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# Optimizing the insertion of renewable energy in the off-grid regions of Colombia

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ABSTRACT

Electricity is essential for the economic growth and welfare of poor communities. However, 15% of the world's population does not have access to it. In Colombia, 52% of the territory is not connected to the national electricity grid, due to remoteness and difficult access from the main urban centers. About 2 million people live there, vulnerable and stricken by severe poverty. Some electricity is available to off-grid areas through fossil-based technologies, which provide a polluting and costly service. Renewable energy could be an opportunity for the development of these off-grid areas, but finding affordable solutions is needed to ensure sustainability. An optimization model for planning appropriate stand-alone, renewable-based electricity systems for off-grid communities is developed. It facilitates the evaluation of different technological configurations of renewables, fossil fuels, and batteries, as well as the randomness of demand and climatic variables to determine most advantageous features. To test this model, a case study was undertaken at the isolated community of Playa Potes in Chocó Department, Colombia. The results suggest, as the best solution, an electricity system based on solar power (22 and 29 kWp) and battery storage (74 and 93 kWh) to satisfy current and future requirements at affordable prices (35–38 ¢/kWh). These results point at the large potential for introducing renewable energy technologies to supply electricity to off-grid communities in Colombia, instead of relying just on fossil-based fuels.


## 1. Introduction

About 1.3 billion people worldwide have no access to electricity; 84% of them live in rural areas in developing countries (Gaona et al., 2015). Lack of access to electricity is a major impediment to the rural population's economic growth and welfare (Guta, 2018; Narula and Bhattacharyya, 2017; United Nations, 2015). One of the United Nations' Sustainable Development Goals is precisely to achieve energy security for poor and vulnerable communities because this would help them fulfil some of their most basic needs, such as those related to health, nutrition and education (Foster and Tre, 2000; Gonzalez et al., 2016; United Nations, 2015).

In Colombia, 52% of the territory is considered off-grid, and over 2 million people live in off-grid communities (Gaona et al., 2015). Stand-alone generation systems, mostly diesel-based, and some run-of-the-river hydropower plants are used to satisfy the demand (IPSE, 2014). Fossil-based technologies are commonly employed because not every community has water resources appropriate for hydroelectricity. Fossil-based technologies can be inappropriate for these communities because they are costly and offer intermittent and unreliable service, making them unsustainable (Rodríguez, 2017; Silva and Nakata, 2009).

Alternative renewable technologies could provide electricity to communities in off-grid areas. They are clean, usually inexpensive, and easy to maintain and operate (Chowdhury et al., 2015). Nevertheless, adopting these technologies is only incipient in Colombia's off-grid territories, and contrasting views have been raised regarding their appropriateness. On the one hand, it has been claimed that renewable energy systems are not economically feasible, and that their implementation can be justified only in environmental terms (Caspary, 2009). On the other hand, it has been argued that reduced costs make them increasingly viable, while the barriers that prevent their wider dissemination are often political or socio-cultural (Gómez-Navarro and Ribó-Pérez, 2018).

Whilst the above arguments indeed reflect the way that the renewable sector has been progressing, investment in small-scale

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renewable energy technologies that are destined to the rural poor still poses numerous challenges. Moreover, identifying a suitable cleaner stand-alone electricity generation technology, or a combination thereof, is often complex. Many technical configurations must be evaluated while intermittence and the unpredictable nature of the relevant natural resources must be considered (Tezer et al., 2017).

Therefore, a model based on implicit stochastic optimization (ISO) is proposed to support electricity planning to facilitate identification of the optimal mix and size of different energy technologies to meet current and future electricity demands in rural communities. A case study in the off-grid community of Playa Potes in Chocó Department, Colombia, is used to test the model and contribute to the community's energy planning, which has high poverty levels and no electricity supply of any kind.

An overview of the current situation in Colombia regarding rural electrification, as well as the model-based planning approaches often reported in the literature are discussed below. An optimization model is then discussed to find the most favorable electricity generation technologies for any given off-grid community. The context of the case study used to apply the model is described, while the results are presented and discussed in the last sections of this article.

## 2. Potential for developing renewable energy in off-grid Colombia

In 2014, 1448 off-grid communities had been registered in Colombia, distributed across 32 counties or departments, which equates to about 52% of the national territory (Fig. 1). Although most communities (79.5%) have access to electricity through off-grid solutions, only in 31.3% of them have service available 24 h daily; in 16.2% it is between 7 and 23 h, and in 32% of the communities only 1–6 h of service a day is possible (Fig. 1a). In as many as 88% of all off-grid communities, diesel generator is the most commonly employed technology. Renewable technology systems, sometimes combined with diesel, are being used only by a few communities, even though Colombia has significant potential for alternative renewable energy, such as solar photovoltaics (PV) and biomass (Fig. 1b) (CNM, 2017, 2018; IPSE, 2014; Rodríguez, 2017).

One of the reasons for such limited adoption of renewable technology has been that, until recently, wind, small hydro, modern biomass and geothermal technologies were not financially feasible in Colombia. Particularly solar PV was estimated to remain uncompetitive until 2030 (Caspary, 2009). However, their prices have come down and the industry is more competitive than before (IRENA, 2018). Yet, their wider dissemination in Colombia is still limited, not just due to previous cost and technical challenges, but because of political and socio-cultural reasons (Cherni et al., 2007; Gómez-Navarro and Ribó-Pérez, 2018; Gonzalez et al., 2016; Mamaghani et al., 2016). The Colombian government thus created incentives for non-conventional energy projects to electrify rural areas through Law 1715, sanctioned in 2014 (UPME, 2015a). Despite this new law, the adoption of alternative renewables is still incipient in these territories.

Whereas the capital cost of renewable energy systems continues

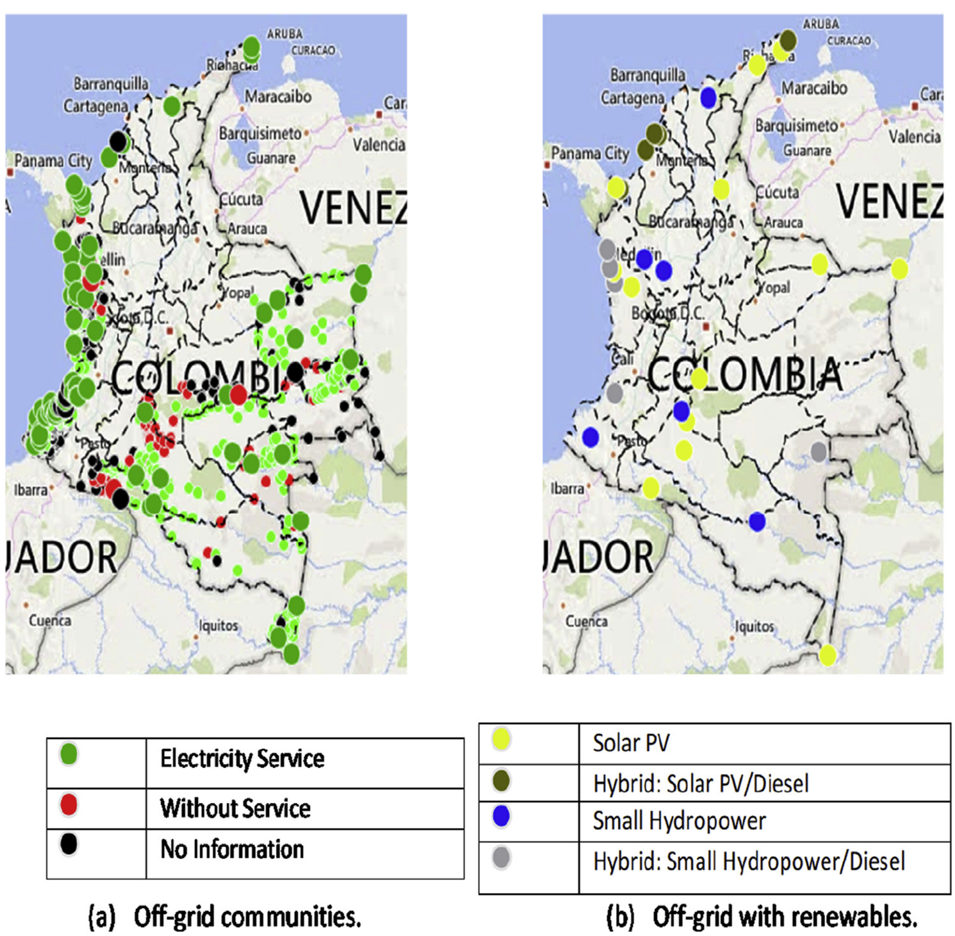



**Fig. 1.** Off-grid communities in Colombia – source: CNM (2018).

to represent the main barrier to their wider adoption, they offer a cheaper option than diesel generators due to their low operating costs (Gómez-Navarro and Ribó-Pérez, 2018; Mamaghani et al., 2016). Another major obstacle for adopting renewables in Colombia's off-grid regions is the Law 1117 - sanctioned in 2006 - and particularly resolution 182138, which subsidize the costs of the transportation and acquisition of the fuels needed to supply an energy service. Law 1117 provides local companies with a constant inflow of resources associated with the operation of the solution, favoring the proliferation of fossil fuels and hindering alternative renewables. Hence, it blocks the effectiveness of Law 1715, because the latter only subsidizes the acquisition of equipment, which occurs only once, at the beginning of the project (Superservicios, 2018; Rodríguez-Urrego and Rodríguez-Urrego, 2018). Moreover, Law 1117 does not make a distinction between polluting and green technologies, nor acknowledges that some solutions are costlier than others to operate. Such environmental and other long-term impacts could add to financial uncertainty to already poor communities. As a result, calls have been made to deviate the resources employed to subsidize fossil fuels to benefit alternative renewables (Gómez-Navarro and Ribó-Pérez, 2018). This consideration would more likely increase the opportunities to develop renewable technology in Colombia's off-grid areas (Gómez-Navarro and Ribó-Pérez, 2018; Rodríguez, 2017).

Finally, a further obstacle is the intermittency of relevant renewable resources. Intermittency represents a serious technological barrier to effective energy supply to off-grid communities in Colombia. Few appropriate solutions have been advanced to address the intermittency challenge. For example, implementing battery storage systems to cope with the variations in renewable generation has been recommended (see Gaona et al., 2015). Mamaghani et al. (2016) used Homer - a commercial software for microgrid design, developed by the National Renewable Energy Laboratory (NREL) - to analyze different hybrid system configurations for three rural communities in Colombia and recommend to back-up renewables using diesel generators. Yet, it has also been argued that small hydropower plants could have been used more extensively in places where diesel-based generators had been implemented without taking into due consideration the potential of available water resources (Morales et al., 2015).

## 3. Planning approaches for stand-alone electricity generation systems

Various approaches have been developed to evaluate the environmental and societal impacts of replacing old fossil-based technologies with alternative renewable energy sources in off-grid areas (Mandal et al., 2018). In terms of modelling approaches for planning electricity generation capacity, optimization techniques stand out because they can determine the best mix of technologies to meet a particular level of demand at the lowest possible cost (Izadyar et al., 2016; Khan et al., 2016; Tezer et al., 2017). The main two types of optimization approaches for energy problems are: deterministic, and stochastic. They differ in the way they handle the uncertainty inherent in this type of energy access problem (Sinha and Chandel, 2015; Zeng et al., 2011). For rural communities in Colombia, there is uncertainty in the atmospheric conditions, financing mechanisms, and level of demand.

In planning and decision-making frameworks, deterministic approaches tend to consider only a single scenario based on the average values of the random variables, e.g., the climate information relevant to renewable energy technologies. Stochastic approaches, on the other hand, take the uncertainty into account by considering several plausible future scenarios. As a result, deterministic approaches tend to be easier to implement, require fewer parameters and lower computational resources, and are more inclined to suggest slimmer and cheaper solutions than stochastic models. The drawback, however, is that because uncertainties are not being taken into consideration, their suggested solutions may be unreliable if the scenario realized is other than the average one. Stochastic models, such as robust optimization and ISO, require more complex inputs (e.g., value ranges, probability distributions or synthetic data) to build the scenarios (Billionnet et al., 2016). Stochastic models tend to suggest more robust but costlier solutions; however, they are superior for dealing with multiple scenarios (Bhattacharyya, 2012; Billionnet et al., 2016; Khare et al., 2016).

A different perspective to optimize energy selection is multicriteria decision analysis (MCDA), which has been employed for planning strategies to supply energy to off-grid communities (Cherni et al., 2007; Rojas-Zerpa and Yusta, 2015). MCDA helps planners and decision makers consider multiple quantitative and qualitative factors, which could conflict with each other. MCDA has also been used to align domestic energy policies with the United Nations' Sustainable Development Goals (Büyüközkan et al., 2018). Finally, Cherni et al. (2007) and Henao et al. (2012) developed a decision support system, SURE-DSS, based on MCDA, to select energy solutions for poor rural communities. By combining concerns over poverty, sustainable development, global climate change, and low-carbon society, the SURE-DSS framework has been perceived to pave the way forward to a sustainable future as it facilitates increased complexity (Brent and Kruger, 2009).

The approach has been piloted and implemented in various countries such as Colombia, Cuba and Perú (Cherni et al., 2016; Cherni and Preston, 2007).

While MCDA can analyze multiple sources of information, it has two main constraints: (1) the requirement for a predefined set of feasible solutions to choose from and (2) uncertainty is not considered explicitly. Therefore, a multi-objective, optimization approach has been proposed to overcome the first limitation of having to provide ready-made solutions (Dufo-López et al., 2016). Nonetheless, the uncertainty component has not been dealt with, even though socio-cultural and environmental criteria had been included alongside the traditional cost-minimization perspective.

To address the uncertainties often found in developing effective sustainable low-carbon energy solutions for off-grid territories, stricken by poverty, climate and other environmental threats and remoteness, an optimization model has been designed that will help plan stand-alone energy systems. The model facilitates comparison of many system configurations to choose the best one for the contextual conditions of the community under consideration. It also minimizes both capital expenditure (capex) and the levelized cost of energy (LCOE), as well as considering the stochastic nature of the random variables through synthetic time series. The next section describes the design of the stochastic optimization model to select energy options that account for environmental, financial and demand uncertainties in detail.

## 4. The proposed optimization model

An optimization model is proposed to define the optimal size and mix of electricity generation resources for off-grid communities. The model considers three types of renewable technology (solar PV, wind power and run-of-the-river hydropower), plus diesel and battery storage systems as potential system backups. First, (i) the model's *decision variables* representing the choices to be made, (ii) an *objective function* that is associated with the costs of the system, and (iii) the system's *constraints* or limitations, are presented. Finally, (iv) the model calibration and (v) the ISO methodology are described.

### 4.1. Decision variables

The optimization model considers five electricity generation technologies: $i$ = S (solar PV), W (wind power), H (hydropower), B (battery storage system) and D (diesel). Thus, the model has five first-stage decision variables, represented by $X_i$. For solar, wind and diesel, $X_i$ defines the power capacity in kilowatts peak (kWp) to be installed for each technology *i*. For batteries, $X_B$ represents the system's storage capacity in kilowatt-hours (kWh). For hydropower, $X_H$ is a binary choice that defines whether to build a run-of-the-river hydropower plant with a predefined set of characteristics. These characteristics need to be defined before using the model because they depend on the context, including the topography of the terrain where the community is located, its pluviosity, river size, etc.

Additionally, the model has second-stage decision variables ($G_{i,t}$) representing the amount of electricity to be generated (in kWh) based on each technology capacity as defined with the first-stage decision variables. This is equivalent to deciding what types of energy facilities are used to meet the community's electricity demand. The model calculates the amount of electricity generated with each energy technology during each hour ($t$) of the day throughout an entire year. The amount depends on the natural resources available and the community's electricity demand at that time. Finally, the model also accounts for the state of charge of the battery storage system through the variables $B_t$ and $G_{B,t}$.

### 4.2. The objective function

The model's objective function seeks to minimize the overall costs of the energy system (Billionnet et al., 2016; Ghorbani et al., 2018; Khan et al., 2019):

$$\min = \sum_i \left[capex_i + fix\_opex_i\right] \times X_i + \sum_i \sum_t variable\_opex_i \times G_{i,t} \tag{1}$$

where: $i$ is the type of energy technology (S, W, H, B or D), $t$ is the hour of the year, capex$_i$ is the capital expenditure for technology $i$ ($US/kWp), *fix_opex*$_i$ is the fix operational costs of technology $i$ associated with the maintenance of the equipment during its life-cycle ($US/kWp), and *variable_opex*$_i$ is the variable operational costs associated with the fuel used by technology $i$ ($US/kWh). The decision variables are $X_i$, which is the capacity to be installed of technology $i$ (kWp), and $G_{i,t}$ that represents the amount of electricity generated by technology $i$ during hour $t$ (kWh).

Two types of costs have been considered. The first is the capex index, which represents the total capital cost of installing the system ($/kWp). It depends on the system's size (Lazard, 2017a) and it is set to its first year of operation. The second cost is associated with system generation, operation and maintenance. LCOE is used for these different costs as it aggregates the total cost of electricity generated during one year (Lazard, 2017a, 2017b). This objective function allows us to find the system configuration with the lowest installation and power generation costs (Billionnet et al., 2016; Dufo-López et al., 2016; Gupta et al., 2011a).

### 4.3. Constraints

The model's constraints are the maximum amount of electricity that can be produced with each technology at each time of the year, the balance of supply and demand, and the operation of the battery system (Diaf et al., 2007).

#### 4.3.1. Solar PV generation

The amount of electricity generated by a solar PV system during hour $t$ depends on the efficiency ($\eta^s$), the amount of solar radiation that falls on a square meter during time $t$ ($R_t$), and the area of the panel arrangement ($A_s$) in m$^2$ (Sinha and Chandel, 2015):

$$G_{s,t} = (\eta^s A_s R_t) \times X_s \tag{2}$$

These technical parameters are predefined for a 1 kWp system of given characteristics (see Appendix 1), so the decision variable $X_s$ reflects the amount of kWp to be installed in the study area.

#### 4.3.2. Wind generation

The power generated by a wind turbine (see Appendix 1) depends on the power capacity installed and the average wind speed during hour $t$. The turbine chosen starts operating at a wind speed of 3 m/s and reaches its maximum power capacity at 10 m/s. A wind speed above 20 m/s causes the turbine to shut down due to the forces on the blades, which may damage them and the rest of the infrastructure. The power generated by a turbine with wind speeds between 3 and 10 m/s depends on the efficiency ($\eta^w$), the air density ($\rho$) in kg/m$^3$, the turbine's swept area ($S^w$) in m$^2$ and the average wind speed ($W_t$) in m/s (Ma et al., 2014; Ramli et al., 2016):

$$G_{w,t} = \begin{cases} 0 & W_t < 3, \\ \left(\frac{1}{2}\rho S^w W_t^3 \,\eta^w\right) \times X_w & 3 \le W_t < 10, \\ X_w & 10 \le W_t \le 20, \\ 0 & W_t > 20, \end{cases} \tag{3}$$

Like solar PV, these parameters were predefined for a 1 kWp system, so the decision variable $X_w$ indicates the number of kWp to be installed.

#### 4.3.3. Hydropower generation

The electricity generated by a run-of-the-river hydropower plant depends on the average water inflow in m$^3$/s ($Q_t$) during hour $t$, the height difference between the inlet and outlet ($ht$) in m, the acceleration due to gravity ($g$) in m/s$^2$, the density of water ($\rho$) in kg/m$^3$ and the efficiency ($\eta_{tg}$) (Gupta et al., 2011a:

$$G_{H,t} = (\rho \times g \times Q_t \times ht \times \eta_{tg}) \times X_H \tag{4}$$

As mentioned earlier, the decision variable $X_H$ is a binary choice that reflects the decision on whether to install a plant with a predefined set of characteristics for a given community. These characteristics must be defined before using the model, because they depend on the problem context only, and cannot be automated within the model.

#### 4.3.4. Diesel-based generation

The maximum amount of power that can be generated by a diesel plant depends on the efficiency of the technology ($\eta^D$) and the capacity installed $X_{D,t}$ in kWp (Eq. (5)). In addition, if a diesel plant is decided to be installed, it should be used above 80% of its maximum capacity to avoid further efficiency reductions - Eq. (6) - (Gupta et al., 2011a; Lagunas et al., 2004):

$$G^D_{max} = \eta^D \times X_D \tag{5}$$

$$0.8 * G^D_{max} \le G_{D,t} \le G^D_{max} \tag{6}$$

### 4.3.5. State of charge of the battery system

The state of charge of the battery system, at the end of hour $t$ ($B_t$), depends on the state of charge at the end of the previous hour ($B_{t-1}$), plus (or minus) the amount of electricity either entering ($EB_t$) or exiting ($G_{B,t}$) the system during hour $t$. The battery system is charged ($EB_t$) when there is a surplus (i.e., when the electricity generated exceeds the demand). The system discharges the battery ($G_{B,t}$) when generation is not sufficient to meet the demand, and it needs to withdraw electricity to satisfy the demand. In addition, the battery's charge status is affected by the self-discharge rate ($\sigma$), which increases with the battery's age, the technology's efficiency ($\eta_{bat}$) and the inverter's efficiency ($\eta_{inv}$) (Diaf et al., 2007):

$$B_t = B_{t-1} \times (1-\sigma) + \left[ (EB_t \times \eta_{bat}) - \left( \frac{G_{B,t}}{\eta_{inv}} \right) \right], \qquad \forall : \ t > 1 \tag{7}$$

In addition, the battery's charge status must be between a minimum and a maximum bound. The upper bound is the maximum storage capacity defined for the system ($X_b$) in kWh, whereas the lower bound is equal to 20% of the maximum storage capacity, which is the technical limit accepted for Lead-Acid battery technology, the type chosen for this model:

$$0.2 \times X_b \le B_t \le X_b \tag{8}$$

### 4.3.6. End uses of the electricity generated with the chosen technologies

Three things can happen to the electricity generated by the alternative renewables (i.e., solar PV and wind power) (Gupta et al., 2011a; Sinha and Chandel, 2015)

$$G_{S,t} + G_{W,t} = EL_t + EB_t + EW_t \tag{9}$$

First, (i) the electricity generated by the renewables can go directly to meet the community's electricity demand ($EL_t$); (ii) If the community's demand is met, any generation surplus is stored in the battery system ($EB_t$); finally, (iii) if the battery system is full, and the community's demand is met, any excess electricity is wasted ($EW_t$).

Thus, the community's electricity demand ($D_t$) is met through a combination of different sources: generated directly by the alternative renewables ($EL_t$), the hydropower plant ($G_{H,t}$) or the diesel generator ($G_{D,t}$), and from the battery storage system ($G_{B,t}$):

$$D_t = EL_t + G_{B,t} + G_{H,t} + G_{D,t} \tag{10}$$

### 4.4. Model calibration

As mentioned at the start of this section, the proposed optimization model can identify the optimal mix of electricity generation systems for off-grid communities. The model uses various parameters that represent technical features, such as efficiencies and capacity factors. The specifications used in the model for each type of technology were chosen because all these technologies are commercially available in Colombia and have been tested in off-grid communities in this country or elsewhere (see Appendix 1).

The equations of the optimization model were calibrated using three separate cases reported in the academic literature, where one of them takes place in a rural village called Titumate also in Chocó department in Colombia (IPSE, 2013; Ma et al., 2014; Gupta et al., 2011b). The calibration consisted of checking whether the model's equations would produce similar energy outputs as those reported in the cases for all the five energy technologies considered by the model (see Appendix 3 for further details).

### 4.5. Implicit stochastic optimization

ISO is commonly employed in the energy industry to model the uncertainty inherent in planning (Labadie, 2004). It is a mathematically and computationally simple approach that uses, repeatedly, deterministic optimization to address a stochastic problem (Henao et al., 2019). It uses value ranks, or synthetic data, to represent future possible scenarios, and then it finds an optimal solution for each scenario:

$$O^*_\omega = \left\{ \begin{array}{c} min\, Z^*(\overrightarrow{X_\omega}, \overrightarrow{G_\omega}) = \{ f(\overrightarrow{X_\omega}, \overrightarrow{G_\omega}) \} \\ st.\ g_i(\overrightarrow{X_\omega}, \overrightarrow{E_\omega}) \le 0; \quad \forall i \\ X \in \overline{X},\ G \in \overline{G} \end{array} \right\} \forall \omega \tag{11}$$

where $O^*_\omega$ represents the optimal solution for a particular scenario $\omega$, $\overrightarrow{X}$ are the first-stage decisions (configuration and system sizing) and $\overrightarrow{G}$ are the second-stage decisions, which are those related to power generation, battery operation, and the demand and supply balance (Henao et al., 2019).

The aim is to find a unique solution, amongst all the solutions obtained, for implementation. Such a solution should be robust or appropriate enough for most of the scenarios considered.

The next section describes a case study applying the optimization model in the isolated community Playa Potes, in Chocó Department, Colombia, and the data used to feed the model.

## 5. Case study and data collection

This paper uses a case study to test the proposed model and, eventually, suggest a plan for optimal energy generation to local authorities. Data were collected for an off-grid coastal rural village, Playa Potes, in Bahía Solano, a municipality of Chocó Department in the north-west Pacific region of Colombia. Rural and coastal communities in the Pacific area are extremely poor and vulnerable. The population of Playa Potes at the time of data collection, in 2016, was 90. The village could be accessed only by boat and its inhabitants practiced mostly fishing as their main source of subsistence (Fig. 2). There was no electricity and attempts to connect Playa Potes to the grid of the nearest town, Ciudad Mutis, had been unsuccessful.

The data and parameters used to set up the optimization model were as follows:

**Fig. 2.** A household in the coastal community of Playa Potes, Bahía Solano, Colombia, 2016.

- The detailed costs for installing and operating each type of technology, and how these are affected when the installation is in a rural, isolated area, were taken from Lazard (2017b, 2017a) and IRENA (2015, 2017).
- In addition, historical climatic data on wind speed and solar radiation were retrieved from the National Renewable Energy Laboratory's satellite database because more precise, local data did not exist (Habte et al., 2017). These data were used to construct a set of 100 synthetic time series for each climatic variable, so to include them as the climatic scenarios needed in the ISO approach mentioned in Section 4.5.
- ARFIMA and SARIMA, which are extensions of the ARMA model, were used to generate the climatic scenarios needed for the ISO approach. ARMA models are powerful statistical tools to generate synthetic time series, based on previous observations (autoregressive part, AR) and their stochastic variability (moving average part, MA) (Philippopoulos and Deligiorgi, 2009). ARFIMA models are commonly used to simulate wind speeds because they allow replicating both, short and long-term correlations inherent in this type of data, in a simple form (Kavasseri and Seetharaman, 2009; Caporin and Preś, 2012; Wang and Li, 2019). In this case, wind speeds were modelled using AR (2) and AR (3) models nested in ARFIMA. Whereas, SARIMA models are frequently used for solar radiation, as they allow replicating accurately the 24-h seasonality of these data (Mukaram and Yusof, 2017). In this case, solar radiation was modelled using SARIMA {(2,0,2); (0,1,2)} (Bouzerdoum et al., 2013; Kushwaha and Pindoriya, 2019). Hydropower generation was not considered for Playa Potes because there were no rivers near the community. For further information regarding ARMA-based models see Morales et al. (2014).
- The Institute of Planning and Promotion of Energy Solutions for off-grid communities in Colombia (IPSE) developed a typical load curve to calculate the demand of the off-grid communities in the country (IPSE, 2014). The curve was empirically estimated by IPSE by averaging the actual consumptions of different isolated communities with productive activities and these data is supplied by The National Monitoring Center – CNM – who regularly collects them through telemetry systems (CNM, 2017). The curve intends to help energy planners estimate the future demand of communities that have no previous data, once productive activities will be developed. The curve was used to estimate the future demand in Playa Potes by adjusting it to its expected future population (see Fig. 6). In the case of the off-grid communities in Chocó, the population growth rate is negative (−12.89%) due to its high poverty levels (Ruiz et al., 2007; UPME, 2015b). Hence, a constant population was assumed for the next ten years. A similar curve is also suggested by Kirubi et al. (2009) for the case of Kenia.
- Finally, a robustness analysis test was performed to check the response of four specific system configurations to the worst-case scenario, which applies extremely unfavorable conditions for electricity generation (poor climatic conditions and high electricity demand). The blackouts that occurred under such a scenario, for each system configuration, were accounted for.

## 6. Results and discussion

### 6.1. Optimization results

As mentioned in the previous section, the optimization model was run 100 times, each one under a different scenario. Thus, 100 different optimal solutions or combinations of energy generation systems were obtained. Fig. 3 summarizes, in a whisker plot diagram, the optimal solutions regarding capacity installations by type of energy technology. The boxes show the optimal values obtained for the decision variables $X_i$. As can be observed, regardless of the scenario analyzed, the optimal mix of technologies for Playa Potes always consisted of a solar PV panel arrangement with a battery storage system. The precise combination of capacity equipment depend on the scenario analyzed, but values varied as follows: the battery storage system recommend was between 74 and 93 kWh, and the solar panels were between 22 and 29 kWp. Notwithstanding such variations, the optimal combination of technologies always remains the same, i.e., solar PV with a battery storage

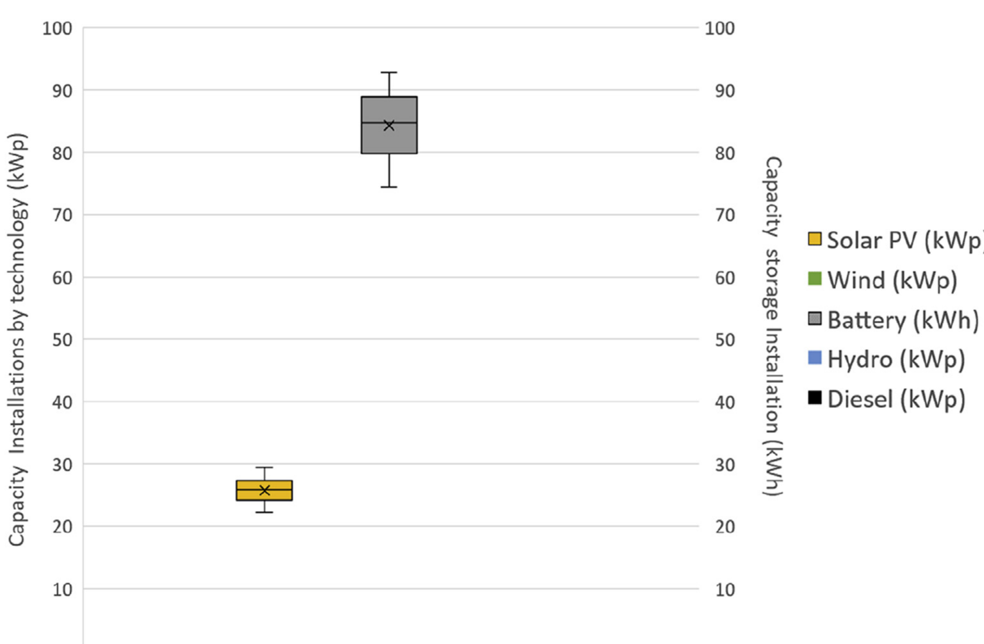



**Fig. 3.** Set of optimal solutions over the entire set of scenarios considered.


**Fig. 4.** Daily solar radiation in Chocó, Colombia.

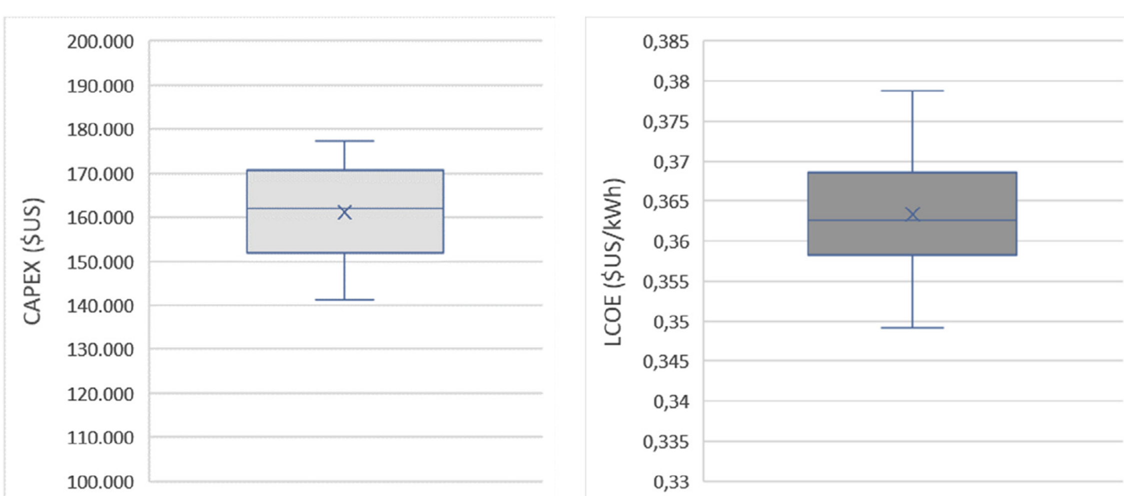
system (see Fig. 3). This could be due to the high levels of solar radiation found in the region (between 3.5 and 4 kWh/m$^2$ day; Fig. 4) and to the low operational costs of PV technology (Kempener et al., 2015; Mamaghani et al., 2016).

The optimal mix of technologies have a capital cost (capex) that varies between $US 141,127 and $US 177,400. In addition, the levelized cost of the electricity (LCOE) produced with the resulting energy systems was calculated using the values of the objective function (see appendi×2 for full details). The LCOE ranges between 0.35 and 0.38 $US/kWh (Fig. 5). Even though the LCOE is higher than the average residential tariff paid in Colombian urban areas (about 0.2 $US/kWh or less), it is cheaper than the current costs in off-grid areas where diesel generators are used as the primary source of electricity. The LCOE for diesel-related electricity varies between 0.86 and 4.51 $US/kWh, depending on the location analyzed (CREG, 2013; Kempener et al., 2015). Diesel-based technologies are costly to operate due to fuel purchase and transportation costs. These costs, when transferred to a low-income community, render the fossil fuel solution of diesel generation unsustainable (Rodríguez, 2017).

The solar panels proposed by the model would generate enough electricity to satisfy the community's demand during the day and charge the battery system to meet the demand during the night. On average, 44.18% of the demand would be satisfied directly by the solar panels, while the remaining 55.82% would come from the battery system. On a 24-h load curve, the battery system satisfies the demand during the dark hours (at night and early morning), while the solar panels satisfy the demand from 06.00 to 16.00 (Fig. 6).

Fig. 7 shows the average operation of the battery system (i.e., its state of charge). At 06.00, the solar panels would start generating electricity (orange line) for consumption and to charge the battery system (blue line). By midday, the battery system should be fully charged, and the charge remains constant until 16.00, when the solar radiation starts fading. By 17.00, the battery begins discharging, which continues through the night until the next morning when the process starts again.

To see how the proposed system configurations discussed above would respond to a scenario with extremely unfavorable conditions for electricity generation (poor climatic conditions and high electricity demand), a robustness analysis test was performed, as




(a) (b)

**Fig. 5.** (a) Capital cost of the system (capex) and (b) levelized cost of electricity (LCOE).

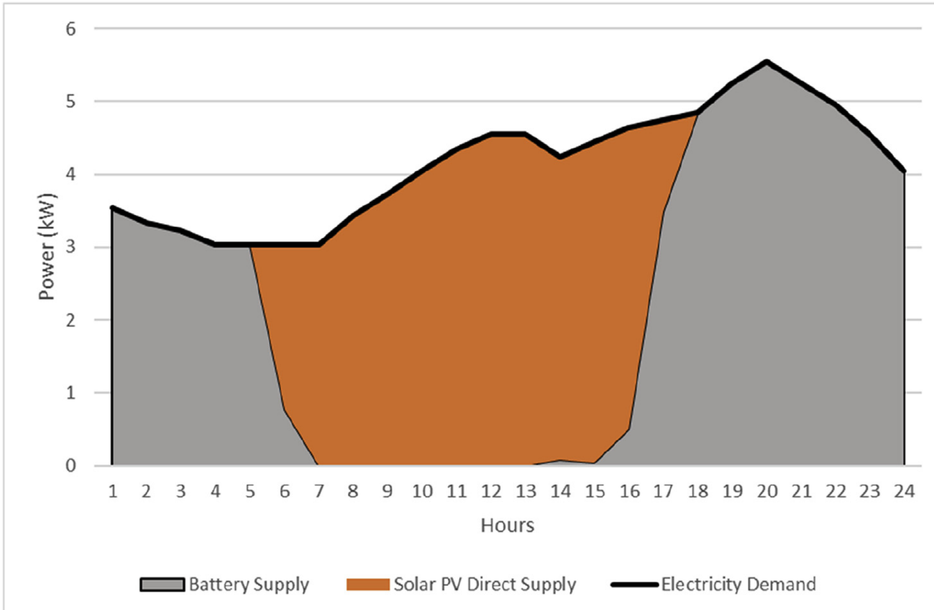



**Fig. 6.** The community's load curve for a typical day and the sources employed to meet the demand.

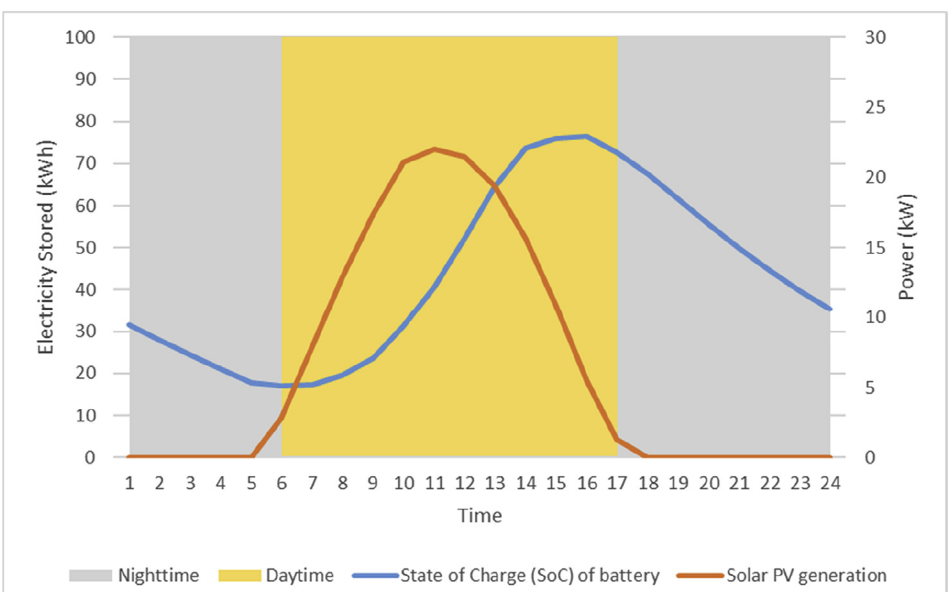



**Fig. 7.** Battery balance (charge and discharge phases).

described in the next section.

### 6.2. Robustness analysis

The results obtained through the proposed optimization model suggest a wide spectrum of energy solutions, which are based on solar panels with the support of batteries. In addition, different system component sizes are proposed depending on the analyzed scenario's characteristics (Fig. 8). There is a linear relation between the solar PV installation and the size of the battery storage system, which is due to the affordability of the scenario analyzed for electricity generation (high solar radiation levels and low electricity demand). That is, larger components are proposed for scenarios that are more difficult. The smallest possible energy system would consist of 22 kWp solar PV panels and 74 kWh of battery storage; at the other extreme, the boundary for the largest possible system is given by 29 kWp solar power and 93 kWh of battery storage. These solutions differ significantly in terms of costs.

Given the wide variability of our results, a robustness analysis was run to see how specific system configurations would respond to the worst-case scenario for electricity generation. The robustness analysis considered four configurations (options 1, 2, 3 and 4 in Fig. 8), which were chosen from the range of options from the optimization model. These four combinations were selected because they represent the extreme and midpoint energy

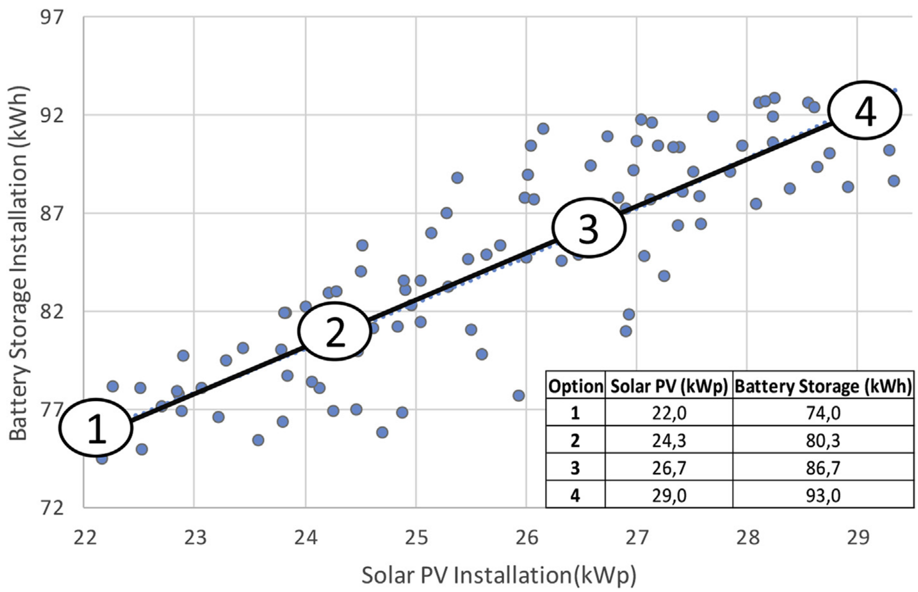



**Fig. 8.** Energy configurations chosen for the robustness analysis.

scenarios. The robustness approach calculates the electricity generated by these four energy configurations to identify blackouts or unmet demand. A reliable energy configuration is one with few or no blackouts in the worst-case scenario.

The robustness analysis results, that is, the percentage of the demand that could not be satisfied by each of the four system configurations, are shown in Fig. 9. As expected, the larger the energy configuration (option 4), the smaller the unmet demand. If the smaller energy configuration (option 1) were employed, then 10% of the demand would be unmet, whereas there would be significantly fewer blackouts if the largest system (option 4) were employed, for which just 0.11% of the demand was unmet. Interestingly, switching from option 1 to 2 halves the chance of a blackout event.

Note that the proportion of electricity supplied by the solar panels remains almost invariant along the four energy configurations, but the proportion of the demand covered by the battery system changes substantially from configuration 1 to configuration 4 (from 48.6% to 57.5%).

The most critical times of the day when, on average, each system configuration might not be able to meet demand are between 04.00 and 06.00, when the battery system is most likely to run out of electricity (Fig. 10). A larger battery installation, such as configuration 4, would reduce the chance of a power blackout.

The trade-off curve between the capital costs (capex) of the energy systems (*x*-axis) and the number of blackout events (*y*-axis) shows the extra costs required to reduce unmet demand (Fig. 11). As can be seen, switching from one system configuration to the next requires about an extra $US 12 to 15 thousand dollars. The number of power blackouts does not reduce proportionally. Thus,

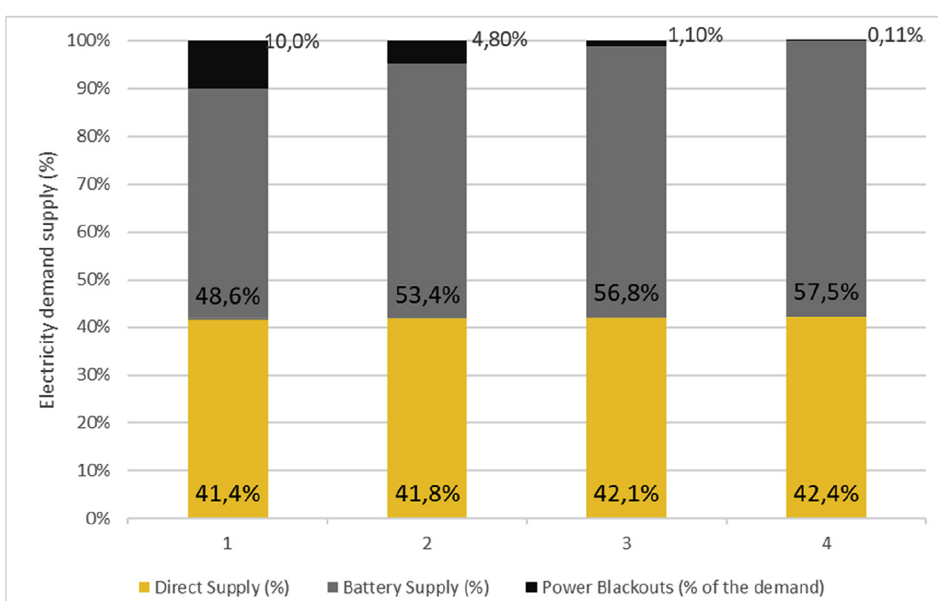



**Fig. 9.** Reliability of four system configurations to deal with a worst-case scenario: supplied and unmet demand.

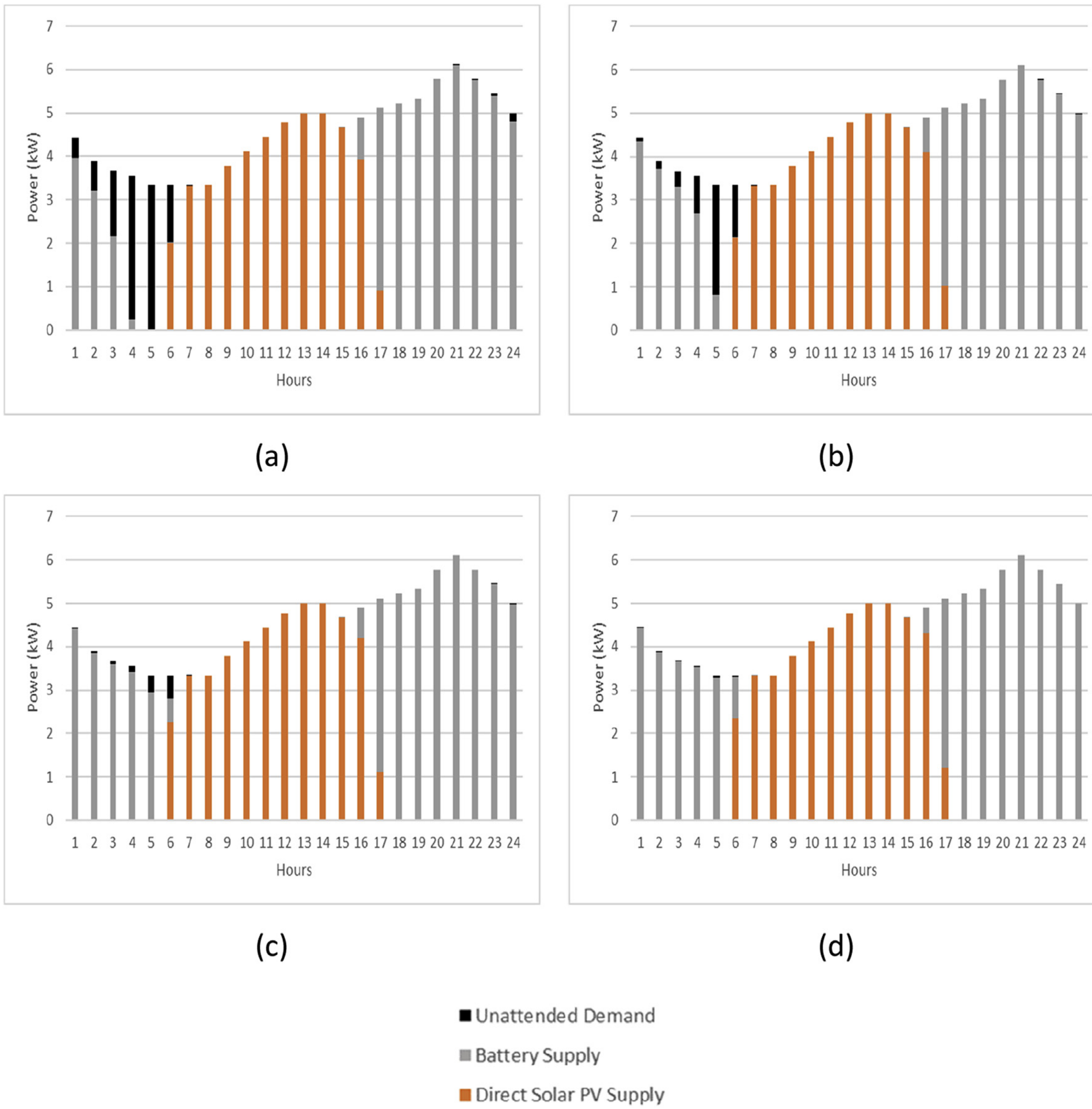



**Fig. 10.** Electricity demand met and unmet by each system configuration.
(a) Configuration 1, (b) configuration 2, (c) configuration 3, and (d) configuration 4.

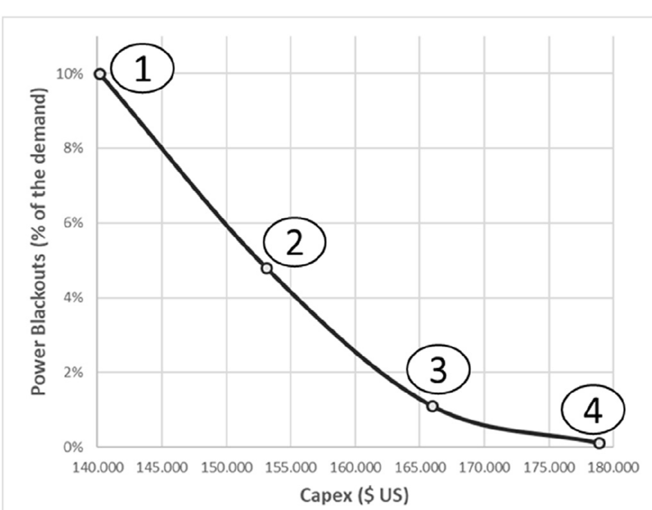



**Fig. 11.** Trade-off curve between capital costs and blackout events.

switching from configuration 1 to configuration 2 gives a 5% reduction in blackouts. Switching from configuration 2 to 3 gives a 3.5% reduction, and the reduction is less than 1% when changing from configuration 3 to 4. For a near 0% probability of a power blackout, the energy system would need to have a battery storage capacity of 94.5 kWh and a solar PV panel arrangement of about 34.7 kWp. The capital cost for such a system would be $US 192,250, which costs $US 52,050 more than the cheapest configuration.

## 7. Discussion

An optimization model was developed to support energy planning for off-grid communities. Using ISO, potential optimal answers were identified to improve energy access in rural and coastal communities that lack a reliable energy supply. In addition, these configurations' reliability have been evaluated using a robustness analysis.

One hundred different scenarios were analyzed for one community to account for the uncertainty inherent in this problem and, as a result, various system configurations emerged (Fig. 3). In all the scenarios considered, the solar PV option with battery storage was the most appropriate choice, while the diesel option was not selected for any scenario. Configuring a renewable-based energy system that combines solar PV technology with a battery storage system is particularly relevant for Colombia due to the availability of natural resources and off-grid communities' precarious economic conditions, which demand energy solutions requiring low operating and maintenance costs.

This work provides the technical evidence in favor of supporting the investment in alternative renewables to electrify off-grid communities in Colombia. However, a wider consensus from stakeholders on the potential benefits of modern renewable technology in isolated rural communities in Colombia is still to be achieved. Despite the existence of law 1715 of 2014, multiple social and policy barriers, as well as misconceptions, seem to have prevented a major adoption of alternative renewables in off-grid communities up to the present. The evidence provided in this paper supports the use of renewables in off-grid regions of Colombia. Appropriate tools to guide decision makers and policy makers, like the one developed here, may help the Colombian government achieve its renewable energy and $CO_2$ emissions targets. These targets relate to Sustainable Development Goal number 7: “assure access to affordable, reliable, sustainable, and modern energy for all” (Chirambo, 2018). It demonstrates that, besides the well-known environmental benefits of alternative renewable energy technologies, there are also potential economic benefits to off-grid communities where the choice procedure is conducted systematically and accounting for people's demand. The current research contributes to the global energy access and poverty reduction debate.

The operating costs of renewable energy technologies have reduced considerably – more so than what could have been expected ten years ago. Moreover, this study has highlighted that the photovoltaic technology in particular, and when backed up by battery for storage, is becoming cheaper than promoting the conventional diesel generators typically used in off-grid communities. This alone makes alternative renewables an attractive option for low-income communities who could eventually be relieved of the economic burden of buying and transporting diesel to generate electricity. However, the capital costs of renewable energy technologies are still higher than those of diesel generators. Colombia is committed through the 2010 Cancun Climate Agreement to targets of 6.5% (grid) and 30% (off-grid) electricity from renewable generation by 2020 (IEA, 2013). Consequently, further policies and incentives to support communities which are keen to install renewable energy may be necessary if Colombia's targets to are to be achieved by 2035.

## 8. Conclusion

This study points that, in the long-run, alternative renewables could be economically attractive when the technologies' capital and operating costs are both considered. The model proposed here, compared, on a purely economic basis, some of the different energy options available to the community of Playa Potes. It showed that a solar PV system, between 22 and 29 kWp, with a battery support, between 74 and 93 kWh, was always the best option for the community under all scenarios that have been explored. This combination of technologies provides a solution that is significantly cheaper for the community than the typical Diesel plats, because no fuel needs to be purchased and transported. This feature alone is key for the sustainability of the solution, since the economic burden of maintaining and operating the systems rests on the communities and nowhere else. In addition, the larger the system installed, the less likely that the service will be interrupted.

The ultimate choice of which energy configuration to choose rests on the policy makers or investors. Therefore, it is crucial that decision-makers are knowledgeable of tools like the optimization model developed and tested in a Colombian off-grid community and discussed here. When opting for a particular bundle of energy and battery to address energy demands, relevant stakeholders, such as the local authorities, investors, and aid agencies, should take into account constraints. Particularly uncertain are factors such as available budgets, atmospheric and climatic conditions, and the socio-economic activities that are expected to evolve within the community as a result of the new energy service provision, as well as decision-makers' own risk aversion.

In terms of future research, the model could be expanded to include multiple objectives representing other dimensions, such as the environmental, human, and social impacts (e.g., Cherni et al., 2007; Henao et al., 2012). This may further support the development of rural communities.

## Acknowledgments

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## Appendix 1. Model parameters

**Table A.1**
Technical parameters employed by type of technology.

| | |
|---|---|
| **Solar PV** (First Solar, Series 4™ PV Module) | |
| CAPEX | \$2.000 \$US/kW |
| Fix_Opex (% CAPEX) | 1.5% * 2000 = 30 \$US/Yr |
| Lifetime | 20 Years |
| Efficiency ($\eta^s$) | 0.153 |
| Area of the arrangement ($A_s$) | 0.72 $m^2$/kW |
| **Wind** (Allwindturbine, Hummer 10 KW Small Wind Turbine) | |
| CAPEX | \$1.800 \$US/kW |
| Fix_Opex (% CAPEX) | 5% * 1800 = 90 \$US/Yr |
| Lifetime | 20 Years |
| Air Density ($\rho$) | 1.3 kg/$m^3$ |
| Swept Area ($S^w$) | 50.27 $m^2$ |
| Efficiency of the technology ($\eta^w$) | 0.35 |
| **Hydropower** (Gupta et al., 2011b) | |
| CAPEX | \$2.000 \$US/kW |
| Fix_Opex (% CAPEX) | 5% * 2000 = 100 \$US/Yr |
| Lifetime | 30 Years |
| Density of water ($\rho$) | 1000 kg/$m^3$ |
| Acceleration due to gravity ($g$) | 9.81 m/$s^2$ |
| Efficiency of the technology ($\eta_{tg}$) | Depends on the case |
| **Diesel** (Hyundai 82HYMIG200) | |
| CAPEX | \$650 \$US/kW |
| Fix_Opex (% CAPEX) | 3% * 650 = 19.5 \$US/Yr |
| Variable_Opex | 0.8 \$US/kWh |
| Lifetime | 20 Years |
| Efficiency of the technology ($\eta^D$) | 0.85 |
| **Battery System** (Enersys. 2019. PowerSafe OPZ) | |
| CAPEX | \$1300 \$US/kW |
| Fix_Opex (% CAPEX) | 2% * 1300 = 26 \$US/Yr |
| Lifetime | 20 Years (Replace after 10 year) |
| Self-discharge Rate ($\sigma$) | 0.0000583 |
| Efficiency of the technology ($\eta_{bat}$) | 0.85 |
| Inverter's Efficiency ($\eta_{inv}$) | 0.92 |

## Appendix 2. Levelized Cost of Electricity

This section shows how the levelized cost of the electricity (LCOE) produced with the resulting optimal energy system throughout its lifetime is calculated (see NREL, 1995, 2019; Ghorbani et al., 2018).

1) First, the value of the objective function is equivalent to the total system cost (TSC):

$$TSC = \sum_i [capex_i + fix\_opex_i)] \times X_i + \sum_i \sum_t variable\_opex_i \times G_{i,t}$$

2) Then, the capital recovery factor (CRF) of the project can be estimated as follows:

$$CRF = \frac{d(1+d)^n}{(1+d)^n - 1}$$

where: $d$ is the discount rate. A typical value employed for rural energy projects is 3% (NREL, 1995); and $n$ is the lifetime of the project, which in this case is taken as 20 years.

3) Finally, the LCOE is calculated with the following equation:

$$LCOE = \frac{TSC}{Q} * CRF$$

where: $Q$ is the annual electricity output of the system.

## Appendix 3. Model calibration

This section describes the procedures followed to calibrate the equations of the optimization model. To do so, three separate cases were employed. Case I was used to calibrate the equations related to the solar PV technology, battery system and diesel generator (Eqs. (2), (5)–(10)); Case II was used to calibrate the equation related to the wind power technology (Eq. (3)); And Case III was used to calibrate the equation of the hydropower technology (Eq. (4)). The details of the cases are presented below:

**Case I.** IPSE (2013) reports the case of an off-grid community in Colombia, called Titumate, where a hybrid system was installed in 2011 to satisfy the community's demand for electricity. It consisted of a 105 kWp Solar PV system, a 902 kWh battery storage system, and a 100 kWp diesel generator. The case reports the system's average daily outputs and those values were used to assess the model's equations (Eqs. (2), (5)–(10)). The case reports that the average daily demand is equal to 601.4 kWh, where 195.9 kWh is supplied directly from the solar PV system, 252.3 kWh are stored and withdraw from the battery system, and 153.2 kWh are supplied by the diesel generator at the evening hours 19 to 22 (IPSE, 2013).

Table A.2 shows the generation of electricity with the three technologies available in Titumate, for a typical day, using the equations of the optimization model. The first column shows the hours of the day; the second column shows solar radiation data for Titumate - withdraw from NREL's satellite database (Habte et al., 2017); and the third column shows the generation of electricity with the solar panels (Eq. (2)). Column 4 shows the portion of the demand that is supplied directly by the solar panels (***$EL_t$***). Here equations (9) and (10) interact to define these values. The difference between columns 3 and 4 define the amount of electricity stored in battery system if enough storage capacity is available (***$EB_t$***). Equations (7)–(9) define the amount of electricity that is stored in the battery system. Column 5 shows the electricity that is withdraw from the battery system and used to meet the demand (***$GB_t$***). Here, equations (7), (8) and (10) intervene. Column 6 the contribution of the diesel generator to meet the demand (***$G_{D,t}$***). This is defined with equations (5) and (6) (upper bound) and 10. Finally, column 7 balances the supply with the demand, which is the role of equation (10).

The total electricity supplied by the model at the end of the day is equal to 601.3 kWh, where 196.7 kWh is supplied directly from the solar PV system, 251.5 kWh are stored and withdraw from the battery system, and the diesel generator supplies 153.2 kWh during the evening hours 19 to 22. These results were considered consistent with those reported by IPSE (2013).

**Case II.** Ma et al. (2014) present a techno-economic evaluation of a hybrid system located on a remote island in Hong Kong. The system combined three technologies: solar PV, wind power and batteries. The wind part of the study was taken to assess Equation (3) of the optimization model. The system has a 10.4 kWp of capacity and the case shows the wind speed data on January 1st, 2009 (see column 8 in Table A.2). These data was used to calculate the generation of electricity with Equation (3) (***$G_{w,t}$***). The case reports that the mean daily power generated during January 2009 was about 4.35 kW. Using just the data of January 1st, 2009, our model reports a mean power of 5.0 kW. Such value was considered congruent with the mean value reported by Ma et al. (2014).

**Case III.** Gupta et al. (2011b) present a case study of a rural village in India, called Pungarh, where a hydropower system is evaluated. The case calculates the potential for hydropower production, which depends on the creek's water inflow ($Q_t$) and height (ht). Equation (4) is employed to estimate the potential for the hydropower in this case. Table A.3 shows the application of Equation (4) in detail. The efficiency parameter $\eta_{tg}$ used is equal to 1, because the case only calculates the potential of the creek and no particular technology is defined to be installed. Gupta et al. (2011b) reports a hydropower potential of 4.2 kW. In our case, the value obtained was 4.12 kW, which was considered consistent with the case.

Table A.3 also shows, as an example, the application of Equations (2) and (3) to calculate the generation of electricity with the solar and wind technologies for the 12th hour of the day (see the row for the 12 h in Table A.2).

**Table A.2**
Calculations made using cases I and II for model calibration.

| (1) Hour | (2) Solar data ***$R_t$*** (kW/m2) | (3) Solar generation ***$G_{s,t}$*** (kW) | (4) Solar to load $EL_t$ (kW) | (5) Battery to load $GB_t$ (kW) | (6) Diesel to load $G_{D,t}$ (kW) | (7) Demand $D_t$ (kW) | (8) Wind data ***$W_t$*** (m/s) | (9) Wind generation ***$G_{w,t}$*** (kW) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 25 | 0 | 25 | 10 | 10 |
| 2 | 0 | 0 | 0 | 25 | 0 | 25 | 8.9 | 8.1 |
| 3 | 0 | 0 | 0 | 25 | 0 | 25 | 8.8 | 7.9 |

**Table A.2** (*continued*)

| (1) Hour | (2) Solar data $R_t$(kW/m2) | (3) Solar generation $G_{s.t}$ (kW) | (4) Solar to load $EL_t$ (kW) | (5) Battery to load $GB_t$ (kW) | (6) Diesel to load $G_{D,t}$ (kW) | (7) Demand $D_t$ (kW) | (8) Wind data $W_t$(m/s) | (9) Wind generation $G_{w.t}$ (kW) |
|---|---|---|---|---|---|---|---|---|
| 4 | 0 | 0 | 0 | 25 | 0 | 25 | 9.0 | 8.4 |
| 5 | 0 | 0 | 0 | 25 | 0 | 25 | 8.9 | 8.1 |
| 6 | 0.03 | 3.48 | 3.5 | 21.5 | 0 | 25 | 8.1 | 6.1 |
| 7 | 0.18 | 18.42 | 17.1 | 6.9 | 0 | 24 | 7.6 | 5.1 |
| 8 | 0.34 | 35.76 | 20.2 | 1.8 | 0 | 22 | 7.7 | 5.3 |
| 9 | 0.49 | 51.45 | 18.2 | 0.4 | 0 | 18.6 | 8.0 | 5.9 |
| 10 | 0.68 | 71.22 | 16.7 | 0.2 | 0 | 16.9 | 7.0 | 4.0 |
| 11 | 0.78 | 82.01 | 16.8 | 0.1 | 0 | 16.9 | 6.0 | 2.5 |
| **12** | 0.79 | **83.06** | 16.8 | 0.1 | 0 | 16.9 | 5.0 | **1.4** |
| 13 | 0.74 | 77.57 | 18.4 | 0.2 | 0 | 18.6 | 5.8 | 2.3 |
| 14 | 0.62 | 65.17 | 20.1 | 0.3 | 0 | 20.4 | 4.0 | 0.7 |
| 15 | 0.45 | 47.52 | 20.1 | 0.3 | 0 | 20.4 | 4.3 | 0.9 |
| 16 | 0.26 | 27.68 | 20.1 | 2.1 | 0 | 22.2 | 4.6 | 1.1 |
| 17 | 0.08 | 8.66 | 8.7 | 11.8 | 0 | 20.4 | 5.5 | 1.9 |
| 18 | 0 | 0 | 0 | 22.2 | 0 | 22.2 | 7.2 | 4.3 |
| 19 | 0 | 0 | 0 | 0 | 38.3 | 38.3 | 8.0 | 5.9 |
| 20 | 0 | 0 | 0 | 0 | 40.1 | 40.1 | 7.5 | 4.9 |
| 21 | 0 | 0 | 0 | 0 | 38.3 | 38.3 | 7.5 | 4.9 |
| 22 | 0 | 0 | 0 | 0 | 36.5 | 36.5 | 8.1 | 6.1 |
| 23 | 0 | 0 | 0 | 32.9 | 0 | 32.9 | 8.8 | 7.9 |
| 24 | 0 | 0 | 0 | 25.7 | 0 | 25.7 | 8.3 | 6.6 |

**Table A.3**
Detailed Application of Equations (2)–(4) (see row 12 columns 3 and 9 on table A.2).

**Solar generation** (application of Eq. (2))

Parameters used for a 1 kWp system: $A_s = 6.545\ m^2$; $\eta^s = 0.153$; $R_{12} = 0.79\frac{kW}{m^2}$; $X_s = 105$.

$G_{s.t} = (\eta^s A_s R_t) \times X_s$

$$G_{s.12} = 0.153 \times 6.545\ m^2 \times 0.79\frac{kW}{m^2} \times 105 = 83.06\ kW.$$

**Wind generation** (application of Eq. (3))

Parameters used for a 10 kWp system: $\rho = 1,3\frac{kg}{m^3}$; $S^w = 50,72\ m^3$; $\eta^w = 0,35$; $X_w = 10$; $W_{12} = 5.0\frac{m}{s}$.

$G_{w,t} = \left(\frac{1}{2}\rho S^w W_t^3\ \eta^w\right) \times X_w$

$$G_{w,12} = \frac{\frac{1}{2} \times 1,3\frac{kg}{m^3} * 50,72\ m^2 \times 0,35 \times 10 \times \left(5.0\frac{m}{s}\right)^3}{1000} = 1.4\ \frac{kg \times m^2}{1000 \times s^3} \sim 1.4\ kW$$

**Hydropower generation** (application of Eq. (4))

Parameters used: $\rho = 1000\frac{kg}{m^3}$; $g = 9.81\frac{m}{s^2}$; $ht = 7\ m$; $Q_t = 0.06\frac{m^3}{s}$ ; $X_H = 1$.

$G_{H,t} = (\rho \times g \times Q_t \times ht \times \eta_{tg}) \times X_H$

$$G_{H,t} = \frac{1000\frac{kg}{m^3} \times 9.81\frac{m}{s^2} \times 0.06\frac{m^3}{s} \times 7\ m \times 1}{1000} = 4.12\ \frac{kg \times m^2}{1000 \times s^3} \sim 4.12\ kW$$

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