International Journal of Applied Metaheuristic Computing
Volume 13 • Issue 1

Whale Optimization Algorithm-Based DG Allotment for Loss Minimization of Distribution Networks

Suvabrata Mukherjee, NSHM College, Durgapur, India*
Provas Kumar Roy, Kalyani Goverment Engineering College, India
https://orcid.org/0000-0002-3433-5808

ABSTRACT

For optimum placement of distributed generation (DG) units in balanced radial distribution network for loss minimization, implementation of whale optimization algorithm (WOA), a state-of-the-art meta-heuristic optimization algorithm is proposed in this paper. Encouraged by bubble-net hunting strategy of whales, WOA mimes the collective practice of humpback whales. For validating performance in solving the mentioned problem, the suggested technique is implemented on IEEE 33-bus and IEEE 69-bus balanced radial distribution test networks. The obtained results demonstrate that feasible and effective solutions are obtained using the proposed approach and can be used as a propitious substitute in practical power systems to overcome the optimum DG siting and sizing issue. Also, to the best knowledge of the authors, it is the first report on the application of WOA in solving optimum DG siting and sizing issue.

KEYWORDS

Distribution Generation Units, Evolutionary Programming, Loss Minimization, Loss Saving, Optimal Siting, Optimal Sizing, Whale Optimization Algorithm

1 INTRODUCTION

In distribution networks the R/X ratio is much higher than in transmission systems. Therefore, throughout the distribution feeders there is a greater loss of power and hence a gradual electrical energy loss (Bansal et al, 2010; Baran & Wu, 1998; Chis et al, 1997; Haque, 199; Haque, 1996). Therefore, minimization of loss has become one of the greater problems for many utilities all over the world that needs to be adhered to. Capacitors placement and network reconfiguration are two extensive well known frequently used techniques minimization of loss in distribution networks (Baran & Wu, 1998; Chis et al, 1997; Haque, 199; Haque, 1996; Narasimham et al, 2013). Lately, because of aspects such as power electronics, restructuring of electricity market and environmental concerns etc. distribution generators (DG) have gained cogent importance (Narasimham et al, 2013; Ackermann et al, 2001). Ranging from some kWs to some MWs, DGs may be considered to be electrical power generating sources linked precisely to distribution networks (Khatod & Viral,

DOI: 10.4018/IJAMC.290537
*Corresponding Author

2012). In recent times, numerous technologies related to DGs have come up covering conventional to non-conventional sources (Ackermann et al, 2001; Khatod & Viral, 2012). Even though energy injection is the primary objective of DG units, however, if arranged and regulated strategically DGs are capable of serving numerous economic and technical utilities to consumers (Khatod et al, 2013). Voltage and loadability improvement, real power loss reduction, increased energy efficiency, upgraded system reliability and security are some results of such benefits (Ackermann et al, 2001; Khatod & Viral, 2012). Some financial benefits include saving of transmission and distribution cost along with reduction in whole sale electricity price, enhanced productivity, reduced fuel costs and saving of world fuel (Hung & Mithulananthan, 2013; Bansal et al, 2013). As far as current power industry deregulation along with the electricity market security is concerned, DGs observe a crucial function in spinning reserve, frequency control, etc. (Al Abri et al, 2013). However, improper operation and poor planning of DG exhibits a few contrary properties in distribution system functioning. Based on size and location, DGs can cause voltage rise, harmonic distortion, reverse power flows, etc. (Al Abri et al, 2013; Esmaili, 2013). Thus reduction in power loss is a crucial factor which is to be adhered to by proper DG operation.

Optimum DG sizing as well as siting for derogation of loss in distribution systems has lately gained substantial diligence of broad class of scientists and researchers. (Khatod & Viral, 2012; Khatod et al 2013; Hung & Mithulananthan, 2013). In many of the prevailing works on appropriation as well as sizing of DGs, researchers have acknowledged various concerns such as stability of system and voltage profile enhancement (Esmaili, 2013), harmonic pollution reduction (Harrison & Ochoa, 2011), profit maximization (Bhattacharya et al, 2004; Celli et al, 2005) and loading margin (Lee & Park, 2009) in either separate or collective-objective issue formation.

Analytical approach (Acharya et al, 2006; Nehrir & Wang, 2004; Gozel & Hocaoglu, 2009), harmony search algorithm (HSA) (Narasimham et al, 2013), evolutionary algorithms (EA) technique (Khatod et al, 2013), particle swarm optimization (PSO) (Harrison & Ochoa, 2011), genetic algorithm (GA) technique (Celli et al, 2005; Ab Kadir et al, 2011), metaheuristic approaches (Bhattacharya et al, 2004), are a few elaborated approaches used to adhere the DG sizing and siting issue. [2](1)A few research has also been carried out in DG siting and sizing using WOA. (Prakash and Lakshminarayana, 2018) proposes the application of WOA with the aim of finding optimal placement and size of DGs for multi-objectives, including power loss minimization, voltage profile improvement and operating cost minimization. Proposed method has been demonstrated on 33-bus and 69-bus radial distribution test systems with each test system being considered for two different cases: case 1: placing Type 1 DGs (only real power injection) and case2: placing Type 2 DGs (both real and reactive power injection). However much improved results are obtained by placement of Type III DG for both the systems.

(Morshidi et al, 2018) has demonstrated the installation of DGs by the application of WOA in transmission lines. Here the authors have used fast voltage stability index (FVSI) to decide the size of the DGs. Thereby in the present article the authors have implemented WOA for both sizing and siting of DGs in distributed systems. (Ang and Leeton, 2018) have implemented WOA for both siting and sizing of DGs in distribution systems. The authors have also implement Type I, Type II and Type III DGs for small and medium distribution systems. Threfore, in the present research work, the authors have also tested the approach for a comparatively bigger systems. (Reddy et al, 2017) has implemented WOA and has also used both Type I and Type III DGs. The authors have demonstrated the optimal sizing of the DGs and has shown that the algorithm is able to provide improved results as compared to some other algorithms. Thus, in the present article, the authors have implemented the mentioned approach in distribution systems and have also tested the approach on small and large systems. (Gnanambal et al, 2017) has used WOA for obtaining improved voltage profile and power loss reduction by using only type III DG. However, the number of iterations and population size is varying. Further more stress has been put on siting of DGs. DGs have been treated as purely active power source in most of the research cited above. However the capability of DGs of absorbing or injecting reactive power within its limits depends on its type (Esmaili, 2013). In addition, for DG siting and sizing most of the common analytical approaches is mostly dependent on exact calculation of loss which requires Jacobian matrix computation. This evaluation of the Jacobian matrix increases the computation time. Therefore application of new metaheuristic approaches providing optimal solution draws further attention.

[1](2)In order to make some remedial action to mitigate the aforesaid drawback, in this article application of a new and cinch meta-heuristic optimization mechanism is suggested. WOA is a recent meta-heuristic optimization algorithm mimicking the hunting behavior of humpback whales and has been able to provide successful results when applied for solving the OPF (Bhesdadiya et al, 2016) and ELD (Touma, 2016) problems. To the best of the authors' acquaintance, there is no prior report in the optimization literature on the application of WOA in solving optimal DG allocation and sizing issue. The authors in present paper have tried to develop a general purpose algorithm using WOA approach that is reliable and robust and uncomplicated implementation to critical power system is feasible.

Remaining article is formed accordingly as: Section 2 illustrates the mathematical interpretation of the DG allocation and siting issue. The whale optimization algorithm (WOA) along with Biogeography based Optimization (BBO) is presented in Section 3. Application of suggested approach to optimum allocation and rating of single and collective DGs for loss minimization has been illustrated in Section 4. Simulation and numerical results obtained on applying the WOA to two IEEE test systems are discussed in Section 5. Non-parametric analysis of WOA and BBO approaches in presented in Section 6. Finally the article sums up with the conclusion in Section 7.

2. MATHEMATICAL INTERPRETATION OF DG ALLOCATION AND SITING

While satisfying certain operating constraints, optimal DG siting in a radial distribution system requires obtaining proper locations in a radial network where a DG can be placed thereby minimizing the power loss. The operating constraints are provided below. By computing and summing up individual losses linked with every branch the total active power loss of the system is calculated. The real and reactive power flow is calculated as:

$$P_{i+1} = P_i - P_{l_{(i+1)}} - R_{i,(i+1)} * \frac{\left(P_i^2 + Q_i^2\right)}{\left|V_i\right|^2} \tag{1}$$

$$Q_{i+1} = Q_i - Q_{l_{(i+1)}} - X_{i,(i+1)} * \frac{\left(P_i^2 + Q_i^2\right)}{\left|V_i\right|^2} \tag{2}$$

Real power loss in the line can be calculated as:

$$P_{i_{(i+1)}} = R_{i,(i+1)} * \frac{\left(P_i^2 + Q_i^2\right)}{\left|V_i\right|^2} \tag{3}$$

Therefore, the loss minimization of total loss can be considered as the objective function and can be represented as:

$$f = min\left(P_{Loss}\right) \tag{4}$$

$$P_{loss} = \sum_{\substack{i=2 \\ k=2}}^{N}\left(p_{g_i} - p_{d_i} - V_i V_k Y_{ik} cos\left(,_i - ,_k + \delta_{ik}\right)|,\right) \tag{5}$$

Equality Constraint

$$[2](2) \sum_{\substack{i=2 \\ k=2}}^{N}\left(p_{g_i} - p_{d_i} - V_i V_k Y_{ik} cos\left(,_i - ,_k + \delta_{ik}\right)|,\right) \tag{6}$$

$$[2](2) \sum_{\substack{i=2 \\ k=2}}^{N}\left(q_{g_i} - q_{d_i} - V_i V_k Y_{ik} sin\left(,_i - ,_k + \delta_{ik}\right)|,\right) \tag{7}$$

Voltage limits

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{8}$$

Thermal limits

$$\left|S_i\right| \leq \left|S_i^{max}\right| \tag{9}$$

DG Capacity Constraint

$$p_{dgi}^{min} \leq p_{dgi} \leq p_{dgi}^{max} \tag{10}$$

Loss Sensitivity Factor

To detect most susceptible node for allocation of distribution generator, the LSF is computed.

$$LSF = \frac{2Q_{k,eff} * R_{ik}}{\left(V_{ik}\right)^2} \tag{11}$$

In the above equations the notations denote the following parameters:

[2](2) P_i : Real power flow at ith bus; Q_i : Reactive power flow at ith bus; P_{i+1} : Real power flow at (i+1)th bus; Q_{i+1} : Reactive power flow at (i+1)th bus; $P_{l_{(i+1)}}$: Real power load connected at (i+1) th bus; $Q_{l_{(i+1)}}$: Reactive power load connected at (i+1)th bus; P_{Loss} : Total active power loss; N : Number of bus; k : receiving end bus; i : sending end bus; p_{g_i} : Active power generation at bus *i*; q_{g_i} : Reactive power supplied from *i*th bus; p_{d_i} : active power demand at bus *i*; q_{d_i} **:** Reactive power demand at *i*th bus; V_i : Voltage at bus *i;* V_k : Voltage at bus *k;* Y_{ik} : Admittance between *i*th and *k*th bus; ¸$_i$ **:***i*th bus phase angle; ¸$_k$: *k*th bus phase angle; δ_{ik} : Load angle between *i*th and *k*th bus; V_i^{min} **:** Minimum allowable working voltage at *i*th bus; V_i^{max} : Maximum allowable working voltage at *i*th bus; $\left|S_i\right|$: Apparent power at *i*th bus; S_i^{max} : Maximum apparent power at *i*th bus; R_{ik} : Resistance between *i*th and *k*th bus; $Q_{k,eff}$: Effective reactive power load connected at *k*th bus.

3. APPLIED METHODOLOGY

Whale Optimization Algorithm

Recently, WOA introduced by (Mirajilili, 2016) which is an efficient optimization approach, has been applied for solving non-linear optimization problems. Whales are supposedly the largest mammals in this world. They can extend upto 30 m in length and 180 ton in weight. Humpback, right, killer, Minke, Sei, ðnback, and blue are 7 different species of whale. The humpback species have a special and interesting hunting technique, where they choose hunting a group of tiny ðshes nighing to the surface.

While satisfying certain operating constraints, optimal DG siting in a radial distribution system requires obtaining proper locations in a radial network where a DG can be placed thereby minimizing the power loss.

Mathematically, WOA can be structured in following three sections:

3.1 Encircling of Prey

This resembles how Humpback whales encircle their prey after recognizing the location of the prey. As best position in search space is unrecognized initially, WOA approach recognizes the immediate best candidate as target victim or is nearest possible optimal value. As soon as the finest search agent gets specified, remaining search agents amend their respective locations in the direction of this search agent, the characteristic of which may be defined as:

$$\vec{z} = k.\overrightarrow{y'}\left(t\right) - \vec{y}\left(t\right) \vee \tag{12}$$

$$\vec{y}\left(t+1\right) = \overrightarrow{y'}\left(t\right) - \vec{c}.\vec{z} \tag{13}$$

In equations (9) and (10) the present iteration is given by t, the coefficient vectors are c and k, the position vector of the of the desired current finest solution is given by y', | | is the absolute value and $\vec{y}$ gives the position vector. For obtaining better solution, it is desirable to highlight that y' must be revised every iteration (Touma, 2013). Vectors c and $\vec{k}$ is computed from the equations given below:

$$\vec{c} = 2\vec{p}.\vec{d} - \vec{p} \tag{14}$$

$$k = 2.\vec{d} \tag{15}$$

The search agent position given by $\left(y, w\right)$, can be amended in accordance with the current best record position given by $\left(x', w'\right)$. By altering the values of $\vec{c}$ and $\vec{k}$ vectors, the various locations surrounding the specified finest agent corresponding to the immediate location, can be achieved. Also it is very much feasible to reach any desired position surrounding the key-points in search space by simply deðning the random vector $\vec{d}$ defined in[0,1] in both exploration and exploitation phases and with increase in number of iterations $\vec{p}$ is varied linearly from 2 to 0 and $\vec{r}$ is a random vector in [0,1]. Also over the course of iterations $\vec{c}$ is linearly varied from 2 to 0 in both exploitation and exploration phases.

3.2 Bubble Net Hunting Mechanism

Humpback whales' bubble-net behavior can be mathematically designed by following processes:

A] Shrinking Encircling Prey

By appropriately minimizing the value of $\vec{p}$ in Eq. (10), the *Shrinking encircling prey* behaviour is achieved. $\vec{c}$ Is an arbitrary value within the interval $\left[-p, p\right]$, where, through the following iterations, $\vec{c}$ is minimized from 2 to 0. The updated amended location of a search agent between the location of present finest agent and original location of the agent, at any point, can be determined by giving random values for $\vec{a}$ in $\left[-1,1\right]$.

B] Spiral Position Updating

Here, initially the distance is calculated at the intervals where the prey is at $\left(y', w'\right)$ and whale is positioned at $\left(y, w\right)$. Since humpback whales follow a helix-shaped movement, an equation (spiral) is formulated amidst the prey location and whale location in order to parrot the helix-shaped advancement. This can be represented as follows:

$$\vec{y}\left(t+1\right) = \overrightarrow{z'} e^{pl} .cos\left(2\pi l\right) + \overrightarrow{y'} \;) \tag{16}$$

Whales continue to swim around its prey while hunting, following the two paths mentioned above. In order to amend the locations of whales, 50% probability is assumed for above mentioned two methods. This is represented as:

$$\vec{y}\left(t+1\right) = \overrightarrow{y'}\left(t\right) - \vec{c}.\vec{z} \text{ if q<0.5} \tag{17}$$

And $\vec{y}\left(t+1\right) = \overrightarrow{z'} e^{pl} .cos\left(2\pi l\right) + \overrightarrow{y'} \;)$ if q³0.5 (18)

Where $\overrightarrow{d'} = \overrightarrow{y'}\left(t\right) - \vec{y}\left(t\right)$ (19)

Eq. (19) describes the radii of whale location and victim location (most appropriate solution). l lies between $\left[-1,1\right]$, q is random number uniformly distributed between $\left[0,1\right]$.

3.3 Search For Prey

The updating is achieved by arbitrarily selected search agents rather than the best agent for attaining global optimal values. This is characterized by:

$$\vec{d} = \vec{c}.\overrightarrow{x_{rand}} - \vec{x} \tag{20}$$

$$\vec{x}\left(t+1\right) = \overrightarrow{x_{rand}} - \vec{a}.\vec{d} \tag{21}$$

In equations (20) and (21) $\overrightarrow{x_{rand}}$ provides the arbitrary number of whales for the present iteration. The symbol || denotes the absolute values.

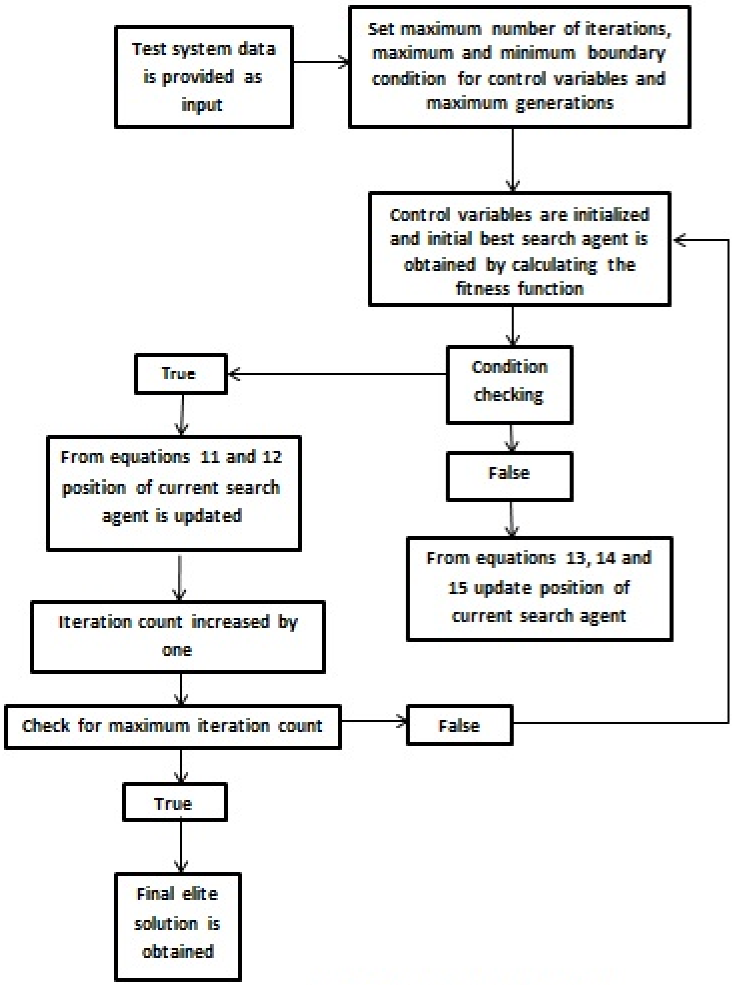
A structural diagram of WOA is represented in Fig. 1.

4. PROPOSED WOA ALGORITHM IMPLEMENTATION TO DG ALLOCATION PROBLEM

WOA based approach for DG allocation takes the sequential steps as mentioned below:

Step 1: Test system values are interpreted.
Step 2: **A**n arbitrary set of values for is initialized; $X_i = \left[Y_{ij}\right]$ for $i = 1N_p; j \in N_{PQ}$
Step 3: Set maximum iterations, maximum search agents, maximum generation, and minimum and maximum boundary limit of control variables.
Step 4: The control variables are randomly initialized within some effective maximum and minimum control variable bounds. NR power flow is run for at least five iterations and the reactive and active powers are obtained.
Step 5: Iteration count is set at one (Itr = 1).
Step 6: Using (6) the objective function is calculated.
Step 7: Depending on the $objectivefunction$ value, the population is sorted and elite solutions are recognized. Here, the term elite has been used to highlight the solution sets, which provides best $objectivefunction$ values. Best solution sets are kept unaltered after individual iteration without applying further modification to it.
Step 8: Tuning operation is applied probabilistically to the control variables of non-elite solutions, to modify the load of the load buses using the behavior of *Bubble net hunting approach, Encircling prey,* and*Search for prey* activity as detailed in section 5.
Step 9: After each controlled variables is tuned, its usefulness as a problem solution should be established. All feasible solutions are separated from those that are infeasible. This approach coevolves the population of infeasible solutions until they become feasible.
Step 10: If maximum specified number of iterations reaches, show results; otherwise return to step 4.

Figure 1.



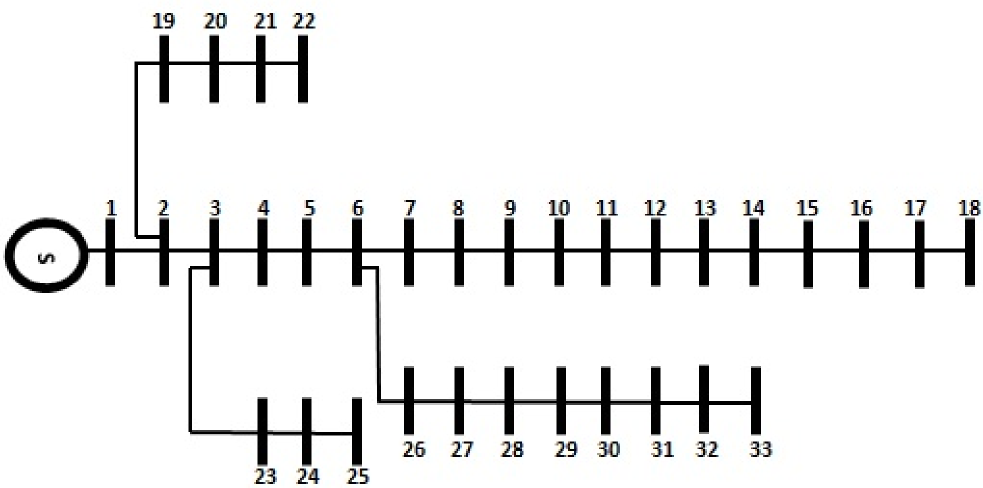
5. RESULT ANALYSIS

WOA have been implemented for solving the allocation as well as sizing of DGs and the results have been compared with BBO. Considering a flat start and providing a convergence tolerance value of 0.0001, the algorithms have been applied on IEEE-33 bus radial test system and IEEE-69 bus radial distribution test networks. [1](5)The authors have kept the population size and the number of iterations fixed for the sake of generalization. Even though for a small system (IEEE 33 bus), the convergance takes place well before 100 iterations, however for larger systems even if the population size is increased to more than 50 and the number of iterations are increased to more than 100, there is negligible change in the fitness value while the computation time increases. The computation tool used is MATLAB in the Pentium Dual core, 1800 MHz system. An approximation of number of DG allocation in the network has been presumed. It is also assumed that there is a constant power generation by the DG units. The performances of the approaches have been observed for four instances and for each instance the outcomes are enumerated depending on the outputs of 50 trial observations.

5.1 IEEE 33-Bus System

Required data have been availed from (Abdelaziz, 2017). A single-line diagrammatic representation of IEEE 33-bus radial distribution network is provided in Fig. 2. Respective values under base-case condition are provided in Table 1. [1](5)Here the population size has been fixed to 50 and the number of iterations has been taken as 100.

Figure 2.



5.1.1 Instance 1: Allocation of Single DG

Single DG type I or type III allocation has been considered for this instance. Base-case results i.e in the absence of a DG, are also computed. After type I DG unit inclusion in the network operating at unity power factor (UPF), a type III DG at combined load power factor (CPF) and a type III DG at effective load power factor (ePF), the real power loss is computed.

As noted from table 2, for DG operation at unity pf for type I DG, the system real power loss about 66.84 kW whereas for CPF and ePF mode operation for a type III DG there is a 44.02 kW and 40.29 kW loss reduction in comparison to the base case values. For validating the results obtained using WOA methodology, a comparative research is carried out with BBO by siting a single DG for calculating DG size and corresponding power loss. The convergence plot at UPF operation for Type I DG and at CPF and ePF operation for Type III DG can be observed from Fig.3. Comparison of the reduction in loss obtained for the proposed approach and BBO is provided in Table 3. It is well realized from the results that in comparison to BBO approach, the suggested WOA approach more preferable as it is able to provide improved DG size and reduced power loss. Also a comparative analysis for single DG placement at the three operating conditions is provided in fig. 4. [3](2)Voltage performance at each bus is provided in fig. 5 and real power loss at the three working modes i.e UPF, CPF and ePF is presented in fig. 6.

5.1. Instance 2: Allocation of Two-DG Units

Placement of two identical DG units at suitable locations has been considered in this instance. The total power loss attained after applying WOA for the three different operation modes along with the most appropriate siting positions for the two DGs to be connected and also the consequent sizes of

Table 1. IEEE 33 bus radial distribution test network base-case values

IEEE 33 bus network	Values
Real Power Demand Reactive Power Demand	3720 kW 2300 kVAr
Working Voltage	12.66 kV
Bus Number/Maximum Voltage Bus Number /Minimum Voltage	1/1.00 18/0.9038
Active Power Loss	210.987 kW
Reactive Power Loss	143.1284 kVAr
Absolute Power Loss	254.9538 kVA

the two DGs providing a much decreased power loss in the network are computed. [1](8)From Table 4, the maximum and minimum voltages at the ith bus location along with the total reduction in power loss can be observed. Comparative analysis of active power loss along with percentage loss minimization attained applying WOA and BBO is provided in Table 5 from which it may be validated that suggested WOA is capable of providing improved power loss reduction and can be considered as a robust alternative approach to most of the methodologies discussed in the literature.

Figure 3.

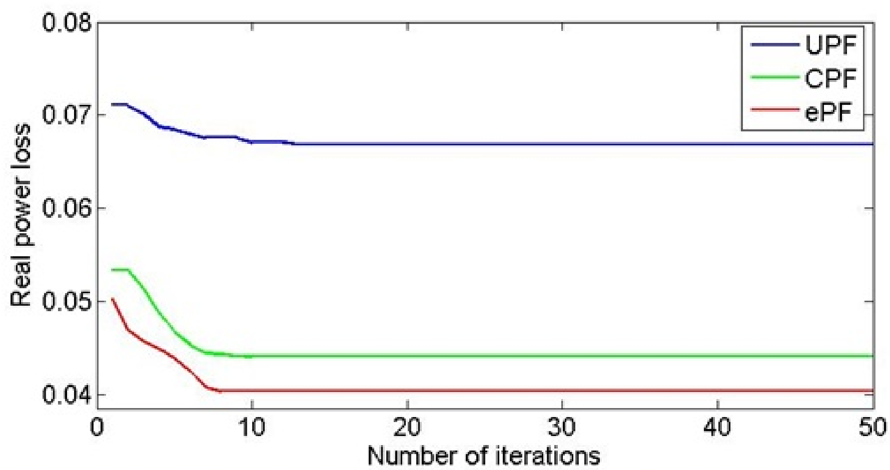


Figure 4.

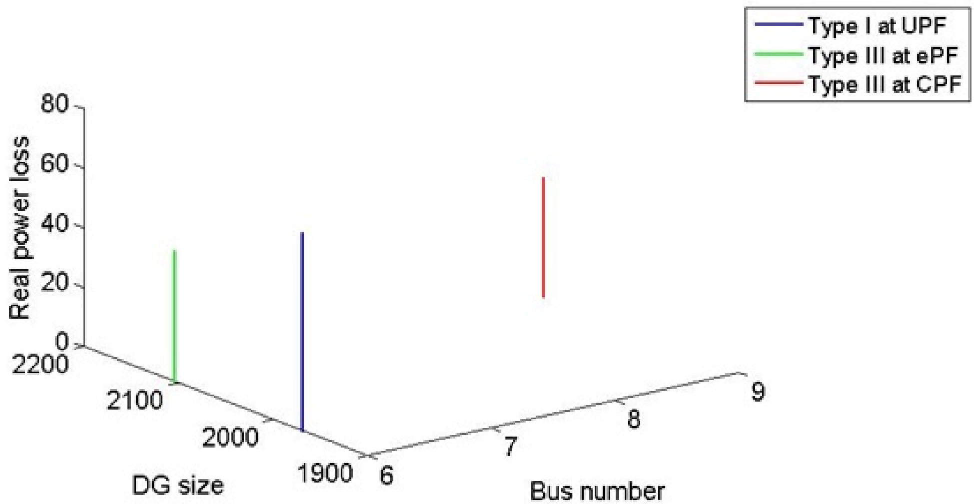


Figure 5.

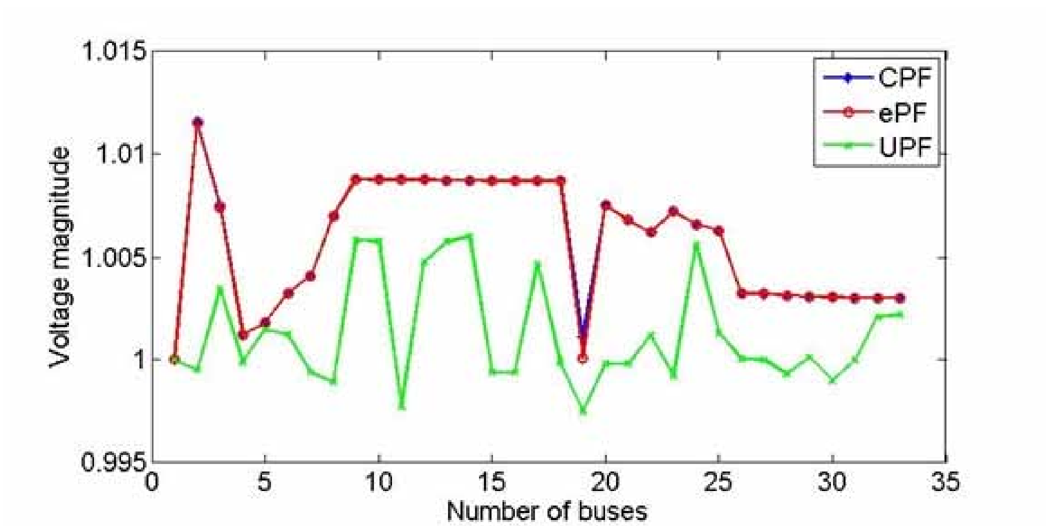


Figure 6.

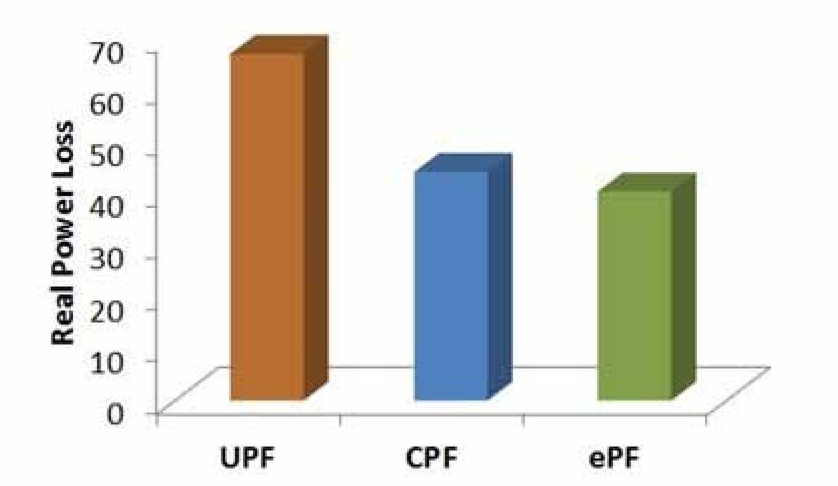


Table 2. Results for IEEE 33-bus distribution network for single DG allocation

Parameters	Single DG unit		
	Type I (UPF)	Type III (CPF)	Type III (ePF)
Bus for DG allocation	6	6	9
Size of DG	1968.2	2103.2	2105.3
Power factor	1	0.85	0.81
Bus/Min. voltage	25/0.9685	3/0.9786	8/0.9931
Bus/Max. voltage	26/1.004	1/1.005	6/1.0051
Active Power Loss	66.84	44.02	40.29
Reactive Power Loss	43.09	28.40	26.00
Absolute Power Loss	79.53	52.39	47.95
Total reduction in loss (%)	68.80	79.45	81.19

Table 3. Correlation of Active Power loss minimization with WOA and BBO

Methods		Real Power loss	Loss Reduction
WOA	Type I	66.84	68.32%
	Type III	44.02	79.14%
	Type III	40.29	80.90%
BBO[25]	Type I	137.85	34.66%
	Type III	87.61	67.69%
	Type III	87.365	67.79%

Table 4. Results after two DG placement

Parameters	Two DG units		
	Type I (UPF)	Type III (CPF)	Type III (ePF)
Bus number for DG placement	27, 11	27, 9	30, 13
Size of DG	857.42, 671.7116	1133.112, 727.1413	1167.14, 889.2
Power factor	1	0.85	0.6081
Bus/Min. voltage	26/0.9721	26/0.9834	26/0.9811
Bus/Max. voltage	1/1.00	13/1.0047	13/1.0044
Active Power Loss	67.8116	28.4738	25.0543
Reactive Power Loss	43.1656	21.1923	17.2166
Absolute Power Loss	80.3846	35.4947	30.3995
Total loss reduction (%)	68.4750	86.0798	88.0780

[3][2] Table 5. Comparison of reduction in power loss of WOA with BBO

Methods		Real Power loss	Loss Reduction
WOA	Type I	67.8116	67.86%
	Type III	28.4738	86.50%
	Type III	25.0543	88.13%
BBO[25]	Type I	87.1656	58.69%
	Type III	31.1825	85.22%
	Type III	30.3177	85.63%

5.2 IEEE 69-Bus System

The suggested approach is applied on IEEE 69-bus radial distribution network for validating the applicability in case of a bigger network. Required information for the mentioned network have been availed from (Aruldoss & Ravindran, 2018). Base-case values are tabulated in Table 6. A single line schematic representation of the network is presented in fig. 7. [1][5]Also for this system, the population size has been fixed to 50 and the number of iterations has been taken as 100.

5.2.1 Instance1: Single DG Placement

A type I or type III single DG unit is infused in the network. Table 6 consists of the results attained under base-case condition. The parametric outcomes attained by application of WOA are provided in Table 7. Reduction in active power loss because of insertion of a DG of type I is approximately 72.4% of base value. By insertion of a type III DG at bus 61 a further reduction in loss by 87.539% (CPF mode) and 88.658% (ePF mode) is obtained in comparison to the base loss. Values attained by application of WOA have been collated with BBO and is given in Table 8. Also a comparative analysis of the mentioned cases is provided in Fig. 8.

Figure 7.

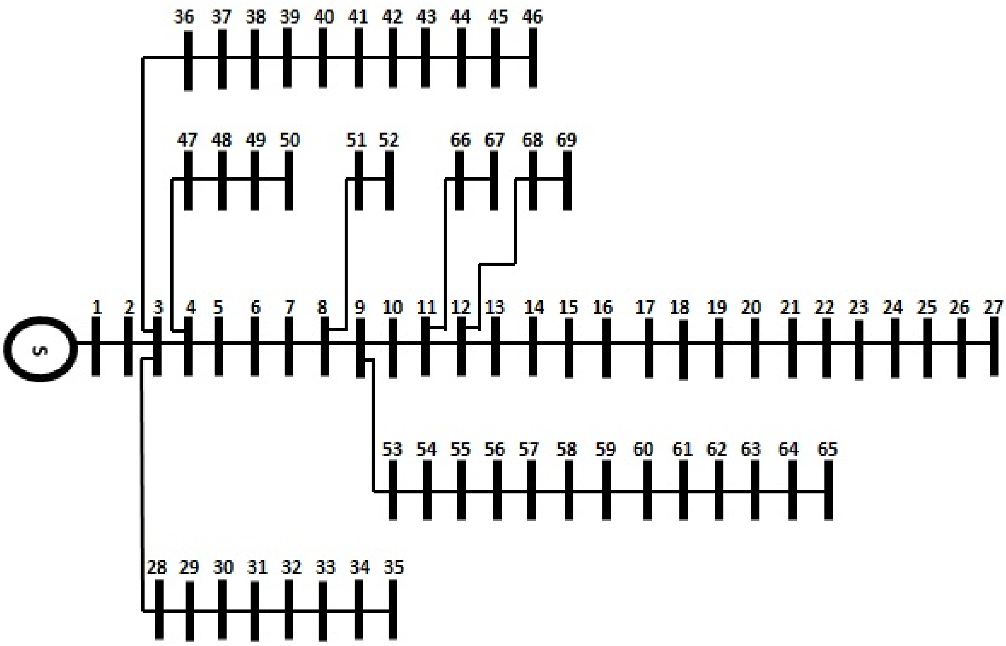


Figure 8.

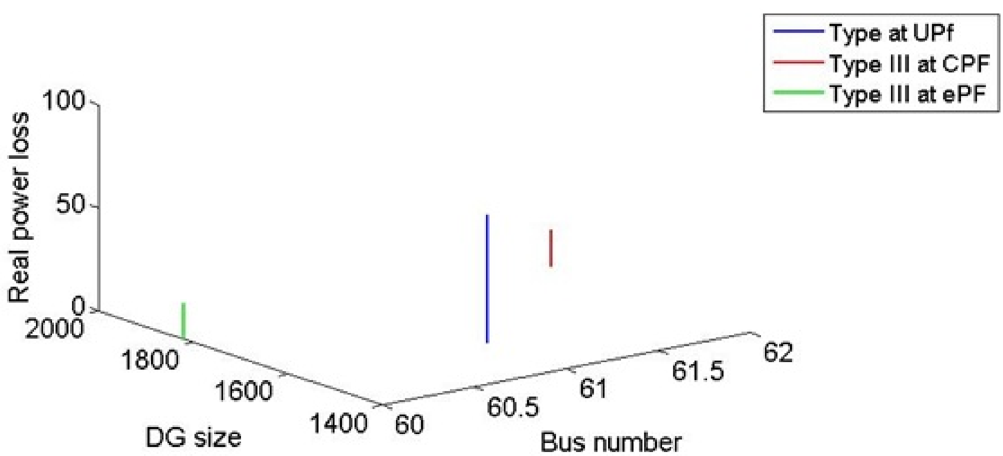


Table 6. Initial values of IEEE 69-bus system

Parameters	IEEE 69- Bus network
Power Demand (Real) Power Demand (Reactive)	3800 kW 2690 kVAR
Working Voltage	12.66 kV
Bus Number /Maximum Voltage Bus Number /Minimum Voltage	1/1.00 65/0.9092
Active Power Loss	225.461 kW
Reactive Power Loss	102.3663 kVAR
Absolute Loss	247.6116 kVA

Table 7. Values obtained for IEEE 69-bus network: single DG siting

Parameters	Single DG unit		
	Type I (UPF)	Type III (CPF)	Type III (ePF)
DG placement	61st bus	62nd bus	60th bus
DG capacity	1567.47	1822.118	1821.116
Power factor	1	0.815	0.814
Bus/Min. voltage	27/0.9717	50/0.9950	50/0.9948
Bus/Max. voltage	1/1	61/1.0058	61/1.0056
Active Power Loss	62.232 kW	17.489 kW	17.3884 kW
Reactive Power Loss	30.572 kVAR	10.372 kVAR	10.2847 kVAR
Absolute Power Loss	69.3359 kVA	20.333 kVA	20.2023 kVA
Total loss reduction (%)	71.9981	91.7883	91.8411

Table 8. Comparison of reduction in power loss of WOA with BBO

Methods		Real Power loss	Loss Reduction
WOA	Type I	62.232	72.397%
	Type III	17.489	92.243%
	Type III	17.388	92.287%
BBO[25]	Type I	93.503	58.528%
	Type III	28.094	87.539%
	Type III	27.572	88.658%

Table 9. Results of IEEE 69-bus network for two DG placement

Parameters	Single DG unit	
	Type I (CPF)	Type III (ePF)
DG placement	61st bus, 17th bus	61st bus, 17th bus
DG capacity	1780.3959,532.9859	2133.6876,633.9703
Power factor	1	0.815
Bus/Min. voltage	50/0.9951	60/0.9967
Bus/Max. voltage	1/1.005	1/1.0042
Active Power Loss	59.2176 kW	5.8123 kW
Reactive Power Loss	28.3361 kVAR	6.0324 kVAR
Absolute Power Loss	65.6480 kVA	8.3769 kVA
Total loss reduction (%)	73.487	96.616

Table 10. Comparison of reduction in power loss of WOA with BBO

Methods		Real Power loss	Loss Reduction
WOA	Type I	59.2176	73.734%
	Type III	5.8123	97.422%
BBO[25]	Type I	72.1174	68.013%
	Type III	7.2211	96.797%

Figure 9.

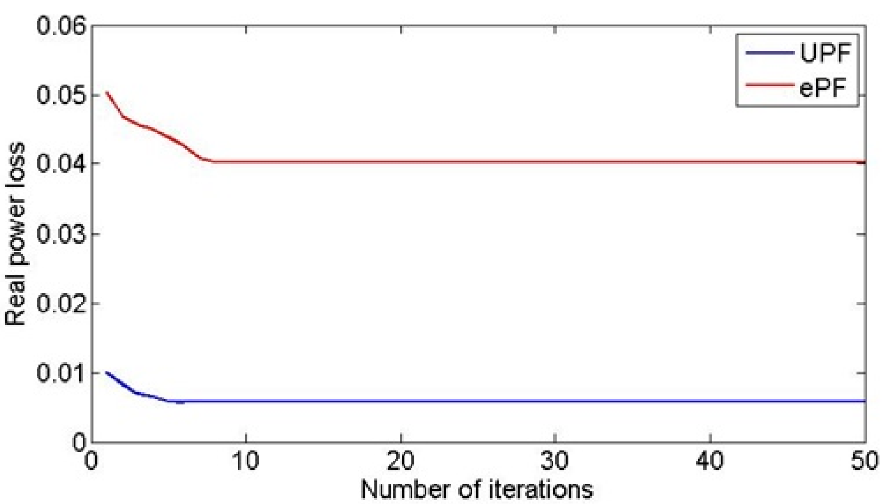


Figure 10.

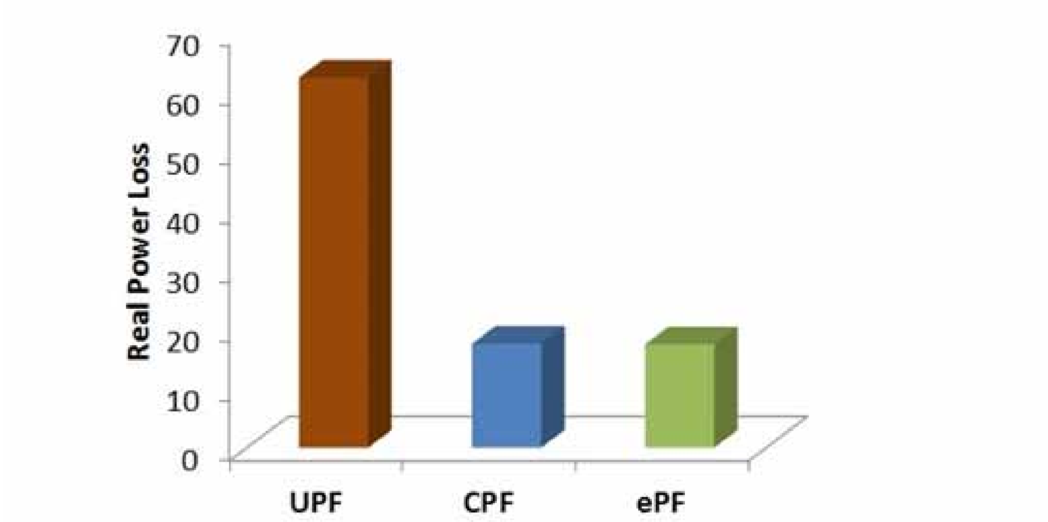
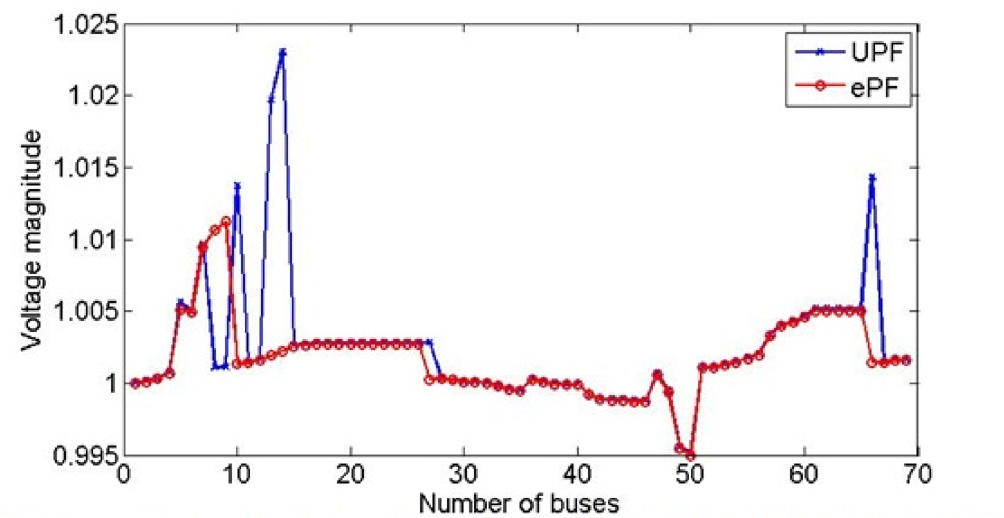


Figure 11.



5.2.2 Instance 2: Placement of Two DG

For validation of WOA based approach for IEEE 69-bus radial DS two identical DG units are positioned at appropriate positions as placement of two DG units concurrently into the network provides more benefit as compared to insertion of a single DG unit. Post computation it was observed that better results are availed if the two DGs are placed at bus numbers 61 and 17. Thus bus number 61 and 17 represents the most appropriate location sequence for the two forms of DG units (Aruldoss & Ravindran, 2018). For Type I DG when operated in UPF mode, 73.73% reduction in loss was attained by implementation of suggested WOA approach in as compared to base case. Insertion of Type III DG units provides a better loss reduction of 97.42% of the base case, representing larger saving of energy. Results are provided in Table 9. The comparison of results for BBO and WOA approaches corresponding to loss reduction is provided in Table 10.

Table 11. Statistical description for IEEE-33 bus system

Methods	**Fitness value (Estimated Error)**					**Computational Time (sec)**
	Minimum	Maximum	Mean	Median	Standard Deviation	
BBO	1.1221	1.2013	1.1617	1.1615	0.2441	0.31
WOA	0.0678	0.0679	0.0678	0.0651	0.0131	0.23

Table 12. Statistical description for IEEE-69 bus system

Methods	**Fitness value (Estimated Error)**					**Computational Time (sec)**
	Minimum	Maximum	Mean	Median	Standard Deviation	
BBO	0.9778	1.0821	1.0299	1.0294	0.2139	0.36
WOA	0.3468	0.3859	0.3663	0.3662	0.0761	0.26

Table 13. p- values of Wilcoxon test for the different bus systems on *comparison of WOA algorithm with BBO algorithm*

Number of Buses	**$N_{S/R}$**	**Z**	**P(1-tail)**
33	10	-2.36	0.0088
69	10	-2.75	0.0026

Table 14. p- values of Friedman test for the different bus systems on *comparison of WOA algorithm with BBO algorithm*

Number of buses	**Significance Level**	**p-value**
33	0.05	0.02534
69	0.05	0.02528

The convergence plot obtained for two-DG placement using WOA for loss minimization is presented in fig. 9. The power loss at the three different operation modes can be observed from fig. 10. [3](2)Also voltages at the various buses at UPF, CPF and ePF operation modes are represented in fig. 11.

6. NON-PARAMETRIC STATISTICS

[1](7),(8)From Table 11 and Table 12, the statistical description for 33 bus system and 69 bus system respectively, can be observed. The mean (average) value obtained in case of WOA is much lower to that as compared with BBO. Also the measure of variabilibility (standard deviation) reduces significantly with the application of WOA as compared to BBO. The effects can be observed for small and large systems with a reduction of almost 50% in both the values as compared to the values obtained by the application of BBO. To further the superiority of WOA over BBO has also been validated by conducting Friedman test and Wilcoxon rank sum test on the two algorithms. Both the tests are non-parametric statistical tests and are carried at 5% level of significance. The null hypothesis is as follows.

H0: The proposed Algorithm (WOA) is statistically better than BBO algorithm.

The respective detailed results (p-value) for the two tests is presented in Table 13 and and Table 14.

7. CONCLUSION

Distributed generators have become important peripherals for power factor compensation as well as power generation because of recent advancements in renewable energy systems. [2](5)Reduction of system power losses, reduction in operating cost and analysis in improvement in voltage profile are the multi objectives taken in this article and is carried out using a more recent algorithm called Whale Optimization Algorithm. Directed by a probability rule WOA can refurbish the habitat fitness values using extensive information. Proposed methodology is tested on 33-bus and 69-bus test systems for two cases: - case-1: single DG placement and case-2: 2 DG placement. The results obtained from the suggested algorithm are compared with other well-known optimization algorithms like BBO and found to be effective for multi objectives and multi constraints. Better results have been achieved with WOA as observed from the simulation results. The results indicates that the overall impact of the DG units on voltage profile is positive and proportionate reduction in power losses is achieved. It can be resolved that best results can be achieved with type III DG, because it generates both real power and reactive power. The results show that the WOA is efficient and robust.

REFERENCES

Ab Kadir, M. Z. A., Aris, I., Akorede, M. F., & Hizam, H. (2011). Effective method for optimal allocation of distributed generation units in meshed electric power systems. *IET Generation, Transmission & Distribution*, *5*(2), 276–287. doi:10.1049/iet-gtd.2010.0199

Abdelaziz, A. Y., Ali, E. S., & Elazim, S. A. (2017). Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations. *Renewable Energy*, *101*, 1311–1324. doi:10.1016/j.renene.2016.09.023

Acharya, N., Mithulananthan, N., & Mahat, P. (2006). An analytical approach for DG allocation in primary distribution network. *International Journal of Electrical Power & Energy Systems*, *28*(10), 669–678. doi:10.1016/j.ijepes.2006.02.013

Ackermann, T., Andersson, G., & Soder, L. (2001). Distributed generation: A definition. *Electric Power Systems Research*, *57*(3), 195–204. doi:10.1016/S0378-7796(01)00101-8

Al Abri, R. S., Atwa, Y. M., & El-Saadany, E. F. (2013). Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. *IEEE Transactions on Power Systems*, *28*(1), 326–334. doi:10.1109/TPWRS.2012.2200049

Ang, S., & Leeton, U. (2018). Optimal Placement and Size of Distributed Generation in Radial Distribution System using Whale Optimization Algorithm. *Warasan Technology Suranaree*, *26*(1), 1–12.

Aruldoss, A. V., & Ravindran, S. (2018). A bio-geography-based algorithm for optimal siting and sizing of distributed generators with an effective power factor model. *Computers & Electrical Engineering*, *72*, 482–501. doi:10.1016/j.compeleceng.2018.10.010

Bansal, R. C., Hung, D. Q., & Mithulananthan, N. (2010). Analytical expressions for DG allocation in primary distribution networks. *IEEE Transactions on Energy Conversion*, *25*(3), 814–820. doi:10.1109/TEC.2010.2044414

Bansal, R. C., Hung, D. Q., & Mithulananthan, N. (2013). Analytical strategies for renewable distributed generation integration considering energy loss minimization. *Applied Energy*, *105*, 75–85. doi:10.1016/j.apenergy.2012.12.023

Baran, M. E., & Wu, F. F. (1998). Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Transactions on Power Delivery*, *4*(2), 1401–1417. doi:10.1109/61.25627

Bhattacharya, K., El-Khattam, W., Hegazy, Y., & Salama, M. M. A. (2004). Optimal investment planning for distributed generation in a competitive electricity market. *IEEE Transactions on Power Systems*, *19*(3), 1674–1684. doi:10.1109/TPWRS.2004.831699

Bhesdadiya, R. H., Bhoye, M., Jangir, P., Jangir, N., Parmar, S. A., & Trivedi, I. N. (2016). Optimal Active and Reactive Power Dispatch Problem Solution using Whale Optimization Algorithm. *Indian Journal of Science and Technology*, *9*(1), 1–6. doi:10.17485/ijst/2016/v9i(S1)/101941

Celli, G., Ghiani, E., Mocci, S., & Pilo, F. (2005). A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. *IEEE Transactions on Power Systems*, *20*(2), 750–757. doi:10.1109/TPWRS.2005.846219

Chis, M., Jayaram, S., & Salama, M. M. A. (1997). Capacitor placement in distribution systems using heuristic search strategies. *IEE Proceedings. Generation, Transmission and Distribution*, *144*(3), 225–230.

Esmaili, M. (2013). Placement of minimum distributed generation units observing power losses and voltage stability with network constraints. *IET Generation, Transmission & Distribution*, *7*(8), 813–821.

Gozel, T., & Hocaoglu, M. H. (2009). An analytical method for the sizing and siting of distributed generators in radial systems. *Electric Power Systems Research*, *79*, 912–918.

Haque, M. H. (1996). Efficient load flow method for distribution systems with radial or mesh configuration. *IEE Proceedings. Generation, Transmission and Distribution*, *143*(l), 33–38.

Haque, M. H. (1999). Capacitor placement in radial distribution systems for loss reduction. *IEE Proceedings. Generation, Transmission and Distribution*, *146*(5), 501–505.

Harrison, G. P., & Ochoa, L. F. (2011). Minimizing energy losses: Optimal accommodation and smart operation of renewable distributed generation. *IEEE Transactions on Power Systems*, *26*(1), 198–205.

Hung, D. Q., & Mithulananthan, N. (2013). Multiple distributed generator placement in primary distribution networks for loss reduction. *IEEE Transactions on Industrial Electronics*, *60*(4), 1700–1708.

Khatod, D. K., Pant, V., & Sharma, J. (2013). Evolutionary programming based optimal placement of renewable distributed generators. *IEEE Transactions on Power Systems*, *28*(2), 683–695.

Khatod, D. K., & Viral, R. (2012). Optimal planning of distributed generation systems in distribution system: A review. *Renewable & Sustainable Energy Reviews*, *16*(7), 5146–5165.

Lee, S. H., & Park, J. W. (2009). Selection of optimal location and size of multiple distributed generations by using Kalman filter algorithm. *IEEE Transactions on Power Systems*, *24*(3), 1393–1400.

Marimuthu, A., Gnanambal, K., & Priyanka, R. (2017). Optimal allocation and sizing of DG in a radial distribution system using whale optimization algorithm. *2017 International Conference on Innovations in Green Energy and Healthcare Technologies (IGEHT)*.

Mirajilili, S. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software*, *95*, 51–67.

Morshidi, N. M., Musirin, I., & Rafidah, S. (2018). Whale Optimization Algorithm Based Technique for Distributed Generation Installation in Distribution System. *Bulletin of Electrical Engineering and Informatics*, *7*(3), 442–449.

Narasimham, S. V. L., Rao, R. S., Ravindra, K., & Satish, K. (2013). Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. *IEEE Transactions on Power Systems*, *28*(1), 317–325.

Nehrir, M. H., & Wang, C. (2004). Analytical approaches for optimal placement of distributed generation sources in power systems. *IEEE Transactions on Power Systems*, *19*(4), 2068–2076.

Prakash, D. B., & Lakshminarayana, C. (2018). Multiple DG placements in radial distribution system for multi objectives using Whale Optimization Algorithm. *Alexandria Engineering Journal*, *57*(4), 2797–2806.

Reddy, D. P., Reddy, V. C., & Manohar, G. T. (2017). Optimal renewable resources placement in distribution networks by combined power loss index and whale optimization algorithms. *Journal of Electrical Systems and Information Technology*, *5*(2), 175–191.

Reddy, D.,P., Reddy, V., C., & Manohar, G., T. (2017). Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems. *Renwables: Wind, Water and Solar, 4*(3).

Touma, H. (2016). Study of The Economic Dispatch Problem on IEEE 30-Bus System using Whale Optimization Algorithm. *International Journal of Engineering Technology and Sciences*, *5*, 11–18.

Zimmerman, R. D., Gan, D., & Murillo-Sanchez, C. E. (2006). *Matlab Power System Simulation Package* (Version 3.1b2). Available at https://www.pserc.cornell.edu/matpower/

Suvabrata Mukherjee was born in 1985 at Asansol, Burdwan, West Bengal, India. He Received the B.Tech Degree in Electrical Engineering from Asansol Engineering College, Asansol, Burdwan, India in 2007; M.E Degree in Control System from Asansol Engineering College, Asansol, India in 2013. Presently he is working as Assistant Professor in the department of Electrical Engineering, NSHM, Durgapur, West Bengal, India. His field of research interest includes Load flow, Radial Distribution System, State Estimation and Evolutionary computing techniques.

Provas Kumar Roy was born in 1973 at Mejia, Bankura, West Bengal, India. He Received the B.E Degree in Electrical Engineering from Regional Engineering College, Durgapur, Burdwan, India in 1997; M.E Degree in Electrical Engineering from Jadavpur University, West Bengal, India in 2001; Ph. D from NIT Durgapur, West Bengal, India. Presently he is working as in the department of Electrical Engineering, Kalyani Government Engineering College, West Bengal, India. His field of research interest includes Load flow, Automatic Generation Control, Economic Load Dispatch, Renewable Energy, Radial Distribution System, State Estimation and Evolutionary computing techniques.