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ORIGINAL PAPER

Optimal allocation and sizing of renewable distributed generation using ant lion optimization algorithm

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Abstract Renewable sources can provide a clean and smart solution to the increased demands. Thus, photovoltaic and wind turbine are considered here as sources of distributed generation (DG). Allocation and sizing of DG have greatly affected the system losses. In this paper, ant lion optimization algorithm (ALOA) is proposed for optimal allocation and sizing of DG-based renewable sources for radial distribution system. First, the most candidate buses for installing DG are suggested using loss sensitivity factors. Then the proposed ALOA is employed to deduce the locations of DG and their sizing from the elected buses. The proposed algorithm is tested on 69 bus radial distribution system. The obtained results via the proposed algorithm are compared with others to highlight its benefits in reducing total power losses and consequently maximizing the net saving. Moreover, the results are introduced to verify the superiority of the proposed algorithm to enhance the voltage profiles for various loading conditions.

Keywords Distributed generation · Renewable energy · Loss reduction · Voltage profiles · ALOA · LSFs

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List of symbols

P_k, Q_k	The total effective active and reactive power supplied behind the bus ‘k’
V_k	The magnitude of voltage at bus k
R_{ik}, X_{ik}	The resistance and reactance of transmission line between bus ‘i’ and ‘k’
V_i	The magnitude of voltage at bus i
K_P	The cost per kW-Hours
n	The maximum number of ants
$r(t)$	A stochastic function
t	The step of random walk (current iteration in this paper)
M_{ant}	The matrix for saving the position of each ant
$\text{Ant}_{i,j}$	The value of the jth variable of ith ant
d	The number of variables
M_{oa}	The matrix for saving the fitness of each ant
$M_{\text{ant lion}}$	The matrix for saving the position of each ant lion
$\text{Ant lion}_{i,j}$	The value of the jth variable of ith ant lion
M_{oal}	The matrix for saving the fitness of each ant lion
A_i	The minimum of random walk of ith variable
C_i^t	The minimum of ith variable at tth iteration
C^t	The minimum of all variables at tth iteration
C_j^t	The minimum of all variables for ith ant
D_i^t	The maximum of ith variable at tth iteration
D^t	The vector including the maximum of all variables at tth iteration
D_j^t	The maximum of all variables for ith ant
Ant lion_j^t	The position of the selected jth ant lion at tth iteration
I	This ratio equals to $10^w \frac{t}{T}$
T	The maximum number of iterations
w	To adjust the accuracy level of exploitation

r_a^t	The random walk around the ant lion selected by the roulette wheel at tth iteration
r_e^t	The random walk around the elite at tth iteration
Ant_i^t	The position of ith ant at tth iteration
P_{Loss}	The total power losses after compensation
F_t	The total objective function
f_1	The part of F_t that express the minimization of power losses
f_2	The part of F_t that express the enhancement of voltage profiles
f_3	The part of F_t that express the improvement of VSI
w_1, w_2, w_3	The weighting factors
P_{Swing}	The active power of swing bus
Q_{Swing}	The reactive power of swing bus
L	The number of transmission line in a distribution system
$Pd(q)$	The demand of active power at bus q
$Qd(q)$	The demand of reactive power at bus q
N	The number of total buses
$V_{\min}$	The minimum voltage at bus i
$V_{\max}$	The maximum voltage at bus i
P_{DG}	The installed active power of the DG
Q_{DG}	The installed reactive power of the DG
N_{DG}	The number of installed unit of the DG
$P_{\mathrm{DG}}^{\min}$, $P_{\mathrm{DG}}^{\max}$	The minimum and maximum real outputs of the DG unit
$Q_{\mathrm{DG}}^{\min}$, $Q_{\mathrm{DG}}^{\max}$	The minimum and maximum reactive outputs of the DG unit
S_{Li}	The actual complex power in line i
$S_{\mathrm{Li(rated)}}$	The rated complex power in that line i

Abbreviations

ALOA	Ant lion optimization algorithm
DG	Distributed generation
LSFs	Loss sensitivity factors
PV	Photovoltaic system
WT	Wind turbine
GA	Genetic algorithm
PSO	Particle swarm optimization
PGSA	Plant growth simulation algorithm
CSA	Cuckoo search algorithm
ABC	Artificial bee colony
ACO	Ant colony optimization
FA	Firefly algorithm
MINLP	Mixed integer non-linear programming
HS	Harmony search
ICA	Imperialist competitive algorithm
BF	Bacteria foraging
VSI	Voltage Stability Index
MTLBO	Modified teaching learning-based optimization
BB–BC	Big Bang–Big Crunch
SGA	Standard genetic algorithm
NR	Not reported

1 Introduction

In recent years, the attention has shifted to projections of energy and related greenhouse gas emissions as a result of increasing environmental concern and global warming [1–3]. Renewable distribution generation (DG) such as wind turbine (WT) and photovoltaic (PV) systems presents a cleaner power production. The main advantages of DG are reduced line losses, increased efficiency, improved system reliability and minimized total costs [4–6].

The problem of DG placements and sizing was solved using various techniques. The authors in [7] used ant colony algorithm (ACA) with harmony search (HS) to solve the network reconfiguration problem. A cat swarm optimization is introduced in [8] for optimal location and sizing of DG units. Two ways to reach integration of multiple DG units in low- and medium-voltage distribution networks while optimizing many relevant objectives are discussed in [9]. Genetic algorithm (GA) combined with fuzzy programming to design multi-objective function for optimal sizing and siting of multiple DGs is illustrated in [10]. Mixed integer non-linear programming (MINLP) is introduced in [11] for multi-objective design to reduce both cost and losses effectively by optimal selection of DG size and location. GA is presented in [12] to determine the optimal size and locations of DGs taking into account system constraints; maximizes system loading margin and voltage profiles. In [13], GA and fuzzy are employed to transform original objectives and constraints into a fuzzy weighted single objective function to optimize DGs. Monte Carlo simulation embedded GA-based approach is displayed in [14] to minimize the DG cost, network loss cost, and capacity cost by optimally siting and sizing of DGs. A combination of GA and particle swarm optimization (PSO) for optimal sizing and siting of DG unit is addressed in [15]. PSO is presented in [16] for determining optimal DG locations, sizes and generated power contract price. Bacterial foraging optimization algorithm for optimal placement and sizing of distributed generation is illustrated in [17]. Firefly algorithm (FA) for optimal sizing and siting of voltage-controlled distributed generators in distribution system to reduce losses is considered in [18,19]. A multi-objective optimization for sizing of DG using cuckoo search algorithm is discussed in [20]. Artificial bee colony (ABC) algorithm is employed in [21] to determine the optimal DG unit's size, power factor and location to minimize the total system real power loss. Differential evolution (DE) is employed in [22,23] to determine optimal DG capacity for minimum power losses. An effective method based on evolutionary programming (EP) and GA is presented in [24] to identify the switching operation plan for feeder reconfiguration and distributed generation size simultaneously. An imperialist competition algorithm (ICA) to maximize the benefits of distribution network, improve voltage stability and reduce costs is discussed in [25,26]. Plant growth simulation algorithm (PGSA) is illustrated in [27,28] for loss reduction and voltage profile improvement in distribution systems.

A new optimization algorithm known as ant lion optimization algorithm (ALOA) has been presented by Mirjalili [29]. It proves its superiority in many fields which are shown in [30–33]. ALOA optimizes DG in distribution system has not been considered yet. This encourages us to develop ALOA to deal with this problem. It is used to determine the optimal locations and sizing of DG in radial distribution systems. The results of the ALOA are compared with various techniques to detect its superiority in solving the problem of optimal locations and sizing of DG and thus reducing the active power losses and mitigating the voltage profiles for various loading conditions.

2 Loss sensitivity factors

LSFs are employed in this paper to assign the candidate buses for DG installation [34]. The area of search is greatly reduced and consequently the time consumed in optimization process using LSFs. A transmission line 'l' connected between 'i' and 'k' buses is given in Fig. 1:

The active power loss in this line is specified by $I_l^2 R_{ik}$, which can be given by,

$$P_{ik\text{-loss}} = \frac{(P_k^2 + Q_k^2) R_{ik}}{(V_k)^2} \tag{1}$$

The LSFs can be computed from the following equation:

$$\frac{\partial P_{ik\text{-loss}}}{\partial Q_k} = \frac{2 Q_k * R_{ik}}{(V_k)^2} \tag{2}$$

The normalized voltages are obtained by dividing the base case voltages by 0.95 [35]. If the values of these voltages are less than 1.01, they can be considered as candidate buses for installing DG.

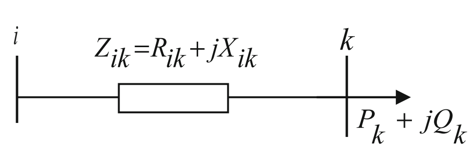


Fig. 1 Radial distribution system equivalent circuit

3 Overview of ant lion optimization algorithm

Ant lion optimizer (ALO) is a novel nature-inspired algorithm presented by Mirjalili in [29]. The ALO mimics the hunting mechanism of ant lions in nature. An ant lion larva digs a cone-shaped pit in sand by moving along a circular path and throwing out sands with its massive jaw [36–38]. After digging the trap, the larva hides underneath the bottom of the cone and waits for insects to be trapped in the pit [39,40]. The edge of the cone is sharp enough for insects to fall to the bottom of the trap easily. Once the ant lion realizes that a prey is in the trap, it tries to catch it. Then, it is pulled under the soil and consumed. After consuming the prey, ant lions throw the leftovers outside the pit and prepare the pit for the next hunt [30]. The pseudo code of the ALO algorithm is shown in appendix.

3.1 Operators of the ALO algorithm

The ALO algorithm mimics the interaction between ant lions and ants in the trap. To model such interactions, ants are required to move over the search space and ant lions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk is chosen for modeling ants' movement as follows:

$$X(t) = [0, \text{cums}(2r(t_1) - 1), \ldots, \text{cums}(2r(t_n) - 1)] \tag{3}$$

where cums calculates the cumulative sum and $r(t)$ is defined as follows:

$$r(t) = \begin{Bmatrix} 1 \text{ if rand} > 0.5 \\ 0 \text{ if rand} \leq 0.5 \end{Bmatrix} \tag{4}$$

The location of ants are stored and used during optimization process in the following matrix:

$$M_{\text{ant}} = \begin{bmatrix} \text{ant}_{1,1} & \text{ant}_{1,2} & \ldots & \text{ant}_{1,d} \\ \text{ant}_{2,1} & \text{ant}_{2,2} & \ldots & \text{ant}_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \text{ant}_{n,1} & \text{ant}_{n,2} & \ldots & \text{ant}_{n,d} \end{bmatrix} \tag{5}$$

The location of an ant refers the parameter for each solution. Matrix M_{ant} is considered to save the position of each ant. The objective function is employed during optimization and the following matrix saves the fitness value for each ant:

$$M_{\text{oa}} = \begin{bmatrix} F_t([\text{ant}_{1,1}, \text{ant}_{1,2}, \ldots \text{ant}_{1,d}]) \\ F_t([\text{ant}_{2,1}, \text{ant}_{2,2}, \ldots \text{ant}_{2,d}]) \\ \vdots \\ F_t([\text{ant}_{n,1}, \text{ant}_{n,2}, \ldots \text{ant}_{n,d}]) \end{bmatrix} \tag{6}$$

In addition, the ant lions are hiding in the search space. The followings matrices are used to save their locations.

$$M_{\text{ant lion}} = \begin{bmatrix} \text{ant lion}_{1,1} & \text{ant lion}_{1,2} & \ldots & \text{ant lion}_{1,d} \\ \text{ant lion}_{2,1} & \text{ant lion}_{2,2} & \ldots & \text{ant lion}_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \text{ant lion}_{n,1} & \text{ant lion}_{n,2} & \ldots & \text{ant lion}_{n,d} \end{bmatrix} \tag{7}$$

$$M_{\text{oal}} = \begin{bmatrix} F_t([\text{ant lion}_{1,1}, \text{ant lion}_{1,2}, \ldots \text{ant lion}_{1,d}]) \\ F_t([\text{ant lion}_{2,1}, \text{ant lion}_{2,2}, \ldots \text{ant lion}_{2,d}]) \\ \vdots \\ F_t([\text{ant lion}_{n,1}, \text{ant lion}_{n,2}, \ldots \text{ant lion}_{n,d}]) \end{bmatrix} \tag{8}$$

3.1.1 Random walks of ants

Ants change their positions randomly based on Eq. (3). To keep the random walks inside the search space, they are normalized using the following equation:

$$X_i^t = \frac{(X_i^t - A_i) \times (D_i - C_i^t)}{(D_i^t - A_i)} + C_i \tag{9}$$

3.1.2 Trapping in ant lion's pits

Random walks of ants are affected by ant lions' traps. To model this supposition, the following equations are introduced:

$$C_i^t = \text{Ant lion}_j^t + C^t \tag{10}$$

$$D_i^t = \text{Ant lion}_j^t + D^t \tag{11}$$

Equations (10, 11) give that ants walk randomly in a hypersphere defined by the vectors C and D around a selected ant lion.

3.1.3 Building trap

A roulette wheel is used to model the ant lion's hunting ability. The ALO algorithm is required to employ a roulette wheel operator for selecting ant lions based of their fitness during iterations. This mechanism shows high chances to the best ant lions for catching ants.

3.1.4 Sliding ants towards ant lion

With the previous mechanisms, ant lions can build traps relative to their fitness and ants are required to move randomly. However, ant lions shoot sands outwards the center of the pit once they sense that an ant is in the trap. This behavior slides down the trapped ant that is trying to escape. To model this behavior, the radius of ant's random walk hyper-sphere is decreased adaptively. The following equations are presented in this regard:

$$c^t = \frac{c^t}{I} \tag{12}$$

$$d^t = \frac{d^t}{I} \tag{13}$$

3.1.5 Catching prey and re-building the pit

In this step, the objective function is calculated. If the ant has a better objective function than the selected ant lion then it changes its position to the latest position of the hunted ant to improve its chance of catching new one. The following equation is illustrated in this regard:

$$\text{Ant lion}_j^t = \text{Ant lion}_i^t \quad \text{if } f(\text{Ant}_i^t) > f(\text{Ant lion}_j^t) \tag{14}$$

3.1.6 Elitism

It is important to maintain the best solution acquired at each step of optimization task. The best ant lion achieved so far in each iteration is saved as the elite. Since the elite is the best ant lion, it should be capable to affect the motions of all ants during iterations. Thus, it is assumed that every ant randomly walks around a selected ant lion by the roulette wheel and the elite simultaneously as follows:

$$\text{Ant}_i^t = \frac{r_a^t + r_e^t}{2} \tag{15}$$

4 Objective function

The proposed objective function is used to reduce the power losses and to improve the voltage profiles and Voltage Stability Index. The DG locations and their sizing can be obtained optimally by solving the following objective function [15,41]:

$$F_t = w_1 f_1 + w_2 f_2 + w_3 f_3 \tag{16}$$

where f_1 can be expressed as shown in the following equation:

$$f_1 = \frac{\sum_{i=1}^{L} (P_{\text{Lineloss}}(i))_{\text{after DG}}}{\sum_{i=1}^{L} (P_{\text{Lineloss}}(i))_{\text{before DG}}} \tag{17}$$

f_2 can be defined as the following equation:

$$f_2 = \frac{\sum_{i=1}^{N} \left|V_i - V_{i,\text{ref}}\right|_{\text{after DG}}}{\sum_{i=1}^{N} \left|V_i - V_{i,\text{ref}}\right|_{\text{before DG}}} \quad (18)$$

f_3 can be defined as:

$$f_3 = \frac{1}{\text{VSI}(k)_{\text{after DG}}} \quad (19)$$

where VSI is formulated as the following Eq. [15,42]:

$$\text{VSI}(k) = |V_i|^4 – 4(P_k X_{ik} - Q_k R_{ik})^2 – 4(P_k R_{ik} + Q_k X_{ik})\,|V_i|^2 \quad (20)$$

w_1, w_2 and w_3 are weighting factors. The sum of the absolute values of the weights assigned to all impacts should add up to one as shown in the following equation:

$$|w_1| + |w_2| + |w_3| = 1 \quad (21)$$

In this paper, w_1 is taken as 0.5 while w_2 and w_3 are taken as 0.25.

4.1 Equality and inequality constraints

Equation (16) is minimized whilst satisfying the following equality and inequality constraints.

4.1.1 Equality constraint

- **Power conservation constraint**

The algebraic sum of all incoming and outgoing power flow over the distribution system should be equal [43]; thus,

$$P_{\text{Swing}} + \sum_{i=1}^{N_{\text{DG}}} P_{\text{DG}}(i) = \sum_{i=1}^{L} P_{\text{Lineloss}}(i) + \sum_{q=1}^{N} Pd(q) \quad (22)$$

$$Q_{\text{Swing}} + \sum_{i=1}^{N_{\text{DG}}} Q_{\text{DG}}(i) = \sum_{i=1}^{L} Q_{\text{Lineloss}}(i) + \sum_{q=1}^{N} Qd(q) \quad (23)$$

4.1.2 Inequality constraints

- **Voltage constraint**

The magnitude of voltage at each bus must be limited by the following equation:

$$V_{\min} \le |V_i| \le V_{\max} \quad (24)$$

where $V_{\min}$ and $V_{\max}$ are taken as 0.95 and 1.05 p.u, respectively, as given in [44].

- **DG limits constraint**

To prevent reverse power flow, the installed capacity of DG in the network has been limited so as not to exceed the power supplied by the substation [43].

$$\sum_{i=1}^{N_{\text{DG}}} P_{\text{DG}}(i) \le \frac{3}{4} \times \left[\sum_{i=1}^{L} P_{\text{Lineloss}}(i) + \sum_{q=1}^{N} Pd(q)\right] \quad (25)$$

$$\sum_{i=1}^{N_{\text{DG}}} Q_{\text{DG}}(i) \le \frac{3}{4} \times \left[\sum_{i=1}^{L} Q_{\text{Lineloss}}(i) + \sum_{q=1}^{N} Qd(q)\right] \quad (26)$$

$$P_{\text{DG}}^{\min} \le P_{\text{DG}}(i) \le P_{\text{DG}}^{\max} \quad (27)$$

$$Q_{\text{DG}}^{\min} \le Q_{\text{DG}}(i) \le Q_{\text{DG}}^{\max} \quad (28)$$

- **Line capacity constraint**

The complex power through any line must be less than its rating value as given by the following equation.

$$S_{\text{Li}} \le S_{\text{Li(rated)}} \quad (29)$$

5 Results and discussion

The effectiveness of the proposed ALOA with LSFs is examined. The results of 69 bus radial distribution systems are given below in details. The proposed algorithm has been performed via Matlab.

5.1 69 bus test system

The suggested algorithm is applied on the 69 bus system. Figure 2 shows the system diagram which consists of main

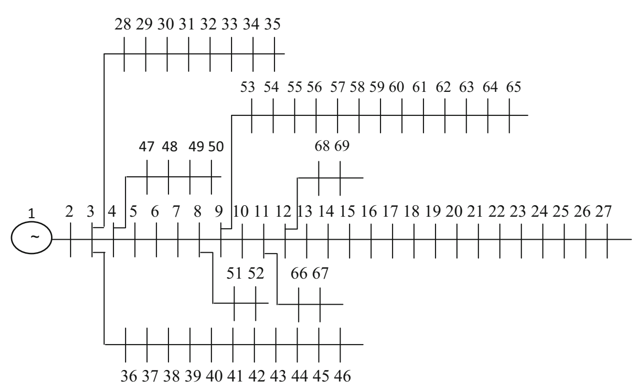


Fig. 2 The line diagram of the 69 bus system

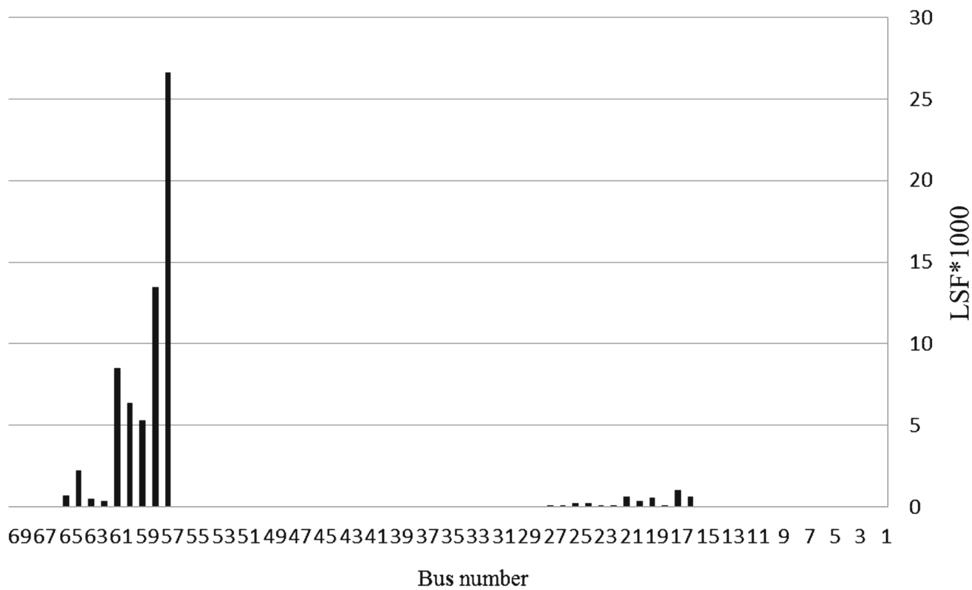


Fig. 3 The values of LSFs for 69 bus system

Table 1 Results for 69 bus system

Items	Without-DG	With DG (kVA/P.F)			
		One DG		Two DG	
		PV	WT	PV	WT
Total losses (kW)	224.94	81.776	23.1622	70.750	20.9342
Loss reduction (%)	–	63.645	89.703	68.547	90.69
Minimum voltage	0.9102	0.9679 @bus 27	0.9716 @bus 27	0.9801 @bus 65	0.9742 @bus 65
Maximum voltage	1.00	1.0 @bus 2	1.0 @bus 2	1.0000 @ bus 2	1.0001 @bus 17
Total DG	–	1800/1 @bus 61	2227.9/0.82 @bus 61	538.777/1 @bus 17	726.627/0.83 @bus 17
				1700/1 @bus 61	1500/0.8 @bus 61
VSI	61.2379	64.4323	65.3523	65.8042	66.2031
Cost of losses ($)	118,228.46	42,981.46	12,174.05	37,186.2	11,003.02
Saving ($/year)	–	75,247	106,054.41	81,042.26	107,225.44

feeders and seven branches. This system has a total load of 3800 kW and 2690 kVAr at 12.6 kV. The system data are given in [45]. The order of candidate buses for this system according to their LSF values is 57, 58, 61, 60, 59, 64, 17, 65, 16, 21, 19, 63, 20, 62, 25, 24, 23, 26, 27, 18 and 22 as appeared in Fig. 3. The superiority of the proposed technique to solve the problem of optimal location and sizing of DG compared with those obtained in [21,43,46–53] is confirmed.

Single DG location

For single DG installation, the optimal location and size are obtained via ALOA. Table 1 summarizes the developed results for installing single and two DGs. Bus number 61 is the best location for DG installation with a size of 1800 kW for PV type. A reduction in the total active power losses to 81.776 kW is resulted which illustrates a 63.645% reduction. The annual energy saving is 75,247$ via the proposed ALOA. The minimum voltage is grown from 0.9102 p.u to 0.9679 p.u. In addition, compared with [21,43,46,48–52] and [53], the proposed algorithm introduces better results in terms of power losses and percentage reduction of power as displayed in Table 2. Moreover, the effects of DG installation on voltage profiles and VSI are given in Figs. 4 and 5, respectively. With WT type, the power losses are constringed to 23.1622 kW with percentage reduction of 89.703. The annual energy saving is 106,054.41$ via the proposed ALOA. The minimum voltage is increased to 0.9716 p.u. Thus, the proposed algorithm outlasts GA, CSA, SGA, PSO and BB–BC in minimizing losses and consequently improving saving. In addition, the designed WT type shows better results than PV type in terms of voltage profiles and VSI as clarified in Figs. 4 and 5.

Two DG locations

For two DG installation, the optimal location and size are gained using ALOA as given in Table 1. For PV type, bus numbers 17 and 61 are the best locations for DG installation with size of 538.777 and 1700 kW, respectively. The power

Table 2 Results for installing one DG in 69 bus system

DG Type	Technique	DG installation		Power loss	
		Size (kVA/P.F)	Bus	Value (kW)	Percentage
–	Without	–	–	224.94	–
PV	ABC [21]	1900/1	61	83.31	62.96
	GA [43]	1872/1	61	83.18	63.02
	Analytical [46]	1810/1	61	81.44	63.79
	Analytical [48]	1807.8/1	61	92	59.1
	Grid search [48]	1876.1/1	61	83	63.1
	GA [49]	1794/1	61	83.4252	62.91
	PSO [50]	1337.8/1	61	83.206	63.01
	CSA [51]	2000/1	61	83.8	62.74
	SGA [51]	2300/1	61	89.4	60.3
	PSO [51]	2000/1	61	83.8	62.75
	MTLBO [52]	1819.691/1	61	83.323	62.95
	BB-BC [53]	1872.5	61	83.2246	63
	Proposed	1800/1	61	81.776	63.645
WT	GA [43]	2155.6/NR	61	38.458	82.9
	CSA [51]	2300 /NR	61	52.6	76.6
	SGA [51]	2600/NR	61	64.4	71.37
	PSO [51]	2300/NR	61	52.6	76.6
	BB-BC [52]	2223/0.81	61	23.1737	89.697
	Proposed	2227.9/0.82	61	23.1622	89.703

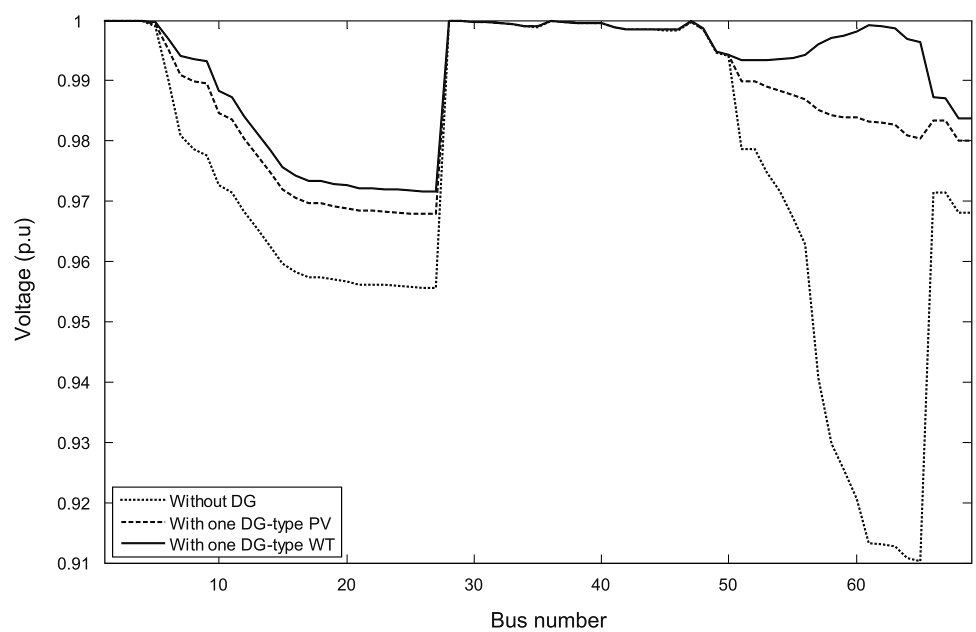


Fig. 4 The effect of installing one DG on voltages of 69 bus system

losses are decreased to 70.75 kW with percentage reduction of 68.547. The annual energy saving is 81,042.26$ via the proposed algorithm. The minimum voltage is modified from 0.9102 p.u to 0.9801 p.u. In addition, compared with [47,49,51,52], the proposed algorithm gives better results in terms of power losses and percentage reduction of power as reported in Table 3. Moreover, the effects of DG installation on voltage profiles and VSI are displayed in Figs. 6 and 7, respectively. With WT type, the power losses are lowered to 20.9342 kW providing a 90.69% reduction in total power losses. The annual energy saving is 107,225.44$ via the proposed ALOA. Thus, the proposed algorithm outperforms CSA, SGA and PSO in diminishing losses and enhancing saving. The minimum voltage is grown to 0.9742 p.u. In

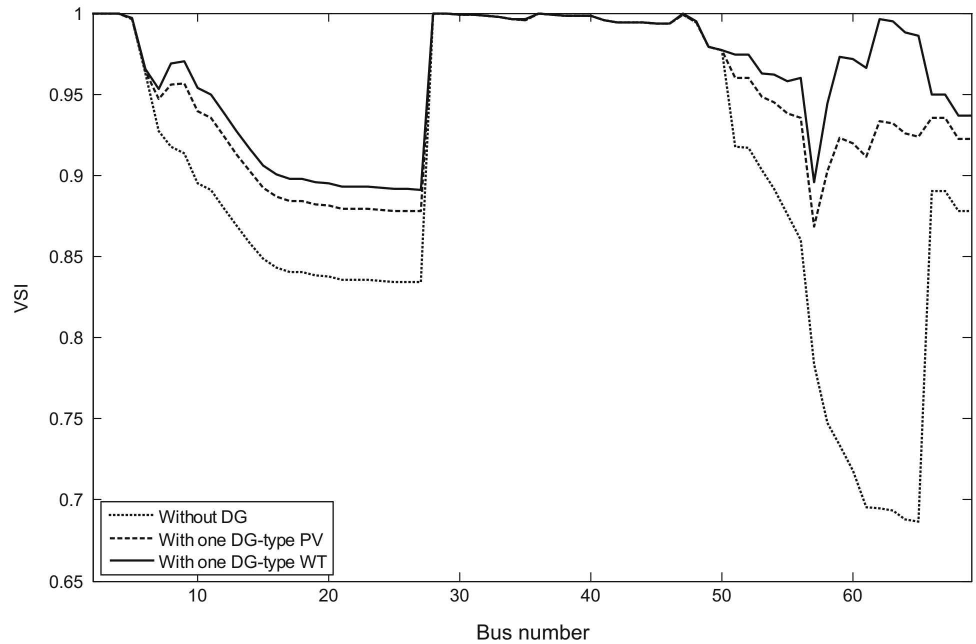


Fig. 5 The effect of installing one DG on VSI of 69 bus system

Table 3 Results for installing two DG in 69 bus system

DG type	Technique	DG installation		Power loss	
		Size (kVA/P.F)	Bus	Value (kW)	Percentage
–	Without	–	–	224.94	–
PV	GA [47]	1777/1	61	71.7912	68.08
		555/1	11		
	GA [49]	6/1	1	84.233	62.55
		1794/1	62		
	CSA [51]	600/1	22	76.4	66
		2100/1	61		
	SGA [51]	1000/1	17	82.9	63.1
		2400/1	61		
	PSO [51]	700/1	14	78.8	64.97
		2100/1	62		
	MTLBO [52]	519.705/1	17	71.776	68.09
		1732.004/1	61		
	Proposed	538.777 /1	17	70.750	68.547
		1700 /1	61		
WT	CSA [51]	800 /NR	18	39.9	82.26
		2000/NR	61		
	SGA [51]	600/NR	18	44	80.4
		2300/NR	62		
	PSO [51]	900/NR	18	42.4	81.15
		1900/NR	62		
	Proposed	726.627/0.83	17	20.9342	90.69
		1500/0.8	61		

Fig. 6 The effect of installing two DG on voltages of 69 bus system

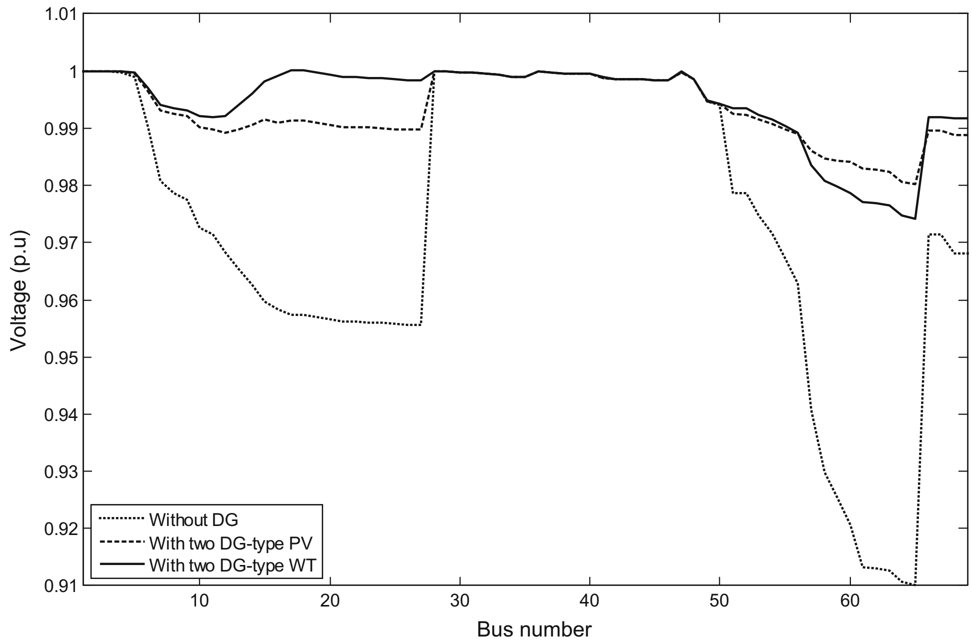
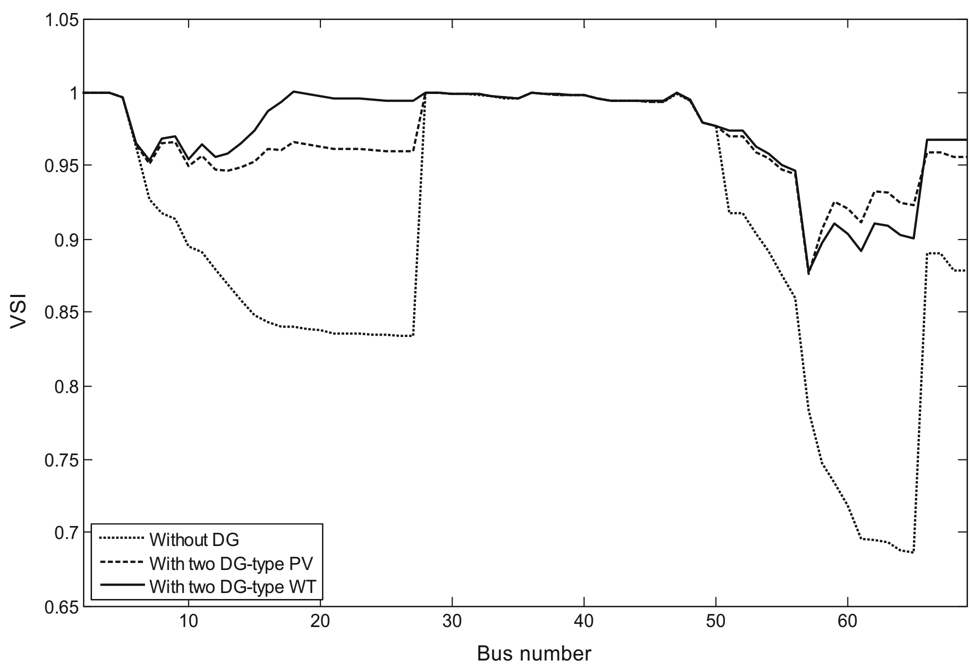


Fig. 7 The effect of installing two DG on VSI of 69 bus system



addition, the designed WT type gives superior results than PV type in terms of voltage profiles and VSI as mentioned in Figs. 6 and 7. In addition, the reactive power capability of WT has a considerable effect on reducing power losses and improving voltage profiles.

Table 4 Duration of different load levels

Load levels	L_1	L_2 (base case)	L_3
Level	0.625	1.0	1.25
Duration time (h)	1000	6760	1000

5.2 Effect of variable load

A constant load over the year is a hypothetical case as the load profile has the impact of seasonal and time variations. To mimic this effect, the load of the entire year has been considered as combination of three load levels of different durations as given in Table 4. ALOA finds the optimal sizes of DG for different load levels. The values of losses, installed DG and

Table 5 Optimal located PV units at different loadings for 69 bus system

No of PV units	Load levels	Size of DG (kW) at bus		Losses (kW)	Minimum voltage	Maximum voltage
		61	17			
One	L_1	1600	–	32.47	0.9792	1.0
	L_2	1800	–	81.776	0.9679	1.0
	L_3	2129.5835	–	130.6164	0.9624	1.0
Two	L_1	1500	500	28.3599	0.9823	1.0
	L_2	1700	538.777	70.750	0.9801	1.0
	L_3	1935.5929	654.5052	112.549	0.9878	1.0

minimum and maximum voltage profiles are displayed for 69 bus system in Table 5 with variable loads. It can be seen that the losses are reduced at different loads as the number of locations increase. Moreover, the voltages are within the specified limits.

6 Conclusions

In this paper, ALOA has been successfully implemented with LSFs for optimal location and sizing of DG-based renewable sources in 69 bus radial distribution system. The designed problem has been formulated as an optimization task with computing of power losses, voltage profiles and VSI. The results have been compared with those obtained using other algorithms. It is obvious from the comparison that the proposed approach provides a notable performance in terms of power losses and saving. Moreover, the proposed ALOA is robust and it can be applied for variable loads demand. Applications of the proposed algorithm to large-scale distribution power systems and unbalanced one are the future scope of this study.

Appendix

The pseudo code of the ALO algorithm is defined as follows:

Step 1: Initialize the first population of ants, ant lions randomly, LSFs and DG. Run load flow and calculate the fitness of ants and ant lions.
Step 2: Find the best ant lions and assume it as the elite.
Step 3: For each ant, select an ant lion using roulette wheel

3.1 Create a random walk and normalize it to keep it inside the search space,
3.2 Update the position of ant,
3.3 Update the values of c and d,
End for

Step 4: Run load flow and **c**alculate the fitness of all ants,
Step 5: Replace an ant lion with its corresponding ant it if becomes fitter,
Step 6: Update elite if an ant lion becomes fitter than the elite,
Step 7: Repeat from step 3 until a stopping criteria is satisfied. ALOA parameters: Number of ant lions = 30, maximum number of iterations = 500.

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