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# OPTIMIZED ALLOCATION AND SIZING OF DISTRIBUTED ENERGY RESOURCE IN DISTRIBUTION SYSTEMS USING CUCKOO SEARCH ALGORITHM

Rafael Santos Freire Ferraz<sup>\*1</sup>, Renato Santos Freire Ferraz<sup>1</sup>, Augusto César Rueda-Medina<sup>1</sup>, Jussara Farias Fardin<sup>1</sup> e Adjeferson Custódio Gomes<sup>2</sup>

> <sup>1</sup>DEE - Federal University of Espírito Santo <sup>2</sup>DCET - Estadual University of Santa Cruz

Abstract - The Distributed Energy Resources (DER) emerged as an alternative to centralized generation since it presents numerous economic and operational benefits, such as, power loss reduction, voltage profile improvement, and relieved system's congestion. These benefits can be obtained by optimized sizing and placement of the DER; however, an improper DER integration can generate problems regarding the levels of current, voltage and power factor of the network. In this paper, the Cuckoo Search (CS) metaheuristic algorithm was applied to solve the allocation and sizing problem in IEEE 13 and 34 node test feeders in order to improve the voltage profile. The results were compared with the Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) with the purpose of validating the CS method. Finally, it was possible to conclude that CS algorithm presented satisfactory results, meeting all constraints regarding the amount of DER, voltage levels and operational limits.

*Keywords*- Allocation, cuckoo search, distributed energy resource, sizing.

## I. INTRODUCTION

The impacts of DER on losses and voltages of networks should be investigated comprehensively on distribution networks operation and planning [1]. It is important to note that inappropriate determination of its size or location may lead to increased system losses and costs which cannot be tolerated by the distribution system operators [2]. Some authors apply analytical approach to solving this problem; in [3], the Kalman filter algorithm was used to determine the optimal size of DER. Moreover, the loss sensitivity factor that is based on the equivalent current injection was developed in [4] to find the optimal size and location of DER. These methods perform well for small and simple systems, however, they are not suitable for a system with large and complex networks, since these methods present high computational effort. Therefore, many researchers have applied different methodologies based on metaheuristics in order to obtain the optimized allocation and sizing of DER in the distribution system.

In [5] and [6], the authors applied the Genetic Algorithms (GA) for DER allocation and sizing in order to improve the voltage profile and to reduce power losses. In [1], [7] and [8], the Particle Swarm Optimization (PSO) was used for the same purpose. In [9] and [10], only the DER allocation problem was performed using GA and PSO, respectively; however, the DER were assumed of the same size. Finally, it is also possible to verify the application of more recent methods such as: Cuckoo Search (CS) and Crow Search Algorithm (CSA) in [11] and [2], respectively.

In this paper, the problem of sizing and allocation of DER, based on photovoltaic systems, was solved with the aim of improving the voltage profile of the system, subject to the operational constraints of the distribution network. For this purpose, the CS optimization algorithm was used due to its reduced number of parameters to be tuned. In order to validate the method, the results were compared with the PSO and GA methods. Moreover, the distribution networks used to evaluate the proposed methodology were the IEEE 13 and 34 node test feeders. The main contributions of this paper are:

- It is possible to observe a comparison of metaheuristicbased optimization methods: CS, GA and PSO.
- In the problem formulation of the DER siting and sizing, the nonlinear operational limits of the DER systems, established in the IEEE 1547-2018, were implemented as constraints in the optimization methods.

The remainder of the paper is organized as follows: Section II describes the methodology about the mathematical formulation of the optimal DER allocation and sizing. Section III presents the optimization methods applied: CS, PSO and GA. In Section IV, the results and discussions related to the optimization problem are shown. Finally, concluding remarks are provided in Section V.

<sup>\*</sup>rafael.ferraz@edu.ufes.br

#### **II. OPTIMAL DER ALLOCATION AND SIZING**

The Objective Function (OF) and constraints are formulated in this section. DER placement and sizing have influenced on the voltage drop in distributions networks; thus, the OF consists in the minimization of the voltage deviation for each phase and for each node of the distribution network, as it can be observed in (1), where  $V_{ij}$  is the voltage in pu at node *i* at phase *j*.

$$OF = \sum_{i=1}^{n} \sum_{j=1}^{m} \left| V_{ij} - 1 \right|$$
(1)

Equations (2) and (3) present some constraints related to the voltage limits and maximum number of DER. The first constraint is about the voltage upper and lower limits which, in this paper, must meet the criteria established by Procedure for Distribution of Electric Energy in the National Electric System (PRODIST) [12], where  $V^{min}$  and  $V^{max}$  are the minimum and maximum voltages, respectively; and, the second constraint is related to the maximum number of DER  $(n_{DER}^{max})$  that can be allocated in the system.

$$V^{min} \le V_{ij} \le V^{max} \tag{2}$$

$$n_{DER} \le n_{DER}^{max} \tag{3}$$

Moreover, there are some constraints based on Standard IEEE 1547-2018 [13]. It specifies the attributes of reactive and active power control requirements of the inverters, which are associated with each DER unit, depending on the category in which this system will operate (Category A or B). Based on [14], only DER units with Category B performance were considered in this paper with the purpose of dealing with power quality issues that the large amount of dispersed generators integrated could cause in the distributed system.

Figure 1 presents the graphic of reactive power capability of the Category B, where the constraints could be observed in the Equations (4), (5), (6) and (7) [13]. The minimum steady-state active power capability corresponds to 5% of the rated active power ( $P_{rated}$ ), the maximum capability of reactive power injection is 44% of the rated apparent power of the inverter based DER ( $S_{rated}$ ) and the maximum capability of reactive power absorption is 44% of  $S_{rated}$  [14].

$$(P_{DER})^2 + (Q_{DER})^2 \le (S_{rated})^2 \tag{4}$$

$$P_{DER} \ge 0.05S_{rated} \tag{5}$$

$$-0.44S_{rated} \le Q_{DER} \le 0.44S_{rated} \tag{6}$$

$$-2.2P_{DER} \le Q_{DER} \le 2.2P_{DER} \tag{7}$$

Finally, the active and reactive power balance in the distribution system, as observed in (8) and (9) respectively, must be guaranteed [14]; where  $P_i^{load}$  and  $Q_i^{load}$  are the load active and reactive power values, respectively;  $i_i$  is the current injection and  $Y_i$  is the shunt admittance. Moreover, these four variables

refer to the node *i*, and *Re* and *Imag* correspond to the real and imaginary parts of the complex values, respectively.

Figure 1: Reactive power capability of the category B based on IEEE 1547-2018.



## **III. OPTIMIZATION METHODS**

In this section, the optimization methods used in this work, GA, PSO and CS, are briefly presented.

### A. Genetic Algorithms

The GA are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology. The algorithms are initialized with a population of guesses, and it is then processed by the three main operators: selection, crossover and mutation [15].

### **B.** Particle Swarm Optimization

The PSO consists in an evolutionary computational algorithm, which was proposed in 1995 by Kennedy and Eberhart [16]. This algorithm is similar to GA. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions called particles fly through the problem space by pursuing the current optimal particles. Each particle keeps track of its coordinates in the problem space which are correlated with the best solution it has attained so far [7].

All particles have their own velocity, which drives the direction they move in. Each particle looks in a particular direction and, while communicating with others, they identify the particle that is in the best location. Accordingly, each particle speeds towards the best particle using a velocity that depends on its current position. Each particle, then, investigates the search space from its new local position, and the process continues until the flock reaches a desired destination [17].

## C. Cuckoo Search

The CS was introduced in 2009 by Yang and Deb [18]. This algorithm was inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of host birds. Some cuckoos have involved in such a way that female parasitic cuckoos can imitate various colors and patterns of the eggs of a few chosen host species. This reduces the probability of the eggs being abandoned so re-productivity increases [19]. Based on [20], this algorithm can be described in 3 steps:

- Each cuckoo lays one egg at a time and dumps it in a randomly chosen nest;
- The best nests with the high quality of eggs will carry to the next generations;
- The number of available host nest is fixed and if a host bird identifies the cuckoo egg with the probability of  $p_a=[0,1]$ , then the host bird can either throw them away or abandon them and build a new nest.

## **IV. RESULTS AND DISCUSSIONS**

In this work, the IEEE 13 node (Figure 2) and 34 node (Figure 3) test feeders were used in order to evaluate the proposed comparisons between the aforementioned methodologies. It is important to note that the voltage regulator between nodes 1-2 of the IEEE 13 node test feeder and the voltage regulators between the nodes 7-8 and 19-20 of the IEEE 14 node test feeder were disregarded with the purpose of analyzing if the DER integration was able to improve the voltage profile between the limits established in [12] for nominal voltage between 1 kV and 69 kV, as observed in Table I, where  $V_n$  is the nominal voltage of the system. Another important observation is that the three-phase power flow solution method used was the Backward-Forward Sweep since this method is robust and features high convergence speed [21].

Regarding the number of DER, in [5], 6 DER were chosen for allocation in IEEE 13, 34 and 123 node test feeders in order to ensure the greatest diversity of buses choices. In [8], tests were carried out on systems with 37 nodes test feeder, selecting 9 and 37 DER. In this paper, the relation chosen between the number of DER and the number of buses in the system was 40%. Thus, 5 and 13 DER were determined for IEEE 13 and 34 node test feeders, respectively.

Figure 2: IEEE 13-Node Test Feeder.





29 Phases ABC Phase A 12 28 ··· Phase B 11 27 10 26 24 1 25 14 23 8 9 32 20 21 33 19 16 17

Table I: Voltage limits.

Service Criteria	Voltage Range		
Adequate	$0.93V_n \le V_{ij} \le 1.05V_n$		
Precarious	$0.90V_n \le V_{ij} \le 0.93V_n$		
Critical	$V_{ij} \le 0.90V_n$ $V_{ij} \ge 1.05V_n$		

Finally, the maximum active power value was determined from the penetration level, which is the percentage of the total load of the system. In [9], tests were performed using 4 different penetration levels: 40%, 60%, 80% and 100%. In this paper, 55% was chosen as penetration level, and it was possible to define the maximum apparent power value of each DER,  $S_{rated}$ , from the Equation (10). Thus, it was determined, based on Equation (10),  $S_{rated}$  equal to 126 kVA and 26 kVA for IEEE 13 and 34 node test feeders, respectively.

$$P_{DER}^{max} = \frac{Mean(Total \ load) * Penetration \ level}{n_{DER}^{max}}$$
(10)

The allocation and sizing of 5 DER were performed using metaheuristic-based optimization methods: CS, GA and PSO. With regard to the IEEE 13 node test feeder, the allocation and sizing of 5 DER were performed using metaheuristic-based optimization methods: CS, GA and PSO. Regarding the GA, it was selected 150, 0.02 and 0.6 for population size, mutation rate and crossover rate, respectively. Regarding the PSO method, the population size was 150, the inertia weights were 0.4 and 0.9, and both acceleration factors were set to 2. Finally, regarding the CS method, it was selected 70 and 0.35 for  $p_a$  and the number of nests, respectively. These parameters were defined from tests, based on the references [10], [11] and [22].

For the IEEE 13 node test feeder, the maximum active power of each DER is equal to 126 kW, and the minimum and maximum reactive power are -55 kVar and 55 kVar, respectively. The OF values for the GA, PSO and CS metaheuristic methods are 1.0879, 1.0333 and 1.0239, respectively. Table II presents the nodes where the DER were allocated for each of the employed methods. Furthermore, the values of the active (*P*) and reactive (*Q*) powers, in kW and KVar, of each DER are showed. From the analysis of Table II, it is observed that the optimization algorithms presented similar results. For the 5 nodes allocated, the results of the methods allocation presented 3 nodes in common: 8, 10 and 11. Furthermore, it is noted that CS and PSO selected values close to the upper limit of reactive power.

Table II: Optimization methods comparison for 13 node test feeder.

CS			GA			PSO		
Node	Р	Q	Node	Р	Q	Node	Р	Q
7	62	55	4	114	50	8	113	54
8	107	55	8	107	53	10	114	54
10	108	55	10	117	43	11	114	54
11	110	55	11	108	53	12	114	54
13	66	55	12	118	26	13	114	54

In Figures 4, 5 and 6, it is possible to compare the voltage values for phases A, B and C, respectively, in which the voltage profile profile of the system without DER is presented in black, whereas the voltage profiles of the system with DER allocated using PSO, GA and CS are presented in blue, pink and red, respectively.

Figure 4: Va results for 13-Node Test Feeder.



In the base case, where no DER are allocated, some voltage values of the IEEE 13 node test feeder, in black in Figures 4, 5 and 6, were lower than 0.93 pu, which is outside the limits established by PRODIST. After the application of the metaheuristic-based optimization methods, the voltage values respected the lower and upper limits of 0.93 and 1.05 pu, respectively. Furthermore, it is concluded that CS and PSO present voltages closer to 1.0 pu than GA, agreeing with the results of OF for both methods.

Figure 5: Vb results for 13-Node Test Feeder.



Figure 6: V<sub>C</sub> results for 13-Node Test Feeder.



For the IEEE 34 node test feeder, 13 DER were allocated, with the maximum values of active power equals to 26 kW, and the minimum and maximum values of reactive power equal to -11 kVar and 11 kVar, respectively. Table III presents the nodes in which the optimization methods allocated the DER. In addition, the active (P) and reactive (Q) powers, in kW and KVar, are also presented for each DER. From the analysis of Table III, it is observed that the optimization algorithms presented similar results; and they selected 3 nodes in common: 30, 32 and 34.

Table III: Optimization methods comparison for 34 node test feeder.

CS			GA			PSO		
Node	Р	Q	Node	Р	Q	Node	Р	Q
8	16	7	4	22	-1	2	18	11
10	3	-2	6	16	-6	3	19	8
11	25	0	11	22	8	7	22	10
17	14	-5	12	25	7	10	21	11
18	15	-11	15	25	5	14	17	-11
26	21	7	17	14	6	16	6	-9
27	24	-1	22	21	7	23	14	-9
29	20	-2	23	21	7	26	23	11
30	11	8	28	23	8	28	22	11
31	22	-1	29	18	5	30	17	-11
32	24	9	30	14	11	32	24	5
33	17	-5	32	20	8	33	21	6
34	20	10	34	19	11	34	21	11

In Figures 7, 8 and 9, it is possible to notice the voltage levels for phases A, B and C, respectively, in which the optimization methods managed to meet the constraints related to the levels established by PRODIST (between 0.93 and 1.05 pu). It is noteworthy that the methods presented similar voltage values, as shown in Figures 7, 8 and 9. Moreover, the values obtained for the OFs for GA, PSO and CS are: 2.6364, 2.4785 and 2.5223, respectively. Thus, all methods presented similar results, as it could be noticed in the Figures 7, 8 and 9.

It is worth noting that all methods allocated most of the DER in the last nodes of the IEEE 13 and 34 node test feeders. This is due to the greater distance between these nodes and the substation, which has, as a result, a greater voltage drop. Thus, DER are allocated in these nodes in order to improve voltage levels.

In the Figures 10 and 11, it is possible to observe in red, the

active and reactive powers of the DER allocated and sized by the CS optimization method of the IEEE 13 and 34 node test feeders, respectively. Therefore, it was possible to meet the operational restrictions established in Standard IEEE 1547-2018.

Figure 7:  $V_a$  results for 34 node test feeder.



Figure 8: Vb results for 34 node test feeder.



Figure 9: V<sub>C</sub> results for 34 node test feeder.



Therefore, the CS optimization method presented similar results to PSO and GA for DER allocation and sizing meeting all constraints: the maximum number of DER, the lower and upper voltage levels established by PRODIST and the operational limits established by the IEEE Standard 1547-2018. This method has, as an advantage over the PSO and GA methods, the reduced amount of adjustment parameters for optimization; thus it is just necessary to adjust two parameters: the number of available host nest and the probability of a host bird identifies the cuckoo egg. As a result, it is potentially more generic to adapt to a wider class of optimization problems [20].

Figure 10: CS results of the reactive power capability for the IEEE 13 node test feeder .



Figure 11: CS results of the reactive power capability for the IEEE 34 node test feeder .



## V. CONCLUSIONS

In this paper, it was proposed the allocation and sizing of DER applying the CS optimization method, as it presents lower parameters to adjust when compared to GA and PSO. For this purpose, the IEEE 13 and 34 node test feeders were used; and, to validate the method, the results were compared with the PSO and GA methods. It is noteworthy that all methods were able to meet all constraints regarding the number of DER, voltage limits and operational limits. For the problem of minimizing the voltage deviation of the IEEE 13 node test feeder, the CS presented the lowest value of OF in relation to the PSO and GA methods. Whereas for IEEE 34 node test feeder, CS presented better results than GA, but similar to PSO. Therefore, CS metaheuristic method presented satisfactory results for the allocation and sizing of DER.

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