Article

The Impact of Policy and Technology Parameters on the Economics of Microgrids for Rural Electrification: A Case Study of Remote Communities in Bolivia

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Abstract: Throughout the developing world, most remote and isolated communities are still without reliable electricity in the twenty-first century, and this is primarily due to the high cost of grid extensions. In communities that do have electricity, they usually rely on diesel generators, though these have high operating and maintenance costs, while also polluting the environment. A more sustainable approach is to deploy microgrids, however, microgrids have a high upfront cost, which is a major obstacle, especially in rural areas of developing countries. This study aims to investigate the parameters that can be influenced to make microgrids more economical for rural electrification. Through sensitivity analyses, five key policy and technology parameters were identified. They include real discount rates, diesel prices, grants, battery chemistry, and operating strategies. The system was then redesigned using scenarios formulated by varying these parameters. Results show that the parameters affect the configuration, levelized cost of energy (LCOE), renewable energy penetration (REP), and pollutant emissions. The study uses three remote communities in the Beni Department of Bolivia as case studies. MDSTool was used as a modeling framework to design the microgrids. The unique insights and lessons learned during the design process are discussed at length because these may be valuable for future microgrid designs for remote communities.

Keywords: microgrid; renewable energy; rural electrification; remote communities; energy policy

1. Introduction

The benefits of rural electrification are well-documented in the literature [1] and include economic, health, educational, social life, and environmental benefits. The economic benefits include an increase in the number of enterprises in the newly-electrified communities, as reported in Bolivia [2]. In a similar study in [3], the enterprises operated by rural households in Indonesia increased by 43% after gaining access to electricity. The health benefits of having reliable electricity were reported in [4], where 35% of newly solar-electrified households in rural Namibia reported an improvement in health [4]. Electrified communities will use less kerosene for lighting and cooking, which, in turn, was noted to reduce fire accidents [5] and prevent health conditions such as lung disease and poisoning [6]. Access to electricity has also been widely reported to immensely benefit education. For example, the primary school completion rate more than doubled for households with access to electricity in rural Nicaragua [7], and similar findings were reported in Vietnam [8] and South Africa [9]. Access to electricity may improve social interactions. Villagers in rural Zambia have greater access to news outside of their community through TV and radio as a result of having reliable access to electricity [10], and another study in Kenya had similar conclusions [11].

Despite these benefits, however, more than one billion people, or about 13% of the world's population, do not have electricity in the 21st century [12]. The United Nations SDG7 calls for universal access to electricity by 2030 [13]. If the current population trends and policies continue, this target will not be achieved; it is currently estimated that up to 674 million people will still be without electricity by 2030 [14]. The majority of these populations live in Sub-Saharan Africa, Latin America, and South Asia. They are mostly living in remote areas far away from the central grid, thereby making grid extensions economically infeasible. The installation of diesel generators can be a quick way to provide electricity to these communities. However, the high fuel price, significant operation and maintenance cost, and the rising concern regarding pollutant emissions are some of the factors making this approach unpopular.

A more sustainable approach is to deploy microgrids that use renewable energy sources (RES), such as solar photovoltaic (PV) and wind turbines (WT) [15]. Microgrids can significantly reduce operation and maintenance costs, are more sustainable, and produce less harmful emissions, among other benefits [16]. However, the considerable upfront cost and risks associated with renewable energy investments are the main obstacles to their widespread adoption in these communities [17]. To overcome these obstacles, various rural electrification initiatives were undertaken in developing countries, with mixed results. Some of these initiatives include Lighting Africa [18] in Sub-Saharan Africa, *Luz para todos* ("Light for all") in Brazil [19], and the IDCOL program in Bangladesh [20,21], among many others [22].

This study aims to find the parameters that most affect the microgrid investment for rural electrification. Through sensitivity analyses, five key policy and technology parameters were identified that most affect the optimal design of remote microgrids. Scenario analyses were used to find the impacts of these five parameters on the configuration, levelized cost of energy (LCOE), renewable energy penetration (REP), and pollutant emissions.

The study was conducted by designing microgrids in three rural communities located near the Bolivia-Brazil border in the Amazon, all located in the Beni Department of Bolivia. The three communities were visited by the authors of this study for data collection and site assessment. This visit was one of the crucial elements of this research, as most studies about remote microgrids (reviewed in the next section) rely solely on estimated data, which may not accurately reflect the real situations faced by communities. MDSTool was used as a modeling framework for the design [23].

In summary, this study has the following main contributions:

- We offer a model that uses various operating strategies to simulate the annual operation of remote microgrids, enabling the study of the impacts that different parameters have on the optimal design of remote microgrids.
- We analyzed case studies of three remote communities in Bolivia, making our findings more rigorous. Unlike grid-connected microgrids, where the site characteristics can differ significantly due to different utility tariffs, local ancillary services, and various regulatory and policy differences (i.e., net metering and demand response), remote microgrids have fewer site differences. Therefore, the conclusions in this study can be easily extended to other remote microgrids in different locations.
- Through sensitivity analyses, we identified five key policies and technological parameters that had the most impact on the design of remote microgrids. Detailed scenario analyses were used to find the effects of these parameters on the configuration, LCOE, REP, and pollutant emissions.

The rest of the paper is structured as follows: Section 2 presents a literature review on the feasibility analysis of microgrid in remote communities. In Section 3, we introduce the design methodology and introduce the modeling tool. The case studies are introduced in Section 4. Results and discussion are presented in Section 5. The paper concludes in Section 6.

2. Related Work

A thorough review of the available literature on the feasibility of microgrids in remote communities was presented in this section. The review was completed to identify the knowledge gap and develop

supporting arguments. The reviewed studies are from various developing countries from all regions of the world, conducted in the last two decades. All the reviewed studies follow either optimization-based approach or simulation-based approach to microgrid design. The optimization-based approach uses an optimization model to find the optimal sizes of DERs in the microgrid. On the other hand, a simulation-based approach finds the optimal DERs sizes by using performance and economic model to simulate the operation and economics of the system, respectively.

The studies that follow the optimization-based approach can be found in [24–28]. They mostly use mixed-integer linear programming (MILP) to solve the optimization problem. In [24], Ho et al. proposed the concept of integrating solar and biomass for electrifying remote communities in tropical countries. The feasibility of microgrids in three villages in Cape Verde was presented in [25]. The three communities were Figueiras, Ribeira Alta, and Achada Leite. The technologies considered included solar PV, WT, and diesel generators. In [26], a model was formulated using MILP to design a microgrid for a cluster of eight remote communities in Narendra Nagar, which is located in Uttarakhand, India. In [27], the MILP model was formulated to solve the integrated problem of sizing and scheduling. This method was verified using the case study of a microgrid for remote industrial facility comprising PV, WT, diesel generators, and BES. In [28], the authors developed a MILP model to design a microgrid containing solar PV and WT in Alto Peru and El Alumbre, both in Peru.

The majority of the studies follow the simulation-based approach to microgrid design. The authors in [29] designed a microgrid in Siyambalanduwa, which is a remote community in rural Sri Lanka. It has 150 households with average daily electricity consumption of 270 kWh. A microgrid was designed in [30] for a remote area in Jaunpur, India. The optimal system was found to be solar PV, WT, and biomass. Authors in [31] simulated various configurations of DER technologies in the remote communities of Cameroon. The technologies considered included micro-hydro, liquefied petroleum gas (LPG) generator, solar PV, and BES. A solar PV and diesel system was designed for 12 small- to medium-size remote communities in the province of Jujuy, Argentina [32]. The design of a microgrid in the rural area of Uttarakhand, India, was presented in [33]. The authors considered various DER technologies, including solar PV, BES, biomass, biogas, diesel, and small micro-hydro. Five un-electrified remote communities were chosen as case studies. The authors in [34] designed a microgrid for a small rural community in Patiala, Punjab, India. It comprises solar PV, WT, BES, and biomass. An artificial bee colony algorithm was used to solve the sizing problem and the results are compared with that obtained from HOMER software. In [35], the study designed a microgrid in a remote community, Rowdat Ben Habbas, in the northeastern region of Saudi Arabia. The system was comprised of solar PV, BES, and diesel generators. The authors in [36] designed a microgrid consisting of solar PV, WT, and BES for an isolated community in Iran. To solve the optimal sizing problem, they used various evolutionary and heuristic algorithms. The authors in [37] assessed the economic feasibility of micro-hydro, solar PV, and BES microgrids for rural electrification. In the study, they investigated the main economic barrier for private sector investment in rural electrification, with the main emphasis on Indonesia. Authors in [38] designed a microgrid comprising solar PV, WT, and small-hydro in rural Nepal. The study was conducted using measured meteorological data at the site and the implementation was tested experimentally. The authors of the study presented in [39] evaluated the use of solar PV, fuel cell, and BES for a remote community in the state of Tocantins, in the Amazon region of Brazil. In [40], the authors designed a microgrid comprising solar PV, WT, and BES in Potou, a remote community on the northern coast of Senegal. The authors in [41] proposed a sizing methodology for microgrids using hybrid solar PV/WT, diesel generators, and BES. In [42], the authors investigated the economic feasibility of various microgrid configurations in four remote communities in Bhutan. The optimal configuration varied across the locations, which was mainly due to the different demand patterns and RES at each location. In [43], the authors proposed a Renewable Energy Premium Tariff as a form of incentive to develop a renewable energy system for remote communities in Ecuador. A feasibility study of a microgrid comprising solar PV, BES, and diesel generators for a remote community in south-east Algeria was conducted in [44]. In [45], a microgrid-sizing methodology was

proposed to size a system comprising solar PV, BES, and diesel generators. The proposed method was applied toward designing a microgrid at a remote community in Alaminos, Philippines. A feasibility study for a microgrid was investigated in [46], where solar PV, WT, diesel generators, and BES were applied in the remote area of Ras Musherib, in the western part of Abu Dhabi. In [47], the authors considered social constraints to design a microgrid in Alto Peru, a remote community located in the Cajamarca region of Peru. The authors in [48] introduced some improvements in microgrid designs for remote communities by considering factors such as various energy storage technologies. They applied the approach to design a microgrid in the remote community of Ain Beida, Morocco. In [49], the authors proposed a sizing methodology of a microgrid for rural electrification using the levelized cost of supplied and lost energy.

Other authors, in addition to feasibility studies, also perform sensitivity analysis. In [50], the authors designed a hybrid solar PV and diesel generator system in the rural area of northern Nigeria. They performed sensitivity analyses to find the effect capital cost and the discount rate on the levelized cost of energy (LCOE). A feasibility analysis was conducted in [51] for a microgrid for a remote community in northern Ghana. Various sensitivity analyses were performed for solar irradiance, wind speed, and diesel prices. In [52], they designed and analyzed a microgrid for a remote community in Bangladesh. The microgrid comprises solar PV, WT, BES, and diesel generators. The impact of fluctuation in solar irradiance, wind speed, and diesel price on the design was investigated using sensitivity analysis. In a similar study, authors in [53] designed a microgrid in a remote community in Bangladesh. It was made of solar PV and diesel generators. The impact of government subsidies, inflation, and fuel price escalation were investigated using sensitivity analyses as well. The study in [54] investigated the economic feasibility of microgrids for a remote community in Ethiopia. The influence of solar PV cost, diesel price, and wind speed were investigated through sensitivity analysis.

All the reviewed studies in this section focused their studies on the feasibility of microgrid for rural electrification, without investigating the impact of policy and technology parameters on the microgrid investment. Even though some studies perform sensitivity analysis [50–54], they do not perform scenario analysis to investigate the effect on the optimal design. It is one of the objectives of this study to narrow this gap in the literature.

3. MDSTool Model Formulations

3.1. MDSTool Overview

The MDSTool is a decision support model for the optimal design of microgrids. The main aim of the model is to find the optimal sizes of DERs, to determine the economic feasibility, and to evaluate energy performance. In addition, various analyses can be performed, such as sensitivity and scenario analyses. The inputs to the MDSTool include detailed hourly load demand and weather resources for a complete year, DER parameters, costs, and finance/incentives information. The outputs of the model are microgrid optimal sizes, its economics, and its energy performance. The tool follows a simulation-based approach to microgrid design. It consists of two sub-models: a performance model and an economic model. The performance model simulates an annual operation of various configurations of the microgrid to determine their technical feasibility. The economic model calculates cash flow (benefits and expenses) of all feasible configurations throughout the analysis period. The feasible configurations are then sorted using an evaluation metric to obtain the optimal configuration. The simplified architecture of MDSTool is shown in Figure 1.

3.2. MDSTool Performance Model

In the performance model, various microgrid configurations were generated. The annual operation of each configuration was then simulated using an operating strategy. All of the simulated configurations were then subjected to a feasibility test, using various reliability metrics. The configurations that passed

the feasibility test were passed on to the economic model for economic analysis. In the following section, the objective function, operating strategies, and reliability metrics are described.

Figure 1. The simplified architecture of MDSTool. Refer to the nomenclature table for the key to acronyms, variables, and abbreviations in the figure.

3.2.1. Objective Function

In the performance model, economic dispatch and unit commitment problem has to be solved to select the combination of DERs which meets the required power at the minimum operating cost while satisfying operation constraints. The operating cost, J , given by Equation (1):

$$J = J_t^{GRID} + J_t^{ESS} + J_t^{DG} \quad (1)$$

where J^{GRID} , J^{ESS} , and J^{DG} denote the grid, storage, and generator cost functions, respectively. Note that even though a diesel generator (DG) is used in this study, the generator generally can be an internal combustion generator that burns any type of fuel.

(1) Grid cost function

The grid cost function accounts for the cost of purchasing power from the grid and the revenue obtained from selling power to the grid:

$$J_t^{GRID} = \Phi^{PUR} \cdot p_t^{PUR} - \Phi^{SALE} \cdot p_t^{SALE} \quad (2)$$

where Φ^{PUR} and Φ^{SALE} are the grid purchase and sale rate in \$/kWh, respectively, and p^{PUR} and p^{SALE} are the grid purchase and sale power in kW, respectively.

(2) Storage cost function

The cost function of ESSs accounts for the degradation and charging costs. The charging cost is the cost of charging the ESS; this can be done by either generator or by purchasing power from the grid. The charging cost is zero if the ESS is charged using renewable energy (PV, WT, etc.) because no additional costs are incurred, unlike charging with a generator or grid, where fuel cost and grid charges applied:

$$J_t^{ESS} = \left[\frac{\Phi^{ESS,REP}}{Q_{ESS} \times N_{ESS} \times \sqrt{\eta_{RTE}}} + \frac{\sum_{t=\Delta t}^{t-1} \Phi_t^{ESS,CH}}{\sum_{t=\Delta t}^{t-1} p_t^{ESS,CH}} \right] \cdot p_t^{ESS,DC} \quad (3)$$

where $\Phi^{ESS,REP}$ is the ESS replacement cost in \$/kWh, Q_{ESS} is the ESS throughput in kWh, N_{ESS} is the number of ESSs in the ESS bank, η_{RTE} is the ESS round-trip efficiency, $\Phi_t^{ESS,CH}$ is the ESS charging cost in \$/kWh, $P_t^{ESS,CH}$ is the ESS charge power in kW, and $P_t^{ESS,DC}$ is the ESS discharge power in kW.

(3) Generator cost function

The operating cost of a generator has two parts: fixed costs and variable costs. The fixed cost is the cost per hour of running the generator. The variable cost is the cost per kWh of producing power from the generator. Fixed cost is calculated as shown below:

$$\Phi^{GEN, FIX} = \Phi^{GEN, O\&M} + \frac{\Phi^{GEN, REP}}{N_{GEN}} + q_0 \times P^{GEN, RTD} \times \Phi^{GEN, FUEL} \quad (4)$$

where $\Phi^{GEN, O\&M}$ is the generator operation and maintenance cost in \$/kW/h, $\Phi^{GEN, REP}$ is the generator replacement cost in \$/kW, N_{GEN} is the generator lifetime in hours, q_0 is the fuel curve intercept in l/h, $P^{GEN, RTD}$ is the generator rated power in kW, and $\Phi^{GEN, FUEL}$ is the fuel price in \$/l. The variable cost is calculated as shown below:

$$\Phi^{GEN, VAR} = q_1 \times \Phi^{GEN, FUEL} \quad (5)$$

where q_1 is the fuel curve slope in l/h/kW. The generator cost function is then given as the summation of the fixed and variable costs:

$$J_t^{GEN} = \Phi^{VAR} \cdot P_t^{GEN} + \Phi^{GEN, FIX} \quad (6)$$

Where P^{GEN} is the generator output power in kW.

The objective function in Equation (1) is subject to the following constraints:

- Power balance constraints ensure that the total power produced in the microgrid is equal to the total power consumed.

$$P_t^{LOAD} = \sum_j P_{j,t}^{OUT} + P_t^{PUR} - P_t^{SALE} \quad (7)$$

where P^{LOAD} is the load demand, P^{OUT} is the output power of DER technologies, both RESs and non-RESs, j is the index of DER technologies. Power loss is assumed to be negligible and therefore not included in the above equation. This assumption is widely adopted in microgrid due to the small size of the distribution network.

- Operation constraints ensure that all DERs operate within their minimum and maximum power, and that grid purchase and sale do not exceed their maximum limits:

$$P_j^{\min} \leq P_{j,t}^{OUT} \leq P_j^{\max} \quad (8)$$

$$P_t^{PUR} \leq P_t^{\max PUR}, P_t^{SALE} \leq P_t^{\max SALE} \quad (9)$$

- Ramp-up/ramp-down constraints ensure that all DERs do not increase or decrease power beyond their ramp-up/ramp-down limits:

$$P_{j,t+1}^{OUT} - P_{j,t}^{OUT} \leq RU_j^{\max} \quad (10)$$

$$P_{j,t}^{OUT} - P_{j,t+1}^{OUT} \leq RD_j^{\max} \quad (11)$$

3.2.2. Operating Strategy

The operating strategies can be broadly classified according to whether the forecast is considered or not. They can be non-forecast-based or forecast-based strategies.

(1) Non-forecast based (NFB) strategy

In an NFB strategy, a unit commitment and economic dispatch were solved at each time step of the simulation, without considering future events. The most widely used NFB strategies are load-following (LF) and cycle-charging (CC), developed in [55]. In the LF strategy, the ESS is charged using RES only, unless the generator is operating below its minimum power. The LF strategy can be subcategorized according to how primary control (voltage/frequency control) is achieved. If the ESS and generator control the voltage/frequency by coordinating as a master/slave, then this is termed load-following off (LF-OFF). Whereas if only the generator is used to control the voltage/frequency, then it will always be running, and this is termed load-following on (LF-ON). In the CC strategy, whenever the generator is in operation, it is used to charge the ESS up to a particular state of charge. A comprehensive description of these strategies is available in [55].

(2) Forecast-based (FB) strategy

The FB strategy operates the system by considering future events. This is possible by using a forecast of the load demand, renewable power, and energy prices. If the forecast is assumed to be perfect, then this strategy will result in the most economical operation. However, in practical application, the forecast will not be perfect, and the forecasting errors will reduce the accuracy of the dispatch. In other words, the advantage of the FB operating strategy depends on the accuracy of the forecasting algorithm.

3.2.3. Reliability Metric

The intermittency of RES, along with the fluctuating power demand will affect the power balance of the microgrid; therefore, evaluating microgrid reliability is necessary. The most widely used metric is the loss of power supply probability (LPSP). The LPSP is the probability that an insufficient power supply will result when the microgrid cannot satisfy the load [56]:

$$LPSP = \frac{\sum_t LPS_t}{\sum_t P_t^{LOAD}} \quad (12)$$

Other metrics used to evaluate microgrid reliability include loss-of-load-probability (LOLP) and unmet load. Reference [57] gave the recommended values of these metrics. These reliability metrics are used in the performance model to select feasible configurations.

3.3. MDSTool Economic Model

All of the feasible configurations simulated in the performance model were subjected to an economic analysis by calculating their cash flow throughout the analysis period. An evaluation metric was then used to select the optimal configuration.

3.3.1. Cash Flow

The economic model of MDSTool uses cash flow analysis to calculate the microgrid pre-tax and after-tax cash outflow (expenses) and cash inflow (revenue).

The pre-tax cash outflow is composed of the costs associated with installation, operation and maintenance (O&M), replacement, fuel, electricity charge cost of utilities, insurance, property tax, and emission penalties. The only cash outflow in year zero is the project equity (F_0^{OUT}), defined as a part of an investment that was directly financed with a down payment:

$$F_0^{OUT} = C^{INSTALL} \cdot (1 - f_d) \quad (13)$$

where $C^{INSTALL}$ is the total install cost, and f_d is the debt fraction.

The cash outflow for subsequent years includes all expenses incurred during the lifetime of the microgrid. The pre-tax cash outflow (F_n^{OUT}) for analysis year n was computed using Equation (14):

$$F_n^{OUT} = C^{O\&M} \cdot (1+r)^n + C^{REP} \cdot (1+r)^{N_j^{REP}} + C^{PUR} \cdot (1+r+\varphi^{GRID})^n + C^{FUEL} \cdot (1+r+\varphi^{FUEL})^n + C^{INS}(1+r)^n + C^{PRT} \cdot [1 - \varphi^{PAV} \cdot (n-1)] + C^{EMP} \cdot (1+\varphi^{EMPR})^n \quad (14)$$

where $C^{O\&M}$ is the annual operation and maintenance cost, C^{REP} is the replacement cost, C^{PUR} is the annual grid purchased, C^{FUEL} is the annual fuel cost, C^{INS} is annual insurance cost, C^{PRT} is the annual property tax, C^{EMP} is the annual emission penalty, r is the inflation rate, and φ is the escalation rate.

Pre-tax cash inflow in year zero (F_0^{IN}) was equal to investment-based incentive (IBI):

$$F_0^{IN} = C^{IBI} \quad (15)$$

In subsequent years, the pre-tax cash inflow (F_n^{IN}) included all of the microgrid's revenue as follows:

$$F_n^{IN} = C^{PBI} \cdot (1+\varphi^{PBI})^n + C^{SALE} \cdot (1+r+\varphi^{GRID})^n + C^{EMRC} \cdot (1+\varphi^{EMRR})^n \quad (16)$$

where C^{PBI} is the production-based incentives, C^{SALE} is the annual revenue from grid sale, and C^{EMRC} is the annual emission reduction credits.

At the end of the analysis period, N , the salvage value was added to the right-hand side of Eq. (12). The total pre-tax cost (F^{PTC}) was the net difference between pre-tax cash inflow (F^{IN}) and cash outflow (F^{OUT}). The total pre-tax cash flow (F^{PTCF}) was the net difference between pre-tax cash inflow and cash outflow, including the value of energy savings ($C^{SAVINGS}$), as a result of microgrid deployment. The F^{PTC} was used to calculate the pre-tax cost metric used for optimal sizing analysis. The F^{PTCF} was used to calculate pre-tax capital budgeting metrics for the financial feasibility analysis:

$$F_n^{PTC} = F_n^{IN} - F_n^{OUT} \quad (17)$$

$$F_n^{PTCF} = F_n^{PTC} + C^{SAVINGS} \cdot (1+r+\varphi^{GRID})^n \quad (18)$$

3.3.2. Evaluation Metric

Several evaluation metrics can be used to select the optimal configuration. These can be economic, environmental, and/or reliability metrics. The metric used in this study was the LCOE. The LCOE is the ratio of all the costs that occur during the lifetime of the microgrid to the useful energy generated during the lifetime of the microgrid, all discounted to the current year.

4. Case Study

4.1. Descriptions of the Communities

Three remote communities were selected as case studies for the design of remote microgrids, including Cachuela Esperanza, Rosario del Yata, and Villa Bella. All of these communities are located in the Beni Department of Bolivia, near the border with the Republic of Brazil, in the middle of the Amazon. The department contains the most remote dwellings in the country and, therefore, this area is one of the most difficult ones to electrify. In May 2019, the authors visited all three communities to conduct socio-economic surveys, study the existing systems, interview community groups, and meet local authorities. Currently, diesel generators power all of the communities. Table 1 summarizes the basic information obtained from the communities.

Table 1. Location of the communities.

Location Information	Cachuela Esperanza	Rosario del Yata	Villa Bella
Latitude	10°32′13″ S	10°59′34″ S	10°23′47″ S
Longitude	65°34′52″ W	65°34′43″ W	65°23′31″ W
Households	150	116	48
Population	800	540	200

Cachuela Esperanza is situated on the Beni River, 30 km before its confluence with the Mamoré River. These rivers form the Madeira River there. The population of the community was 800 people living in 150 households, at the time of the investigation. Rosario del Yata is part of the Guayaramerin municipality in the province of Vaca Díez. It has a population of 540 people living in 116 households.

There are 15 commercial buildings and two government buildings in this community. Villa Bella is a small community located in northern Bolivia, near the border with Brazil. It has a total population of 200 people living in 48 households. Among these households, only 28 were connected to the electricity supply. The main economic activities of these communities include fishing, hunting, cattle raising, and agriculture. Figure 2 shows the locations of these communities.

Figure 2. Location of Cachuela Esperanza, Rosario del Yata, and Villa Bella. Source: Google Maps.

4.2. Electricity Demand Assessment

Detailed electricity demand data are perhaps the most critical data required for hybrid energy system design. However, the data are often unavailable in remote communities. In most cases, a survey is used to create the data, but the accuracy of this method has been questioned by many researchers [58,59]. Therefore, a survey approach was not used in this study. During the site visits, the authors obtained a detailed, hourly load profile of several days of May 2019. The data were complemented with additional information acquired from the local utility company, Empresa Nacional de Electricidad, to create the demand profile for other months. Two additional criteria were considered for creating load profiles: seasonal differences and future load growth. The climate of Bolivia has two seasons, the rainy season and the dry season. The climate is hot and humid, and it is characterized by heavy rainfall caused by winds blowing from the Amazon rainforest. Therefore, the load was scaled to be higher in the rainy and hot season for six months (October to March) and lower in the dry season

for the other six months (April to September). The demand during the rainy and hot season was higher than during the dry season, due to the more frequent usage of lighting and fans because of the higher temperatures and humidity. The obtained load profiles show peaks during the early hours of the day, before the start of school and other commercial activities, as well as high demand in the afternoon and another peak toward the end of the day. Future load growth was considered after the initial deployment of the microgrids. This is important because many microgrids report explosive load growth after initial deployment. An example of this includes microgrids on Dongfushan Island, Beiji Island, and Nanji Island, which are all located in the East China Sea [60]. For this reason, the load was scaled up by 25%. Table 2 summarizes the average load, peak load, load factor, and the total annual load of the three communities.

Table 2. Summary of the electricity demand of the communities.

Parameter	Cachuela Esperanza	Rosario del Yata	Villa Bella
Peak demand (kW)	72	54	27
Min. demand (kW)	24	14	8
Avr. demand (kW)	47	27	14
Load factor	0.67	0.50	0.52
Ann. average (kWh/day)	1,138	643	336

4.3. Weather Resources Analysis

To estimate the energy production from the solar PV, Global Horizontal Irradiance (GHI) data are required. GHI is the total irradiance from the sun that falls on a horizontal surface on Earth. The data were obtained from the database of NASA Surface Meteorology and Solar Energy [61]. The location of the communities is about 300 meters above sea level, which makes the solar radiation lower in comparison to other regions of Bolivia, which can be as high as 5,000 meters above sea level. The monthly average GHI and clearness index of the region are shown in Figure 3.

Figure 3. Monthly average GHI and clearness index.

4.4. DER Technical Parameters

The DER technical parameters were required to conduct performance simulations. The parameters were taken from manufacturer datasheets. The PV module was monocrystalline technology. In selecting the BES technology, factors such as technological maturity, economy, safety, and environmental impacts were considered. Lithium nickel manganese cobalt oxide (NMC) was selected in this study due to its several advantages over other battery chemistries. The NMC batteries have a high rate of discharge, good round-trip efficiency, long lifetime, and a low self-discharge rate. The parameters of all the DER are summarized in Table 3.

Table 3. Technical parameters of DER technologies.

Parameters	Value	Units
<i>Photovoltaic</i>	-	-
Module power	370	Wdc/module
Nominal efficiency	19.0	%
Max. power voltage/current	39.8/9.29	Vdc/Adc
Lifetime	25	yr.
<i>BES</i>	-	-
Type	Li-ion	-
Chemistry	NMC	-
Round-trip efficiency	95	%
Depth of discharge	90	%
Lifetime (throughput)	2,000	kWh/1 kWh
Lifetime (calendar)	12	Yr.
<i>Converter</i>	-	-
Rated AC frequency	50	Hz
European weighted efficiency	98.0	%
CEC weighted efficiency	98.2	%
Lifetime	12.5	yr.
<i>Diesel generator</i>	-	-
Minimum load ratio	25	%
Engine speed	1,500	RPM
Frequency	50	Hz
Lifetime	60,000	Hours

4.5. DER Costs

The International Renewable Energy Agency (IRENA) has compiled a dataset of solar PV and BES installation costs for commercial and utility-scale projects [62]. The DER costs of this database are used in this study, which is broken down as follows: hardware costs, installation costs, and soft costs. In addition, there are control and monitoring costs, which are estimated to be \$100,000 for each microgrid. These costs are summarized in Table 4.

Table 4. Costs of DER technologies.

Parameters	Value	Units
<i>Photovoltaic</i>	-	-
Capital cost	1,500	\$/kW
O&M cost	10	\$/kW/yr
<i>BES</i>	-	-
Capital cost	420	\$/kWh
O&M cost	10	\$/kWh/yr
Replacement cost	200	\$/kWh
<i>BSS inverter</i>	-	-
Capital cost	200	\$/kW
Replacement cost	200	\$/kW
<i>Diesel generator</i>	-	-
Capital cost	500	\$/kW
O&M cost	0.03	\$/kW/hr
Replacement cost	500	\$/kW
Fuel cost	1.41	\$/l
Control & monitoring	100,000	\$

4.6. Financial Parameters and Assumption

A discount rate is one of the key parameters in any economic analysis. It is required to discount the future cash flow back to the investment year. Many factors affect the choice of a discount rate, among which are the interest rate, investor's rate of return, analysis period, and risk premium, among others [63]. IRENA uses 7.5% for the Organization for Economic Cooperation and Development countries and China and 10% for the rest of the world as a real discount rate for evaluating renewable energy investment [64]. Considering that Bolivia is a developing country, a real discount rate of 10% was used in this study. This value is corroborated by the Bolivian Electricity Law, which states that the electricity sector shall use a real discount rate of 10% [65].

5. Results and Discussion

5.1. Cases and Scenarios Definition

Three types of analyses were performed. The first was the base case analysis, presented in Section 5.2. The base case system was simulated using the parameters described in the previous section. The second was a sensitivity analysis, presented in Section 5.3, where the impacts of various policy and technology parameters were investigated. This analysis was performed by keeping the optimal sizes of the DERs in the base case fixed. Therefore, the analysis does not produce other design alternatives, but rather, it shows the impact of varying the selected parameters on the economics of the system (LCOE). Lastly, scenario analyses were presented in Section 5.4. Scenario analysis aims to explore the impacts of the most sensitive policy and technology parameters on configuration, LCOE, REP, and pollutant emissions. Note that the parameters used for scenario analyses were the most sensitive parameters identified in the sensitivity analysis. Therefore, scenario analysis is about producing other design alternatives. For example, it answers questions such as what are the other design alternatives if different discount rates were used. This is important, as it helps to elucidate the sensitive parameters affecting the optimal configuration.

5.2. Base Case Results and Analysis

The results presented in this study for all three communities include optimal sizing, economic summary, and a summary of system performance. The optimal sizing results provided the optimal size of each DER technology in the microgrid: PV, BES, BES inverter, and DG. The economic summary provided results such as LCOE, capital expenditure (CAPEX), and operating expenditure (OPEX). The summary of system performance provided results regarding the technical performance of the system by reporting metrics such as BES lifetime, fuel consumption, and pollutant emissions.

The results of the base cases were tabulated in Tables 5–7. The reference case and four microgrid cases were simulated. All of the microgrid base cases were simulated using LF-OFF operating strategies, which is the most common strategy for operating stand-alone microgrid. The reference case was the existing system where all demand was met by using DGs. This case was important because it served as the reference against which the other cases were compared. This case had the lowest CAPEX and highest LCOE and OPEX. The next case was the optimal microgrid system. The optimal system was the microgrid that had the lowest LCOE. In all three communities, the REP of the optimal system was greater than 70%, indicating that high renewable penetration was economically feasible, even though the CAPEX was high. Three more cases were simulated using various REPs of 30%, 50%, and 70%. The results indicated that the increasing REP would increase CAPEX and decrease OPEX in all the communities, as shown in Figure 4. As shown in Figure 5, across the three communities, Cachuela Esperanza had the lowest LCOE, followed by Rosario del Yata and Villa Bella, indicating that the size of the community, and hence the load demand, affected the LCOE. This was expected for two reasons. The first reason is technical, because Cachuela Esperanza had the highest energy demand, it had relatively lower excess energy. The second reason was due to the economy of scale. Since it

is the bigger system, its fixed cost per kW was lower, leading to lower LCOE. In general, the results indicated that deploying a microgrid in all three communities was economically feasible.

Table 5. Results of the baseline cases for Cachuela Esperanza.

Parameters	Ref.	30 % REP	50 % REP	70 % REP	Optimal
PV (kW)	-	100	170	270	295
BES (kWh)	-	100	350	575	780
Inverter (kW)	-	70	80	100	120
DG (kW)	80	80	80	80	80
REP (%)	0	30.6	50.2	70.0	80.5
LCOE (\$/kWh)	0.506	0.439	0.419	0.408	0.398
CAPEX (\$)	140,000	346,000	558,000	806,500	934,100
OPEX (\$/y)	195,011	144,247	112,502	80,582	62,495
Battery life (y)	-	8.4	8.7	7.8	8.3
Fuel (L/y)	120,581	85,297	61,716	37,486	24,279
Emission (ton/y)	315.7	223.3	161.6	98.1	63.6

Table 6. Results of the baseline cases for Rosario del Yata.

Parameters	Ref.	30 % REP	50 % REP	70 % REP	Optimal
PV (kW)	-	65	140	140	160
BES (kWh)	-	60	140	385	400
Inverter (kW)	-	50	50	60	60
DG (kW)	60	60	60	60	60
REP (%)	0	31.7	49.5	70.2	74.6
LCOE (\$/kWh)	0.543	0.468	0.465	0.432	0.431
CAPEX (\$)	130,000	262,700	408,800	513,700	550,000
OPEX (\$/y)	111,098	80,863	64,080	44,828	40,548
Battery life (y)	-	7.3	6.9	8.6	8.3
Fuel (L/y)	66,918	45,747	33,798	19,961	17,033
Emission (tCO ₂ /y)	175.2	119.8	88.5	52.3	44.6

Table 7. Results of the baseline cases for Villa Bella.

Parameters	Ref.	30 % REP	50 % REP	70 % REP	Optimal
PV (kW)	-	30	50	70	90
BES (kWh)	-	50	125	220	225
Inverter (kW)	-	20	30	30	40
DG (kW)	30	30	30	30	30
REP (%)	0	31.7	51.0	70.0	78.1
LCOE (\$/kWh)	0.690	0.590	0.551	0.513	0.501
CAPEX (\$)	115,000	185,000	248,500	318,400	352,500
OPEX (\$/y)	71,989	51,956	40,158	27,786	22,606
Battery life (y)	-	9.9	9.2	9.5	8.4
Fuel (L/y)	44,409	30,810	22,322	13,608	9,927
Emission (ton/y)	116.3	80.7	58.4	35.6	26.0

Figure 4. The capital (CAPEX) and operating (OPEX) expenditures under various REP.

Figure 5. A plot of REP and LCOE.

5.3. Sensitivity Analysis

In a sensitivity analysis, some selected input parameters are varied over a strategically pre-determined range in order to find which of these parameters results in a greater variation in the output. It is, therefore, possible to use sensitivity analysis to find the parameters that have a significant impact on the economics of the microgrid. In this study, policy and technology parameters were selected for sensitivity analysis. These parameters, shown in Table 8, were strategically chosen based on several factors such as degree of uncertainty and market trends.

Table 8. Range of the parameters for sensitivity analysis.

Parameter	Nominal	Variation	Ref.
<i>Policy</i>	-	-	-
Discount rate	10%	3%–12%	[64,65]
Diesel price	1.41 \$/l	0.16–1.41 \$/l	[66]
Grant	0%	0%–100%	-
<i>Technology</i>	-	-	-
BES lifetime	2000 cycles	500–4000 cycles	[64]
Operating strategy	LF	CC, LF-ON, FB	[55]
PV efficiency	19%	13%	-
Fuel type	Diesel	LPG	-
Operating reserve	80% of PV power	70–90%	[67]
Solar irradiance	NASA	Pvwatts	[61]

Figure 6 shows the results of the sensitivity analyses for the three communities. Generally, as is evident from the figure, some parameters affect the LCOE more than others. In particular, discount rate, diesel price, grants, BES lifetime, and operating strategies have the most significant impact on the

LCOE. Sensitivity to the operating reserve and solar irradiance is negligible, meaning these parameters have only a small effect on the LCOE. Sensitivity to fuel type is considerable and exceeds both operating reserve and solar irradiance.

Figure 6. Variation in LCOE due to the variation of the nine parameters investigated.

5.4. Scenario Analysis

Through sensitivity analyses in the previous section, five parameters were identified as having the greatest impact on the LCOE of the microgrids: discount rate, diesel price, grants, battery lifetime, and operating strategies. Using these parameters, five scenarios were formulated.

5.4.1. Scenario 1: Discount Rate

The base cases in this study were simulated with a real discount rate of 10%. However, the cost of debt and the required return on equity, as well as several other factors, will affect the actual value of the discount rate. Consequently, four scenarios were developed using discount rates of 3%, 5%, 7.5%, and 10%.

Figure 7 shows the results of the cases, indicating that lowering the discount rate results in reducing the LCOE and increasing the REP. This highlights an important policy issue: policies and regulations can be used to minimize the risks for renewable energy investments, therefore, lowering the discount rate, consequently reducing the LCOE. Furthermore, these results suggest that all things being equal, microgrids in developed countries will be more economical and have higher REP than in developing countries. This is because discount rates in developed countries are lower since the cost of borrowing is low and there are regulatory policies that tend to reduce the perceived risk of renewable energy projects. The detailed results of this scenario are tabulated in Appendix A, Table A1.

Figure 7. The results of Scenario 1 for the three communities: (a) The microgrid configurations under various discount rates; (b) LCOE, REP, and tCO₂ under different discount rates. The y-axes are normalized to the base cases. The discount rate applied in each scenario was as follows: Scenario 1A (S1A) was 10%; Scenario 1B (S1B) was 3%; Scenario 1C (S1C) was 5%; Scenario 1D (S1D) was 7.5%.

5.4.2. Scenario 2: Diesel Price

The average diesel price varied considerably across countries. For example, as of 2016, diesel prices were 0.22 \$/liter in Iran, 0.65 \$/liter in the United States, and 1.63 \$/liter in Iceland [68]. Even within a country, several factors affect the price, including pricing framework, sub-national tax, distribution costs (distance between suppliers to end-users), marketing costs, and refining costs (environmental regulations) [69]. At the time of this study, the average pump price of diesel in Bolivia was 0.55 \$/liter. However, in remote areas, the average price was 1.41 \$/liter. The Bolivian Government subsidizes diesel used for power generation in remote areas to 0.16 \$/liter. At the world and regional level, the world's average pump price was 0.82 \$/liter, and the average pump price in Latin America and the Caribbean was 0.74 \$/liter. These prices were used to formulate the scenarios in this section.

The results of these scenarios are shown in Figure 8. Both the optimal sizes of PV and BES increased with increasing diesel prices, leading to lower LCOE and signaling that higher prices of diesel would make microgrid investments attractive. This leads to an important policy dilemma because, while subsidizing diesel would force the LCOE to be lower for a diesel-only system, the subsidy would make microgrid investments less attractive, thereby discouraging renewable energy investments in microgrids. As shown in Figure 8, Scenario 2E, with subsidized diesel, diesel-only systems were more attractive, meaning no investments in PV and BES. The detailed results of this scenario are tabulated in Appendix A, Table A2.

5.4.3. Scenario 3: Grants

Renewable energy projects may enjoy some grants/incentives or subsidies from governments, non-governmental organizations, and/or international donor organizations. Therefore, cases were developed where their impacts on the design were developed. Four scenarios were formulated with the grants of 0%, 25%, 50%, 75%, and 100%, and the results are shown in Figure 9.

Figure 8. The results of Scenario 2 for the three communities: (a) The microgrid configurations under various diesel prices; (b) LCOE, REP, and tCO₂ under different diesel prices. The y-axes are normalized to the base cases. The diesel price applied in each scenario was as follows: Scenario 2A (S2A) was 1.41 \$/l; Scenario 2B (S2B) was 0.82 \$/l; Scenario 2C (S2C) was 0.74 \$/l; Scenario 2D (S2D) was 0.55 \$/l; Scenario 2E (S2E) was 0.16 \$/l.

Figure 9. The results of Scenario 3 for the three communities: (a) The microgrid configurations under various amounts of grants; (b) LCOE, REP, and tCO₂ under various amounts of grants. The y-axes are normalized to the base cases. The amount of grants applied in each scenario were as follows: Scenario 3A (S3A) was 0%; Scenario 3B (S3B) was 25%; Scenario 3C (S3C) was 50%; Scenario 3D (S3D) was 75%; Scenario 3E (S3E) was 100%.

Grants can significantly lower the LCOE and increase the REP. It is important to note that, while grants lower the LCOE, they may lead to systems with significantly higher excess renewable energy. The important policy issue here is that, instead of giving more grants to a particular microgrid that may produce excess energy, it would be more efficient from both a cost and an emission reduction perspective to spread the grants to other communities. The detailed results of this scenario are tabulated in Appendix A, Table A3.

5.4.4. Scenario 4: Battery Technology

Other scenarios were produced utilizing other battery technologies: Lithium-ion, lead-acid, and flow batteries. These battery technologies were widely used in hybrid energy systems in remote communities around the world [70]. For example, lithium-ion batteries have been used in the Gasa Island microgrid in South Korea [71], lead-acid batteries have been used in the Beiji Island microgrid in China [72], and flow batteries have been used in Ban Pha Dan microgrid in northern Thailand [73]. Among the three types of battery technologies investigated, each one has its pros and cons. Lithium-ion batteries have a better energy density, a high depth of discharge, higher efficiency, and low self-discharging. However, they are generally more expensive than lead-acid batteries. Conversely, lead-acid batteries are typically cheaper and easier to recycle, but they have a relatively low energy density, a low depth of discharge, and are less efficient. Flow batteries have high upfront investment costs compared to other battery technologies. However, these have a lifetime that typically exceeds 10,000 full cycles, enabling them to make up for the high initial cost.

The following battery chemistries were used to produce the scenarios in this section: lithium nickel manganese cobalt oxide (NMC), lithium iron phosphate (LFP), flooded lead-acid batteries (FLA), valve-regulated lead-acid batteries (VRLA), vanadium redox flow batteries (VRFB), and zinc-bromine flow batteries (ZBFB). The details of the battery parameters were taken from [64] and are summarized in Table 9.

Table 9. Summary of the properties of various types of batteries.

Properties	Lithium-ion Battery		Lead-acid Battery		Flow Battery	
	NMC	LFP	FLA	VRLA	VRFB	ZBFB
Installation cost (\$/kWh)	420	578	147	263	347	900
Throughput lifetime (cycles)	2000	2500	1500	1500	13000	10000
Calendar lifetime (years)	12	12	9	9	12	10
Depth of discharge (%)	90	90	50	50	100	100
Round-trip efficiency (%)	95	92	82	80	70	70

The results indicate that battery chemistry significantly affects both the optimal sizes of PV and BES, as well as other economic and technical parameters, as shown in Figure 10. For lithium-ion batteries, the results suggest that even within the same technology, the configuration and economics of the systems may differ, based on battery chemistry (NMC and LFP). The ZBFB produced the configuration with the highest LCOE, whereas VRFB led to the lowest LCOE. Overall, the battery technology choice results in relatively flat LCOE, regardless of the chemistry used. The large variation of LCOE in the sensitivity analysis is because only the lifetime is varied, while other properties remained fixed. The implication is more on capital costs, replacement schedules, REP, and pollutant emissions. The detailed results of this scenario are tabulated in Appendix A, Table A4.

Figure 10. The results of Scenario 4 for the three communities: (a) The microgrid configurations under various battery technologies; (b) LCOE, REP, and tCO₂ under various battery technologies. The y-axes are normalized to the base cases. The battery technology used in each scenario was as follows: Scenario 4A (S4A) was NMC; Scenario 4B (S4B) was LFP; Scenario 4C (S4C) was FLA; Scenario 4D (S4D) was VRLA; Scenario 4E (S4E) was VRFB; Scenario 4F (S4F) was ZBFB.

5.4.5. Scenario 5: Operating Strategy

As described in Section 3, there are four general types of operating strategies that can be used to simulate the operation of a remote microgrid, including LF-OFF, LF-ON, CC, and FB. The base case was simulated using the LF-OFF operating strategy.

As shown in Figure 11, the type of dispatch strategy used to simulate the system affects the configuration, economics, REP, and pollutant emissions. The LF-OFF and FB dispatch strategies consistently had the lowest LCOE and highest REP in all the communities investigated. The FB strategy, which assumed the perfect knowledge of 48 hours of incoming demand of renewable energy, was the most economical. However, the difference between the FB and LF-OFF strategies was negligible. This is consistent with the findings of [55], in which they argued that either CC or LF, whichever was more economical, would be very close to the FB strategy. The LF-OFF strategy allowed for the highest REP because it turned off the diesel generator whenever the PV and BES could meet the load demand. It also utilized BES more efficiently by not charging it with a diesel generator. The LF-ON strategy was the most inefficient and resulted in higher LCOE. This strategy also allowed the least REP because the diesel generator was always running, resulting in higher curtailment of renewable energy. As mentioned previously, the LF-OFF and FB strategies achieved the lowest LCOE and highest REP. However, there was a drawback to these strategies. The switching on and off between BES and the diesel generators led to reliability issues. For this reason, one alternative is to use droop control, which has been proposed in the literature [74]. This method of plug and play makes it possible for all the DER to share power between them, without any communication. The method was successfully tested experimentally and has been applied to some remote communities. However, its widespread adoption has not yet taken place. The detailed results of this scenario are tabulated in Appendix A, Table A5.

Figure 11. Results of Scenario 5 for the three communities: **(a)** The microgrid configurations under various operating strategies; **(b)** LCOE, REP, and tCO₂ under different dispatch strategies. The y-axes are normalized to the base cases. The operating strategy applied in each scenario was as follows: Scenario 5A (S5A) was LF-OFF; Scenario 5B (S5B) was LF-ON; Scenario 5C (S5C) was CC; Scenario 5D (S5D) was FB.

5.5. Discussion

5.5.1. Implications for Policymakers

The study identifies three policy parameters that microgrid investment can be influenced. These parameters include the discount rate, diesel price, and grant. The discount rates in developing countries are relatively high. In Bolivia, for example, the government fixed 10% as a discount rate to be used for evaluating energy projects in the public sector. This value is high, and our results indicate that lowering this value will increase the REP and lower LCOE. For private investment, where governments have no direct control over the discount rates, policymakers can still lower it indirectly by adopting policies that will lower risks associated with renewable energy investment. For fuel prices, there is an existing fuel subsidy in most developing countries. In Bolivia, diesel enjoys a huge subsidy. The subsidy, while helping in improving energy access to remote communities, will make microgrids less economical. These are conflicting objectives that policymakers need to address. Regarding grants, various governments in developing countries offer generous grants for renewable energy projects. This helps in lowering the LCOE of microgrids. However, policymakers need to make a careful evaluation of a better strategy of implementing these grants. For example, instead of subsidizing the upfront cost of microgrid, another alternative is to offer grants to people willing to start entrepreneurship activities. This will consequently lower the LCOE of microgrids due to more energy consumption, and at the same time increasing the ability to pay, making the systems to be more sustainable in the long term. The IDCOL initiative in Bangladesh is an example of this approach to giving grants.

5.5.2. Implications for Microgrid Planners

The study identifies two technology parameters that microgrid investment can be influenced. These are battery technology and operating algorithm. Through careful evaluation of battery technologies,

the economics of microgrids could be influenced. Our results suggest that LCOE varies slightly for different battery technologies. However, battery technology can be selected to influence the economic behavior of microgrid in a variety of ways. For example, if the upfront cost is the main concern, a battery technology with less capital cost, such as lead-acid types, can be used. On the other hand, frequent replacements can be avoided by selecting battery technology with a longer lifetime. For the operating algorithm, the method adopted will dictate the types of the controller to be used. Controller cost forms a substantial part of upfront cost, therefore, by carefully selecting an appropriate control technique, the economics of microgrid could be influenced by microgrid planners.

6. Conclusions

In this study, the impacts of policy and technology parameter variations on the economics of microgrids for rural electrification were investigated. The investigation was conducted on case studies of three rural communities in the Beni Department of Bolivia using the MDSTool as a modeling tool. The microgrid investment was robust across a wide range of parameters.

It was found that the discount rate, diesel prices, grants, battery technology, and operating strategy, have a significant impact on the configuration, LCOE, REP, and pollutant emission. Remarkably, policymakers and microgrid planners have an influence on these parameters. For policymakers, the implications of this study are threefold. First, making policies that will lower the discount rate can be a useful tool in reducing the LCOE of microgrids, making them more attractive. Second, fuel subsidies, while helping to make electricity more affordable to the rural communities, would discourage investment in microgrids. Third, grants can be used to influence the size of a microgrid, which will consequently make it more economical. For microgrid planners, this study revealed two areas where microgrid investments could be influenced. First, even though different battery technology results in relatively flat LCOE, they can be used to influence capital costs, replacement schedules, REP, and pollutant emissions. Second, the operating strategy will dictate the type of control approach to be adopted, such as centralized, decentralized, or peer-to-peer control. The choice of control will have a significant impact on the cost, reliability, and scalability of the microgrid. In future studies, the authors are interested in investigating the interaction of policy and technology parameters and how they can influence the potential of various microgrid business models for rural electrification.

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Acronyms

CAPEX	Capital expenditure
CC	Cycle-charging
BES	Battery energy storage
DER	Distributed energy resources
DG	Diesel generator
EMR	Emission reduction
ESS	Energy storage system
FLA	Flooded lead-acid battery
LCOE	Levelized cost of energy
LF	Load-following
LF-OFF/ON	Load-following off/on

LFP	Lithium iron phosphate
LOLP	Loss-of-load-probability
LPG	Liquefied petroleum gas
LPSP	Loss of power supply probability
MILP	Mixed-integer linear programming
NMC	Lithium nickel manganese cobalt oxide
NFB	Non-forecast based
OPEX	Operating expenditure
PV	Photovoltaic
REP	Renewable energy penetration
RES	Renewable energy sources
VRFB	Vanadium redox flow batteries
VRLA	Valve-regulated lead-acid batteries
WT	Wind turbine
ZBFB	Zinc bromine flow batteries

Appendix A

Table A1. Scenario 1: Discount rate.

Community	Parameters	Ref. System	S1A (10%)	S1B (3%)	S1C (5%)	S1D (7.5%)
Cachuela Esperanza	PV (kW)	-	295	375	350	325
	BES (kWh)	-	780	850	850	825
	REP (%)	0	80.5	87.7	86.4	84.3
	LCOE (\$/kWh)	0.506	0.398	0.275	0.309	0.354
	Emission (ton/y)	315.7	63.6	39.8	44.2	51.2
Rosario del Yata	PV (kW)	-	160	200	180	165
	BES (kWh)	-	400	525	475	415
	REP (%)	0	74.6	83.9	80.4	76.0
	LCOE (\$/kWh)	0.543	0.431	0.302	0.338	0.384
	Emission (tCO ₂ /y)	175.2	44.6	28.2	34.3	42.1
Villa Bella	PV (kW)	-	90	110	100	95
	BES (kWh)	-	225	300	275	250
	REP (%)	0	78.1	86.3	83.5	81.1
	LCOE (\$/kWh)	0.690	0.501	0.340	0.384	0.442
	Emission (ton/y)	116.3	26.0	16.2	19.5	22.4

Table A2. Scenario 2: Diesel prices.

Community	Parameters	Ref. System	S2A (1.41 \$/l)	S2B (0.82 \$/l)	S2C (0.74 \$/l)	S2D (0.55 \$/l)	S2E (0.16 \$/l)
Cachuela Esperanza	PV (kW)	-	295	110	110	100	-
	BES (kWh)	-	780	110	110	110	-
	REP (%)	0	80.5	32.6	32.6	30.9	0
	LCOE (\$/kWh)	0.506	0.398	0.317	0.301	0.263	0.144
	Emission (ton/y)	315.7	63.6	216.6	216.6	222.5	315.7
Rosario del Yata	PV (kW)	-	160	55	55	50	-
	BES (kWh)	-	400	40	40	40	-
	REP (%)	0	74.6	27.4	27.4	26	0
	LCOE (\$/kWh)	0.543	0.431	0.351	0.334	0.295	0.187
	Emission (tCO ₂ /y)	175.2	44.6	127.2	127.2	129.7	175.2
Villa Bella	PV (kW)	-	90	40	40	30	-
	BES (kWh)	-	225	40	40	40	-
	REP (%)	0	78.1	35.7	35.7	30.9	0
	LCOE (\$/kWh)	0.690	0.501	0.437	0.418	0.371	0.238
	Emission (ton/y)	116.3	26.0	76.1	76.1	81.5	116.3

Table A3. Scenario 3: Grants.

Community	Parameters	Ref. System	S3A (0%)	S3B (25%)	S3C (50%)	S3D (75%)	S3E (100%)
Cachuela Esperanza	PV (kW)	-	295	325	380	475	1100
	BES (kWh)	-	780	790	800	800	775
	REP (%)	0	80.5	83.3	86.7	90.3	97.5
	LCOE (\$/kWh)	0.506	0.398	0.368	0.333	0.291	0.223
	Emission (ton/y)	315.7	63.6	54.7	43.4	31.5	7.0
Rosario del Yata	PV (kW)	-	160	170	200	260	350
	BES (kWh)	-	400	405	400	400	450
	REP (%)	0	74.6	76.2	79.2	83.1	89.4
	LCOE (\$/kWh)	0.543	0.431	0.403	0.371	0.332	0.275
	Emission (tCO ₂ /y)	175.2	44.6	41.7	36.5	29.6	18.7
Villa Bella	PV (kW)	-	90	100	110	170	300
	BES (kWh)	-	225	220	235	250	250
	REP (%)	0	78.1	79.5	82.4	89.9	95.5
	LCOE (\$/kWh)	0.690	0.501	0.470	0.434	0.388	0.311
	Emission (ton/y)	116.3	26.0	24.3	21.0	12.1	5.4

Table A4. Scenario 4: Battery technology.

Community	Parameters	Ref. System	S4A NMC	S4B LFP	S4C FLA	S4D VRLA	S4E VRFB	S4F ZBFB
Cachuela Esperanza	PV (kW)	-	295	300	325	175	350	150
	BES (kWh)	-	780	775	1550	300	800	60
	REP (%)	0	80.5	80.1	80.2	40.7	80.9	33.6
	LCOE (\$/kWh)	0.506	0.398	0.429	0.405	0.438	0.391	0.446
	Emission (ton/y)	315.7	63.6	65.1	64.9	190.8	62.6	213.7
Rosario del Yata	PV (kW)	-	160	150	170	100	180	80
	BES (kWh)	-	400	380	800	220	420	40
	REP (%)	0	74.6	71.2	73.5	41.1	74.1	31.5
	LCOE (\$/kWh)	0.543	0.431	0.458	0.437	0.473	0.425	0.483
	Emission (tCO ₂ /y)	175.2	44.6	50.5	46.4	103.3	45.5	120.1
Villa Bella	PV (kW)	-	90	90	100	100	100	50
	BES (kWh)	-	225	210	430	410	230	30
	REP (%)	0	78.1	75.8	77.3	75.7	76.6	35.6
	LCOE (\$/kWh)	0.690	0.501	0.530	0.507	0.555	0.495	0.598
	Emission (ton/y)	116.3	26.0	28.8	27.0	29.0	27.9	76.1

Table A5. Scenario 5: Operating strategy.

Community	Parameters	Ref. System	S5A LF-OFF	S5B LF-ON	S5C CC	S5D FB
Cachuela Esperanza	PV (kW)	-	295	70	150	290
	BES (kWh)	-	780	50	185	775
	REP (%)	0	80.5	20.0	37.1	79.3
	LCOE (\$/kWh)	0.506	0.398	0.473	0.421	0.398
	Emission (ton/y)	315.7	63.6	259.2	192.7	66.0
Rosario del Yata	PV (kW)	-	160	45	75	150
	BES (kWh)	-	400	90	60	385
	REP (%)	0	74.6	21.3	30.5	71.2
	LCOE (\$/kWh)	0.543	0.431	0.521	0.467	0.431
	Emission (tCO ₂ /y)	175.2	44.6	138.1	121.5	50.4
Villa Bella	PV (kW)	-	90	30	90	85
	BES (kWh)	-	225	60	285	225
	REP (%)	0	78.1	26.1	74.5	75.8
	LCOE (\$/kWh)	0.690	0.501	0.655	0.538	0.501
	Emission (ton/y)	116.3	26.0	26.1	27.9	28.0

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