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.

Keywords:
Ant-colony optimization
Power loss minimization
Distributed generation
Distribution systems
Voltage stability

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 enhancement 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 observed 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$_c$) algorithm in radial distribution system. The rationale of using ACO$_c$ 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$_c$. All the mathematical equations related to the modelling of the optimization problem are explained in section 2.1, while the algorithm of ACO$_c$ 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).

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

(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
- \( a_{ij}, \beta_{ij} \) = Loss coefficient

Constraint

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

\[
V_{i,\text{min}} \leq V_i \leq V_{i,\text{max}}
\]

(2)

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

\[\text{(3)}\]

**Control variable**
The control variable for this study is the capacity of DG for every individual 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).

\[
S = [P_{DG1}, P_{DG2}, ..., P_{DGm}, ..., P_{DGN}]
\]

\[\text{(4)}\]

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. Algorithm 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 implement ACO\(_R\) as the search engine in optimal DG placement problem. Figure 1 presents the pseudocode of ACO\(_R\).

![Figure 1. Pseudocode of ACO\(_R\)](image-url)

**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**

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 \(X_i, i = 1, ..., n\). 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
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.

\[
G^i(x) = \sum_{k=1}^{K} \omega_k \frac{1}{\sqrt{\sigma^2 \pi}} e^{-\frac{(x-x_k)^2}{2\sigma^2}}
\]

(5)

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

\[
\omega_l = \frac{1}{q_l \sqrt{\pi}} e^{-\frac{(l-1)^2}{2\eta^2}}
\]

(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).

\[
p_1 = \frac{\omega_l}{\sum_{l=1}^{L} \omega_l}
\]

(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 \( g^i(x) \) chosen in phase one.

Next, to calculate the standard deviation \( \sigma_i^2 \) 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 \( \xi \). This is given in (8).

\[
\sigma_i^2 = \xi \sum_{k=1}^{K} \frac{|s_i - s_k|}{k-1}
\]

(8)

The scaling parameter \( \xi \) should be greater than 0. The higher the value of \( \xi \), 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 preferred 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 (∆P_{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 ∆P_{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 ∆P_{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) | ∆P_{loss} (%) | t_c (s) |
|------------|-------------|----------------|--------------|---------------|---------|
| Before DG placement | 0.0000 | 0.8975 | 0.2765 | - | - |
| 1 | 4.5242 | 0.9005 | 0.2643 | 4.413 | 11.328 |
| 2 | 4.0203 | 0.9140 | 0.2136 | 22.73 | 11.328 |
| 3 | 3.0807 | 0.9262 | 0.1796 | 35.03 | 11.471 |
| 4 | 2.9517 | 0.9419 | 0.1451 | 47.52 | 10.571 |
| 5 | 2.8974 | 0.9410 | 0.1480 | 46.48 | 10.513 |
| 6 | 2.2815 | 0.9321 | 0.1566 | 43.35 | 10.758 |
| 7 | 2.0594 | 0.9288 | 0.1679 | 39.28 | 11.183 |
| 8 | 1.6327 | 0.9226 | 0.1742 | 37.00 | 10.503 |
| 9 | 1.5752 | 0.9243 | 0.1759 | 36.83 | 10.434 |
| 10 | 1.5162 | 0.9209 | 0.1774 | 35.81 | 10.287 |
| 11 | 1.2924 | 0.9176 | 0.1850 | 33.08 | 10.415 |
| 12 | 1.0908 | 0.9147 | 0.1888 | 31.70 | 10.400 |
| 13 | 1.1041 | 0.9148 | 0.1913 | 30.82 | 10.217 |
| 14 | 1.4923 | 0.9202 | 0.2037 | 26.30 | 10.444 |
| 15 | 0.7042 | 0.9088 | 0.2079 | 24.81 | 10.281 |
| 16 | 0.8023 | 0.9102 | 0.2074 | 24.97 | 10.617 |
| 17 | 0.9075 | 0.9000 | 0.2771 | -0.215 | 12.135 |
| 18 | 0.4093 | 0.9000 | 0.4057 | -46.75 | 11.724 |
| 19 | 4.097 | 0.9000 | 0.4369 | -58.03 | 12.001 |
| 20 | 1.4105 | 0.9000 | 0.5089 | -84.05 | 12.245 |
| 21 | 2.4425 | 0.9076 | 0.2274 | 17.76 | 10.337 |
| 22 | 1.8879 | 0.9053 | 0.2335 | 15.55 | 10.526 |
| 23 | 1.3439 | 0.9035 | 0.2404 | 13.04 | 10.806 |
| 24 | 2.8900 | 0.9443 | 0.1460 | 47.20 | 10.384 |
| 25 | 2.3771 | 0.9406 | 0.1481 | 46.44 | 10.436 |
| 26 | 2.2315 | 0.9385 | 0.1480 | 46.46 | 10.297 |
| 27 | 1.9232 | 0.9342 | 0.1471 | 46.79 | 10.293 |
| 28 | 1.9029 | 0.9339 | 0.1475 | 46.66 | 10.493 |
| 29 | 1.6284 | 0.9298 | 0.1585 | 42.68 | 10.450 |
| 30 | 1.1204 | 0.9225 | 0.1701 | 38.49 | 10.286 |
| 31 | 1.6324 | 0.9296 | 0.1692 | 38.79 | 10.480 |

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

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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 (\(P_{\text{load}}\) and \(Q_{\text{load}}\)). Table 2 tabulates the results, while Figure 4 and Figure 5 give the graphical illustration of \(V_{\text{min}}\) and \(P_{\text{loss}}\) with respect to the three loadings.

![Graph showing \(P_{\text{loss}}\) after individual DG placement at every bus](Image)

Figure 3. \(P_{\text{loss}}\) after individual DG placement at every bus

| Loading | \(P_{\text{load}}\) (MW) | \(Q_{\text{load}}\) (MVar) | \(P_{\text{DG}}\) (MW) | \(V_{\text{min}}\) (p.u.) | \(P_{\text{loss}}\) (MW) | \(\Delta P_{\text{loss}}\) (%) | \(t\) (s) |
|---------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1       | 0.3             | 0.7             | No DG           | 0.9103          | 0.2252          | 42.81           | 11.283          |
| 2       | 0.4             | 0.8             | No DG           | 0.9040          | 0.2497          | 45.26           | 10.514          |
| 3       | 0.5             | 0.9             | No DG           | 0.8975          | 0.2765          | 46.66           | 10.493          |

![Graph showing voltage improvement under various loadings](Image)

Figure 4. Voltage improvement under various loadings

![Graph showing losses minimization under various loadings](Image)

Figure 5. Losses minimization under various loadings

Based on Figure 4, the value of \(V_{\text{min}}\) 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 \(P_{\text{loss}}\) based on Figure 5. At all loadings, the percentage of loss reduction \(\Delta P_{\text{loss}}\) 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.

| Loading | Number of DG | Algorithm | $V_{min}$ (p.u.) | $P_{loss}$ (MW) | $\Delta P_{loss}$ (%) | $t_c$ (s) |
|---------|--------------|-----------|-----------------|-----------------|----------------------|-----------|
| $P_{load}$ (MW) | $Q_{load}$ (MVar) | One DG   | ACOr   | 0.9524       | 0.0664     | 75.97                | 10.183    |
|         |              | EP       |       | 0.9454       | 0.0676     | 75.56                | 21.069    |
| Two DG  | ACOr        | 0.9845   | 0.1849       | 33.12         |          | 11.214               |           |
|         | EP          | 0.9883   | 0.2345       | 15.19         |          | 20.406               |           |
| Three DG| ACOr        | 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 $\Delta P_{loss}$ of 76% for one DG. When two DG were installed, ACOr results in better $\Delta P_{loss}$ than EP: 33.12% for ACOr 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, $t_c$. ACOr 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 ACOr 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 ACOr 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 reliability assessment and energy efficiency in power system.

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