Optimal Location and Size of Distributed Generators in an Electric Distribution System based on a Novel Metaheuristic Algorithm

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Abstract—**This paper proposes a method for optimizing the location and size of Distributed Generators (DGs) based on the Coyote Algorithm (COA), in order to minimize the power loss in an Electric Distribution System (EDS). Compared to other algorithms, COA does not need control parameters during its execution. The effectiveness of COA was evaluated in an EDS with 33 nodes for two scenarios: the optimization of location and capacity of DGs in an initial radial configuration, and the best radial configuration for power loss reduction. Results were compared with other methods, showing that the proposed COA is a reliable tool for optimizing the location and size of DGs in an EDS.**

Keywords-distributed generators; coyote algorithm; electric distribution system; power loss; radial configuration

I. INTRODUCTION

Distributed Generators (DGs) are connected to an Electric Distribution System (EDS) offering economic benefits and energy security, and their appearance has increased rapidly. An EDS performs the task of supplying electric energy to consumers, ensuring power quality, reliability, and safety requirements within the permitted limits. Meanwhile, it also brings many other benefits, such as reducing the load on the grid, improving voltage, reducing losses, and supporting the grid. Some of the problems related to connecting DGs in an EDS consist of the increasing penetration of renewable DGs, the maximization of emitted power and reliability, the minimization of investment, operating costs and total payments, the reduction of system losses, and the improvement of voltage configuration, maximizing social welfare and profit margin. Depending on the goals, it is possible to combine DGs appropriately to reduce the line overload and increase the operating range of the system, in order to operate more flexibly. Exploiting the maximum potential benefits of DGs with minimum cost must be satisfied with technical constraints and the optimization of economic objectives [1, 2]. When considering connecting DGs to an EDS, it is necessary to consider their location and their allowable amount, in order to get their maximum size pumped into the grid, minimizing loss to attract investment, ensuring the reliability of electric supply, and gaining economic benefits. Therefore, the problem of determining the location and capacity of DGs for power loss reduction is important [3, 4].

Various methods have been employed in order to determine the location and capacity of DGs in an EDSs. Some classical methods are linear and non-linear programming (NLP) [5], mixed integer NLP [6], dynamic programming [7], ordinal optimization [8], and optimal power flow (OPF) [9]. The disadvantages of these methods are the slow convergence to optimal results, or the fall into local extremes. Metaheuristic methods have been applied for solving this problem, such as Genetic Algorithm (GA) [10, 11], Particle Swarm Optimization (PSO) [11-13], symbiotic organisms search [14], Artificial Bee Colony algorithm (ABC) [15], invasive weed optimization [16], Cuckoo Search (CSA) [17], Fireworks Algorithm (FWA) [18], Stochastic Fractal Search (SFS) [19], Harmony Search Algorithm (HSA) [20], and Salp Swarm Algorithm (SSA) [21]. These methods have the advantage of handling conveniently problem's constrains. In addition, the solutions obtained are usually better than these obtained by the classical methods. However, finding suitable, stable, and reliable methods for each specific problem is a complicated task. Therefore, finding new methods to solve the problem of optimizing location and capacity of DGs in an EDS is a desired task. The Coyote Algorithm (COA) is based on the social life of coyotes, and [22] validated its efficiency using forty benchmark functions.

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However, the application of COA on engineering problems, such as DGs placement in order to examine its effectiveness, is a worthy consideration. This paper describes the application of COA in optimizing the location and size of DGs for power loss reduction in an EDS with 33 nodes, and the comparison of the obtained results with other metaheuristic methods.

II. PROBLEM OF OPTIMAL PLACEMENT OF DGS

The objective function of the DGs' location and size optimization in an EDS is the reduction of the active power loss, formulated as:

$$f = min(\sum P_{loss}) \quad (1)$$

where $\sum P_{loss}$ is the total power loss in the EDS. The placement of DGs in the EDS should satisfy the following constraints:

- Power balance: The sum of output power from the slack bus and the DGs must be equal to the sum of loads and power loss in the EDS.
- The limits of nodes' voltage and branches' current are:

$$\begin{cases} V_{min}^{lim} \leq V_i \leq V_{max}^{lim}, & i = 1,2,\cdots,N_{bus} \\ LCF_i \leq LCF_{max,i}^{lim}, & i = 1,2,\cdots,N_{branch} \end{cases} \quad (2)$$

  where LCF is the load carrying factor of the i[th] branch.
- The power limits of DGs are:

$$P_{DG,i,min} \leq P_{DG,i} \leq P_{DG,i,max}, \; i = 1,2,\cdots,N_{DG} \quad (3)$$

III. APPLICATION OF COYOTE ALGORITHM

A. The Coyote Algorithm (COA)

Unlike other metaheuristic methods, COA does not need control parameters, enhancing its performance stability on the DGs optimization procedure. In order to search the solution in the search space, COA uses a population of coyotes divided into groups, and the social condition of each coyote in its group is considered as a candidate solution. Candidate solutions are generated based on the interaction among coyotes in each group and the interaction among groups of the population. The interactions are described as follows:

1) Renewal of the Social Condition of Coyotes in Each Group

The behavior of each coyote depends on the leader of its group, while each group usually has its own characteristics. The process of finding new solutions is as follows: In the g^{th} group, the coyote having the best adaptive function value is chosen as alpha (al^g). Subsequently, the culture tendency (ct^g) of the group is determined by the median social condition of the group's coyotes, and a new social condition of each coyote is generated as:

$$n\_sc_c^g = sc_c^g + r_1.(al^g - sc_1^g) + r_2.(ct^g - sc_2^g) \quad (4)$$

where $n\_sc_c^g$ and sc_c^g are new and current social conditions of the c^{th} coyote in the g^{th} group, sc_1^g and sc_2^g are the social conditions of two coyotes selected randomly in the g^{th} group, and finally r_1 and r_2 are random numbers in the range of [0, 1].

2) Birth of a New Coyote to Replace an Old One in Each Group

The coyote having the worst social condition, in the group, will die, and a newborn puppy will replace it, as:

$$x_{puppy,j}^g = \begin{cases} x_{1,j}^g, & r_{3,j} < k_1 \\ x_{2,j}^g, & r_{3,j} < k_1 + k_2 \\ x_{r,j}^g, & otherwise \end{cases} \quad (5)$$

where $x_{puppy,j}^g$ *(j=1, 2, ..., D)* is the j^{th} variable of the puppy's social condition vector solution, *D* is the dimension of the problem, $x_{1,j}^g$ and $x_{2,j}^g$ are the variables of two solutions chosen randomly in the group, $r_{3,j}$ is a random number in the range of [0, 1], and $x_{r,j}^g$ is a random variable, and k_1 and k_2 are the probabilities of scatter and association, which guide the cultural diversity of the coyotes from the group, determined as:

$$\begin{cases} k_1 = 1/D \\ k_2 = (1 - k_1)/2 \end{cases} \quad (6)$$

3) Interchange of Coyotes Between Groups

Although coyotes are living in groups, sometimes some individuals leave their group in order to live alone or join another group. Based on this feature, to expand the process of creating new solutions, coyotes are exchanged among groups of the population. The probability (P_l) of a coyote leaving one group to join another and vice versa is determined as:

$$P_l = 0.005 \times N_c^2 \quad (7)$$

where N_c is the number of coyotes in the group.

B. COA in Optimizing Location and Size of DGs

This section presents the application of the COA in optimizing the location and size of DGs, in order to minimize the active power loss in an EDS. The following steps describe the overall procedure:

- Step 1: Select the parameters of COA, including group number (N_g), group size (N_c), and the maximum number of generations (G_{max}).
- Step 2: The initial population of coyotes is represented as $sc_c^g = [L_{1,c}^g, ..., L_{N_{DG},c}^g, P_{1,c}^g, ..., P_{N_{DG},c}^g]$ with $g = 1,2,...,N_g$ and $c = 1,2,...,N_c$. Variables $L_{k,c}^g$ and $P_{k,c}^g$ represent location and power of the k^{th} DG, initialized as:

$$L_{k,c}^g = round[2 + \text{rand}(0,1).(N_{bus} - 2)] \quad (8)$$

$$P_{k,c}^g = \text{rand}(0,1) \times (P_{k,max}^g - P_{k,min}^g) + P_{k,min}^g \quad (9)$$

  where $P_{k,max}^g$ and $P_{k,min}^g$ are the maximum and minimum power of the k^{th} DG.
- Step 3: The initialized population is evaluated based on a fitness function, determined as:

$$fit = f + K \times [max(V_{min}^{lim} - V_{min}, 0) + max(V_{max} - V_{max}^{lim}, 0) + max(LCF_{max} - LCF_{max}^{lim}, 0)] \quad (10)$$

where K is a penalty factor set to 1000, V_{min} and V_{max} are the minimum and maximum voltages in the EDS, and LCF_{max} is the maximum load carrying factor in the EDS.

- Step 4: The main loop begins from this step until Step 8, and it is repeated until the preset generation value is reached. The inner loop in Steps 5-6 is repeated until the last group of the population is reached.
- Step 5: The social condition of the coyotes in each group is renewed. For each group, the alpha coyote is selected, and the median of all coyotes is determined. A new social condition is generated for each coyote using (4). The fitness value is calculated for the new social condition. If the social condition is better than the previous one, it will replace it.
- Step 6: A puppy coyote, generated by (5), replaces an old one. The fitness value of the puppy's social condition is calculated. If the puppy's social condition is better than the worst social condition in the group, it will replace it. If the current group is not the last group of the population, Step 5 is repeated, otherwise, this inner loop ends, and Step 7 is executed.
- Step 7: A coyote is interchanged between the groups. If $rand\ (0,1)\ < P_l$, two groups are randomly selected for exchanging coyotes. In the selected groups, two coyotes are randomly chosen, and they are interchanged between the two chosen groups.
- Step 8: In the proposed COA method, the stopping criterion is based on a maximum number of generations. The algorithm terminates when the generation reaches a maximum value. Otherwise, a new generation starts from Step 4. As the maximum number of generations is reached, the best social condition of all coyotes in the population is considered as the optimal solution for the DGs' location and size optimization.

IV. NUMERICAL RESULTS

In order to demonstrate the efficiency of the COA on the DGs' location and size optimization, the algorithm was implemented in Matlab 2016a. Its performance was evaluated in an EDS with 33 nodes [23], considering two scenarios:

- Scenario 1: Location and size of DGs are optimized in the EDS with the initial radial configuration with open switches {33-34-35-36-37}.
- Scenario 2: Location and size of DGs are optimized in the EDS with the optimal radial configuration for power loss reduction with open switches {7-9-14-28-32}.

COA, for both scenarios, employed 5 groups, with 6 coyotes in each group, and the number of maximum generations was set to 300. The obtained results were compared with other methods in the literature, such as GA [11], PSO [11], CSA [17], FWA [18], SFS [19], HSA [20], and SSA [21]. In order to obtain optimal results, COA was executed in independent runs, and the best result was considered as the optimal solution. The results of the DGs' location and size optimization in scenario 1 are shown in Table I. After placing DGs in the nodes 30, 14 and 24 with corresponding power 1.07144, 0.75396 and 1.09944MW, power loss reduced from 202.6863 to 71.4599kW, corresponding to 64.74% power loss reduction. The minimum voltage amplitude in the EDS enhanced from 0.9131 to 0.9687p.u.. In comparison with other methods, the obtained results are better than the ones obtained by GA, PSO, CSA, FWA and HSA. Power loss reduction from COA was 64.74%, being 17.19, 16.69, 1.38, 8.49 and 12.48% higher than GA, PSO, CSA, FWA and HSA. Compared to SFS and SSA, power loss obtained from COA is nearly the same.

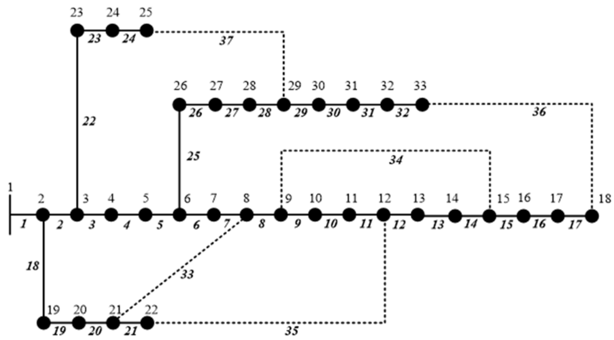

Fig. 1. The EDS with 33 nodes

TABLE I. OPTIMAL DG PLACEMENT FOR SCENARIO 1

Method	DG size in MW (node)	Power loss (kW)	Loss reduction (%)	V_{min} (node)
Initial	-	202.6863	-	0.9131 (18)
COA	1.07144 (30) 0.75396 (14) 1.09944 (24)	71.4599	64.74	0.9687 (33)
GA [11]	1.5 (11) 0.4228 (29) 1.0714 (30)	106.3	47.55	-
PSO [11]	0.9816 (13) 0.8297 (32) 1.1768 (8)	105.3	48.05	-
CSA [17]	0.7798 (14) 1.1251 (24) 1.3496 (30)	74.26	63.36	0.9778
FWA [18]	0.5897 (14) 0.1895 (18) 1.0146 (32)	88.68	56.25	0.9680
SFS [19]	0.7540/(14) 1.0994/(24) 1.0714/(30)	71.47	64.74	0.9687
HSA [20]	0.1070 (18) 0.5724 (17) 1.0462 (33)	96.76	52.26	0.9670
SSA [21]	0.7536 (33) 1.1004 (23) 1.0706 (29)	71.45	64.75	0.9686 (32)

The results of the DGs' location and size optimization in the system with scenario 2 are shown in Table II. Using the radial configuration of {7-9-14-28-32} after placing DGs in nodes 16, 12 and 25 with corresponding power 0.50263, 0.53576 and 1.61605MW, power loss reduced to 56.2782kW, corresponding to 72.23% power loss reduction. The minimum voltage amplitude in the EDS was enhanced to 0.9722p.u. at node 32. The obtained results from COA are better than these obtained from CSA, SFS and SSA. Power loss reduction from

COA was 72.23%, being 1.24%, 1.28% and 1.27% higher than CSA, SFS and SSA. Comparing scenarios 1 and 2, power loss obtained in the former was 71.4599kW (64.74%), and 56.2782kW, (72.23%) in scenario 2. In addition, the minimum voltage amplitude in scenario 2 improved more than in scenario 1. The voltage profile of the system after optimizing the location and size of DGs using COA is shown in Figure 2. The voltage of the nodes improved after installing DGs, while the installation of DGs according to scenario 2 gained better voltage profile than scenario 1. Moreover the load carrying factor of the system, shown in Figure 3, reduced after optimizing the location and size of DGs using COA, as its maximum, being 0.8250 in the initial configuration, reduced to 0.4475 and 0.4640 for scenarios 1 and 2, respectively.

TABLE II. OPTIMAL DG PLACEMENT FOR SCENARIO 2

Method	DG size in MW (node)	Power loss (kW)	Loss reduction (%)	V_{min} (node)
COA	0.50263 (16) 0.53576 (12) 1.61605 (25)	56.2782	72.23	0.9722 (32)
CSA [17]	1.7536 (29) 0.5397 (12) 0.5045 (16)	58.79	70.99	0.9802
SFS [19]	1.0682/(24) 0.9503/(30) 0.9317/(8)	58.88	70.95	0.9741
SSA [21]	0.932 (8) 1.068 (24) 0.950 (30)	58.87	70.96	0.9741 (33)

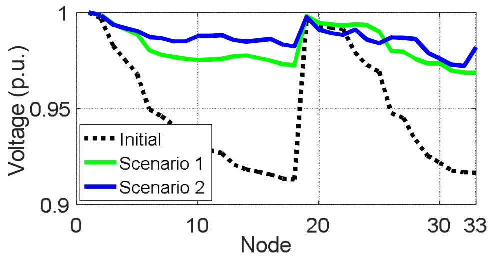

Fig. 2. The voltage profile of the 33-node EDS

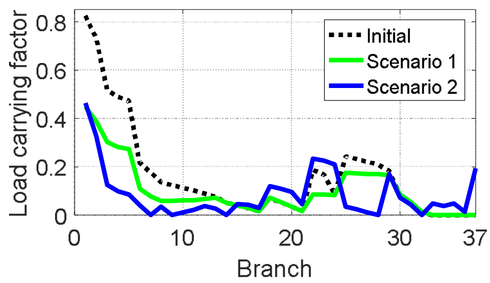

Fig. 3. The load carrying factor of the 33-node EDS

The mean and minimum convergence curves in 50 independent runs for both scenarios are shown in Figures 4 and 5. The figures show that the mean and minimum curves converge to nearly equal values. This shows the stability and reliability of the COA in each run for the DGs' location and size optimization in the EDS.

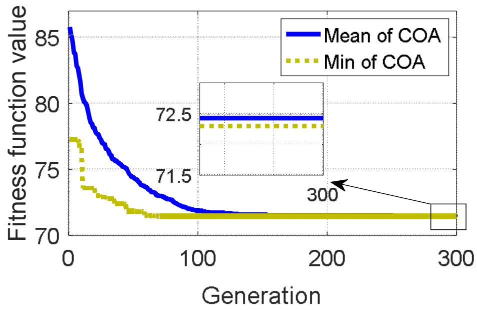

Fig. 4. The convergence curves of COA in scenario 1

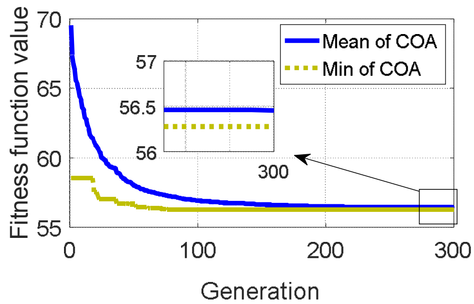

Fig. 5. The convergence curves of COA in scenario 2

V. CONCLUSION

This paper presented a method based on COA for optimizing the DGs location and size in an EDS, in order to reduce power loss. The effectiveness of the COA was evaluated in an EDS with 33 nodes. Two scenarios of DGs' radial configuration were considered: the initial radial configuration, and placement in the optimal radial configuration with minimum power loss. Numerical results showed that COA is better than methods such as GA, PSO, CSA, FWA, HAS, SFS and SSA. In addition, there is no need for control parameters in the process of applying COA to the optimization problem. Moreover, the numerical results in 50 independent runs showed that COA is a reliable method for the problem of optimizing the location and capacity of DGs in an EDS to satisfy other goals.

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