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Multi-objective optimization applied for designing hybrid power generation systems in isolated networks

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ABSTRACT

The use of hybrid power generation systems is an attractive alternative to conventional fossil fuel generation since they may assist in mitigating the emission of gases that are harmful to the atmosphere when using clean and renewable sources of energy. However, finding the ideal configuration for the installation of a hybrid system composed of solar photovoltaic (PV)-diesel generation is a complex task. In this sense, the objective of this study is to develop an approach to select the optimal configuration of hybrid power generation systems for isolated regions by means of combining the techniques of Mixing Design of Experiments, Normal Boundary Intersection and analysis of super efficiency using Data Envelopment Analysis. The proposed approach is applied to a set of four isolated regions in the northern region of Brazil, more specifically in the state of Amazonas. The results show that for each region a different configuration is selected but with large shares of diesel generation at first. On the other hand, all these cases represent points in the Pareto frontier that are the most inefficient due to the high volume of CO_2 emissions. From the application of the proposed approach, significant CO_2 emission reductions are obtained by selecting the optimal configurations represented as the most efficient points in the Pareto frontier. Our results show that due to conflicting characteristics of the selected objectives, the installation of such hybrid power generation systems produces an increase in LCOE, mainly related to the high costs of the batteries, although less accentuated than the reductions in emissions.

1. Introduction

In isolated regions, where there is no access to interconnected power systems, the service to provide and ensure a reliable electricity supply while satisfying the load at all times is a critical task for system operators and planners (Roy and Kulkarni, 2016). According to Mohammed et al. (2015), the integration of renewable energy resources, especially in remote areas where the network connection is not available, has been widely used all over the world due to economic and technical aspects. In addition, as highlighted by Rezzouk and Mellit (2015), Renewable Energy Sources (RESs) are considered a good alternative to fossil fuels since they assist in mitigating the emission of gases that are harmful to the atmosphere as they use clean and regularly regenerative energy (sun, wind, water, etc.). In this context, several RES-related projects have been developed in the last two decades (Yahiaoui et al., 2016).

Regarding isolated regions, hybrid systems, which combine more than one generation source, have often been an attractive alternative to the supply of electricity. A hybrid system can be formed by two or more sources, either renewable or conventional forms of generation. Mohammed et al. (2015) highlight the use of solar photovoltaic (PV) systems with a diesel generator in hybrid power generation system to supply demand in isolated areas. According to Kaabeche and Ibtiouen (2014), the use of renewable energy systems based on solar energy has been showing high growth rates in recent years. According to Silveira et al. (2013), the use of solar PV generation has gradually presented itself as an important alternative because it is economically feasible, environmentally accepted and well adapted to isolated areas, where the installation costs of conventional systems are relatively high.

Trepani and Millar (2016) report that because of the variability and

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Nomenclature

C_t	total energy consumed
D	the fraction of debt in the investment
E	the fraction of equity in the investment
E_t	total energy produced
E(x)	response variable function
$f_i(x)$	objective function
$\overline{f}(x)$	normalized value of the objective function
F^U	utopia points
F^N	nadir points
g(x)	inequality constraints
h(x)	equality constraints
h	number of decision variables
K_d	the cost of debt
K_e	the cost of equity
m	polynomial degree
m	number of objective functions
n	number of DMU's
N	number of points of a simplex lattice
q	number of technology of energy generation
r_f	the risk-free rate
r_c	the credit risk premium
r_b	the country risk premium
r	number of DEA inputs
s	number of DEA outputs
$S(x)$	entropy function
t	the income tax
u_j	decision variable (multiplier of the output Y)
v_i	decision variable (multiplier of the input X)
w	vector of weights of each objective function
x_i	fraction of each technology of the system total generation capacity
X	DEA input
Y	Response Variable Function
Y	DEA output
β	leveraged beta
β_i^*	contribution of each component in the response variable
θ_k	efficiency of DMU k
$\varnothing$	payoff matrix
δ_{ij}	the effect of the combination of components i and j

Abbreviations

ANEEL	Brazilian Electricity Regulatory Agency
BCC	Banker, Charnes e Cooper
CAPEX	*Capital Expenditure* (Investments)
CCR	Charnes, Cooper e Rhodes
DEA	*Data Envelopment Analysis*
DMU	*Decision Making Unit*
DOE	*Design of Experiments*
EPE	Brazilian Energy Planning Company
EPG	Global Percentage Error
GRG	Generalized Reduced Gradient
LCE	*Equivalent Carbon Dioxide Life Cycle Emissions*
LCOE	*Levelized Cost of Electricity*
MCS	Monte Carlo Simulation
MDOE	*Mixture Design of Experiments*
MME	Ministry of Mines and Energy
MNBI	*Modified Normal Boundary Intersection*
NBI	*Normal Boundary Intersection*
OPEX	*Operational Expenditure*
PV	*Photovoltaic*
RES	Renewable Energy Source
SPEA	*The Strength Pareto Evolutionary Algorithm*
TOPSIS	*Technique for Order Performance by Similarity to Ideal Solution*
TOTEX	*Total Expenditure*
VRS	*Variable Returns of Scale*
WACC	*Weighted Average Cost of Capital*

intermittence of the electricity generated from solar PV systems, these will probably not replace a definitive diesel generator set in isolated systems without the aid of energy storage systems. However, the solar PV system will have to operate in parallel with diesel engines and potentially with other plants that can store electricity, forming the so-called hybrid systems. It is worth emphasizing, that it is important to guarantee the diversity of hybrid PV-diesel systems, since such configuration implies in greater reliability, robustness and supply quality.

Nevertheless, finding the ideal configuration for the installation of PV-diesel hybrid systems is a complex task, since the use of diesel generators, which is a less costly decision nowadays for remote areas, implies increasing pollutant emissions. According to Bernal-Agustín et al. (2006), considering cost and emission minimization in this type of system is a conflicting problem, since cost reduction implies an increase in pollutant emissions and vice versa. This fact is due to the characteristics of the decision variables associated with the hybrid system (share of production from diesel generators and from solar PV systems).

Several studies in the literature present the use of optimization techniques applied to create designs of hybrid systems (Kaabeche and Ibtiouen, 2014). Due to often conflicting goals, some studies have been employing multi-objective optimization methods to verify the best configuration of hybrid systems by analyzing different trade-offs between objectives. We can highlight the work of Bernal-Agustín et al. (2006), Dufo-López et al. (2011), Izadbakhsh et al. (2015), Gitizadeh et al. (2013), which use multi-objective programming in the context addressed. Bernal-Agustín et al. (2006) apply a Pareto Evolutionary Algorithm (SPEA) for the multi-objective optimization of an isolated PV-wind-diesel system in which the objectives to be minimized are the total cost and the CO_2 emissions. Like Bernal-Agustín et al. (2006), Dufo-López et al. (2011) describe an application of SPEA to perform multi-objective optimization of an autonomous PV-wind-diesel system with storage using batteries. Nevertheless, in this case, the objectives to be minimized are the levelized cost of electricity (LCOE) and the equivalent life-cycle emissions of carbon dioxide (LCE).

Among the several multi-objective optimization methods that are able to construct the Pareto frontier, the Normal Boundary Intersection method (NBI), developed by Das and Dennis (1998), is one of the most promising methods available in the literature (Naves et al., 2017). Izadbakhsh et al. (2015) analyze the scheduling of energy sources in a microgrid consisting of micro-turbines, solar PV panels, fuel cells, battery storage and wind turbines. The authors use multi-objective optimization with the NBI method to simultaneously deal with minimization of total operational costs and gas emissions minimization. The main objective is to enable the system operator to adopt the most desired operating strategy considering economic and environmental strategies. Through the technique Modified Normal Boundary Intersection (MNBI), Gitizadeh et al. (2013) solve a problem of Generation Expansion Planning considering three objectives (maximization of economic returns, minimization of CO_2 emissions and minimization of the risk related fuel consumption due to the use of non-renewable energy sources). To our knowledge, there is a gap in the literature to explore a combined approach using Mixture Design of Experiments (MDOE) (Montgomery, 2013), NBI and super-efficiency Data envelopment analysis (super-efficiency DEA) (Andersen and Petersen, 1993; Charnes et al., 1978) to support and enhance decision-making in multi-objective programming problems.

In this context, the objective of this study is to develop an approach to select the optimal configuration of hybrid power generation systems for isolated regions by means of integrating MDOE, multi-objective programming via NBI and supper-efficiency DEA in a single decision-making framework. The main contribution of this work is to present and use this structured framework to define the optimal configuration of the power generation system considering the LCOE and greenhouse gas emissions as target metrics. Firstly, the MDOE technique is employed to estimate the model of objective functions. The NBI approach is used to establish the optimal Pareto frontier considering different power generation system configurations. Then, the super-efficiency DEA method is employed in the decision-making process, considering the diversity of hybrid systems by using entropy as a DEA product. Finally, the approach is applied to analyze a set of 4 isolated regions in Brazil located in the state of Amazonas.

The remainder of this article is organized as follows: Section 2 presents the mathematical tools used in this article to comply with the proposed method. Section 3 presents the proposed method for optimal configuration of a hybrid system as well as the "problem variables". Section 4 then presents the case study and the results with detailed discussion. Finally, some relevant conclusions are drawn in Section 5.

2. Project of experiments and mathematical optimization

As discussed by Gomes (2013), in order to promote the optimization of various processes, the analyst must follow a sequence of steps for mathematical formulation and problem analysis, consisting of the definition of decision variables, structural constraints and limits, objective functions, allocation of weights for the objective functions and identification of the optimal solutions and the analysis of the results. In this context, the objective of this Section is to present the mathematical tools used in this work to fulfill the aforementioned steps.

2.1. Design and analysis of experiments

The design of experiments (DOE) is a form of experimental design that uses statistical methods to plan and execute experiments (Montgomery, 2013 and Box et al., 1978). According to Solvason et al. (2009), for a model to represent the response surface, the experimental design points are placed in areas where observations can be collected and the model can be assembled. For Montgomery (2013) and Myers and Montgomery (2002), with respect to experimental projects, the most used techniques are the complete factorial planning, fractional factorial planning, the Taguchi arrangements, the response surface methodology and the mixing experiments.

In the present study, it is desired to find the optimal configuration of a hybrid system from a multi-objective formulation. That is, we seek to find the ideal quantity of each component that will compose this system. In this way, the use of the MDOE is indicated, since this type of design input variables are components of a mixture and the responses are functions of the proportions of each component (Coronado et al., 2015). Thus, for a problem involving q components, the sum of the fractions of each component (y_i) is equal to one, as shown in (1).

$$\sum_{i=i}^{q} x_i = 1, x_i \geqslant 0 \ (i = 1,...,q) \tag{1}$$

Thus, the feasible region of the two-component mixture is represented by a straight segment shown in Fig. 1.

The vertices of this convex region represent the pure mixture, the points within the region are mixtures in which none of the components is absent and the centroid (point in the center of the simplex) is the mixture with equal proportions of each component (Oliveira, 2009). From these characteristics, it becomes necessary to plan and conduct the mixing experiments through specific arrangements and, in this case, simplex arrangements have been the most used (Cornell, 2002). According to Montgomery (2013), simplex lattice design is used to study the effects of the mixture components in the response variable. A m-degree polynomial for a mixture of components, denoted by $\{q,m\}$, consists of points defined by the following proportions:

$$x_i = 0,\frac{1}{m},\frac{2}{m},...,1 \quad i = 1,2,...,q \tag{2}$$

For example, if the number of mixture components (q) is equal to 2 and the polynomial degree (m) is equal to 5, then:

$$x_i = 0,\frac{1}{5},\frac{2}{5},\frac{3}{5},\frac{4}{5},1 \quad i = 1,2 \tag{3}$$

Thus, the {2, 5} simplex lattice consists of six points in the boundary, as presented in 4.

$$(x_1,x_2) = (1,0),(0,1),\left(\frac{1}{5},\frac{4}{5}\right),\left(\frac{2}{5},\frac{3}{5}\right),\left(\frac{3}{5},\frac{2}{5}\right),\left(\frac{1}{5},\frac{4}{5}\right) \tag{4}$$

In (4) it is possible to observe that the first two components are pure mixtures (triangle vertex) and the other components are binary mixtures

In general, the number of points of a simplex lattice is given by:

$$N = \frac{(q + m-1)!}{m!(q-1)!} \tag{5}$$

However, Montgomery (2013) notes that simplex lattice arrangements are border point projects. Thus, if the analyst wants to make predictions about the properties of complete mixtures, it would be highly desirable to have more experiments inside the simplex. In this case, it is recommended to add the axial points and the center point (if the centroid is not already a design point) to the simplex lattice. For example, Montgomery (2013) recommends that the axial point should be between the central point and the vertex, that is, $= (q-1)/2q$. Thus, considering the previous example {2, 5} simplex lattice, adding the axial points and the centroid would result in the following form:

$$(x_1,x_2) = (1,0),(0,1),\left(\frac{1}{5},\frac{4}{5}\right),\left(\frac{2}{5},\frac{3}{5}\right),\left(\frac{3}{5},\frac{2}{5}\right),\left(\frac{1}{5},\frac{4}{5}\right),\left(\frac{1}{4},\frac{3}{4}\right),\left(\frac{3}{4},\frac{1}{4}\right),\left(\frac{1}{2},\frac{1}{2}\right) \tag{6}$$

where, the seventh and the eighth points are the axial points and the last point is the centroid.

As for the mathematical models used to represent the answers, according to Oliveira (2009) from this technique it is possible to establish a relation between the response variables and the relative proportion of components in terms of a mathematical equation, usually a polynomial model, which provides the identification of the influence associated with each component proportion and its combination with other components in the response variable. Generally, the polynomial can be linear, quadratic or cubic, however, in (7) the formulation is presented for a complete cubic model.

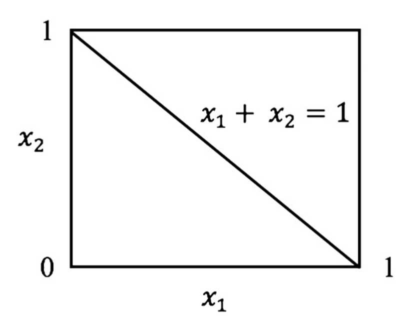


Fig. 1. Restricted factor space for blends with 2 components.

$$f(x) = \sum_{i=1}^{q} \beta_i^* x_i + \sum \sum_{i<j}^{q} \beta_{ij}^* x_i x_j + \sum \sum_{i<j}^{q} \delta_{ij} x_i x_j (x_i - x_j) + \sum \sum_{i<j<l}^{q} \sum \delta_{ijl}^* x_i x_j x_l \quad (7)$$

The coefficient β_i^* represents how much each component contributes to the response variable (f (x)). The terms β_{ij}^* and δ_{ij} indicate the effect of the combination of components i and j. According to Cornell (2002), the algorithm Ordinary Least Square can be used to find these coefficients.

2.2. Normal Boundary Intersection

Given the approximate functions resulting from the experiments performed with the MDOE, the optimization model can be formulated as (8).

$$\begin{aligned} &\min F(x) = (f_i(x),\ldots,f_m(x))^T \\ &\text{s.t.}: \{x \in R | g(x) \leqslant 0, h(x) = 0\} \end{aligned} \quad (8)$$

In (8), $f_i(x)$ represents the objective function to be minimized (these objective functions correspond to the response variable measured using the MDOE) and m corresponds to the index representing the last objective function of the set, i = 1, 2, … , m; g(x) are inequality constraints and h(x) are equality constraints related to each problem instance to be analyzed. According to Ahmadi et al. (2015) and Izadbakhsh et al. (2015), for the NBI method, the payoff matrix (∅) has to be generated first. In general, each objective function must be minimized to develop the payoff matrix with m competing objective functions. The solution that minimizes the objective function $f_i(x)$, denoted x_i^*, indicates the minimum value of the function represented by $f_i^*(x_i^*)$. The values associated with other evaluated objective functions are indicated as $f_1(x_i^*), \ldots, f_{i-1}(x_i^*), f_{i+1}(x_i^*), \ldots, f_m(x_i^*)$. Thus, the i-th column of the payoff matrix is written as follows:

$$\begin{aligned} &[f_1(x_i^*),\ldots,f_{i-1}(x_i^*), f_{i+1}(x_i^*),\ldots,f_m(x_i^*)]^T \\ &\text{s.t.} \ \ \{x \in R | g(x) \leqslant 0, h(x) = 0\} \end{aligned} \quad (9)$$

where x_i^* is the optimal value that minimizes f_i.

Thus, all columns of the payoff matrix are calculated and represented as follows:

$$\varnothing = \begin{pmatrix} f_1^*(x_1^*) & \ldots & f_1(x_i^*) & \ldots & f_1(x_m^*) \\ \vdots & \ddots & \vdots & & \vdots \\ f_i(x_1^*) & \ldots & f_i^*(x_i^*) & \ldots & f_i(x_m^*) \\ \vdots & & \vdots & \ddots & \vdots \\ f_m(x_1^*) & \ldots & f_m(x_i^*) & \ldots & f_m^*(x_m^*) \end{pmatrix} \quad (10)$$

From this matrix, it is possible to highlight two specific points, the utopia point and the nadir point. According to Naves et al. (2017), the utopia point corresponds to all the best possible values of the objective functions. In contrast, according to the aforementioned authors, the nadir point corresponds to all of the worst possible values associated with the objective functions. Thus, one can represent the utopia and nadir points as:

$$F^U = [f_1^*(x_1^*),\ldots,f_i^*(x_i^*),\ldots,f_m^*(x_m^*)]^T \quad (11)$$

$$F^N = [f_1^N,\ldots,f_i^N,\ldots,f_m^N]^T \quad (12)$$

Given, F^U defined as the utopia points and F^N defined as the nadir points,

$$\begin{aligned} &f_i^N = \max f_i(x). \\ &\text{s.t.}: \{x \in R | g(x) \leqslant 0, h(x) = 0\} \end{aligned} \quad (13)$$

The points defined by (12) refer to the pseudo nadir points, since in (13) it is used to define f^N. The pseudo nadir point is defined as the vector that contains the worst values of each objective function. Despite this, in order to obtain a fairly representative set of Pareto solutions, in situations where the objective functions have different magnitudes or physical meanings, the objectives must first be normalized. To calculate the normalized value of the objective function ($\overline{f}(x)$), we use the utopia points and the pseudo nadir points, defined by (11) and (12).

$$\overline{f}(x) = \frac{f_i(x) - f_i^U}{f_i^N - f_i^U}, i = 1,\ldots,m \quad (14)$$

From the normalized values, the normalized payoff matrix ($\overline{\varnothing}$), presented by (15), is developed.

$$\overline{\varnothing} = \begin{pmatrix} \overline{f_1^*}(x_1^*) & \ldots & \overline{f_1}(x_i^*) & \ldots & \overline{f_1}(x_m^*) \\ \vdots & \ddots & \vdots & & \vdots \\ \overline{f_i}(x_1^*) & \ldots & \overline{f_i^*}(x_i^*) & \ldots & \overline{f_i}(x_m^*) \\ \vdots & & \vdots & \ddots & \vdots \\ \overline{f_m}(x_1^*) & \ldots & \overline{f_m}(x_i^*) & \ldots & \overline{f_m^*}(x_m^*) \end{pmatrix} \quad (15)$$

Thus, in possession of the vector $\overline{f}(x)$ in association with the vector of weights w, a classic NBI formulation of two objectives can be described as follows (COSTA et al., 2016).

$$\begin{aligned} &\min \overline{f_1} \\ &\text{s.t.} \ \ \overline{f_1}(x) - \overline{f_2}(x) + 2w - 1 = 0 \\ &g_j(x) \geqslant 0 \ , \forall j \\ &0 \leqslant w \leqslant 1 \end{aligned} \quad (16)$$

where $\overline{f_1}(x)$ and $\overline{f_2}(x)$ are used to define the constraint set for the experimental regions. In the present study, the objective functions consider the LCOE and CO_2 emissions, $g_j(x)$ and $0 \le w \le 1$ are the constraint sets for the experimental region and the cuboidal region, respectively. Thus, the optimization problem is solved for different weight values (w) and the Pareto frontier is developed.

According to Ahmadi et al. (2015), the next step after finding Pareto optimal solutions is to find the best frontier solution, i.e., it is necessary to choose among the possible efficient solutions (from the Pareto frontier) the one that has the best performance considering the selected metrics. From a decision maker's point of view, the choice of a solution among the Pareto frontier optimal solutions is called a posteriori method and the use of a mathematical technique is necessary. Several tools are used for this purpose in the literature, with emphasis to the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) can be highlighted in Ahmadi et al. (2015), the fuzzy method presented by Izadbakhsh et al. (2015), the Percentage Error Global (EPG) and the entropy applied by Rocha et al. (2015a,b). In this paper, the super-efficiency DEA method is proposed as the method responsible for choosing the optimal solution after the Pareto frontier is established.

2.3. Super-efficiency data envelopment analysis

DEA corresponds to a nonparametric technique that allows one to evaluate the relative efficiency between decision making units (DMU's) that perform the same operations and, therefore, use multiple similar inputs to generate multiple similar products (Banker et al., 2011).

Based on the concepts of productivity and efficiency present in Farrell (1957), the initial DEA model was originally developed by Charnes et al. (1978). In relation to the existing models, two are considered classic: the Constant Returns of Scale (CCR), originally presented by Charnes et al. (1978) and the Variable Scale Returns (BCC), proposed by Banker et al. (1984). The latter model is also known as Variable Returns to Scale (VRS). Both the CCR model and the BCC model can be input or output oriented. Basically, in the input-oriented model, the objective is to change the inputs in order to achieve maximum productivity, keeping the observed product constant. Already in the product-oriented model is based on a vertical projection in the efficient frontier, in order to achieve maximum productivity from the alteration of products, while preserving the inputs unchanged.

However, the models presented show a limitation that is evident when the objective is to rank the most efficient productive units, since it is possible that more than one DMU present similar efficiency levels, making it impossible to determine the most efficient DMU (Xue and Harker, 2002). In order to circumvent this limitation Andersen and Petersen (1993) developed a modified version of DEA based on the comparison of efficient DMU's. Basically, the procedure provides a framework for classifying efficient units and facilitates comparison with rankings. Since our goal is to rank the DMU and choose the most efficient one from the Pareto frontier, we rely on the super-efficiency DEA technique. Next, the super-efficiency DEA model formulation developed in the input-oriented DEA CCR model is presented.

$$\max\theta_k = \sum_{j=1}^{s} u_j Y_{jk}$$
$$\text{s.t. } sum_{i=1}^{r} v_i X_{ik} = 1$$
$$\left(\sum_{\substack{j=1\\ z\neq k}}^{s} u_j Y_{jz}\right) - \left(\sum_{\substack{i=1\\ z\neq k}}^{r} v_i X_{iz}\right) \leqslant 0, \forall z$$
$$u_j, v_i \geqslant 0, \ \forall\, i,j \tag{17}$$

Given that θ_k as the efficiency of DMU k under analysis, the exemplified case considers the existence of DMU's, $z = 1,2,\ldots,n$, which use r inputs, $i = 1,2,\ldots,r$ to produce s products, $j = 1,2,\ldots,s$. The weighting multipliers of the input quantities X and Y outputs, i.e. the decision variables of the problem, are represented by v_i and u_j, respectively. For more information about the supper-efficiency DEA technique *see* (Andersen and Petersen, 1993).

3. Proposed method

This section is intended to describe the proposed method, which as mentioned previously consists in a combination of the techniques of MDOE, NBI and supper-efficiency DEA. This approach is intended to support decision-making by providing optimal configuration designs for hybrid power generation systems in isolated regions. Fig. 2 presents a structured framework for decision-making process.

As can be seen in Fig. 2, the first phase consists of the problem definition. That is, at this stage the decision variables (proportion of each energy source to be installed hydro power generation system) and the response variables of the problem are defined. The optimal sizing of an isolated system is directly conditioned by the response variables to be optimized. In this phase, the decision maker must first select which characteristics need to be optimized. It is critical to emphasize the importance of this procedure, since the optimal configuration of the hybrid system depends on the appropriate choice of the response variables and, therefore, a choice made in the wrong way can produce undesirable consequences for the decision maker.

The second phase of the method consists of the model design, where a mathematical model is estimated for each response variable as a function of the decision variables. In the present study, the estimated response variables used are the LCOE and the CO2 emissions as a product of the shares of diesel and PV in the composition of the total system generation capacity. In this step, the MDOE is used, since for this type of project the input variables are components of a mixture and the answers are functions of the proportions of each component. Thus, in this phase, the objective is to estimate the approximate function that relates the response of interest to the process variables.

Thus, considering the estimated functions, the third phase consists of the development of the Pareto frontier to determine the optimal hybrid power generation system configurations using the NBI method. After the development of Pareto frontier, the decision maker will have at his disposal the optimal configurations of the hybrid power generation system. However, which configuration should be selected? In other words, what is the most efficient border solution? To find this answer, the DEA supper-efficiency method is used in the last phase.

3.1. Stage I – problem definition

According to Roy and Kulkarni (2016), supplying all energy demand with the diesel or PV generation group may not be viable, thus highlighting the importance of integrating these sources. Generally, the combination of renewable and conventional energy sources allows the optimization of energy generation systems from technical, economic and environmental points of view, providing continuous and stable energy, reducing the operation and maintenance costs of diesel generators, minimizing fuel dependency and pollutant emissions (Rehman and Al-Hadhrami, 2010). In this sense, for the application of the proposed method, three possible subsystems are considered for the isolated hybrid system: solar PV system, battery storage and diesel generators. The energy demand profile, as well as the general technical characteristics of commercially available equipment, are selected. The goal is the ideal system configuration that minimizes LCOE and CO_2 emissions. More specifically, it aims to determine the installed capacity of solar PV panels, diesel generators and batteries (that provide the storage capacity needed to increase the utilization of solar PV energy). Fig. 3 shows the model to be optimized.

3.2. Phase II – Objective function modeling

The second phase of the proposed method aims to provide objective functions formulations. Within the context of this study, in which it is desired to find the optimum configuration of the hybrid power generation system, we use MDOE since for this type of project the input variables are components of a mixture and the responses are functions of the proportions of each component. Therefore, in this step, the objective is to estimate the approximate function that relates the response of interest to the process variables. For this, a structure composed of 3 steps is highlighted next.

3.2.1. A. Planning the experiments

The experiments were planned following a {2,5} simplex lattice with two axial points and a central point, defined in (6), which resulted in nine experiments using the variables e. The responses analyzed include LCOE and CO_2 emission.

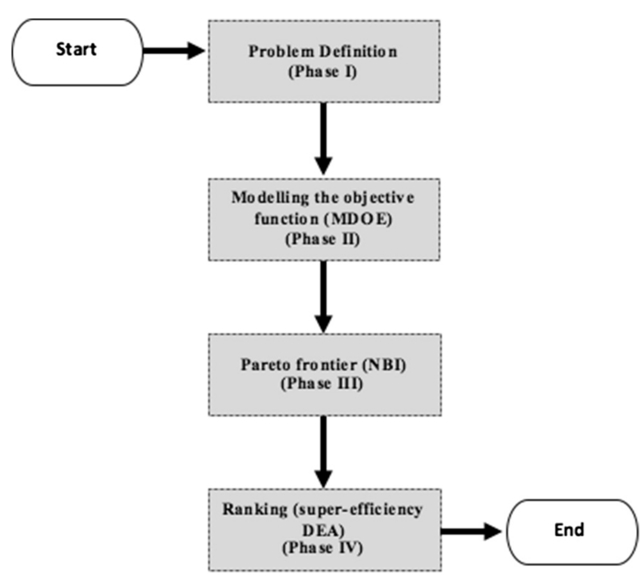


Fig. 2. Proposed method.

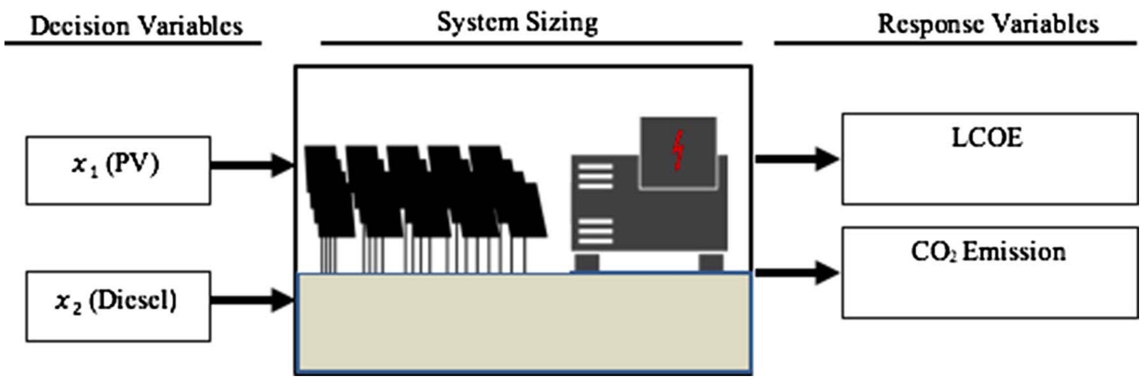


Fig. 3. Problem definition.

3.2.2. B. Experimental procedure and data collection

After the experimental planning stage, the second stage consists of the implementation of the experiments, performed through the sizing of the hybrid system for each point defined by (6). To perform the experiments, it is necessary to size the hybrid system for each point selected in the application of the mixing experiments. Thus, LCOE and CO_2 emission are estimated for the points $(x_1,x_2) = (1,0),(0,1),\left(\frac{1}{5},\frac{4}{5}\right),\left(\frac{2}{5},\frac{3}{5}\right),\left(\frac{3}{5},\frac{2}{5}\right),\left(\frac{1}{5},\frac{4}{5}\right),\left(\frac{1}{4},\frac{3}{4}\right),\left(\frac{3}{4},\frac{1}{4}\right),\left(\frac{1}{2},\frac{1}{2}\right)$ defined in the experimental planning.

For this problem, a number of uncertainties can be represented together. Thus, for the experimental procedure we use Monte Carlo Simulation (MCS) combined with the optimization process to define different values for the response variables. In the MCS implementation, the uncertainties inherent to the determinant variables for the response variables calculation (LCOE and CO_2 emissions) must first be inserted through probability distributions attributed to the variables. The next step is to simulate scenarios and collect the response variables average values. The response variables averages, simulated through the MCS compose the experimental matrix that is used as data source for the modeling and optimization process.

3.2.3. C. Modeling objective functions

The objective functions modeling associated with LCOE and CO_2 emissions are determined from the model defined by (7). Thus, using two decision variables we can obtain the polynomial represented by (18). The coefficients β_1^*, β_2^*, β_{12}^* and δ_{12}^* values are estimated using the Ordinary Least Squares method using the Minitab® software (Monticeli et al., 2016).

$$Y = \beta_1^* x_1 + \beta_2^* x_2 + \beta_{12}^* x_1 x_2 + \delta_{12}^* x_1 x_2 (x_1 - x_2) \tag{18}$$

3.3. Step III – Pareto frontier

Once the approximate functions resulting from the experiments are obtained, the optimization problem can be formulated. With this, it is possible to develop a multi-objective formulation for the problem at hand, as described in Section 2.2. To construct the Pareto frontier, it is worth noting that we opted to make changes in the order of 0.1 in the weights (w) used in the objective functions. In addition, it is possible to identify constraints that will be considered in the formulation of the optimization models. These constraints are presented in (19):

$$\begin{aligned} &0 \leqslant (x_1) \leqslant 1 \\ &0 \leqslant (x_2) \leqslant 1 \\ &(x_1 + x_2) = 1 \end{aligned} \tag{19}$$

where x_1 and x_2 represent, respectively, the percentage of solar PV generation and the percentage of diesel generation in the composition of the total hybrid power generation system capacity in the isolated region under analysis. The nonlinear programming models developed here were computationally implemented and solved using an existent solver that employs the Generalized Reduced Gradient (GRG) method, for more details about the GRG method *see* (Lasdon et al., 1974).

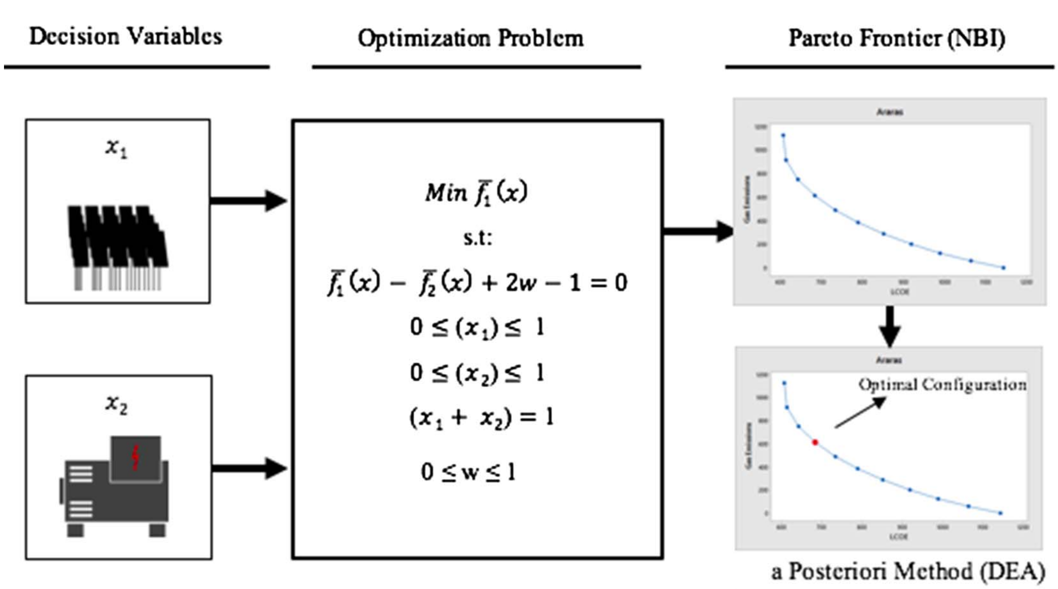


Fig. 4. Optimization method.

After the Pareto frontier is elaborated, the decision maker will have the optimal configurations of the hybrid system at their disposal. However, which configuration should be chosen? That is, what is the most efficient frontier solution for the objectives in question? The next session describes the use of the DEA method as a posteriori analysis to make the choice of the most efficient Pareto frontier solution.

3.4. Step IV – identifying the optimal design

The super-efficiency DEA model, developed from the input-oriented DEA CCR model, is used to rank optimal Pareto frontier configurations as discussed in Section 2.3. For the formulation of the problem to be solved by the DEA model, it is worth mentioning that the selected DMUs are the Pareto frontier solutions generated from the use of the NBI method applied to the multi-objective optimization model. In addition, it is necessary to determine the inputs and outputs of the process under analysis. In this sense, a series of variables can be selected, such as TOTEX, CAPEX, OPEX, LCOE, emission, area for installation and entropy, among others.

Besides the variables used in the NBI method (LCOE and emissions), we aim to find designs that diversify the generation system using the entropy as a product of the DEA analysis. Thus, the variables selected for efficiency analysis are LCOE, configured as input, avoided emission and entropy, configured as process products (or outputs). Finally, the proposed optimization model, developed according to the described approach, is schematized according to Fig. 4.

3.5. Problem variables

3.5.1. A. Levelized cost of electricity

LCOE is an investment analysis metric often used in the literature as a method to evaluate power generation costs from different types of technology and sources (Singh and McFarland, 2015). This metric is widely used by policymakers (Irena, 2015; Borenstein, 2012). According to Singh and McFarland (2015), the LCOE is calculated by amortizing capital and operating cost over the lifetime of the system. The use of LCOE allows the direct comparison of different technologies. Following the definition of Rezzouk and Mellit (2015), (20) presents how the LCOE is computed.

$$\mathrm{LCOE} = \frac{\mathrm{TOTEX}}{\mathrm{E_t}} \tag{20}$$

where TOTEX (or Total Expendidure) represents the sum of the present values of the costs associated with each system component, including investment, replacement, operation and maintenance, as well as fuel costs. $\mathrm{E_t}$ is the total energy produced by the system. However, in isolated systems the total consumption ($\mathrm{C_t}$) is considered as the denominator instead of $\mathrm{E_t}$, and (20) can be adapted to (21) (Dufo-López et al., 2011), shown below.

$$\mathrm{LCOE} = \frac{\mathrm{TOTEX}}{\mathrm{C_t}} \tag{21}$$

It is worth noting that both the calculation of TOTEX and the estimation of total consumption should be discounted from the annual values by the Weighted Average Capital Cost (WACC) as can be seen in Flowers et al. (2016). In this study, the WACC calculation follows the formulation presented in Aquila et al. (2016), and defined herein by (22).

$$\mathrm{WACC} = K_d D(1-t) + K_e E \tag{22}$$

Given that K_d represents the cost of debt, D denotes the portion of debt in the investment (%), t is the income tax, K_e is the cost of equity and E denotes the fraction of total capital represented by equity (%). For the calculation of the cost of third-party capital (K_d) the methodology indicated by ANEEL (2016) stands out. This methodology considers the sum between the risk-free rate, the credit risk premium and the country risk premium, as presented in (23).

$$K_d = r_f + r_c + r_b \tag{23}$$

Given r_f as the risk-free rate, r_c the credit risk premium, r_b the country risk premium. In the calculation of equity (K_e), a widely used approach in the literature is the Capital Asset Pricing Model (CAPM), presented by Sharpe (1964) .The formulation proposed by Sharpe is represented in (24). Where, the risk of the project in relation to the market (leveraged beta) is represented by β and r_m denotes the expected return of the market.

$$K_e = r_f + \beta x(r_m - r_f) + r_b \tag{24}$$

3.5.2. B. CO_2 emissions

CO_2 is the main greenhouse gas that has contributed to the aggravation of the problem related to global warming (Seddighi and Ahmadi-Javid, 2015) which affects society in several spheres such as health (McMichael et al., 2007), energy (Pereira et al., 2013; De Queiroz et al., 2016), economy (Mendelsohn and Neumann, 2004), sustainability (MacDonald, 2010), and many others (De Carvalho et al., 2015). CO_2 emissions are also an important source of ocean acidification when CO_2 dissolves in water to form carbonic acid (National Research Council, 2010). Razykov et al. (2011) reports that around 20 TW of non-CO_2-emitting energy will be needed worldwide to stabilize the volume of this gas present in the atmosphere by the middle of the century, highlighting the use of renewable energy sources such as the solar PV system. It is worth noting that the present work presents the variable CO_2 emission as being exclusively derived from the burning of the fuel, in the same way as it was proposed by Bernal-Agustín et al. (2006).

3.5.3. C. Entropy

According to Rocha et al. (2015b), the entropy proposed by Shannon (1948), can be defined as a measure of probabilistic uncertainty and its use is indicated in situations where probability distributions are unknown, in search of diversification. According to the above-mentioned author, the entropy $S(x)$ is calculated using the responses generated by the Pareto frontier, as shown in (25).

$$S(x) = -\sum_{i=1}^{h} x_i \ln(x_i) \tag{25}$$

Given h as the number of decision variables and the values of these variables that are part of the system to be diversified, assuming that the sum of these values must be equal to 1. From the entropy measure it is possible to find an optimal point with the maximum diversification in a system with different components. For the calculation of the entropy defined in (25), h is the number of decision variables. That is, in the case presented $h = 2$ and, as presented above, x_i represents the fraction of each technology in the composition of the system total generation capacity.

4. Case study and simulation results

This Section present the application of the proposed methodology to a real system representation.

4.1. Case study

The application of the proposed methodology is performed using real data for an isolated system in the Northern region of Brazil (Eletrobras, 2016 and EPE, 2016). In Brazil, a significant portion of the population does not have access to electricity (CGEE, 2010). This problem is even more pronounced in rural areas or in isolated systems. According to Silveira et al. (2013) for part of the population living in these areas the cost of access to energy distribution systems can be extremely high and often economically unfeasible. As an example, the aforementioned authors cite the small villages of the Amazon region, because they do not have access to power distribution networks, they rely on diesel generating systems for electricity production, since investments in energy transport systems to connect to interconnected networks are not economically attractive.

According to the MME (2009), in the Amazon region, an area that represents 61% of the Brazilian national territory and encompasses nine states in Brazil belonging to the Amazon Basin, it is estimated that around 300,000 isolated communities do not have access to electricity, harming both the provision of essential services such as health, communication and education, as well as local living conditions, social development and the regional economy. The generation of energy through small diesel generators is the main source of electric power for the communities in this region. However, this type of generation technology imposes serious restrictions on the operating conditions, in which the frequent occurrences service interruptions, low quality performance and high maintenance costs can be observed (Silva et al., 2013).

For the application of the proposed methodology, four isolated systems from the state of Amazonas (Araras, Boca do Acre, Canutama and Tapauá) in Brazil were selected that were the focus of the government technical planning report in 2016 (EPE, 2016). The choice of these four regions seeks to represent different sizes, characteristics of consumption and resources, as well as logistic complexity. In addition, the work uses data from these regions presented by Eletrobras (2016), as can be seen in Table 1. The time horizon considered for the analysis is 15 years, consistent with the information provided in Eletrobras (2016).

The location of these regions, represented by the latitude and longitude of each site, as well as the energy demand, are presented in Table 1.

According to Seddighi and Ahmadi-Javid (2015), in addition to gas emission levels, uncertainty over fuel costs has a major impact on energy generation and transmission planning, resulting in a complex, multi-dimensional problem. In this model, the information considered as uncertainties and treated as stochastic parameters are fuel consumption (related to CO_2 emissions), fuel cost and cost of solar PV systems (related to LCOE). The choice of fuel costs and costs of solar PV systems is based on the findings of the sensitivity analysis developed for the regions under analysis obtained from EPE (2016). According to this analysis, this information can suffer significant variations, mainly due to the logistic complexity and difficulty of access to the regions.

With respect to fuel and solar PV generation costs, a triangular probability distribution is attributed. According to Aouni et al. (2009), triangular pertinence functions can be used to insert uncertainty into the input and output parameters of a model, since they represent well the human expertise in correctly judging the behavior of common variables in various practical situations. Thus, the parameters of the triangular distribution (optimistic value, probable value and pessimistic value) are established based on the increase in diesel costs, indicated in Table A.5, by 25% and a cost reduction of 25% according to (EPE, 2016). This procedure is justified due to the uncertainty of fuel costs during the contractual period and the fact that it is an expense that persists throughout the period. With regard to the costs of the solar PV systems, the most probable cost value is defined at 1.73 US $/Wp, and the optimistic and pessimistic values are equal to 1.38 US $/Wp and 2.07 US $/Wp respectively.

Dufo-López et al. (2011) point out that a typical diesel generator consumes around 0.32 and 0.53 [l/kWh]. Thus, to calculate CO_2 emissions, the fuel consumption is considered to vary according to a uniform probability distribution in the range [0.32, 0.53]. Thus, from the MCS, 1000 scenarios were simulated using Crystal Ball® software, since according to Kushary et al. (2000) this amount is enough to eliminate the estimator bias.

4.2. Results

With the application of the proposed methodology, a Pareto frontier is obtained based on the optimal configurations, in each of the analyzed systems. Then, using the super-efficiency DEA model, the best hybrid system configuration for each location is analyzed. The Pareto boundaries, formed in 11 optimal configurations in each system, are presented in Fig. 5.

It can be seen from Fig. 5 that there is a tendency for the most inefficient configurations for each system to be located at the ends. This effect is observed due to the use of entropy as a product of the supper-efficiency DEA analysis, since this variable allows the diversification of hybrid systems. In association, it can be observed that in all cases the Pareto frontier indicates the highest shares of diesel in the composition are the most inefficient of the Pareto frontier, due to the high volume of CO_2 emissions in these scenarios. In addition, it can be seen from Table 2 that although these points are selected as points of the Pareto frontier the supper-efficiency DEA define them as inefficient points, since they have efficiency values lower than one. Finally, as can be seen in Table 2, for each region a different configuration was selected and in all cases presented predominant shares of diesel generation are observed in the selected configurations.

After selecting the optimal configurations for each region, the LCOE values and the CO_2 emission volumes referring to the optimal configurations are compared with the system composed only of diesel generators, as presented in Table 3.

It can be seen from Table 3 that there is a significant reduction of CO_2 emissions with the optimal configurations selected, since the installation of these hybrid systems provides savings of approximately 43.60% when compared to 100% diesel systems. On the other hand, since the use of solar PV systems is a more expensive solution due mainly to the high costs involved for the allocation of batteries that are considered. The installation of such hybrid systems generates a 36.32% increase in LCOE. These answers highlight the conflicting effect of changes in the decision variables on the objectives of the problem, since an increase in the share of solar PV systems reduces CO_2 emissions and increases the TOTEX that directly influences the LCOE. Therefore, it is possible to establish the trade-off between the objective functions when these settings are changed. In Fig. 6, the straight lines represent the different trade-offs for the four regions in study.

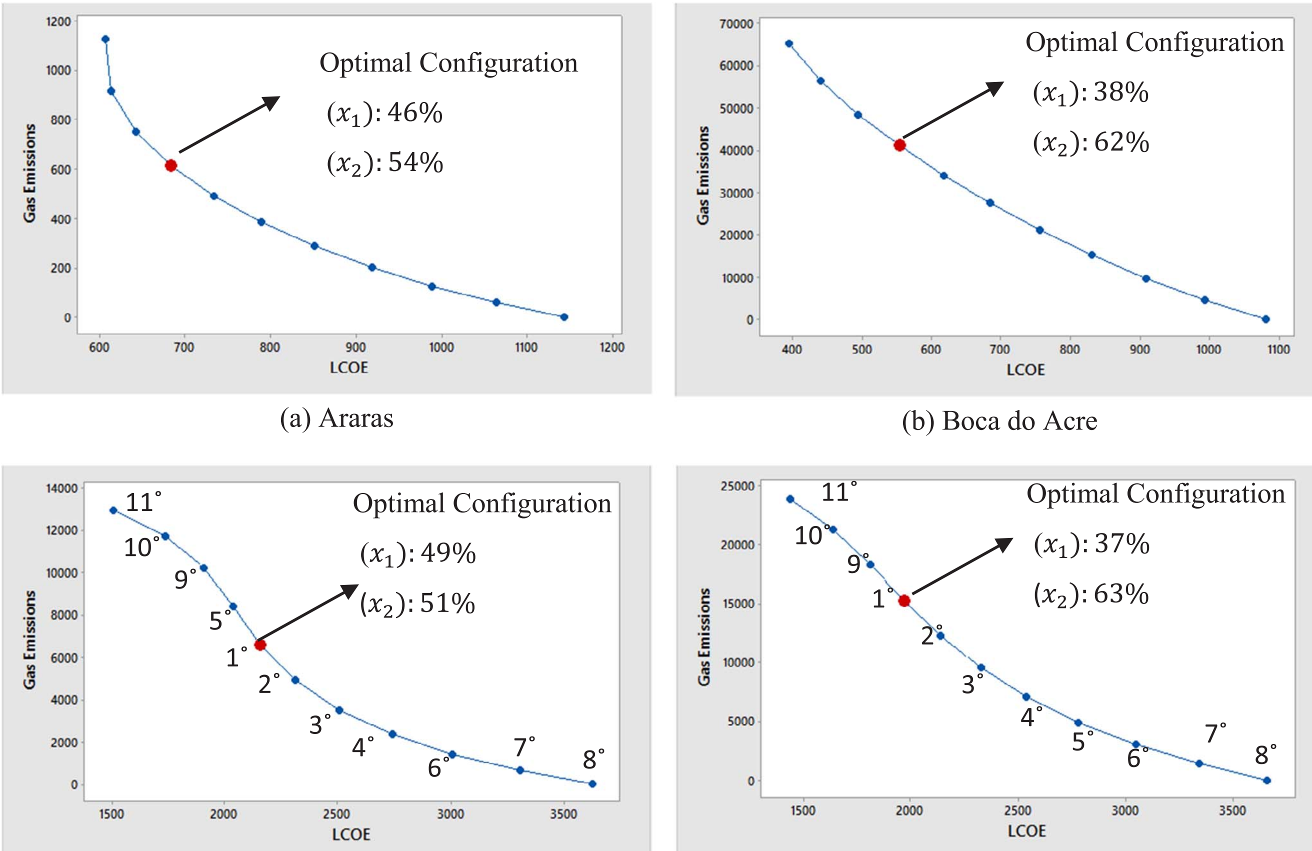
In Fig. 6, the value 100 is assigned for CO_2 emissions and LCOE values in the 100% diesel configuration (base case). The point at the other end of the line represents CO_2 emissions and LCOE values of the optimal configuration obtained in proportion to the 100% diesel configuration. The slope of the lines presented by indicates that a reduction of the CO_2 emissions are more significant than the increase in LCOE when selecting the optimal configuration obtained from the proposed method. In addition, it is possible to infer that the improvement in the results is more pronounced for the Araras region than for other localities, since it achieves a larger CO_2 emission reduction associated to a smaller LCOE increase.

4.3. Discussion of results

It is important to emphasize that the main objective of applying the proposed method is the emission reduction characteristic of diesel

Table 1
Location and energy demand.

Region	Latitude	Longitude	Energy market (kWh/day)
Araras	03°24′58″S	61°21′53″W	2419
Boca do Acre	08°46′05″S	67°19′08″W	139,071
Canutama	06°32′04″S	64°23′01″W	27,575
Tapauá	05°37′17″S	63°11′16″W	51,016



(a) Araras (b) Boca do Acre

(c) Canutama (d) Tapauá

Fig. 5. Pareto frontier and optimum setting in each location.

Table 2
Optimum allocations and efficiencies of each DMU.

	Araras			Boca do Acre			Canutama			Tapauá		
Order	x_1 (PV)	x_2 (Diesel)	DEA efficiency	(PV)	x_2 (Diesel)	DEA efficiency	x_1 (PV)	x_2 (Diesel)	DEA efficiency	x_1 (PV)	x_2 (Diesel)	DEA efficiency
1	46%	54%	1.042	38%	62%	1.043	49%	51%	1.052	37%	63%	1.034
2	56%	44%	1.023	48%	52%	1.023	61%	39%	1.031	48%	52%	1.031
3	65%	35%	1.021	57%	43%	1.014	71%	29%	1.024	59%	41%	1.024
4	73%	27%	1.014	66%	34%	1.013	80%	20%	1.022	68%	32%	1.023
5	80%	20%	1.013	74%	26%	1.013	36%	64%	1.001	77%	23%	1.012
6	87%	13%	1.004	83%	17%	1.012	87%	13%	0.992	85%	15%	1.001
7	35%	65%	1.002	91%	9%	1.001	94%	6%	0.961	93%	7%	0.983
8	94%	6%	0.993	27%	73%	0.993	100%	0%	0.923	100%	0%	0.951
9	100%	0%	0.972	100%	0%	0.992	23%	77%	0.884	25%	75%	0.934
10	21%	79%	0.831	15%	85%	0.801	11%	89%	0.611	12%	88%	0.691
11	0%	100%	0.064	0%	100%	0.074	0%	100%	0.064	0%	100%	0.062

Table 3
Comparison of optimum configuration with 100% diesel solution.

Region	LCOE [US$/MWh]			Emissionde CO_2 [t/ano]		
	Opt. Config.	Config. 100% Diesel	Difference	Opt. Config.	Config. 100% Diesel	Difference
Araras	683.67	584.32	17.00%	611.69	1,163.03	−47.41%
Boca do Acre	553.24	392.68	40.88%	41,019.28	66,865.72	−38.65%
Canutama	678.77	457.35	48.41%	6,558.02	13,258.58	−50.54%
Tapauá	618.86	445.29	38.98%	15,264.25	24,531.32	−37.78%
Average			36.32%			−43.60%

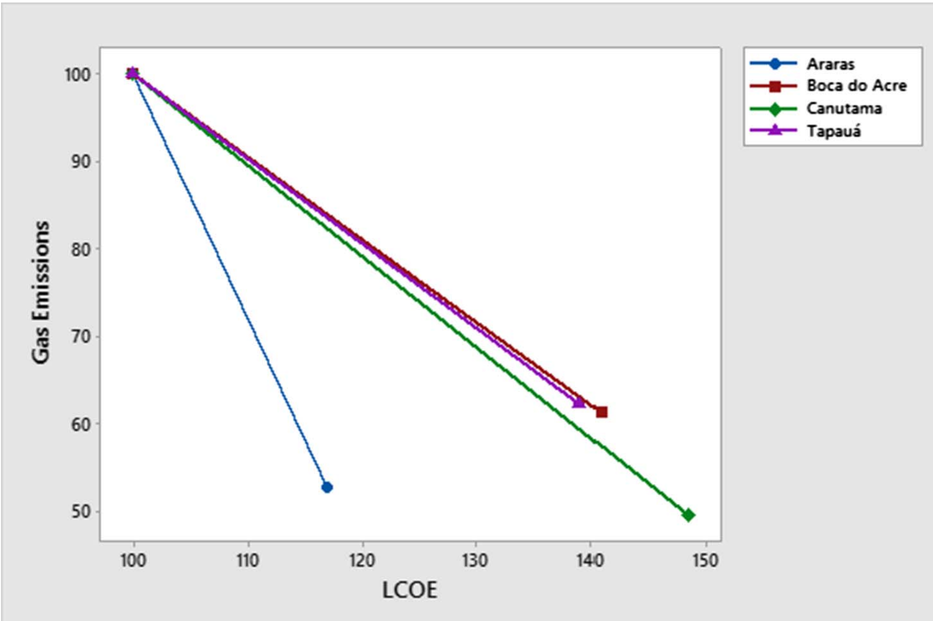


Fig. 6. Trade-off (gas emissions and LCOE).

systems currently used for power generation in isolated areas in the Amazon region. In this sense, the investment decision-making is necessarily related to the regulations established by the regulatory agencies that have the responsibility to ensure the quality of energy services. In another sense, investors will opt for diesel-only systems, if this option is available, since the emission reductions from the installation of hybrid systems (PV & Diesel) occurs to the detriment of the investment cost increase and, therefore, of LCOE, reducing the project profitability. This is due to the high costs related to solar PV systems in Brazil, since most of the equipment is imported.

Therefore, it is plausible to analyze the importance of fiscal incentives by the government while focusing on reducing the greenhouse gas emissions. In this context, according to Aquila et al. (2016), Brazil seeks to promote special lines of credit for contracting renewable energy generation projects in long term auctions. Since such incentives can override the additional costs, it is possible to motivate producers to invest in hybrid projects, with the insertion of renewable energy sources, even if they will present higher TOTEX.

In addition, it is important to note that although LCOE increases considerably in pure photovoltaic systems, other financial mechanisms beyond government-subsidized credit lines can improve the economic viability of such projects, such as possible carbon credit markets that would correspond to alternative sources of revenue. Corroborating this claim, Aquila et al. (2016) states that it is possible for the renewable energy producer to apply for participation from the Clean Development Mechanism, a program in which it is possible to receive carbon credits from the avoided emission.

Despite the application of the method in hybrid PV-diesel systems in regions of the Brazilian state of Amazonas, it is expected that the proposal presented in this article may be applicable to different hybrid systems, contributing, through their results, to the optimal configuration analysis in different situations. In addition, the proposed methodology could be used by government agencies that manage the energy auction processes in the definition of possible incentives that will mitigate the emission of gases associated with the most efficient points of the Pareto frontier. This would increase the competitiveness of hybrid generation systems with respect to pure diesel systems to supply demand in isolated regions.

Possibilities for future work include the use of other methods to generate the Pareto frontier and to select the optimal configuration. It is also suggested the use of other a posteriori methods to select the optimal configuration providing a possible comparison with the results obtained here from the use of the super-efficiency DEA model. In addition, it is worth mentioning that there is a possibility for using other inputs and other products in the super-efficiency DEA model to determine the most efficient configurations based in other criteria. As a suggestion one can consider the optimization of the area required for the installation of hybrid power generation systems and include other generation sources such as wind power. Also, the possibility of using other experimental arrangements for the planning and realization of the experiments should be an interesting area of work.

In this paper, uncertainty was considered with respect to investment and fuel costs through MCS, however, other kinds of uncertainty could be further incorporated in the model such as electricity demand, solar PV generation and reliability of power generators. That would require further enhancements in the decision-making framework established in this work. Also, with respect to the use of batteries in combination with renewables one important problem that arises is how to control the scheduling of such devices as noted in (Hafiz et al., 2017), this idea could be extended to this context where investment decisions could be combined with the optimal operation of the system. In this case, other operational issues related to voltage violations, active and reactive power flows could be included in the analysis.

5. Conclusion

With regard to the multi-objective optimization techniques, especially with respect to the application in hybrid power generation systems with renewable energy sources, the present study proposed a structured framework to determine the best compositions for the systems in isolated communities. The present work uses the NBI method, presenting a proposal that stands out in relation to others because it indicates as a solution equidistant points of the optimal configuration. In addition, the present methodology presents a method to select the optimum configuration of the system a posteriori, which allows the decision maker to selected the most efficient point in the Pareto frontier. Thus, comparisons of the optimal configuration results with a 100% diesel system were feasible through the development and application of the super-efficiency DEA model in the Pareto frontier.

In relation to the results obtained from the practical application, it is possible to infer that, because they presented high volumes of CO_2 emissions, the 100% diesel configurations were considered the least efficient in the Pareto frontiers. Nevertheless, it can be noticed that in both cases the optimal configuration prevails that composed predominantly by diesel generators. Also, as one should expected, the use of entropy as a product of the DEA model allowed the diversification of the hybrid power generation systems. Moreover, it is clear that there is a trade-off between the LCOE and CO_2 emissions, since the increase in LCOE implies more emission reductions and vice versa.

Acknowledgments

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Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Appendix A

Radiation data were collected from the NASA surface and solar energy data set with the aid of PVSYST® software. In order to determine the incidence of solar radiation in the inclined plane, it is necessary to consider the inclination value of the photovoltaic modules as input data in said software. As indicated by Villalva (2015), the slope value for sites with a latitude of less than 10°, which is the case for study object regions, should be considered as 10°. Since, for system design, it is considered the lowest value of solar availability (G_w), only the lowest value of solar radiation incidence in the inclined plane is presented in Table A.1.

The technical note provided by EPE (2016) presents the cost and investment assumptions for photovoltaic systems, inverters and batteries, which are presented in Tables A.2 and A.3

As can be seen in Table A.3, the cost of replacing the batteries after the service life was 50% higher, due to the need to remove the old batteries from the place and to arrange an adequate disposal, according to the current legislation.

The following data are presented regarding the diesel generation technology used for system design, according to the values presented by EPE (2016). While Table A.4 presents the normal cost assumptions for the regions, Table A.5 shows the estimates of CAPEX (investments in generators

Table A1
Solar radiation.
Source: PVSYST® software.

Region	G_w (kWh/m²/day)
Araras	4.28
Boca do Acre	5.24
Canutama	4.69
Tapauá	4.48

Table A2
Cost assumptions (PV).
Source: EPE (2016).

Cost	Assumption
Annual Fixed Cost Photovoltaic Modules	2% do $CAPEX_m$
Fixed Cost Investors - Annual	1% do $CAPEX_i$
Fixed Cost Batteries - Annual	1% do $CAPEX_i$
Cost of Battery Substitution	150% battery value

Table A3
Investment assumptions (PV).
Source: EPE (2016).

Investment	Value
Photovoltaic Systems in USD /W_p - ($CAPEX_m$)	1.73
Investors in USD//W - ($CAPEX_i$)	0.63
Battery in USD/kWh - ($CAPEX_b$)	471.70

Table A4
Cost assumptions (diesel generator).
Source: EPE (2016).

Cost	Assumption
Annual Fixed Cost	5% do CAPEX
Variable Cost	US$ 7.90/MWh
General Maintenance Cost[a]	60% of generator value

[a] It is estimated that every 15,000 operating hours require the general maintenance of the equipment.

Table A5
Investments and cost of fuel (diesel generator).
Source: EPE (2016).

Region	Capex (USD/kW)	Cost of fuel (USD/MWh)
Araras	1,249.00	392.77
Boca do Acre	936.00	319.00
Canutama	1,182.39	357.23
Tapauá	1,1131.13	283.96

Table A6
Assumptions for calculating WACC.
Source: Eletrobras (2016).

Cost of equity (K_e)	13% a.a
Third-party capital cost (K_d)	13.50% a.a
% of equity (E)	30%
% of third-party capital (D)	70%

and system installation) and the cost of fuel, which will vary according to each region, mainly because of access to the region and fuel storage. It should be noted that the values of investments in generators correspond to 35% of CAPEX and the rest refers to the system installation values.

To calculate the LCOE it is necessary to estimate the WACC. In this context, Eletrobras' reference project (2016) provides the values of cost of third-party capital, cost of equity, third-party capital and share of capital (Table A.6) to calculate WACC.

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