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Black hole optimizer for the optimal power injection in distribution networks using DG

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Abstract. The optimal sizing of Distributed Generators (DG) in electric power distribution networks is carried out through a metaheuristic optimization strategy. To size DG it is proposed an optimal power flow model is formulated by considering that the location of these sources has been previously defined by the distribution company. The solution of the optimal power flow is reached with the Black Hole Optimizer (BHO). A methodology is used master-slave optimization methodology, where the BHO (i.e., master stage) defines the sizes of the DG and the slave stage evaluates the objective function with a load flow algorithm, this work using the triangular-based power flow method. Numerical results in the 33-node and the 69-node test system demonstrates the effectiveness and robustness of the proposed approach when compared with literature results.

1. Introduction

The main characteristic of electrical distribution networks is associated with their construction, since these are typically designed in radial form to minimize investment costs in conductors [1], and also for simplifying the coordination of the protective devices [2]. These features in the electrical distribution networks make these highly affected by energy losses inherent to the distribution tanks, since part of the purchase energy at the substation node is transformed into heat energy [3]. The problem of power losses in electrical distribution networks in the specialized literature has been proposed multiple compensation strategies that include: (i) installation of capacitor banks and distribution system compensators (D-STATCOM) [4]; (ii) installation of battery energy storage systems [5]; (iii) grid reconfiguration [6]; and optimal placement and sizing of DG [7]. All of these approaches have positive effects regarding the amount of power losses reduction, being the optimal location and sizing of the DG the approach that allow reductions higher than 50 % [8].

In the literature have been proposed multiple optimization approaches that use exact and metaheuristic optimization approaches to solve this Mixed-Integer Nonlinear Programming (MINLP) model. Regarding exact approaches, [9] have presented a mixed-integer convex methodology that allows transforming the exact MINLP model into a mixed-integer second-order cone programming (MISOCP), that allows solving the location and sizing of DG using the combination of the branch & bound and the interior point method. The disadvantage of this approach is the usage of convex optimization packages that works with binary variables such as CVX and the GUROBI solver, which is not available in all the programming platforms. Authors



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of [10] have presented a combination of the sine-cosine algorithm in its discrete form with the conic formulation of the optimal power flow problem to solve the problem of optimally siting and sizing of DG in electrical distribution networks; however, the implementation also requires packages that solve SOCP models efficiently. In references [7, 11] and [12] have formulated MINLP models to locate and dimension DG and their solutions have been obtained using GAMS, the main advantage of these implementations is that the authors have concentrated their efforts to obtain accurate optimization models for representing the optimization problem; however, the GAMS package has a high probability of reporting local solutions due to the non-convex nature of the exact MINLP model. Regarding the combinatorial optimization, i.e., metaheuristics, in literature can be found multiple approaches to solve the optimal location and sizing DG, some of them are: krill-herd optimization algorithm [1, 13]; genetic algorithms [14, 15, 16, 17]; particle swarm optimization [3, 18, 19]; sunflower optimization algorithm [20]; population-based incremental learning [8]; tabu search algorithm [21, 22]; and flower pollination algorithm [23, 24], among others.

The main characteristic of the aforementioned metaheuristic approaches is that these work under a master-slave optimization approach [17], where the master-stage is entrusted with the optimal location of the DG, while the slave-stage set the optimum size of the DGs [8]. In the solution of the slave stage are typically used combinatorial optimization methods, being the particle swarm optimizer the most classical method in this stage [3, 16]. According to the literature review, for the problem of the optimal location and sizing of DG [10], the slave stage is the most sensitive part of the optimization algorithm, since the reduction of the power losses is completely dependent on the sizes of the DG; which implies that in this stage are require simple but efficient optimization techniques that ensure an adequate performance between the optimal solution and the processing times. According to what was previously written, this research proposed the application of the BHO for solving the slave stage (i.e., optimal power flow) in the problem of the optimal placement and sizing of DG in electrical distribution networks, by assuming that the distribution company provides the points where the DG will be located. The BHO is selected since in the current literature only the authors of [25] present the application of this method for the optimal dispatch of constant power sources for direct-current networks which are simplest when compared with AC electrical distribution grids addressed in this research.

In the current literature, the BHO has been proposed for solving different optimization problems, such as: data clustering [26]; set covering problem [27]; minimization of nonlinear and non-convex functions [28]; spam detection [29]; biclustering microarray gene expression data [30]; and optimal power flow solutions in DC networks [25, 31], among others. It is worth mentioning that the application of the BHO has no been previously reported in the specialized literature corresponds to the main contribution of this research to solve the problem of the optimal sizing of the DG in AC electrical distribution networks considering their locations perfectly known.

The article has six sections: Section 2 presents the mathematical formulation of the optimal location and optimal sizing of DG in AC electrical distribution grids in the complex domain, where the binary variables regarding the location of the generators are introduced for the completeness in the mathematical formulation. Section 3 presents the main characteristics of the BHO approach. This section also presents the power flow methodology used to determine the power losses once the optimal sizes of the DG are defined by the BHO. Section 4 presents the radial test systems used. Section 5 presents the numerical results of the proposed optimization approach and its comparisons with literature reports. Finally, Section 6 presents the conclusions of this research.

2. Mathematical formulation

The problem of the optimal sizing of DG in electrical distribution networks can be formulated with a MINLP model, where the binary part regarding the location of the distributed sources

is assumed known; and the continuous part is associated with the resulting optimal power flow model, which allows determining the optimal sizes of the distributed sources. The complete optimization model, including the binary variables is formulated as follows.

2.1. Objective function

For the optimal sizing of DG is to the minimization of the amount of active power losses during the peak load condition, which is presented in Equation (1).

$$\min p_{\text{loss}} = \text{Real} \{ \mathbf{V}^T \mathbf{Y}_{\text{bus}}^* \mathbf{V}^* \}, \quad (1)$$

Where p_{loss} is the amount of active power losses in all the branches of the network; $\mathbf{V} \in \mathcal{C}^{n \times 1}$ is the vector that contains the complex voltages in all the nodes of the network, being n the total nodes of the network; $\mathbf{Y}_{\text{bus}} \in \mathcal{C}^{n \times n}$ is the bus admittance matrix that has the information about the physical interconnection among nodes. Note that \mathcal{C} represents the set of complex numbers.

2.2. Set of constraints

The problem of the optimal sizing of distributed sources in electrical distribution grids is typically constrained by power balance equations, the capacities of the generators and the voltage regulation bounds, among others (Equations (2) - (6)).

$$\mathbf{S}_{gc}^* + \mathbf{S}_{dg}^* - \mathbf{S}_d^* = \mathbf{diag}(\mathbf{V}^*) \mathbf{Y}_{\text{bus}} \mathbf{V}, \quad (2)$$

$$\mathbf{S}_{gc}^{\min} \leq |\mathbf{S}_{gc}| \leq \mathbf{S}_{gc}^{\max}, \quad (3)$$

$$x \cdot \mathbf{S}_{gd}^{\min} \leq |\mathbf{S}_{dg}| \leq x \cdot \mathbf{S}_{gd}^{\max}, \quad (4)$$

$$\mathbf{V}^{\min} \leq |\mathbf{V}| \leq \mathbf{V}^{\max}, \quad (5)$$

$$\mathbf{1}^T x \leq N_{\text{max}}^{gd}, \quad (6)$$

Where $\mathbf{S}_{gc} \in \mathcal{C}^{n \times 1}$, $\mathbf{S}_{gd} \in \mathcal{C}^{n \times 1}$, and $\mathbf{S}_d \in \mathcal{C}^{n \times 1}$ are the column vectors with all the associated variables associated with the conventional and DG, and the load parameters, respectively; $\mathbf{S}_{gc}^{\min} \in \mathcal{R}^{n \times 1}$ and $\mathbf{S}_{gc}^{\max} \in \mathcal{R}^{n \times 1}$ are the vectors that contain the lower and upper apparent power bounds associated with the conventional sources; $\mathbf{S}_{gd}^{\min} \in \mathcal{R}^{n \times 1}$ and $\mathbf{S}_{gd}^{\max} \in \mathcal{R}^{n \times 1}$ represent the minimum and maximum apparent power injection bounds regarding the DG that will be installed in the electrical distribution grid; x is the binary vector that decides in where nodes will be located or no a DG; $\mathbf{V}^{\min} \in \mathcal{R}^{n \times 1}$ and $\mathbf{V}^{\max} \in \mathcal{R}^{n \times 1}$ are the vectors that contain all the minimum and maximum voltage regulation bounds of the grid; $N_{\text{max}}^{gd} \in \mathcal{R}$ is an scalar which represents with the maximum number of DG available for installation. \mathcal{R} is the set that contains the real numbers; $w \cdot y$ represents the element-wise product between two vectors, i.e., w and y ; $\mathbf{diag}(w)$ is a mathematical operation that becomes the vector w in a diagonal matrix; and $\mathbf{1} \in \mathcal{R}^{n \times 1}$ is a column vector of ones. Additionally, is assumed that these operate with unity power factor, which implies that $\mathbf{S}_{dg} = \mathbf{P}_{dg}$.

2.3. Model interpretation

The MINLP model defined from (1) to (6) is an optimization model defined in the complex domain, where: Equation (1) defines the objective function associated with the minimizing of the active power losses in all the conductors of the network; Equation (2) represents the complex apparent power balance in all the nodes of the network, i.e., the application of the second Tellegen's theorem at each node of the network; Inequality constraints (3) and (4)

correspond to the restrictions associated with the minimum and maximum power generation limits in the conventional and DG; Inequality constraints (5) is known as the voltage regulation constraint which is entrusted with guaranteeing all the voltages in the distribution network in their admissible bounds. These limits are typically defined by the grid operator based on the applicable regulatory policies [11]. Finally, Inequality constraint (6) determines the maximum number of DG available for installation inside of the distribution network.

In this research is assumed that: (i) the location of the DG were previously defined by the grid operator, which implies that to compare numerical results regarding the power losses minimization, the different locations provided in literature will be tested with our proposal optimization algorithm, and (ii) to solve the problem of the optimal sizing is proposed the application of a master-slave optimization strategy, where the master stage corresponds to the BHO which is entrusted with the determination of the DG sizes, and the slave stage is a power flow method which allows calculating the objective function value. The description of the optimization methodology will be presented in the next section.

3. Black hole optimizer

The BHO is a continuous metaheuristic optimization algorithm belonging the nature-inspired techniques that emulates the interaction among stars and black holes located in the center of the galaxies [25]. An exemple of this interaction is show in Fig. 1. The black optimization use the position of the stars at the black hole as potential solutions nonlinear programming models with multiple constraints [32]. Next, the aspects of the BHO for the solution nonlinear programming problems by presenting its main characteristics.

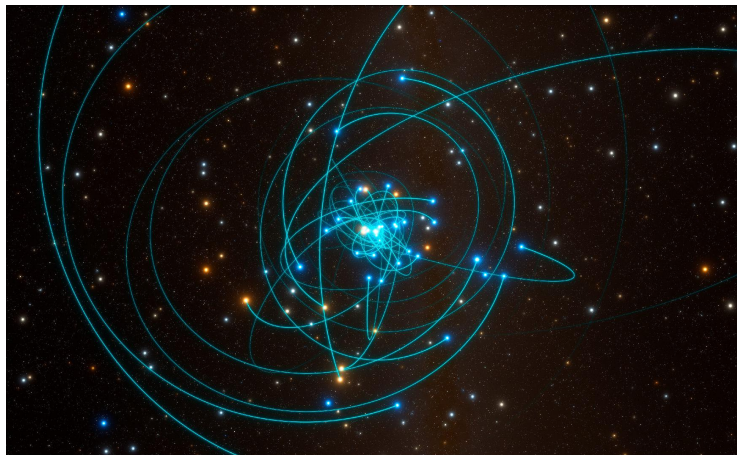


Figure 1. Interaction between starts and black holes (taken from [33])

3.1. Creation of the stars

The BHO is an optimization algorithm that works with a population that evolve through the solution space which have a similar behavior of the classical particle swarm optimization approach [25, 34]. To create the initial population (distribution of the stars about the solution

space) is made a random procedure with the following structure:

$$P^t = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n_v} \\ p_{21} & p_{22} & \cdots & p_{2n_v} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n_i1} & p_{n_i2} & \cdots & p_{n_in_v} \end{bmatrix} \quad (7)$$

Where n_i and n_v correspond to the scalars of the the number of individuals and the number of variables. Note that each row of the population is a star positioned on the solution space, where its coordinates are calculated as follows:

$$p_{ij} = p_j^{\min} + \alpha (p_j^{\max} - p_j^{\min}) \quad (8)$$

Where α is a random number between 0 and 1 generated with a normal distribution, p_{ij} is the active power component of the start i associated with the node j , being p_j^{\min} and p_j^{\max} the minimum and maximum power injections admissible for the DG connected at node j as was defined in Equation (4).

P^t represents the current population, each individual (star) inside of it represents the total generation at all nodes that have connected DG. In addition, the best solution contained in P^t is chosen as the current hole location [25].

3.2. Stars' movements

The movement of each individual, i.e., each star P_i^{t+1} , through the solution star is governed by the current position of this and the current position (p_i^{BH}) of the black hole. The position of the star is modified by applying the Equation (9).

$$P_i^{t+1} = p_i^t + \beta (p_i^{BH} - p_i^t), \quad \forall i = 1, 2, \dots, n_i \quad (9)$$

Where β is a random number between 0 and 1 generated with a normal distribution. It is important to highlight that for each component of the new star P_i^{t+1} is mandatory to revise that the upper and lower bounds in Equation (4) must be satisfied; otherwise, Expression (8) is used to guarantee the feasibility of the solution space.

3.3. Updating the position of the black hole

The position of the black hole corresponds to the best solution found in the current population during the search process through the solution space. The position of the black hole will be updated if in the descending population of stars (see Equation (9), the objective function the i^{th} individual is lower than the current black hole, i.e., $z_f(P_i^{t+1}) < z_f(P_i^{BH})$, which implies that $P_{t+1}^{BH} = P_i^{t+1}$. Otherwise, the position of the black hole remains unaltered.

Note that the evaluation of the objective function $z_f(\cdot)$ requires the implementation of a power flow methodology to determine the voltages in the nodes, which allow determining the level of power losses and the voltage regulation bounds. Here is adopted the power flow methodology named the triangular-based power flow method recently reported in [35].

3.4. Stars' substitution

One of the main aspects of the BHO approach is the methodology to replace some of the stars in the current population that no meet the diversity criterion [25]. In the theoretical physics concerning black holes, an stars that is in the neighborhood of the event horizon is destined to the destruction, since this star can be absorbed/or ejected due to the strong gravitational forced

acting on it [32]. To represent the possibility that an arbitrary star in P_i^{t+1} is absorbed/ejected by the black hole, the radius of the event horizon can be defined as presented below:

$$EH_R = \frac{\sum_{i=1}^{n_i} z_f(P_i^{t+1})}{z_f(P_{BH}^{t+1})}, \quad (10)$$

Where the denominator in Equation (10) represents the best objective function in the current population, i.e., the objective function value of the current black hole, and the numerator in Equation (10) corresponds to the algebraic sum of the objective function associated with all the stars in the population.

To know if an arbitrary star crosses the event horizon, the norm-2 (i.e., Euclidean norm) of such star with respect to the black hole's location is used:

$$D_{BH,i} = ||P_{BH}^{t+1} - P_i^{t+1}||, \quad (11)$$

Note that if $EH_R \leq D_{BH,i}$, a new star is generated randomly to replace the star absorbed by the black hole; otherwise, the star P_i^{t+1} continues being part of the current population. It is worth mentioning that the birth of new stars increases the possibility of the BHO to explore new regions of the solution space, being the generation of new stars a global exploration criteria [25].

3.5. Stop criterion

The exploration and exploitation ends if one of the following criteria meets:

- ✓ The maximum number of iteration, i.e., t_{\max} is reached.
- ✓ After k consecutive iterations the location of the BH has not presented any improvement.

4. Test feeders' information

To evaluate the proposed strategy in the problem optimal dimensioning of DG, two classical radial distribution test feeders composed of 33 and 69 nodes are used. Electrical configurations of these test feeders are depicted in Figs. 2(a) and 2(b). The complete information regarding lines, branches and loads for both test feeders can be consulted in [11].

5. Numerical validation

To evaluate the efficiency of the proposed strategy, we evaluate different reports presented in the literature for both test feeders. The methods used for the comparative analysis with the following:

- ✓ Krill-herd Algorithm (KHA) [13].
- ✓ Loss-sensitivity Factor with Simulated Annealing (LSFSA) [36].
- ✓ Genetic Algorithms (GA) [16].
- ✓ Particle Swarm Optimization (PSO) [16].
- ✓ Hybrid GA/PSO [37].

5.1. IEEE 33-bus system

The results of the comparative methods and the black-hole optimization approach applied to the IEEE 33-bus system is described in Table 1. The proposed BHO in all the comparative cases has positive improvements, being the GA/PSO method the worst approach to determine the size of the dispersed generators with a difference 29.11 % when compared with the BHO; while

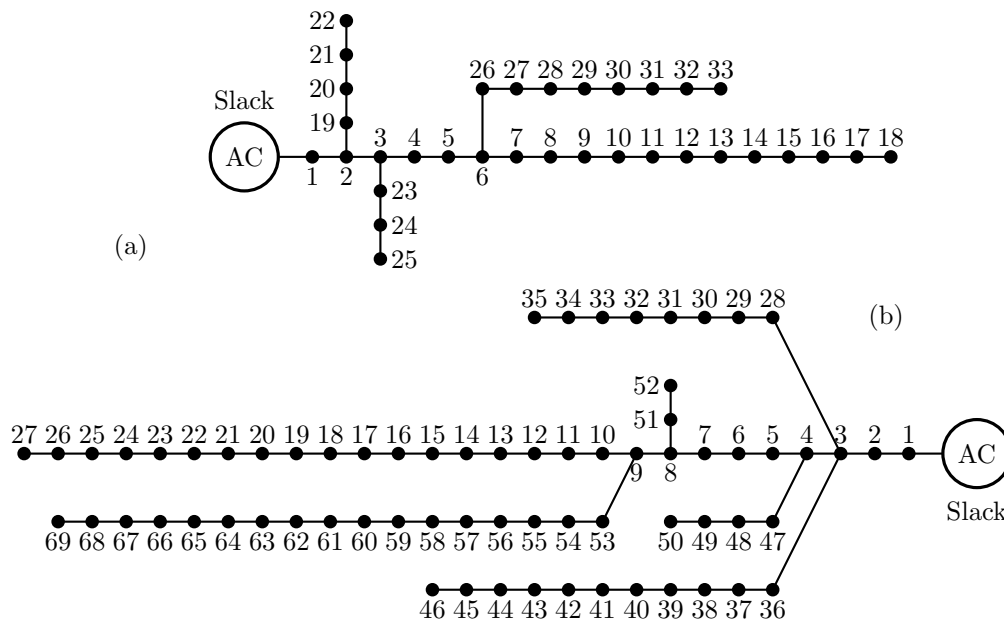


Figure 2. Electrical configurations of the test systems: (a) IEEE 33-bus, and (b) IEEE 69-bus.

Table 1. BHO performance in the IEEE 33-bus system.

Method	Literature reports			Black-hole optimizer		
	Location	Size (pu)	Losses (kW)	Size (pu)	Losses (kW)	Improv. (%)
KHA	13	0.8107	75.3977	0.8129	73.5036	2.51
	25	0.8368		0.8708		
	30	0.8410		1.0736		
LSFSA	6	1.1124	82.0418	1.2670	81.8575	0.22
	18	0.4874		0.4840		
	30	0.8679		0.7805		
GA	11	1.5000	106.0682	0.9681	86.5173	18.43
	29	0.4228		0.5571		
	30	1.0714		0.6068		
PSO	8	1.1768	105.3296	0.7475	82.9698	21.23
	13	0.9816		0.5644		
	32	0.8297		0.8388		
GA/PSO	11	0.9250	121.3259	0.6721	86.0127	29.11
	16	0.8630		0.3738		
	32	1.2000		0.9231		

the LSFSA approach only presents a difference about 0.22 % being the second best approach to determine the size of the generators behind of the proposed BHO.

Comparative results in Table 1 show that the selection of the location points for the disperse generators influence directly the possibility of reducing the amount of power losses with respect to the base case; being nodes 11, 29, and 30 with generators with nominal rates of 0.9681 MW, 0.5571 MW, and 0.6068 MW that produce the higher level of power losses with a value of 86.5173 kW, which represent a reduction about 58.99 % with respect the base case, i.e., 210.9876 kW without insertion of dispersed generation. On the other hand, when the disperse

generators are located in nodes 13, 25, and 30 with nominal rates of 0.8129 MW, 0.8708 MW, and 1.0736 MW, which produce a total power losses of 73.5036 kW when is used the proposed BHO. This represents a reduction in the amount of power losses with respect to the benchmark case about 65.16 %.

5.2. IEEE 69-bus system

The results of the comparative methods and the black-hole optimization approach for the IEEE 69-bus system is described in Table 2. For this system, it is observed that the BHO presents improvements regarding the final value of the power losses when compared with the literature reports. In this system the second best method corresponds to the KHA with a difference of 0.19 % with respect to the BHO; while the worst method corresponds to the PSO approach with a difference of 18.23 %.

Table 2. BHO performance in the IEEE 69-bus system.

Method	Literature reports			Black-hole optimizer		
	Location	Size (pu)	Losses (kW)	Size (pu)	Losses (kW)	Improv. (%)
KHA	11	0.4962	69.7144	0.5486	69.5841	0.19
	22	0.3113		0.3506		
	61	1.7354		1.7194		
LSFSA	18	0.4204	77.2461	0.5252	76.6236	0.81
	60	1.3311		1.3590		
	65	0.4298		0.4563		
GA	21	0.9297	89.0286	0.4903	73.1102	17.88
	62	1.0752		1.4710		
	64	0.9925		0.2925		
PSO	17	0.9925	83.9634	0.5267	71.6566	18.23
	61	1.1998		1.4614		
	63	0.7956		0.3210		
GA/PSO	21	0.9105	84.7498	0.4894	72.1063	14.92
	61	1.1926		1.4701		
	63	0.8849		0.3143		

In addition, the effect of the points where the dispersed sources are located have important incidences in the final power losses. For example, for nodes 11, 22, and 61, the BHO reports generation sizes of 0.5486 MW, 0.3506 MW, and 1.7194 MW. These power injections allows a final power losses of 69.5841 kW; i.e., 69.08 % respect to the benchmark case (225.0718 kW). When the distributed sources are assigned at nodes 18, 60, and 65 with nominal rates of 0.5252 MW, 1.3590 MW, and 0.4563 MW, the power losses is reduced to 65.96 %.

6. Conclusions

Was addressed in this research he optimal injection of active power in dispersed generator with black hole optimizer.. This is an easily implementable metaheuristic optimization technique with few parameters to tune. Numerical results demonstrate that the proposed BHO improves all the final power losses for all the comparative methods in both test feeders. In the case of the IEEE 33-node test system the BHO reaches improvements between 0.22 % and 29.11 % when compared with the LSFSA and the GA/PSO approaches. For the IEEE 69-bus system the proposed approach reaches improvements between 0.19 % and 18.23 % when compared with the KHA and the PSO methodologies.

The incidence of the points where the dispersed sources are located was evidenced in the total reduction of the power losses. For the IEEE 33-bus system, the minimum reduction of the power losses was about 58.99 % with the generators located at nodes 11, 29, and 30; while the best reduction was about 65.16 where the dispersed sources were connected in nodes 13, 25 and 30. For the IEEE 69-bus system when the dispersed sources were located in nodes 11, 22, and 61 the reduction of the power losses was about 69.08 % which was the best reduction for this system; while when the distributed sources are located in nodes 18, 60, and 65, the reduction of the power losses was about 65.96 %, i.e., the worst reduction scenario.

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