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OPTIMAL ALLOCATION AND SIZING OF DISTRIBUTED GENERATION USING AN ADAPTED FLOWER POLLINATION ALGORITHM AND SENSITIVITY ANALYSIS

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ABSTRACT

This paper proposes a method based on adapted Flower Pollination Algorithm (FPA) and the use of Sensitivity Analysis (SA) to determine the optimal allocation and sizing of Distributed Generation (DG) in radial distribution Systems. The most suitable set of buses for allocation is defined through SA at an initial stage. The FPA adaptation consists in splitting the search process between the allocation and sizing phases in order to increase the search efficiency. Tests on 33-bus and 69-bus radial network demonstrate that the method can provide significant reduction in active losses and improvement on voltage profile and compared with similar methods. In addition, a study considering variations in the DGs power factor (pf) highlights the benefits of carrying out the allocation process when the distributed generators also provide reactive power.

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INTRODUCTION

Nowadays, there is a strong worldwide trend to connect renewable energy sources at distribution level, reaching increasingly high levels of penetration [1]. Traditionally, centralized power plants have been the major source of power supply [2]. The concept of Distributed Generation (DG) has emerged to complement or replace the conventional model of energy production by integrating small generation units into the electrical grids, gaining special attention due to its several technical, economic and environmental benefits [3]. DG can be renewable (PV solar, wind, geothermal, biomass, etc.) and non-renewable (oil, gas, turbine, etc.). The power generated at locations geographically close to the centers of consumption is a helpful alternative to improve the efficiency of the traditional energy system [4]. There is a little consensus on the precise definition of DG among the academy and power industry [5]. However, in general, DG is characterized by generation units directly connected at distribution level or through residential, commercial, or even industrial facilities. As reported by [6], despite being considered a viable alternative, DG can impose several operational problems such as the presence of bidirectional power flows and island operation of microgrids [1]. In this respect, some studies have emerged to overcome these issues [7]. On the other hand, DGs can not only be used to reduce technical losses but also optimize economic and environmental costs [8].

The problem of Optimal Placement of Distributed Generation (OPDG) is a well-known topic usually addressed through Mixed-integer Nonlinear Programming (MINLP). These characteristics make it difficult to obtain the optimal solution, regardless of the technique used. One of the most important goals is allocation DGs in distribution systems is to minimize electrical losses. However, the inadequate placement and/or sizing can lead to sub-optimal results, or even increase system losses [9]. Several approaches have been proposed to solve OPDG [10-13]. Many of them employ analytical ("exact") methods [14], numerical programming (NP) [15], heuristics [16], [17] or metaheuristics [8], [10]. In general, the computational complexity increases with the network size and the presence of discrete variables [18]. Analytical methods usually work a numerical equation with advantages of low computational effort and accuracy of the solution, however, the simplification of the problem may threaten the accuracy of the solution when the problem inclines to be complex [19]. In [20], an analytical method is used for allocation and sizing of distributed generation to reduce power line losses. In [21], analytical expressions are used to calculate the optimal size and the best location for DG to decrease the power losses in primary distribution systems. A review of optimization methods using exact and approximate techniques for DG placement is presented in [14-22]. The OPDG problem can be efficiently addressed with heuristics, yet final solutions may not be optimal [10]. It has been noticed that metaheuristics algorithms are the most promising optimization methods to solve the DG planning optimization problem [19]. As main characteristics, they work with discrete and continuous variables and present low computational effort in comparison with the exact methods. However, due to stochastics characteristics of these methods, it is not possible to assure convergence to the global optimum. Methods based on Computational Intelligence (CI) such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are advocated in [23]–[26]. In [27], the author developed a method for allocating DG into distribution systems using Cuckoo Search Algorithm (CSA). A similar process is carried out in [28] applying Water Cycle Algorithm (WCA) for placement. In [29], the authors performed a study of DG allocation to distribution system using Coyote Optimization Algorithm (COA). It is clear to observed that, the diversity of methods to solve the problem, also highlighting the Flower Pollination Algorithm (FPA), applied to several optimization problems [30], [31]. This search for new methods is associated with the importance of the OPDG problem, motivated by the increasing penetration of DGs in electrical networks.

Some studies have considered strategies to improve the optimization process such as reducing the search space. In [32], used the power index to indicates the candidate buses for capacitors. Similarly, in [33] the most candidate buses for installing capacitors are suggested using loss sensitivity factors. The study conducted by [34] has considered applying loss sensitivity factors for DG allocation. In [35], the authors used the Loss Sensitivity Factor (LSF) for reduce the search space and then the Sine Cosine Algorithm (SCA) is applied for DG allocation. In this respect, we propose a method for solving the OPDG problem based on Sensitivity Analysis (SA) and Adapted Flower Pollination algorithm (AFPA). In traditional FPA, the search is carried out simultaneously (placement and sizing), which difficult the convergence of the algorithm in the OPDG problem. In the proposed AFPA, the search process occurs independently for the allocation variables (discrete) and sizing (continuous), since they are quantities of different natures. Sensitivity indices are obtained using SA via Lagrange Multipliers (LM), being used to limit the search space. Thus, the AFPA with Sensitivity performing Adapted Flower Pollination Algorithm with Sensitivity (AFPA-S). Initially, uses SA to limit the set of candidate buses for placement of DGs, and then applies the AFPA to place and size DGs allocation.

The contributions of this study can be summarized in:

I. Adaptation of conventional FPA to the OPDG problem – AFPA algorithm;
II. Combination of AFPA with SA to reduce the search space – proposed method AFPA-S;
III. The optimization of DG at Unit-power factor (Upf), and Optimal-power factor (Opf), considering possible real situations.

The AFPA-S resulted in the solution set having less dispersion with high-quality solutions, and this is the main contribution of work. Additionally, different power factor (pf) including the optimum pf calculation were analyzed in order to evaluate the placement and size in situations where DGs also inject reactive power into the grid, which is an important study for DGs allocation. The paper is organized as follows. After this introductory section, in Section 2 the modeling used in the problem is defined. Section 3 describes the aspects of the proposed methodology. In Section 4 the results of the computational tests obtained are shown and in Section 5 the conclusions of the work are presented.

PROBLEM FORMULATION

The OPDG problem consists in determining the location and size of DGs in order to minimize network losses and reinforce voltage profile, satisfying technical and system constraints. The objective function is mathematically modeled to minimize the total network losses in lines. In this paper, the objective function (1) is represented as in [28], where the installation costs are neglected.

$$\min f(x) = \sum_{i=1}^{n_L} R_i I_i^2 \tag{1}$$

where:
$f(x)$ losses of the systems (W);
n_L number of lines of the system;
R_i branch resistance$i$;
I_i electric current circulating in the branch i.
The objective function (1) is subjected to the following constraints.

Load Flow constraints: Equations (2)e (3)represents the active and reactive power balance, respectively.

$$0 = PG_k + PG_{G_k} - PC_k - V_k \sum_{m \in K} V_m (G_{km} \cos\theta_{km} + B_{km} \sin\theta_{km}) \tag{2}$$

$$0 = QG_k + QG_{G_k} - QC_k - V_k \sum_{m \in K} V_m (G_{km} \sin\theta_{km} - B_{km} \cos\theta_{km}) \tag{3}$$

where:
PG_k, QG_k active and reactive power injected into the bus$k$, neglecting DGs;
PG_{G_k}, QG_{G_k} active and reactive power injected into the bus k, by DGs;
PC_k, QC_k active and reactive power of the loads on the bus k;
V_k, V_m magnitudes of the voltage in the bus k;
G_{km}, B_{km} real and imaginary part of the element km of the admittance matrix ($Y = G + jB$).

Bus voltage constraints: Inequalities (4) represents the minimum and maximum limits imposed on voltage V_k.

$$V_k^{min} \le V_k \le V_k^{max} \tag{4}$$

Where the min and max superscripts mean the minimum and maximum limit of the variable, respectively.

DG constraints: Inequalities (5) e (6)represents the minimum and maximum limits of power injected at location j.

$$PG_{G_k}^{min} \le PG_{G_k} \le PG_{G_k}^{max} \tag{5}$$
$$QG_{G_k}^{min} \le QG_{G_k} \le QG_{G_k}^{max} \tag{6}$$

Number of DGs constraints: This restriction aims to restrict the amount of DGs allocated.

$$N_{DG} = N_{DG}^{max} \tag{7}$$

Where N_{DG} is the number of DGs that will be allocated in the system.

SOLUTION APPROACH

When a metaheuristic is applied to a problem that has different variables and different magnitudes, the search for the optimal solution can be compromised. This is the case of OPDG problem, where the variables related to the location are distinct and have different magnitudes. Another consideration is that the most metaheuristics consider the entire search space (all buses of the system) for the allocation of DGs, as an example, we can mention the hybrid algorithm Grasshopper Optimization Algorithms (GOAs) – Cuckoo Search Algorithm (CS) [36], Empirical Discrete metaheuristic (EDM) [8] and WCA [28]. We know, for example, that buses close to the substation are less favorable to allocation than buses far from the substation. Due to the characteristics of the problem, some strategies can be applied seeking a greater efficiency of the algorithm, as proposed in this work. The next steps describe the solution approach used for OPDG problem.

The Flower Pollination Algorithm: The FPA is a bio-inspired metaheuristic initially proposed in [37] that imitates the reproductive process in flowering plants. Pollen transfer is associated to pollinators agents such as insects, birds, bats and other animals, and can take two significant forms, abiotic and biotic. About 90% of plants succeed the biotic pollination shape, carried out by active agents like insects and animals. In the biotic form, the pollination process is based on nonliving agents such as wind and water. The reproductive process can be completed through cross-pollination, where pollination occurs in the same flower or plant, or self-pollination, among flowers from different plants [38]. The aim of flower pollination is the survival and reproduction of the most suitable plants, which can be considered as a process for optimizing plant species. Biotic cross-pollination can be viewed as a kind of global pollination, where pollinators move at long distance performing Levy flight [38]. Abiotic and self-pollination are a form of local pollination activities can take place at both local and global scales. In FPA, the optimization process is achieved locally and globally, controlled by a switch probability parameter $p \in [0; 1]$ updated after each generation. The global pollination step is represented as in (8):

$$X_i^{t+1} = X_i^t + L(X_i^t - g_*) \tag{8}$$

where:

X_i^t is the $i - th$ pollen grain (or solution vector x_i) at iteration t;
g_* is the current best solution among all grains at the current generation/ iteration;
L is the pollination *strength*, which essentially is a step size related to the Levy flight. The Levy flight parameter is given as in (9):

$$L \sim \frac{\lambda \gamma(\lambda) \sin\left(\frac{\pi \lambda}{2}\right)}{\pi} \frac{1}{S^{1+\lambda}} \tag{9}$$

Where $\gamma(\lambda)$ is the standard gamma function valid for large steps $S \gg 0$.

Local pollination and flowers constancy (the tendency of pollination agents to visit certain types of flowers) can be represented as (10):

$$X_i^{t+1} = X_i^t + \varepsilon\left(X_j^t - X_k^t\right) \tag{10}$$

where:
X_j^t and X_k^t are pollen grains from flowers of the same plant species;
ε is a random number from a uniform distribution in [0,1].

Parameter p gives an efficient mechanism to switch between common global pollination and intensive local pollination, resulting in enhanced search capabilities. In conventional FPA, each pollen (X_i^t) represents a candidate solution. In the present work, due to the nature of the problem variables, allocation (discrete variables obtained from candidate buses to allocation) and sizing (continuous variables that represent the DG capacity), the original algorithm [37] was adapted, so that the search space take place separately, seeking to improve the solution strategy. The proposed strategy, called AFPA, is illustrated in Fig. (1), where each pollen (X_{in}^L) is related with the allocation process and $\left(X_{in}^S\right)$ with the sizing of DGs.

Allocation *(L)*				Size *(S)*			
X_{i1}^L	X_{i2}^L	...	X_{in}^L	X_{i1}^S	X_{i2}^S	...	X_{in}^S

Figure 1. Search strategy of the AFPA algorithm

Sensitivity Analysis via Lagrange Multipliers: The LM provide an important information about a restrict optimization problem, helping in its general understanding and in the generation of relationships between the input and output of system parameters and variables. The LM can be used to estimate changes in the objective function in with respect to a change in the constraints [39]. As an example, consider the problem as in (11).

$$\begin{aligned} &\min L(x) \\ &\text{s.a } g_i(x) = b_i i = 1, \dots, m \end{aligned} \tag{11}$$

Where g_i can be interpreted as a limitation of the resources available in the equation i. Suppose you intend to analyze the behavior of the optimal value of the objective function L for a variation in g_i. Let $x^*(g)$ be the optimal value, depending on the availability of g resources. In this sense, we have to [40]:

$$\frac{\partial L\left(x^*(g)\right)}{\partial(g_i)} = \lambda_i \tag{12}$$

Where λ_i is the LM associated with the equality constraint i, which represents the marginal change from the optimal value in the objective function to a small variation of g_i, that is, the increase or decrease in the objective function by unit increase or decrease of resources. In a problem of OPDG which the minimization of active losses is considered, the LM of active power provides an estimate of the objective function when a unit of active power is changed in the active power balance constraint (2). Due to non-linear characteristic of the problem, a larger perturbation leads to errors in the estimation of values. However, this information can help to solve the problem. In this paper, the objective is to list the most suitable buses that favor the minimization of losses. Thus, the ranking of LM related to active power balance restrictions have been used to limit the search space, in order to eliminate non-significant buses from the set of candidate buses for allocation.

The proposed AFPA-S Algorithm: AFPA is used in this paper for allocation and size of DGs, where each pollen (X_i^t) is a candidate solution in the search space. In order to execute a low computational effort and obtain quality solutions, a sensitivity analysis via LM is used to reduce the search space and improving the overall optimization process. An outline of the proposed AFPA-S algorithm is shown in Fig. (2). The inputs are the network data, the predetermined DGs number, and the configuration parameters of FPA: p, population size, maximum iteration (i^{max}) and probabilities p_L andp_S. Then, execute the SA to limit the search space, and following the allocation (X_i^L) and sizing $\left(X_i^S\right)$ vectors are randomly generated. The initial value for solution (g_*) is also defined. An initial topology preprocessing for radial networks is recommended to improve Load Flow (LF) efficiency, since the Backward-Forward-Sweep (BFS) algorithm will be used. The process of optimization of $\left(X_i^L\right)$ and $\left(X_i^S\right)$ will occur separate. The values drawn for the variables (μ_L) and (μ_S) in each iteration determine which pollination will be of the global type (8), otherwise are less than the respective exchange probabilities p_L and p_S, or local (10). After the evaluation the fitness of the solution vector $X = \left[X_i^L, X_i^S\right]$, the value of the best solution (g_*) is updated. The process is repeated until the maximum number of iterations is reached. For each iteration, random (μ_L) and $(\mu_S)(0 \leq \mu \leq 1)$ are initially generated to decide whether AFPA will follow global or local pollination to optimize (X_i). In general, if $(\mu < p)$, global pollination via Levy flights is employed using (8), otherwise, local pollination is applied, using (10). Once the solution vectors (X_i) are computed, the actual evaluation of the cost function is calculated by the LF. The fitness values are then computed, and the AFPA resumes its execution by updating the current best solution (g_*). The iterative process ends when the maximum number of iterations is reached. The final solution (g_*) is then presented.

TEST RESULTS AND DISCUSSION

In this section, the proposed algorithm to solve the OPDG problem is tested on 33-bus [41] and 69-bus [42] distribution system, aiming to determine the best places and capacities for DG with a view to minimize the power losses. The proposed methodology was implemented in MATLAB® using a computer with an Intel® Core™ i3-3110M CPU @ 2.40, 4GB of RAM and Windows 10 Home operating system – 64 bits. The best solutions of 30 testing are considered. The parameters considered in the simulations are shown in Table 1, values collected empirically. The voltage (V_k) should lie within 0.9 per unit (p.u) as $\left(V_k^{min}\right)$ and 1.0 (p.u) as (V_k^{max}). For case studies, the total size of the DGs does not exceed the total load of the system. A BFS [43] method is used to obtain the LF solutions. A topological preprocessing of the system is previously made in order to enhance the algorithm efficiency.

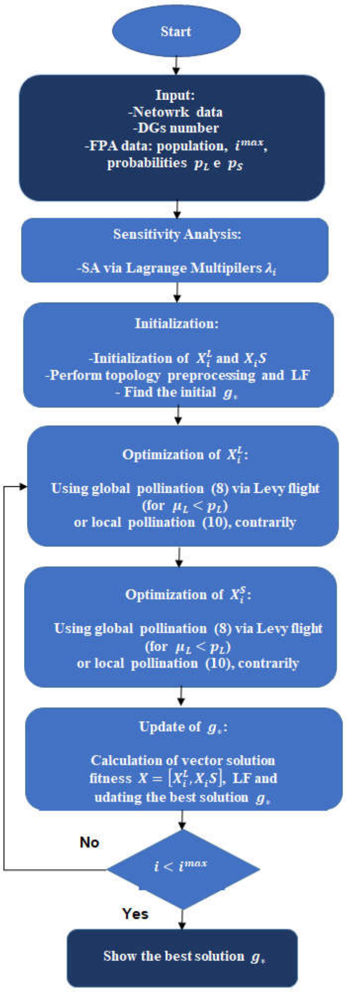

Figure 2. Flowchart of the proposed AFPA-S

Table 1. Parameters Considered

Population	*Iteration*	p	p_L	p_S	λ
70	350	0.2	0.2	0.4	1.5

Diminish the Search Space by SA: The total number of solutions (n_s) (only buses for allocation) to the OPDG problem in (N_b) buses of the system can be obtained by (13):

$$n_s = \frac{(N_b - N_\lambda)!}{(N_b - N_\lambda - N_{DG})!\,N_{DG}!} \tag{13}$$

Where (N_{DG}) is the predetermined amount of DGs, and (N_λ) represents the number of buses not considered for allocation. It is, therefore, a combinatorial problem [9]. By applying SA it is possible to significant reduce the search space without prejudice to the quality of the solutions. As an example, consider the system ($N_b = 33$); ($N_{DG} = 1$) and applying SA via LM, 16 buses can be excluded from analysis without prejudice the results, reducing the search space in 50%. If consider ($N_{DG} = 2$) or ($N_{DG} = 3$) the reduction is about 25% and 12% respectively. These are conservative values and were obtained empirically. In this sense, computational improvement can be reached by using SA in the OPDG problem. The ranking with the most favorable buses for the 33-bus and 69-bus systems are in Table 2 and Table 3 respectively. The last buses can be suppressed of the search process keeping the percentages presented.

Table 2. 33-bus system: LM (λ_i) and percentages in relation to the buses with higher sensitivity (DG = 1)

#	λ_i	$\lambda_i^{\%}$	#	λ_i	$\lambda_i^{\%}$	#	λ_i	$\lambda_i^{\%}$
18	-0.14	100	30	-0.11	79.63	25	-0.04	33.6
17	-0.14	99.1	10	-0.11	78.87	24	-0.04	30.0
16	-0.14	96.7	29	-0.11	75.95	4	-0.04	27.3
15	-0.13	97.8	9	-0.10	71.42	23	-0.03	22.8
14	-0.13	92.8	28	-0.10	68.88	3	-0.02	18.9
13	-0.13	90.2	8	-0.09	63.48	22	-0.01	8.51
33	-0.12	85.9	27	-0.08	59.01	21	-0.01	7.95
32	-0.12	85.7	7	-0.08	56.67	20	-0.01	7.30
31	-0.12	84.6	26	-0.08	56.27	19	-0.00	3.77
12	-0.12	82.3	6	-0.07	54.18	2	-0.00	3.25
11	-0.12	82.3	5	-0.05	35.82			

Table 3. 69-bus system: LM (λ_i) and percentages in relation to the buses with higher sensitivity (DG = 1)

#	λ_i	$\lambda_i^{\%}$	#	λ_i	$\lambda_i^{\%}$	#	λ_i	$\lambda_i^{\%}$
65	-0.17	100	13	-0.05	34.54	43	-0.00	0.93
64	-0.16	99.35	55	-0.05	32.40	42	-0.00	0.90
63	-0.16	97.12	69	-0.05	31.73	34	-0.00	0.87
62	-0.16	96.67	68	-0.05	31.73	41	-0.00	0.71
61	-0.16	96.34	12	-0.05	31.38	5	-0.00	0.66
60	-0.14	87.86	67	-0.04	28.08	48	-0.00	0.63
59	-0.13	81.59	66	-0.04	28.08	33	-0.00	0.55
58	-0.12	76.38	11	-0.04	28.02	32	-0.00	0.30
57	-0.10	63.11	54	-0.04	27.78	40	-0.00	0.25
27	-0.07	44.27	10	-0.08	26.86	39	-0.00	0.25
26	-0.07	44.25	53	-0.04	24.46	32	-0.00	0.30
25	-0.07	44.17	52	-0.03	20.54	38	-0.00	0.22
24	-0.07	43.99	51	-0.03	20.53	31	-0.00	0.2
23	-0.07	43.74	8	-0.03	20.5	30	-0.00	0.18
21	-0.07	43.73	7	-0.03	18.31	37	-0.00	0.11
20	-0.07	43.21	6	-0.01	9.24	47	-0.00	0.1
19	-0.07	42.88	50	-0.00	2.53	4	-0.00	0.08
18	-0.07	42.38	49	-0.00	2.29	29	-0.00	0.07
17	-0.07	42.37	46	-0.00	0.99	36	-0.00	0.04
16	-0.07	41.4	45	-0.00	0.99	28	-0.00	0.03
15	-0.06	40.82	35	-0.00	0.93	3	-0.00	0.03
14	-0.06	37.69	44	-0.00	0.93	2	-0.00	0.02
56	-0.06	36.95	40	-0.00	0.25			
9	-0.03	21.63	39	-0.00	0.25			

Allocation of DGs with Unit-pf on 33-bus system: This first analysis, consider the 33-bus system, the system is balanced three-phase networks, so they can be represented as a single line network as in Fig. (3). The system presents 12.66 kV having 33 buses and 32 branches based on [3].

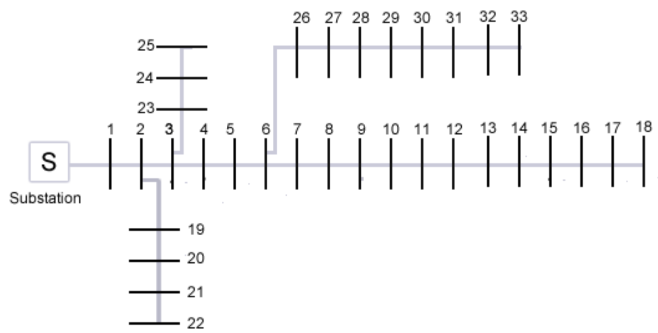

Figure 3. 33-bus system (Source: Authors, based on [3])

Assumed the allocation of DGs ($N_{DG} = 1; 2; 3$), as similar [17-45], assuming Unity-pf. Before DG placement, the total losses amount is 210.99 (kW). After 30 runs, the proposed AFPA-S reached the lowest level of losses as listed in Table 5. The best results are compared to the similar methods based on Backtracking Search Optimization Algorithm (BSOA) [44], hybrid-1 algorithm [46], hybrid-2 algorithm

[17], and Improved Analytical (IA) [47]. The AFPA-S data assign to the best solution in 30 runs. It is shown that AFPA-S achieves a loss reduction of power losses, a little lower than the compared approaches. The best results of implemented algorithms (FPA*) demonstrate that the proposed AFPA-S has presented more accurate solutions in terms of losses as summarized in Table 4. In Fig. (4) the voltage profile with and without the allocation of DGs is shown, where it is possible to observe the improvement in the voltage profile with allocation of only active power. the AFPA-S when compared to the similar works. Additionally, the voltage profile has been improved when DG is capable to inject both active and reactive power by optimal pf control as presented in Fig. (5).

Allocation of DGs with Unit-pf on 69-bus system: In this last case, the proposed AFPA-S was tested on 69-bus system, represented in Fig. (6). The system is three-phase balanced network and presents 12.66 kV having 69 buses and 68 branches based on [42].

Table 4. Comparison of the obtained results by the application of the investigated algorithms for 33-bus system

Method	*Average (kW)*	*Best (kW)*	*Worst (kW)*	*Deviation (kW)*
FPA	73.54	72.79	74.31	0.3772
AFPA	73.44	72.78	74.20	0.3636
AFPA-S	73.29	72.78	73.75	0.3346

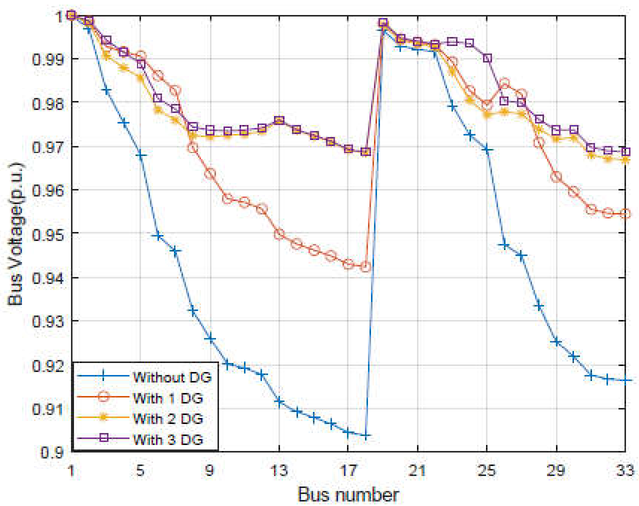

Figure 3. Voltage profile: 33-bus system (unity-pf DG)

Table 5. Comparison of AFPA-S and similar approaches results for 1, 2 and 3 DGs with unity pf for 33-bus system

Method	*Unity-pf 1 DG*		*Unity-pf 2 DG*		*Unity-pf 3 DG*	
	size (place)	*losses (kW)*	*size (place)*	*losses (kW)*	*size (place)*	*losses (kW)*
Base-case	---	210.99	---	210.99	---	210.99
BSOA	1857.5 (8)	118.12	880 (13); 924 (30)	89.34	632 (12); 487 (28); 550 (31)	89.05
Hybrid-1	2490 (6)	111.17	830 (13); 1110 (30)	87.28	790 (13); 1070 (24); 1010 (30)	72.89
Hybrid-2	2598 (6)	111.03	---	---	755 (14); 1073 (24); 1068 (30)	72.81
IA	2600 (6)	110.10	1020 (12); 1020 (30)	87.55	900 (13); 900 (24); 900 (30)	74.20
AFPA-S	2509 (6)	111.02	851 (13); 1157 (30)	87.16	801 (13); 1091 (24); 1053 (30)	72.78

Table 6. Comparison of AFPA-S and similar approaches results for 2 and 3 DGs with optimal pf for 33-bus system

Method	*Optimal-pf 2 DGs*			*Optimal-pf 3 DGs*		
	size (place)	*Optimal pf*	*losses*	*size (place)*	*Optimal pf*	*losses*
Base-case	---	---	210.99	---	---	210.99
BSOA	777 (13); 1032 (29)	0.88; 0.70	31.98	698 (13); 402 (29); 658 (31)	0.86; 0.71; 0.70	29.65
BFOA	---	---	---	600 (14); 598 (25); 934 (30)	0.89; 0.83; 0.88	27.50
IA	2195 (13); 1095 (30)	0.82; 0.82	44.39	1098 (6); 768 (14); 1098 (30)	0.88; 0.82; 0.82	22.29
Hybrid	1039 (13); 1508 (30)	0.91; 0.72	28.60	873 (13); 1186 (24); 1439 (30)	0.90; 0.89; 0.71	11.70
PSO	914 (13); 1535 (30)	0.91; 0.73	28.60	537 (13); 1058 (24); 967 (30)	0.66; 0.78; 0.75	19.63
AFPA-S	845 (13); 1137 (30)	0.90; 0.73	28.50	793 (13); 1071 (24); 1029 (30)	0.90; 0.71; 0.71	11.74

Allocation of DGs with optimal-pf on 33-bus system: In this simulation, the injection of reactive power by DGs is enabling by means of optimal power factor control. Several analyseswere performed on the AFPA-S algorithm considering pf variations. The results of total losses, total active and location of the DGs are listed in the Table 7 for a single DG and Table 6 for two and three operation DG. The best results are compared to the similar methods based on Backtracking Search Optimization Algorithm (BSOA) [44], Bacterial Foraging Optimization Algorithm (BFOA) [48], Improved Analytical (IA) [47], hybrid-2 algorithm [17] and Particle Swarm Optimization (PSO) [49].It was found that, the lowest power losses are provided by

The original losses are 225 (kW), without any compensation. The best results of implemented algorithms (FPA*) on 69-bus demonstrate that the proposed AFPA-S has presented more accurate solutions in terms of losses as summarized in Table 8. Table 9 shows the results by AFPA-S, MINLP [50], Modified Teaching-Learning Optimization Algorithm (MTLBO) [51], and Hybrid Grey Wolf Optimizer (HGWO) [52]. Although the proposed method is in many cases similar to HGWO, the AFPA-S provides more accurate solutions, especially with the advantage to explore a few portion of the search space as mentioned previously. Fig. (7) display the voltage enhancement take into account when DG operate at unity-pf.

Allocation of DGs with optimal-pf on 69-bus system: In this experiment, have been considered DGs operating with the optimal-pf on 69-bus system. Table 10 shows the solutions come by AFPA-S, Artificial Bee Colony (ABC) [53], MINLP [50], IA [47], Krill Herd Algorithm (KHA) [54], and Analytical Method (AM) [55] for a single DG and Table 12 for two and three operation DG.The best solution is achieved by the proposed AFPA-S 23.17 (kW). Moreover, the gain of voltage profile is presented in Fig. (8) when DG injects both active and reactive power.

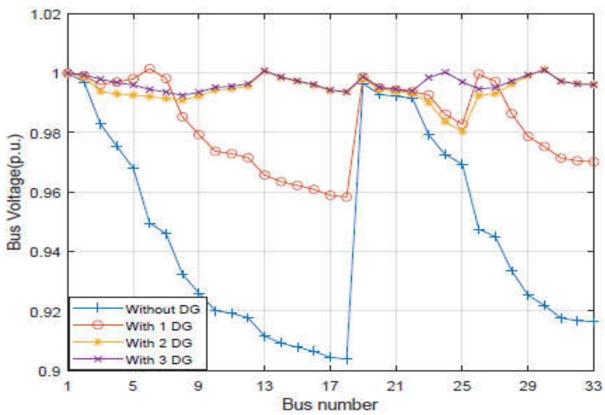

Figure 4. Voltage profile: 33-bus system (optimal-pf DG)

Table 7. Comparison of AFPA-S and similar approaches results for 1 DG with optimal pf for 33-bus system

Method	*Optimal-pf 1 DG*		
	size (place)	*Optimal-pf*	*losses (kW)*
Base-case	---	---	210.99
BSOA	1857.5 (6)	0.82	87.78
BFOA	2019 (9)	0.86	76.14
IA	3107 (6)	0.82	67.90
Hybrid	3028 (6)	0.82	67.90
PSO	2558.2 (6)	0.82	67.86
AFPA-S	2558 (6)	0.82	67.86

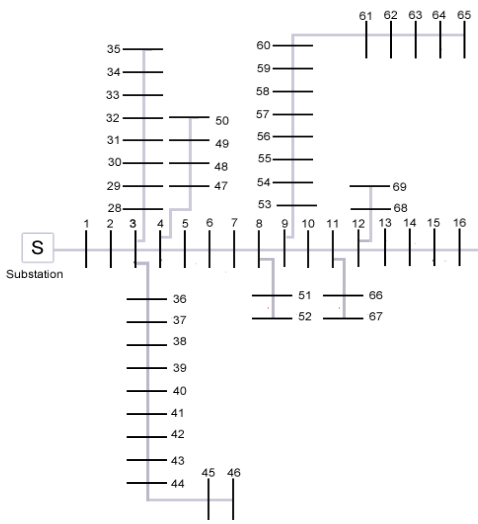

Figure 5. 69-bus system (Source: Authors, based on [2])

Table 8. Comparison of the obtained results by the application of the investigated algorithms for 69-bus system

Method	*Average (kW)*	*Best (kW)*	*Worst (kW)*	*Deviation (kW)*
FPA	70.55	69.49	74.31	0.8776
AFPA	69.59	69.49	75.00	0.3352
AFPA-S	69.42	69.42	69.48	0.3333

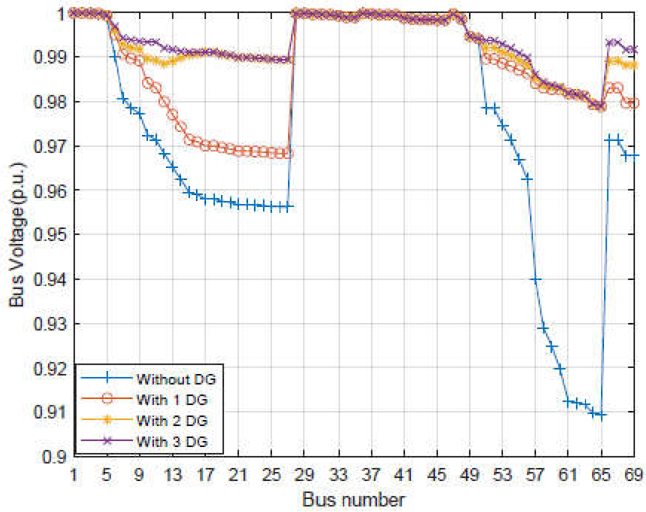

Figure 7. Voltage profile: 69-bus system (unity-pf DG)

It is well-know that, when DG is capable to provide both active and reactive power the losses can decrease drastically. Other important metric is related to number of DGs, increasing the generators units losses can reduce. Furthermore, the total of active losses is less with the optimal-pf than only inject active power. In Fig. (9) is shown the both tested systems in terms of power losses.

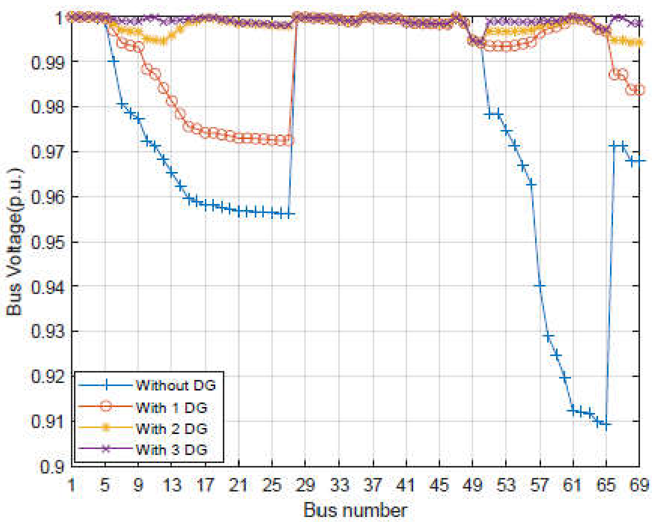

Figure 8. Voltage profile: 69-bus system (optimal-pf DG)

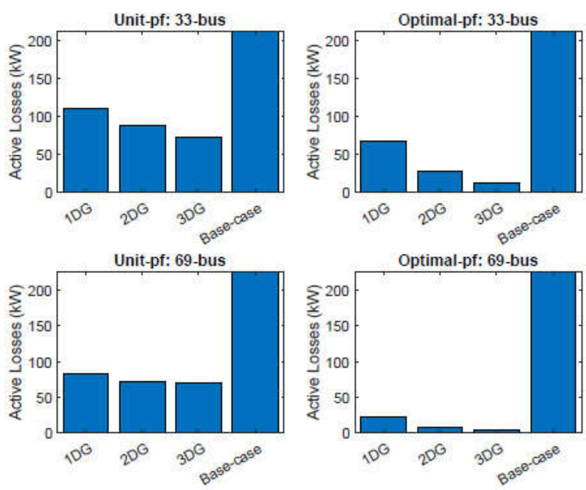

Figure 6. Effect of number of DG and control-pf for the tested systems

Table 9. Comparison of AFPA-S and similar approaches results for 1, 2 and 3 DG with unity pf for 69-bus system

Method	*Unity-pf 1 DG*		*Unity-pf 2 DG*		*Unity-pf 3 DG*	
	size	*losses (kW)*	*size (place)*	*losses (kW)*	*size (place)*	*losses (kW)*
Base-case	---	225	---	225	---	225
IA	1900 (61)	83.55	510 (17); 1700 (61)	71.92	510 (11); 340 (17); 1700 (61)	70.23
MINLP	1870 (61)	83.48	530 (17); 1780 (61)	71.92	530 (11); 380 (17); 1720 (61)	69.67
MTLBO	1819 (61)	83.32	519 (17); 1732 (61)	71.77	493 (11); 378 (18); 1672 (61)	69.53
HGWO	1872 (61)	83.22	531 (17); 1781 (61)	71.67	527 (11); 380 (17); 1718 (61)	69.42
AFPA-S	1872 (61)	83.22	531 (17); 1781 (61)	71.67	526 (13); 380 (24); 1718 (30)	69.42

Table 10. Comparison of AFPA-S and similar approaches results for 1 DG with optimal pf for 69-bus system

Method	*Optimal-pf 1 DG*		
	size (place)	*Optimal-pf*	*losses (kW)*
Base-case	---	---	225
ABC	1870 (61)	0.85	23.92
MINLP	1828 (61)	0.81	23.31
IA	1839 (61)	0.82	23.24
KHA	1877 (61)	0.82	23.22
AM	1798 (61)	0.81	23.20
AFPA-S	1828 (61)	0.81	23.17

Table 11. Comparison of AFPA-S and similar approaches results for 2 and 3 DG with optimal pf for 69-bus system

Method	*Optimal-pf 2 DGs*			*Optimal-pf 3 DGs*		
	size (place)	*Optimal pf*	*losses (kW)*	*size (place)*	*Optimal pf*	*losses (kW)*
Base-case	---	---	225	---	---	225
ABC	510 (17); 1785 (61)	0.85; 0.85	7.99	---	---	---
IA	540 (17); 1799 (61)	0.82; 0.82	7.45	630 (17); 900 (50); 900 (61)	0.82; 0.82; 0.82	5.09
MINLP	522 (17); 1735 (61)	0.82; 0.81	7.20	494 (11); 379 (17); 1674 (61)	0.81; 0.82; 0.81	5.09
HGWO	514 (17); 1722 (61)	0.82; 0.81	7.20	497 (11); 375 (18); 1665 (61)	0.81; 0.83; 0.81	4.26
AFPA-S	522 (17); 1734 (61)	0.82; 0.81	7.20	493 (11); 378 (18); 1674 (61)	0.81; 0.83; 0.81	4.26

CONCLUSION

This paper presented a proposal for the allocation of DGs using an adaptation of the metaheuristic FPA in order to make the optimization process of the allocation and size process independent. Additionally, in order to improve computational efficiency, an SA technique was used to reduce the search space at initial stage; this has improved the optimization process. The objective function considered the minimization of losses in the distribution network seeking an efficient operation of the system. It was demonstrated that, the allocation of DGs using the proposed approach AFPA-S reduced the active losses and improved the voltage profile in the system. The results were compared to other approximate techniques such as BSOA, BFOA, Hybrid Algorithm (1 and 2), IA, MINLP, MTLBO, HGWO, ABC, KHA, and AM, in addition to the regular FPA and AFPA method is discussed in this study. An additional study with variations of pf was carried out, showing the benefits for the network when DGs is capable to inject reactive power. It is concluded that, the algorithm can be an excellent tool for the planning of distribution systems, and can be easily adapted to problems such as the allocation and sizing of capacitor banks.

REFERENCES

Lopes J. A. P. *et al.*, "The future of power systems: Challenges, trends, and upcoming paradigms," *Wiley Interdiscip. Rev. Energy Environ.*, vol. 9, no. 3, pp. 1–16, 2020.

Mena, A. J. G. and J. A. Martín García, "An efficient approach for the siting and sizing problem of distributed generation," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 167–172, 2015.

Nagaballi, S. and V. S. Kale, "Pareto optimality and game theory approach for optimal deployment of DG in radial distribution system to improve techno-economic benefits," *Appl. Soft Comput. J.*, vol. 92, p. 106234, 2020.

Alanne K. and A. Saari, "Renewable and Sustainable Energy Reviews," *Renew. Sustain. Energy Rev.*, vol. 10, pp. 539–558, 2006.

Mehigan, L., J. P. Deane, B. P. Ó. Gallachóir, and V. Bertsch, "A review of the role of distributed generation (DG) in future electricity systems," *Energy*, vol. 163, pp. 822–836, 2018.

Quadri, I. A., S. Bhowmick, and D. Joshi, "A comprehensive technique for optimal allocation of distributed energy resources in radial distribution systems," *Appl. Energy*, vol. 211, no. July 2017, pp. 1245–1260, 2018.

Bakr, H. M., M. F. Shaaban, A. H. Osman, and H. F. Sindi, "Optimal allocation of distributed generation considering protection," *Energies*, vol. 13, no. 9, 2020.

Coelho, F. C. R., I. C. da Silva Junior, B. H. Dias, W. Peres, V. H. Ferreira, and A. L. M. Marcato, "Optimal distributed generation allocation in unbalanced radial distribution networks via empirical discrete metaheuristic and steepest descent method," *Electr. Eng.*, vol. 103, no. 1, pp. 633–646, 2020.

Mahmoud, K., N. Yorino, and A. Ahmed, "Optimal Distributed Generation Allocation in Distribution Systems for Loss Minimization," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 960–969, 2016.

Bayat, K. and A. Bagheri, "Optimal active and reactive power allocation in distribution networks using a novel heuristic approach," *Appl. Energy*, vol. 233–234, no. April 2018, pp. 71–85, 2019.

Da Rosa, W. M., P. Rossoni, J. C. Teixeira, E. A. Belati, and P. T. L. Asano, "Optimal allocation of capacitor banks using genetic algorithm and sensitivity analysis," *IEEE Lat. Am. Trans.*, vol. 14, no. 8, 2016.

Gil-González, W., O. D. Montoya, A. Rajagopalan, L. F. Grisales-Noreña, and J. C. Hernández, "Optimal selection and location of fixed-step capacitor banks in distribution networks using a discrete version of the vortex search algorithm," *Energies*, vol. 13, no. 18, pp. 1–21, 2020.

Kim, B., N. Rusetskii, H. Jo, and I. Kim, "The optimal allocation of distributed generators considering fault current and levelized cost of energy using the particle swarm optimization method," *Energies*, vol. 14, no. 2, 2021.

Ehsan, A. and Q. Yang, "Optimal integration and planning of renewable distributed generation in the power distribution networks : A review of analytical techniques," *Appl. Energy*, vol. 210, no. November 2017, pp. 44–59, 2017.

Theo, W. L., J. S. Lim, W. S. Ho, H. Hashim, and C. T. Lee, "Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods," *Renew. Sustain. Energy Rev.*, vol. 67, pp. 531–573, 2017.

Ahmadigorji, M. and N. Amjady, "Optimal dynamic expansion planning of distribution systems considering non-renewable distributed generation using a new heuristic double-stage optimization solution approach," *Appl. Energy*, vol. 156, pp. 655–665, 2015.

Muthukumar, K. and S. Jayalalitha, "Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique," *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 299–319, 2016.

Rao, R. S., S. V. L. Narasimham, and M. Ramalingaraju, "Optimal capacitor placement in a radial distribution system using Plant Growth Simulation Algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 5, pp. 1133–1139, 2011.

Abdmouleh, Z., A. Gastli, L. Ben-Brahim, M. Haouari, and N. A. Al-Emadi, "Review of optimization techniques applied for the integration of distributed generation from renewable energy sources," *Renew. Energy*, vol. 113, pp. 266–280, 2017.

Gözel, T. and M. H. Hocaoglu, "An analytical method for the sizing and siting of distributed generators in radial systems," *Electr. Power Syst. Res.*, vol. 79, no. 6, pp. 912–918, 2009.

Acharya, N., P. Mahat, and N. Mithulananthan, "An analytical approach for DG allocation in primary distribution network," *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 10, pp. 669–678, 2006.

Pesaran, M. H.A, P. D. Huy, and V. K. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms," *Renew. Sustain. Energy Rev.*, vol. 75, no. May, pp. 293–312, 2017.

Zhao, Z. and J. Mutale, "Optimal conductor size selection in distribution networks with high penetration of distributed generation using adaptive genetic algorithm," *Energies*, vol. 12, no. 11, 2019.

Almabsout, E. A., R. A. El-Sehiemy, O. N. U. An, and O. Bayat, "A Hybrid Local Search-Genetic Algorithm for Simultaneous Placement of DG Units and Shunt Capacitors in Radial Distribution Systems," *IEEE Access*, vol. 8, pp. 54465–54481, 2020.

Das, S., D. Das, and A. Patra, "Operation of distribution network with optimal placement and sizing of dispatchable DGs and shunt capacitors," *Renew. Sustain. Energy Rev.*, vol. 113, no. September 2017, p. 109219, 2019.

Farshad, M. "Distributed generation planning from the investor's viewpoint considering pool-based electricity markets," *Electr. Power Syst. Res.*, vol. 187, no. June, p. 106474, 2020.

de Oliveira, V. Y. M., R. M. S. de Oliveira, and C. M. Affonso, "Cuckoo Search approach enhanced with genetic replacement of abandoned nests applied to optimal allocation of distributed generation units," *IET Gener. Transm. Distrib. Gener. Transm. Distrib.*, vol. 12, no. 13, pp. 3353–3362, 2018.

El-Ela, A. A. A., R. A. El-Sehiemy, and A. S. Abbas, "Optimal Placement and Sizing of Distributed Generation and Capacitor Banks in Distribution Systems Using Water Cycle Algorithm," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3629–3636, 2018.

Chang, G. W. and N. Cong Chinh, "Coyote optimization algorithm-based approach for strategic planning of photovoltaic distributed generation," *IEEE Access*, vol. 8, pp. 36180–36190, 2020.

Namachivayam, G., C. Sankaralingam, S. K. Perumal, and S. T. Devanathan, "Reconfiguration and Capacitor Placement of Radial Distribution Systems by Modified Flower Pollination Algorithm," *Electr. Power Components Syst.*, vol. 44, no. 13, pp. 1492–1502, 2016.

José da Silva, D., E. Antonio Belati, and E. Werley Silva dos Angelos, "FPAES: A Hybrid Approach for the Optimal Placement and Sizing of Reactive Compensation in Distribution Grids," *Energies* , vol. 13, no. 23. 2020.

Abdelaziz, A. Y., E. S. Ali, and S. M. Abd Elazim, "Flower pollination algorithm for optimal capacitor placement and sizing in distribution systems," *Electr. Power Components Syst.*, vol. 44, no. 5, pp. 544–555, 2016.

Abd Elazim, S. M. and E. S. Ali, "Optimal locations and sizing of capacitors in radial distribution systems using mine blast algorithm," *Electr. Eng.*, vol. 100, no. 1, 2016.

Li, Y., B. Feng, G. Li, J. Qi, D. Zhao, and Y. Mu, "Optimal distributed generation planning in active distribution networks considering integration of energy storage," *Appl. Energy*, vol. 210, no. July 2017, pp. 1073–1081, 2018.

Selim, A., S. Kamel, A. A. Mohamed, and E. E. Elattar, "Optimal Allocation of Multiple Types of Distributed Generations in Radial Distribution Systems Using a Hybrid Technique," *Sustainability*, no. 13, pp. 2–31, 2021.

Suresh, M. C. V. and J. B. Edward, "A hybrid algorithm based optimal placement of DG units for loss reduction in the distribution system," *Appl. Soft Comput. J.*, vol. 91, p. 106191, 2020.

Yang, X. S., "Flower pollination algorithm for global optimization," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 7445 LNCS, pp. 240–249, 2012.

Yang, X. S., "Firefly algorithms for multimodal optimization," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 5792 LNCS, pp. 169–178, 2009.

Belati, E. A., A. M. De Souza, and G. R. M. Da Costa, "Influence of the operational constraints in the active transmission losses allocation via Lagrange multipliers," *IEEE Lat. Am. Trans.*, vol. 8, no. 1, pp. 58–64, 2010.

Helmult, F. *Programação não Linear: Análise e métodos*, 1 st. São Paulo, 1978.

Sahoo, N. C. and K. Prasad, "A fuzzy genetic approach for network reconfiguration to enhance voltage stability in radial distribution systems," *Energy Convers. Manag.*, vol. 47, no. 18–19, pp. 3288–3306, 2006.

Baran, M. E. and F. F. Wu, "Optimal capacitor placement on radial distribution systems," *IEEE Trans. Power Deliv.*, vol. 4, no. 1, pp. 725–734, 1989.

Rupa, J. A. M. and S. Ganesh, "Power Flow Analysis for Radial Distribution System Using Backward / Forward Sweep Method," *Int. J. Electr. Comput. Electron. Commun. Eng.*, vol. 8, no. 10, pp. 1527–1531, 2014.

El-Fergany, A., "Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 1197–1205, 2015.

Devabalaji, K. R., K. Ravi, and D. P. Kothari, "Optimal location and sizing of capacitor placement in radial distribution system using Bacterial Foraging Optimization Algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 71, pp. 383–390, 2015.

Kansal, S. V. Kumar, and B. Tyagi, "Hybrid approach for optimal placement of multiple DGs of multiple types in distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 226–235, 2016.

Hung, D. Q. and N. Mithulananthan, "Multiple distributed generator placement in primary distribution networks for loss reduction," *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1700–1708, 2013.

Devabalaji, K. R. and K. Ravi, "Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using Bacterial Foraging Optimization Algorithm," *Ain Shams Eng. J.*, vol. 7, no. 3, pp. 959–971, 2016.

Prakash, D. B. and C. Lakshminarayana, "Multiple DG Placements in Distribution System for Power Loss Reduction Using PSO Algorithm," *Procedia Technol.*, vol. 25, no. Raerest, pp. 785–792, 2016.

Kaur, S. G. Kumbhar, and J. Sharma, "A MINLP technique for optimal placement of multiple DG units in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 609–617, 2014.

Martín García, J. A. and A. J. Gil Mena, "Optimal distributed generation location and size using a modified teaching-learning based optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 50, no. 1, pp. 65–75, 2013.

Sanjay, R., T. Jayabarathi, T. Raghunathan, V. Ramesh, and N. Mithulananthan, "Optimal allocation of distributed generation using hybrid grey Wolf optimizer," *IEEE Access*, vol. 5, pp. 14807–14818, 2017.

Abu-Mouti, F. S. and M. E. El-Hawary, "Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm," *IEEE Trans. Power Deliv.*, vol. 26, no. 4, pp. 2090–2101, 2011.

Sultana, U., A. B. Khairuddin, A. S. Mokhtar, N. Zareen, and B. Sultana, "Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system," *Energy*, vol. 111, pp. 525–536, 2016.

Tah, A. and D. Das, "Novel analytical method for the placement and sizing of distributed generation unit on distribution networks with and without considering P and PQV buses," *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 401–413, 2016.

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