Optimal Distributed Energy Resources Allocation Using Ant-Lion Optimizer for Power Losses Reduction

Hany S. E. Mansour, Abdelazeem A. Abdelsalam
Electrical Engineering Dept., Faculty of Engineering
Suez Canal University
Ismailia, Egypt
e-mail: hany_salem@eng.suez.edu.eg, aaabdelsalam@eng.suez.edu.eg

Abdelhay A. Sallam
Electrical Engineering Dept., Faculty of Engineering
Port Said University
Port Said, Egypt
e-mail: aasallam@eng.psu.edu.eg

Abstract—**This paper proposes a novel optimization algorithm called ant-lion optimizer (ALO) for optimal distributed energy resources (DERs) allocation in various radial distribution networks. The objective function is to maximize the percentage of power losses reduction. The proposed algorithm is executed on IEEE 34 and 118-bus radial distribution networks with different number of installed DERs. The simulation results using Matlab programming environment show that the effectiveness of the proposed methodology to minimize the losses and to enhance the system voltage profile. A comparison between the results of proposed ALO and those of other optimization methods such as cuckoo search, grid search, oppositional gravitational search, simulated annealing, quasi-oppositional teaching learning based optimization, and chaotic symbiotic organisms search is introduced to verify the superiority of ALO.**

Keywords-distributed energy resources; optimization; ant-lion; power losses reduction; voltage profile

I. INTRODUCTION

In general, electric systems consist of three networks; generation, transmission, and distribution. The distribution network provides a final link between the high voltage transmission network and the consumers. A radial distribution system has main feeders and lateral distributors. The main feeder originates from substation and passes through different consumer loads and laterals are connected to individual loads. Radial distribution systems are used because of their simplicity. Power losses in a distribution system is very high because of low voltage and hence high current and it is about 70 % of the total losses [1]. Normally, the real power losses draws more attention for the utilities, as it reduces the efficiency of transmitting energy to customers. It is impossible to reach the losses to the zero level, but it is possible to maintain them to a minimum level. Several efforts were made through researchers to solve these problems. Efforts include DERs installation, shunt capacitor banks connection [2]–[5], and system reconfiguration [6]–[8]. This work details a simple and flexible approach for optimal DERs allocation (location and size) in distribution networks.

A literature survey on optimal DERs placement can be found in [9]. Also, the optimization techniques of DERs allocation are subdivided into two main categories; analytical methods, and artificial intelligent methods. The analytical methods produce algebraic expressions that can be utilized for solving the optimization problem. These approaches are characterized by short computing time and easy to implement. But, when the optimization problem becomes complex, the used assumptions to simplify the problem may override accuracy of solution. In [10], the optimal locations and capacities of DERs were selected analytically based on losses sensitivity factor (LSF). The objective function was to minimize the active power losses. The proposed approach was tested on 12, 34, and 69-bus radial distribution systems. Also, in [11] the losses sensitivity factor was used to determine the candidate buses for installing DERs. Only 30% of the LSF priority list was selected as candidate locations for DERs connection. Then the size of each DER was vary from zero MW to a higher value to satisfy the minimum power losses. The suggested technique was tested on 30, 33, and 69-bus radial distribution systems.

The artificial intelligent methods is an exhaustive search that tries all candidate solutions from a prescribed set and then chooses the best one. Optimal placement of DERs was formulated using genetic algorithm (GA) in such a way to minimize the power losses and node voltage deviation indices with considering the bus voltages limits. The proposed GA was applied on IEEE 33-bus and IEEE 69-bus test systems [12]. Particle swarm optimization (PSO) was presented to determine the optimal locations and capacities of DERs with different penetration levels to be connected to distribution networks. The objective function was to minimize the power losses and the economic evaluation was not considered. The proposed method was applied on the IEEE 33 and IEEE 118 bus systems [13]. A combination of GA and PSO was suggested for solving optimal DERs allocation on distribution systems problem. The fitness function was adopted to minimize power losses, improve voltage regulation and enhance the voltage stability within the system operation constraints in radial distribution networks. The proposed approach was carried out on IEEE 33-bus and IEEE 69-bus distribution systems to ensure its efficiency [14].

Firstly, LSF was used to determine the candidate locations for DERs connection. Then intelligent water drop (IWD) algorithm was utilized for finding the optimal sizes of installed DERs. The objective function was to minimize the total power losses of the distribution system. The proposed

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algorithm was executed on IEEE 10-bus, IEEE 33-bus, and IEEE 69-bus distribution systems [15]. In [16], determined the optimal locations and the output power of DERs using artificial bees colony (ABC) algorithm. The objective function was formulated to minify the power losses. The suggested approach was applied on IEEE 33-bus and IEEE 69-bus test systems. A Modified Teaching–Learning Based Optimization (MTLBO) algorithm was suggested to find the optimal sites and sizes of DERs in distribution systems. The objective function was to minimize total power losses. To show the effectiveness of the proposed approach it was applied on IEEE 69-bus and IEEE 118-bus test systems. Installing single and multi-DERs were investigated [17].

This paper proposes a novel algorithm called ant-lion optimizer (ALO) for solving DERs allocation problem. The objective function is designed to maximize the power losses reduction percentage. To ensure the validity of the proposed approach, it is evaluated using IEEE 34-bus and IEEE 118-bus test systems.

II. PROBLEM FORMULATION

A. Load Flow Analysis

The application of Newton-Raphson or Gauss-Seidel methods for power flow solutions is not appropriate for radial distribution system as a result of its higher R/X quantitative relation and unbalanced loading nature. To find the power flow solutions in radial distribution system, many types of distribution load flow methods are projected and most of these methods are established on Kirchhoff's current and voltage laws. Backward/Forward sweep (BFS) is one of efficient and simplest techniques. It calculates currents at all nodes from the end node towards the source node within the backward sweep mode, whereas respective bus voltages are calculated from the source node towards the end node within the forward sweep mode [18].

B. The Objective Function

The objective function of the DERs allocation problem in this study is to maximize the power losses reduction percentage as follows:

$$Objective\ Function = Max\ (\ PLRP) \tag{1}$$

where, PLRP is power losses reduction percentage and can be calculated as follow:

$$PLRP\ (\%) = \frac{P_{losses_{without\ DERs}} - P_{losses_{with\ DERs}}}{P_{losses_{without\ DERs}}} * 100 \tag{2}$$

C. Problem Constraints

The power losses reduction percentage has to be maximized with the following constraints.

- Voltage profile limit: The voltage magnitude at different buses must be maintained within predetermined limits (±10%) and is expressed as,

$$|V_{min}| \le |V| \le |V_{\max}| \tag{3}$$

where, $|V_{min}|$ and $|V_{\max}|$ are the lower and upper limits of bus voltage.

- Power balance constraint

$$P_s + \sum_{k=1}^{NDER} P_{DER} = P_D + P_{loss} \tag{4}$$

where, N_{DER} is the total number of DERs, P_s is the feeder power, and

P_D is the demand power.

III. THE PROPOSED ALO ALGORITHM

A. ALO Inspiration

The ALO algorithm is a novel nature inspired method proposed by seyedali Mirjalili in 2015 [19]. The ALO algorithm simulates the hunting mechanism of antlios (ALs) in nature. ALs belong to category of net winged insects. The names of ALs come from their unique hunting behavior and their favored prey. The life cycle of ALs includes two main phases: larvae and adult. A natural life-time can take up to three years, which mostly happens in larvae (only three – five weeks for adulthood). They principally hunt in larvae and the adulthood phase is for reproduction. An AL larva digs a cone-shaped hole in the sand by moving along a circular path and throwing out sands with its huge jaw. After digging the gin, the larva hides beneath the bottom of the cone and waits for the prey (preferably ant) to be restricted in the hole. The rim of the cone is sharp enough for ants to fall to the bottom of the gin easily. Once the AL sense that a prey is in the gin, it tries to catch it.

B. ALO Operators

Hunting process is based on six main steps; two steps pertained to ant-lion and four steps pertained to ants.

Steps for ant-lion:

Step #1: Building trap

A roulette wheel selection is used to express the ant-lions' hunting ability. It is important to select ant-lions according to their fitness during optimization. This step gives high chances to the fitter ant-lions for catching.

Step #2: Catching prey and re-building the pit

Finally, whenever the ant reaches the bottom of the trap and is caught in the ant-lion's jaw, the AL pulls the prey inside the sand and consumes its body. For imitate this interaction, it is assumed that catching ant happens whenever ant becomes fitter than its corresponding ant-lion, i.e goes inside sand. Then, the ant-lion is needed to refresh its location to the latest one of the hunted ant to enhance its chance of catching new ant. The following equation is presented in this regard:

$$\mathrm{Ant-lion}_j^t = \mathrm{Ant}_i^t \qquad \text{if } f(\mathrm{Ant}_i^t) > f(\mathrm{Ant-lion}_j^t) \tag{5}$$

where, t indicates the current iteration, $\mathrm{Ant-lion}_j^t$ express the position of selected jth ant-lion at tth iteration, and Ant_i^t indicates the position of ith ant at tth iteration.

Steps for ants:

Step #1: Random Walks of ants

Since ants move stochastically in nature whenever searching for food, a random walk is chosen for modelling ants' movement as follows:

$$X(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1)] \quad (6)$$

where, cumsum calculates the cumulative sum, n is the maximum number of iteration, t is the step of random walk (iteration in this study), and r(t) is a random function defined as:

$$r(t) = \begin{cases} 1 & if \text{ rand } > 0.5 \\ 0 & if \text{ rand } \leq 0.5 \end{cases} \quad (7)$$

However, Eq. (7) is not directly utilized for updating the position of ants. For holding the random walks inside the search space, they must be normalized using the following equation:

$$X_i^t = \frac{(X_i^t - \mathrm{a}_i) * (d_i - c_i^t)}{(d_i^t - \mathrm{a}_i)} + c_i \quad (8)$$

where, a_i and b_i are the minimum and maximum of the random walk of i^{th} variable, respectively, c_i^t is the minimum of i^{th} variable at t^{th} iteration, and d_i^t indicates the maximum of i^{th} variable at t^{th} iteration.

Step #2: Trapping in ant-lion's pit

Random walks of ants are influenced by ant-lions' traps. In order to mathematically model this supposition, the following equations are presented:

$$C_i^t = \text{Ant} - \text{Lion}_j^t + C^t \quad (9)$$

$$d_i^t = \text{Ant} - \text{Lion}_j^t + d^t \quad (10)$$

where, C^t is the minimum of all variables at t iteration, d^t shows the vector including the maximum of all variables at t^{th} iteration, C_i^t and d_i^t are the minimum and maximum of all variables for i^{th} ant, respectively, and $\text{Ant} - \text{Lion}_j^t$ expresses the position of the selected j^{th} ant-lion at t^{th} iteration.

Step #3: Sliding ants towards ant-lion

With the mechanisms proposed so far, ant lions are capable of building traps proportional to their fitness and ants are required to move randomly. When ant-lions sense that an ant is in the ambush, they shoot sands outwards the center of the hole. This behavior slides down the trapped ant that is trying to run away. For mathematically modeling this behavior, the radius of ants' random walks hypersphere is decreased adaptively. The following equations are proposed in this regard:

$$C^t = \frac{c^t}{I} \quad (11)$$

$$d^t = \frac{d^t}{I} \quad (12)$$

where, I is a ratio, c^t indicates the minimum of all variables at t^{th} iteration, and d^t shows the vector including the maximum of all variables at t^{th} iteration. In Equations (11) and (12), $I = 10w\frac{t}{T}$ where, t is the current iteration, T is the maximum number of iterations, and w is a constant based on the current iteration (w = 2 when t > 0.1T, w =3 when t > 0.5T, w = 4 when t > 0.75T, w = 5 when t > 0.9T, and w = 6 when t > 0.95T). Basically, the constant w can adjust the precision level of exploitation.

Step #4: Elitism

Elitism is a significant characteristic of evolutionary algorithms that permit them to keep the best solution(s) obtained at any step of the optimization process. Since the elite is the fittest ant-lion, it should be able to influence the movements of all the ants through iterations. Therefore, it is assumed that every ant randomly walks around a selected ant-lion by the roulette wheel and the elite together as follows:

$$\text{Ant}_i^t = \frac{\mathrm{R}_\mathrm{A}^t + \mathrm{R}_E^t}{2} \quad (13)$$

where, R_A^t shows the random walk around the ant-lion selected by the roulette wheel at t^{th} iteration, R_E^t indicates the random walk around the elite at t^{th} iteration, and Ant_i^t express the position of i^{th} ant at t^{th} iteration. The mechanism of proposed ALO is illustrated by a flow chart as shown in Fig. 1.

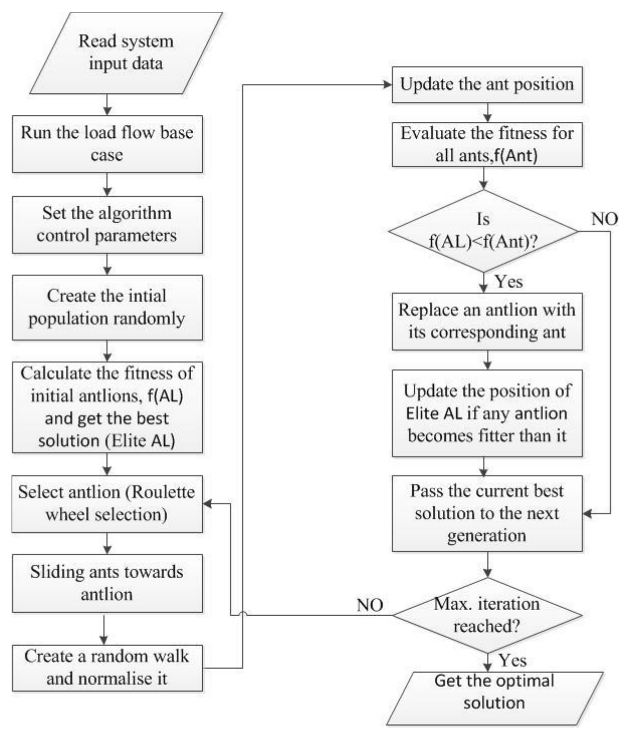

Figure 1. Flow chart of ALO.

IV. TEST SYSTEMS DESCRIPTION

In order to evaluate the effectiveness and performance of the proposed ALO in solving the problem of DERs allocation, two test radial distribution systems are used. The proposed approach has been applied using MATLAB programming environment.

A. *Test System I*

IEEE 34-bus distribution system is the first test system in this study [20]. It is operating at 11 kV. The single line diagram of the system is displayed in Fig. 2. It consists of single main feeder, four lateral feeders, and no sublateral feeders. The total real and reactive power demand is 4636.5 kW and 2873.5 kVAr, respectively.

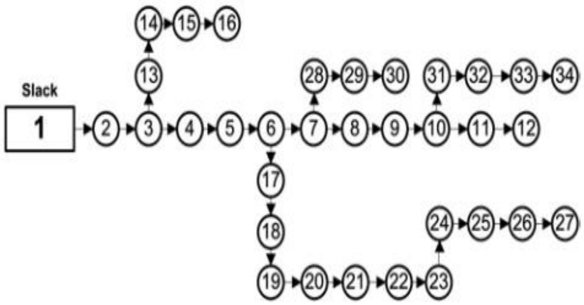

Figure 2. Single line diagram of test system I.

B. *Test System II*

IEEE 118-bus distribution system is the second test system in this study [21]. It is operating at 11 kV. The single line diagram of the system is shown in Fig. 3. It consists of one slack bus and 32 load buses. The total real and reactive power demand is 22709.72 KW and 17041.07 KVAr, respectively.

V. SIMULATION RESULTS AND DISCUSSION

A. *The Base Case*

The base case is that case without connecting DERs to the systems. The main results is obtained after applying BFS are listed in Table I . The active power losses is 221.77 kW and 1294.3 kW for IEEE 34-bus and IEEE 118-bus test systems, respectively.

TABLE I. BASE CASE RESULTS

Test System	IEEE 34-bus	IEEE 118-bus
V_{max} (pu), @bus	0.994 @2	0.996 @100
V_{min} (pu), @bus	0.942 @27	0.873 @77
P_{losses} (kW)	221.77	1294.3
Q_{losses} (kVAr)	65.11	976.544

B. *Test System I*

The results of connecting single or multi-DERs to IEEE 34-bus test system is organized in Table II. In case of installing single DER, the optimal bus to be connected with it is #21 with optimal size equals to 2.95 MW. The objective function (PLRP) is maximized to 57.73 %. While in case of connecting two DERs, the optimal locations and sizes are (#24, 1.5 MW) are (#31, 1.35 MW). The active power losses is decreased to 77.83 kW with PLRP reaches to 64.9 %. In case of connecting three DERs to buses #21, #25, and #31 with optimal size of 0.95 MW at each location, the PLRP is more increased to 67.63 %. It is observed that, with increasing the number of locations for installing DERs, The PLRP increases as displayed in Fig. 4. The positive impact of connecting DERs with different number on system voltage profile is displayed in Fig. 5. The minimum voltage is corrected from 0.942 pu at bus #27 to 0.978 pu, 0.981 pu, and 0.983 pu at bus #34, #21, and #23 in case of connecting single, two, and three DERs, respectively.

A comparison with the results of other optimization methods; analytical, grid search (GS), cuckoo search optimization (CSO), and oppositional gravitational search algorithm (OGSA), is listed in Table III. The proposed ALO achieves the maximum PLRP, 67.63 %. This results ensure the effectiveness and validity of the proposed ALO for solving optimal DERs allocation problem.

TABLE II. RESULTS OF DERS ALLOCATION IN IEEE 34-BUS SYSTEM

	Single DERs	2 DERs	3 DERs
DERs (Location, DERs Size (MW))	(#21, 2.95)	(#24, 1.5) (#31, 1.35)	(#21, 0.95) (#25, 0.95) (#31, 0.95)
Total $DERs_{installed}$ (MW)	2.95	2.85	2.85
V_{max} (pu) @bus	0.997 @2	0.997 @2	0.997 @2
V_{min} (pu) @bus	0.978 @34	0.981 @21	0.983 @23
P_{losses} (kW)	93.75	77.83	71.78
PLRP (%)	57.73	64.9	67.63

TABLE III. COMPARING THE RESULTS OF THE PROPOSED ALO WITH THOSE OF OTHER OPTIMISTION METHODS FOR IEEE 34-BUS SYSTEM

	Analytical [10]	GS [10]	CSO [22]	OGSA [23]	Proposed ALO
Total $DERs_{installed}$	2.8848	2.9665	2.3278	2.966	2.85
P_{losses} (kW)	99	93.7	98.42	93.65	71.78
PLRP (%)	55.36	57.75	55.62	57.77	67.63

C. *Test System II*

Table IV tabulates the results of installing three, five, and seven DERs in IEEE 118-bus test system. In case of connecting three DERs, the optimal locations are #73, #110, and #40 and the optimal sizes are 2.45 MW, 2.5 MW, and 2.45 MW, respectively. The objective function is maximized to 46.35 %. While in case of connecting five DERs with optimal capacity equals to 10.45 MW, the PLRP is more increased to 54.15 %. In case of connecting seven DERs with optimal size of 11.6 MW, the PLRP is more increased to 57.44 %. It is observed that, with increasing the number of locations for installing DERs, The PLRP increases as displayed in Fig. 6. The positive impact of connecting DERs with different number on system voltage profile is displayed in Fig. 7. The minimum voltage is corrected from 0.873 pu at bus #77 to 0.949 pu, 0.942 pu, and 0.943 pu at bus #43 in case of connecting three, five, and seven DERs, respectively.

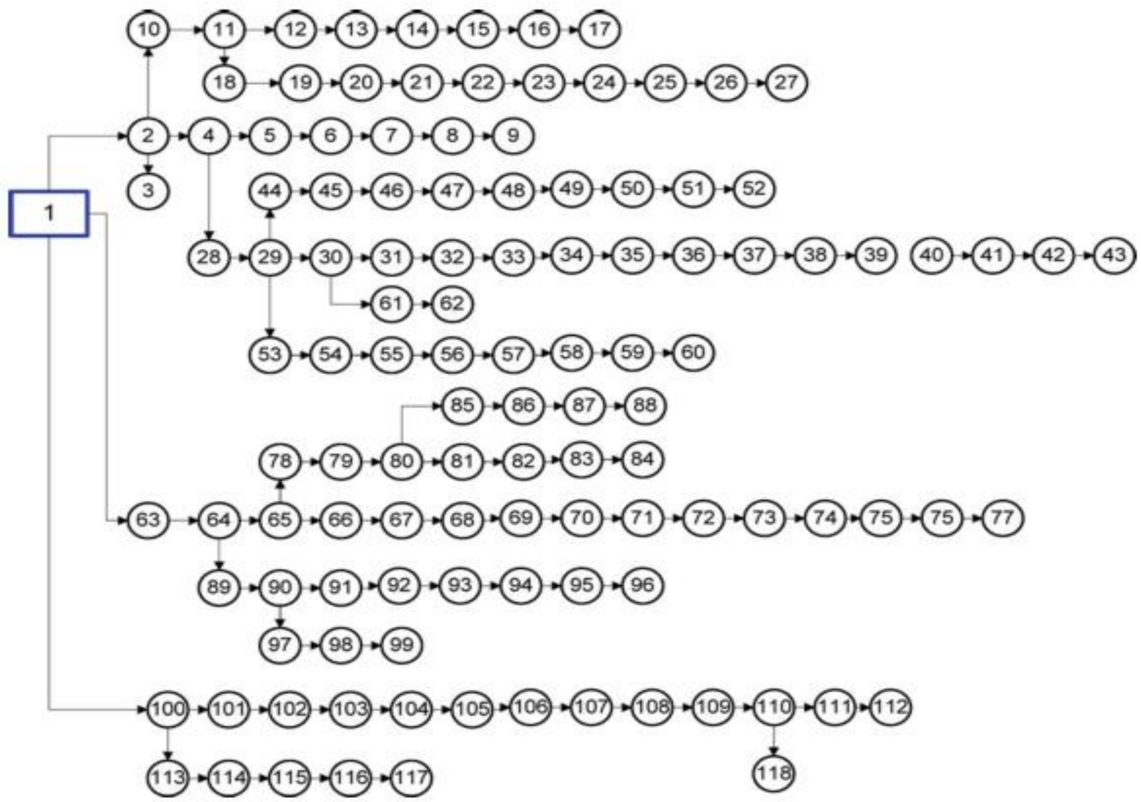

Figure 3. Single line diagram of test system II.

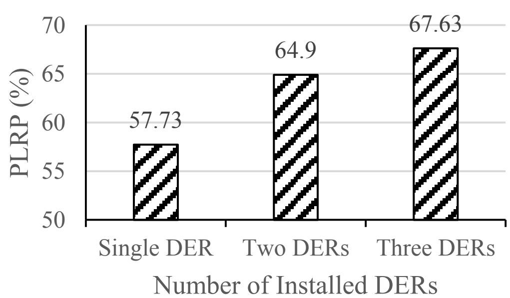

Figure 4. Impact of connecting DERs with different numbers to IEEE 34-bus system on the objective function.

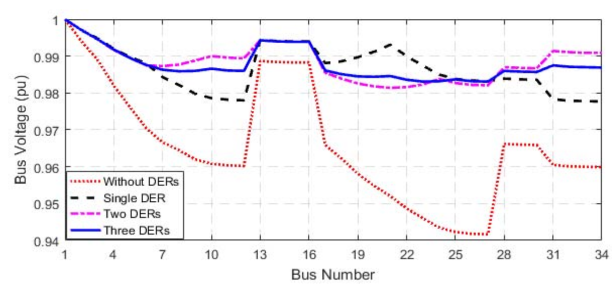

Figure 5. Voltage Profile of IEEE 34-bus system when connecting DERs with different numbers.

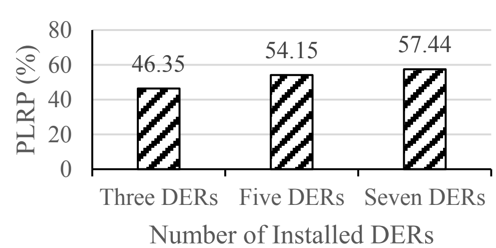

Figure 6. Impact of connecting DERs with different numbers to IEEE 118-bus system on the objective function.

A comparison with the results of other optimization methods; simulated annealing (SA), quasi-oppositional teaching learning based optimization (QOTLBO), and chaotic symbiotic organisms search (CSOS), is listed in Table V. The maximum PLRP is 60.13 % that is achieved through applying CSOS in opposite to 57.44 % to the proposed ALO. It is obvious that the difference in the total size of installed DERs. Where, 15.519 MW was connected to the system in case of CSOS in opposite to only 11.6 MW in case of the proposed ALO.

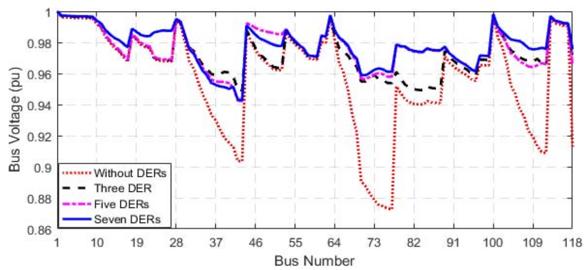

Figure 7. Voltage Profile of IEEE 118-bus system when connecting DERs with different numbers.

VI. CONCLUSIONS

A novel optimization technique based on the Ant-Lion Optimizer (ALO) algorithm is presented in this paper to solve DERs allocation problem in the radial distribution network. The proposed ALO is characterized by simplicity and effectiveness. It may be observed that the proposed method is able to find out the optimal location and size of DERs, while, at the same time, it decreases active power losses and improves voltage profile of the system. The objective function is to maximize the percentage of the power losses reduction. The presented optimization algorithm has been applied on two test systems; IEEE 34-bus and 118-bus radial distribution systems with different cases of the number of installed DERs. The simulation results using MATLAB programming environment show that the proposed approach is able to maximize the power losses reduction percentage. A comparison between the proposed ALO and other optimization methods is introduced to verify the superiority of ALO.

TABLE IV. RESULTS OF DERS ALLOCATION IN IEEE 118-BUS SYSTEM

	3 DERs	5 DERs	7 DERs
DERs (Location, DERs Size (MW))	(#40, 2.45) (#73, 2.45) (#110, 2.5)	(#40, 2) (#50, 1.7) (#74, 2.2) (#80, 2.25) (#111, 2.3)	(#25, 0.8) (#41, 1.8) (#50, 1.1) (#74, 2.3) (#80, 2.25) (#106, 1.35) (#111, 2)
Total $\text{DERs}_{\text{installed}}$ (MW)	7.4	10.45	11.6
V_{max} (pu) @bus	0.998 @100	0.998 @100	0.998 @100
V_{min} (pu) @bus	0.949 @43	0.942 @43	0.943 @43
P_{losses} (kW)	694.45	593.4	550.89
PLRP (%)	46.35	54.15	57.44

TABLE V. COMPARING THE RESULTS OF THE PROPOSED ALO WITH THOSE OF OTHER OPTIMISTION METHODS FOR IEEE 118-BUS SYSTEM

	SA **[24]**	QOTLBO **[25]**	CSOS **[26]**	Proposed ALO
Total $\text{DERs}_{\text{installed}}$	13.4953	18.324	15.519	11.6
P_{losses} (kW)	858.81	677	516	550.89
PLRP (%)	33.75	47.69	60.13	57.44

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