Comprehensive optimization of distributed generation considering network reconstruction based on Archimedes optimization algorithm

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Abstract. To mitigate the effect of the distributed generation (DG) connection on the voltage profile and power loss, the DG optimal configuration and network reconfiguration are used in distribution automation. In this paper, a new optimization method named Archimedes Optimization Algorithm (AOA) is proposed, unifying the DG optimal configuration and network reconfiguration. The DG locations and capacities are coded by integral and real numbers simultaneously in the proposed method. The integer mesh-network coding method is integrated into the new method to solve the network reconfiguration problem. The new method is compared with the Improved Genetic Algorithm (IGA) as well as the Particle Swarm Optimization (PSO). Results demonstrate that the proposed method has advantages in improving the voltage profile and reducing the power loss.

1. Introduction
As the penetration level of distributed generation (DG) increases, the network planning, operation, and control in distribution automation are complicated[1]. The DG optimal configuration and network reconstruction are predominately used in the network planning and operation[2-3]. The optimal DG locations and capacities can be obtained by the DG configuration, while the optimum topology can be achieved through the network reconstruction. Since DG allocation and network reconfiguration are interrelated, the maximum optimization of the distribution network cannot be achieved by a single adjustment. Therefore, it is crucial to discuss the two together.

The DG configuration and network reconfiguration involve large-scale nonlinear optimization problems, which are studied extensively in the literatures. The representative optimization techniques such as Genetic Algorithm (GA)[4], Firework Algorithm (FWA)[5], Particle Swarm Optimization (PSO)[6], were successfully applied to solve the above problems. Imran et al.[7] obtained the optimal DG capacities by FWA and found the best locations of DG by Voltage Stability Index (VSI). Remha et al.[5] used Bat Algorithm (BA) to get the best position and capacities of DG with the minimum network loss. Shahzad et al[8] applied load concentration factor (LCF) to select the optimal locations for DG placement and used analytical method to calculate the optimal sizing. Pegado et al.[9] took the minimum power loss into the objective function and proposed Improved Selective Binary Particle Swarm Optimization (ISPSO) to solve the network reconstruction. Nguyen et al.[10] used Enhanced Binary Cuckoo Search Algorithm (EBCSA) to solve the problem of distribution network reconfiguration which aimed to reduce power losses in distribution networks. However, less research has been done to apply
the intelligent algorithms when solving the DG configuration in parallel with the network reconstruction. Most of the literatures either apply the intelligent algorithms to get the best DG sizing or use analytical sensitivity method to obtain the optimal DG locations, which makes it difficult to guarantee the optimum operation of the distribution networks. Archimedes Optimization Algorithm (AOA) can solve the complex optimization problems with faster speed and better global optimization ability, which has been successfully applied to welded beam design, pressure vessel design, and speed reducer design problems[11]. However, there is little literature solving the DG configuration and network reconstruction problems by AOA.

This paper presents a new meta-heuristic technique called AOA to solve the DG comprehensive optimization problem. The DG locations and capacities are coded by integer real numbers and switch combination are handled by the integer ring coding. The model presented in this paper is solved by AOA and compared with Improved Genetic Algorithm (IGA) and PSO. The results show that the new method can achieve the optimum results in DG comprehensive optimization problem with a faster speed and stronger convergency. The organization of this paper is as follows: Section II discusses the problem formulation of DG comprehensive optimization while detailed description of AOA technique is presented in Section III. Section IV presents the simulation results as well as the discussion. Finally, Section V states the conclusion.

2. Problem Formulation

2.1 Objective function

This paper focuses on the power loss after the DG comprehensive optimization, the objective in this work is to minimize the system network loss. The objective function is as follows:

$$\min f = P_{\text{loss}} = \sum_{i=1}^{N} R_i \frac{P_i^2 + Q_i^2}{U_i^2}$$  \hspace{1cm} (1)

where N is the total number of branches, $P_i$ and $Q_i$ are the active and reactive power flowing through the end of the branch $i$, $R_i$ is the resistance of branch $i$.

2.2 Constraint equations

On the basis of the objective function, DG configuration and network reconstruction must meet the following constraints[12]:

2.2.1 Power flow equation constraints

$$\begin{cases} P_{Gi} - P_{Li} - U_i \sum_{j=1}^{N} (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \\ Q_{Gi} - Q_{Li} - U_i \sum_{j=1}^{N} (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \end{cases}$$  \hspace{1cm} (2)

where $P_{Gi}$ and $Q_{Gi}$ are the active and reactive power supply at node $i$, $P_{Li}$ and $Q_{Li}$ are the active and reactive power of the load at node $i$, respectively. $G_{ij}$ and $B_{ij}$ are system admittance. $\theta_{ij}$ is the phase angle difference of voltage between node $i$ and $j$.

2.2.2 Node voltage constraints

$$U_{i_{\text{min}}} \leq U_i \leq U_{i_{\text{max}}}$$  \hspace{1cm} (3)

where $U_{i_{\text{max}}}$, $U_{i_{\text{min}}}$ are the upper and lower voltage limits of node $i$, and $U_{i_{\text{max}}}$ takes 1.05 (p.u.), $U_{i_{\text{min}}}$ takes 0.95 (p.u.).

2.2.3 DG injection power constraint

$$P_{\text{DG}_{\text{min}}} \leq P_{DG,i} \leq P_{\text{DG}_{\text{max}}}$$  \hspace{1cm} (4)
where $P_{DG_{max}}$ and $P_{DG_{min}}$ represent the upper and lower limits of DG inject capacity, and $P_{DG_{i}}$ is DG size at the node $i$.

2.2.4. Distribution network topological constraints

Distribution network is usually "closed loop design, open-loop operation[13]". Thus, the ring network and islanding situations cannot occur after network reconstruction[14]:

$$k_r \in G$$

(5)

where $k_r$ indicates the network structure after each reconstruction, and $G$ represents all the network architecture to meet a set of radial operation.

2.3 Power flow with DG

The common methods of power flow calculation are Newton Raphson method, P-Q decomposition method and backward forward power flow method[15]. The backward forward method has stronger adaptability and faster convergence speed than the other two methods while calculating the power flow of the radial distribution network.

The focus of power flow calculating with DG is to process DGs of various node types, and the common method is to divide DGs into PQ, PV, PQ(V), or PI nodes. While PI, PV, and PQ(V) nodes can all be converted into PQ nodes for calculation in a certain way[16]. Therefore, this paper takes PQ-type DG as an example to simplify the calculation. The backward forward method is adopted to study the DG comprehensive optimization[17].

3. Solution Approach

The proposed Archimedes optimization algorithm (AOA) is a population-based algorithm which is devised with inspirations from Archimedes’ principle[11]. The principle states that when an object is fully or partially immersed in fluid, the fluid exerts an upward force on the object, which is equal to the weight of the fluid discharged by the object. AOA imitates the principle of buoyant force exerted upward on an object, partially or fully immersed in fluid, was proportional to weight of the displaced fluid[18]. The objects immersed in fluid have different densities and volumes that causes different accelerations.

3.1 Archimedes optimization algorithm (AOA)

AOA is based on population, and the immersed objects are regard as the population individuals. Like other population-based metaheuristic algorithms, AOA starts the search process with initial population of objects with random volumes, densities, and accelerations. Theoretically, AOA can be considered as a global optimization algorithm as it encompasses both exploration and exploitation processes. Mathematically, steps of the proposed AOA are detailed as follows.

Step 1- Initialization:

AOA initializes the positions of all objects using (6):

$$O_i = l_b + rand \times (ub - lb); i = 1,2,\ldots,N$$

(6)

where $O_i$ is the $i^{th}$ object in a population of $N$ objects. $lb$ and $ub$ are the lower and upper bounds of the search space, respectively.

AOA initializes the volume ($vol$), density ($den$) and acceleration ($acc$) for each $i$ object randomly. In this step, the algorithm evaluates initial population and selects the object with the best fitness value. The best value are assigned to $x_{best}$, $d_{en_{best}}$, $vol_{best}$, and $acc_{best}$.

Step 2- Update densities, volumes:

The density and volume of object $i$ for the iteration $t + 1$ is updated using (7):

$$den_i^{t+1} = den_i^t + rand \times (den_{best} - den_i^t)$$

$$vol_i^{t+1} = vol_i^t + rand \times (vol_{best} - vol_i^t)$$

(7)

where $vol_{best}$ and $den_{best}$ are the volume and density associated with the best object found so far, and $rand$ is a uniformly distributed random number.
Step 3 - Transfer operator and density factor:
The transfer operator $TF$ helps AOA transform search from exploration to exploitation, defined using equation (8):

$$TF = \exp\left(\frac{t - t_{\text{max}}}{t_{\text{max}}}\right)$$

(8)

where transfer $TF$ increases gradually with time until reaching 1. Here $t$ and $t_{\text{max}}$ are the current iteration number and maximum iterations, respectively. Similarly, density decreasing factor $d$ also assists AOA on global to local search which decreases with time using equation (9):

$$d^{t+1} = \exp\left(\frac{t_{\text{max}} - t}{t_{\text{max}}} - \frac{t}{t_{\text{max}}}\right)$$

(9)

where $d^{t+1}$ decreases with time that gives the ability to converge in already identified promising region. Proper handling of this variable will ensure balance between exploration and exploitation in AOA.

Step 4.1- Exploration phase (collision between objects occurs):
If $TF \leq 0.5$, collision between objects occurs, AOA selects a random material ($mr$) and update object’s acceleration for iteration $t + 1$ using equation (10):

$$acc_i^{t+1} = \frac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}}$$

(10)

where $den_i$, $vol_i$, and $acc_i$ are density, volume, and acceleration of object $i$, respectively, while $acc_{mr}$, $den_{mr}$, and $vol_{mr}$ are the acceleration, density, and volume of material $mr$. It is important to mention that $TF \leq 0.5$ ensures exploration during one third of iterations. Applying value other than 0.5 will change exploration-exploitation behavior.

Step 4.2 - Exploitation phase (no collision between objects):
If $TF > 0.5$, there is no collision between objects, the algorithm updates object’s acceleration for iteration $i + 1$ using equation (11):

$$acc_i^{t+1} = \frac{den_{\text{best}} + vol_{\text{best}} \times acc_{\text{best}}}{den_i^{t+1} \times vol_i^{t+1}}$$

(11)

where $acc_{\text{best}}$ is the acceleration of the best object.

Step 4.3 - Normalize acceleration:
The normalized acceleration is calculated by equation (12):

$$acc_{i_{\text{norm}}}^{t+1} = \frac{u \times acc_{i_{\text{norm}}}^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + l$$

(12)

where $u$ and $l$ set to 0.9 and 0.1, respectively. The $acc_{i_{\text{norm}}}^{t+1}$ determines the percentage of step that each agent will change. In normal case, the acceleration factor begins with large value and decreases with time. This helps search agents move towards the global best solution and at the same time they move away from local solutions.

Step 5 - Update position:
If $TF \leq 0.5$ (exploration phase), AOA updates the $i^{th}$ object’s position for next iteration $t + 1$ using equation (13):

$$x_i^{t+1} = x_i^t + C_1 \times \text{rand} \times acc_{i_{\text{norm}}}^{t+1} \times d \times (x_{\text{rand}} - x_i^t)$$

(13)

where $C_1$ is constant equals to 2. Otherwise, if $TF > 0.5$ (exploitation phase), the objects update their positions using equation (14):

$$x_i^{t+1} = x_i^t + C_2 \times \text{rand} \times acc_{i_{\text{norm}}}^{t+1} \times d \times (T \times x_{\text{best}} - x_i^t)$$

(14)

where $C_2$ is a constant that equals to 6. $T$ increases with time and it is directly proportional to transfer operator. $F$ is the flag to change the direction of motion using equation (15):
\[ F = \begin{cases} +1, & \text{if } P \leq 0.5 \\ -1, & \text{if } P > 0.5 \end{cases} \]  

(15)

where \( P = 2 \times \text{rand} - C_d \).

Step 6 – Evaluation:
AOA evaluates each object using objective function \( f \) and save the best solution found so far. The best value are assigned to \( x_{\text{best}}, \text{den}_{\text{best}}, \text{vol}_{\text{best}}, \text{and } \text{acc}_{\text{best}} \).

3.2 Optimization process based on AOA
The comprehensive optimization model established in this paper involves multi-dimensional variables which including integer and real number. The original encoding in AOA is no longer applicable. Thus, real-integer mixed coding method is adopted, where the DGs locations use the integer encoding while the capacities are coded by real. The switch combinations during network reconstruction are coded by integer ring method. The code vector \( P \) for comprehensive optimization of DG is formed as follows:

\[ P = \{ S_1, S_2, S_3, S_4, S_5, L_1, L_2, L_3, H_1, H_2, H_3 \} \]  

(16)

where \( S_1, S_2, S_3, S_4 \) and \( S_5 \) are five opened switches corresponding to tie switches, \( L_1, L_2, L_3 \) and \( H_1, H_2, H_3 \) are locations and capacities of DGs respectively.

The process of AOA to solve the specific problems in this paper is shown in Figure 1.

Figure 1. Flow chart of AOA.

In order to further verify the effectiveness of AOA in solving the problems in the paper, AOA, IGA and PSO algorithms are used to optimize model, and the results of the three algorithms are compared. Roulette method is commonly used in traditional genetic algorithms for selection operations, which may eliminate individuals with higher fitness values when solving the model in this paper, elite retention and elimination mechanism are considered for ensuring the coexistence of global and local optimization capability. In this paper, the protection probability of IGA is 10\%, and the elimination probability is 25\%. This paper takes the learning factor \( c_1 = c_2 = 1.5 \), and the inertia weight \( w = 0.65 \) in PSO.
4. Simulations and Discussion

In order to verify the performance of the proposed algorithm and model in DG optimization configuration and network reconfiguration, the related program is written on the MATLAB platform, and the IEEE33 bus system is used for simulation verification.

4.1 IEEE33 bus system

The IEEE33 bus system consists of 1-32 sectionalized switches normally closed and 33-37 tie switches that are normally opened [19], which system topology is shown in Figure 2. The total real and reactive power loads are 3715 kW and 2300 kvar, respectively. The system base capacity is 10 MVA and base voltage is 12.66 kV. The limits of real power injected by DGs are 0 to 2 MW.

Figure 2. IEEE33 bus system topology.

4.2 Case Study

This paper sets up five specific cases for discussion, and three algorithms are used to optimize and solve the specific problems in each case respectively. The population size of all the three algorithms is 50. The specific cases are as follows:

- **Case1**: Only consider the power loss of the original network;
- **Case2**: Only consider the network reconstruction;
- **Case3**: Three DGs inject before network reconstruction;
- **Case4**: Three DGs inject after network reconstruction;
- **Case5**: Three DGs inject while network reconstruction.

Case 1 considers the original network power loss which can be seen as a reference case. The power loss under Case 1 is 202.64 kW, and the network disconnect switch is 33, 34, 35, 36, 37.

The results of Case 2 to Case 5 optimized by three algorithms are shown in Table 1. Three techniques have obtained the optimal scheme in Case 2, which the switch opened combination is 7-14-9-32-37, and power loss is reduced to 139.44 kW. It can be observed from Table 1 that all three algorithms find the best DG locations, while the optimal DG capacities are acquired by AOA in Case 3 and Case 4. And the power loss in Case 3 and Case 4 is reduced to 71.43 kW and 58.80 kW, respectively, after optimization.

It can also be observed that the result of Case 5 is the best compared with others’ in which the power loss is reduced to 50.46 kW by AOA, and AOA finds the optimal switch opened combination and DG configuration scheme compared with the other two algorithms. The percentage power loss reduction for Case 2 to Case 5 was 31.19%, 64.75%, 70.98% and 75.10%, respectively, with AOA. It is clear that AOA needs fewer iterations than the other two techniques. The results show that AOA is more efficient in solving the model than IGA and PSO in this paper.

| Switches opened | DG location and capacity (kW) | P Loss (kW) | Reduction | V_min (p.u.) | Iterations |
|-----------------|------------------------------|-------------|-----------|--------------|------------|
| Case 2          | AOA 7-14-9-32-37             | 139.44      | 31.19%    | 0.9479       | 50         |
|                 | PSO 7-14-9-32-37             | 139.44      | 31.19%    | 0.9470       | 300        |
|                 | IGA 7-14-9-32-37             | 139.44      | 31.19%    | 0.9473       | 300        |
| Case 3          | AOA 33-34-35-36-37           | 71.43       | 64.75%    | 0.9715       | 100        |
|                 | PSO 33-34-35-36-37           | 71.43       | 64.70%    | 0.9715       | 200        |
|                 | IGA 33-34-35-36-37           | 71.50       | 64.72%    | 0.9709       | 200        |
Figure 3 shows the comparison of node voltage curves after AOA optimized for each case. Case 1 in the figure is the node voltage curve in the initial state of the IEEE33 bus system. It can be seen from the curves in the figure that the voltage curve of Case 5 is the most ideal in comparison. Taking node 18 as an example, the voltage amplitude (p.u.) of node 18 in case 1 is 0.9133. After AOA optimization, the voltage amplitude (p.u.) of node 18 in case 2-5 is increased to 0.9479, 0.9715, 0.9716, and 0.9747, respectively. Among them, the voltage amplitude of node 18 in case 5 is improved 6.72% compared to case 1. It shows that AOA have obvious effects on network reconstruction and DG comprehensive optimization, which improves the qualified level of node voltage and further enhances the reliability of the system.

Figure 4 shows the convergence curves of the three algorithms for case 5. From the comparison of the curves, it can be seen that PSO has a faster convergence speed. But in the search process, AOA considers the global search and local search capabilities, and finally converges to the global optimal solution, while neither PSO nor IGA can search for the global optimal solution.

As can be seen from the above analysis, the changes of network structure directly affect the optimization of the DG configuration. The power loss of case 2 to case 5 decreases in turn after
optimization, and case 5 is the best solution with the minimal power loss and better voltage profiles. The results verify the idea for studying the DG optimal configuration considering the reconstruction, and prove the advantages of AOA in power losses reduction and voltage profiles improvement.

5. Conclusion
This paper conducts a comprehensive research and analysis on DG optimal configuration considering the network reconfiguration. Based on the analysis of the types of DG grid-connected nodes, a DG comprehensive optimization model with minimum power loss as the goal is proposed, and a method for solving the model is presented based on AOA. The paper handles DG locations and capacities in parallel while dealing with the problem of DG optimal configuration. The configuration schemes after optimization ensure the system operate in an optimal state while meeting the goal of minimizing the power loss, which has a certain guiding significance for the optimal operation of the distribution network.

Comparing the results of AOA with IGA and PSO in this paper, AOA has faster convergence speed and more stable results in dealing with reconfiguration problems, and there is no local optimal situation. Meanwhile, AOA has a shorter running time and a stronger global search capability than the other two algorithms in dealing with DG comprehensive optimization problems. The results show that the AOA has obvious advantages in solving the DG configuration problem under the consideration of reconstruction.

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