ISSN 2278-3091
Volume 11, No.6, November - December 2022
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse021162022.pdf
https://doi.org/10.30534/ijatcse/2022/021162022

Optimal Placement and Sizing of DGs in Distribution Networks Using Dandelion Optimization Algorithm: Case Study of an Algerian Distribution Network

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Received Date: October 17, 2022 Accepted Date: November 22, 2022 Published Date: December 06, 2022

ABSTRACT
The optimal placement of distributed generation (DG) in power distribution systems involves identifying the best locations for the generators to be installed and sizing them appropriately, to optimize the performance of the system. In this paper, the recently proposed nature-inspired optimization algorithm namely: Dandelion Optimizer (DO) has been used for the optimal placement and sizing of DG in the radial distribution network. The objectives are to minimize active power loss and voltage deviation and to enhance the voltage stability of the distribution network. The efficiency of the proposed method has been verified over the IEEE 33-bus and Algerian 112-bus distribution systems. The result comparisons indicated that the proposed method can obtain higher quality solutions than many other methods for the considered scenarios from the test systems. Therefore, the DO algorithm can be a very effective method for solving the optimal allocation of the DG problem.

Key words: Distribution network, Distributed generation, Dandelion optimizer, Power losses, Voltage deviation, Voltage stability.

1. INTRODUCTION

The electric power system can be divided into four major components; generation, transmission, distribution and utilities. Amongst these four components, the distribution network is the final and most critical link in the power system [1]. It is a more complex network and has a higher power loss as compared to a transmission network due to the high R/X ratio. Previous literature studies show that losses in the distribution network are high and can exceed 13% [2].

The integration of distributed generation (DG) in the distribution networks has several benefits such as reducing power losses, improving voltage profile along feeders and increasing the maximum transmitted power in cables and transformers [3]. However, the installation of DG in the distribution systems requires consideration of their appropriate locations and sizes. A non-optimal location with an optimal size or a non-optimal size with an optimal location can result in an increase in system losses and costs, and degradation in voltage profile, protection and stability. Thus, the simultaneous optimization of location and sizing of DGs in distribution systems can be very useful for the distribution power system [4].

In recent years, several meta-heuristic optimization techniques have been employed for solving the optimal placement and size of DG sources connected to the distribution network. These methods apply an iterative procedure to find the optimal solution or sub-optimal solutions to an optimization problem. Some of the methods that adopt meta-heuristics notions include Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Non-dominated Sorting GA-II (NSGA-II), Plant Growth Simulation Algorithm (PGSA), Artificial Bee Colony Algorithm (ABC), Bacterial Foraging Algorithm (BFA), Cat Swarm Optimization (CSO), Grey Wolf Optimization (GWO), Krill Herd Algorithm (KHA) and Invasive Weed Optimization (IWO) [6, 7, 8].

In this paper, the recently proposed met-heuristic method named Dandelion Optimization (DO) algorithm [9] has been adopted for multiple DG allocation and sizing to minimize active power loss, voltage deviation, and voltage stability improvement in the distribution network. Case studies with standard IEEE 33-bus and Algerian 112-bus distribution networks are performed. The obtained results have indicated that the proposed algorithm provides higher-quality solutions than several other algorithms in the literature for the considered scenarios.

The rest of this paper is organized as follows: Section 2 deals with the formulation of the optimal placement and sizing of the DG problem. The general framework of the employed Dandelion optimization (DO) algorithm is presented in Section 3, whereas Section 4 and 5 illustrates the numerical simulations to investigate the performance of the solutions obtained by the optimization algorithm. Finally, conclusions are drawn in Section 6.

2. PROBLEM FORMULATION

2.1 Objective function

Objective functions can be classified as single-objective or multi-objective. The single objective functions are such as minimizing system power losses, cost, or enhancing voltage profile or system stability, etc. and multi-objective functions would be the combination of two or more single objective functions by considering suitable parameters and constituting the objective function [10].

A. Single objective function

The main objective of DG siting and sizing in the distribution network is to minimize network active power losses while satisfying some operating constraints. The objective function for the minimization of active power loss is described as:

$$F_1 = \min\left(P_{loss}\right) \quad (1)$$

where P_{loss} is the total active power loss of the system expressed as follows:

$$P_{loss} = \sum_{i=1}^{N_{br}} R\left|I_i\right|^2 \quad (2)$$

where I_i and R_i are the current magnitude and the resistance of the *i*th branch, respectively, N_{br} is the number of branches.

B. Multi-objective function

To represent all the objectives in a combined mathematical expression, we divide every single objective function by its base value and link them together by coefficients. The use of weighting coefficients helps transform three single objective functions into one objective function, and the whole fitness function is given by:

$$F_2 = \min\left(w_1 \frac{P_{loss}}{P_{loss\_base}} + w_2 \frac{VD}{VD_{base}} + w_3 \frac{VSI^{-1}}{VSI^{-1}_{base}}\right) \quad (3)$$

VD is the total voltage deviation given by:

$$VD = \sum_{i=1}^{N_{bus}} \left(V_i - V_{rated}\right)^2 \quad (4)$$

where V_i is the voltage magnitude at bus *i*, V_{rated} is the rated voltage (1.0 p.u.) and N_{bus} is the number of buses in the distribution network.

VSI is the voltage stability index given by the following equation [11]:

$$VSI_j = \left|V_i\right|^4 - 4\left(P_j x_{ij} - Q_j r_{ij}\right)^2 - 4\left(P_j r_{ij} - Q_j x_{ij}\right)\left|V_i\right|^2 \quad (5)$$

where VSI_j is the voltage stability index of bus *j*, x_{ij} is the reactance of the line connected between buses *i* and *j*.

w_1, w_2 and w_3 are penalty factors. These factors are attuned based on the significance of the objective function. In this paper, w_1, w_2 and w_3 are taken as 0.6, 0.3 and 0.1, respectively.

2.2 Constraints

Two types of constraints, which include equality and inequality constraints, are considered in the optimization problem.

The power flow equations are defined as equality constraints in the optimal allocation of DGs problem. The mathematical model is given by [12]:

$$P_{G,i} - P_{l,i} = \left|V_i\right| \sum_{j=1}^{N_{bus}} \left|Y_{ij}\right|\left|V_j\right| \cos\left(\delta_i - \delta_j - \theta_{ij}\right) \quad (6)$$

$$Q_{G,i} - Q_{l,i} = \left|V_i\right| \sum_{j=1}^{N_{bus}} \left|Y_{ij}\right|\left|V_j\right| \sin\left(\delta_i - \delta_j - \theta_{ij}\right) \quad (7)$$

where $P_{G,i}$ is the active power output of the generator at bus *i*; $P_{L,i}$ is the active power of load at bus *i*; $Q_{G,i}$ is the reactive power output of the generator at bus *i*; $Q_{L,i}$ is the reactive power of load at bus *i*; and Y_{ij} and θ_{ij} are the modulus and angle of *i*th element in the admittance matrix of the system related to bus *i* and bus j, respectively.

The inequality constraints subjected to DG setting and sizing problems include [12]:

$$V_{\min} \le \left|V_i\right| \le V_{\max} \qquad i = 1, 2, ..., N_{bus} \quad (8)$$

where V_{min} and V_{max} are taken as 0.95 and 1.05 (p.u), respectively.

$$I_i \le I_{i\max} \qquad i = 1, 2, ..., N_{br} \quad (9)$$

$$P_{DG}^{\min} \le \left|P_{DGi}\right| \le P_{DG}^{\max} \quad (10)$$

$$2 \le \left|DG_{bus}\right| \le N_{bus} \quad (11)$$

where DG_{bus} is the bus number of the DG installation, V_i is the bus voltage, I_i is the current of the DG at branch *i*, P_{DG} is the total power of DG, N_{br} is the total number of branches.

3. DANDELION OPTIMIZATION ALGORITHM

Dandelion optimization (DO) is a new swarm intelligence bioinspired optimization algorithm was proposed by Zhao et al in 2022 [9]. DO simulates the process of dandelion seed long-distance flight relying on wind. The mathematical modelling of the DO can be summarized as follows:

3.1 Initialization

Similar to other natured-inspired metaheuristic algorithms, DO fulfils population evolution and iterative optimization on the basis of population initialization. In the proposed DO algorithm, it is assumed that each dandelion seed represents a candidate solution, whose population is expressed as:

$$population = \begin{bmatrix} x_1^1 & \dots & x_1^{Dim} \\ \vdots & \ddots & \vdots \\ x_{pop}^1 & \dots & x_{pop}^{Dim} \end{bmatrix} \quad (12)$$

Where *pop* denotes the population size and *Dim* is the dimension of the variable. Each candidate solution is randomly generated between the upper bound (*UB*) and the lower bound (*LB*) of the given problem, and the expression of the i_{th} individual X_i is:

$$X_i = rand \times (UB - LB) + LB \quad (13)$$

where i is an integer between 1 and pop and $rand$ denotes a random number between 0 and 1. LB and UB are expressed as:

$$LB = [lb_1, ..., lb_{Dim}] \tag{14}$$

$$UB = [ub_1, ..., ub_{Dim}] \tag{15}$$

During initialization, DO regards the individual with the optimal fitness value as the initial elite, which is approximately considered the most suitable position for the dandelion seed to flourish. Taking the minimum value as an example, the mathematical expression of the initial elite X_{elite} is:

$$f_{best} = \min(f(X_i)) \tag{16}$$

$$X_{elite} = X(find(f_{best} = f(X_i))) \tag{17}$$

Where *find* () denotes two indexes with equal values.

3.2 Rising stage

In the rising stage, dandelion seeds need to reach a certain height before they can float away from their parent. Under the influence of wind speed, air humidity, etc., dandelion seeds rise to different heights. Here, the weather is divided into the following two situations.

Case 1: On a clear day, wind speeds can be regarded to have a lognormal distribution $\ln Y \sim N(\mu, \sigma 2)$. Under this distribution, random numbers are more distributed along the Y -axis, which increases the chance for dandelion seeds to travel to far regions. Therefore, DO emphasizes exploration in this case. In the search space, dandelion seeds are blown randomly to various locations by the wind. The rising height of a dandelion seed is determined by wind speed. The stronger the wind is, the higher the dandelion flies and the farther the seeds scatter. Affected by wind speed, the vortexes above the dandelion seeds are constantly adjusted to make them rise in a spiral form. The corresponding mathematical expression in this case is:

$$X_{t+1} = X_t + \alpha \times v_x \times v_y \times \ln Y \times (X_s - X_t) \tag{18}$$

Where X_t represents the position of the dandelion seed during iteration t. X_s represents the randomly selected position in the search space during iteration t. Eq. (19) provides the expression for the randomly generated position.

$$X_s = rand(1, Dim) * (UB - LB) + LB \tag{19}$$

$\ln Y$ denotes a lognormal distribution subject to $\mu = 0$ and $\sigma 2 = 1$, and its mathematical formula is:

$$\ln Y = \begin{cases} \dfrac{1}{y\sqrt{2\pi}} \exp\left[-\dfrac{1}{2\sigma^2}(\ln y)^2\right] & y \geq 0 \\ 0 & y<0 \end{cases} \tag{20}$$

In Eq. (20), y denotes the standard normal distribution N (0, 1). α is an adaptive parameter used to adjust the search step length, and the mathematical expression is:

$$\alpha = rand() \times (\frac{1}{T^2}t^2 - \frac{2}{T} + 1) \tag{21}$$

α is a random perturbation between [0, 1] in the process of a nonlinear decrease that approaches 0. Such fluctuations make the algorithm pay much attention to the global search in the early stage and turn to a local search in the later stage, which is beneficial to ensure accurate convergence after a full global search. v_x and v_y represent the lift component coefficients of a dandelion due to the separated eddy action. Eq. (22) is utilized to calculate the force on the variable dimension.

$$\begin{aligned} r &= \frac{1}{e^{\theta}} \\ v_x &= r \times \cos\theta \\ v_y &= r \times \sin\theta \end{aligned} \tag{22}$$

where θ is a random number between $[-\pi, \pi]$.

Case 2: On a rainy day, dandelion seeds cannot rise appropriately with the wind because of air resistance, humidity and other factors. In this case, dandelion seeds are exploited in their local neighbourhoods, and the corresponding mathematical expression is:

$$X_{t+1} = X_t \times k \tag{23}$$

where k is used to regulate the local search domain of a dandelion, and Eq. (24) is used to calculate the domain.

$$q = \frac{1}{T^2 - 2T + 1}t^2 - \frac{2}{T^2 - 2T + 1}t + 1 + \frac{1}{T^2 - 2T + 1} \tag{24}$$

Where k=1-*rand*()×q.

In conclusion, the mathematical expression of dandelion seeds in the rising stage is

$$X_{t+1} = \begin{cases} X_t + \alpha \times v_x \times v_y \times \ln Y \times (X_s - X_t) & \text{randn<1.5} \\ X_t \times k & \text{else} \end{cases} \tag{25}$$

Where *randn*() is the random number that follows the standard normal distribution.

Figure 1 shows the behaviour of dandelion seeds flying under different weather conditions. The approximate regeneration locations of dandelion seeds are given in the figure. First, when the weather is clear, dandelion seeds are updated based on randomly selected location information to emphasize the exploration process. The eddy above the seed acts on the moving vector by multiplying the x and y components to correct the direction of the dandelion's movement in a spiral. In the second case, dandelion seeds are exploited in all directions in the local community. The normal distribution of random numbers is used to dynamically control exploitation and exploration. To make the algorithm more global search-oriented, the cut-off point is set to 1.5. This setting makes dandelion seeds traverse the entire search space as much as possible in the first stage to provide the correct direction for the next stage of iterative optimization.

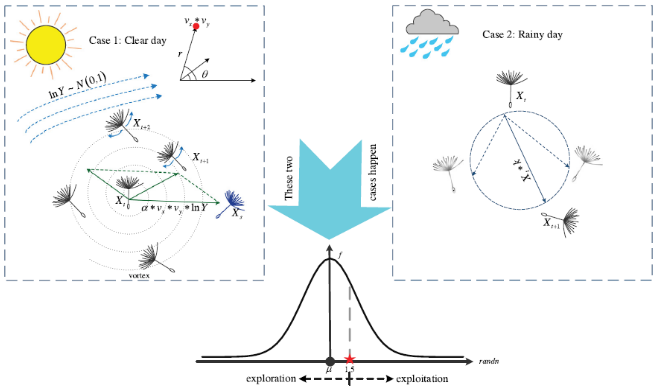

Figure 1: Schematic diagram of the rising stage of dandelion seeds.

3.3 Descending stage

In this stage, the proposed DO algorithm also emphasizes exploration. Dandelion seeds descend steadily after rising to a certain distance. In DO, Brown motion is used to simulate the moving trajectory of dandelions. It is easy for individuals to traverse more search communities in the process of iterative updating because Brownian motion obeys a normal distribution at each change. To reflect the stability of dandelion descent, the average position information after the rising stage is employed. This facilitates the development of the population as a whole towards promising communities. The corresponding mathematical expression is

$$X_{t+1} = X_t - \alpha * \beta_t * (X_{mean\_t} - \alpha * \beta_t * X_t) \tag{26}$$

where β_t denotes Brownian motion and is a random number from the standard normal distribution.

X*mean_t* denotes the average position of the population in the i_{th} iteration, and its mathematical expression is

$$X_{mean\_t} = \frac{1}{pop}\sum_{i=1}^{pop} X_i \tag{27}$$

Figure 2 shows the regeneration process of dandelion seeds during descent. According to this figure, the average position information of the population is essential for the iterative updating of individuals, which directly determines the evolution direction of individuals. The trajectory of Brownian motion, which is based on a global search, is also presented in the figure. The irregular movement causes the search agents to escape the local extremum with a high probability during the iterative update and then pushes the population to seek the region near the global optimum.

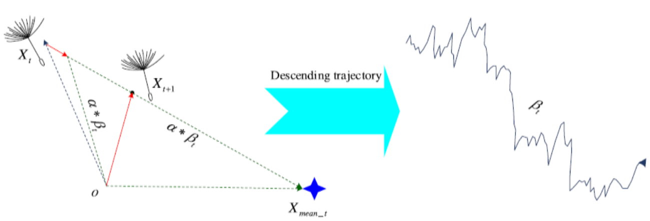

Figure 2: Schematic diagram of the descending stage of dandelion seeds

Figure 3 shows the process of the search agent gradually updating to the global optimal solution in the final phase. To accurately converge to the global optimum, the linear increasing function is applied to individuals to avoid excessive exploitation. In this stage, the Levy flight coefficient is used to simulate the individual movement step size. The reason is that the Levy flight coefficient can be used by agents to stride to other positions with a large probability under a Gaussian distribution, which develops more local search domains with a limited number of iterations.

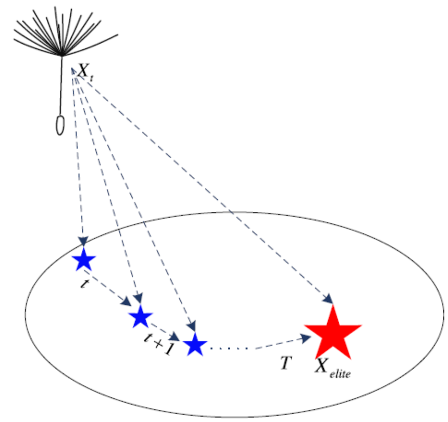

Figure 3: Schematic diagram of the dandelion seed landing stage

3.4 Landing stage

In this part, the DO algorithm focuses on exploitation. Based on the first two stages, the dandelion seed randomly chooses where to land. As the iterations gradually progress, the algorithm will hopefully converge to the global optimal solution. Therefore, the obtained optimal solution is the approximate position where dandelion seeds will most easily survive. To accurately converge to the global optimum, search agents borrow the eminent information of the current elite to exploit in their local neighbourhoods. With the evolution of the population, the global optimal solution can eventually be found. This behaviour is expressed in Eq. (28).

$$X_{t+1} = X_{elite} + levy(\lambda) \times \alpha \times (X_{elite} - X_t \times \delta) \tag{28}$$

where X_{elite} represents the optimal position of the dandelion seed in the i_{th} iteration. *Levy* (λ) represents the function of Levy flight and is calculated using Eq. (29) [13].

$$levy(\lambda) = s \times \frac{\omega \times \sigma}{|t|^{\frac{1}{\beta}}} \tag{29}$$

In Eq. (29), β is a random number between [0, 2] (β = 1.5 in this paper). s is a fixed constant of 0.01. w and t are random numbers between [0, 1]. The mathematical expression of σ is:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{30}$$

where β is fixed at 1.5. δ is a linearly increasing function between [0, 2] and is calculated by Eq. (31).

$$\delta = \frac{2t}{T} \tag{31}$$

4. IMPLEMENTATION OF DO FOR OPTIMAL ALLOCATION OF DG

The flowchart of the optimal allocation and sizing of DG for power loss reduction, voltage deviation minimization and voltage stability improvement, using the DO algorithm, can be summarized in the following steps.

Step 1: Read the bus and branch data of the considered network.
Step 2: Read DG data (DG power limits).
Step 3: Set the parameters of the DO algorithm and the limits of decision variables (locations and sizing of DG).
Step 4: Generate the initial population for the decision variables (DG locations and sizes).
Step 5: Run backwards and forward to sweep power flow, incorporating DG.
Step 6: Compute the active power loss (P_{loss}), voltage deviation (*VD*), and voltage stability index (*VSI*).
Step 7: Compute the objective functions represented by Eq. (1) and Eq. (3).
Step 8: Update the fitness of the objective function.
Step 9: Repeat steps 5–8 until the maximum number of iterations is reached.
Step 10: Print the optimal solution (optimal location and sizing of DG).

5. RESULTS AND DISCUSSIONS

The proposed algorithm is tested on IEEE 33-bus and Algerian 112-bus radial distribution networks taking into account the following cases.

- **Case 1**: in this case, a single objective function of minimizing active power loss (P_{loss}) is considered.
- **Case 2**: in this case, a multi-objectives function is considered. This function includes the minimization of active power loss (P_{loss}), the minimization of voltage deviation (*VD*) and the enhancement of voltage stability (*VSI*).

The setting parameters of DO have been taken as follows: Population size=50, the maximum number of iterations=200. While the generated power from the DG units is in the range [0 3] MW.

5.1 Test system 1: IEEE 33-bus system

The IEEE 33-bus test system consists of 33 buses, and 32 branches along with a total load of 3.72 MW and 2.30 MVAr. The substation voltage is 12.66 kV. The single-line diagram of the IEEE 33-bus system is shown in Figure 4 and the overall data of this system is available in [14].

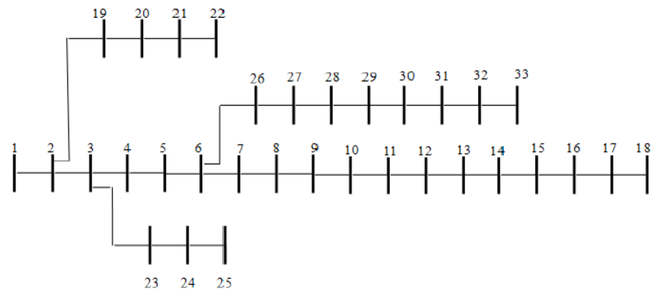

Figure 4: Single-line diagram of the IEEE 33-bus system

A. Case 1: Active power loss minimization

The performance of the DO algorithm is tested, firstly, for active power loss minimization.
Figure 5 shows the convergence track of the DO algorithm. The convergence of the DO algorithm occurs on the first iterations, showing the algorithm's ability to explore the search space quickly.
Figure 6 shows how the voltage profile was improved in the IEEE 33-bus system after DG units integration at buses 14, 24 and 30. Table 1 shows the best solutions obtained by DO, algorithm and the comparison with other optimization techniques in the literature. From these tables, it can be seen that the proposed algorithm has greatly reduced the real power loss and improved the voltage deviation and voltage stability of the distribution network. Moreover, this algorithm has shown high performance compared to competitive optimization algorithms in the literature.

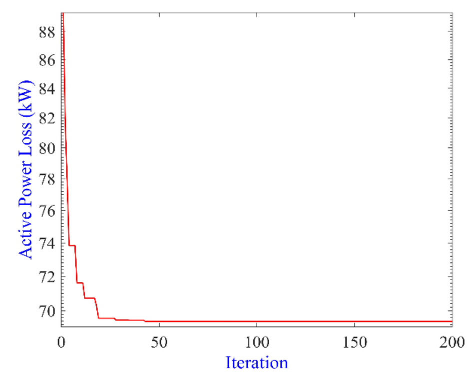

Figure 5: DO convergence characteristic for 33-bus system (Case 1)

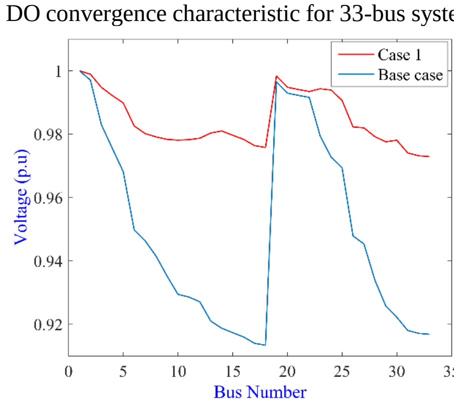

Figure 6: Voltage profile of 33-bus system (Case 1)

Table 1: Results for installing DGs in the 33-bus system (Case 1)

Algorithm	P_L without DG (kW)	With DGs Bus no.	DG size (kW)	P_L (kW)	P_L reduction (%)
DO	201.8925	14	759.08	69.3833	65.6335
		24	1071.1		
		30	1099.9		
QOGWO [15]	210.98	14	801.81	72.784	65.5019
		24	1091.29		
		30	1053.01		
QOCSOS [16]	210.99	13	801.7	72.7869	65.5000
		24	1091.3		
		30	1053.7		
	210.98	13	801.8	72.785	65.5000
OTCDE [17]		24	1091.31		
		30	1053.6		
	210.98	13	802	72.785	65.50
CMSFS [18]		24	1091		
		30	1054		
MRFO [19]	210.98	13	788.27	72.876	65.4583
		24	1017.1		
		30	1035.3		
CBGA-VSA [20]	210.98	13	801.8	72.785	65.50
		24	1091.3		
		30	1053.6		
HHO [21]	210.98	14	745.69	72.98	65.40
		24	1022.69		
		30	1135.78		
IHHO [21]	210.98	14	757.54	72.79	65.50
		24	1080.83		
		30	1066.69		
DA [22]	201.89	14	760	69.3833	65.6335
		24	1070		
		30	1100		
CSCA [23]	202.68	13	871.00	71.94	64.5056
		24	1091.47		
		30	954.08		
CTLBO [24]	210.99	13	801.7	72.79	65.5007
		24	1091.3		
		30	1053.6		
SFSA [12]	210.988	13	802.0	72.785	65.50
		24	1092.0		
		30	1053.7		

B. Case 2: Multi-objective function

In this sub-section, the proposed DO algorithm was employed to site three DG units in the IEEE 33-bus system, aiming to minimize the active power loss and voltage deviation and to improve voltage stability.

The convergence characteristic of the DO algorithm for the best solution found is given in Figure 7.

The voltage profiles of the IEEE 33-bus test system with and without DG are given in Figure 8. In comparison to the base case, the voltage profile with DG units has significantly improved.

As can be seen from Table 2, the active power losses and the voltage deviation were severely reduced by proper DG allocation. It can be seen also that the voltage stability was improved. The results shown in this case reveal that the DO algorithm is effective in site DG units in distribution networks, finding better solutions and presenting lower losses, lower voltage deviation as well as higher voltage stability index when compared to the other metaheuristics.

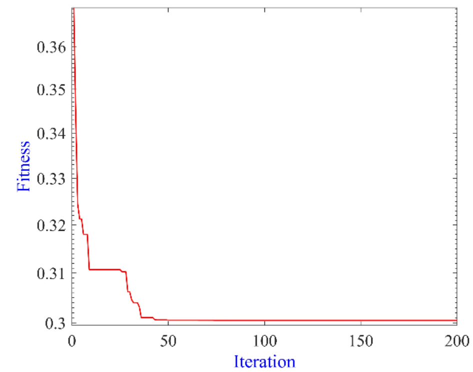

Figure 7: DO convergence characteristic for 33-bus system (Case 2)

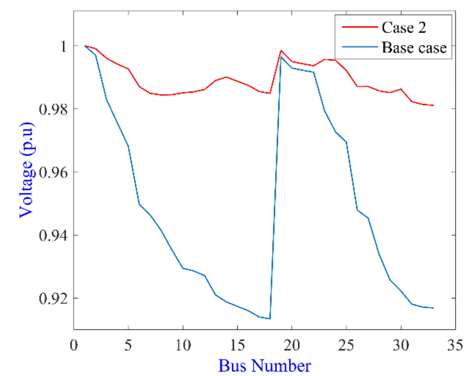

Figure 8: Voltage profile of 33-bus system (Case 2)

5.2 Test system 1: Algerian 112-bus system

The Algerian 112-bus radial distribution system, shown in Figure 9, has a total active load of 3.36 MW and, a total reactive load of 3.72 MVAr. The rest of the system data is available in [25].

A. Case 1: Active power loss minimization

In this sub-section, the effectiveness of the proposed DO for solving optimal allocation of DG problem considering active power loss minimization is demonstrated.

The convergence characteristic for the best fitness obtained after applying DO is shown in Figure 10.

Table 2: Results for installing DGs in the 33-bus system (Case 2)

Algorithm	Without DG P_L (kW)	*VD* (p.u.)	*VSI*	With DG Bus no.	Size(kW)	P_L (kW)	P_L reduction (%)	*VD* (p.u.)	*VSI*
DO	201.89	0.1164	0.69	14	879.4796	71.7686	64.4521	0.0047	0.93
				24	1096.7				
				30	1281.0				
QOCSOS [16]	210.99	0.1338	0.67	13	956.4	77.0414	63.4857	0.0065	0.91
				24	1030.9				
				30	1293.5				
SCA [23]	202.68	0.1337	0.67	13	1247.61	89.92	55.6344	0.0023	0.95

				25	1061.68				
				32	1023.50				
CSCA [23]	202.68	0.1373	0.67	13	1098.02	88.43	56.3796	0.0016	0.96
				24	986.57				
				30	1584.90				
SFSA [12]	210.98	0.1338	0.67	13	964.7	77.41	63.31	0.0062	0.92
				24	1133.7				
				30	1301.8				
CTLBO [24]	210.99	-	0.67	13	1192.6	96.17	54.41	0.0009	0.96
				25	870.6				
				30	1629.6				

An enhanced voltage profile is obtained with DG integration in the Algerian network, as shown in Figure 11.

The final results of real power losses and the optimal allocation of DGs obtained by the DO algorithm are shown in Table 3. The best objective function value of 43.6717 kW is obtained via the integration of DGs at buses 15, 24, and 94 with sizes in kW, 1533.9, 1129.4 and 488.7845.

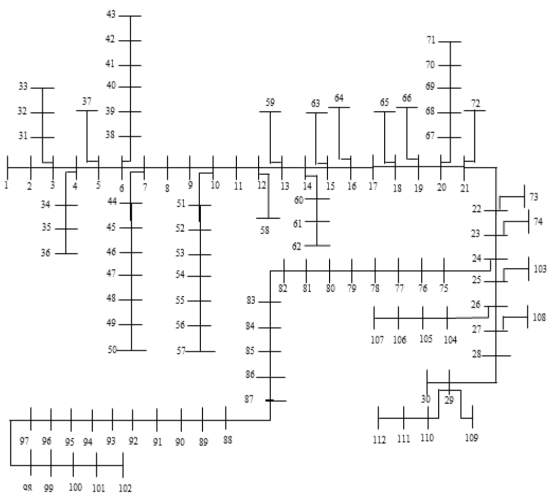

Figure 9: Single-line diagram of the Algerian 112-bus system

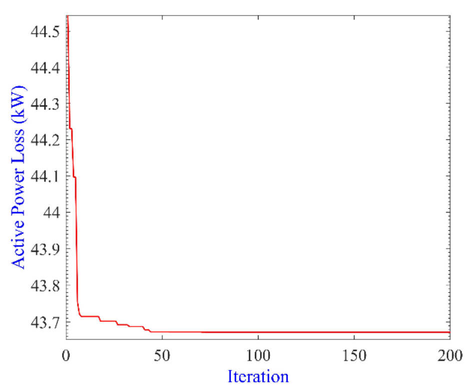

Figure 10: DO convergence characteristic for 112-bus system (Case 1)

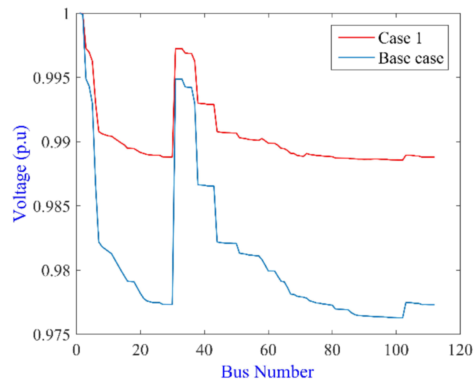

Figure 11: Voltage profile of 112-bus system (Case 1)

Table 3: The best solution obtained by the DO algorithm for the 112-bus system (Case 1)

P_L without DG (kW)	With DGs			
	Bus no.	DG size (kW)	P_L (kW)	P_L reduction (%)
77.9423	15	1533.9	43.6717	43.9708
	24	1129.4		
	94	488.7845		

B. Case 2: Multi-objective function

In this case, the DO algorithm is applied to optimize the multi-objective function of active power loss, voltage deviation plus voltage stability index via optimally simultaneous allocation of three DGs in the system.

Figure 12 shows the convergence curve for the objective function over the iterations of the DO algorithm.

The voltage profiles of the test system in the base case and with DGs are given in Figure 13. It is clear that the voltage profile of the Algerian network is improved when DGs are installed.

The power loss reduction, the percentage power loss reduction, the voltage deviation and the minimum voltage stability index are presented in Table 4.

As shown in this table, the best locations for DGs units installation are buses 15, 75 and 94, and the best sizes in kW are 1829.9, 1420.0 and 624.5237, respectively.

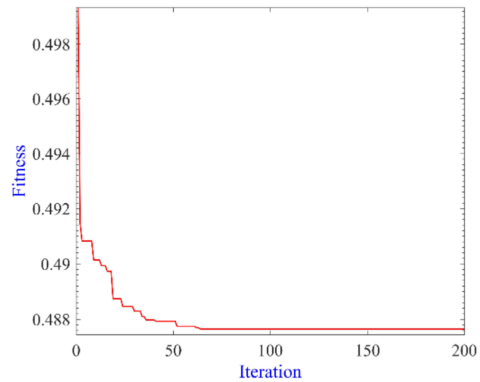

Figure 12: DO convergence characteristic for 112-bus system (Case 2)

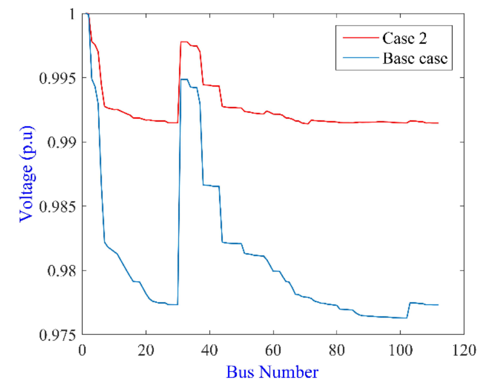

Figure 13: Voltage profile of 112-bus system (Case 2)

Table 3: The best solution obtained by the DO algorithm for the 112-bus system (Case 2)

Without DG			With DG					
P_L (kW)	*VD* (p.u.)	*VSI*	Bus no.	Size (kW)	P_L (kW)	P_L reduction (%)	*VD* (p.u.)	*VSI*
77.9423	0.1164	0.69	15 75 94	1829.9 1420.0 624.5237	45.4798	41.6511	0.0065	0.96

6. CONCLUSION

In this paper, optimal allocation and sizing of DGs are determined in a radial distribution network through Dandelion Optimizer (DO) to achieve the benefits of power loss reduction along with improvement of bus voltage profile and voltage stability. The DO algorithm is tested with the optimal location and sizing of three DGs in IEEE 33-bus and Algerian 112-bus systems. A comparative study has been carried out to evaluate the performance of the DO algorithm among other algorithms in the literature. The obtained results reveal that the DO algorithm outperforms other existing methods such as SCA, HHO, DA, QOGWO, CTLBO and SFSA.

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