Continuous domain ant colony optimization for distributed generation placement and losses minimization

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ABSTRACT

This paper proposes a method for distributed generation (DG) placement in distribution system for losses minimization and voltage profile improvement. An IEEE 33-bus radial distribution system is used as the test system for the placement of DG. To facilitate the sizing of DG capacity, a meta-heuristic algorithm known as Continuous Domain Ant Colony Optimization (ACO_R) is implemented. The ACO_R is a modified version of the traditional ACO which was developed specially for solving continuous domain optimization problem like sizing a set of variables. The objective of this paper is to determine the optimal size and location of DG for power loss minimization and voltage profile mitigation. Three case studies were conducted for the purpose of verification. It was observed that the proposed technique is able to give satisfactory results of real power loss and voltage profile at post-optimization condition. Experiment under various loadings of the test system further justifies the objective of the study.

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1. INTRODUCTION

The growth of energy consumption in the recent power systems necessitates for additional power supplies. The additional supplies must be cost-effective and, with the rising issue of global warming and uncontrolled pollution, environmentally friendly. To meet the consumer demand, utilities have struggled to employ embedded generation in their distribution system [1-3]. This embedded generation, which is a form of electricity generation close to distribution systems and even to the load points, is called distributed generation (DG). In traditional centralized power systems, the generation of electricity is mostly at power plants and away from distribution systems. In other words, the generation and distribution of electricity are separated by a transmission system. However, with the invention of various small-scale electricity generation technologies (such as solar photovoltaics, wind turbines, micro-turbines and fuel cells), the power systems are experiencing a decentralization of electricity generation. In such a decentralized power system, there will be high penetration of DG into distribution systems to provide additional power support to the loads [4-8]. There are many types of DG technologies available, either renewable or non-renewable, but it would be easier to categorize them based on the real and reactive power supplied or consumed. There are four types of DG as follows: type 1 injects real power to the system, example is solar photovoltaic; type 2 injects reactive power to the system, example is capacitor bank and synchronous condenser; type 3 injects both real and reactive power to the system, example is micro-turbine; and type 4 injects real power and consumed reactive power, example is wind turbine. Regarding the size or capacity of DG, there are four scales as follows: micro

DG from 0.001 MW to 0.005 MW, small-sized DG from 0.005 MW to 5 MW, medium-sized DG from 5 MW to 50 MW and large-sized DG from 50 MW to 300 MW. In the study of optimal DG placement, location and size (or capacity) are the main issues to be concerned [9-13]. The aims of the study can be various, but most of the them focus on losses minimization, voltage stability improvement, reliability enchancement and installation cost. Article [14] implemented Grasshopper Optimizer Algorithm (GOA) for placement and sizing of multiple distributed generation and battery swapping stations (DG-BSS). The study aimed to improve loadability and energy losses reduction using the developed GOA. It was obeserved that the method has reduced significantly the energy losses and improved loadability at the same time. Next, article [15] proposed optimal sizing of DG considering multi-energy supply systems using Genetic Algorithm (GA). In the study, GA was used along with the mixed integer linear programming, where the goal is to minimize the total investment costs. It was revealed that investment cost and the whole system structure are all influence the proposed sizing results. Later, article [16] proposed optimal sizing of DG in a hybrid power system. The wind and energy storage units considering uncertainties of wind speed were considered in the study. The self-adapted evolutionary strategy in combination with Fischer–Burmeister algorithm was applied, in which resulted in minimum investment cost and provide remarkable insights for suitable capacity installation. Afterwards, article [17] implemented the Ant Lion Optimization Algorithm (ALOA) for optimal placement of DG. Wind turbine (WT) and photo-voltaic (PV) type were used as DG sources, while the Loss Sensitivity Factor (LSF) technique was for suitable locations identification. After experiment, the study revealed that the power loss, voltage profile as well as loading conditions were all considerably improved. Other studies on optimal DG placement problems can be reviewed in [18-25].

This study proposes an optimal DG placement technique using Continuous-Domain Ant Colony Optimization (ACO_R) algorithm in radial distribution system. The rationale of using ACO_R is due to its fast convergence behaviour and its ability to produce accurate solution within tolerable computation time. The aims of this study is to reduce real power loss and improve voltage profile though proper DG placement.

2. RESEARCH METHOD

This section explains the proposed problem formulation in DG sizing problem using ACO_R. All the mathematical equations related to the modelling of the optimization problem are explained in section 2.1, while the algorithm of ACO_R is presented in section 2.2.

2.1. Proposed problem formulation

The objective function, fitness, decision variables, constraints and test system are presented in this section.

Objective function

The objective function of this study is the minimization of total real power losses in distribution system. Hence, the objective function can be represented by power loss equation as in (1).

$$P_L = \sum_{i=1}^{NB}\sum_{j=1}^{nb}\left[\alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j + P_iQ_j\right)\right] \tag{1}$$

Where,

nb	=	Total number of branches
P_L	=	Total power losses of distribution system
NB	=	Total number of buses
P_i, Q_i	=	Net active and reactive power flow
α_{ij}, β_{ij}	=	Loss coefficient

Constraint

In term of voltage stability, each bus voltage must be maintained within their nominal range, which is specified as [V_{i_min} , V_{i_max}], where V_{i_min} and V_{i_max} are the minimum and maximum permissible voltage at bus *i*. This can be represented mathematically as in (2).

$$V_{i\_min} \leq V_i \leq V_{i\_max} \tag{2}$$

The capacity of each DG (P_{DGi}) will be varied within its specified range of injected real power to the system. This is specified as [P_{DG_min}, P_{DG_max}], where P_{DG_min} and P_{DG_max} are the minimum and maximum DG capacity. Hence, the constraint to be fulfilled in the proposed problem formulation is given in (3).

$$P_{DG\_min} \leq P_{DGi} \leq P_{DG\_max} \quad (3)$$

Control variable
The control variable for this study is the capacity of DG for every indivual or agent of optimization. Since this study considers solar photovoltaic DG, only real power injection (P_{DG}) shall be considered. Thus, the control variable for the optimization problem is represented in (4).

$$S = [P_{DG1}, P_{DG2} \ldots P_{DGm} \ldots P_{DGN}] \quad (4)$$

Where, S is the population matrix of ACO_R, P_{DG1} to P_{DGN} are the DG capacity of every m-th agent.

Test System
In this study, the IEEE 33-bus radial distribution system is used as the test system. There are 32 buses available for the placement of DG and 32 feeders serve for the load buses. At every iteration of ACO_R, the fitness evaluation is conducted such that every optimization agent will be evaluated by injecting the value of P_{DG} at every bus of the test system. Then, the subsequent simulation is performed by running load flow program for calculating the corresponding real power loss as in (1).

2.2. Algorith development

Ant Colony Optimization (ACO) was introduced in 1990's by M. Dorigo to solve complex combinatorial optimization problems [26]. The ACO was inspired by the foraging behavior of real ants. In the foraging process, each ant will start by exploring the area around their nest randomly. Once the ant finds a source of food, it tests them and bring some of the foods back to the nest. The ant deposits a pheromone trail on the ground during its return trip. The amount of pheromone deposited by the ant depends on quality and quantity of the food, which will guide and lead the other ants to the food source. Later, K. Socha in [27] proposed a new version of ACO that really suits for continuous domain optimization problems, such as sizing a set of decision variables. The new version is known as Continuous Domain Ant Colony Optimization (ACO_R). Because of its good convergence behavior and suitability for power system problems, it has motivated this study to impelement ACO_R as the search engine in optimal DG placement problem. Figure 1 presents the pseudocode of ACO_R.

```
Start
    Initialization
        ACO_R Parameters
        Random solution generation
    For ant = 1:m
        Construct ant-based solution
            Formation of Gaussian functions
            Sampling
            Standard deviation calculation
        Updating solution
            Increase & decrease pheromone level
    end
    Fitness evaluation
        Rank the best and the worst ant
        Update archive T
    Convergence test
End
```

Figure 1. Pseudocode of ACO_R

Step 1: Initialization
At first, the parameters that need to be initialized are the population number, number of ants, size of solution archive T, tolerance value, scaling parameters and elitism parameters.
Step 2: Initialization of archive
Solution vector will be randomly generated which is represented by a set of decision variables. Until the population has been filled with the initial solutions, the fitness of every solution is then calculated.
Step 3: Construct ant-based solution
Each ant construct a solution by performing n construction steps based on the given decision variable X_i, $i = 1, \ldots n$. The ant will choose a value for variable X_i at the construction step. The Gaussian kernel is collected from several regular Gaussian functions. The number of functions used is equal to the size k of the

solution archive T. The information about the i-th dimension (decision variable X_i) is used at construction step i. Hence, at each step i, the resulting Gaussian kernel, G^i is a different one. By using (5), the G^i could be defined accordingly.

$$G^i(x) = \sum_{l=1}^{k} \omega_l \frac{1}{\sigma_l^i \sqrt{2\pi}} e^{-\frac{(x-u_l^i)^2}{2\sigma_l^{i^2}}} \quad (5)$$

The sampling process is computed as follows. First, the elements of the weight vector ω_l are computed using (6).

$$\omega_l = \frac{1}{qk\sqrt{2\pi}} e^{-\frac{(l-1)^2}{2q^2k^2}} \quad (6)$$

Then, the sampling is done in two phases. The first phase consists of choosing one of the Gaussian functions that compose the Gaussian kernel. The probability p_i of choosing the i-th Gaussian function is given in (7).

$$p_1 = \frac{\omega_l}{\sum_{r=i}^{k} \omega_r} \quad (7)$$

The second phase consist of sampling the chosen Gaussian function. This phase is carried out by using a random number generator that can generate random numbers according to a parameterized normal distribution. This two-phase sampling is equivalent to sampling the Gaussian kernel G^i as defined in (5). At step i, the standard deviation needs to be known for the single Gaussian function $g_l^i(x)$ chosen in phase one.
Next, to calculate the standard deviation σ_l^i at construction step i, calculation has to be made to obtain the average distance from the chosen solution s_i to other solutions in the archive, and multiply it with the scaling parameter ξ. This is given in (8).

$$\sigma_l^i = \xi \sum_{e=1}^{k} \frac{\left|s_e^i - s_l^i\right|}{k-1} \quad (8)$$

The scaling parameter ξ should be greater than 0. The higher the value of ξ , the lower the algorithm convergence speed.
Step 4: Updating value of archive
The objective of pheromone update is to increase the pheromone values of acceptable or assuring solutions and to decrease the pheromone values of the bad ones. Acceptable solutions found earlier by the ants are used to update the pheromone in order to increase the probability of the search by subsequent ants in the promising regions of the search space.
Step 5: Fitness evaluation
After all ants finish updating their solutions, their fitness will be assessed and ranked accordingly. In this study, fitness will be evaluated after placement of DG using a load flow program. The program will perform the simulation to obtain the fitness, which are the voltage profiles and real power losses. Whichever ant that has the best quality of fitness will be placed at the topmost of the population, while the one that has the worst solution will be at the bottommost.
Step 6: Convergence check
Until all ants have approximately the same fitness values (depending on the prefered tolerance), the whole processes from step 3 to step 5 will continue to run repeatedly.

3. RESULT AND DISCUSSION

In this study, the performance of the proposed technique will be assessed through three case studies as follows:
Case 1 – single DG placement
Case 2 – DG placement under various loadings
Case 3 – algorithm performance
The simulation of the test system and ACO_R algorithm was implemented in MATLAB software.

3.1 Case 1: single DG placement

Table 1 tabulates the results after individual placement of DG at every bus in the test system. In the table, the size of DG (P_{DG}), resulted minimum voltage (V_{min}) and real power loss (P_{loss}), percentage of loss reduction (ΔP_{loss}) and required computation time (t_c) are shown in every column. The voltage profiles and real power loss are presented graphically in Figure 2 and Figure 3 respectively.

The comparison of V_{min} and ΔP_{loss} are made with respect to that of before DG placement as in Table 1. Based on Figure 2, there are four possible locations for DG placement that offer an improvement on the V_{min}, namely bus 6, 7, 26 and 27 with their respective voltage of 0.9419 p.u., 0.9410 p.u., 0.9443 p.u. and 0.9406 p.u. In addition, Figure 3 indicates that the four locations are also suitable for losses minimization with their respective ΔP_{loss} of 47.52%, 46.48%, 47.20% and 46.44% for bus 6, 7, 26 and 27 respectively. This can be a good indicator for DG placement as those locations provide consistent improvement on both the voltage profile and real power loss. In contrast to that, failure to determine proper locations will cause losses increment instead of reduction. This happened at bus 19, 20, 21 and 22 where their percentage of loss reduction are negative: –0.215%, –46.75%, –58.03% and –84.05% respectively. The overall computation time, t_c taken by ACO_R for all buses are less than 15 seconds, which is considered to be satisfactory.

Table 1. Voltage profile and real power loss at every bus

Bus number	P_{DG} (MW)	V_{min} (p.u.)	P_{loss} (MW)	ΔP_{loss} (%)	t_c (s)
Before DG placement	0.0000	0.8975	0.2765	-	-
2	4.5242	0.9005	0.2643	4.413	11.328
3	4.0203	0.9140	0.2136	22.73	10.399
4	3.7462	0.9224	0.1962	29.04	10.502
5	3.0807	0.9262	0.1796	35.03	11.471
6	2.9517	0.9419	0.1451	47.52	10.571
7	2.8974	0.9410	0.1480	46.48	10.513
8	2.2815	0.9321	0.1566	43.35	10.758
9	2.0594	0.9288	0.1679	39.28	11.183
10	1.6327	0.9226	0.1742	37.00	10.503
11	1.7552	0.9243	0.1759	36.38	10.434
12	1.5162	0.9209	0.1774	35.81	10.287
13	1.2924	0.9176	0.1850	33.08	10.415
14	1.0908	0.9147	0.1888	31.70	10.400
15	1.1041	0.9148	0.1913	30.82	10.217
16	1.4923	0.9200	0.2037	26.30	10.444
17	0.7042	0.9088	0.2079	24.81	10.281
18	0.8023	0.9102	0.2074	24.97	10.617
19	3.8775	0.9000	0.2771	-0.215	12.135
20	4.0993	0.9001	0.4057	-46.75	11.724
21	4.0697	0.9000	0.4369	-58.03	12.001
22	4.1905	0.9000	0.5089	-84.05	12.245
23	2.4425	0.9076	0.2274	17.76	10.337
24	1.8879	0.9053	0.2335	15.55	10.526
25	1.4349	0.9035	0.2404	13.04	10.806
26	2.8500	0.9443	0.1460	47.20	10.384
27	2.3771	0.9406	0.1481	46.44	10.436
28	2.2315	0.9385	0.1480	46.46	10.297
29	1.9232	0.9342	0.1471	46.79	10.293
30	1.9029	0.9339	0.1475	46.66	10.493
31	1.6254	0.9298	0.1585	42.68	10.450
32	1.1204	0.9225	0.1701	38.49	10.286
33	1.6324	0.9296	0.1692	38.79	10.480

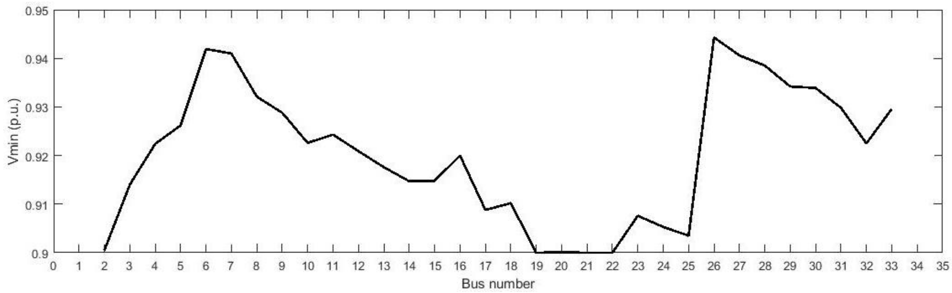

Figure 2. V_{min} after individual DG placement at every bus

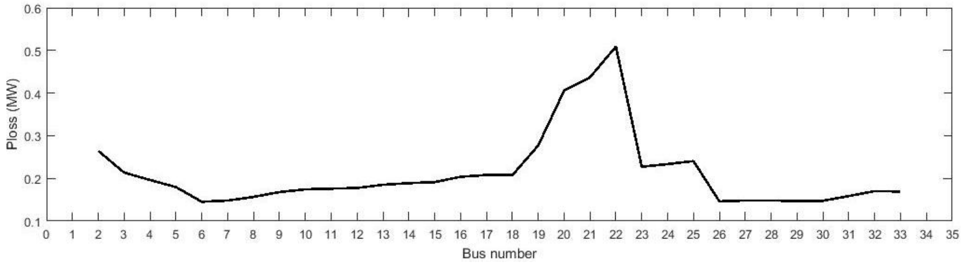

Figure 3. P_{loss} after individual DG placement at every bus

3.2 Case 2: DG placement under various loadings

The second case further verifies the performance of ACO_R in DG placement problem under various loadings. In this case, the placement of DG was done under three loadings, which are represented in the form of real and reactive power at load buses (P_{load} and Q_{load}). Table 2 tabulates the results, while Figure 4 and Figure 5 give the graphical illustration of V_{min} and P_{loss} with respect to the three loadings.

Table 2. Voltage profile and real power loss under various loadings

Loading	P_{load} (MW)	Q_{load} (MVar)	P_{DG} (MW)	V_{min} (p.u.)	P_{loss} (MW)	ΔP_{loss} (%)	t_c(s)
1	0.3	0.7	No DG 1.3961	0.9103 0.9317	0.2252 0.1288	42.81	11.283
2	0.4	0.8	No DG 1.7340	0.9040 0.9340	0.2497 0.1367	45.26	10.514
3	0.5	0.9	No DG 2.3415	0.8975 0.9339	0.2765 0.1475	46.66	10.493

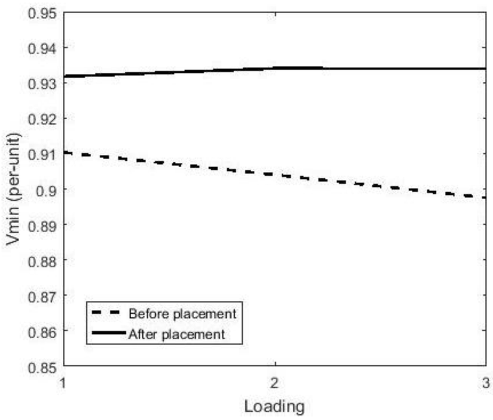

Figure 4. Voltage improvement under various loadings

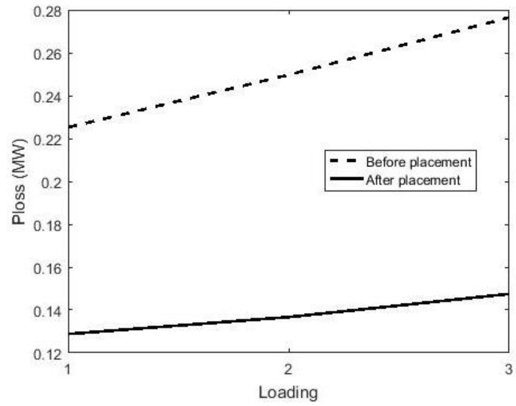

Figure 5. Losses minimization under various loadings

Based on Figure 4, the value of V_{min} before DG placement tends to drop as the loading increases. However, with proper DG placement the system has a steady and consistent voltage of approximately 0.93 p.u. regardless of the loadings. In the case of losses minimization, there is an obvious reduction of P_{loss} based on Figure 5. At all loadings, the percentage of loss reduction ΔP_{loss} is between 42% to 46%. The computation time taken by ACO_R to achieve convergence is less than 15 seconds at all loadings. These findings justify the performance of ACO_R in providing consistent voltage profile improvement and losses minimization with tolerable computation time.

3.3 Case 3: algorithm performance

The third case measures the performance of ACO_R as the search engine in the DG placement problem. There are different numbers of DG installed in the system: one, two and three. To evaluate the performance, the Evolutionary Programming (EP) was used as a benchmark in the optimization problem. Table 3 tabulates the results for both algorithms.

Table 3. Performance of ACO_R and EP in DG placement problem

Loading P_{load} (MW)	Loading Q_{load} (MVar)	Number of DG	Algorithm	V_{min} (p.u.)	P_{loss} (MW)	ΔP_{loss} (%)	t_c (s)
0.5	0.9	One DG	ACO_R	0.9524	0.0664	75.97	10.183
			EP	0.9454	0.0676	75.56	21.069
		Two DG	ACO_R	0.9845	0.1849	33.12	11.214
			EP	0.9883	0.2345	15.19	20.406
		Three DG	ACO_R	0.9921	0.4437	-60.47	12.287
			EP	0.9879	0.4542	-64.29	20.059

From the table, it is obvious that both algorithms result in almost the same magnitude of V_{min}: approximately 0.95 p.u. for one DG, 0.98 p.u. for two DG and 0.99 p.u. for three DG. In the case of losses minimization, both algorithms have the same ΔP_{loss} of 76% for one DG. When two DG were installed, ACO_R results in better ΔP_{loss} than EP: 33.12% for ACO_R and 15.19% for EP. For three DG, both algorithms result in losses increment instead of reduction. This signifies that three DG placement is not recommended to the system. A more obvious difference in the performance of both algorithms is the computation time, t_c. ACO_R requires less than 15 seconds to complete the optimization, while EP needs almost 20 seconds.

4. CONCLUSION

In conclusion, this study has successfully justified the capability of ACO_R as the search engine for optimal DG placement in IEEE 33-bus radial distribution system. The algorithm suits for continuous domain optimization problem as discussed in this paper. The capacity of DG in the form of real power injection has been determined by the developed algorithm for voltage profile mitigation and losses minimization. Experiment on the three case studies has verified the strength of the algorithm for proper DG sizing. Furthermore, a comparison with EP algorithm also validates the results and accuracy of ACO_R algorithm in DG placement problem. For future recommendation, it is aspired that the proposed technique can be applied in other problems related to distribution system, such as realibility assessment and energy efficiency in power system.

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