Optimal Sizing of Stand-alone Hybrid Photovoltaic-wind-battery Energy System using PSO

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Abstract

The optimization of a photovoltaic-wind-battery hybrid renewable energy system (HRES) for a site in the Northeast region of Brazil is undertaken in the present paper. A yearlong of hourly measured weather and load profile data of the location were used and the chosen optimization method was Particle Swarm Optimization (PSO). The main goals of the study were to fulfill the electricity demand of the chosen site by designing an optimization problem based on the Net Present Cost (NPC). The basic configuration chosen for the problem is a photovoltaic-wind-battery system given the much favorable weather condition for solar and wind energy systems at the site. The results show that the PSO could size the system for the set of defined constraints, minimizing the total cost for the 4 scenarios proposed. The optimal results for the proposed case study showed that a hybrid renewable energy system is less costly than a single source photovoltaic-battery or wind-battery system for most scenarios. It is also shown the influence of the reliability factor in the cost function showing it to be a key parameter of decision and the importance of the wind turbine hub height in the optimization.

Keywords: HRES, PSO, NPC, optimization, photovoltaic-wind-battery.

1. Introduction

Energy is vital in the age of modernization and economic development. The demand has increased exponentially, and the scarcity of conventional energy sources fuel has contributed to the promotion of renewable energy around the globe. One of the primary challenges nowadays is to meet the growing demand without exhausting the resources available to us (Goel and Sharma, 2017). Hybrid renewable energy systems, HRES, are energy generation systems composed of two or more energy sources that can be autonomous or grid-connected. Hybrid photovoltaic-wind-battery systems, with the complementary characteristics between the solar and wind energy sources can be, for certain locations, an unbeatable option for the supply of electrical loads (Diaf et al., 2007). Research shows that hybrid systems have been chosen as a reliable and suitable option that offers techno-economic advantages compared to single-source renewable systems.

The optimization process of a stand-alone hybrid renewable energy system using Particle Swarm Optimization (PSO) to a specific site in the Northeast region of Brazil is presented in this paper. The construction of the optimization function is discussed along with specific characteristics of the chosen site. The optimization process is done using classic methodologies present in the literature, and four scenarios are built to discuss and analyze the adopted optimization process and results obtained. The presented work has as main objective to present a simple, easy to build, and free algorithm to size a HRES for a site in the northeast region of Brazil. Other goals are to analyze the impacts of some aspects on the optimization function and propose important considerations to make the optimization process closes to the weather and techno-economic situation on the site. Particle Swarm Optimization (PSO) was chosen since it is easy to program in different program languages and software, and it presents great performance what permits a high number of executions in a small window of time. Section 2 presents the characterization of HRES, section 3 gives a brief explanation of PSO, sections 4 and 5 the methodology, site and equipment's costs and characteristics, section 6 the results and case study and section 7 de conclusion.

2. Hybrid renewable energy systems

Hybrid renewable energy systems (Fig. 1) are defined as systems composed of one or more renewable sources of energy, a management system, optional auxiliary source, and optional conventional source, designed to supply a

doi:10.18086/swc.2019.32.02 Available at http://proceedings.ises.org

load under a set of operational and constructive constraints. Conventional sources can be considered as grid interaction for on-grid system or micro-hydro, thermal or other kinds of generators for stand-alone systems. Auxiliary sources can be battery banks, hydrogen tanks, and even diesel generators that depending on the systems configurations can be applied as a conventional source or as an auxiliary one. HRES present lower emission of pollutants in comparison with conventional systems, high reliability with lower investments in comparison with conventional generation and single-source renewable system and fewer impacts in the network for on-grid systems.

Optimization of HRES classifies as a global optimization problem and two different approaches can be taken: classic and meta-heuristic methods. On the one hand, classic methods can be very useful to obtain the optimal solution of problems, involving continuous and differentiable function, constrained or unconstrained, to reach minimum points. However, they are likely to get stuck in a local minimum. To overcome this, the method can be repeated many times with randomly chosen initial conditions, and the best result is considered a global minimum for the function. This increases computational time and there is no guarantee that the optimal solution will be found (Tezer et al., 2017). Given this characteristic, classic methods are not very often applied to HRES optimization. On the other hand, meta-heuristics are built as metaphors based on natural processes such as swarm's intelligence and behavior and are equipped with the right tools to avoid local minimum of functions.

Between the many meta-heuristic methods, there are two different branches: the algorithms based on one solution being estimated at a time and the ones that process a whole population of solutions at a time, or iteration. The first kind can be classified as neighborhood or trajectory meta-heuristics and as examples, we have Simulated Annealing, Tabu Search, etc. The second can be defined as population-based algorithms, and commonly found in the literature are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) (Tezer et al., 2017). GA, as a population-based algorithm, tests numerous solutions at a time and is very successful in finding a global minimum as is PSO. There are also many versions of both algorithms in the literature that have proven to be successful in single and multi-objective optimizations. Compared to other algorithms, PSO presents the simplicity of coding, easy use, low convergence time, minimum storage and, smaller dependence of the initial population (Kennedy and Eberhart, 1995). All advantages that contribute to making PSO a strong algorithm that is largely used for sizing HRES.

In this paper, an optimization method is presented to perform the optimal sizing of an HRES for a site located in the Northeast region of Brazil. In this algorithm, one year of wind speed and solar irradiation data from the region is used along with one year of load profile. Photovoltaic and wind power are considered the primary sources that supply the load as a stand-alone system, and a battery bank is used as an auxiliary power source. The optimization is done using PSO and the main objective is to fulfill the electricity demand by considering the Net Present Cost (NPC) for the optimization, and the loss of power supply probability (LPSP) as a reliability factor. Thus, the optimization is approached as follows: evaluation of the conditions of the chosen site, definition of the system's configuration, development of HRES model, sizing of the system components, simulation of operation and analyses.

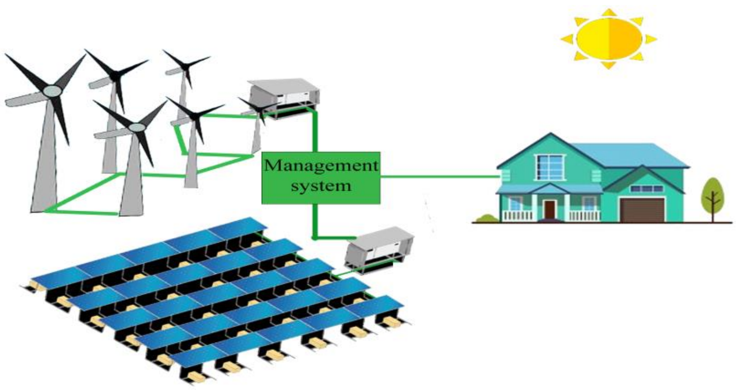

Fig. 1: Hybrid renewable energy system

The advantages presented are associated with the complementary characteristics of sources that compose the system contributing for a more reliable and less costly system with no oversizing of components, and many different possible configurations that can be thought for a HRES according to the weather in the installation site, available resources, engineer preferences of project, etc.

In recent years, several researches have been performed to determine the capacity of hybrid renewable sources by different approaches. Diaf et al. (2007) present an optimal modeling approach for an autonomous hybrid PV-wind system. The method aims to meet the reliability requirements with the lowest value of Levelized Cost of Energy (LCE). The reliability factor applied is the Loss of Power Supply Probability (LPSP). Celik (2002) designs an optimal autonomous small-scale PV/wind HRES and realizes a techno-economic analysis comparing the HRES with PV or wind system. 8 years of data were used, and the months were classified as solar-biased, wind-biased, and even. The results show that a combination of technologies presents higher technical performance and lower costs. Belmili et al. (2012) present a review of tools used for HRES optimization and presents a new program based on models of generators, storage capacity model, LPSP and a proposed techno-economic algorithm with the aim of guarantee a reliable energy system with the lowest possible investment. Bashir and Sadeh (2012) present an optimal sizing of a wind-PV-battery system considering the uncertainty of wind speed and solar irradiance. The optimization is carried out by considering the Net Present Cost (NPC) method and the reliability index used is the Equivalent Loss Factor (ELF).

For the optimization technique, Borowy and Salameh (1996) present a graphic optimization for a battery bank and PV array of a wind-PV HRES. Bashir and Sadeh, (2012) apply Genetic Algorithm, Bilil et al. (2014) suggests the use of the fast and elitist multiobjective genetic algorithm: NSGA-II. Alireza (2017) presents a new approach using Harmony Search (HS) named HS-II. Amer et al. (2013).

There are many approaches proposed to reach the optimal operation of an HRES. Kaldellis (2010) states that there is not a globally accepted approach to address the problem. The optimization of HRES can be classified as a complex optimization problem with variables that can affect the application and success of any solution (e.g. weather characteristics of the site, technical details). Energy system models are generally used to represent energy-related problems and are well applied for HRES optimization. One way to treat an energy model of an HRES is dividing into three specific problems: the problem of synthesis (configuration), the problem of design (sizing), and the operation problem. In the synthesis problem, the configuration of the system is addressed. What can be, but it is not restricted to, the technologies to compose the system (wind, photovoltaic, hydro), the capacity, backup system options, etc. This can be solved as an optimization problem on its own or as part of the complete problem. In the design problem, the sizing and the number of components is addressed. The problems of design and synthesis are often looked simultaneously because the structure and main dimensions of the system tend to be decided together. The operation problem is extensively used and concerns the strategies of operation adopted for the operation of the system. It attempts to simulate the system by iterative solutions. The complete problem may be addressed from different perspectives; economic and techno-economical are the most common ones and, among them, several subdivisions can be found.

3. Particle swarm optimization

Particle Swarm Optimization (PSO) is inspired by the social behavior of animals like flocking birds, insects or fishes. This idea was developed in the year of 1995 by the social-psychologist James Kennedy and by the electrical engineer Russel Eberhart (Kennedy and Eberhart, 1995). Particle Swarm Optimization (PSO) is part of a family of algorithms that aim to find a global optimization using techniques inspired by biological evolution known as evolutionary computation.

The algorithm has a set of particles that flies through the hyperspace of the problem searching for the best solution. Each particle keeps track of its best solution and is called personal best (Pbest). Every new position the particle moves to is tested against the particle Pbest so far. If the current position of the particle presents a better solution (fitness), the Pbest of the particle is replaced by the current position. PSO also tracks the best value got by all the particles. This value is called global best (Gbest) and is equal to the personal best with the best fitness in the entire swarm. The final solution will be the Gbest that obtained the best fitness. The concept of PSO can be simply understood as acceleration each particle towards its personal best and the global best location until a certain number of iterations is done or a defined tolerance is obtained. Each particle moves based on the current position, the current velocity and distance between the current position to Pbest and the distance between the current position to the Gbest using Eq. 1.

$$v_{i,j}^{k+1} = wv_{i,j}^{k} + c_1 rnd_1\left(\text{Pbest}_{i,j}^{k} - x_{i,j}^{k}\right) + c_2 rnd_2(\text{Gbest}_{i,j}^{k} - x_{i,j}^{k}) \quad \text{(eq. 1)}$$

where $v_{i,j}^{k}$ velocity in iteration k; w is a weighting function defined as $w = w_{máx} - k.x(w_{máx} - w_{min})/Maxitec$; rnd_1 and rnd_2 are random variables uniformly distributed between 0 and 1; $x_{i,j}^{k}$ is the current position; c_1 and c_2 are weighting factors; $\text{Pbest}_{i,j}^{k}$ is the personal best of the particle; $\text{Gbest}_{i,j}^{k}$ is the global best of the swarm.

The new position of the particle is calculated by the summation of the current position with the new velocity using Eq. 2.

$$x_{i,j}^{k+1} = x_{i,j}^{k} + v_{i,j}^{k+1} \quad \text{(eq. 2)}$$

PSO is known as an algorithm easy to program given it has only a few parameters to adjust and presents good results with tough functions with many local minima. Also, to better attend the presented optimization problem, modifications were made in the conventional PSO equations to make the algorithm well suited for integer optimization variables. It can be done by rounding the variables at each iteration (Strasser et al., 2016).

4. HRES model and optimization function

Here, the steps to design the system's model are presented. The first step consists of the configuration's definition for the system; the second step is divided into the photovoltaic generation model, the wind generation model, and the state of charge of the battery bank; and, in the last step is the presentation of the cost function, reliability factor, the set of constraints, and the chosen operation strategies.

4.1. System configuration

The chosen configuration defined for the system a stand-alone photovoltaic-wind-battery system. This configuration was defined in consideration of the characteristics of the installation site, that are favorable to photovoltaic and wind systems.

4.2. System design

- Photovoltaic generation model

The power output from the photovoltaic array is calculated using the equation (Alireza, 2017):

$$P_{PV}(t) = \text{I(t)} n_{PV} n_{conv} A_{PV} \quad \text{(eq. 3)}$$

where $P_{PV}(t)$ is the power generated at the instant t; I(t) is the solar irradiance at the instant t; n_{PV} is the photovoltaic panel efficiency; n_{conv} is the converter efficiency, and A_{PV} is the PV area.

- Wind turbine generation model

The power output from a wind turbine depends mainly on three factors (i.e. the power output curve, the wind speed at the installation site, and the hub height of the turbine tower). Therefore, choosing a model is extremely important (Yang et al., 2007). The most simplified model is presented in (Eq. 4) (Ren and Gao, 2010), (Athari and Ardehali, 2016):

$$P_{GE}(t) = \begin{cases} P_{máx}\dfrac{(V(t) - V_c)}{(V_r - V_c)} & V_r \leq V(t) \leq V_c \\ P_{máx} & V_r \leq V(t) \leq V_f \\ 0 & V_c \geq V(t) \text{ and } V(t) \geq V_f \end{cases} \quad \text{(eq. 4)}$$

where $P_{GE}(t)$ is the power generated at the instant t; $P_{máx}$ is maximum power generated by the wind turbine; $V(t)$ is the wind speed at the instant t ; V_c is the cut-in speed; V_r is the rated speed and V_f is the rated cut-off speed. For the result calculated to be correct, $V(t)$ must be entered in the equation estimated for the height at which the wind turbine will be installed. The actual wind speed that will hit the wind turbine blades must be considered.

The power law can be used to estimate the wind speed at a wanted height, giving the wind speed at a knowing height. Power law is presented in Eq. 5.

$$v(h) = V_{ref}\left(\frac{h}{h_{ref}}\right)^{\alpha} \qquad \text{(eq. 5)}$$

where $v(h)$ is the wind speed at the desired height h; V_{ref} is the wind speed at a known height h_{ref} and α is a dimensionless constant that varies according to the geographical characteristics of the site. Typical values of α are presented in Tab.1.

Tab. 1: Reference values of α

Site characteristics	**α**
Smooth surface, lake or ocean	0.1
Short grass	0.14
Undergrowth and Occasional Trees	0.16
Bushes and occasional trees	0.2
Trees and occasional buildings	0.22 – 0.24

- Battery bank

In HRES a common method to calculate battery banks' capacity is the State of Charge (SOC). The SOC of a battery bank is defined as the capacity of the battery bank at an instant t, and it goes from SOC minimum that happens when the battery bank is at its lowest and cannot supply the load anymore and SOC maximum that means the battery bank is fully charged and cannot be charged at instant t.

At any instant (t), when the total power output of the photovoltaic arrays and the wind generators is more than the energy demand, the battery bank can is charging (Eq. 6). If it is not at the SOC maximum. When the SOC minimum is reached, the batteries cannot be charged anymore. And, when the total power output is less than the energy demand at an instant t, the battery bank is discharging (Eq. 7) to supply the load unless it is at its SOC minimum and will not be able to be more discharged.

$$C_{bat}(t) = C_{bat}(t-1)(1-\sigma) + \left(P_{HRES}(t) - \frac{P_{\ load}(t)}{n_{inv}}\right)\Delta t n_{Cha} \qquad \text{(eq. 6)}$$

$$C_{bat}(t) = C_{bat}(t-1)(1-\sigma) - \left(\frac{P_{load}(t)}{n_{inv}} - P_{HRES}(t)\right)\Delta t n_{Disch} \qquad \text{(eq. 7)}$$

where $C_{bat}(t)$ and $C_{bat}(t-1)$ are the battery bank capacity at a time (t) and (t-1); σ is a constant related to the batteries self-discharge; $P_{HRES}(t)$ is and $P_{\ load}(t)$ are the power output of the HRES and power consumed by the load at the instant (t); t is the simulation step ($\Delta t = 1\ hour$); n_{inv} is the efficiency of the inverter efficiency; n_{cha} and n_{Disch} are the batteries charge and discharge efficiency.

The battery bank capacity is constraint by $C_{bat\ min} \leq C_{bat}(t) \leq C_{bat\ max}$ where $C_{bat\ max}$ and $C_{bat\ min}$ are the SOC maximum and minimum.

4.3. System operation

- Cost function

A techno-economic optimization was chosen for this work. The cost function is constructed with the Net Present Cost (NPC) method. The NPC method is one of the most common methodologies to combine costs and has been applied to many fields. The costs considered in NPC calculation are the capital cost that is the initial cost of buying and installing a system, the operation and maintenance throughout the lifetime cycle, and the replacement cost for components of the system that the lifetime is inferior then the lifespan of the complete system. The objective function of the optimization is the NPC function and is formulated as Eq. (8) (Bashir and Sadeh, 2012). The lifetime of the project is considered of 20 years and the optimization variables (N) are the number of wind turbines, photovoltaic arrays, and capacity of the batteries bank. Hence, the cost function is a function of these three variables with the previously defined costs considered for each variable. For the configurations proposed for this work, only batteries have a lifetime inferior of the system, hence, replacement costs are considered for batteries.

$$NPC = \sum_{i=1}^{L} N_i(CC_i + RC_i.K_i + M\&O_i.PWA(ir,R)) \quad \text{(eq. 8)}$$

where CC_i is the capital cost of equipment i; RC_i replacement cost of equipment i; $M\&O_i$ maintenance and operation of i; L is the number of sources (3: photovoltaic, wind and battery); N_i is the number of each renewable source and batteries in the battery bank.

For converting replacement costs to present, K_i is considered (Eq. 9):

$$K = \sum_{n=1}^{L_1} \frac{1}{(1+ir)^{n.L_2}} \quad \text{(eq. 9)}$$

where L_1 number of times each renewable component is replaced trough lifetime; L_2 total lifetime of renewable component; ir is the interest rate, here 6 %; For components that lifetime is system's lifetime, $K = 0$.

$PWA(ir,R)$ is used to convert maintenance and operation cost to preset cost and can be calculated using (Eq. 10):

$$PWA(ir,R) = \frac{(1+ir)^R - 1}{ir(1+ir)^R} \quad \text{(eq. 10)}$$

where R is the lifetime of the HRES.

- Power reliability analyses

The resources characteristics (e.g. wind strength, solar irradiation) strongly influence energy production and because of their intermittency, and despite the fact the HRES is less intermittent than the single-source renewable system, a power reliability analysis is an important step in the design process and performance assessment (Singh and Fernandez, 2018). There are several methods to access the reliability of HRES and loss of power supply probability (LPSP) is the most popular method. LPSP is defined as the probability of an insufficient power supply occurs and consequently, the load is not attended (Askarzadeh, 2017). Therefore, an LPSP of 0 (0 %) would happen when the load is fully attended by the HRES and the probability of a loss of power is null, and a LPSP of 1 (100 %) would happen when the load is not attended at all for the HRES (Eteiba et al., 2018). LPSP can be calculated using Eq. 11 and is applied as one of the constraints in the optimization process. Thus, to assure the reliability desired for the design, LPSP must be equal or less than a specific $LPSP_{max}$. In the results section, some $LPSP_{max}$ values are tested in the optimization and their effects on the optimization process discussed.

$$LPSP = \frac{\sum_{t=0}^{T} LPS(t)\Delta t}{\sum_{t=0}^{T} P_{Load}\,(t)\Delta t} \quad \text{(eq. 11)}$$

where $LPS(t)$ is the loss of power supply that occurs during a time interval Δt and $P_{Load}\ (t)$ is the power required by the load at interval Δt.

- Operation strategies

The power output of the system is the only source to supply the load demand and charge the battery bank. If $P_{Load}\ (t) > P_{HRES}\ (t)$ and the battery bank capacity is somewhere between $C_{bat\ min}$ and $C_{bat\ max}$, the battery bank will supply the load; If $P_{Load}\ (t) > P_{HRES}\ (t)$ but the battery bank capacity is at its minimum, the load will not be supplied what configures a loss of power supply; If $P_{HRES}\ (t) > P_{load}\ (t)$ and the battery bank capacity is somewhere between $C_{bat\ min}$ and $C_{bat\ max}$, the load will be supplied and the battery bank will be charged; If $P_{HRES}\ (t) > P_{load}\ (t)$ and the battery bank capacity is at $C_{bat\ max}$, the load will be supplied but battery bank will not be charged.

5. Summarized methodology and optimization variables characteristics

A site in Campina Grande-Paraíba, located in the Northeast region of Brazil, is assumed as the installation area for the system, therefore, wind speed and solar irradiation data for the city are used. The Northeast of Brazil was declared by the Brazilian Atlas of Wind Energy (2001) as one of the most promising places for wind systems installation because of its high potential estimated in 75 GW which is larger than the sum of the other four regions of the country potential. In addition, the Northeast presents the greater solar potential in the country with 5.52 kWh/m2 per day of solar irradiance (Brazilian Atlas of Solar Energy, 2006). Wind and solar energy are rising technologies in Brazil, and the wind generation is already responsible for 9.1% of the power generation in the country. The huge potential for renewable energies such as solar and wind in the region can be understood because of its geographic location, entirely within the earth's tropical zone. The region is the third-largest region of five and occupies 18.2% of the country's territory with hot and semi-arid climate and vegetation varying from Caatinga, Atlantic Forest and parts of the Cerrado. Thus, given the stated conditions and project preferences, photovoltaic and wind were chosen as renewable energy sources of the proposed HRES with a battery bank as auxiliary and no conventional generation.

A year (2017) of irradiance, wind speed, and load profile from the site was selected as a typical year for the optimization. For the city of the case study was found that the mean irradiance in the year was 402.31 w.m-2 and the mean wind speed was 3,51 m.s-1 and 5.01 m.s-1 at the height of the selected wind turbine. The data is presented in fig. 2 and were obtained from the national institute of metrology (INMET). In the institute website is possible to download up to a year of data from any of their weather stations and more data can be obtained by email request. The load profile data was provided by the Companhia Hidrelétrica do São Francisco (Chesf).

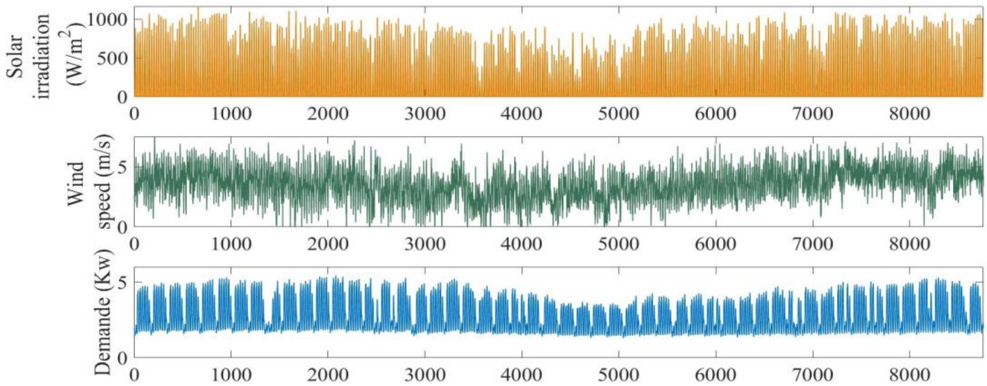

Fig. 2: Weather and demand used in the case study

In order to make the optimization as close as the site reality as possible, PV panels, wind generators, and batteries commonly used in Brazil were considered. Tab. 2 presents the costs considered in the algorithm which were calculated as estimations made from information obtained from projects that disclosed their cost per KW, quotes from sellers, and other works in the recent literature. The costs presented were converted to US dollars considering the value of the dollar in Brazil in December 2018.

Tab. 2: Costs considered

Economic parameter	**Unit**	**PV panel (250 W)**	**Wind turbine (2400 W)**	**Lead-acid battery (12 V 150 Ah)**
Capital cost	US $/ unit (US $ / kWh for batteries)	725	8810	300
Lifespan	years	25	20	5
Interest rate (ir)	%	6	6	6
$PWA(ir, R)$	-	0.2330	0.3118	0.7973
Replacement cost	US $/ unit (US $ / kWh for batteries)	-	-	300
maintenance and operation	%	1 % initial cost	3 % initial cost	0.5 % initial cost
maintenance and operation	US $/ unit (US $ / kWh for batteries)	7.2	88.1	1.5

5.1. Summarized methodology

- Objective function and constraints

Thereby, the final objective function is presented in (eq. 12), subject to the constraints (eq. 13 – eq. 16):

$$Objective\ function = Min. NPC(N_{PV}, N_{WG}, N_{Bat.}) \quad \text{(eq. 12)}$$

Subject to:

$$N_{PV}^{Min.} \leq N_{PV} \leq N_{PV}^{Max.} \quad \text{(eq. 13)}$$

$$N_{WG}^{Min.} \leq N_{WG} \leq N_{WG}^{Max.} \quad \text{(eq. 14)}$$

$$N_{Bat.}^{Min.} \leq N_{Bat.} \leq N_{Bat.}^{Max.} \quad \text{(eq. 15)}$$

$$C_{bat\ min} \leq C_{bat}(t) \leq C_{bat\ max} \quad \text{(eq. 16)}$$

$$LPSP \leq LPSP_{max} \quad \text{(eq. 17)}$$

Where N_{PV}, N_{WG} and $N_{bat.}$ are the number of PV panels; wind generators and, batteries. $N_{PV}^{Min.}, N_{WG}^{Min.}$ and $N_{Bat.}^{Min.}$ are the lower bounds for the optimization variables; $N_{PV}^{Max.}, N_{WG}^{Max.}$ And $N_{Bat.}^{Max.}$ are the upper bounds of the optimization variables; $C_{bat}(t)$ is the capacity of the batteries bank, $C_{bat.\ min.}$ and $C_{bat.\ max.}$ are lower and upper capacities of the battery bank; $LPSP_{max}$ is the defined reliability index and $LPSP$ is the calculated loss of power supply probability.

Briefly, the methodology adopted in this paper is presented in Fig. 3.

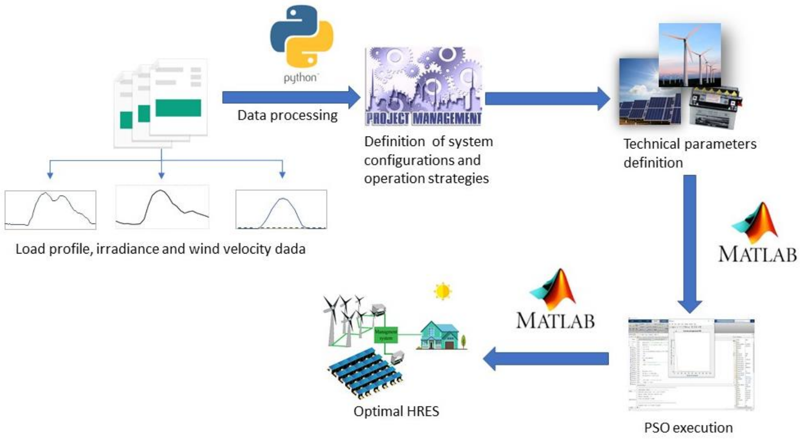

Fig. 3: Methodology

6. Results and discussion

In this section, the results are presented and discussed. The methodology was tested steep by steep as the algorithm was being built and, to avoid misleading results with the function stuck in a local minimum, each simulation was composed by ten PSO executions and the result for the simulation resulted from the best execution. Since there is a compromising to make the optimization method closer to the reality of the chosen site, four scenarios were proposed to analyze the impacts of some aspects on the optimization process. The scenarios are: Single source systems with different LPSP values, LPSP variation with fixed equipment characteristics, wind turbine tower hub height variation without cost variation and, wind turbine tower hub height variation with cost variation.

The main goal of the scenarios is to analyze the influence of aspects into the optimization process to provide a better understanding of it. This knowledge is considered extremely valuable in the decision-making process of executing a project or improving an optimization method. For all the scenarios, the operation strategy is applied as defined in section 4 and summarized in section 5; Therefore, the set of constraints and the objective function are the same for the four scenarios.

5.1. Single source systems with different LPSP values

In this first scenario, the costs of PV-battery and Wind-battery optimal systems are analyzed considering different values for the reliability index. In order to have the optimization algorithm work to provide a PV-battery system, the constraint of the number of wind generators (N_{WG}) was used. Its lower ($N_{WG}^{Min.}$) and upper bound ($N_{WG}^{Max.}$) were set to zero. The same thing was done to the constraint of the number of PV panels (N_{PV}) to use the algorithm to size a Wind-battery system. Thus, the system is configured only as photovoltaic-battery first and then wind-battery for different levels of loss of power supply probability (LPSP). The tower hub height considered in the simulations is 15 meters which is within the recommended height of installation range recommended in the manual from the manufacture.

Tab. 3: Results for scenario 1

LPSP ≤	Photovoltaic-battery system			Wind-battery system		
	Number of solar panels	**Bank of batteries capacity**	**Total cost [US $]**	**Number of wind turbines**	**Bank of batteries capacity**	**Total cost [US $]**
15%	49	51753 = 29 units	44,147.01	4	14720 = 8 units	40,307.84
10%	53	58893 = 33 units	48,231.87	4	53106 = 30 units	46,641.53
5%	61	64164 = 36 units	54,915.10	5	79869 = 45 units	60,527.18
1%	75	110118 = 62 units	72,671.16	6	276383 = 154 units	102,421.75

The results show a comparison between single-source systems for five different levels of LPSP. Going from a system that is 75% reliable to a system that is 99% reliable. Tab. 3 shows that the Photovoltaic-battery configuration presented lower costs for most of the reliability levels considered and, for the less reliable index (LPSP ≤ 15%), the Wind-battery system presented the lower cost.

Fig. 4 shows a graph with the costs and land occupied for the system for each of the tested LPSP values. 3/4 of an acre is used for a 1 MW wind turbine, therefore here a quarter of it is used for each wind turbine (758.7 m2), and the total area of the panel plus 10% for installation, is considered for each photovoltaic panel (2 m2). The area for storage is not considered. The results show that Photovoltaic-battery and Wind-battery systems with the same reliability occupy different extensions of land and its cost and availability could be factors that influence the project.

The results for the first scenario show financial advantages for each of the configurations depending on the considered LPSP and available area. This first scenario will also serve as a comparison in the cost analyses of the three following scenarios.

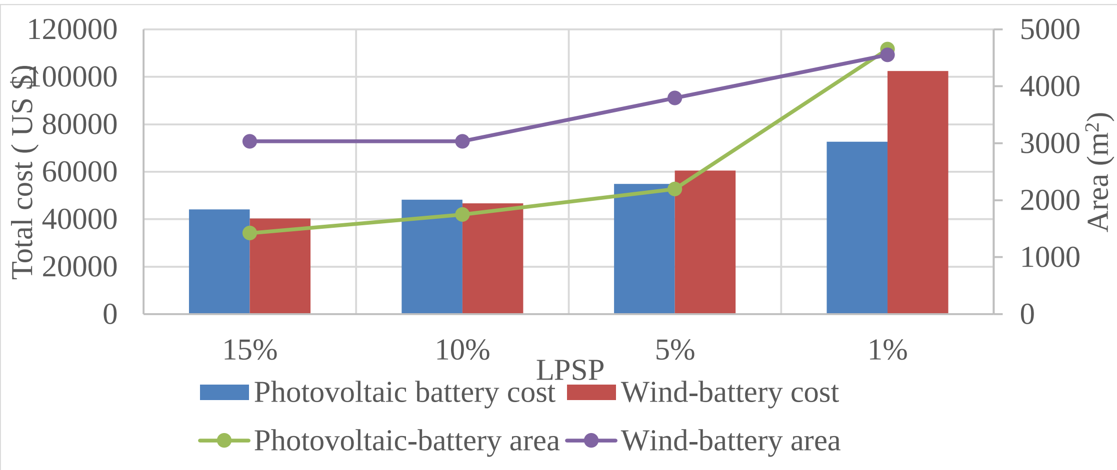

Fig. 4: Area and costs for the systems for each LSPS considered

5.2. LPSP variation with fixed equipment characteristics

In this scenario, the lower bound of the optimization variables continues set to 0 but the upper bounds of the three variables were set to 300, thus the number of wind turbines, batteries and, photovoltaic panel for each case is decided by the optimization. Different levels of reliability are considered from 75% to 99% of reliability. The results are presented in Tab. 4.

Tab. 4: Results for scenario 2

Component	**LPSP ≤ 15%**	**LPSP ≤ 12%**	**LPSP ≤ 10%**	**LPSP ≤ 8%**	**LPSP ≤ 5%**	**LPSP ≤ 3%**	**LPSP ≤ 1%**
Number of wind turbines	3	2	3	4	4	1	-
Number of solar panels	7	23	14	7	12	54	75
Bank of batteries capacity	19927 = 11 units	26780 = 15 units	25510 = 14 units	32278 = 18 units	54025 = 30 units	57439 = 32 units	110118 = 62 units
Total cost [US $]	36,784.06	40,072.07	42,792.08	48,291.73	55,513.43	58,188.41	72,671.16

The results for this scenario showed firstly that HRES configuration presents a smaller cost when compared with Photovoltaic-battery and Wind-battery systems presented in scenario 1. The relationship between the system's reliability and cost can be also observed. As expected, for a system that has high reliability (99% of reliability or LPSP ≤ 1%), the system's cost is 70% higher than the cost for a system with an LPSP of 15%. This result can be useful as decision-making tool to considering grid-connection (if available) or addition of a complementary source such as diesel generators.

5.3. Wind turbine hub height variation without cost variation

In this scenario, the height of the wind turbine varies between 15 m and 35 m, covering the range for installation suggested in the manual. By varying the installation height, a higher wind speed affects the wind turbine blades and consequently more power is generated. However, choosing to use higher towers considerably increases the costs of a project depending on the chosen hub height, the site characteristics and, the wind turbine itself. Installation height is also limited by safety settings provided by the equipment manufacturer.

Therefore, to evaluate the installation wind turbine height effects, scenarios 3 and 4 were constructed. The optimization was performed for both scenarios considering an LPSP value less than or equal to 5%. Scenario 3 considers only the effects of increasing the wind turbine hub height and scenario 4 considers the costs effects of increasing the height of the wind turbine. Tab. 5 shows the results for this scenario.

Tab. 5: Results for scenario 3

Component	**15 m**	**20 m**	**25 m**	**30 m**	**35 m**
Number of wind turbines	2	3	4	3	3
Number of solar panels	35	18	-	9	4
Bank of batteries capacity	42228 = 24 units	35584 = 20 units	37757 = 21 units	29243 = 16 units	33472 = 19 units
Total cost [US $]	51,506.26	47,361.04	44,108.94	39,774.57	36,838.91

Scenario number three results show that increasing the wind turbine hub height can be very beneficial for lowering the costs and an even more interesting option when photovoltaic arrays installation area is limited given the fact that at higher heights the wind turbines will produce more power. For the height of 25 meters a bigger number of wind turbines is selected in the optimization and in higher heights than 25 meters a smaller number is chosen. This happened because at 25 meters some wind speed data values were between the rated speed of the wind turbine and the cut-off speed. Higher than 25 meters, a large percentage of the wind speed data is bigger than the cut-off speed, which reduces the power generated by the wind turbines.

5.4. Wind turbine tower height variation with cost variation

In this last scenario, the conditions of the previous scenario are repeated with the addition of the consideration of increasing installation costs while varying the wind turbine hub height. Here, installation costs (capital cost of the wind turbines) are increased by 5% each time the installation height increases. Tab. 6 shows the results for scenario 4.

Tab. 6: Results for scenario 4

Component	15 m	20 m	25 m	30 m	35 m
Number of wind turbines	2	2	2	3	3
Number of solar panels	35	30	26	8	4
Bank of batteries capacity	43120 = 24 units	41245 = 23 units	39940 = 22 units	33563 = 19 units	33472 = 19 units
Total cost [US $]	52,435,42	49,439.57	47,269.46	45,442.54	43,941.23

The last scenario presents a more realistic approach to investigate the impacts of tower hub height in the optimization, given the fact that the hub height affects costs directly. The costs of the systems with higher wind turbine hub, for example, 35 meters, are approximately 30% higher than the costs for the system with the same configuration in scenario two. Although the costs can increase, the height of installation is a component that should be considered in the optimization of systems for lower costs and especially when installation area may be restricted.

7. Conclusion

A methodology for the optimal sizing of a photovoltaic-wind-battery hybrid renewable energy system for a site in the city of Campina Grande-PB (Brazil) is presented. The method is based on a techno-economic analyses realized considering the net present cost as a cost function and the loss of power supply (LPSP) as a reliability factor. State of charge of the battery bank is the adopted method for the sizing of the battery bank and along with the LPSP factor used as a constraint for the optimization.

An analysis of four scenarios was developed, in which different conditions were simulated and analyzed. The results showed that the proposed method could optimize a hybrid renewable energy system under different constraints and considerations with good performance. The good performance of the algorithm is attributed to the use of particle swarm optimization, which is well suited to the problem and performs with high speed.

For the case study, the first scenario showed a comparison for two single-source systems: a photovoltaic-battery system and a wind-battery system. For the different loss of power supply probability (LPSP) presented the wind-battery system presented better results (lower costs) for LPSP's of 15, 10 and 5% and the photovoltaic-battery system presented lower costs for an LPSP of 1%. The second scenario showed that a hybrid renewable energy system (HRES) is less costly in comparison with a single-source system. Scenario two also presented the relationship between the reliability factor and the system's cost. When considering an off-grid system, reliability is very important because the power generated by the system and supplied by the battery bank are the only sources available to supply the load demand. Therefore, it is important to balance the reliability required from the load characteristics (that is, the nature of the load) with the system's components in the system's configuration steep. Scenarios three and four presented the variation of the wind turbine hub height and its effects on the optimization.

8. Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior- Brasil (CAPES) - Finance Code 001, and carried out with the support of CNPq, National Council of Scientific and Technological Development – Brazil.

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