewer resources and less computational effort.	- Aggregated data may obscure the impact of individual appliances and household-level variations.
	Macroscale	+ Efficient for studying large quantities of communities, particularly in large-scale rural electrification projects.	- Misses household-level demand variations, which can affect energy planning. Productive uses vary considerably between communities.
Modelling	Deterministic	+ Easier to interpret and communicate results, requiring less computational effort.	- Lacks realism, as consumption does not follow standard patterns or standard days, affecting system sizing and reliability.
	Stochastic	+ More realistic for both consumption and generation modelling, particularly for renewable energy systems, which are inherently stochastic.	- Requires more computational resources and correlations. Limited to software that includes this function.
	Hybrid	+ Provides a balance between realistic representation and computational efficiency by combining stochastic and deterministic models.	- May require fine-tuning to prevent overcomplicating the model.

Approach		**Strengths**	**Limitations**
Resolution	High	+ Provides highly detailed insights, useful for fine-tuning energy system designs.	- Requires significant computational resources, and data is not always readily available at this resolution. It can introduce noise and inconsistencies across studies.
	Medium	+ Offers a balanced level of granularity, often sufficient for practical optimisation without being overly data-intensive.	- While more manageable than high-resolution data, it can still introduce complexity
	Low	+ Computationally efficient for optimisation algorithms, widely available, and balances between granularity and statistical significance. Enables comparison with a wide range of existing studies.	- May smooth out short-term demand spikes and considerable consumption patterns
Time Frame	Short-term	+ More agile and responsive for emergency planning or rapid deployment, where quick solutions are prioritised.	- Limited depth and accuracy for long-term development, focusing more on what is feasible than on ideal solutions.
	Medium-term	+ Provides a balanced view between short-term agility and long-term planning, often incorporating lessons from both.	- More complex than short-term studies, and still subject to considerable uncertainty as time progresses.
	Long-term	+ Incorporates broader economic, political, social, and environmental factors, facilitating better long-term energy planning.	- Increases complexity and data requirements, with more uncertainty as the time frame extends.

Framework Development

The framework for estimating load curves in off-grid communities under data-scarce conditions is presented in Figure 2. It integrates the perspectives, commonalities, and methodological approaches reported in previous studies, reflecting prior experiences in the field. Essentially, it summarises the key steps required to carry out the load curve estimation process in a structured and systematic way.

Phase 1 focuses on achieving a comprehensive understanding of the specific context of the community under study. Phase 2 involves selecting an appropriate methodological approach, along with the tools required for its implementation. Phase 3 is dedicated to the collection of relevant data, which is then processed and analysed in Phase 4. Finally, Phase 5 assesses the results by comparing them with national datasets, existing literature, and other validated sources.

The phases are intentionally designed to be generic and independent of the chosen modelling approach, enabling flexibility in application. The primary variation across different approaches lies in the type and granularity of input data required. Furthermore, the framework can be iterative, allowing for gradual improvement in the accuracy and reliability of the resulting load curve as new data and insights become available.

<u>Phase 1. Contextual Diagnosis</u>. The first step in the load curve determination process involves evaluating what information, skills, and resources are available or can be obtained to support the estimation of electricity demand, particularly in data-scarce communities. This includes identifying existing data sources, such as previous surveys, metered consumption, or statistical reports. When direct data from the target community is unavailable, proxy data from nearby or similar communities within the same region, country, or continent can be considered, as recommended in previous studies [9], [12], [24].

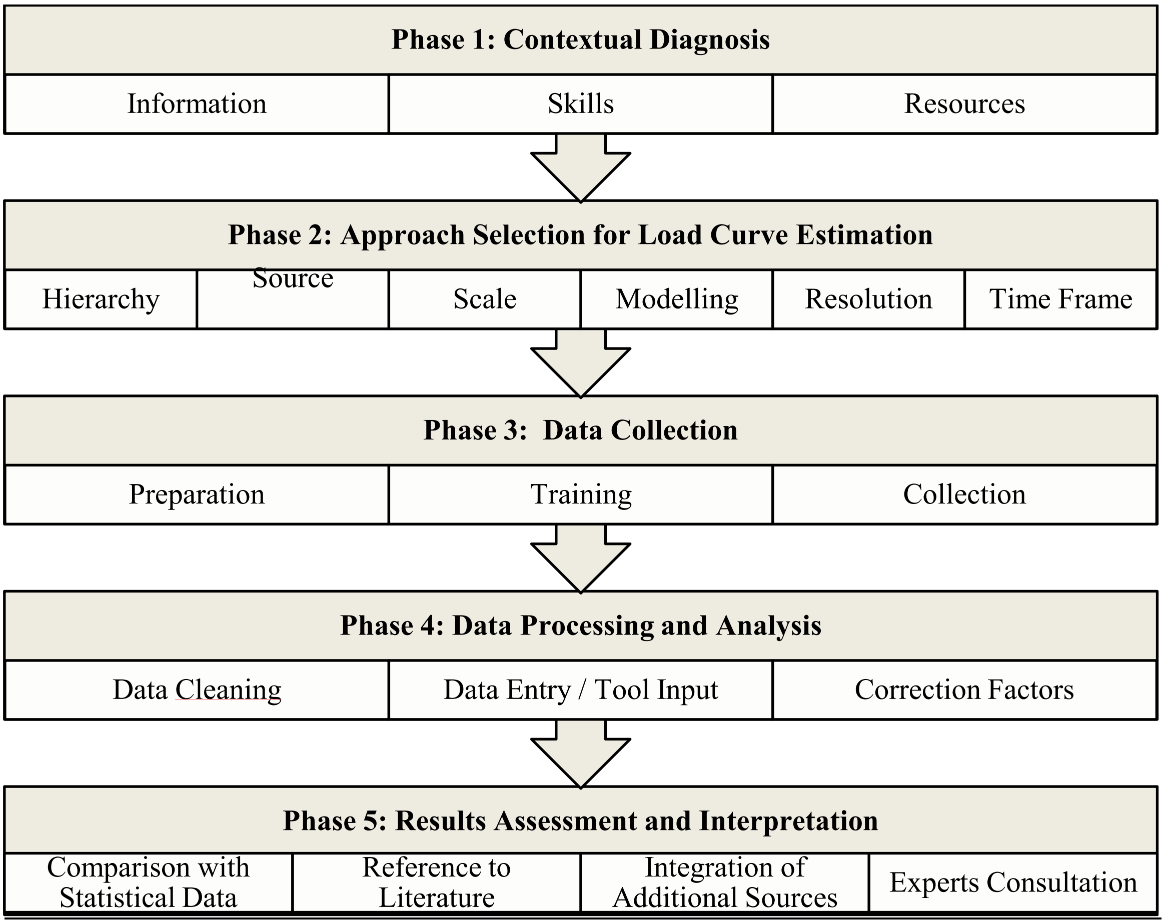

Figure 2. Guideline framework for estimating load curves in off-grid electricity access projects

It is also necessary to clarify who will be responsible for the process—engineers, local technicians, researchers, community representatives, etc.—and to define the objective of the load curve estimation, which can be to guide the design of a renewable energy system that is technically feasible, cost-effective, and aligned with the local resources, needs and capacities of the community. The accuracy and representativeness of the load curve are determined by the trade-off between time, cost, and scope. This assessment will provide an important input for Phase 2, where the most suitable methodological approach for the load curve estimation will be selected.

Phase 2. Method Selection for Load Curve Estimation. Building on the diagnosis from Step 1, the second phase focuses on how to construct the load curve, considering the context, available data, and resources. Drawing on the synthesis of previous studies, this step refers to **Table 1**: Approaches for the load curve determination in off-grid communities with no previous access to electricity, which summarises general approaches, and **Table 2**: Methodological approaches applied in previous studies for load curve determination in off-grid communities, which provides concrete examples and classifications from the literature. Additionally, the analysis in **Table 3**: Strengths and limitations of approaches can inform the selection process.

The first criterion could be Hierarchy, which considers whether a top-down, bottom-up, or hybrid structure influences the granularity and aggregation level of the data. The Source of Information reflects on whether the model will rely on primary measurements, secondary sources, or inferential data-driven techniques. The Scale defines the spatial sample size, which could be micro (individual users or devices), meso (household level) or macro (clusters, archetypal, or the entire community). The Model decision refers to the analytical nature, such as deterministic (based on fixed rules and inputs), stochastic (incorporating uncertainty), or hybrid approaches. Time Resolution considers how finely the data is broken down over time, ranging from hourly to finer intervals. The Time Frame defines the projection period, which may vary from short-term to long-term and influences assumptions about growth in both demography and socioeconomic factors.

It should be noted that the present study focuses on load-curve estimation at community and microgrid scale, particularly in isolated or data-scarce contexts, where short- to medium-term demand characterisation is typically prioritised for system sizing and operational design. In contrast, long-term energy planning—widely addressed in national and regional energy transition modelling—usually concentrates on capacity expansion, policy pathways, or macro-scale scenario analysis rather than detailed load-profile reconstruction. Therefore, the distribution observed in Table 2 is consistent with the methodological focus of this framework and should not be interpreted as an underrepresentation of long-term energy planning research in general.

Furthermore, it is recommended to determine the load curve for different periods and scenarios. This structured approach aims to support informed decision-making. Overall, the framework offers a flexible yet systematic method to align modelling choices with the constraints of data-scarce environments, enabling the development of contextually appropriate load curves.

Table 4 outlines a range of tools that can be used in the load curve determination process in data-scarce, off-grid contexts. These tools are grouped into deterministic, stochastic, and hybrid models. This classification supports the systematic selection of suitable tools based on the specific modelling approach to be adopted. Some tools are freely accessible or can be implemented using open-access software—for example, Mini Grid Builder, Demand Analysis, NREL Microgrid Load Profile Explorer, and regression methods (linear, multiple linear, LASSO), as well as ARIMA and SARIMA models—and thus may be more suitable for low-resource applicability. Other open-source tools, such as the Load Profile Generator and RAMP, also have publicly available code on GitHub and can be consulted. In contrast, proprietary software such as ESCOBox and HOMER, as well as advanced stochastic methods using neural networks or genetic algorithms, may require paid licenses, specialised training, and computational resources, which may limit their applicability.

Table 4. Modelling tools relevant for estimating load curves in off-grid electricity access projects. Classification by deterministic, stochastic, and hybrid approaches

Modelling	Tool
Deterministic	Mini Grid Builder [22]
	Demand Analysis [75]
	ESCOBox [32]
	NREL Microgrid Load Profile Explorer [76]
	Linear, Multiple Linear Regression or LASSO [28], [31]
Stochastic	Neural Networks and Genetic Algorithms [60], [62]
	ARIMA, SARIMA [77]
Hybrid	Load Profile Generator + RAMP [14, 78]
	HOMER [39]

Additionally, many of these tools rely on detailed input data to generate accurate load curves. In data-scarce off-grid contexts, such data may be unavailable, which can reduce the accuracy of these approaches. Previous studies have shown that assuming one community is similar to another or using proxy datasets can introduce significant errors, highlighting the limitations of purely data-driven tools [36].

Based on their comparison, Herraiz-Cañete *et al.* (2022) [15] recommend using deterministic methods during the early project phases for initial demand assessment and resource comparisons, while advocating for stochastic approaches in later design stages to improve load curve reliability. This staged application can balance practical feasibility with accuracy throughout the project lifecycle by implementing an iterative, multi-horizon load curve estimation. Agent-based and bottom-up synthetic load-generation models can be integrated within the framework as specific modelling options when sufficient data and modelling capacity are available, particularly in later design stages.

From a methodological perspective, the choice between deterministic, stochastic, and hybrid approaches involves balancing accuracy, uncertainty representation, computational complexity, and data requirements. Deterministic methods are generally simpler to implement, require fewer computational resources, and are therefore well suited to preliminary planning or data-scarce contexts. Moreover, these approaches are generally easier to explain and communicate to non-expert stakeholders, including the potential beneficiaries who participate in the load estimation process. However, because they rely on fixed assumptions, they have a limited ability to represent the uncertainty and variability inherent in electricity demand and may therefore underestimate demand fluctuations.

In contrast, stochastic methods explicitly account for the probabilistic nature of user behaviour and appliance usage, producing more realistic load profiles and improving robustness under variable operating conditions, albeit at the expense of higher data requirements, calibration effort, computational complexity and reduced interpretability.

Hybrid approaches seek to combine the strengths of both paradigms by retaining the transparency and practicality of deterministic models while incorporating stochastic representations where demand variability is most relevant.

Consequently, no single approach is universally preferable; the most appropriate method depends on the objectives of the study, the availability and quality of data, the required temporal resolution, the available computational resources, and the level of accuracy required. These trade-offs reinforce the need for a flexible, decision-oriented framework capable of guiding method selection according to the characteristics and constraints of each electrification project, rather than promoting a single modelling approach.

Other useful tools, although not specifically designed to determine load curves, can nonetheless support related processes. One example is the tool developed by TFE Energy [51], which aids in identifying viable energy projects by combining data-driven approaches with machine learning techniques and satellite imagery. This may offer valuable insights during early planning stages, particularly in data-scarce contexts. Similarly, Odyssey [50] uses a combination of deterministic models based on customer equipment usage and stochastic simulations that account for demand variability and future growth, while the OnSSET tool [79], [80] is widely used for geospatial electrification planning and spatial resource assessment when determining grid extension, mini-grid, or stand-alone systems. Additional tools for microgrid design, planning, and monitoring are discussed in [81]. Together, these tools offer a broader perspective on available resources and help situate the proposed methodological framework within the overall microgrid design process.

<u>Phase 3. Data Collection</u>. To respond to varying operational realities, the data collection phase is designed to follow two complementary pathways: one based on direct field engagement, and another adapted for situations where field access is constrained or not feasible. Both pathways aim to support the development of a plausible and context-sensitive load curve,

building upon the contextual insights established in Phase 1 and the modelling decisions set out in Phase 2. Despite their differences, both approaches are organised around three shared components: preparation, training or tool familiarisation, and data acquisition.

When fieldwork is possible. the process draws on primary data collected directly from communities. During the preparation stage, the data requirements are defined based on the selected modelling approach. These typically include household characteristics (e.g. household size and composition), the geolocation of dwellings, willingness and ability to pay for electricity services (WTP and ATP), willingness and capacity to adopt specific appliances, the availability of energy-efficient and conventional appliances in local markets, accessibility and affordability of these technologies, and expected patterns of electricity use over time (habits). Data collection tools—such as structured surveys and observation templates—are developed accordingly, and field logistics, including sampling strategies and team coordination, are arranged.

The training component aims to improve and calibrate tools use reliably and ethically. This includes instruction on the instruments, data collection practices, and procedures for informed consent. A pilot study, where feasible, can help to test and refine the instruments. Data acquisition is then carried out through a combination of methods, such as household surveys, interviews, and group discussions (some examples can be consulted in **[13]**, **[18]**, **[22]**, **[28]**, **[42]**, **[66]**). Quantitative and qualitative data are gathered to capture both energy behaviours and the social context in which they occur. Although this approach involves more effort, it tends to yield richer and more locally grounded insights. As suggested by several authors, this stage offers an important opportunity for co-creation with the community, enabling active participation in the solution and fostering engagement and long-term project sustainability.

When fieldwork is not possible. due to logistical, financial, or other constraints, the process is adapted to rely on secondary and tertiary data. The preparation stage remains oriented by the modelling framework, but attention shifts to identifying existing datasets that may offer relevant proxies. These might include national and/or regional household surveys, census data, previous energy access studies, or open-access databases. A set of informed assumptions is developed based on this material, and appropriate analytical tools or simulation methods are selected. In the absence of fieldwork, tool familiarisation becomes the focus.

This involves ensuring the analysis team can effectively manage secondary data, work with available modelling tools, and assess the reliability of different data sources. The acquisition stage then involves compiling and organising these inputs. Literature reviews, expert consultations (possibly conducted remotely), and data from analogous case studies can provide supporting evidence. In some cases, geospatial or remotely sensed data can further strengthen the analysis by highlighting patterns in infrastructure or population distribution. While this pathway may involve more uncertainty, it remains a practical option when direct access is not viable.

Both approaches are intended to generate useful inputs for estimating demand in off-grid communities. Field-based methods offer more granular, context-specific insights, while secondary and tertiary data approaches provide a means to proceed when primary data cannot be collected. In either case, careful documentation of the sources used and the assumptions made can maintain the integrity of the modelling process and support future refinement. Additionally, this phase should remain connected to earlier stages in the overall process. Unexpected findings or inconsistencies—whether in the field or in secondary sources—may require revisiting earlier assumptions or modifying the chosen modelling framework. This feedback loop strengthens the robustness and relevance of the resulting load curve.

Phase 4. Data Processing and Analysis. Following data collection, the information needs to be prepared for use in modelling. This phase includes three key tasks: cleaning the data, organising it for input into selected tools, and applying correction factors where needed. These steps help ensure that the dataset is coherent, usable, and aligned with the modelling approach.

Data cleaning involves checking for missing values, inconsistencies, and errors. For primary data, this may mean reviewing survey responses and addressing outliers. For secondary and tertiary sources, the focus is on assessing quality and resolving mismatches across datasets. A clear reference to earlier documentation helps maintain consistency in interpretation.

The data input step structures the cleaned data according to the requirements of the chosen tools—whether spreadsheets, statistical models, or simulation platforms. This may require aggregating or harmonising data to match the scale and categories used in the modelling framework. Some correction factors may be applied to address known limitations, such as underrepresentation in sampling or discrepancies in secondary sources or adjustments with affordability constraints such as ATP and WPT (see [22]). These adjustments can be based on literature, expert input, or national statistics. Throughout this phase, feedback loops with earlier stages remain important. Data processing may reveal issues that require returning to initial assumptions or revising parts of the collection process. This iterative approach helps improve the accuracy and contextual relevance of the final demand estimates. In essence, this phase translates raw data into a usable format while applying adjustments to account for known constraints.

<u>Phase 5. Results Assessment and Interpretation</u>. Once the data has been processed and the initial load curves are constructed, Once the initial load curves are constructed, their validity, coherence, and relevance is assessed. In off-grid, data-scarce communities, historical statistical data may be limited; therefore, the evaluation draws on the outputs generated during Phase 3 (Data Collection) and Phase 4 (Data Processing and Analysis).

The assessment triangulates multiple sources to support plausibility and usefulness. Proxy statistical data from analogous communities or regional surveys, when available, provide quantitative reference points. Literature documenting similar contexts or energy-use patterns offers additional benchmarks, while geospatial or remotely sensed data can further contextualise results. Expert consultation, drawing on local knowledge and stakeholder feedback, contributes to judging plausibility and identifying potential inconsistencies. Monitoring energy use (ideally with smart meters) during the early stages of a project provides a practical means to validate the estimated load curve and track its evolution over time, offering the opportunity to adjust the system if initially undersized or oversized.

By integrating these elements, Phase 5 helps ensure that the resulting load curves are reasonable, transparent, and actionable, even in the absence of direct historical measurements, reinforcing the framework's flexibility and applicability under limited-data conditions while maintaining methodological rigour. To build on Phase 5, Step 4 presents a more comprehensive assessment, comparing the framework's outputs against reference values from the literature, national surveys, and international benchmarks to evaluate their applicability and contextual relevance.

Application to a Case Study

The proposed methodological framework was applied to an ongoing rural electrification project aimed at the design and assessment of basic hybrid renewable energy systems for isolated communities in developing countries. Previous research conducted within this project developed a methodology for the design of hybrid renewable energy microgrids, illustrated through a case study in Zambia [68], and subsequently performed an ex ante life cycle assessment to evaluate the environmental performance of a proposed system for a rural community in Honduras [82].

Building on these contributions, the present study illustrates the applicability of the proposed framework to the off-grid community of El Santuario (13°29′22.9″N, 87°13′14.9″W), located in the department of Choluteca, Honduras. El Santuario comprises 75 scattered households with a total population of approximately 561 inhabitants and currently has no access to electricity. The nearest viable connection point to the national electricity grid is more than 6 km away, across mountainous terrain, making grid extension technically and economically infeasible in the short and medium term. The rural electrification project has recently been implemented, and the methodological framework proposed in this study was applied during the definition of the community's load. Further details on the case study are available in [15], [71], [82], [83].

For Phase 2, based on the approaches for estimating load curves in off-grid electricity access projects presented in Table 1, a bottom-up method based on primary data collection was selected. This approach was deemed the most appropriate due to the absence of historical electricity demand data. The analysis was conducted at a mesoscopic scale, representing the community through individual households. Then, a hybrid deterministic–stochastic model was employed, with hourly temporal resolution to capture representative daily load profiles and peak demand. A medium-term planning horizon (5–10 years) was adopted to reflect the expected evolution of electricity demand during project implementation. The selected methodological configuration was considered appropriate for the objectives of this illustrative application. This approach aims to balance realism, data availability, and modelling complexity.

For Phase 3, primary data were collected through household interviews, with the questionnaire employed in the study provided in APPENDIX D. In parallel, field observations helped to characterise the expected electricity demand of the community. The projected demand included 75 households assigned Tier 3 electricity access, as agreed with the community during the planning process. In addition, several productive and communal electricity uses were identified. For each consumer category, the expected daily energy demand was defined and combined with the corresponding hourly operating schedules to generate the individual load profiles used in the subsequent load curve construction. Table 5 summarises the end-users considered in the case study. The complete appliance inventory, including the rated power, operating schedules, and estimated energy consumption for each end-user, is provided in APPENDIX B.

Table 5. End-users considered for the load curve estimation

Category	User	Units	Daily energy (kWh/day.user)
Residential	Households	75	1–3.4 Avg 2.2
Productive	Bar/Restaurant	2	2.8
	Shop/Kiosk	2	1.6
	Other productive activities	1	1.8
Communal	School	1	3.2
	Street lighting system (21 LEDs)	1 system	13.7
	Church	1	0.7
	Health care facility	1	1.7
	Community hall	1	1.4
	Biomass shredder	1	10.0
	Solar pumping	1	7.5

Following the data collection process, Phase 4 focused on data processing and analysis. As defined in the methodological framework, a deterministic load curve was constructed using the bottom-up approach selected in Phase 2. The procedure consisted of three consecutive steps: (i) estimating the hourly demand of each expected end-user, (ii) aggregating individual demand profiles according to consumer category, and (iii) combining these categories to obtain the total community load curve. Subsequently, the deterministic profile was refined through stochastic modelling to represent demand variability and uncertainty.

The hourly electricity demand of each expected consumer was estimated from the appliance inventory and operating schedules identified during the fieldwork (for more details, consult APPENDIX B). In the first iteration of the case study, 87 expected end-users were identified, comprising 75 households, 5 productive users, and 7 communal facilities. Household demand was defined to satisfy the expected MTF Tier 3 electricity access level with an average 2.2 kWh/day per household. **Figure 3**. presents the resulting deterministic load curves for all individual consumers. These profiles represent the demand estimation developed during the planning stage of the ongoing project and may be refined as additional information becomes available.

Figure 3 shows the hourly load profiles considered. The lighting load operates primarily during nighttime hours and remains off during the day due to the availability of natural daylight. The solar water pumping system is scheduled to operate between 09:00 and 20:00, following the solar irradiation profile. The biomass crusher, used to prepare feedstock for the proposed biomass gasification plant, represents the highest power demand (5 kW) but operates for only two hours per day. The remaining curves correspond to residential loads, with daily energy consumption ranging from 1 to 3.4 kWh and peak power limited to 1.2 kW per household. As expected, residential demand increases during the evening (19:00–21:00), reflecting typical household electricity consumption patterns.

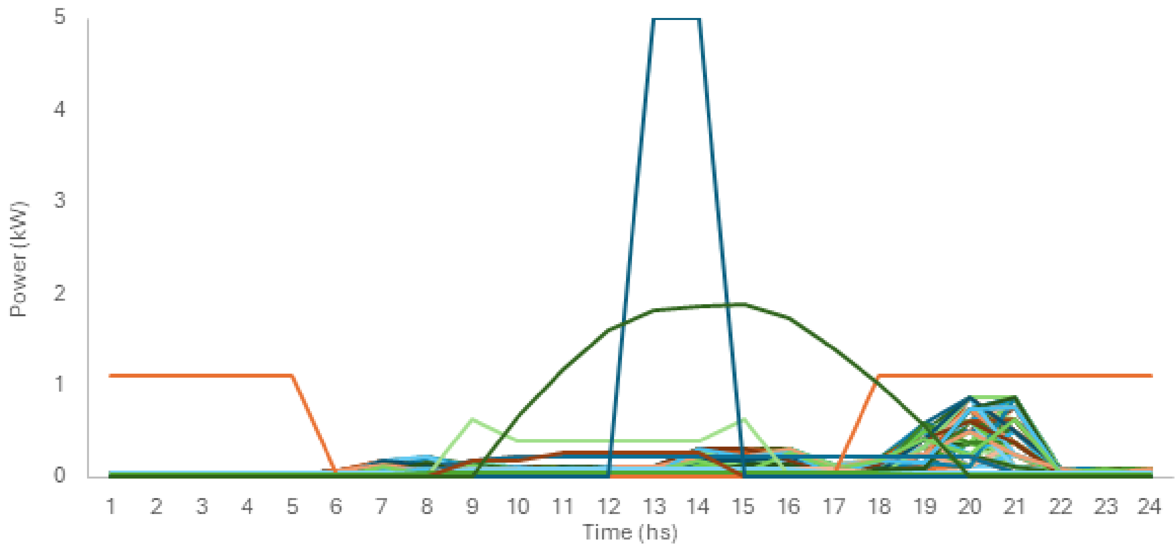

Figure 3. Individual deterministic load curves for end-users (n=87)

The aggregated deterministic load curve is presented in **Figure 4**. The profile combines household, productive, and communal electricity demand, resulting in a peak demand of approximately 31 kW at around 20:00. The estimated daily electricity demand is 221 kWh/day, of which household, communal, and productive demand account for 166 kWh (75%), 43 kWh (20%), and 11 kWh (5%), respectively.

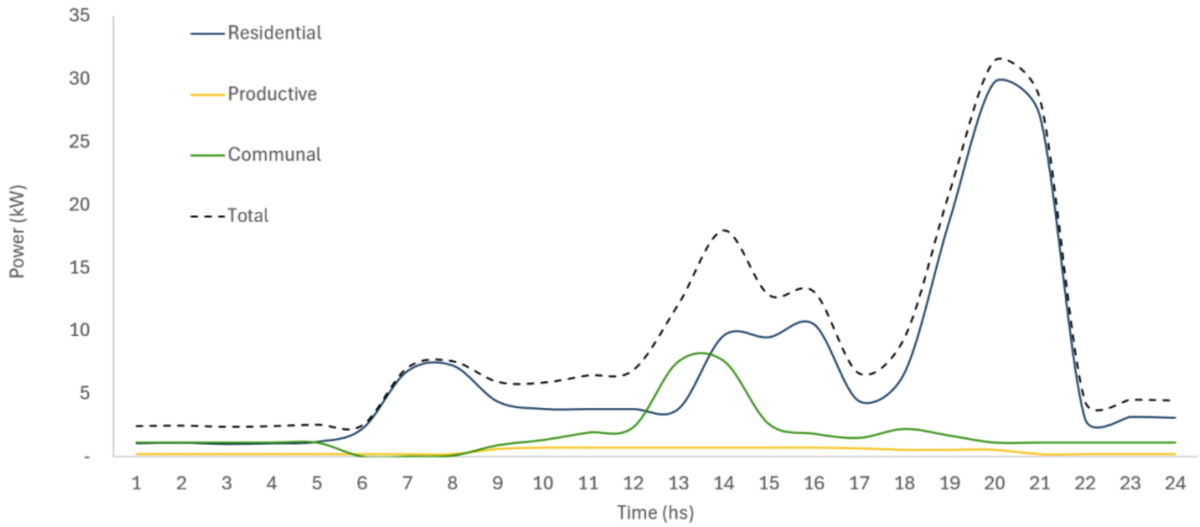

Figure 4. Aggregated deterministic load profile showing separate curves for household, productive, and communal electricity demand

The stochastic load curve was generated from the deterministic profile using the synthetic load variation function available in HOMER. In this example, daily and time-step variability values of 10% and 15%, respectively, were adopted to represent plausible demand fluctuations in the case study community. Figure 5 presents the resulting stochastic load curve for a random week of the year, highlighting the temporal variability in electricity demand.

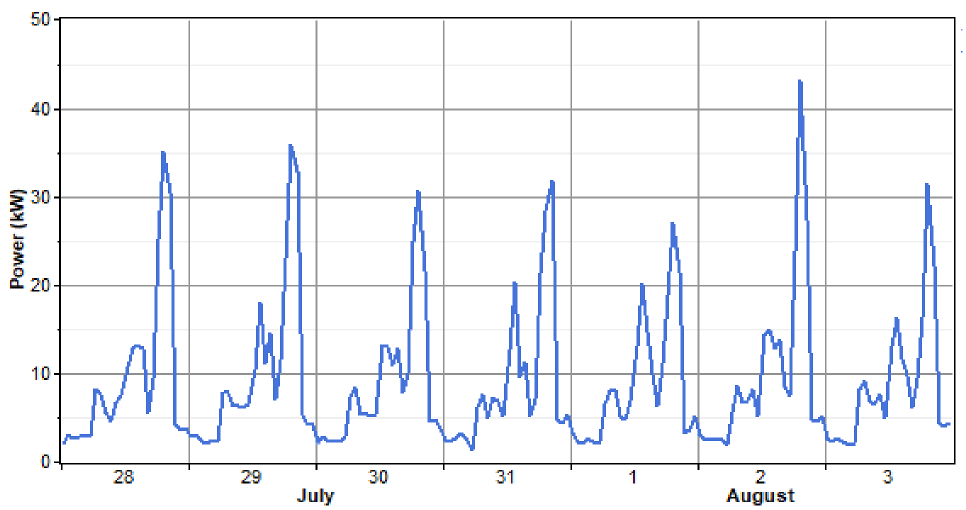

Figure 5. Stochastic load curve for the community. Illustration of a random week

The annual stochastic load curve is shown in Figure 6. The profile exhibits an average demand of approximately 9 kW, a load factor of 0.19, and a maximum demand of 48 kW. The load duration curve illustrates how the estimated demand profile can support the subsequent sizing of the planned mini-grid by balancing reliability requirements and investment costs. More details about the stochastic load curve can be consulted in APPENDIX C**.**

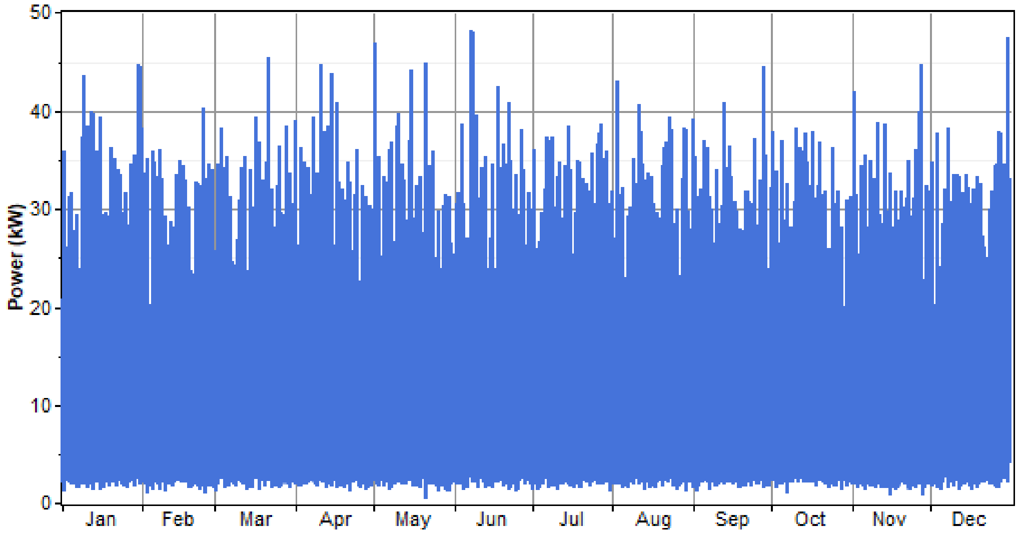

Figure 6. Annual stochastic load curve for El Santuario

At this stage, no load correction factors have been applied to the estimated demand profile. During system sizing, however, several demand adjustment factors may be introduced. These include simultaneity (or diversity) factors to account for the non-coincident operation of individual loads, utilisation factors to reflect partial appliance loading, occupancy and behavioural factors to capture user consumption patterns, seasonal factors to represent temporal variations in electricity demand, demand growth factors to account for future increases in electricity consumption, and system loss factors to incorporate distribution and conversion losses. The selection of these factors depends on the expected diversity of electricity use, user behaviour, planning horizon, system reliability requirements, budget and design methodology adopted.

Discussion of Applicability

The proposed framework is designed to be compatible with a range of existing electrification planning tools. By producing context-specific load profiles, it can feed directly into deterministic tools such as Mini Grid Builder, ESCOBox, and NREL Microgrid Load Profile Explorer for initial assessments, as well as stochastic or hybrid platforms like Neural Networks, ARIMA/SARIMA models, HOMER, or Load Profile Generator + RAMP for later design stages. Agent-based or bottom-up synthetic load-generation models can also be applied within the framework when sufficient data and modelling capacity exist. In addition, the framework can be integrated with a geospatial energy planning tool, e.g. OnSSET, to improve bottom-up electrification planning by providing more accurate and context-specific demand inputs. Tools such as TFE Energy and Odyssey can further complement the framework during early planning by providing project identification insights or accounting for demand variability.

Furthermore, the results can be compared with national or regional data, such as household energy consumption averages, regional surveys, or utility datasets, where available. This comparison helps to identify discrepancies that could indicate an over- or underestimation in the model. While some variation is to be expected, especially in off-grid regions, significant deviations should lead to a revision of the assumptions or data used in the analysis. For example, **Table 6** provides comparisons based on frameworks such as the MTF [84], the IEA energy access definitions [48], and World Bank reports [85]. These classifications help define different levels of energy access and consumption at the household level.

The case study in Honduras considers an average household demand of 2.2 kWh/day (MTF Tier-3), which is above basic subsistence and essential energy access levels but below the IEA extended standard appliance level. It also remains below the current rural average consumption

Table 6. Reference values for household energy access. Average daily consumption

Reference	Category	Avg. Daily Consumption (kWh/day)
Multi-Tier Framework for Energy Access (MTF) [84]	Tier-0	Up to 0.01
	Tier-1	Up to 0.2
	Tier-2	Up to 1.0
	Tier-3	Up to 3.4
	Tier-4	Up to 8.2
IEA energy access definition [48]	Basic Subsistence	1.0
	Essential	1.4
	Extended (Standard Appliances)	3.4
	Extended (Efficient Appliances)	1.2
World Bank Reports, e.g. in Honduras [85]	Urban	5.7
	Rural	2.8
	Nationwide	4.3

reported by the World Bank (2.8 kWh/day), representing a realistic intermediate demand for decentralised household energy systems. This value is particularly relevant as it defines the potential long-term energy access status of the community, representing a transition from isolated household systems toward rural consumption levels

Furthermore, comparisons can be made with similar communities, drawing on academic studies, project documentation, or case studies. This step helps verify whether the magnitude and patterns of demand align with trends observed in similar settings. It also supports the interpretation of qualitative patterns, such as peak demand hours or the influence of behavioural practices and seasonality. For example, to contextualise the energy demand results, **Table 7** presents a comparative summary of relevant literature on household energy consumption in off-grid rural communities.

The selected studies span various geographic regions and employ a range of methodological approaches, including empirical surveys, synthetic modelling, and both deterministic and stochastic modelling. The average daily energy consumption per household reported in these studies typically ranges between 0.2 and 3.5 kWh/day. This comparative overview helps position the study's findings within the broader landscape of off-grid communities' energy demand assessment research and underscores the diversity in both consumption patterns and modelling practices.

In addition, it is necessary to distinguish household usage from productive and communal uses. These non-household categories can vary widely between communities, ranging from minimal to dominant shares of total demand. Importantly, electricity availability alone does not directly determine the extent of productive or economic activity, as these depend on a complex set of conditions; e.g. the share of productive electricity use varies notably between the two communities studied empirically by Wassie *et al.* (2024) [36]. In Omorate, productive users account for over 50% of the total electricity demand, whereas in Tum, they represent only 28% of total consumption. This difference highlights how productive activities can constitute a majority or a much smaller portion of total electricity use, depending on local economic conditions and user composition. Such variation reinforces the importance of separately analysing productive loads when assessing overall community electricity demand. Similarly, for communal, social and other uses of electricity.

Table 7. Comparative overview of average daily household energy demand in off-grid communities' studies

Reference	Study Location	Study Focus and Context	Avg Daily Consumption (kWh/day)
Mandelli *et al.*, (2016) [6]	Sub-Saharan Africa	Synthetic load profiles for off-grid rural households	0.5 – 2.5
Blodgett *et al.*, (2017) [13]	East Africa	Accuracy of energy-use surveys on mini-grids	0.3 – 1.5
Lombardi *et al.*, (2019) [14]	Various remote and off-grid settings worldwide	High-resolution multi-energy load profile generation	0.2 – 3.0
Lorenzoni *et al.*, (2020) [35]	61 load profiles from multiple case studies	Demand estimation with a data-driven foundation	0.5 – 2.0
Wassie & Ahlgren, (2024)[36]	Two East African communities	Empirical study of residential load profiles	1.7 – 3.5
Narayan *et al.*, (2020) [34]	Developing countries in general	Stochastic load profile modelling by access tier	0.5 – 3.0
Herraiz-Cañete *et al.*, (2021) [15]	Honduras	Comparison of deterministic and stochastic demand	~2.8
Boait *et al.*, (2015) [32]	Developing countries in general	Estimation of demand diversity for off-grid rural demand profiles	1.0 – 2.5
Martinez *et al.*, (2023) [68]	Zambia	Case study of household demand for mini-grid design	~1.5

In addition, it is necessary to distinguish household usage from productive and communal uses. These non-household categories can vary widely between communities, ranging from minimal to dominant shares of total demand. Importantly, electricity availability alone does not directly determine the extent of productive or economic activity, as these depend on a complex set of conditions; e.g. the share of productive electricity use varies notably between the two communities studied empirically by Wassie *et al.* (2024) [36]. In Omorate, productive users account for over 50% of the total electricity demand, whereas in Tum, they represent only 28% of total consumption. This difference highlights how productive activities can constitute a majority or a much smaller portion of total electricity use, depending on local economic conditions and user composition. Such variation reinforces the importance of separately analysing productive loads when assessing overall community electricity demand. Similarly, for communal, social and other uses of electricity.

Additional sources of insight, such as expert consultations, stakeholder feedback, or insights from earlier fieldwork, can further inform the assessment. When unexpected or inconsistent results emerge, these external inputs can offer valuable context or clarification. In the desk research, other dimensions were considered, particularly in the socioeconomic or behavioural spheres, but the authors did not consider them to provide any additional relevant nuances. In the end, this proposal discarded all the factors that did not have a proven influence on the way the load curve is determined.

A potential extension of the proposed framework is the integration of Artificial Intelligence (AI) techniques to support specific stages of the methodology. In contexts where data are fragmented, incomplete, or derived from multiple heterogeneous sources, AI-based methods could support tasks such as data integration, missing-data imputation, pattern recognition, clustering of similar communities, and the identification of non-linear relationships between socio-economic characteristics and electricity demand. These techniques could enhance the robustness of demand estimation while complementing, rather than replacing, the deterministic and bottom-up approaches considered in this work. However, the implementation, validation, and comparison of AI-based methods require dedicated methodological development and case-specific evaluation. Consequently, the integration of AI is considered a promising avenue for future research and lies beyond the scope of the present study.

As a reflection, electricity access alone does not automatically translate into economic, social, or environmental improvements. It should be understood as a process, and its full potential can be realised when combined with complementary capacity-building initiatives, such as energy literacy, efficient use of electricity, climate awareness, operation and maintenance of equipment, administrative management, and basic economic training. Establishing a community energy committee can play a valuable role in supporting these processes and promoting electricity use; conversely, without engagement, consumption may remain low or irregular, resulting in a flatter load curve. Nevertheless, electricity itself can have a substantial and immediate impact on people's lives, providing benefits in education, healthcare and enabling productive activities, thereby improving their Human Development Index (HDI). This dual perspective highlights the importance of both the technological provision and the accompanying human and institutional capacities to improve the positive outcomes of electrification projects.

CONCLUSION

This study addressed the research question of which methodological approaches and tools are most effective for estimating context-specific load curves in off-grid communities with no prior electricity access. The review revealed that, although several methods exist, they are often fragmented and largely unconnected, particularly in data-scarce contexts. By synthesising and critically analysing these contributions, existing approaches were classified according to Hierarchy, Source of Information, Scale, Modelling, Resolution, and Time Frame. Based on this analysis, a structured five-phase methodological framework is proposed, comprising community diagnosis, methodological selection, data collection, data processing and modelling, and result assessment.

The framework guides the estimation process and facilitates the comparison and evaluation of different approaches. It extends existing guidelines by organising, synthetising and integrating diverse methodological approaches into a flexible, iterative process flexible, iterative process that adapts to each community's objectives, scope, and available resources, making it practical for data-scarce, off-grid contexts. This flexible framework recognises that no single approach fits all contexts; the choice of method depends on factors such as the available data, the resources—both financial and human—dedicated to the estimation process, and the objectives and scope of the study.

The illustrative case study presented in this work provides an example of how the proposed framework can support the definition of a context-specific household load profile in a data-scarce off-grid context. The estimated demand profile reflects the integration of contextual information and methodological choices, highlighting the need to balance accuracy, resources, and scope during load curve development.

By organising, synthesising and integrating previously disconnected approaches, the framework supports context-specific load curve estimations, providing a structured reference to support energy planners, utility operators, project developers, NGOs, researchers, policymakers, etc., in estimating context-specific load curves for electrification planning, particularly in data-scarce contexts. This study has some limitations, including its reliance on previous studies, which may have overlooked relevant contributions. Its effectiveness depends on the quality and availability of data. It should also be acknowledged that the proposed framework has not yet been empirically validated. Nevertheless, it provides a structured, decision-oriented approach by synthesising existing methods for load estimation in off-grid communities, grounded in evidence from the literature.

Future work will focus on applying the framework to diverse real-world case studies to assess its practical reliability, guide refinements, explore the integration of Artificial Intelligence techniques to support selected methodological tasks, and explore integration with other electrification design tools. Additionally, the integration of the framework with electrification planning tools could be explored to systematically incorporate context-specific load profiles into broader energy access and transition analyses.

Overall, the proposed framework provides a practical guideline to support systematic off-grid electrification planning and the expansion of sustainable electricity access to accelerate progress towards achieving SDG 7.

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APPENDIX A

The narrative literature review followed a structured search and screening process for transparency and reproducibility in identifying, screening, and selecting relevant studies [86] (see Figure 3). The search was conducted primarily in the Scopus database and was complemented by desk research, including technical reports and backwards and forward citation tracking, as described in the methodology section. The search query implemented in the document search engine was:

```
(TITLE-ABS-KEY((load curve OR load profile OR demand curve OR demand assessment OR energy demand OR electricity demand OR electrification OR minigrids OR mini-grids) AND (off grid OR remote OR isolated OR rural ) AND (communities OR community OR village) AND NOT (cities OR urban)) AND PUBYEAR > 2010 AND PUBYEAR < 2025) AND (LIMIT-TO(SUBJAREA, ENER) OR LIMIT-TO(SUBJAREA, ENGI)) AND (LIMIT-TO(DOCTYPE, ar) OR LIMIT-TO(DOCTYPE, ch) OR LIMIT-TO(DOCTYPE, bk)) AND LIMIT-TO(LANGUAGE, English)
```

The search yielded 324 records. Additional sources included 5 records from organisational websites and 3 records from citation tracking, while no relevant registers were identified. After removing 14 duplicate records, 310 unique records remained for screening. These records were screened based on titles and abstracts, resulting in 242 exclusions. A total of 68 documents were sought for full-text assessment, of which 2 could not be retrieved. An additional 8 documents were identified through supplementary sources and were all retrieved and assessed. Overall, 74 documents (66 from the main search and 8 from additional sources) were assessed for eligibility.

Studies were excluded if they did not meet the methodological criteria: insufficient methodological transparency (11), focus on grid-connected systems only (7), lack of an explicit load estimation method (6), or conceptual discussion without empirical or methodological basis (3). After applying these criteria, 39 new studies and 8 new reports were included in the final review.

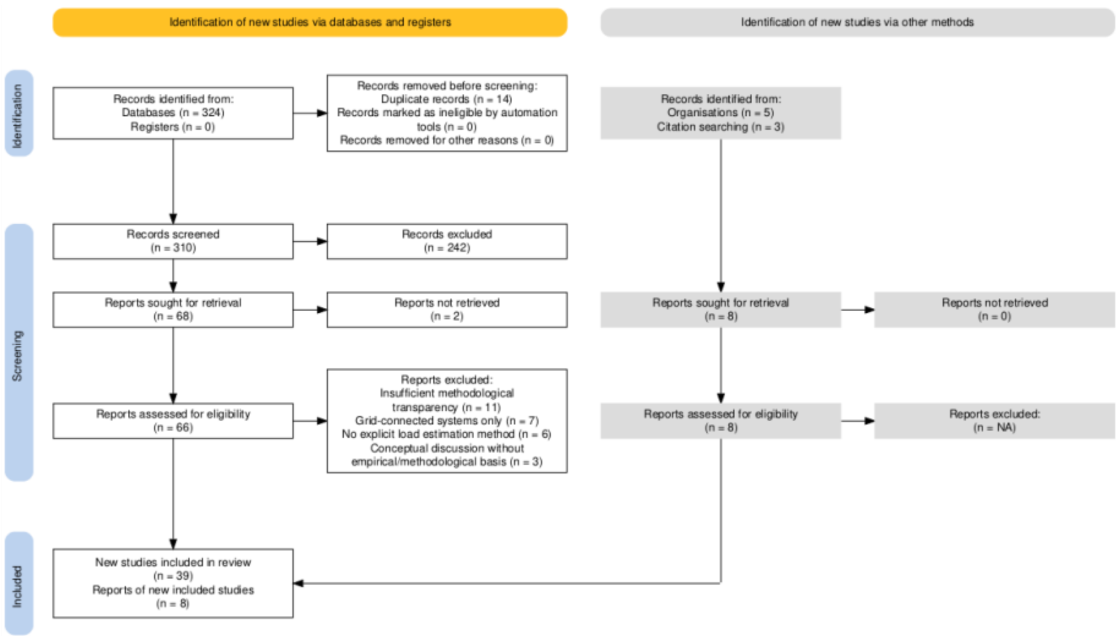

Figure 7. Flow diagram of the literature search and study selection process, adapted using the PRISMA 2020 flow diagram template [86]

APPENDIX B

The appliance inventory and operating schedules were defined for each expected electricity end-user based on the field data collection process (see APPENDIX D) and the service level requirements established for the community. These data were used as the primary inputs for the bottom-up construction of the deterministic load curves. For each appliance, the rated power and expected operating schedule were used to estimate the hourly electricity consumption profile. The aggregation of individual appliance demand profiles resulted in the deterministic load curve of each end-user, which was subsequently combined with other users according to their category (residential, productive, and communal) to obtain the overall community demand profile. Table 8 summarises the appliance characteristics, operating hours, and estimated daily energy consumption considered for each end-user.

Table 8. Appliance inventory, operating schedules, and estimated daily energy consumption for the electricity end-users considered in the community load curve construction

Category	End-user	Appliance	Quantity	Power (W/unit)	Operating time (h/day)	Energy (Wh/day)
Residential	Tier 3 household	Lamp (inside)	4	15	4	240
		Lamp (outside)	1	15	10	150
		Phone charging or small batteries	3	6	3	54
		Radio or Stereo	1	50	2	100
		Fan	1	50	8	400
		TV	1	150	2	300
		Computer	1	200	1	200
		Refrigerator	1	400	2	800
		Household total				**2,244**
Productive	Bar/Restaurant	Freezer	1	800	2.2	1,760
		Large TV	1	200	4	800
		Lamps	4	15	4	240
		Bar/Restaurant total				**2,800**
Productive	Shop/Kiosk	Freezer	1	600	2.2	1,320
		Radio	1	50	0.8	40
		Lamps	4	15	4	240
		Shop/Kiosk total				**1,600**
Communal	School	School lighting	4	15	5	300
		School printer	1	500	2	1,000
		School computer	1	250	5	1,250
		School fan	2	50	5	500
		School router	1	6	24	144
		School total				**3,194**
Communal	Street lighting	LED street lamp	21	50	13	13,650
Communal	Church	Lamps	4	15	8	480
		Fan	1	50	4	200
		Church total				**680**
Communal	Health care facility	Refrigerator	1	400	2	800
		Lamps	4	15	8	480
		Fan	1	50	8	400
		Health care facility total				**1,680**

Category	End-user	Appliance	Quantity	Power (W/unit)	Operating time (h/day)	Energy (Wh/day)
Communal	Community hall	Lamps	4	15	4	240
		Fan	1	50	4	200
		Computer	1	250	4	1,000
		Community hall total				**1,440**
Productive	Biomass gasification plant	Wood chipper	1	5,000	2	10,000
Productive	Solar pumping	Water pump	1	1,500	5	7,500

Notes: i) The street lighting system was assumed to comprise 21 LED luminaires (50 W each) installed along the main community roads and public areas. A typical spacing of approximately 40 m between luminaires was considered, resulting in an estimated lighting coverage of approximately 0.8 km. ii) The wood chipper represents the biomass preprocessing equipment considered within the project. The unit was assumed to operate for approximately 2 h/day at a rated power of 5 kW, corresponding to a daily electricity demand of 10 kWh/day. iii) The solar pumping system was considered as a community productive-use load, with a 1.5 kW pump operating for 5 h/day (equivalent solar hours per day), resulting in a daily electricity demand of 7.5 kWh/day.

Table 9. Typical Power Ratings of Residential Electrical Appliances Used in Honduras. Source ENEE [87]

Appliance	Approximate Power Rating
LED light bulb	5–20 W
LED television	50–150 W
Domestic refrigerator	100–400 W
Commercial/very large refrigerator	500–1500 W
Electric fan	40–100 W
Laptop computer	50–100 W
Desktop computer	200–600 W
Wi-Fi router	5–20 W
Cell phone charger	5–25 W
Microwave oven	800–1500 W
Blender	300–700 W
Coffee maker	600–1200 W
Clothes iron	1000–2000 W
Hair dryer	1000–2000 W
Washing machine	400–1000 W
Residential air conditioner	700–2500 W
Electric stove burner	1000–2000 W
Electric oven	1500–3500 W
Small water pump	400–1500 W

APPENDIX C

This appendix presents additional outputs generated in HOMER to characterise the stochastic community load profile. Figure 8 summarises the annual load statistics, including the representative daily profile, demand map, monthly load distribution, and key indicators such as average demand, peak demand, and load factor. These results were used to verify the consistency of the generated load profile and support the subsequent sizing and optimisation of the hybrid renewable energy system.

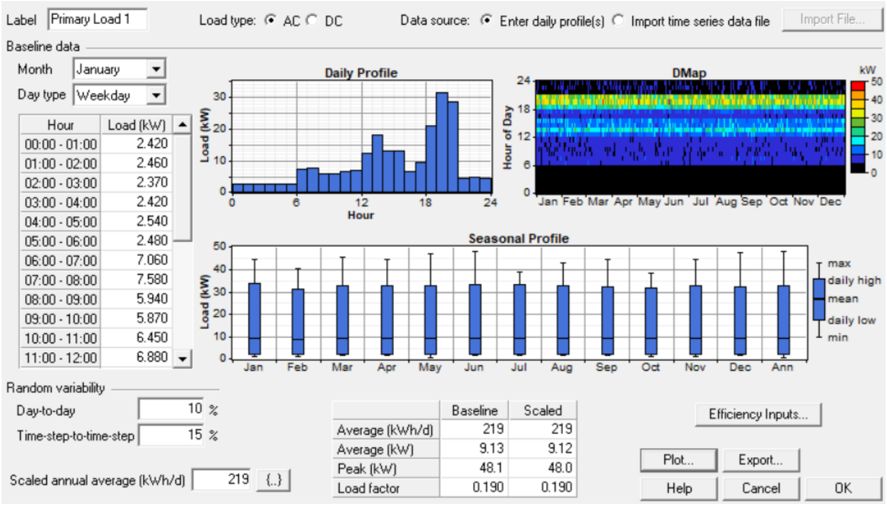

Figure 8. Summary statistics and temporal characteristics of the stochastic community load profile

Figure 9 shows the Probability Density Function (PDF), indicating the frequency distribution of hourly electricity demand levels. **Figure 10** presents the Cumulative Distribution Function (CDF), showing the percentage of time that demand remains below a specific load value. **Figure 11** illustrates the Load Duration Curve (LDC), which ranks hourly loads from highest to lowest and provides information on load persistence for system sizing and reliability analysis.

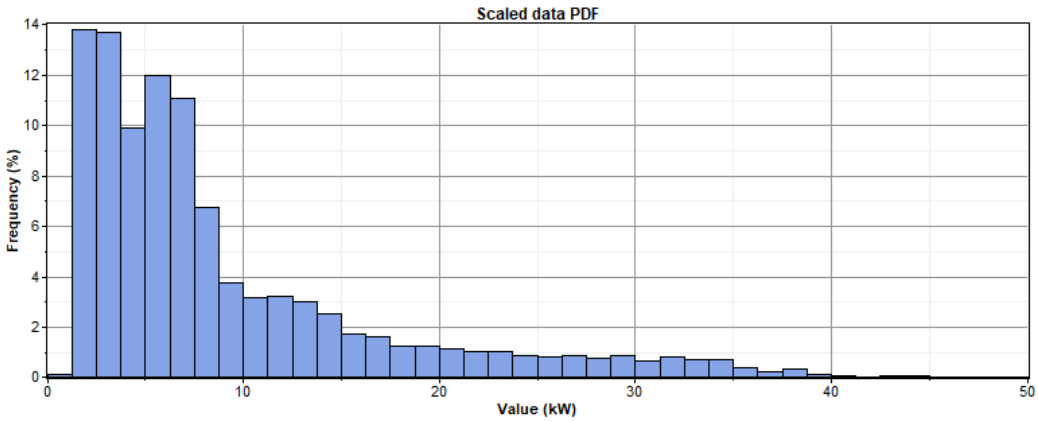

Figure 9. Probability Density Function of Hourly Electricity Demand

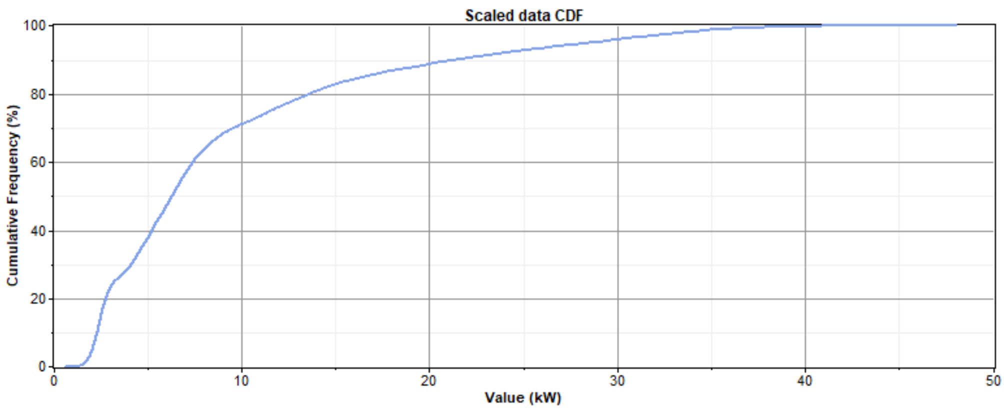

Figure 10. Cumulative Distribution Function of Hourly Electricity Demand

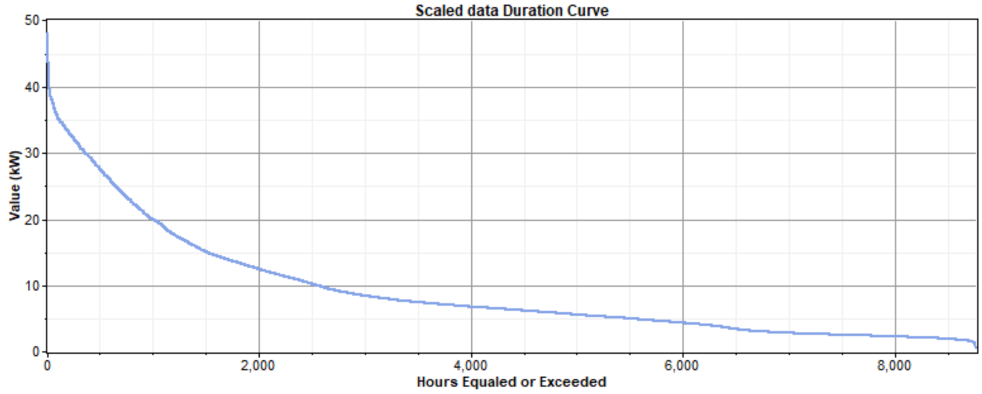

Figure 11. Load Duration Curve of Hourly Electricity Demand

APPENDIX D

The household questionnaire was developed to collect primary data on household characteristics, desired electricity services, potential productive uses, socioeconomic conditions, and ability/willingness to pay for electricity. The survey was applied to households during Phase 3 to support the assessment of future electricity demand and energy service requirements. The questionnaire structure is presented in Table 10.

Table 10. Household energy access survey questionnaire

Section	Question / Variable	Response
1. Household Identification	Household ID number	
	Head of household	
	Telephone number	
	Geographic coordinates (Latitude, Longitude)	
2. Desired Electricity Service Level (5-10 year perspective)	Tier 1: Lighting + phone charging + radio	
	Tier 2: Fan + television	
	Tier 3: Refrigerator, washing machine	
	Tier 4: Air conditioning, microwave, electric kettle	
	Tier 5: Domestic hot water, electric stove	
	Other desired electricity services	Specify:
3. Productive Uses of Electricity	Are you interested in starting a productive activity using electricity? If yes, which type of productive activity	No, Yes (Bar / Restaurant / Shop / Barber-hairdresser / Guesthouse / Sewing / Milling / Other)
4. Daily Habits and Activity Patterns	What time do you get up?	
	What time do you have breakfast?	
	What time do you have lunch?	
	What time do you come back home?	
	What time do you have dinner?	
	What time do you go to sleep?	
5. Socioeconomic Characteristics	Employment status	Employee / Self-employed / Unemployed
	Main occupation	Agriculture / Business / Commercial / Teacher / Other
	Monthly income	USD/month
	Current energy expenditure	USD/month

Section	Question / Variable	Response
6. Ability to Pay (ATP) and Willingness to Pay (WTP)	Ability to pay for electricity (ATP)	10% of monthly income USD/month
	Will electricity improve your life/business?	Yes / No / Do not know
	Preferred electricity service model	Free / Commercial
	Who will pay for electricity?	Myself / My employer / Government / Not interested in having electricity
	Percentage of income willing to spend on electricity services	<5% / 5–10% / 10–20% / 20–30% / >30%

The Community Energy Committee questionnaire was designed to identify collective electricity needs and community-level loads, including agricultural activities, industrial uses, social services, and other electricity demands. Information on equipment quantity, rated power, and operating time was collected to estimate community electricity demand profiles and support energy system planning. The questionnaire structure is presented in Table 11.

Table 11. Community electricity demand assessment questionnaire.

Category	Electricity Use / Activity	Quantity (units)	Power Requirement (W/unit)	Operation Time (hours/day)	Comments
Agricultural Services	Mill				
	Irrigation system (water pump)				
	Other agricultural services				
Industrial Activities	Production of liqueurs or fermented beverages				
	Production of jams or preserves				
	Fruit dryer				
	Other industrial activities				
Social and Community Services	School				
	Church				
	Healthcare facility				
	Community hall				
	Water pumping system				
	Street lighting				
	Other social services				
Other Electricity Loads	Internet tower				
	Other loads				

The electricity uses listed in the questionnaire represent the main expected categories identified during the survey design. Additional electricity uses, or community-specific activities not included in the table, can be identified and recorded by the respondents to ensure that all relevant current and future electricity demands are considered.

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