DOI: 10.48011/sbse.v1i1.2386

Minimization of Risks of Voltage and Frequency Violations in Islanded Microgrids using Robust Probabilistic Optimal Power Flow

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Abstract: The main aim of this paper is to propose a robust probabilistic optimal power flow model to determine the droop control parameters for the Distributed Generators (DG) of a islanded microgrid. The term robust is related to the droop control parameters being immune to uncertainties associated with: load forecast errors, DG outages and variability of power output in renewable DG. This optimization problem is solved by an improved gravitational search algorithm (GSA). The test results demonstrated that the proposed method can achieve significant reductions in the load curtailments due to frequency and voltage violations. In addition, a comparison between GSA and the Particle Swarm Optimization (PSO) demonstrated that GSA is more suitable for evaluating the droop control parameters than PSO in relation to the computational cost and the optimal quality of the solution.

Resumo: O principal objetivo deste artigo é propor um modelo de fluxo de potência ótimo probabilístico robusto para determinar os parâmetros do controle droop para os Geradores Distribuídos (DG) de uma microrrede ilhada. O termo robusto está relacionado com os parâmetros do controle droop devido serem imunes as incertezas associadas com erros de previsão de carga, falhas de GD e variabilidade na potência de saída de GD renováveis. Este problema de otimização é resolvido por um Algoritmo de Busca Gravitacional (ABG) melhorado. Os resultados dos testes demonstraram que o método proposto pode obter reduções significantes nos cortes de carga nodais devido a violações de tensão e de frequência. Além disso, a comparação entre o ABG e a otimização via enxame de partículas demonstrou que o ABG é mais adequado para calcular os parâmetros do controle droop em relação ao custo computacional e a qualidade da solução ótima.

Keywords: gravitational search algorithm; islanding; microgrids; probabilistic power flow; reliability

Palavras-chaves: algoritmo de busca gravitacional; ilhamento; microrredes; fluxo de potência probabilístico; confiabilidade

1. INTRODUCTION

1.1 Islanded Operation of Microgrids

This islanded operation of microgrids poses a technical challenge to engineers because customers in the microgrid must have their load supplied with reliable energy supply–just how they were connected to the utility grid. Some of the difficulties that must be overcome for a reliable microgrid operation are (Abdelaziz et al. 2013; Araújo et al. 2017): (a) bidirectional power flows, since the grid is no longer radial in the islanded mode; (b) stability problems, since the interaction between different sources of energy can lead to oscillations in frequency and voltage; (c) grid modelling, because a distribution system with several energy sources is similar to a transmission system, but for the islanded microgrid it is not possible to take into account the existence of a slack bus; (d) uncertainties in energy sources, since each distributed generator has its own failure rate and the renewable also depend on the random nature of their primary sources (for example, wind speed for wind turbines and solar irradiation for photovoltaic modules - PV modules).

When a microgrid is operating in islanded mode, the main components responsible for ensuring the feasibility of this mode of operation are DG units connected to the microgrid. Generally, the DG units are operated according to the droop control strategy. In this control strategy, the active/reactive power sharing among DG is based on the frequency/voltage deviations and the set points for active/reactive power generation. Consequently, the adjustment of these parameters has a significant influence on the microgrid capability to avoid violations of the operating constraints in the islanded mode of operation. This fact motivated the development of several techniques to optimize the microgrid performance in the islanded operation by adjusting the following parameters: droop constants, topology, frequency/voltage reference values, set points for DG output power, etc. The next subsection presents a bibliographical review on microgrid optimization.

1.2 Literature Review of Microgrid Optimization

In general, papers that address the subject of microgrid optimization can be grouped according to the objective of optimization: reduce operational costs or improve operational quality.

1.2.1 *Reduce Operating Costs*

Li et al. (2016) proposed a fuzzy multi-objective optimization model with constraints to minimize total economic cost and microgrid losses. Shadmand & Balog (2014) presented an optimization technique based on a multi-objective genetic algorithm that uses high resolution solar radiation data. This optimization model minimized the system cost required to meet the load demand in a DC microgrid. Wang et al. (2015) proposed a dynamic algorithm for the distributed management of the microgrid that optimized operational costs considering influences from external conditions (solar radiation, wind speed, load variation, etc.). Moradi et al. (2015) presented a method of energy management by optimizing the type and capacity of the distributed microgrid generators as well as the capacity of the energy storage devices in order to minimize costs. Maknouninejad & Qu (2014) have proposed cooperative distributed optimization for the optimal reactive power dispatch from distributed DG microgrid. The objective function of this paper was the minimization of a cost function composed of the sum of the quadratic voltage errors in the DG buses and other risky buses.

1.2.2 *Improving the Operational Power Quality*

Urias et al. (2015) presented an optimization model for microgrids with the objective of reducing the amount of energy acquired from utility and maximizing the energy supplied by the distributed generators. The optimization was based on a recurrent neural network. Nafisi et al (2016) presented a two stage optimization method to minimize losses in a microgrid with different levels of electric vehicle penetration. Abdelaziz et al. (2014) proposed a new formulation for the optimal reconfiguration of islanded microgrids. The problem was considered as multiobjective to: minimize fuel consumption of the microgrid, ensure that the microgrid is capable of meeting the maximum possible demand, improving its voltage stability and minimizing the switching operating costs. Abdelaziz et al. (2016) proposed a new probabilistic algorithm to determine the optimal choice of droop parameters for the individual distributed generators, in order to increase the demand margin of the microgrid. This algorithm takes into account variations in load and generation. It uses a state enumeration method to model uncertainties and applies a hierarchical constraint method to optimize droop values. Araújo et al. (2017) determined the set points for the output powers and voltage magnitudes of the DG used in the droop control by solving optimal power flow (OPF) problems for a set of specified operation conditions. The objective function of this OPF is to minimize generation costs subject to: power flow equality constraints, voltage limits and limits for the output power of the DG. A disadvantage of this OPF model is that the operation condition for which optimal reference values are determined is subject to uncertainties. Thus, the adequacy of the microgrid can be deteriorated in the islanded operation due to differences between observed and forecasted values of microgrid variables, such as: peak load, power output of the renewable DG (solar and wind) and availability of DG.

1.2.3 *Problem Characteristics*

From the above literature review it can be concluded that an algorithm to optimize performance indices of an islanded microgrid should have the following characteristics:

i) Stochastic: consider uncertainties associated with: the load, the output power of the renewable DG and the components unavailability.

ii) Robustness: the optimal solution generated by the algorithm must be immune to the uncertainties present in the model.

iii) Multi-objective: the adequacy of the operation of the microgrid must meet multiple operational objectives, for example: the voltage profile and the frequency deviation.

iv) Flexibility to model non-differentiable objective functions: the need for robust solutions requires the objective function of the microgrid optimization problem to be expressed through the risk of threshold violation for performance indices. Therefore, the objective function will not be differentiable.

v) Quality and Efficiency: the solution algorithm must provide optimal solutions that establish an acceptable compromise among accuracy, quality, and computation cost.

From the above mentioned characteristics, it can be concluded that the most suitable algorithms for the optimization of the microgrid performance in the island mode are the metaheuristic algorithms. On the other hand, the most appropriate techniques to model uncertainties are probabilistic methods. The choice of probabilistic methods is due to the availability of statistical data to characterize uncertainties through probability distributions, for example, meteorological data associated with wind speed and solar radiation.

However, probabilistic techniques based on state selection, such as Monte Carlo Simulation (MCS) and State Enumeration, are not suitable for optimization problems because of its time-consuming feature. Instead, the use of analytical techniques such as discrete convolution, cumulants, and point estimation has lower computational costs and can make probabilistic methods more efficient. These techniques are called Probabilistic Power Flow (PPF) analytical methods. The next section will present the mathematical formulation of a methodology designed to address the microgrid optimization requirements in the island mode of operation.

2. MICROGRID PRE-DISPATCH OPTIMIZATION

The main aim of this paper is to provide an optimization methodology to minimize the risk of voltage and frequency violation of a microgrid in islanded mode of operation. These risks are minimized by a Robust Probabilistic OPF (RPOPF) that adjusts the droop control parameters (set points for voltage magnitude and active/reactive output powers) for the DG. The RPOPF is mathematically formulated as follows:

$$\text{Minimize } P_{risk}(\boldsymbol{X}) = P_{TLOC_f}(\boldsymbol{X}) + \sum_{i=1}^{N_b} P_{PLOC_i}(\boldsymbol{X}) \quad (1)$$

Subject to:

$$P_{g_k} - P_{d_k}(V_k, f) - P_k(V, \theta) = 0 \; for \; k = 1, \dots, N_b \quad (2)$$

$$Q_{g_k} - Q_{d_k}(V_k, f) - Q_k(V, \theta) = 0$$
$$for\ k = 1, \dots, N_b \tag{3}$$

$$\left(P_{g_i}^{ref} - P_{g_i}\right) + \frac{1}{K_i^P}\left(f^{ref} - f\right) = 0\ for\ i \in \mathcal{G} \tag{4}$$

$$\left(Q_{g_i}^{ref} - Q_{g_i}\right) + \frac{1}{K_i^Q}\left(V_i^{ref} - V_i\right) = 0\ for\ i \in \mathcal{G} \tag{5}$$

$$\theta_s^{esp} - \theta_s = 0 \tag{6}$$

$$V_{min} \le V_i^{ref} \le V_{max}\ for\ i \in \mathcal{G} \tag{7}$$

$$P_{g_i}^{min} \le P_{g_i}^{ref} \le P_{g_i}^{max}\ for\ i \in \mathcal{G} \tag{8}$$

$$Q_{g_i}^{min} \le Q_{g_i}^{ref} \le Q_{g_i}^{max}\ for\ i \in \mathcal{G} \tag{9}$$

Where: $\boldsymbol{X}$ is the vector of references obtained by the MPD; P_{g_k} $\left(Q_{g_k}\right)$ is the generated active (reactive) power in bus k; $P_{d_k}(V_k, f)$ $\left(Q_{d_k}(V_k, f)\right)$ is the active (reactive) load demand in bus k as a function of the voltage magnitude V_k and the microgrid frequency f; $P_k(V, \theta)$ $(Q_k(V, \theta))$ is the injected active (reactive) power in bus k as a function of voltages magnitudes vector V and voltages angles vector θ; $P_{g_i}^{ref}$ $(Q_{g_i}^{ref})$ is the reference value for the active (reactive) power generation associated with the generator i; K_i^P and K_i^Q are the droop coefficients for the generator i; P_{g_i} $\left(Q_{g_i}\right)$ is the active (reactive) power output for the generator i; f^{ref} is the reference value for the microgrid frequency; V_{min}, f_{min} , $P_{g_i}^{min}$ and $Q_{g_i}^{min}$ (V_{max}, f_{max} , $P_{g_i}^{max}$ and $Q_{g_i}^{max}$) are the minimum (maximum) values for V_k, f, P_{g_i} and Q_{g_i}, respectively; θ_s^{esp} is the specified voltage phase for the bus s that serves as the angular reference for the microgrid; N_b is the number of buses; $\mathcal{G}$ is the set of generator buses; $P_{TLOC_f}(\boldsymbol{X})$ is the probability of the total load curtailment (TLOC) due to frequency violation; $\boldsymbol{X} = \left\{\boldsymbol{V}^{ref}, \boldsymbol{P}_g^{ref}, \boldsymbol{Q}_g^{ref}\right\}$; $\boldsymbol{V}^{ref} = \left\{V_1^{ref}, \dots, V_{N_g}^{ref}\right\}$; $\boldsymbol{P}_g^{ref} = \left\{P_{g_1}^{ref}, \dots, P_{g_{N_g}}^{ref}\right\}$; $\boldsymbol{Q}_g^{ref} = \left\{Q_{g_1}^{ref}, \dots, Q_{g_{N_g}}^{ref}\right\}$; $P_{PLOC_i}(\boldsymbol{X})$ is the probability of partial load curtailment (PLOC) in bus i due to voltage violation and $P_{risk}(\boldsymbol{X})$ is the probability (risk) of frequency and voltage violations.

The objective function (1) minimizes the risk of frequency and voltage violations simultaneously. That is, the original multi-objective problem (to minimize voltage and frequency violations) is converted into a single objective problem due to the mapping of system state variables in the probability domain. In addition, the uncertainties of the microgrid are taken into account because the objective function (1) is risk based. Consequently, the RPOPF achieved through the solution of (1)-(9) is immune with respect to the uncertainties, since the objective function considers several microgrid scenarios resulting from uncertainties rather than only the base case.

The $P_{TLOC_f}(\boldsymbol{X})$ term in the objective function (1) represents the risk of frequency violation in the microgrid. This probability is obtained directly from the probability density function of the microgrid frequency and can be expressed as follows:

$$P_{TLOC_f}(\boldsymbol{X}) = 1 - \int_{f_{min}}^{f_{max}} g_f(f)df \tag{10}$$

Where, $g_f(f)$ is the probability density function for the microgrid frequency.

The values f_{min} and f_{max} are defined based on the limits for the secure operation of the microgrid DG. For example, the blades of the turbines can be damaged due to mechanical resonance for high frequency deviations Reimert (2005). In this way, the IEEE Standard 1547 (IEEE 2009) establishes that the distributed generation resources must be disconnected from the grid if the system frequency is lower than 59.8 Hz or higher than 60.5 Hz. Therefore, in this paper the limits of the IEEE standard 1547 (IEEE 2009) for the microgrid frequency were adopted. If the microgrid frequency is outside this range, a TLOC event is considered to exist because all microgrid DG are tripped out by their frequency protections and the loads cannot be supplied.

The $P_{PLOC_i}(\boldsymbol{X})$ index in the objective function (1) represents the risk of voltage deviation for a specific bus i of the microgrid. This probability is obtained directly of the probability density function of the microgrid bus voltages and can be expressed as follows:

$$P_{PLOC_i}(\boldsymbol{X}) = 1 - \int_{V_{min}}^{V_{max}} g_{V_i}(V_i)dV_i \tag{11}$$

Where, $g_{V_i}(V_i)$ is the probability density function associated with the voltage magnitude in the bus i.

The values for V_{min} and V_{max} were established based on the sensitivity of customer equipment regarding to voltage violations and protection devices settings for voltage variations (Wan et al. 2000). In this way, it is considered that $V_{min} = 0.95$ and $V_{max} = 1.05$ pu (Wan et al. 2000). Therefore, if the nodal voltage V_i is outside this range, there is a PLOC event in bus i since a protection device has operated or the loads have been turned off by themselves.

The constraints of equality (2)-(6) correspond to the system of nonlinear equation associated with the distributed slack bus power flow in the microgrid (Abdelaziz et al. 2013; Gatta 2012). That is, these constraints establish the active/reactive power balance in each bus and determine the frequency deviation due to the unbalance between generation and load plus losses.

The inequality constraints (7)-(9) guarantee the feasibility of the references obtained by the RPOPF in relation to: voltage magnitude and active/reactive output power of the DG.

The optimization problem defined in (1)-(9) is stochastic due to uncertainties in: load, variability of the output power of renewable DG and equipment unavailability. The next section presents the probabilistic models used to represent these uncertainties in MPD.

3. MICROGRID UNCERTAINTIES MODELLING

3.1 Probabilistic Load Model

The RPOPF is performed for a given hour in the study period, for example, daily, weekly or yearly. Consequently, the uncertainty related to the load that will be considered in this paper is the load forecasting error. This type of uncertainty can be modelled through a normal distribution as (Araújo et al. 2017; Morales & Perez-Ruiz 2007):

$$L_{peak} = \tilde{L}_{peak} + z\tilde{L}_{peak}\left(\frac{\tilde{\sigma}}{100}\right) \qquad (12)$$

Where: L_{peak} is the microgrid peak load, z is a normally distributed random number, $\tilde{L}_{peak}$ is the forecast value for the microgrid peak load and e ($\tilde{\sigma}$) is the forecast error expressed as a percentage of $\tilde{L}_{peak}$.

3.2. Gas Fueled Generators Probabilistic Models

Gas fuelled generators can be modelled using a discrete Bernoulli distribution that considers only two possible states for a generator: operating, with probability p and failed, with probability q. Thus, $p + q = 1$ (Araújo et al. 2017; Morales & Perez-Ruiz 2007). In this way, the outage probability for a set of N_g generator units can be expressed through the Binomial distribution as follows:

$$Prob[k] = {}_{N_g}C_k(1 - FOR)^k FOR^{N_g - k} \qquad (13)$$

Where: $Prob[k]$ is the probability of having k generators in operation and ${}_{N_g}C_k$ is the number of combinations with k generators selected from N_g generators.

3.3 Probabilistic Models of Wind Turbine and Wind Speed

The variability in the output power of a wind turbine is due to the random behavior of wind speed. The data collected in anemometric measurement stations show that the probability distribution that better describes the wind speed is the bivariate or trivial Weibull distribution (Araújo et al. 2017). The Weibull probability density function for the trivariate case is given by:

$$f(\upsilon) = \left(\frac{\beta}{\alpha}\right)\left(\frac{\upsilon - \tau}{\alpha}\right)e^{-\left(\frac{\upsilon-\tau}{\alpha}\right)^{\beta}} \qquad (14)$$

In which: υ is the wind speed, in which β is called form parameter, α is called scale parameter and τ is the localization parameter.

3.4 Probabilistic Model of the PV Module

The production of energy in a PV module depends on several factors, among them: PV module area, irradiation of sunlight, air humidity, ambient temperature and PV module efficiency (Fan et al. 2012). A basic model to represent the active output power of a PV module can be expressed as (Fan et al. 2012):

$$P = rA\eta(1 - k\Delta T) \qquad (15)$$

where r is the solar irradiance, A is the total area of the PV module, η is the efficiency of the PV module, k is the temperature coefficient and ΔT is the forecast error of the PV module temperature and represents the difference between the temperature of the module and its standard test temperature, which is assumed to be 298K (or 25 ° C) (Fan et al. 2012). Solar irradiance can be probabilistically modelled by a beta distribution defined as:

$$f(r) = \frac{\Gamma(\mathrm{a}+\mathrm{b})}{\Gamma(\mathrm{a})\Gamma(\mathrm{b})}\left(\frac{r}{r_{max}}\right)^{a-1}\left(1 - \frac{r}{r_{max}}\right)^{b-1} \qquad (16)$$

where r is the solar irradiance, r_{max} is the maximum solar irradiance recorded in the measurement period and Γ is the gamma function. The parameters a and b can be defined according to (17).

$$a = \mu\left[\frac{\mu(1-\mu)}{\sigma^2-1}\right];\ b = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2-1}\right] \qquad (17)$$

where μ and σ represent the mean and standard deviation of the gamma distribution estimated for a sample of solar irradiance data.

The next section presents the PPF technique used to include the microgrid uncertainties in the estimation of the frequency and voltage violation risks.

4. PROBABILISTIC POWER FLOW (PPF)

As mentioned earlier, the optimization problem (1)-(9) is stochastic and nonlinear. Consequently, the most appropriate approaches to solve this type of optimization problem are the meta-heuristic. When a meta-heuristic is applied to solve an optimal power flow problem under uncertainty, the tool used to evaluate the objective function and constraints is the PPF. Basically, the meta-heuristic selects reference values for the MPD (X vector) that are used as inputs for the PPF algorithm. In turn, the PPF generates probability distributions for system state variables. These distributions are used to evaluate the constraints and the objective function for each candidate solution produced by the meta-heuristic. However, there is no closed analytical form for the integrals defined in (10) and (11). An alternative to evaluate these integrals is to use the MCS. Nevertheless, the MCS has a high computational cost that restricts its application in meta-heuristic algorithms to evaluate the objective function.

In this paper, the PPF associated with the probabilistic MPD is solved using the Point Estimate Method (PEM) (Morales & Pérez-Ruiz 2007; Hong 1998). The PEM is a technique that allows to find the moments of random variable output Z that relates to one or more random input variables through a function F. The function F is evaluated in a total of K times for each of the m known input random variables, replacing one random variable by its concentrations and keeping the other $m - 1$ variables in their mean values. The concentrations are obtained through the moments of the random variables. The number of locations K for each known input random variable depends on the scheme used. The $2m + 1$ scheme, that uses 3 points per location (one of these points being located in the mean value of the input random variables), will be used in this paper to estimate the statistics of the output random variables.

Consequently, there will be $m \times K$ values of the output variable Z for the selected concentrations of the input variables. These values are used to estimate the moments of the output variable Z by a weighted sum. The relationship between PEM and PPF is described below:

i) Input variables: power injections under uncertainty due to: load forecasting error defined in (12), variable output of renewable DG in accordance with (14)-(16) and unavailability of DG defined in (13).

ii) Output variables: frequency and magnitude and angle of the nodal voltages.

iii) Function F: nonlinear equation system associated with the distributed slack bus power flow in the microgrid.

The moments of the output variable Z are used to achieve the probability distribution of the variable Z. Generally, this distribution is obtained using series of orthogonal functions, such as Gram-Charlier, Edgeworth and Cornish-Fisher (Fan et al. 2012). However, these series only provide accurate approximations for a probability distribution when it is unimodal. This condition cannot be found in the microgrid PPF because the probability distributions of the state variables are multimodal due to the unavailability of the DG that is modelled using a discrete distribution (Binomial Distribution defined in the subsection III-B). This problem can be overcome using a Gaussian Mixture Method (Prusty & Gena 2016). That is, a non-Gaussian probability distribution is approximated by a weighted sum of the Gaussian probability distributions. The weights in this sum are obtained from the moments of the non-Gaussian probability distribution. In the microgrid PPF, the non-Gaussian random variables are the frequency and magnitude and angle of the nodal voltages whose moments were obtained by PEM.

The next section describes the basic principles of the algorithm used to solve the RPOPF: the GSA. Then, the application of the GSA to the RPOPF is presented.

5. SOLUTION OF THE PROBABILISTIC MPD

This paper uses a meta-heuristic optimization algorithm called the Gravitational Search Algorithm (GSA) to solve the RPOPF. Due to its complexity, it is not recommended to use an analytical method to solve the RPOPF, as mentioned previously. The GSA was chosen because of its superior performance when compared to PSO and other optimization meta-heuristics, as described in Xing & Gao (2013).

5.1 Gravitational Search Algorithm (GSA)

Based on the laws of universal gravitation, Rashedi et al. (2009) developed an optimization algorithm called the gravitational search algorithm. In this algorithm, every individual of the population can be considered as a mass and, through Newton's law of universal gravitation, all masses attract each other mutually, this attraction being so much greater than the active gravitational masses of bodies.

Each mass in the GSA has four characteristics: position, active gravitational mass, passive gravitational mass and inertial mass. The position of a mass corresponds to a solution of the optimization problem, while the other quantities refer to the value of the objective function (fitness). That is, if x_i represents the position, then $f(x_i)$ corresponds to the fitness value of x_i. The GSA can be resumed in the following steps:

i) First, choose an N number of masses in an m-dimensional problem and create a vector of positions X_i, where the i-th mass position is defined as:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{id}, \dots, x_{in}), \qquad i = 1, 2, 3, \dots, N \tag{18}$$

Where: x_{id} is the position of the i-th mass in the d-th dimension, n is the number of problem dimensions (number of variables) and N is the number of masses (bodies).

ii) Secondly, the gravitational force $F_{ij_d}(t)$ acting on mass j due to mass i in dimension d at time t can be defined as:

$$F_{ij_d}(t) = G(t)\frac{M_{pi}(t) \cdot M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left[x_{jd}(t) - x_{id}(t)\right] \tag{19}$$

Where: $M_{pi}(t)$ is the passive gravitational mass related to the body i; $M_{aj}(t)$ is the active gravitational mass related to the body j, $G(t)$ is the value of the gravitational constant at time t; ε is a small constant and $R_{ij}(t)$ is the Euclidean distance between bodies i and j, defined as:

$$R_{ij}(t) = \left\|X_i(t), X_j(t)\right\|^2 \tag{20}$$

iii) Third, to evaluate the acceleration of a body i in the intant t and dimension d, the total force exerted by the other bodies can be defined as:

$$F_{id}(t) = \sum_{j=1, j\neq i}^{N} rand_j F_{ij_d}(t) \tag{21}$$

Where: $rand_j$ is a random number uniformly distributed in the interval [0,1].

iv) Fourth, based on the total forces, the acceleration of mass i at time t and dimension d is given by:

$$a_{i_d}(t) = \frac{F_{i_d}(t)}{M_{ii}(t)} \tag{22}$$

Where M_{ii} is the inertial mass of the body i.

v) Fifth, the new speed of a body can be evaluated as a function of its current speed plus its acceleration. The speed of the body and its position are given, respectively, by:

$$v_{i_d}(t+1) = rand_i \times v_{i_d}(t) + a_{i_d}(t) \tag{23}$$

$$x_{i_d}(t+1) = x_{i_d}(t) + v_{i_d}(t+1) \tag{24}$$

where $x_{i_d}(t)$ and $v_{i_d}(t)$ are the position and speed of body i at time t and dimension d, respectively, and $rand_i$ is a random number uniformly distributed in the interval [0,1], which increases the randomness of the search.

vi) Finally, after assessing the objective function for each body of the current population, the gravitational and inertial masses can be updated, respectively, using:

$$m_i(t) = \frac{fitness_i(t) - worst(t)}{best(t) - worst(t)} \quad (25)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (26)$$

Where, $fitness_i(t)$ represents the fitness value of body i at time t, best and worst represent the $best$ and the $worst$ fitness value of the objective function among all m masses. These values are defined based on the type of problem being solved: maximization or minimization problem.

In addition, to enhance the exploration of the GSA, an agent called k_{best} is employed. It is a function of time that has as initial value $k_0 = N$ and its value decreases with time linearly. Thus, the equation of the total force can be rewritten as:

$$F_{id}(t) = \sum_{j \in k_{best}, j \neq i}^{N} rand_j F_{ij_d}(t) \quad (27)$$

That is, fewer bodies will exert force on others with time, only those with the best value of the objective function and larger masses, until only one body exerts force on the others. The value of the constant $G(t)$ also varies with time according to (28).

$$G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^{\beta}, \beta < 1 \quad (28)$$

Where, $G(t_0)$ is the value of the gravitational constant at the origin of the universe, t is the age of the universe and β is a constant that depends on the constitutional characteristics of the universe itself.

5.2 Applying GSA to RPOPF

The application of GSA to the pre-dispatch optimization problem is straightforward, since bodies can be defined as the vector of values of the RPOPF parameters. That is:

$$x_{id} = \begin{cases} V_k^{ref} & for\ j = 1, \dots, |\mathcal{G}|;\ k = \mathcal{G}_j \\ & and\ d = j \\ P_{g_k}^{ref} & for\ j = 1, \dots, |\mathcal{G}|;\ k = \mathcal{G}_j \\ & and\ d = |\mathcal{G}| + j \\ Q_{g_k}^{ref} & for\ j = 1, \dots, |\mathcal{G}|;\ k = \mathcal{G}_j \\ & and\ d = 2|\mathcal{G}| + j \end{cases} \quad (29)$$

Where: $|\mathcal{G}|$ is the dimension of the set $\mathcal{G}$ and $\mathcal{G}_j$ is the j-th element of the set $\mathcal{G}$. Consequently, the number of dimensions $n = 3|\mathcal{G}|$.

The fitness function is defined in (1) and is used to obtain the gravitational and inertial masses as:

$$m_i^{(t)} = \frac{P_{risk}\left(\boldsymbol{x}_i^{(t)}\right) - worst(t)}{best(t) - worst(t)} \quad (30)$$

and, as the risk must be reduced, the optimization problem is a minimization problem. Therefore:

$$\begin{cases} best(t) = \min_{i \in 1,2,\dots,N} P_{risk}\left(\boldsymbol{x}_i^{(t)}\right) \\ worst(t) = \max_{i \in 1,2,\dots,N} P_{risk}\left(\boldsymbol{x}_i^{(t)}\right) \end{cases} \quad (31)$$

The flowchart of the GSA algorithm used in the solution of the RPOPF for islanded microgrids is presented in Figure 1.

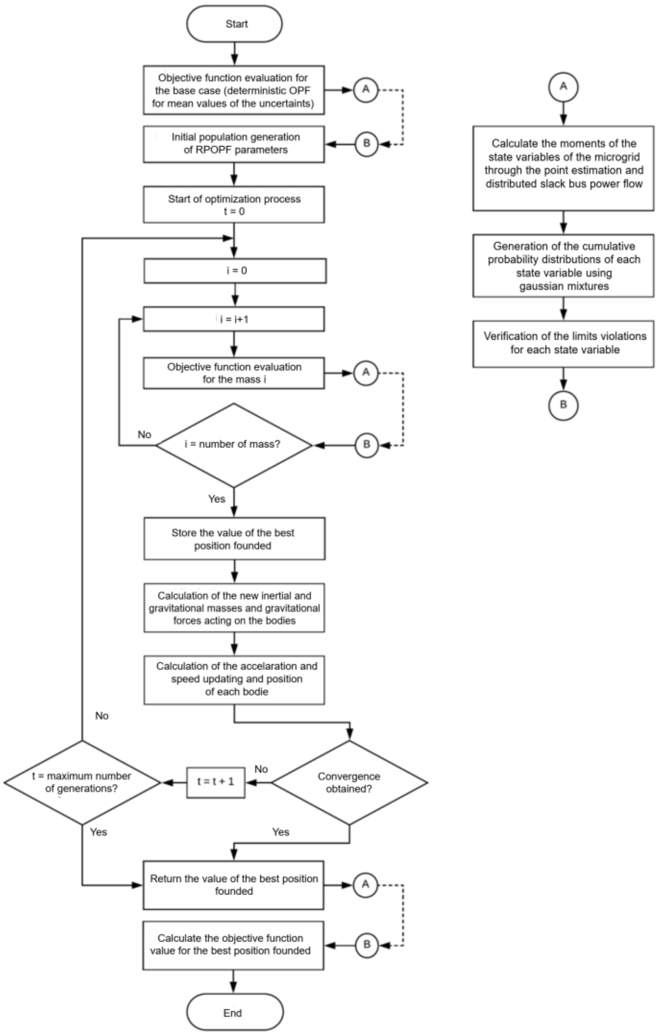

Fig. 1 Flowchart of the GSA used to solve the RPOPF.

6. TESTS AND RESULTS

6.1 Simulation Data

The methodology proposed in this paper was tested in a microgrid of 38 bus proposed in (Abdelaziz et al. 2013). The complete data for this test system are presented in (Abdelaziz et al. 2013; Araújo 2017).

To perform the RPOPF via GSA, the following set of parameters was considered: $a = 0.01$, $G_0 = 0.1$, $t_{max} = 100$, $\varepsilon = 0.002$, $N = 5$ and the maximum number of generations/iterations is 20 for PSO and GSA. This number was specified because no improvement in the objective function was achieved with additional generations/iterations.

As a way of demonstrating the optimization benefits, the RPOPF was compared to deterministic OPF. In other words, it is assumed that there are no uncertainties in the microgrid parameters. The deterministic OPF is performed by minimizing the operating costs of the DG subject to power flow equations, voltage limits and bounds for output power DG. The deterministic OPF is considered the base case in this paper. To calculate the frequency and voltage violations indices, $P_{TLOC_f}(\boldsymbol{X})$ and $P_{PLOC_i}(\boldsymbol{X})$, respectively, it was considered that:

i) Frequency violations occur whenever the deviation in the microgrid frequency is greater than 0.83% or less than 0.33% of the base value, 60 Hz. This means that whenever the microgrid frequency is greater than 60.5 Hz or less than 59.8 Hz, all DGs will be turned off to protect them from damage resulting from under or over frequency condition. As a result, the microgrid undergoes a TLOC event.

ii) Voltage violations on each bus occur whenever the deviation bus voltage is greater than ± 5% from the base value, 1 p.u. That means that whenever the bus voltage is above 1.05 p.u. or below 0.95 p.u., there will be loss of load in buses where the voltages are violated to avoid damage to the electric devices. Consequently, there is a PLOC event for the microgrid.

The results obtained with the GSA were compared with those obtained by the PSO. Both algorithms were implemented using the MATLAB® programming language in a PC with: Windows® 7 OS of 64 bits, Intel® Core i5 processor of 3.20 GHz and 4GB of RAM. The PSO was also tested with the same number of particles/bodies and generations of GSA in order to provide a fair comparison between them. Finally, to obtain a probability distribution of the risk index both PSO and GSA 100 test were performed with individuals and masses randomly initialized, respectively.

6.2 Results

As mentioned above, both PSO and GSA were used in the RPOPF to obtain the statistics for the violation indices. Figure 2 shows the mean values of voltage violation risk in each microgrid bus, obtained by GSA and PSO.

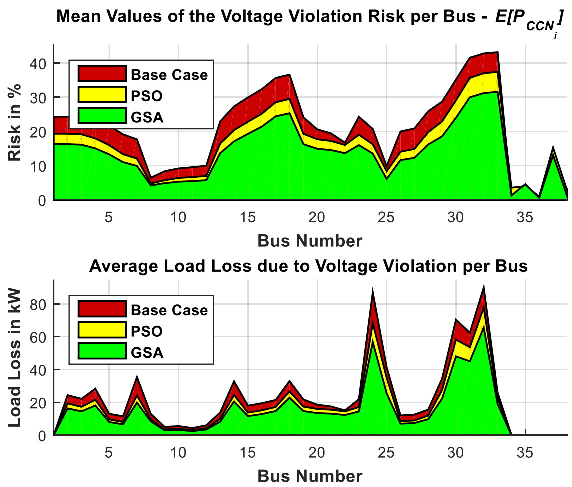

Fig. 2 Mean Values of the Voltage Violation Risk and Load Loss per Bus.

From the Figure 2, it can be observed that the risk of violation is smaller in buses 8, 12 and 25 than in other buses because there are DGs connected to them. This result is due to the var/volt support provided by the DGs which helps to maintain the voltage violation risk low in these buses.

Figure 2 also shows the expected nodal load loss due to voltage violations. It is observed a behaviour similar to the risk of voltage violation, making it again clear that the presence of the DGs favours the reduction of the average loss of load due to voltage problems. In both graphs, it can be seen that the GSA found an MGP that provided the lowest risks. The PSO, although also showing a good result in relation to the base case (deterministic OPF), could not surpass the GSA, which presented better results in almost all buses.

Regarding the base case, it can be seen in Figure 3 that the relative percentage reductions in the risk of voltage violation were lower in the solutions obtained by the PSO when compared to the results obtained by the GSA.

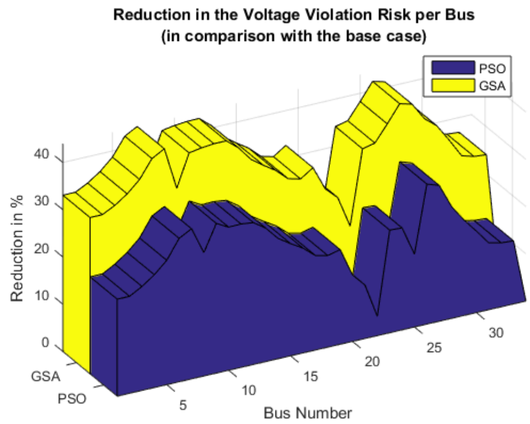

Fig. 3 Reduction in the Voltage Violation Risk per Bus (regarding to the base case).

Figure 4 shows the probability distribution of the $P_{TLOC_f}(\boldsymbol{X})$ for a sample of 100 test runs for the PSO and GSA. This figure shows that the GSA also presented better results than the PSO in relation to the risk of frequency violation. In other words, the GSA is able to achieve reference values for MPD that provide smaller total load loss in the microgrid when compared to those achieved by the PSO.

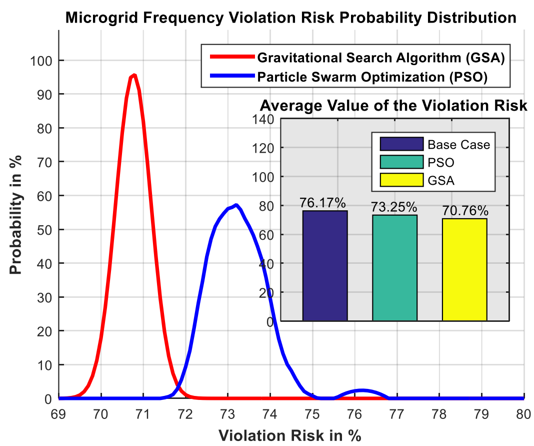

Fig. 4 Probability distribution of the frequency violation risk.

Finally, the average CPU times required by the GSA and PSO for the 100 test runs are 325.85 and 775.91 seconds, respectively. That is, the GSA converges to an optimal solution about twice faster than the PSO. In this way, the GSA is also more suitable for RPOPF than the PSO in relation to the computational cost to achieve an optimal solution.

7. CONCLUSIONS

This paper presents a methodology for the Robust Probabilistic Optimal Power Flow (RPOPF) oriented to improve the reliability of islanded operation of microgrids. The proposed approach is based on the combination of Probabilistic Power Flow (PPF) and Gravitational Research Algorithm (GSA). The comparison between optimization methods used to solve RPOPF demonstrated that reference parameters of the distributed generators can be used as decision variables to obtain a more reliable operation of the microgrid in islanded mode. It was found that GSA achieved a better result in this regard than the Particle Swarm Optimization (PSO). The GSA optimal solutions achieved a reduction in the risks of frequency and voltage violation higher than those achieved with the PSO.

The results presented in this paper motivate future research work associated with the following topics:

i) Multiobjective formulation of RPOPF based on weights or Pareto's Theory to model the objective function components associated with frequency and voltage violations.

ii) The tests carried out in this paper considered the frequency limits presented in (IEEE 2009). However, there is new IEEE Standard for the interconnection of distributed resources published in 2018. In this way, the authors intend to carry out tests with the RPOPF with the frequency limits defined in the IEEE standard of 2018.

iii) RPOPF based on phase coordinates to take into account the unbalanced nature of power distribution networks.

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