Energy for Sustainable Development 66 (2022) 101–116

Contents lists available at ScienceDirect

Energy for Sustainable Development

Forecasting energy demand in isolated rural communities: A comparison between deterministic and stochastic approaches

Ángela Herraiz-Cañete [a], David Ribó-Pérez [b,*], Paula Bastida-Molina [b], Tomás Gómez-Navarro [b]

[a] Genia Global Energy, Avenida Ronda de Nazaret 9, 46024 València, Spain
[b] Institute for Energy Engineering, Universitat Politècnica de València, Camí de Vera S/N, 46022, Valencia, Spain

ARTICLE INFO

Article history:
Received 28 July 2021
Revised 4 November 2021
Accepted 24 November 2021
Available online xxxx

Keywords:
Rural electrification
Demand forecasting
SDG7
Deterministic methods
Stochastic methods

ABSTRACT

Off-grid renewable energy grids will contribute to the achievement of SDG 7 on universal energy access, especially in off-grid communities. But the scarcity of resources for development aid requires very tight designs that minimize the cost of investment and operation of the mini-grid. To do this, the future energy demand of the community must be analysed very well, which is very difficult due to the lack of previous data. In the literature, two main approaches to analyse future energy demand, deterministic and stochastic methodologies. In this article, we compare both methodologies for a real case study in Honduras and discuss their advantages and disadvantages. Although the deterministic approach requires less information and less mathematical processing, it generates less accurate results. In contrast, the stochastic approach consumes more resources but gives more realistic results for the correct design of the mini-grid. In conclusion, the deterministic approach methods can be useful for the early stages of the project, when the investment is being sized. But for the advanced phases of the project, when the installation is being designed, the stochastic approach is recommended.

Introduction

Electricity access is a key element to achieve social development and improve living conditions (Aevarsdottir et al., 2017; Mandelli et al., 2016a). Electrification correlates with reductions in poverty and migration, and improvements in gender equality, education, and health (Kanagawa & Nakata, 2008) and its absence corresponds principally with rural areas in developing countries (IEA, 2020). As a result, developing countries and development aid are carrying out significant efforts for rural electrification over the last years. But, the lack of capital, institutions, and regulatory frameworks are among the main barriers to progress (IEA, 2017). Therefore, there is a need for sustainable and cost-effective solutions for the electrification of rural areas (IRENA, 2018). The industrialized countries' model of oversizing electricity generation and distribution cannot be applied. Among the solutions, isolated mini-grids have been considered a cost option for rural electrification (IEA, 2017; Alliance for Rural Electrification, 2015) as they present several benefits, including technical and operational flexibility as well as wider power operation rates (GIZ, 2016; IRENA, 2017; RECP, 2014).

Mini-grids design has to provide solutions that are safe, efficient, scalable, and adequate (SEforALL, 2019). Forecasted and expected energy demand is one of the parameters with a greater impact on the design. It influences the system's size, and thus, costs and operational parameters (GIZ, 2016). Despite that, no common methodology for the assessment of the energy demand of rural areas in developing countries has been defined yet, mainly due to the difficulties and unavailability of data (Blodgett et al., 2017; Lombardi et al., 2019; Louie & Dauenhauer, 2016; Mandelli et al., 2016b). The criticality of this parameter is strongly accentuated in rural isolated areas of developing countries where lack of previous electricity and uncertainty in the data directly influence the quantification of the energy demand, thus resulting in under and over-dimensioned mini-grids (Lombardi et al., 2019).

Over the last years, mini-grids designers and research institutions have tested and applied different methodologies, approaches, and models implemented in computational tools aiming at reducing uncertainty in the data and obtaining more accurate estimations of the energy demand, hence more reliable mini-grids designs. These designs depend on the curve and total energy needed to select the optimal energy technologies (Ribó-Pérez et al., 2020). Hence, a proper demand analysis must be done as it directly affects the cost of producing energy and the reliability of the system. On the one hand, oversizing will increase investment and operational and maintenance costs and thus the payback period. On the other hand, an undersized system will result in a lack of reliable and continued energy supply, generating discontent in the customers. Besides, it reduces the operational life of the components

* Corresponding author.
E-mail address: david.ribo@iie.upv.es (D. Ribó-Pérez).

https://doi.org/10.1016/j.esd.2021.11.007

because of overusing, thus, increasing operational and maintenance costs (GIZ, 2016).

Forecasting demand is a laborious and challenging work, especially for off-grid rural areas in developing countries, as they are characterized by the unavailability of load data (Mandelli et al., 2016b). It results in difficulty to analyse electricity demand in rural communities that never had electricity before. But, assessing forecasts with more complex approaches that gather more data imply an exponential growth in the efforts required (GIZ, 2016). These approaches vary in several dimensions: usage of historical data or specifically obtained data, and deterministic or stochastic predictions. Approaches with real data and on-site surveys combined with stochastic predictions are the most labour intensive methods but also the more accurate as (Lombardi et al., 2019; Mandelli et al., 2016b) expose.

Researchers have traditionally employed two main methodologies for load forecasting in rural communities: deterministic and stochastic methods. On the one hand, the first ones assume that there is an exact relationship among the variables, thus there is no error when obtaining the results. In this regard, Mahmud (2011) proposed a linear regression deterministic model to forecast load demand of isolated areas, with application to the Swandip community of Bangladesh. Islam et al. (2013) also applied linear regression in their research, together with inverse matrix calculation. On the other hand, stochastic models consider the randomness of the variables that define load prediction. Hence, Boait et al. (2015) introduced a stochastic methodology to determine load prediction in rural communities considering a bottom-up basis from three data elements: the population that will potentially use each type of electrical device, their corresponding load, and their probability of use. Moreover, Mandelli et al. (2016b) developed a novel stochastic procedure to forecast load profiles in off-grid rural areas based on the software LoadProGen. Finally, other researchers just based load prediction on simple estimations (Bastida-Molina et al., 2020a; Gambino et al., 2019). Although these estimations can provide a general overview of the energy needs, they lack accuracy and generate big divergences.

The suitability of using deterministic and stochastic methodologies has been proven separately, especially for deterministic methods. For instance, Murugaperumal et al. (2020) and Murugaperumal and Raj (2019) presented comparisons among three load curves obtained with three deterministic models: neural network, regression trees, and multiple linear regression model. However, and to the best of the authors' knowledge, no previous research compares the performance of deterministic and stochastic methodologies for assessing load demand forecasting in rural isolated communities. Therefore, there is a need to understand the trade-offs between different approaches and their potential misguided solutions arising from one or another. Consequently, designers and project developers need to have funded judgment on how and when to use each methodology to provide a balance between cost and accuracy depending on the size, uncertainty, and project stage.

In this paper we study the trade-offs and differences obtained with demand forecasting methodologies, considering both deterministic and stochastic approaches in a real case of study in El Santuario, Honduras. An almost 500 people non-electrified rural community in the Mesoamerican dry corridor. We assume that predicting the future demand of a non-electrified area is a challenging but also necessary process. So here, we inquire and compare the two methodologies that approach the problem with more detail. By doing so, we draw a set of conclusions and good practices that can allow practitioners and designers to decide and choose between these methods when forecasting electricity demand in future off-grid mini-grids.

The rest of the paper is organised as follows, Literature overview section discusses the current literature around demand forecasting methodologies, Materials and methods section presents both methodologies applied. Case study: El Santuario Honduras section presents the case study while Results and discussion section shows the results from both approaches and compares them. Finally, Conclusion section concludes summarizing the main findings.

Literature overview

Among the scientific literature, only a few studies evaluate the energy needs and load profiles (Mandelli et al., 2016b). Moreover, they do no reach an agreement in terms of a commonly accepted approach to predict the load (Mandelli et al., 2017). This fact is mainly due to several factors affecting the demand profile. One approach is to consider any community or village is exactly alike to another (GIZ, 2016). Therefore, varying the number of consumers, consumer type and activities, consumer penetration or growth rates can help to predict the load.

Some studies base the demand assessment on expert knowledge in similar installations' experiences (Blodgett et al., 2017), usually assuming averaged daily constant load profiles (Louie & Dauenhauer, 2016). However, other researchers propose mathematical models based on statistics. These models require input specific data for each area and can only be gathered through on-site surveys and measurements, therefore providing more detailed results for a more reliable project design.

Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), in its manual “Which size shall it be?” (GIZ, 2016), proposes recommendations for mini-grids designing, mostly based on the demand assessment step, as it is crucial for system design and sizing, especially for obtaining proper results through simulation tools such as HOMER Software. Fig. 1 shows a flow chart that contains the different actions required and the results obtained for the electrical demand assessment process.

The demand assessment process starts with an initial assessment of the requirements of the area or community. Overall, surveys are the most common approach and have been widely used for energy demand assessment (Blodgett et al., 2017; Oladeji & Sule, 2016; Sahu et al., 2013; Singh, 2011). However, questions need to be well defined specifically for each area (GIZ, 2016). Due to unfamiliarity with energy services or data, surveys can cause prediction errors, which can result in the improper design of the energy installation.

According to the Renewable Energy Cooperation Programme (RECP) (RECP, 2014), the electricity demand depends also on other factors such as the incomes of the customers and their ability to pay for electrical services. These factors are known as Ability to Pay (ATP), which depends on incomes and current energy sources expenses (GIZ, 2016), and Willingness to Pay (WTP): “the maximum amount that an individual indicates that he or she is willing to pay for a good or service” (NRECA, 2016). GIZ (2016) proposes the application of certain correlation factors to obtain the Effective Demand, “demand for goods and services that are backed by the resources to pay for it” (NRECA, 2016).

Future Demand Forecasting depends on several factors that may vary during the lifetime of the mini-grid. Not only socioeconomic factors (Blodgett et al., 2017; GIZ, 2016) as population growth, economic growth, lifestyle, and consumption patterns, which will result in an increased number of customers and kWh consumed per year but also other factors such as time factors (season, type of day, hour of the day, day of the week) or climate conditions variations (mainly temperature and humidity) should be considered (Feinberg & Genethliou, 2005).

When estimating the demand and load profile of an area, both the period and the ranking of the study have to be determined (Hong & Shahidehpour, 2015). Short-term (less than 5 years) is the optimal and most used approach for energy demand forecasting, as for medium- and long-term historical series and data are needed, which are not often available for isolated rural areas, and when assumed as known, can cause errors in the amount of energy demand estimated or the load profiles formulated (Islam et al., 2013). Regarding the ranking of the data, the bottom-up approach is recommended despite being inefficient in terms of the amount of data to be gathered (individual data for each consumer o group to be extrapolated), as this approach provides more accurate results.

We carried out a review with the aim of identifying the main models, approaches, and methods that have been used for future demand prediction in isolated areas. From the analysis, it can be concluded that the current approaches for future demand estimation are mainly

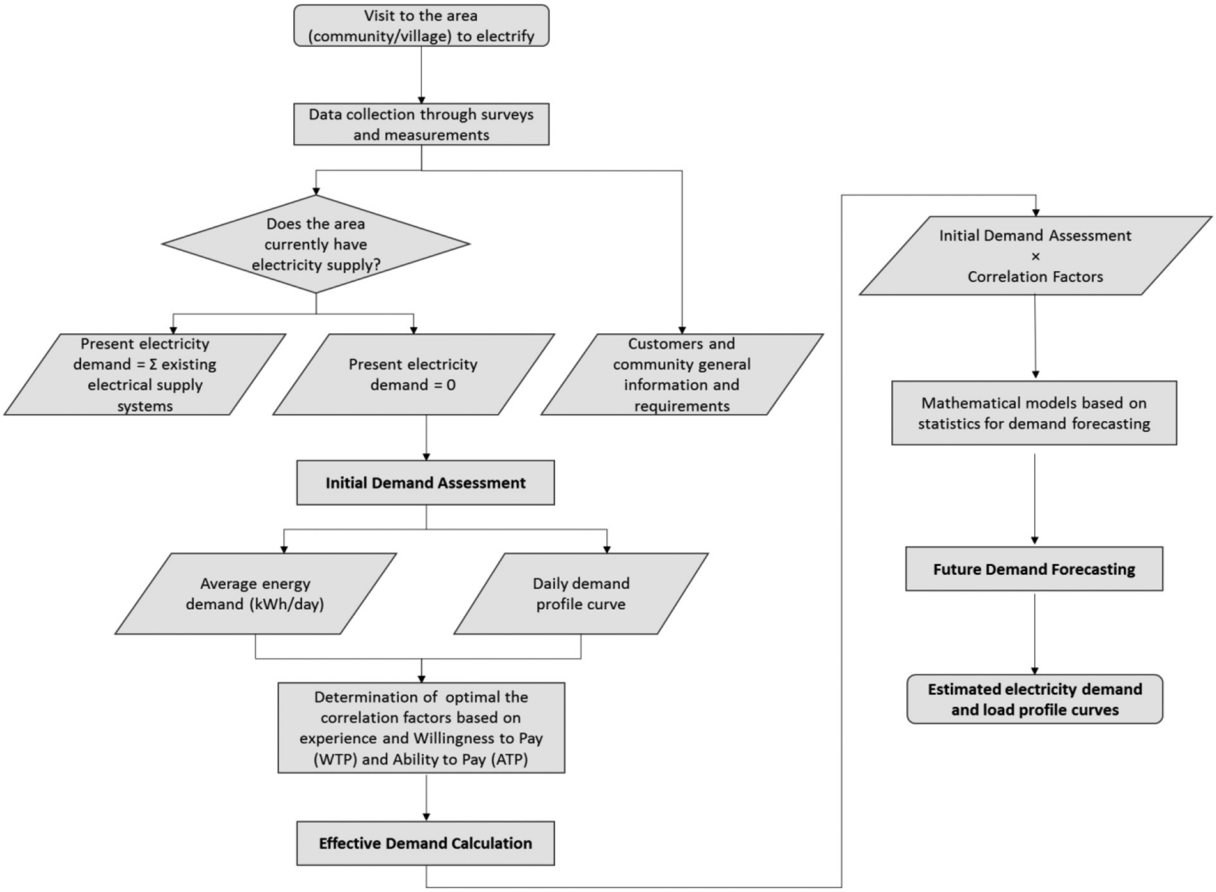

Fig. 1. GIZ assessment methodology. Own production based in GIZ (2016).

based on statistics (deterministic, non-deterministic or stochastic). Additionally, some researchers base load prediction on simple estimations. These studies estimate the typical use schedule of the potential consumers of the region in question that ensure a decent standard of living for their inhabitants (Bastida-Molina et al., 2020a). They do not look for great accuracy, but they provide a quick overview of the energy needs. Hence, Gambino et al. (2019) introduced an inclusive method for this aim, which can be adaptable for each case study. Aberilla et al. (2020) proposed a load prediction curve based on a simple estimation for a prototypical rural community in the Philippines while Bastida-Molina et al. (2020a) focused on the specific case study of Masitala, in Malawi.

Deterministic models assume that there is an exact relationship among the variables, thus there is no error when obtaining the results. This fact directly implies the necessity of specific and enough initial data. Even though obtaining accurate data to ensure precise results is especially complicated in rural isolated areas of developing countries without previous electricity access, deterministic statistical models have been used in order to estimate the energy demand in different cases.

Linear regression analysis (LRA) has been widely studied for demand forecasting among several scientific papers (Islam et al., 2013; Mahmud, 2011), or combinations with other techniques (Miswan et al., 2016). It is a statistical technique developed by Dr. A. Hoque in 1990 based on the identification of the factors on which electrical load growth depends that may vary depending both on the type of load and the area (Mohiuddin, 1997). Inverse matrix calculation analysis also considers the dependence of a total load of an isolated area on certain variables. The difference is that in this method, the variables are expressed by a matrix and the results are obtained from its inverse. Islam et al. (2013) considered the two methods for short term load forecasting on isolated areas worldwide with a lack of previous load data, inverse matrix calculation, and linear regression analysis, obtaining similar results for both.

The main advantage of these statistical methods is that the demographic data needed for the calculation can be gathered from countries' statistics offices or other sources, so the process is simplified. However, the predictions are more general, and thus the mini-grid design less reliable (Blodgett et al., 2017), and the methods require both data from the area to be analysed and from another similar area, which increases the prediction error.

Stochastic models consider the randomness of the variables that define load prediction, i.e., population or economic growth. In the last years, non-deterministic or stochastic models have been developed and programmed by scholars. The *ESCOBox* mini-grid load model is a tool developed by De Montfort University under the *ESCOBox* programme, which, given a certain group of consumers and their appliances, can predict the peak and average electricity demand (Boait et al., 2017). For the prediction of the energy demand curve the central limit theorem is used. The result is that the variation of the total electric consumption decreases as the number of connected appliances increases, by a factor of $1/\sqrt{n}$ (Boait et al., 2015). Demand Analyst© is a tool developed by a consulting and engineering firm, the Innovation Énergie Développement (IED) of France. The tool estimates the future energy demand and how it will grow during the years for different customers of a community or village (residential, public services, and economic activities) based on on-site surveys' data and regional socio-economic parameters.

Non-deterministic models assume that different results can be obtained from the same input data. These approaches are more suitable for demand estimation for rural electrification in rural isolated areas

Table 1
Literature review about methodologies used to forecast load demand in rural communities.

Reference	Method	In situ surveys	Uncertainty in input data	Tools
Aberilla et al. (2020)	Simplified estimation	No	Not considered	Simple assumption of a typical load profile
Bastida-Molina et al. (2020a)	Simplified estimation	No	Not considered	Simple assumption of a typical load profile
Gambino et al. (2019)	Simplified estimation	Yes	Not considered	Simple assumption of a typical load profile
Islam et al. (2013)	Deterministic	No	Not considered	Regression lineal and inverse matrix
Mahmud (2011)	Deterministic	No	Not considered	Linear regression
Miswan et al. (2016)	Deterministic	No	Not considered	ARIMA and regression modelling
Allee et al. (2021)	Deterministic	Yes	Not considered	Model LASSO (machine learning)
Murugaperumal and Raj (2019), Murugaperumal et al. (2020)	Deterministic	No	Not considered	Neural network, regression tress and multiple linear regression models
Boait et al. (2015), Boait et al. (2017)	Stochastic	Yes	Not considered	*ESCOBox*
IED (2021)	Stochastic	No	Not considered	IED-Demand Analyst
Mandelli et al. (2016b)	Stochastic	No	Considered	LoadProGen
Lombardi et al. (2019)	Stochastic	No	Considered	LoadProGen with definition of duty cycles
Narayan et al. (2020)	Stochastic	No	Not considered	Multi-tier framework

due to the uncertainty in the input data. Mainly, those models require as inputs at least: period, population, the load of each electrical appliance, and the assessment of the probability that the electrical appliance will be used at a given time of a day, which is known as the "Coincidence Factor". Based on this information, a software determines randomly a load profile for each time interval and generates the aggregate demand curve.

According to Mandelli et al. (2016b), who reviewed the scientific literature regarding the most common approaches used to formulate load profiles for off-grid rural areas, two main characteristic methods are found depending on the Coincidence Factor's approach. The first method considers a 100% Coincidence factor by assuming that all the devices will be operating at the same time for all the customers. This results in overestimated load curves with high peaks of demand. The second approach distributes the maximum power required of a type of appliance for all the customers along the whole usage period. Therefore, it leads to underestimated load curves and flat profiles. In addition, in both approaches, only one single profile is generated. Therefore, the intrinsic uncertainty in the input data for non-electrified areas is not approached.

Among the different models for load forecasting identified in the literature review, the Software LoadProGen combined with the RAMP model has been identified as one of the most complete and functional tools for forecasting the demand of rural isolated communities in developing countries (Lombardi et al., 2019; Mandelli et al., 2016b, 2017). Especially for those off-grid areas without previous access to electricity. Load Profile Generator (*LoadProGen*) is a software developed by the Energy4Growing research group of Politecnico di Milano that is implemented in MATLAB and it generates load profiles from field information about the area (audits or interviews) using a stochastic approach by considering the different profile parameters and building up the coincidence behaviour of the appliances and the power peak value (Mandelli et al., 2017). Then, the RAMP model builds on the previous work developed in LoadProGen and it develops to include other energy uses (Lombardi et al., 2019).

Moreover, it results important considering how a load profile may change in the future years, especially in recently rural electrified areas (Debnath et al., 2015). Demand in such areas increases year by year, since new households connect to the novel microgrids (Rajbhandari et al., 2022). For instance, (Rajbhandari et al., 2022) revealed a yearly increase of 38% in rural electrified zones of Nepal. Focusing on each consumer, Nixon established that the electrification of rural isolated areas to basic electricity stimulates the future increasing of power demands. Main reasons for this statement lied in the results extracted from their survey-gathered data: once households get access to basic electricity, they begin to realise its socio-economic benefits and start to desire more luxurious appliances, especially through social pressure and neighbourhood influence (Opiyo, 2020).

In this regard, different techniques have been applied in research to forecast electricity demand increase. Bastida-Molina et al. considered an unchanged demand curve affected by a multiplying factor, which represented the proportional relation between the future electricity demand, based on extrapolation, and the current one (Bastida-Molina et al., 2020b). Adeoye and Spataru forecasted annual electricity demand for 14 West African countries from 2016 to 2030 using multiple regression analysis (Adeoye & Spataru, 2019). Finally, Riva et al. relied on System Dynamics, based on a load stochastic tool (LoadProGen) to predict future rural electricity demand, considering the community of Ikondo (Tanzania) (Riva et al., 2019).

To sum up, Table 1 reflects the literature review about the three main methodologies for load prediction in isolated communities of developing countries. This table shows how no comparisons between different methodologies exist in the literature.

Materials and methods

As advanced, the paper proposes a comprehensive comparison of approaches for Energy Demand Analysis for mini-grid designing in rural electrification. Choosing the right analysis method will help to reduce investment and maintenance costs while ensuring reliability in the energy supply. Whereas it is applicable to any rural electrification projects, it is specially oriented to off grid mini-grids design in non-electrified areas, due to the inherent uncertainty of the data.

In order to minimize the prediction error, the two main demand assessment procedures have been applied and tested for sizing a mini-grid in a rural isolated community. Definitions and processes proposed by (GIZ, 2016) regarding Energy Demand Analysis have been taken as starting the point for developing the comparison:

- **Initial Energy Demand**: preliminary estimation of the energy needs of the area based on the data collected. It includes the average energy demand of the area in kWh, besides the load profile for a certain period.
- **Effective Energy Demand**: it is the result of the application of socio-economic correlation factors specific to the area's context.
- **Future Energy Demand**: To apply probabilistic models implemented in computational tools in order to obtain more accurate demand assessment, including average energy demand of the area in kWh and load profile for a certain period.

Fig. 2 shows a flowchart of the followed Energy Demand Analysis methodology and its integration in rural electrification projects through mini-grids. The area selected for the development of a rural electrification project requires a preliminary overall context analysis. In order to set an enabling environment for the development of the project, several factors may be assessed, which include countries' policies and regulatory framework regarding rural electrification promotion and reliable

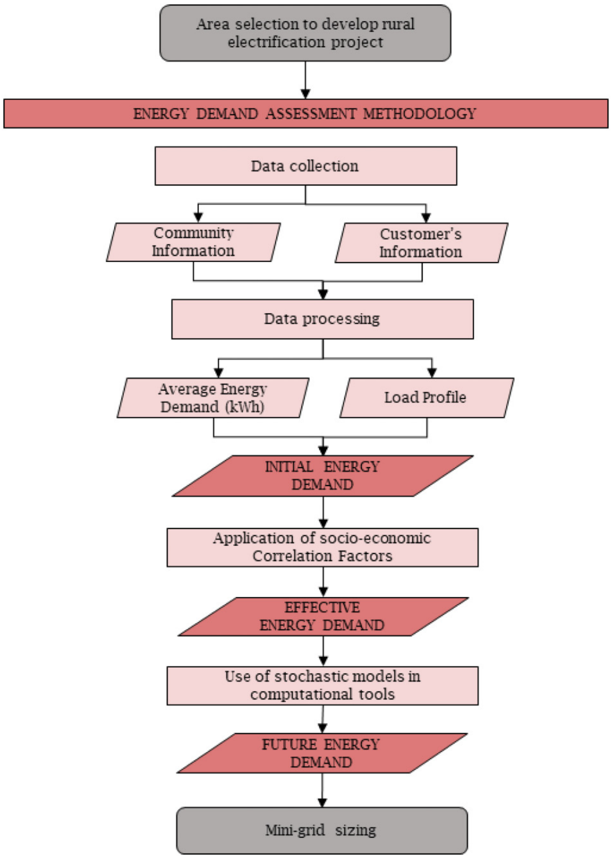

Fig. 2. Methodology followed during the study.

economic feasibility (financial model, access to funding or grants), etc. The first observations should be oriented to identify information such as the availability and adequacy of renewable energy sources or the availability of land where to install the mini-grid, as well as ensuring the proactivity and involvement of the customers in the decision-making process.

The result of the application of the proposed methodology is the Energy Demand of the area for a certain period, which will be used as input for mini-grid sizing through simulation computational tools or mathematical models.

Data collection

Data collection is the first and main step in the Energy Demand Analysis process for rural electrification. In order to reach more accurate results, it is recommended to follow a bottom-up approach through surveys. The more individuals are interviewed, the more accuracy will be achieved. In that regard, customers need to be segmented into groups or facilities. The questionnaires should be designed to evaluate both general information about the customers and their load requirements, as well as their present electricity demand, in case the area was already electrified or had electricity consuming devices. Visits' periods should be used as well to identify community background. Reference data regarding economic activities may be useful for identifying future needs, barriers, or possibilities for the development of financial models (Table 2).

Deterministic energy demand assessment

Based on this gathered data, the initial demand assessment can be carried out. Experts need to process the gathered data and translate it into useful data for performing the energy demand assessment. The average daily energy demand of the area in kWh/day can be obtained as shown in Eq. (1), as a result of the sum of the load's power requirements multiplied per the number of usage hours within a day of all the consuming devices that the community and individual customers are expected to use (Mandelli, 2015):

$$D = \sum_{j}^{\text{User class}} N_j * \left(\sum_{i}^{\text{Appliance}} n_{ij} * P_{ij} * h_{ij} \right) [\text{kWh/day}] \quad (1)$$

where i refers to the type of electrical appliances and j to the type of customer, thus N_j is the number of users and n_{ij} the type of appliance of each customer class (TVs, lights, phones, etc.); P_{ij} represents the nominal power of the different type of appliances for each customer, and h_{ij} the daily hours that are turned on.

The daily demand profile of the area can be obtained from the aggregation of hourly load's power requirements for each individual customer or sector (residential, commercial, productive activities, communitarian or street lighting, among others). Load peak and load factor can be also obtained from the analysis (GIZ, 2016). This daily load profile can be assumed constant and extrapolated to the whole year. However, other segmentations, for instance depending on the season (summer/winter, rainy/dry) are also possible and will result in a more accurate and reliable system design (Sahu et al., 2013).

The load curve represents the temporary evolution of the electrical power requirements of the community throughout a typical day. Once coincidence factors for different appliances are defined, the daily load curve can be obtained as the result of the sum of the hourly power demanded by each appliance multiplied by the coincidence factor of each appliance every hour.

$$D_h = \sum_i P_{ih} * f_{ih} \quad (2)$$

where

h: Time-step. In this case hourly time-steps have been considered

Table 2
Required information in a bottom up method.

Information type	Required information
Community	• Total population of the area. • Main productive activities (agriculture, fishery, farming, forestry, etc.). • Number of households and GPS coordinates. • Number of community facilities and GPS coordinates (schools, health services buildings, religious buildings etc.), usage schedule, load requirements (type, quantity and power (W)). • Distance among the consumers. • Street lighting requirements (load type, quantity and power (W)). • Land conditions and available area for installing the mini grid.
Customers	• Serial number. • Name, age and contact. • Type of customer (Household, Business or other). • Current energy sources, usage schedule and cost (if any): - Solar Home Systems (SHS): installed power (W) and battery capacity (Ah and V). - Electric generators: power (W) and consumption (diesel/-month or year) - Other: Kerosene, batteries, wood etc. and daily/monthly/yearly consumption. • Current or desired electricity consuming devices: - Type of load (most common for rural communities are: lights, TVs, radios, fridges, fans, water heaters, motors for pumping, etc.). - Power for each (in W). - Usage hours. • Average monthly or yearly incomes (USD) and ability to pay for energy services (USD/kWh). • Willingness and ability to pay for energy services.

i: Individual appliances, e.g. TVs, lights, phones, etc.
f_{ih}: Coincidence factor for each individual appliance i in each time step h.
P_{ih}: Electrical power demanded by each individual appliance i for each time-step h.

Finally, the total daily energy consumption of the community is obtained as the sum of all the hourly load consumptions throughout a day. The total yearly energy consumption is obtained by multiplying the total daily energy consumption by 365 days:

$$E_{year} = 365 \times E_{day} = 365 \times \sum_{h=1}^{24} D_h \tag{3}$$

The demand estimation and load profile formulation must be in line with the requirements of the customers. However, expertise is crucial to formulate the load profiles. For instance, some appliances present more flexible usage schedules that the designers can readapt to distribute and equilibrate the energy consumption during the day. This will allow maximising the use of energy sources and the correct operation of the system.

Once the Initial Energy Demand Analysis is carried out, it is recommended to apply certain Correlation Factors to minimize the error associated with the demand assessment in rural areas. Those factors depend on the area socioeconomic background. Therefore, they need to be defined specifically for each project, depending on the amount of data or experience in the assessment process. Generally, it is recommended to base the correlation factors on customers' Willingness and Ability to pay for energy services. By applying Correlation Factors, the Effective Energy Demand is calculated.

In addition, it is recommended to validate the data by comparing the obtained one with other similar electrification projects and energy consumption standards.

Stochastic demand forecasting

Complementary approaches or tools are needed to forecast the future demand of the community, which is defined as Future Demand Forecasting. This will allow to minimize as much as possible the prediction error and ensure accuracy, reliability, and economic sustainability in the hybrid mini-grid design. In that regard, the term “forecasting” is used as a generic concept, but it is intended to refer to the “estimation” of the future energy needs and the formulation of load profiles by means of models or methodologies. Therefore, both terms will be used throughout the paper.

Considering how a load profile may change in the future years is essential, especially in recently rural electrified areas (Debnath et al., 2015). Nixon states that novel consumers of these areas begin to realise their new socio-economic benefits and start to desire more luxurious appliances, especially through social pressure and neighbourhood influence (Opiyo, 2020). This situation leads to future yearly electricity demand increases. Several researches demonstrate this electricity demand increase in recently rural electrified areas. For instance, study (Rajbhandari et al., 2022) revealed a yearly increase of 38% in rural electrified zones of Nepal, whereas results from Adeoye and Spataru (2019) also indicate that in 2030, electricity demand in the West African region is estimated to be five times its 2016 level.

As mentioned, non-deterministic or stochastic models are proposed to reduce uncertainty in demand estimation for rural electrification projects. In that regard, LoadProGen is identified as a complete and functional tool and will be the basis of the proposed method for Future Energy Demand forecasting (Mandelli et al., 2016b).

The input data to introduce in the software to obtain the daily load profile curves can be divided into electrical appliances and customers. Regarding electrical appliances (TVs, radios, lights, phone chargers, etc.) a type classification and quantification should be carried out. The nominal power of each electrical appliance in Watts needs to be recorded. Customers need to be counted grouped (residential, school, commercial, agriculture, etc.).

These specifications can be assumed or collected through field surveys or audits resulted from previous steps of the demand-assessment process. However, to address uncertainty, stochastic models require certain value's assumptions due to the intrinsic characteristic of isolation in rural areas (Mandelli et al., 2017):

- **Functioning cycle** is defined as the minimum time that an appliance is functioning after is turned on. It is defined for each appliance and customer and is measured in time units, normally minutes or hours.
- **Daily functioning time** represents the total amount of time during a day that a type of appliance is turned on, again for each appliance and customer, and measured in time units.
- **Functioning windows** for each appliance and customer, are periods during the day that exists a probability to the appliances to be turned on.
- **Random variation of functioning time/window**. A certain percentage is set considering that the daily functioning time and functioning window can experiment with certain variations.

Those parameters may be set up based on similar context assumptions or information provided by the customers. However, following the Software's logic formulation to address uncertainty, the functioning cycle must be shorter than the functioning time; and the functioning time must be shorter or equal to the total duration of the functioning window (wf_{ij}).

Once the input data is introduced in the stochastic software, the number of profiles to generate and the sample time (1 s, 1 min, 15 min, or 1 h) must be defined. Consequently, the simulations are carried out. The output file of the software is a file in the form of a m × n matrix, in which the number of rows (m) is equal to the number of profiles generated and the number of columns (n) depends on the selected sample time. The software also allows to visualise the generated profiles in the users´ interface. Due to the stochastic nature of the Software, the greater the number of profiles n that are simulated, the more accurate the results will be.

Once the software generates the profiles, to determine the representative number of profiles to reduce the uncertainty to the maximum, the convergence criteria proposed by is considered. This criterion establishes that the percentage variation of the average load profile values generated, and its average standard deviation must be less or equal to 0.25% for more than 95% of the values generated or time-steps. The convergence conditions are defined as in Eqs. (4) and (5):

$$\frac{\overline{y}(k)_n - \overline{y}(k)_{n+1}}{\overline{y}(k)_n} \le 0.25\% \text{ for } k \ge 95\% \text{ of time steps} \tag{4}$$

$$\frac{\overline{\mathrm{std}}\left[\overline{y}(k)_n\right] - \overline{\mathrm{std}}\left[\overline{y}(k)_{n+1}\right]}{\overline{\mathrm{std}}\left[\overline{y}(k)_n\right]} \le 0.25\% \text{ for } k \ge 95\% \text{ of time steps} \tag{5}$$

where,

- k: Profile time steps. In this case, the load profiles are constituted by averaged values over 1-hour time-steps.
- $\overline{y}(k)_n$: Average load profile value of the n generated profiles at the time step k.
- $\overline{\mathrm{std}}\left[\overline{y}(k)_n\right]$: Average standard deviation of the average load profile value of the n generated profiles at the time step k.

From the results, the Energy Demand for the community is a short-term forecast. An average load profile for a certain period of time as well as the amount of energy demanded in kWh are obtained. The results might be valid for at least 5 years of mini-grid life.

Case study: El Santuario Honduras

The proposed methodology has been applied for the assessment of the energy demand of an isolated community as part of a rural electrification project through a mini-grid in Honduras. The selected community is physically isolated and has no access to the national electricity grid either, which is not expected to change in the short or medium term. Inhabitants' needs, and willingness to pay were assessed from the beginning to set a proper socio-economic context of the area and ensure the long-term sustainability of the project. The rural community of El Santuario, belonging to the San Ramón de Arriba Village, is in the department of Choluteca, Honduras. Fig. 3 shows the location of the community.

The community is composed of 77 households, 71 in the main urban area and the other 6 located 1.75 km from the rest. Households have on average 5 members, and 4.4 rooms each. Communitarian buildings include a church, which the inhabitants use for meetings and other activities, a school, and a kindergarten. Inhabitants use kerosene, fuel cells, and candles for generating electricity and for the illumination of the households. Firewood is the main energy source and is used for cooking, lighting, and heating; fuel cells are used for radios and lanterns. Moreover, 7 households have small photovoltaic systems, with 100 W panel, inverter and storage, which cover part of the lighting, and phone charging needs.

Surveys were carried out at different levels following a bottom-up approach. Individuals were interviewed face to face and in different groups; and then were grouped by gender, age, and occupation. Further information of the project can be found in (Ribó-Pérez et al., 2020, 2021a,b). Tables 7, 8, and 9 in the Annex show the questionnaire distributed along with the inhabitants. Overall, questions were orientated to gather information about demographic status, current energy sources and use, energy requirements, the potential of renewable energy resources, incomes, and ability to pay for electricity services, among others. The data gathered requested information about basic electric appliances. Inhabitants were asked about their forecasts for the use of electrical appliances. As the community was not previously electrified, information about basic electrification needs was shared with inhabitants. Finally, specific questions were addressed to establish inhabitants Willingness To Pay (WTP) for energy services. WTP is crucial over time, as access to electricity might become a new resource, which has, as a result, an increase in the consumption and a decrease in the WTP for that resource.

Overall, inhabitants showed support to the electrification project. Among the 69 surveyed representatives of each family, 93% state that electricity access would improve their livelihoods, the other 7% did not know and none of them showed upset or opposition to the electrification process.

Results and discussion

This section presents the results from the survey and their application to the energy demand analysis above mentioned. Showing a comparison between the deterministic model and the stochastic predictions.

Data collection

The energy needs identified and expressed by the inhabitants of the community were limited to electricity. On the one hand, regarding the thermal energy needs, the tropical climate characteristics of the area make unnecessary both the heating and cooling of the households. On the other hand, the mechanical energy needs were also discarded as currently the agriculture is not mechanized in the community and other sources of mechanical energy needs such as construction or transport were not identified.

Energy demand profiles

Table 3 shows a summary of the expected electricity needs in the households. The power of the loads in W was estimated based on data from typical electrical appliances of the area and the national electricity company's (ENEE) publication (ENEE, 2017).

Currently, most of the electrical appliances does not exist in the community, thus, the acquisition will not be immediate. Moreover, if the economy of the community grows, the number of devices and usage hours may increase. Among the interviewees, 78% agreed on the possibility of paying for electricity services, which would contribute to cover the costs of the installations such as the replacement, operation, and maintenance costs or further extensions. The preliminary total energy consumption estimated in households per day is 142,375 kWh/day, reaching a value of 51,967.8 kWh/year.

Regarding the community energy needs, they were also identified according to the needs expressed by the inhabitants. 86% of the interviewees expressed interest in using electricity in agricultural applications, especially in the irrigation of the small family gardens. Other electricity needs were identified in the church, school, kindergarten, and street lighting. Therefore, the technical proposal includes the installation of 20 street lights, 2 fans per building, and lighting for the church, school, and kindergarten according to international standards, as well as IT equipment, including a computer and a printer, for the improvement of communications in the community.

The water pump for irrigation activities has been selected for a pumping head of 80 m. It will pump the groundwater located 14 m deep to a small water reservoir used for gravity-fed irrigation of the family gardens. Its usage is estimated at 4 h per day. Finally, as it is expected to include a biomass gasifier in the energy installation, it has also been considered the energy requirements of a biomass chipper. It

Fig. 3. Location of the El Santuario community.

Table 3
Household energy needs in El Santuario.

Electrical appliances	Units	Power (W)	Units/household	Usage hours (h/day)	Total energy consumption (kWh/day)
Lighting	267	15	3.76	8.50	34.0425
TV	40	150	0.56	5.20	31.200
Radio	43	20	0.61	14.00	12.040
Phone	39	10	0.55	6.00	2.340
Fan	34	50	0.48	3.75	6.375
Fridge	16	500	0.23	1.24	9.920
Other electrical appliances	19	1000	0.27	2.40	45.600
Computer	1	200	0.01	4.30	0.860
Total					142.3775

is expected to be used 2 h per day, as will be explained later. Table 4 summarizes the electricity needs in the community.

It is important to highlight that whereas some of the community needs, such as the street or school lighting, have a fixed usage schedule, others such as the water pump or the biomass chipper have more flexibility. For instance, it is preferable that the two devices are not used simultaneously (i.e. one can be used in the morning and the other in the afternoon) to contribute to balance the demand curve and ensure the optimum operation of the energy installation. The daily preliminary energy consumption estimated per communitarian services is 58.65 kWh/day, making 21,408 kWh/year. In total, the preliminary estimation of the energy demand of the community has a value of approximately 201 kWh/day and 73,000 kWh/year.

Deterministic load profile

Tables 5 and 6 show the Coincidence Factor set for each electrical appliance during a typical day. For instance, it can be observed that for the household's lights, although the maximum power is 4.00 kW (267 units of 15 W), it is only reached during the first hours in the day and after the working hours in the evening, thus the coincidence factor will be equal to 1. The total installed power for fridges is 8.00 kW but they will be working at low power during most of the day, thus the energy consumption is reduced. Another example is the water pump that is expected to be used at maximum power only during central hours on the day to take advantage of the solar resource. Correlation factors have been considered equal to 100%, due to inhabitants Ability and Willingness to Pay for energy services. A self-sustaining financial model, in which inhabitants act as “prosumers” (producers and consumers of energy at once) will be developed and implemented in order to avoid over-consumption of energy.

In the analysis, the load profile has been divided into two: one for households and the other for communitarian consumptions, according to the electricity needs identified, and it is assumed that does not change during the year. Fig. 4 shows the deterministic load curve estimated for households and community services, as well as the total consumption of the community.

The maximum load peak is produced between 6 p.m. and 9 p.m., by the end of the day, and has a value of approximately 18 kW. Another

Table 4
Community energy needs in El Santuario.

Electrical appliances	Units	Power (W)	Usage hours (h/day)	Total energy consumption (kWh/day)
Water pump	1	2000	4	8.00
Street lighting	20	50	10.50	10.05
Fan	8	100	10.00	8.00
Lights school, kinder and church	78	15	8.25	9.652
IT (computer and printer)	3	300	12.50	11.25
Biomass chipper	1	7500	1.50	11.25
Total				58.202

Table 5
Application to the design of off-grid electric mini-grids for rural communities without previous supply.

Deterministic approach	Stochastic approach
– Requires an accurate baseline, based on field work, to determine safety margins for capacity and safety measures to prevent unexpected occasional outages.	– Requires less accuracy for the baseline, based on field work, to determine stochastic factors and safety measures to prevent expected occasional outages.
– Delivers straight forward results	– Delivers a complex result that needs interpretation
– Results are a simplification of future reality	– Results include the uncertainty of future reality
– Simpler data processing	– Larger cost in data treatment, analysis and recompilation
– Can be done with simple tools and resources	– Requires complex models and/or specific software. Also, fast computers and specifically trained people.
– Due to higher electricity demand peaks, it tends to oversize the installation	– Due to lower average electricity demand peaks, and identified occasional high peaks, allows a tailored sizing of the installation

load peak is observed around 4 a.m., when the activity in the community starts. The increased power consumption between 10 a.m. and 2 p.m. is due to the biomass chipper and water pump, which were programmed to work non-simultaneously and to take advantage of the sun hours. The estimated daily energy consumption per family in households is 2.83 kWh/day and 0.06 kWh/house day per communitarian services. The total yearly energy consumption of the community is approximately 73,000 kWh/year and would be the energy that the hybrid mini-grid system should generate.

Stochastic load profile

To generate the stochastic load profile customers were divided into three user classes: Households, Communitarian Services, and Productive Services. Each class includes a certain number of users (N_j): The Household user class includes the 77 households of the community; the Communitarian Services include the communitarian buildings (church, school, and kindergarten); and the Productive Services category is divided into the water pump and the biomass chipper.

Households: For the Households user class, the type of electrical appliances required coincides with most of the users. However, the number of applications varies depending on the Household. In order to avoid long runtimes of the software for the generation of 71 different profiles, an average value per household has been considered. Overall, whereas all the inhabitants required light bulbs, not all of them showed interest in other devices such as TV, radios, etc., mainly due to the lack of these devices nowadays. Only one of the interviewed showed interest in a computer. The nominal power needed (P_{ij}) of each device was estimated considering typical electrical appliances of the area and ENEE's publications.

Regarding the daily functioning time of each appliance, it has been defined taking into account the equivalent hours per day that the devices are expected to be used according to the typical daily schedule of the inhabitants. The same assumption was considered for the functioning window. In addition, for some devices, such as lights or TVs, users have notable differences in the power requirements depending on the time frame, thus presenting different functioning times and functioning windows that must be considered in the analysis in order to obtain more accurate results. All parameters are summarized in Appendix B.

The random variation of the functioning time and windows has been fixed in 15% following other similar cases of LoadProGen application (Berti, 2016), except for the fridge in which the variation of both parameters has been fixed in 5% as it is expected to be turned on during the whole day with minimum variation. The functioning cycle would be less than 1 h for the most part of the devices, but when performing hourly simulations is the minimum possible value to set.

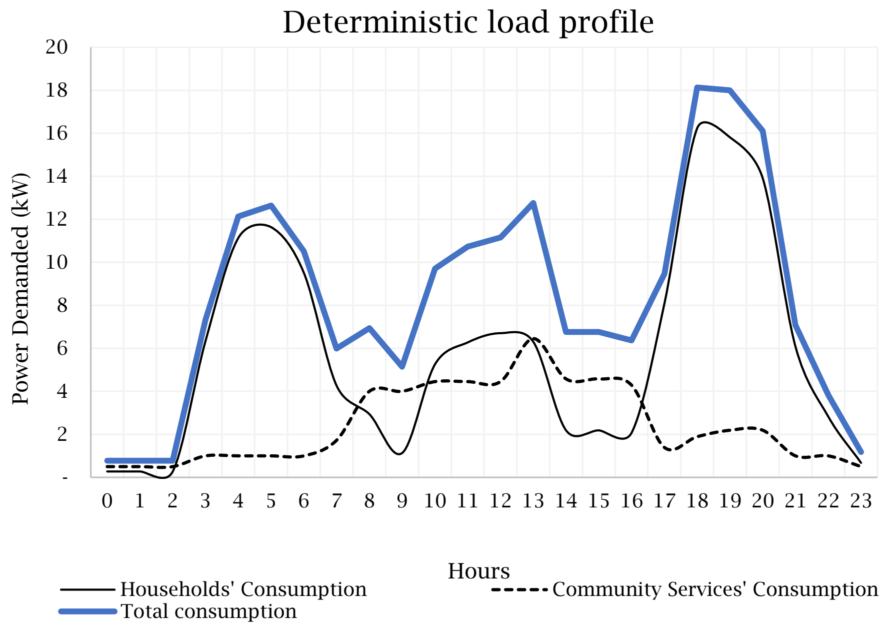

Fig. 4. Results of the deterministic load profile forecasting in El Santuario.

Communitarian Services: For the Street Light class, 20 units of 50 W were identified during the field visit as approximately required for lighting the main street. It is assumed that the devices will be working continuously during the first hours of the morning and the last of the evening, for instance during no-sun hours. A certain random variation of the functioning window has been fixed to 10%.

The lighting requirements for the school and kindergarten have been defined according to international standards. Moreover, 2 units of fan per building have been considered in order to ensure good conditioning. IT services (computer and printer) have been also added to the analysis considering their importance to enhance communication and learning in the community. Both buildings have an almost fixed schedule from 7 a.m. to 8 p.m., but a random variation of the functioning window of 30% has been assumed according to similar rural electrification projects (Mandelli et al., 2016a). Again, all parameters are summarized in Appendix B.

Productive Services: This category includes the water pump, selected for a pumping head of 80 m, and the biomass chipper, with a power of 7500 W according to the results of the first estimation of energy needs. Currently, the main economic activity of the community is subsistence agriculture. For these devices, the functioning windows and time are more flexible. Therefore, the functioning window has been fixed during sun hours, and trying that both devices do not work simultaneously. The value of random variation has been fixed at 40%, as its usage depends on other parameters e.g. if the solar resource is not enough during a certain period of time, it will be necessary to use the biomass chipper out of the expected usage schedule. All the parameters are summarized in Appendix B.

The simulations were performed with an hourly resolution. The processing time required by the Software to obtain the load profiles was around 9 h. The number of load profiles was set randomly in 300, thus the Software LoadProGen generates 300 different possible realistic load profiles from the input data. The output file of the Software is a 24 × 300 matrix (i.e. 24 columns representing the 24 h per day, and 300 rows representing the 300 different possible load curves), graphically represented in Fig. 5.

From these 300 number of profiles set up primarily, the convergence is reached at 211 profiles following the convergence criteria. Therefore, the optimum number of realistic profiles and that will be used for the load profile analysis is 211.

Fig. 6 shows the estimated future load curve for the rural community of “El Santuario”. The black line represents the average value of the total 211 profiles simulated. The uncertainty band (area between the maximum and minimum load curve) represents the maximum and minimum values among which the Software has evaluated scenarios, but do not present significant probability of occurrence. As can be seen, the uncertainty band is very broad. According to Berti (2016) this might be due to the large number of profiles simulated. It can also be due to different load with variable usage times.

As can be observed in Fig. 6, the load peak occurs around at 7 p.m. in the evening, when inhabitants come back home after the working hours. There is also another peak early in the morning, between 5 a.m. and 6 a.m., time in which the activity starts in the community. Both peaks are in line with the trend observed in load curves estimation for rural isolated communities. Moreover, another peak occurs between 10 a.m. and 14 p.m., due to the productive services that include the water pump and the biomass chipper, which are high-energy consumption devices. Even though a wide random variation of the functioning window has been considered for these devices, for further studies it would be interesting to consider different scenarios, e.g. weekday/weekend or dry/wet season, as the operating hours will differ for both devices.

Discussion

Deterministic and stochastic load profiles have been compared to assess the impact of the energy demand assessment methodology in the design of mini-grids for rural electrification. The parallel work allows a comparison of the two approaches in terms of performance, feasibility, reliability and resources requirement in order to discuss their usefulness for mini-grid design. Starting by the performance, Fig. 7 shows the comparison of load profiles following both approaches.

Regarding the daily energy demand estimation, represented by the area below the load curve, no significant differences in the values are observed between the two cases. The total demand reaches 201.09 kWh/day for the deterministic procedure, which turns out to be 2% higher than the obtained with the average stochastic one: 197.752 kWh/day.

However, some differences can be observed in the shape of both curves. While load peaks occur in the same time range following both approaches, load peak values obtained with the average curve in the

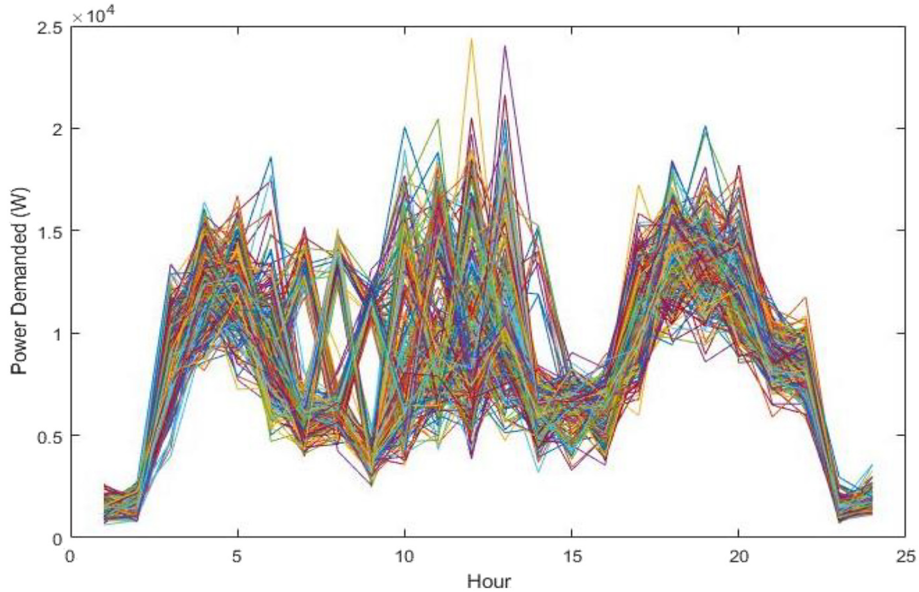

Fig. 5. 300 hourly profiles randomly generated.

stochastic procedure are lower (18.13 kW against 13.76 kW respectively). In contrast, if we compare the maximum possible levels at the stochastic curve, we can state that peaks also occur during midday and they reach 24 kW, 20% than the initial evening peak obtained with the deterministic curve. So, if aiming to deliver all the possible stochastic scenarios, a mini grid designed solely based on the deterministic curve, could present unexpected outages. Hence, the stochastic simulation provides a more complete forecast of the future consumption, enabling a more tailored design of the mini-grid.

The fact that the average stochastic load profile is flatter is extremely linked with the stochastic nature of the procedure. The formulation of load profiles for rural isolated areas without previous access to electricity brings aside the intrinsic uncertainty of the input data due to the users' subjectivity in its definition. Therefore, the common approaches for load profile formulation in rural areas should consider uncertainty in the input data, thus formulating a certain number of profiles for representing a more realistic situation (Mandelli et al., 2016a). In deterministic procedures, one single profile is formulated whereas stochastic simulation included 211 different probable profiles based on a convergence criterion.

Another finding of the comparison is related to the data and resources needed for their application, i.e., its feasibility. Demand forecasting is a complex and work intensive process in the two approaches. A successful process demands a correct baseline, normally based in costly field work, validate the data obtained with similar projects and case studies, process the raw data with the methodologies and methods presented, and study the possibility to use specialised software to help with the process. The deterministic approach requires less data and simpler software, but more accurate and precise information. This is really convenient at the early stages of the design, when understanding the problem and sizing, i.e. budgeting, are the main concerns, not technical optimization.

However, the inherent uncertainty in forecasting the future energy consumption makes it almost impossible to get the actual future load profile right, and the smaller the community the more so. Then, safety margins are applied to avoid outages due to occasional unforeseen

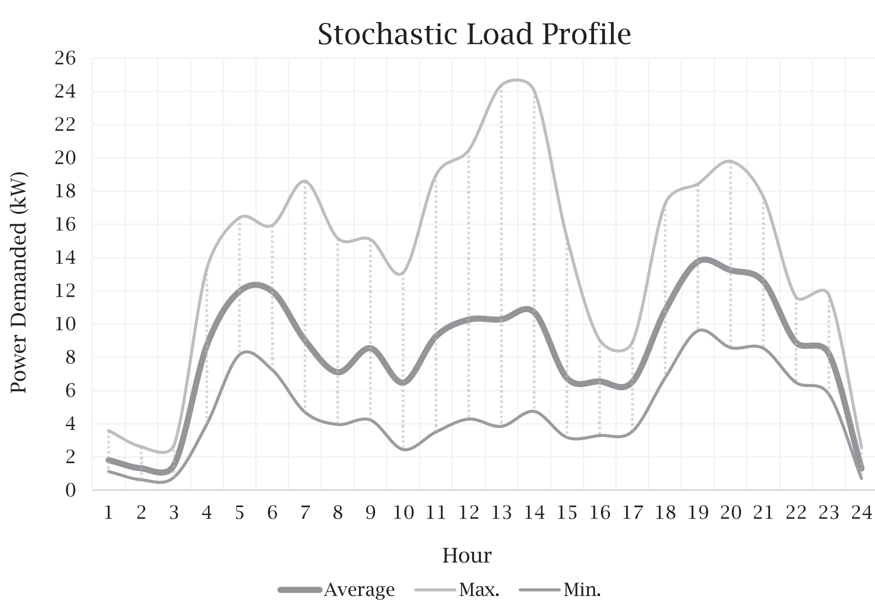

Fig. 6. Results of the stochastic load profile forecasting in El Santuario.

Energy for Sustainable Development 66 (2022) 101–116

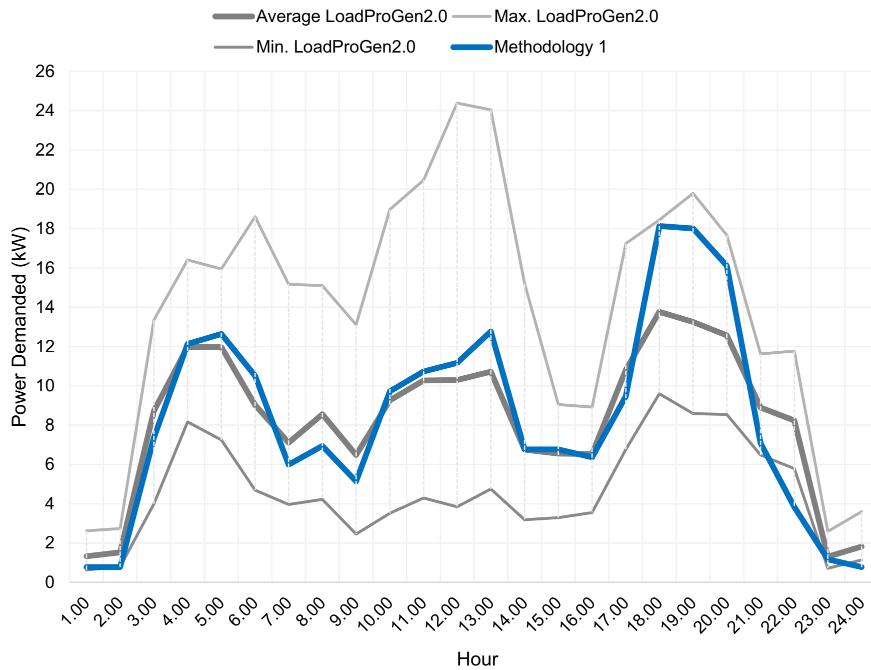

Fig. 7. Comparison of the results of the deterministic (blue) and stochastic (grey) load profiles forecasting in El Santuario. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

peaks in demand. A frequent solution is to combine doubling the capacity, compared with the peak demand, with the prevention of unexpected demand high peaks through safety systems. These disconnect loads that were not foreseen at that time, or that turn out to be higher than expected.

Thus, should that solution remain the initial design of the mini-grid, the stochastic calculation shows that it would be oversized. The safety systems to prevent mini-grid outages are recommended by both approaches, producing local outages where demand exceeds the set threshold. But the stochastic approach offers a more detailed understanding of the causes of occasional peaks, optimizing the design, and reducing problems for users.

On the other hand, the stochastic approach requires more input information, much of which is difficult to find or estimate: functioning windows, random variation, functioning cycles, etc. And the whole calculation demands a sophisticated mathematical model or software, which in turn involves some training. That said, the stochastic approach allows working with less accurate data. The more accurate the data, the smaller the random variations, and vice versa. Furthermore, reflecting on its feasibility, fast and robust computing equipment is needed if the model is very complex. The model in this case study can be said of low to medium complexity, yet required a long period of dedicated computing time for an average quality PC (9 h for the 300 profiles, with an hourly functioning cycle, as explained in the previous section). Hence, for larger communities, with a greater variety of electricity demands, and a desired greater temporal detail, the necessary computing equipment is not common with current versions of the software.

The implications of these findings for off-grid mini-grid design for rural electrification can be summarized as follows:

In sum, stochastic methods allow to provide more realistic information, to minimize the prediction error and to ensure accuracy in mini-grid's design, which directly impacts on project cost and reliability of energy supply. However, they require more effort in both producing and using the results in a context where even stochastic results face a degree of uncertainty. On the other side, deterministic models are still costly, but they produce straight forward results that are easily interpreted. Thus, the usage of one method or another would depend on the available resources, detailed needs, and the answers required, understanding that each of them has positive and negative elements.

In fact, advancing conclusions, if possible, combining both approaches mini-grid designers could benefit from the strengths of both. A deterministic study could be performed first, and gross decisions could be made based on the outcomes. And, if the facility is deemed feasible, a stochastic approach based in the data of the former, adding the completing information, would allow to tailor the mini-grid's design, optimizing the size and safety systems against general outages.

Conclusion

Forecasting the future energy demand in rural electrification projects is a key element that directly influences the size and design of mini-grids relating to the costs and the operation of the system. There are no standard methodologies for assessing this demand. When designing mini-grids, academics, policymakers and developers use generalised data and deterministic or stochastic methods. While the first option is just an approach to the real situation, models aim to reproduce the load curve that will exist in the mini-grid but require intensive data collection and mathematical modelling techniques.

Here, we present a comparison between the two approaches applied to a case study in a rural community in Honduras. We follow both procedures to obtain and compare the demand curves that will presumably occur in the community to see the differences and evaluate the costs of using each methodology. In sum, deterministic models are easier to use and understand but produce rigid results with a lower amount of information. While stochastic methods are resource intensive and result and require more complex mathematical models and interpretations, but they provide a more accurate picture of the scenarios in which demand will occur.

Finally, as a recommendation, the methods of the deterministic approach can be useful for the early stages of the project, when sizing the demand and comparing it with available renewable energy resources, economic resources, or others. However, in the advanced phases of the project, when the installation is being designed, the stochastic approach is recommended to ensure the satisfactory performance of the mini-grid.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported in part by the Spanish public administration under the grant FPU2016/00962, by the regional public administration of Valencia under the grant ACIF/2018/106, by the Food and Agriculture Organisation under the Letter of Agreement (PO number: 332412). And finally, by the Cátedra de Transición Energética Urbana (Las Naves-FVCiE-UPV).

Appendix A. Questionnaire used

Table 6
Demand assessment questionnaire, household data, energy consumption, and future needs.

Type of user	Household	Business	Other	
Reference data customer information	Address:			
	Name:			
	Contact:			
	Number of people in the household:			
	Number of rooms per household:			
	Internal power grid		Yes	No

	Type of source	Weekly expenditure	Unit price
Current energy sources and expenses	Diesel		
	Kerosene		
	Candles		
	Batteries		
	Charge of batteries		
	Wood		
	Coal		
	Wood fuel		
	Pellets		
	Low pressure gas		
	Oil fuel		
	Natural gas		
	Total		

	Appliances	Power (W)	Units	Daily schedule (h)	Usage hours
Current energy needs	Light bulbs (8–20)				
	TV (45–120)				
	Radio (20–60)				
	Iron				
	Cooking pot				
	Microwave				
	Laundry machine 5 kg				
	Electric boiler				
	Phone				
	Fan				
	Fridge				
	Computer				
	Irrigation				
	Food processing				
	Other:				
	Total:				

	Activity	Total Power Inst. (W)	Daily schedule (hours)	Electricity consumption (kWh)
Electricity consumption per activity	Construction			
	Shop			
	Hairdressing			
	Small-scale industry			
	Bar			
	Restaurant			
	Other:			

	Source	Amount (low season)	Amount (high season)
Sources of incomes	1		
	2		
	3		
	4		
	5		
	Total		

Expressed ability to pay	Monthly amount (low season)	Monthly amount (high season)

Table 7
Demand assessment questionnaire, expected evolution.

Expected appliances	Year 1	Year 2	Year 3	Year 4	Year 5
Light bulbs (8–20)					
TV (45–120)					
Radio (20–60)					
Iron					
Cooking pot					
Microwave					
Laundry machine 5 kg					
Electric boiler					
Phone					
Fan					
Fridge					
Computer					
Irrigation					
Food processing					
Other:					
Total:					

Table 8
Demand assessment questionnaire, qualitative factors for electricity consumption.

Which factor is more important for you regarding to the electrical service?	Cost	Quality		Access time	
What would encourage your connection to the grid?	Neighbours with access	Own need		Low price of connection	
Would electricity access enhance your life or business in any way?	Yes	No		Don't know	
How do you think electricity should be provided?	Free			Commercially	
Who decides the payment for electricity?	Myself	My supervisor		Family	
Do you possess any single-user electricity generation system?	Yes	No		Under consideration	
Are you satisfied with your current electric system?	Yes	No		Neutral	
Is your current electric system able to cover your electricity needs?	Yes	No		Percentage	
Would you be interested on using electricity for agricultural activities?	Yes	No			
If the answer is yes, in which agricultural activities are you interested?	Irrigation	Cold chain	Drying	Packaging	Other

Appendix B. Deterministic approach coincidence factors

Table 9
Coincidence factors and power needs in households' appliances.

Households																
Hour	Lights		Fridge		TV		Radio		Phone		Fan		Computer		Other appliances	
	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)
0:00	–	–	0.01	80	–	–	0	0	0.5	195	0	0	0	0	0	0
1:00	–	–	0.01	80	–	–	0	0	0.5	195	0	0	0	0	0	0
2:00	–	–	0.01	80	–	–	0	0	0.5	195	0	0	0	0	0	0
3:00	–	–	0.05	400	0.25	1500	0.5	430	0.5	195	0	0	0.1	20	0.2	3800
4:00	0.50	2003	0.10	800	0.50	3000	1	860	0.5	195	0.25	425	0.25	50	0.2	3800
5:00	1.00	4005	0.10	800	0.25	1500	1	860	0.5	195	0.25	425	0.25	50	0.2	3800
6:00	1.00	4005	0.10	800	–	–	0.5	430	0	0	0.25	425	0.25	50	0.2	3800
7:00	0.75	3004	0.05	400	–	–	0.5	430	0	0	0.25	425	0	0		0
8:00	0.50	2003	0.01	80	–	–	0.5	430	0	0	0.25	425	0	0	0	0
9:00	0.05	200	0.01	80	–	–	0.5	430	0	0	0.25	425	0	0		0
10:00	0.05	200	0.05	400	–	–	0.5	430	0	0	0.25	425	0	0	0.2	3800
11:00	0.05	200	0.10	800	0.10	600	0.5	430	0	0	0.25	425	0.1	20	0.2	3800
12:00	0.05	200	0.10	800	0.10	600	1	860	0	0	0.25	425	0.1	20	0.2	3800
13:00	0.05	200	0.05	400	0.10	600	1	860	0	0	0.25	425	0.1	20	0.2	3800
14:00	0.05	200	0.01	80	0.10	600	1	860	0	0	0.25	425	0.1	20	0	0
15:00	0.05	200	0.01	80	0.10	600	1	860	0	0	0.25	425	0.1	20	0	0
16:00	0.05	200	0.05	400	0.10	600	0.5	430	0	0	0.25	425	0.1	20		0
17:00	0.50	2003	0.10	800	0.10	600	0.5	430	0	0	0.25	425	0.1	20	0.2	3800
18:00	1.00	4005	0.10	800	1.00	6000	1	860	0.5	195	0.25	425	0.75	150	0.2	3800
19:00	1.00	4005	0.10	800	1.00	6000	1	860	0.5	195	0	0	0.75	150	0.2	3800
20:00	1.00	4005	0.05	400	0.75	4500	1	860	0.5	195	0	0	0.75	150	0.2	3800
21:00	0.50	2003	0.05	400	0.50	3000	0.5	430	0.5	195	0	0	0.25	50	0	0
22:00	0.25	1001	0.01	80	0.25	1500	0	0	0.5	195	0	0	0.25	50	0	0
23:00	0.10	401	0.01	80	–	–	0	0	0.5	195	0	0	0	0	0	0
Total	8.50	34,043	1	9920	5	31,200	14	12,040	6	2340	3.75	6375	4.3	860	2.4	45,600

Table 10
Coincidence factors and power needs in community appliances.

Communitarian services												
Hour	Water pump		Chipper		Streetlights		IT services		Lights		Fan	
	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)	CF	Power (kW)
0:00	–	–	–	–	0.50	500	–	–	–	–	–	–
1:00	–	–	–	–	0.50	500	–	–	–	–	–	–
2:00	–	–	–	–	0.50	500	–	–	–	–	–	–
3:00	–	–	–	–	1.00	1000	–	–	–	–	–	–
4:00	–	–	–	–	1.00	1000	–	–	–	–	–	–
5:00	–	–	–	–	1.00	1000	–	–	–	–	–	–
6:00		–	–	–	1.00	1000	–	–	–	–	–	–
7:00		–		–	–	–	0.50	450	0.75	878	0.50	400
8:00	–	–	0.25	1875	–	–	0.50	450	0.75	878	1.00	800
9:00	–	–	0.25	1875	–	–	0.50	450	0.75	878	1.00	800
10:00	–	–	0.25	1875	–	–	1.00	900	0.75	878	1.00	800
11:00	–	–	0.25	1875	–	–	1.00	900	0.75	878	1.00	800
12:00	–	–	0.25	1875	–	–	1.00	900	0.75	878	1.00	800
13:00	1.00	2000	0.25	1875	–	–	1.00	900	0.75	878	1.00	800
14:00	1.00	2000	–	–	–	–	1.00	900	0.75	878	1.00	800
15:00	1.00	2000	–	–	–	–	1.00	900	0.75	878	1.00	800
16:00	1.00	2000	–	–	–	–	1.00	900	0.50	585	1.00	800
17:00	–	–	–	–	–	–	1.00	900	0.25	293	0.25	200
18:00	–	–	–	–	0.50	500	1.00	900	0.25	293	0.25	200
19:00	–	–	–	–	1.00	1000	1.00	900	0.25	293	–	–
20:00	–	–	–	–	1.00	1000	1.00	900	0.25	293	–	–
21:00	–	–	–	–	1.00	1000	–	–	–	–	–	–
22:00	–	–	–	–	1.00	1000	–	–	–	–	–	–
23:00	–	–	–	–	0.50	500	–	–	–	–	–	–
Total	4.00	8000	1.50	11,250	10.50	10,500	12.50	11,250	8.25	9653	10.00	8000

Appendix C. Load Pro Gen parameters by user class

Table 11
Household parameters in LoadProGen A.

Household user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
Lights	71	3.76	15	1	8	15	15
TV	71	0.56	150	1	5	15	15
Radio	71	0.6	20	1	14	15	15
Fan	71	0.478	50	1	4	15	15
Fridge	71	0.22	500	1	1	5	5
Other	71	0.267	1000	1	2	15	15
Computer	71	0.014	200	1	3	15	15
Phone	71	0.55	10	1	6	15	15
Lights 2	71	3.76	15	1	1	15	15
TV 2	71	0.56	150	1	1	15	15
Computer 2	71	0.014	200	1	1	15	15

Table 12
Household parameters in LoadProGen B.

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
Lights	4	8	17	22	–	–
TV	3	5	18	23	–	–
Radio	3	21	0	0	–	–
Fan	4	18	0	0	–	–
Fridge	1	24	–	–	–	–
Other	3	6	10	16	17	20
Computer	3	4	18	22	–	–
Phone	1	5	18	24		–
Lights 2	9	16	23	24	–	–
TV 2	11	17	–	–	–	
Computer 2	11	17	–	–	–	–

Table 13
Streetlight parameters in LoadProGen.

Streetlights user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
External lights	1	20	50	1	11	10	10

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
External lights	1	6	18	24	–	–

Table 14
Church parameters in LoadProGen.

Church user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
Lights	1	6	15	1	8	30	30
Fans	1	4	100	1	10	30	30

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
Lights	7	20	–	–	–	–
Fans	7	18	–	–	–	–

Table 15
School parameters in LoadProGen.

School and kindergarten user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal Power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
Lights	1	72	15	1	8	5	5
Fans	1	4	100	1	10	5	5
IT	1	3	300	1	13	5	5

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
Lights	7	20	–	–	–	–
Fans	7	18	–	–	–	–
IT	7	20	–	–	–	–

Table 16
Water pump parameters in LoadProGen.

Water pump user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal Power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
Water pump	1	1	200	1	4	40	40

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
Water pump	13	16	–	–	–	–

Table 17
Biomass chipper parameters in LoadProGen.

Biomass chipper user class							
Type of appliance	Users (Ud.)	Electrical appliances per user (Ud.)	Nominal Power of appliances (W)	Functioning cycle (hour)	Functioning time (hour)	Variation of functioning time (%)	Variation of functioning window (%)
Chipper	1	1	7500	1	2	40	40

Type of appliance	Functioning window 0 (wf_0)		Functioning window 1 (wf_1)		Functioning window 2 (wf_2)	
Chipper	8	13	–	–	–	–

References

Aberilla, J. M., Gallego-Schmid, A., Stamford, L., & Azapagic, A. (Jan. 2020). Design and environmental sustainability assessment of small-scale off-grid energy systems for remote rural communities. *Applied Energy*, *258*, Article 114004.

Adeoye, O., & Spataru, C. (May 2019). Modelling and forecasting hourly electricity demand in West African countries. *Applied Energy*, *242*, 311–333.

Aevarsdottir, A. M., Barton, N., & Bold, T. (2017). *The impacts of rural electrification on labor supply, income and health: Experimental evidence with solar lamps in Tanzania.*

Allee, A., Williams, N. J., Davis, A., & Jaramillo, P. (Jun. 2021). Predicting initial electricity demand in off-grid Tanzanian communities using customer survey data and machine learning models. *Energy for Sustainable Development*, *62*, 56–66.

Alliance for Rural Electrification (2015). *Risk management for mini-grids: A new approach, 1–66.*

Bastida-Molina, P., Hurtado-Pérez, E., Pérez-Navarro, Á., & Alfonso-Solar, D. (2020). Light electric vehicle charging strategy for low impact on the grid. *Environmental Science and Pollution Research*, 1–17 Apr.
Bastida-Molina, P., Hurtado-Pérez, E., Vargas-Salgado, C., & Ribó-Pérez, D. (2020). Microrredes híbridas, una solución para países en vías de desarrollo. *Técnica Industrial*, *325*, 28–34.
Berti, L. (2016). *Access to energy in rural Tanzania: Electrical load curves evaluation and energy demand assessment of 13 villages in Njombe Region Relatore*. Politecnico di Milano.
Blodgett, C., Dauenhauer, P., Louie, H., & Kickham, L. (2017). Accuracy of energy-use surveys in predicting rural mini-grid user consumption. *Energy for Sustainable Development*, *41*, 88–105.
Boait, P., Advani, V., & Gammon, R. (2015). Estimation of demand diversity and daily demand profile for off-grid electrification in developing countries. *Energy for Sustainable Development*, *29*, 135–141.
Boait, P., Gammon, R., Advani, V., Wade, N., Greenwood, D., & Davison, P. (2017). ESCoBox: A set of tools for mini-grid sustainability in the developing world. *Sustainability*, *9*(5), 1–15.
Debnath, K. B., Mourshed, M., & Chew, S. P. K. (2015). Modelling and forecasting energy demand in rural households of Bangladesh. *Energy Procedia*, *75*, 2731–2737.
ENEE (2017). Cuadro de Consumo promedio mensual de Electrodomésticos. [Online]. Available: http://www.enee.hn/index.php/atencion-al-cliente/110-consumo-electrico (Accessed: 18-Dec-2017).
Feinberg, E. A., & Genethliou, D. (2005). *"Chapter 12 load forecasting," no. August, 269–285.*
Gambino, V., Del Citto, R., Cherubini, P., Tacconelli, C., Micangeli, A., & Giglioli, R. (Feb. 2019). Methodology for the energy need assessment to effectively design and deploy mini-grids for rural electrification. *Energies*, *12*(3), 574.
GIZ (2016). *What size shall it be? A guide to mini-grid sizing and demand forecasting.*
Hong, T., & Shahidehpour, M. (2015). *Load forecasting case study*. U.S. Dep. Energy.
IEA (2017). *Special report: Energy access outlook.*
IEA (2020). Access to electricity – SDG7: Data and Projections. [Online]. Available: https://www.iea.org/reports/sdg7-data-and-projections/access-to-electricity (Accessed: 26-May-2020).
IED (2021). *Demand Analyst®.*
IRENA (2017). *Accelerating off-grid renewable energy: Key findings and recommendations from IOREC 2016, 1–24.*
IRENA (2018). *"Off-grid renewable energy solutions," no. 2015, 1–20.*
Islam, A., Hasib, R. S., & Isalm, S. M. (2013). Short term electricity demand forecasting for an isolated area using two different approaches. *Journal of Power Technologies*, *93*(4), 185–193.
Kanagawa, M., & Nakata, T. (2008). Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries. *Energy Policy*, *36*, 2016–2029.
Lombardi, F., Balderrama, S., Quoilin, S., & Colombo, E. (Jun. 2019). Generating high-resolution multi-energy load profiles for remote areas with an open-source stochastic model. *Energy*, *177*, 433–444.
Louie, H., & Dauenhauer, P. (2016). Effects of load estimation error on small-scale off-grid photovoltaic system design, cost and reliability. *Energy for Sustainable Development*, *34*, 30–43.
Mahmud, M. A. (2011). Isolated area load forecasting using linear regression analysis: Practical approach. *Energy and Power Engineering*, *03*(04), 547–550.
Mandelli, S. (2015). *Strategies for access to energy in developing countries: methods and models for off-grid power systems design*. Politecnico di Milano.
Mandelli, S., Barbieri, J., Mereu, R., & Colombo, E. (2016a). Off-grid systems for rural electrification in developing countries: Definitions, classification and a comprehensive literature review. *Renewable and Sustainable Energy Reviews*, *58*, 1621–1646 May.
Mandelli, S., Brivio, C., Moncecchi, M., Riva, F., Bonamini, G., & Merlo, M. (2017). Novel LoadProGen procedure for micro-grid design in emerging country scenarios: Application to energy storage sizing. *Energy Procedia*, *135*, 367–378.
Mandelli, S., Merlo, M., & Colombo, E. (2016b). Novel procedure to formulate load profiles for off-grid rural areas. *Energy for Sustainable Development*, *31*, 130–142 Apr.
Miswan, N. H., Said, R. M., & Anuar, S. H. H. (2016). ARIMA with regression model in modelling electricity load demand. *Journal of Telecommunication, Electronic and Computer Engineering*, *8*(12), 7–11.
Mohiuddin, A. H. M. (1997). *A new technique of loaf forecasting for an isolated area*. Bangladesh University of Engineering and Technology.
Murugaperumal, K., & Raj, P. A. D. V. (Aug. 2019). Feasibility design and techno-economic analysis of hybrid renewable energy system for rural electrification. *Solar Energy*, *188*, 1068–1083.
Murugaperumal, K., Srinivasn, S., & Satya Prasad, G. R. K. D. (Feb. 2020). Optimum design of hybrid renewable energy system through load forecasting and different operating strategies for rural electrification. *Sustainable Energy Technologies and Assessments*, *37*, 100613.
Narayan, N., Qin, Z., Popovic-Gerber, J., Diehl, J. C., Bauer, P., & Zeman, M. (Feb. 2020). Stochastic load profile construction for the multi-tier framework for household electricity access using off-grid DC appliances. *Energy Efficiency*, *13*(2), 197–215.
NRECA (2016). *Guides for electric cooperative development and rural electrification.*
Oladeji, A., & Sule, B. (2016). Electrical load survey and forecast for a decentralized hybrid power system at Elebu, Kwara State, Nigeria. *Nigerian Journal of Technology*, *34*(3), 591.
Opiyo, N. N. (Dec. 2020). How basic access to electricity stimulates temporally increasing load demands by households in rural developing communities. *Energy for Sustainable Development*, *59*, 97–106.
Rajbhandari, Y., et al. (Jan. 2022). Load prioritization technique to guarantee the continuous electric supply for essential loads in rural microgrids. *International Journal of Electrical Power & Energy Systems*, *134*, Article 107398.
RECP (2014). *Mini-grid policy toolkit. Policy and business frameworks for successful mini-grid roll-outs.*
Ribó-Pérez, D., Bastida-Molina, P., Gómez-Navarro, T., & Hurtado-Pérez, E. (Sep. 2020). Hybrid assessment for a hybrid microgrid: A novel methodology to critically analyse generation technologies for hybrid microgrids. *Renewable Energy*, *157*, 874–887.
Ribó-Pérez, D., Herraiz-Cañete, Á., Alfonso-Solar, D., Vargas-Salgado, C., & Gómez-Navarro, T. (2021). Modelling biomass gasifiers in hybrid renewable energy microgrids; a complete procedure for enabling gasifiers simulation in HOMER. *Renewable Energy*, *174*, 501–512 Aug.
Ribó-Pérez, D., Herraiz-Cañete, Á., Casamayor-Segarra, P., del Castillo Velázquez, K., Gómez-Navarro, T., & Zelaya-Bonilla, S. (2021a). Electrificación de la última milla del corredor seco mesoamericano.|ENERLAC. Revista de energía de Latinoamérica y el Caribe. *ENERLAC. Revista de energía de Latinoamérica y el Caribe*, *5*(1), 10–33.
Riva, F., Sanvito, F. D., Tonini, F. T., Colombo, E., & Colombelli, F. (Jun. 2019). Modelling long-term electricity load demand for rural electrification planning. *2019 IEEE Milan PowerTech, PowerTech 2019.*
Sahu, A. K., Shandilya, A. M., & Bhardwaj, S. K. (2013). *Forecasting and management of load for rural areasVol. 3, no. 1.*
SEforALL (2019). *Clean energy mini-grids - Sustainable energy for all.*
Singh, S. N. (2011). *Electric power generation, transmission, and distribution* (2nd ed.). PHI Learni.