Model-Base cost evaluation of Microgrids systems for rural Electrification and energy planning purposes

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Abstract

With pressing priorities in the development agenda, policy makers in developing countries are in the difficult situation of prioritizing policy actions. Limited government and utility budgets need cost effective solutions to bring the desired development benefits of electrification, health, education and food security among others. Energy access is a pre-requisite for economic activity and for human development as interacts in synergy with other development needs. As rural electrification models usually focus on the supply of electricity solely, thermal energy needs, such as cooking and water heating remain unattended and satisfied by non-renewable energy fuels.

To this aim, we explore optimal electrification solutions addressing two types of energy demands, electricity and thermal energy demands for cooking. Our model builds on a 3-step electrification methodology proposed by Peña et al. including electricity as a modern source of clean energy for cooking in rural communities. The total investments needed to build and operate the microgrids, including distribution costs, is 332 million USD. This is equivalent to 1129 USD/per inhabitant. This amount does not account however the health and environment benefits that e-cooking can bring to inhabitants in Bolivian low-lands.

Keywords: Electrical cooking, Rural electrification, Bolivia, Microgrids.

1. Introduction

Countries around the world are preparing to give the last leap towards 100 % of rural electrification (Doukas and Ballesteros, 2015). To this end, energy planning is of great importance as it estimates the cost of a range of technologies to meet desired energy demand characteristics in remote areas. This involves the analysis of a great number of different un-electrified communities with different social, economic and geographical characteristics.

Future electrification pathways will rely on mini-grids in a large extent. The International Energy Agency (IEA) anticipates that more than 50% of rural electrification will be supplied via mini-grids (IEA, 2018). Mini-grids are small-scale electricity generation systems with size ranging from 10 kW to few MW. These serve to a limited number of consumer and productive activities and can operate in complete isolation or can interact with the grid.

Traditional electricity planning has relied on top-down projections of future demand based on

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extrapolation of historic demand patterns, or on economic growth correlations. These methods do not consider the peculiarities of the energy needs among consumers that usually have strong social, cultural, climatic and geographical components. Electricity demand surveys and demand load modeling enable bottom-up electricity demand forecasting techniques that provide a more dis-aggregated perspective that allows capturing electricity needs across different consumers segments.

The literature reports several modeling tools to determine the best electrification technology to attend under-served and/or un-electrified populations. Technologies range from grid-extension, micro-grid to standalone systems solutions. Information on demand, cost estimates and available natural resources are used to recommend the electrification technology that best serves under cost and/or reliability optimization functions. Examples of recent developments in modelling tools that combine geographical information systems and energy system simulation/optimization algorithms to provide electrification solutions include: The Reference Electrification Model (Ellman, 2015), OpeN Source Spatial Electrification Toolkit (Mentis et al., 2017) and (Szabo et al., 2011).

On the other hand, the International Energy Agency Reports that approximately 2.7 billon people do not have access to clean cooking technologies (IEA, 2018). These people rely on bio-mass cooking stoves to satisfied their needs; however, this technology has severe effects in the health of its users and in the environment (Kim et al., 2012). Historically, the cooking problem has been tackled by giving improved cooking stoves to the users (Urnee et Gyamfu, 2014) or the transition to more efficient fuels (Mehetre et al 2017). These techniques have been proved not able to meet the health targets set by the World Health Organization for air pollution (Aung et al., 2016; Pope et al., 2017). Another viable solution that at the same time minimize the pollutants emitted during the cooking process is the use of electrical cooking (e-cooking), this technology can be competitive with other alternatives to cook food in a rural context (Lombardi et al., 2019a).

In this work, we estimate the investment costs needed to provide electricity to a number of villages from the low lands in Bolivia under the scenario in which electricity for cooking is introduced as a complementary policy. The methodology relies on the Open Source Spatial Electrification Tool (OnSSET), which uses a bottom up optimization model together with georeferenced information to evaluate the least cost electrification technology to supply electricity to rural villages (Mentis et al., 2017). Surrogate models are then coupled to OnSSET capturing both, high-resolution peculiarities of electricity demand and cost-optimal micro-grid configurations (Balderrama et al., 2019a).

2. Methodology

The methods builds on a three-step methodology (Peña et al. 2019) shown in Fig. 1. In the first step plausible stochastic load profiles are created using RAMP (Lombardi et al., 2019b) for different villages sizes. In a second step, a linear programming (LP) sizing model (Balderrama et al., 2019b) creates a data base with the net present cost (NPC) or the levelized cost of energy (LCOE) as the dependent variables. Afterwards a multivariable regression is applied to the data base to derive a surrogate model capable of calculate the NPC/LCOE of an optimize system. This model is finally coupled to OnSSET where it is used to calculate the cost of implementing isolated microgrids in rural villages that cannot be reached by the grid. This is done by using a previous collected data base with GIS information of all the communities in Bolivia, in which is included information such as electrification status, population, yearly global irradiation, etc. The derived equation can be applied in every population to calculated the NPC of the system under different circumstance by varying its input parameters.

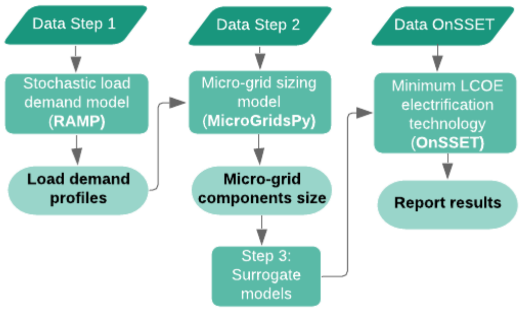

Fig 1. Three-step core components of the modelling framework taken from: (Peña et al. 2019).

2.1 Stochastic load generation

To generate stochastic profiles from rural villages, this work relies on RAMP. This software is based on the definition of several user classes, each of which is associated to a set of appliances (Fig. 2). Each appliance is defined by a nominal capacity, total functioning time along the day, and possible time of use. Based on this information, and pre-defined ranges of stochastic variation between use, it is possible to account for uncertainty and random users behavior. The model allows to compute the total load curve of a village.

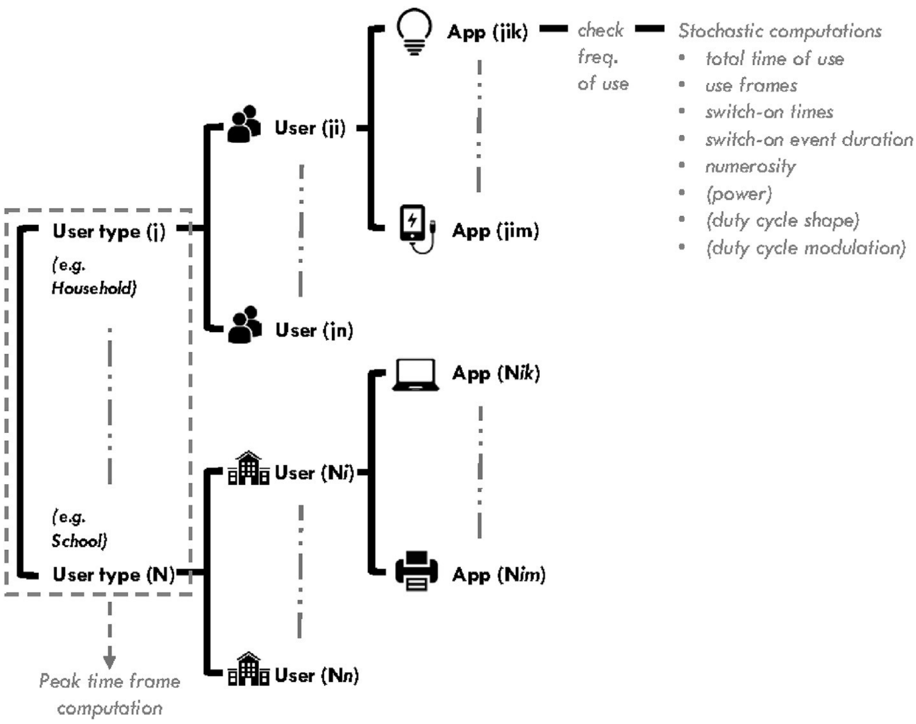

Fig 2. Graphical sketch of the modelling layers constituting the simulation process. taken from: (Lombardi et al., 2019b).

2.2 Sizing model

The sizing model is based on LP framework, that minimize the NPC of a microgrid constrained by technical, economic and energetic limitations (Balderrama et al., 2019b). To ensure the capacity of the system to meet different demand scenarios, the sizing model opts for a two-stage stochastic approach. In which the first stage variables are the nominal capacities of the different energy sources and the recursive actions done to deal with the uncertainty in the demand are the energy flows. In addition to this, it also includes a feature to allow a percentage of the total load not to be met, as supplying a 100 % of the demand in isolated systems can increase considerably the total cost of the system (Stevanato et al., 2019).

2.3 OnSSET

OnSSET uses georeferenced information systems (GIS) data and identifies the least cost electrification solution to serve each population/community/village over a portfolio of electrification technologies (Mentis et al., 2017). The algorithm is divided in two parts, the first part estimates which villages are most likely electrified on information of proximity to the grid, roads, population density and nightlights. In the second part, the LCOE of grid and off-grid electrification solutions are compared for each village to determine the least cost solution. To do so, grid extension algorithms compute the cost of extending the grid (high voltage, medium voltage, low voltage, transformers and substations) within a distance limit of 50 km from MV lines. At the same time, the LCOE form off-grid alternatives is calculated and compared to feasible grid extension results for each village.

3. The case of Bolivia

Bolivia is a country located in the central part of South America with more than 1 million Km^2 comprising different regions and climates. It has 11 million inhabitants with a share of 32.7% living in rural settlements. It has reached a 90 % of total electrification in 2018 and has an ambitious plan to reach a 100 % of coverage by 2025 (Ministerio de Hidrocarburos y Energía, 2014). Despite these important advances in access to energy, still 68 % of the rural population cook with wood or similar fuels (Instituto Nacional de Estadistica, 2012). As mentioned before, this has an important impact on the health and in the environment. This work estimates the cost of electrification including the energy necessary to cook meals with electricity in villages of the lowlands of Bolivia far away from the reach of the grid (<800 m.a.s.l and between 30 to 250 households). The steps 1 and 2 of this methodology were realized in: (Balderrama et al., 2019a). The most important results and characteristics from that work are presented on the following subsections.

3.1 Demand Scenarios

The acceptance of electrical cooking (e-cooking) is hard to evaluate (Murphy, 2001). To asses changes in the system due to uncertain penetration levels of e-cooking in villages, several scenarios were proposed. This is done to ensure the systems capability to meet different levels of demand. The possible demand scenarios are listed below, and average daily profiles are shown in Fig. 3.

1. Base scenario (Profile 1): accounting only for basic (i.e. no e-cooking) domestic

appliances. No public services are considered;

2. Low Penetration of Simple Task e-Cooking (Profile 2): only the higher income households make use of e-cooking and only to fulfill the simplest tasks, such as boiling water for preparing tea or mate. No public services are considered;
3. High Penetration of Simple Task e-Cooking (Profile 3): all the households make use of e-cooking but only to fulfill the simpler tasks, such as boiling water for preparing tea or mate. No public services are considered;
4. High Class e-Cooking (Profile 4): only the higher income households use e-cooking at its full potential (i.e. preparing all the meals with such technology), while the rest of the households use e-cooking only to boil water for tea. No public services are considered;
5. Basic Energy Profile + Public Services (Profile 5): specifically, public services include a school, a hospital, a church and a public lighting system;
6. Low Penetration of Simple Task e-Cooking + Public Services (Profile 6);
7. High Penetration of Simple Task e-Cooking + Public Services (Profile 7);
8. High Class e-Cooking + Public Services (Profile 8).

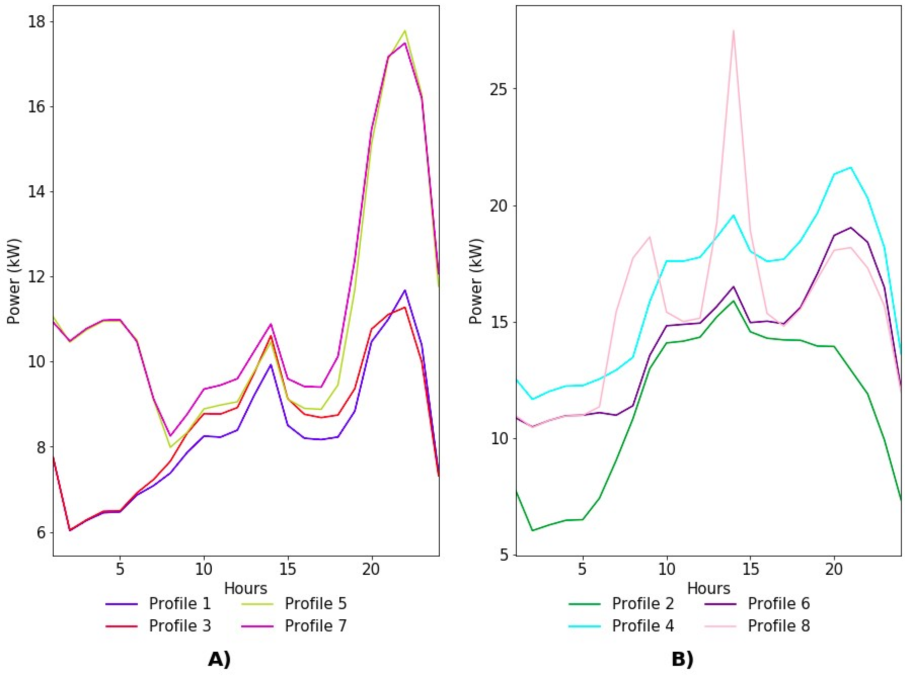

Fig 3: Daily average demand profiles for a village with 128 households: A) Typical demand profiles for a rural village. B) Demand profiles that include e-cooking.

In addition to household demands different combination of services are included in the load creation. The population range was varied from 80 to 200 households with a step of 12. A total of 88 plausible demand scenarios were created.

3.2 Data base creation

Once the demand scenarios are defined, techno-economic data is collected, the mutable parameters in the optimization can be selected (Table 1). In this case, economic parameters from the technologies in the system are selected to explore how political decision (subsidies) can impact in the overall electrification cost. Also, the demand and radiation are selected to characterize different community sizes and locations during the electrification process. In order to reduce the computational burden of the problem a Latin Hipercube with the number of samples set to 10 is used. During this process, 1100 different optimizations were realized. The main results of the optimization process are presented in Table 2.

Table 1: Mutable parameters during the optimization

Parameter	Unit	Range
LLP	%	0 -5
Battery Invesment cost	USD/Wh	0.4 - 0.6
PV Invesment cost	USD/W	1.3 - 1.8
Generator Invesment cost	USD/W	1.3 - 1.7
Diesel Cost	USD/l	0.28 - 1.28
Demand	Scenarios	88
PV Energy output	Scenarios	10

Table 2: Summary of the optimization results

Variable	Average Value	Max Value	Min Value	Standard Deviation
NPC (thousands USD)	208	404	71	70
LCOE (USD/kWh)	0.27	0.41	0.14	0.06
PV nominal capacity (kW)	25	73	0	13
Battery nominal capacity (kWh)	17	191	0	32
Genset nominal capacity (kW)	14	28	4	4

4. Results

In order to reduce the computational requirements of performing a large number of optimizations, a multivariable regression is applied to the generated data base. The resulting regression model has a $R^2 = 0.98$ and a mean average error of 1.2 %. The indicators show that the model has a high performance to predict the target dependent variable with the selected independent variables.

Once the surrogate model has been derived from the data set and its ability to predict LCOE has been verified. It is possible to integrate the OnSSET algorithm with the model to find the cost of electrification for the villages that meet the characteristics needed for a microgrid that includes e-cooking loads. The data base from the 2012 census and the techno-economic data for high, medium and low voltages extension are used to calculate all the villages that can be electrified with the grid. From the villages that cannot be electrified with this method, the ones that have m.a.s.l < 800 and beetwen 30 to 250 households are selected. A total of 1425 villages meets the criteria to implement isolated microgrids, their locations are shown in Fig. 4. The cost of each technology is shown in Table 3. The most important results are shown in table 4. The NPC to build and operate 1425 hybrid microgrids, including transmission costs, is 332 million USD during 20 years. This represent 1129 USD/per inhabitant or 3861 USD/per household. In a similar work (Peña et al., 2019.), it was found that electrifying all the populations in Bolivia will have cost between 241 to 1380 USD/per household, with an average cost of 1134 USD/per household for the microgrid hybrid systems. On this work only 5 % of the richer class were doing e-cooking. This means that solving the problem of clean cooking technologies in the lowlands of Bolivia will need almost three times more than only provide electricity for non-cooking uses. If the LLP is set to 5 %, the cost of the diesel is set to is value in the Bolivian market (0.53 USD/liter) and a subsidy of 1/3 of the investment cost on the PV and battery is applied. The new cost becomes 2705 USD/per household, which is a more affordable quantity.

Fig 4: Locations of the selected settlements

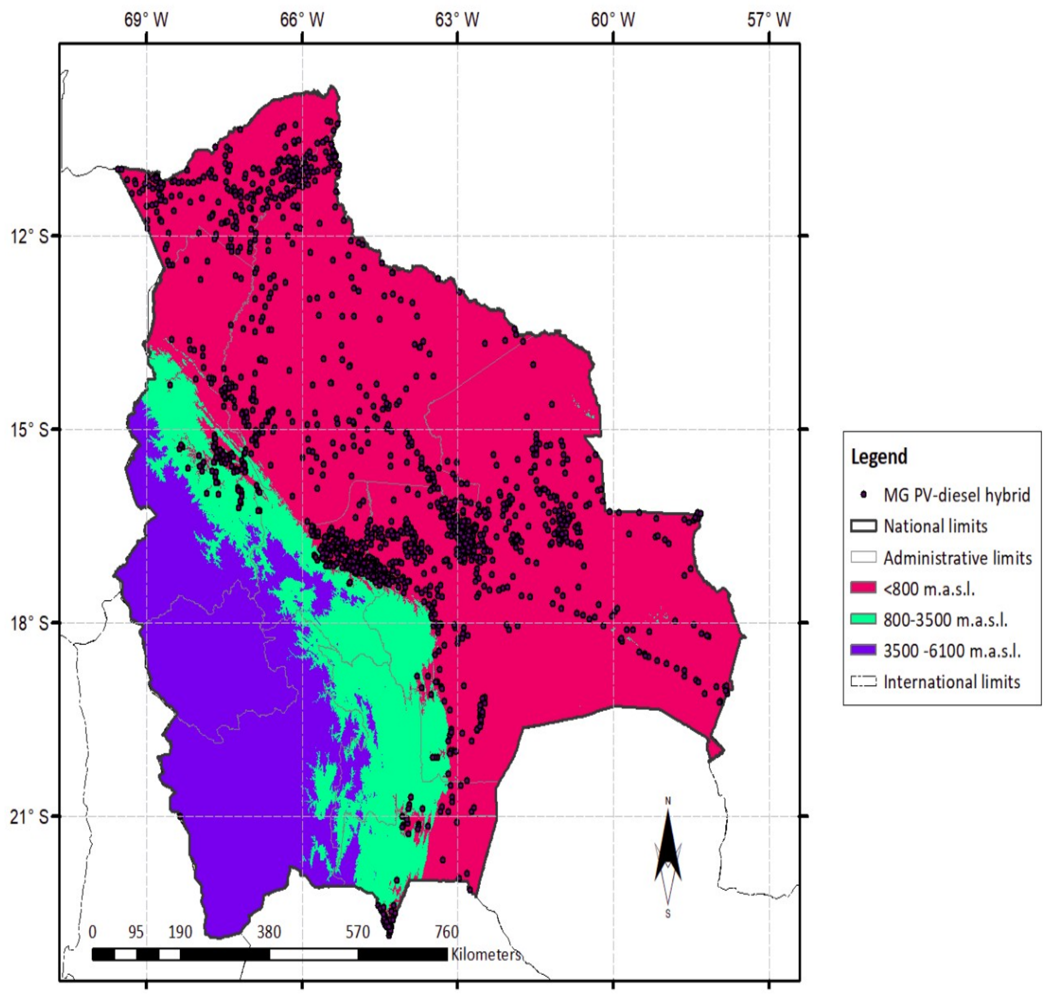

Table3: Cost of the different technologies taken from (Peña et al., 2019)

Parameter	Unit	Value
Diesel cost	USD/l	0.8
Lost load	%	1
Battery investment cost	USD/Wh	0.6
PV investment cost	USD/W	1.5
Generator investment cost	USD/W	1.48

Table 4: Results from the selected microgrids.

Variable	Unit	Base case	Subsidy case
Average LCOE	USD/kWh	0.42	0.34
Total investment	Millones USD	332	245
Total population	Thousands of persons	294	294

5. Conclusions

The total cost to electrify medium size isolated lowland villages in Bolivia with microgrids that include e-cooking is calculated in this work. To do so, a multivariable regression calculates the LCOE of hybrid microgrids for villages medium size village in the Bolivian lowlands, with high penetration of e-cooking. The surrogate model then is coupled to OnSSET to find the least cost electrification solution for each village. Finally, investment cost are computed and results are plotted.

The total investment needed to tackle this problem although it is an important quantity specially for a development country. But when it is seen in perspective with the number of people and the problems that a project of this magnitude can solve, it becomes an reasonable amount. Furthermore, if the principal actors in rural electrification coordinate, they could subsidize part of the cost of electrification leading to important reduction on the energy cost. It is important to highlight than in Bolivia the subsidize price for isolated grids is 0.18 USD/liter. Under this context, the propose scenario in this paper of having a share subsidy between the different technologies is realistic. Moreover, It is important to take in account that having such an important decrease in price for diesel will artificially stop the growth of renewable energies in rural areas. At the end of the day, politicians must take the final decision if it worth to have big subsidies in polluting technologies. Future work will include other Bolivian regions and increase the available energy sources and cooking methodologies to bring a holistic solution to the energy availability in Bolivia.

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