# Optimal Placement and Sizing of DG considering Power and Energy Loss Minimization in Distribution System

Arnab Pal, Ajoy Kumar Chakraborty, and Arup Ratan Bhowmik

Department of Electrical Engineering
National Institute of Technology Agartala
Agartala, India
arnabpal1994@gmail.com, akcall58@gmail.com, arup.ee_nita@yahoo.com

*Abstract:* Optimal placement of Distributed Generation (DG) in the distribution network is a significant solution to resolve the power loss issue. Selection of the optimal locations and sizes of the DG is a practical problem and challenging job to achieve the minimum loss. In this work, the optimal location and appropriate size of the DGs have been found out to minimize the total active power loss of the distribution system with less penetration level of the DG considering of 24 hours duration. A modified search algorithm has been proposed in this paper which is capable to obtain the best solutions. Moreover, several reputed soft computing techniques have been applied to solve the problem and validate the optimal results. Technical aspects like energy losses have been minimized instead of power loss and practical factors like hourly basis solar output, wind generation and load variation have been considered to make this work more realistic. The solution techniques have been tested on the IEEE 33, IEEE 69 and 118 radial distribution test bus systems and results have been compared with recent literature. The quality of the results establishes the efficiency of the proposed modified algorithm to solve the optimal location and sizing problem with the effect of PV and wind power variation along with the variable load.

*Keywords*: Distributed generation; optimal DG placement; renewable generation; energy loss minimization; optimization techniques.

## 1. Introduction

DG is a small scale electrical power generator typically located at near to the load in the distribution system. DG plays a very important role to minimize the power loss and voltage improvement of the system, its size is around 50 kW to 100 MW [1]. The energy loss can be reduced and the voltage profile can be improved of the distribution network by placing DGs optimally. The DG also helps to improve the reliability of the power system. DG is beneficiary for the consumer and utility both, particularly where the central generation or utility is unfeasible or transmission system is weak to transmit sufficient power to fulfill the load demand. Since DG is connected close to the load at distribution network, the loss for the power travel through transmission and distribution line can also be avoided. Most importantly, it can supply the power to the consumer as well as to the grid if generation is more than the local demand.

But DG should be placed at such locations so that minimum loss can be achieved considering the constraints of the system. DG placement at non-optimal place can cause maximization of power losses, over voltage or under voltage and may be the cause of violation of the line capacities. Also DG penetration limit is a very important issue to the researchers because there is some limitation to inject power into the distribution system. The system may not be healthy or stable by injecting more and more power by DG as high penetration can create high node voltages, high fault current and impact on grid stability [2]. Many optimization techniques have been proposed and applied so far in the literature to get the optimal location as well as the size of DG. Most of the earlier proposed algorithms were mainly based on classical mathematical programming methods. These techniques could not

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explain the complex objective functions which are not differentiable, mostly with complicated constraints, as today's DG placement problem is not a mathematically convex problem.

In [3], H.L.Willis has discussed zero point analysis migrating zero point of DG and an analytical 2/3 method has been used for the optimal placement and sizing of DGs. However, this method is not suitable for non-uniform loads. Wang et. al [4] have presented analytical approaches for the optimal placement of DG with unity power factor in power systems. DGs have been allocated in IEEE 33 bus system to minimize the power loss [5]. Optimal load flow with second order algorithm method [6] has been used to determine the optimal location of DG for minimum power losses. In [7], particle swarm optimization has been used for the optimal placement of DG and the results have been compared to the analytical approach. The approaches like prime dual interior point method [8], mixed integer nonlinear programming [9], trade-off method [10], genetic algorithm [11] also have been employed to solve the DG allocation in distribution systems. In [12], Ant Lion Optimization (ALO) has been imposed to allocate DG on different distribution network at optimal places with optimal sizes which are mainly renewable generation. Active power loss minimization has been done in [13] by placing DG at optimal locations by applying Genetic Algorithm. In [14], authors have used a new metaheuristic technique and hybrid GWO to allocate DGs optimally in different radial bus systems such as IEEE 33, 69 and Indian 85 for loss minimization and bus voltage improvement. The PSO method has been implemented for DG allocation to get the benefit of voltage improvement and reduction of transmission line losses in [15]. In [16], placement of multiple DGs has been done in a microgrid. In [17], DG allocation at optimal locations using a combination tool of genetic algorithm and simulated annealing. The optimal results have been compared with using simple genetic algorithm and tabu search in [18]. To find out DG's optimal location in distribution (radial) system an improved multi-objective harmony search (HS) has been used in [19]. The nonlinear constraints have been considered for placing and sizing of DG in the radial bus system in [20]. Article [21] has been presented as system loss minimization considering yearly load variation in an existing distribution system and optimal DG size and location have been found out by cuckoo search algorithm. In [22] Mukul Dixit et al. have utilized Power Loss Index (PLI) approach and Index Vector Method (IVM) to determine the appropriate allocation of DGs and shunt capacitors. Ankit Uniyala and Ashwani Kumar have considered three objective functions and solved with NSGA-II with fuzzy satisfying method to get optimal sizes and locations of DG in [23]. In [24] Imran Ahmad Quadri et al. have used teaching learning-based optimization to reduce the distribution system loss, improve the voltage and annual energy saving. Asmaa H. Ali et al. in [25], have used ALO to allocate DG in 33 and 69 RDN considering the renewable sources. In [26] Imen Ben Hamida et al. have reconfigured the distribution to minimize the loss of the system with DG integration considering the variation of load and DG generation. Nazari-Heris et al. have used Q-PSO in [27]. In [28], R. Arulraj and N. Kumarappan have proposed the allocation of a single DG and multiple DG in the distribution system by SLPSO. In [29] Coelho, F.C et al. have planned a new metaheuristic technique named War Optimization to get the right places and sizes for DG in order to achieve the minimum active power loss. In [30], Karar Mahmoud and Yorino Naoto have shown a combination of analytical expressions and OPF to obtain the optimal places, sizes and DG type. T. Yuvaraj et al. have used the Bat Algorithm to optimal allocate DG on IEEE 33 RDS in [31]. In [32], Belkacem Mahdad and K. Srairi have allocated multi-type DG in presence of SVC in the system by adaptive DS. In [33], E. S. Ali has applied ALOA in only 69 distribution bus system for allocation of renewable DG. In [34] loss–voltage–cost index method has been incorporate for optimization and placed capacitor bank and DG in distribution system to achieve stable voltage, optimal annual operating cost and minimum power loss. Optimal locations and sizing for renewable generation, capacitor bank and energy sources have been done by an integrated planning framework in [35]. DGs have been considered as solar PV source to get highest voltage stability in the system, and a new power flow algorithm developed to avoid iteration for optimal allocation of DG considering line sensitivity factor using HOMOR software in [36]. Transient performance of power system has been enhanced with the help of DG in [37]. Energy storages and fuel cells have been allocated as DG in distribution network in [38]. Locations and sizes of DG have been found out optimally in [39] using a robust algorithm. Authors have minimized the power loss of radial distribution network by optimal network reconfiguration in [40]. Coordination of protection device has been done in presence of DG in [41]. Optimal reconfiguration has been presented considering the DG in [42]. Authors in [43], have introduced an optimization method to allocated DGs in distribution system. In [44] and [45], optimal allocation of renewable DG and storage has been done in distribution network. Network reconfiguration of the distribution network and DG allocation both have been done in [46 – 48]. An innovative algorithm has been proposed in [49] to allocate DG in radial network and [50] has presented a hybrid technique for the same. GWO has been used in [51] to allocate electric vehicle charging station in IEEE 33 distribution network. [52 – 54] are also good work of allocation problem on distribution network.

Mirjalili. S. et al. [55] have presented a bio inspired optimization technique named Salp Swarm Algorithm in 2017 to solve engineering problems with a single objective or multi-objective function. The outcomes on the numerical capacities demonstrate that the SSA algorithm can enhance the underlying arbitrary arrangements viably and join towards the ideal. The aftereffects of the genuine contextual investigations show the benefits of this algorithm proposed in taking care of true issues with troublesome and obscure pursuit spaces. Whale Optimization Algorithm [56] is a metaheuristic optimization technique inspired by nature. It is copied from hunting behaviour of humpback whales i.e. bubble-net searching technique. Mirjalili. S. et al. have tested with 29 mathematical and 6 design problems with this optimization technique and the results are far better than other conventional techniques. In [57], Mirjalili et al. have proposed an effective optimization algorithm to solve the real problem called Moth Flame Optimization. The technique inspired by the transverse orientation which is the navigation system of moths. By this technique, they can travel a long distance in a straight line and trapped other small insects around the artificial light. MFO has been tested and got the impressive result with 29 benchmark problem and 7 practical engineering problems. Pal, A. et al. [58] in 2017 have introduced two new algorithms to determine optimal locations for DG. Algorithm 1 is capable to find the best optimal locations by searching all the possible combination of DG's locations for a certain number of DG but it searches a large number of combinations and takes huge time. Algorithm 2 finds the same optimal locations as algorithm 1 but it consume very less time. In 2018 Pal, A. et al. [59] have proposed an algorithm named One by One Search Algorithm (OBOSA) to find out only optimal locations of DG but the sizes were predefined. The obtained results are far better than other optimization techniques because it searches all the possible location one by one and computing time is also very less, unlike optimization techniques.

In this work, the OBOSA has been modified to make it robust to solve the sizing problem along with the locations of the DG. Moreover, state of the art technique such as grey wolf optimizer (GWO), salp swarm algorithm (SSA), whale optimization algorithm (WOA) and moth-flame optimization (MFO) have been applied to solve the same problems. Therefore, various optimization techniques and modified one by one search algorithm (MOBOSA) have been used to determine validated results of the optimal nodes and respective sizes of the DG on IEEE 33, IEEE 69 and 118 (appendix – A) distribution systems. Each technique has strength and weakness depending on different problem. For some cases, one technique is performing well but for other cases, it is not able to provide a good result that's why in this paper many techniques have been applied to find out optimal locations as well as the sizes of the DG. But the most beauty of this paper is energy loss minimization because the distributed generators are renewable based like solar power and wind power generation. These sources are non-dispatchable energy source which totally depends upon the weather condition and human doesn't have any control of their output. Therefore, solar irradiance, wind speed and load are changing with the time. Hence, which is an optimal location at a particular time it would not be optimal at another time because by that time, the DG power output and load have changed. For this reason, the energy loss minimization has been formulated in this work to minimize the losses in 24 hours duration. An annual daily average of PV and wind power output on hourly basis have been taken to make this research realistic. Finally, the DGs have been allocated at optimal nodes for which the energy loss of the system will be minimum for the entire day considering the hourly variation of PV and wind power along with the variable load. As R/X ratio is high for the distribution network, the conventional load flow method is not suitable. Therefore, the energy losses, node voltages and line current have been calculated by BIBC BCBV based forward-backwards sweep (FBS) load flow.

## 2. Problem Formulation

*A. Power Loss Minimization*

The main objective is to find out the locations and sizes of the DGs for which it will offer the minimum power/energy loss when the voltage of the nodes are within the acceptable limits. The losses and voltages of the radial distribution network can be calculated with the help of forward-backwards sweep load flow [60]. Let's take a 6 bus distribution system as an example shown in Figure 1.

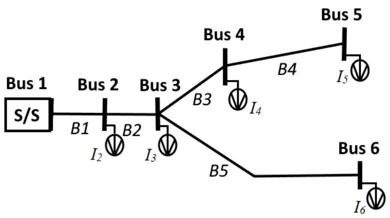


Figure 1. Example of 6 test bus system

where $B_1, B_2, B_3, ..., B_6$ are the branch currents, like $B_1$ is the branch current in between bus number 1 and 2. $I_1, I_2, I_3, ..., I_6$ are the equivalent current injection at the respective bus. Now, branch current can be calculated using the KCL.

$$\begin{aligned} B_1 &= I_2 + I_3 + I_4 + I_5 + I_6 \\ B_2 &= I_3 + I_4 + I_5 + I_6 \\ B_3 &= I_4 + I_5 \\ B_4 &= I_5 \\ B_4 &= I_6 \end{aligned} \tag{1}$$

Therefore, the relations matrix with branch currents and current injection can be developed as

$$\begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \end{bmatrix} \tag{2}$$

Let's consider this matrix as a general form, where BIBC is the matrix containing only 0 and 1.

$$[B] = [BIBC][I] \tag{3}$$

where BIBC is 'bus injection to branch current'. Using KVL, the relation between branch current and bus voltage can be expressed as below.

$$\begin{aligned} V_2 &= V_1 - B_1 Z_{12} \\ V_3 &= V_2 - B_2 Z_{23} \\ V_4 &= V_3 - B_3 Z_{34} \\ V_5 &= V_4 - B_4 Z_{45} \\ V_6 &= V_3 - B_5 Z_{36} \end{aligned} \tag{4}$$

where $V_1$ is the voltage at the substation, $V_2, V_3, \ldots, V_6$ are the voltages of the respective bus and $Z$ is line impedance. Using equation (5) all the voltages can be replaced with $V_1$, as:

$$V_6 = V_1 - B_1 Z_{12} - B_2 Z_{23} - B_5 Z_{36} \tag{5}$$

Therefore, the bus voltage can be presented only with the help of branch current and line parameter as below

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix} = \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & Z_{45} & 0 \\ Z_{12} & Z_{23} & 0 & 0 & Z_{36} \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{bmatrix} \tag{6}$$

Equation (6) can be written in general form as

$$[\Delta V] = [BCBV][B] \tag{7}$$

where BCBV is 'branch current to bus voltage' and bus voltage can be calculated by

$$\begin{aligned} [\Delta V] &= [BCBV][BIBC][I] \\ &= [DLF][I] \end{aligned} \tag{8}$$

where DLF is the 'Distribution Load Flow', which is the simple multiplication of BCBV and BIBC matrixes. The voltages and currents can be updated using equation (9 – 11) by an iterative process.

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left( \frac{P_i + jQ_i}{V_i^k} \right)^* \tag{9}$$

$$\left[\Delta V^{k+1}\right] = [DLF]\left[I^k\right] \tag{10}$$

$$\left[V^{k+1}\right] = \left[V^0\right] + \left[\Delta V^{k+1}\right] \tag{11}$$

where $I_i^k$ is the injected current at $k^{th}$ iteration at the bus number $i$ and $V^0$ is the initial voltage. $I_i^r, I_i^i$ are the real and imaginary part of the current respectively. The calculation for the power loss has been presented below:

$$P_l^i = (IB^i)^2 * Z^i \tag{12}$$

$$Z^i = R^i + jX^i \tag{13}$$

where $PL$ is total system loss, $P_l^i$ is the branch loss, $IB^i$ is branch current, $Z^i$ is the impedance, $R^i$ is the resistance and $X^i$ is the reactance of the $i^{th}$ branch.

Active Power Loss = $\mathrm{Re}(P_l^i)$

Reactive Power Loss = $\mathrm{Im}(P_l^i)$

When the objective is to minimize the total power loss, the objective function can be written as

$$\min(f) = \sum_{i=1}^{n} \mathrm{Re}\{(IB^i)^2 * Z^i\} \tag{14}$$

Where $n$ = number of branch.

*B. Energy Loss Minimization*

Objective Function has been presented below for energy loss minimization considering the hourly variation of load, PV, wind power.

$$\min(f) = \sum_{t=1}^{24} \sum_{i=1}^{n} \mathrm{Re}\{(IB_t^i)^2 * Z^i\} \tag{15}$$

where $t$ is the hour in a day and $IB_t^i$ is the current flowing through the $i^{th}$ branch at time $t^{th}$ hour.

*C. Constraints*

- Voltage constraint:

The allowable voltage limits should be maintained at the time of DG allocation. DG should not create under or over voltage in the system.

$V_{\min} \le V_t^i \le V_{\max}$ where $i$=1 to $nb$ and $t$ = 1 to 24 (15.1)

where $V_{\min}$ = 0.94 and $V_{\max}$ = 1.06

When PV and wind generation have been considered as DG, the lower limit of the voltage constraint have not been taken into account because PV/wind power output may be less or zero at a particular time in a day, which depends on solar irradiance and wind speed. Therefore, it may not maintain the desired voltage improvement.

- DG penetration limit constraint:

Total DG output power should be less than or equal to the total load (100% penetration level). Over penetration may cause unstable and disturbance in the system [61, 62] because the total DG output more than the total load can create over voltage, high fault current, and reverse power flow.

$$\sum_{i=1}^{nDG} P_i^{DG} \le 100\% \; of \; the \; lotal \; load \tag{15.2}$$

- Power balance constraint:

The summation of the total load and power losses should be supplied from the DG and utility as follow

$$P_U + P_{DG} - P_{loss} - P_{load} = 0 \tag{15.3}$$

Where, $P_U$ = Power consumption from central generation, $P_{DG}$ = Total power delivered from all DG, $P_{loss}$ = Total power loss in the network, $P_{load}$ = Total load in the network.

## 3. Methods and Tools

*A. Salp Swarm Algorithm (SSA) [55]*

The main objective of Salp Swarm Optimizer is to find out the global optimal point. The leader salp goes at the food direction and follower salps follow that. So, the total salp chain will travel in the direction of the food or the optimal point.

With random positions, initialize the multiple salps to start close to the global optimum point SSA algorithm starts close to the global optimal. Then find out the best fitness salp by calculating each salp's fitness. As the target of the salp chain is to find out the food location, we have to set the best salp to the variable F. Using equation (17) update the coefficient for every dimension. Then need to update the position to go towards food and to get back the outsider salps into the boundaries. Update the leader salp's position using equation (16) and the position update formula is equation (19) for the follower salps. These steps will continue until it is not fulfilling the end condition. This updated technique has the potential to chase that food source which is moved during the search.

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & c_3 \ge 0 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & c_3 < 0 \end{cases} \tag{16}$$

Equation (16) is the updated formula for the leader salp even the food location has changed. Where

$x_j^1$ = Position of the leader salp (first salp in the chain) in the $j^{th}$ dimension.

$F_j$ = Food location at the $j^{th}$ dimension.

$c_1, c_2$ and $c_3$ are the random numbers.

$lb_j$ = Lower bound of the $j^{th}$ dimension.

$$c_1 = 2e^{-(\frac{4l}{L})^2} \tag{17}$$

In SSA, $c_1$ is such a coefficient that helps to maintain the exploitation and exploration balanced. Equation (17) is the expression for $c_1$. Where, $L$ = Max iteration number, $l$ = Iteration number

$$x_j^i = \frac{1}{2}at^2 + v_0 t \quad (18)$$

Equation (18) is for the position update formula for follower salps. Where $x_j^i$ = follower salps position in $j^{th}$ dimension and $i \geq 2$. $v_0$ = Starting speed, $t$ = Time. $a = \frac{v_{final}}{v_0}$, where, $v = \frac{x - x_0}{t}$.

The mismatch between iteration and $v_0$ is 1, so the equation can be expressed as follow:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \quad (19)$$

- Pseudocode for the SSA [55]:

Salp population Initialization $x_i$ ($i$ = 1, 2, ..., $n$) using *ub* and *lb*
while (not satisfied the stop condition)
fitness calculation for each salp
*F*=the best salp (search agent)
Update $c_1$ by equation (17)
for each salp ($x_i$)
if ($i$ ==1)
Position update of the leading salp using equation (16)
else
Position update of the follower salp using equation (19)
end
end
Improve the salps according to the variables' upper and lower bounds.
end
return *F*

*B. Whale Optimization Algorithm [56]*

WOA may be the global optimizer as it incorporates with exploitation and exploration skill. It allocates a search space near the best solution and permits other search agents to utilize the best point by using a hyper-cube mechanism. Only two parameters $A$ and $C$ need to adjust. Some iterations are committed for exploration $(|\vec{A}| \geq 1)$ and remaining for exploitation $(|\vec{A}| < 1)$ by decreasing the $A$ for the smooth movement between exploitation and exploration.

The whale optimization starts directly with random solution, then they update their positions with the best position acquired so far or random search agents. To assign exploration and exploitation, decreased the parameter $a$ from 2 to 0. When $(|\vec{A}| > 1)$, a search agent is chosen randomly, and the best solution is chosen when $(|\vec{A}| < 1)$ for position update of the search agents. WOA is capable to shift between circular or spiral movement. When the stop criterion is satisfied then the algorithm will terminate.

$$\vec{D} = \left| \vec{C}.\vec{X^*}(t) - \vec{X}(t) \right| \quad (20)$$

$$\vec{X}(t+1) = \vec{X^*}(t) - \vec{A}.\vec{D} \quad (21)$$

Equation (20) and Equation (21) are the position update formula of the whale to catch the victim. Where,

$\vec{D}$ = Distance calculation between whale and victim.

$t$ = Iteration Number.

$X^*$ = Obtained best position.

$\vec{X}$ = Position Vector.

$\vec{A}$ and $\vec{C}$ = Coefficient vector, which can be calculated by equation (22) and equation (23).

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{22}$$

$$\vec{C} = 2.\vec{r} \tag{23}$$

Where $\vec{a}$ decreased the value 2 to 0, $\vec{r}$ = Random vector.

$$\vec{X}(t+1) = \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X^*}(t) \tag{24}$$

For the spiral position update using equation (24) to target the food by calculating the distance between whale and victim. Where the formula to calculate distance is

$$\vec{D'} = \left|\vec{X^*}(t) - \vec{X}(t)\right| \tag{25}$$

Where $b$ = Constant, $l$ = Random number in between -1 and 1.

$$\vec{X}(t+1) = \begin{cases} \vec{X^*}(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X^*}(t) & if\ p < 0.5 \end{cases} \tag{26}$$

Here $p$ = Random number in between 0 and 1.

$$\vec{D} = \left|\vec{C}.\vec{X_{rand}} - \vec{X}\right| \tag{27}$$

$$\vec{X}(t+1) = \vec{X_{rand}} - \vec{A}.\vec{D} \tag{28}$$

With the help of equation (27) &equation (28) find the location of the victim by varying the vector $\vec{A}$ within -1 to 1. Where $\vec{X_{rand}}$ = Random position of the whale.

- Pseudocode for the WOA [56]:

Whales population Initialization $X_i$ $(i = 1, 2, 3..., \mathrm{n})$
fitness calculation of each whale agent
$X^*$=the best search agent
while (t < max number of iterations)
for each agent
$a, A, C, l$ and $p$ update
if$(p < 0.5)$
if (|A| < 1)
current search agent position update by the Eq. (20)
else if (|A|>1)
Select a random search agent ($X_{rand}$)
Update the position of the current search agent by the Eq. (28)
end
else if $(p \geq 0.5)$
Position update of the current search by the Eq. (24)
end
end
Take back those agents who have gone out of the search boundary.
Calculate every search agent's fitness
If better solution obtained then Update $X^*$

*t=t+1*
end
return $X^*$

*C. Moth-Flame Optimization (MFO) [57]*

MFO is the moth populations based search, where moths are the search agents search the optimal point by considering the moonlight as the reference with a fixed angle. By this way, they can obtain long straight accurately and by changing the position vector, they can fly 1, 2, 3 and hyper dimension. At any point the best positions of moths are called flame, then each moth follows the flame's position in a spiral path to update theirs for a better position. MFO algorithm mainly depends upon three functions.

i.e. $MFO = (I, P, T)$ (29)

where *I* is a function that creates moths' position randomly in search space and generates the population matrix *M* which will be updated and calculate their fitness values.

$$I : \varphi \rightarrow \{M, OM\} \tag{30}$$

*M* describes the position of the moths and *OM* is their fitness.

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots & m_{n,d} \end{bmatrix} \tag{31}$$

where *d* = number of variable, *n* = number of moths

Calculated fitness values from objective function for each corresponding population set will be store in OM matrix.

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{32}$$

Flames are also playing a very important role to update the positions of moths. Matrix for flames is similar to position matrix for moths.

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n,2} & \cdots & F_{n,d} \end{bmatrix} \tag{33}$$

where *d* = number of variable, *n* = number of flames. The fitness values for the flame's position will be store in OF matrix as

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{34}$$

*P*: The function *P* generates the matrix when moths are fly in the search space. After that update it according to the fitness function value.

$$P : M \rightarrow M \tag{35}$$

T: The function T is a simple true or false generator, when the stop condition will be satisfied then it gives true, and false when it is not satisfied to stop the search.

$$T : M \rightarrow [true, false] \tag{36}$$

To update the position of the moths according to flame position use the following equation.

$$M_i = S(M_i, F_j) \tag{37}$$

$$S(M_i, F_j) = D_i * e^{bt}\cos(2\pi t) + F_j \tag{38}$$

where logarithmic spiral function is S and $D_i$ is the distance between $i^{th}$ moth and $j^{th}$ flame, $t$ is a random number in between -1 and 1 and $b$ is a constant with gives the shape to that spiral path.

$$D_i = \left|F_j - M_i\right| \tag{39}$$

where $F_j$ and $M_i$ are the fitness values of flame and moth respectively.

Try to make an adaptive reduction of flames with the iteration process by using the following equation

$$flame\,no = round\left(N - l * \frac{N-1}{T}\right) \tag{40}$$

where $T$ = maximum iteration number, $N$ = maximum flame number, $l$ = current iteration number.

*D. Modified One By One Search Algorithm*

This technique is not like other optimization. It searches all the possible locations one by one and highlights the best solution. The major steps of the modified one-by-one search algorithm (MOBOSA) are as follows:

*Step 1*: Set *DGn* = Number of DG, *DGpen* = total penetration by the DG, *PLmin* = Total loss without DG. Initiate *EL* as a zero matrix.

*Step 2*: Start counting of the hour in a day, $t$ = 1 to 24.

*Step 3*: $i$ = 2 to number of bus, DG can be connected at $i^{th}$ bus. As bus number 1 is considered as substation.

*Step 4*: Insert the network data without DG i.e. bus data, line data and loads at the $t^{th}$ hour as the load is variable.

*Step 5*: Check the available power output from the solar PV and wind generator at the $t^{th}$ hour as solar irradiance and wind speed is not fixed.

*Step 6*: Connect PV/Wind at the $i^{th}$ bus and check the total power loss of the system and store the loss value at $EL_{i,t} = EL_{i,t} + loss$ when DG is connected at $i^{th}$ bus at $t^{th}$ hour.

*Step 7*: $i = i+1$ and go to step 4. Stop when $i$ = total number of DG to be connected.

*Step 8*: $t = t + 1$ and go to step 3, stop when $t$ = 24.

*Step 9*: From *EL* matrix calculate the energy loss for each bus to find out the bus numbers which are suitable for all over the day as well as year considering all constraints i.e. equation 15.1 to 15.3.

*Step 10*: Find the bus numbers from *EL* matrix where DGs provide minimum energy loss.

*E. Grey wolf optimization (GWO) [63]*

GWO is a strong metaheuristic optimization technique proposed by S. Mirjalili et al. in 2014 [63]. This method is based on the hunting tactic of the grey wolf. The implementation of this algorithm to solve the proposed problem has been shown in Figure 2 using a flowchart.

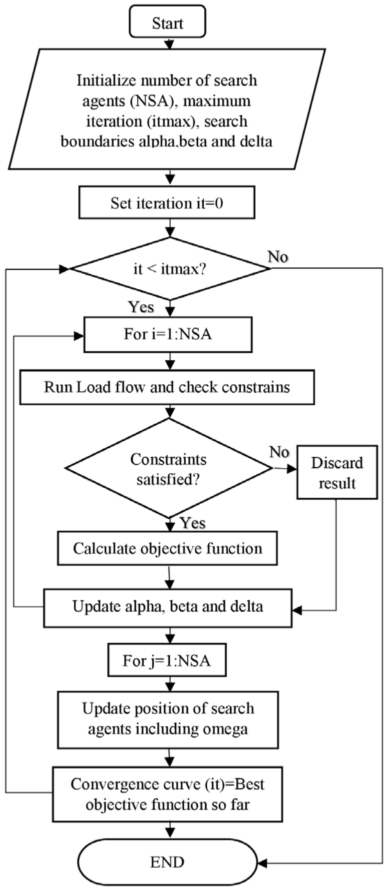


Figure 2. Flow chart of GWO [64]

## 4. Results and Discussion

All programs have been written in MATLAB programming language on a computer having 2.27 GHz Intel core (TM) i3 CPU M 350 with 3-GB RAM.

Total active and reactive load and total active power loss and reactive power loss have been shown in below Table 1.

Table 1. Total load and loss of different distribution system

| Bus System | Real Power Load | Reactive Power Load | Real Power Loss | Reactive Power Loss |
|---|---|---|---|---|
| IEEE33 | 3715 kW | 2290 kvar | 202.4733 kW | 135.0311 kvar |
| IEEE69 | 3802.29 kW | 2694.1 kvar | 224.9827 kW | 102.1584 kvar |
| 118 | 22709.72 kW | 17041.067 kvar | 935.6724 kW | 707.7794 kvar |

*A. Optimal Locations and Sizes of DG for Power Loss Minimization*

GWO, SSA, WOA, MFO and MOBOSA techniques have been implemented to the DG allocation problem to find out the optimal locations and as well as the sizes of the DG on IEEE 33, IEEE 69 and 118 test distribution systems. Tables 2 – 6, tables 7 – 11 and tables 12 – 16 are for IEEE 33, IEEE 69 and 118 radial bus systems respectively to allocate 5 and 10 DGs using different solving tool.

The results for the IEEE 33 distribution system have been presented in Table 2 – 6 with optimal DG locations and respective sizes using different techniques along with their computational time. The power losses, with and without DG also have been shown below with the total DG penetration.

Table 2. Optimal allocation of DG on IEEE 33 bus system using GWO

| GWO-33 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 13 | 24 | 30 | 31 | 14 | 5 | 26 | 24 |
| Optimal DG Size (kW) | 850 | 1104 | 1101 | 647 | 603 | 72 | 949 | 962 |
| Convergence Time (sec) | 241.33 | | | 267.20 | | | | |
| Total Loss (kW) | 73.06 | | | 66.18 | | | | |
| Total Loss Without DG (kW) | 202.4733 | | | 202.4733 | | | | |
| Total DG Penetration (kW) | 3055 < 3715 | | | 3233 < 3715 | | | | |

Table 3. Optimal allocation of DG on IEEE 33 bus system using SSA

| SSA-33 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 24 | 13 | 30 | 7 | 9 | 31 | 24 | 14 |
| Optimal DG Size (kW) | 913 | 867 | 1009 | 514 | 112 | 699 | 1363 | 619 |
| Convergence Time (sec) | 389.51 | | | 412.93 | | | | |
| Total Loss (kW) | 71.9386 | | | 67.6754 | | | | |
| Total Loss Without DG (kW) | 202.4733 | | | 202.4733 | | | | |
| Total DG Penetration (kW) | 2788 < 3715 | | | 3307 < 3715 | | | | |

Table 4. Optimal allocation of DG on IEEE 33 bus system using WOA

| WOA-33 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 25 | 12 | 30 | 31 | 24 | 10 | 14 | 26 |
| Optimal DG Size (kW) | 858 | 912 | 1034 | 669 | 986 | 255 | 489 | 783 |
| Convergence Time (sec) | 256.39 | | | 300.22 | | | | |
| Total Loss (kW) | 72.5409 | | | 65.3723 | | | | |
| Total Loss Without DG (kW) | 202.4733 | | | 202.4733 | | | | |
| Total DG Penetration (kW) | 2804 < 3715 | | | 3182 < 3715 | | | | |

Table 5. Optimal allocation of DG on IEEE 33 bus system using MFO

| MFO-33 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 24 | 14 | 30 | 10 | 14 | 26 | 24 | 32 |
| Optimal DG Size (kW) | 1100 | 754 | 1071 | 310 | 456 | 799 | 983 | 639 |
| Convergence Time (sec) | 447.61 | | | 511.51 | | | | |
| Total Loss (kW) | 71.2696 | | | 65.511 | | | | |
| Total Loss Without DG (kW) | 202.4733 | | | 202.4733 | | | | |
| Total DG Penetration (kW) | 2925 < 3715 | | | 3187 < 3715 | | | | |

Table 6. Optimal allocation of DG on IEEE 33 bus system using MOBOSA

| MOBOSA-33 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 30 | 12 | 24 | 14 | 31 | 25 | 7 | 3 |
| Optimal DG Size (kW) | 973 | 973 | 973 | 684 | 684 | 684 | 684 | 684 |
| Convergence Time (sec) | 1.64 | | | 2.55 | | | | |
| Total Loss (kW) | 72.2 | | | 65.45 | | | | |
| Total Loss Without DG (kW) | 202.4733 | | | 202.4733 | | | | |
| Total DG Penetration (kW) | 2919 < 3715 | | | 3420 < 3715 | | | | |

From Table 2 to table 6, the loss reduction with DG allocation can be observed. The allocation of 5 DG creates more benefit in term of minimization of loss. The total DG penetrations are within the limit for all the cases. It also can be seen that to allocate 3 DG on

IEEE 33 bus system the MFO technique gives the minimum loss and for 5 DG allocation WOA gives the best result among others. By using the proposed MOBOSA method nearly same results have been achieved with very less converging time. To optimal allocate 3 DG on 33 bus system MFO consumes 447.61 seconds and MOBOSA requires only 1.64 seconds for the same.

Table 7 – 11 shows the results of optimal DG allocation on IEEE 69 bus system using different solution techniques. The optimal nodes and respective DG sizes have been presented below with system power loss and DG penetration.

Table 7. Optimal allocation of DG on IEEE 69 bus system using GWO

| GWO-69 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 11 | 18 | 61 | 61 | 8 | 67 | 58 | 17 |
| Optimal DG Size (kW) | 541.5 | 406.39 | 1751.43 | 1624 | 329 | 427 | 101 | 274 |
| Convergence Time (sec) | 357.39 | | | 453.05 | | | | |
| Total Loss (kW) | 69.51 | | | 69.60 | | | | |
| Total Loss Without DG (kW) | 224.9827 | | | 224.9827 | | | | |
| Total DG Penetration (kW) | 2699.3 < 3802.3 | | | 2750 < 3802.3 | | | | |

Table 8. Optimal allocation of DG on IEEE 69 bus system using SSA

| SSA-69 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 67 | 62 | 15 | 36 | 61 | 66 | 21 | 53 |
| Optimal DG Size (kW) | 197 | 1808 | 335 | 882 | 1823 | 419 | 260 | 294 |
| Convergence Time (sec) | 422.85 | | | 476.09 | | | | |
| Total Loss (kW) | 72.8715 | | | 70.2786 | | | | |
| Total Loss Without DG (kW) | 224.9827 | | | 224.9827 | | | | |
| Total DG Penetration (kW) | 2340 < 3802.3 | | | 3678 < 3802.3 | | | | |

Table 9. Optimal allocation of DG on IEEE 69 bus system using WOA

| WOA-69 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 20 | 28 | 61 | 12 | 51 | 61 | 48 | 38 |
| Optimal DG Size (kW) | 502 | 772 | 1786 | 674 | 390 | 1701 | 535 | 415 |
| Convergence Time (sec) | 303.97 | | | 381.62 | | | | |
| Total Loss (kW) | 71.9555 | | | 71.7266 | | | | |
| Total Loss Without DG (kW) | 224.9827 | | | 224.9827 | | | | |
| Total DG Penetration (kW) | 3060 < 3802.3 | | | 3715 < 3802.3 | | | | |

Table 10. Optimal allocation of DG on IEEE 69 bus system using MFO

| MFO-69 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 11 | 61 | 18 | 9 | 61 | 66 | 18 | 50 |
| Optimal DG Size (kW) | 527 | 1719 | 380 | 376 | 1689 | 319 | 393 | 718 |
| Convergence Time (sec) | 483.47 | | | 599.23 | | | | |
| Total Loss (kW) | 69.4109 | | | 67.747 | | | | |
| Total Loss Without DG (kW) | 224.9827 | | | 224.9827 | | | | |
| Total DG Penetration (kW) | 2626 < 3802.3 | | | 3495 < 3802.3 | | | | |

In table 7 – 11, it can be noticed that the losses have been reduced after DG allocation and more number of DG helps to reduce more loss. MFO gives the best loss minimization among all the applied techniques for optimal DG allocation on IEEE 69 bus system for 3 and 5 DG allocation both. MOBOSA gives a better result than SSA where the total DG penetration is 2340 kW by SSA but MOBOSA achieved less loss with 1740 kW penetration even with very less computation time consumption. All the DG penetration levels are within the limits.

Table 11. Optimal allocation of DG on IEEE 69 bus system using MOBOSA

| MOBOSA-69 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 62 | 61 | 17 | 64 | 62 | 61 | 21 | 16 |
| Optimal DG Size (kW) | 580 | 580 | 580 | 199 | 199 | 199 | 199 | 199 |
| Convergence Time (sec) | 2.61 | | | 5.61 | | | | |
| Total Loss (kW) | 72.19 | | | 73.9 | | | | |
| Total Loss Without DG (kW) | 224.9827 | | | 224.9827 | | | | |
| Total DG Penetration (kW) | 1740 < 3802.3 | | | 995 < 3802.3 | | | | |

The optimal results for the DG allocation on the 118 bus distribution system have been presented below using different techniques in Table 12 – 16. The results have been shown with optimal locations of the 3 and 5 DGs with respective optimal sizes. The total losses of the system with and without DG also have been shown in the tables.

Table 12. Optimal allocation of DG on 118 bus system using GWO

| GWO-118 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 87 | 63 | 72 | 111 | 34 | 70 | 80 | 75 |
| Optimal DG Size (kW) | 1166 | 1655 | 2010 | 1640 | 3293 | 1681 | 1047 | 3246 |
| Convergence Time (sec) | 591.72 | | | 651.01 | | | | |
| Total Loss (kW) | 727.3143 | | | 593.77 | | | | |
| Total Loss Without DG (kW) | 935.6724 | | | 935.6724 | | | | |
| Total DG Penetration (kW) | 4831 < 22709.72 | | | 10907 < 22709.72 | | | | |

Table 13. Optimal allocation of DG on 118 bus system using SSA

| SSA-118 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 31 | 73 | 117 | 108 | 17 | 2 | 64 | 73 |
| Optimal DG Size (kW) | 6574 | 1553 | 1930 | 4578 | 2570 | 236 | 4152 | 1693 |
| Convergence Time (sec) | 668.76 | | | 701.12 | | | | |
| Total Loss (kW) | 719.8513 | | | 633.6502 | | | | |
| Total Loss Without DG (kW) | 935.6724 | | | 935.6724 | | | | |
| Total DG Penetration (kW) | 10056.466 < 22709.72 | | | 13228.6 < 22709.72 | | | | |

Table 14. Optimal allocation of DG on 118 bus system using WOA

| WOA-118 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 91 | 31 | 70 | 47 | 28 | 65 | 110 | 73 |
| Optimal DG Size (kW) | 436 | 5863 | 3953 | 3892 | 3351 | 438 | 2815 | 2246 |
| Convergence Time (sec) | 582.61 | | | 721.44 | | | | |
| Total Loss (kW) | 671.6666 | | | 486.1729 | | | | |
| Total Loss Without DG (kW) | 935.6724 | | | 935.6724 | | | | |
| Total DG Penetration (kW) | 10252 < 22709.72 | | | 12742 < 22709.72 | | | | |

Table 15. Optimal allocation of DG on 118 bus system using MFO

| MFO-118 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 35 | 110 | 71 | 50 | 96 | 109 | 4 | 72 |
| Optimal DG Size (kW) | 3516 | 2843 | 2950 | 2562 | 1809 | 3087 | 6772 | 2583 |
| Convergence Time (sec) | 772.03 | | | 891.74 | | | | |
| Total Loss (kW) | 500.6186 | | | 433.5778 | | | | |
| Total Loss Without DG (kW) | 935.6724 | | | 935.6724 | | | | |
| Total DG Penetration (kW) | 9309 < 22709.72 | | | 16813 < 22709.72 | | | | |

Table 16. Optimal allocation of DG on 118 bus system using MOBOSA

| MOBOSA-118 Bus | 3 DG | | | 5 DG | | | | |
|---|---|---|---|---|---|---|---|---|
| Optimal DG Location | 71 | 110 | 50 | 72 | 110 | 50 | 79 | 40 |
| Optimal DG Size (kW) | 2893 | 2893 | 2893 | 2688 | 2668 | 2668 | 2668 | 2668 |
| Convergence Time (sec) | 5.91 | | | 7.87 | | | | |
| Total Loss (kW) | 493.32 | | | 433.42 | | | | |
| Total Loss Without DG (kW) | 935.6724 | | | 935.6724 | | | | |
| Total DG Penetration (kW) | 8679 < 22709.72 | | | 13340 < 22709.72 | | | | |

From Table 12 - 16, proposed MOBOSA provides the best result with the minimum loss for the 3 and 5 DGs allocation both with less penetration and less computational time. For all the cases, The loss has been minimized after allocating the DGs and the total DG penetration levels are within the limits. It has also been observed that the more number of DG can reduce more power loss.

It can be seen from the above tables (Table 2 – 16), most of the cases MFO provides good results. SSA performs well when the number of nodes is less, but when search space is large such as in the case of 69 and 118 bus systems, it is not efficient. In the opposite hand, WOA performs moderately in the case of 69 and 118 bus systems. The proposed MOBOSA gives the best result for the 118 bus system which is a larger system. By this proposed algorithm, DGs have been allocated with equal optimal sizes in a particular distribution system. For 33 and 69, MOBOSA has performed moderate but the advantage is that it provides the minimum loss with less penetration of DG power compare to other methods. Consequently, equal DG sizes and less penetration level could be huge cost beneficiary and easily maintainable.

It has been found that the voltage improvements of the systems are remarkable with the results of MFO. Therefore, Figure 3 – 8 show the voltage profiles of the 33/69/118 bus systems for the placement of 5 DGs using MFO technique. Figure 3 presents the voltage profile of IEEE 33 distribution system without any DG. The improvement of the voltage profile of the 33 bus system can be noticed in Figure 4 when 5 DGs have been allocated optimally with optimal size. Likewise, the improved voltage profile of IEEE 69 bus system has been presented in Figure 6 with 5 DGs, where Figure 5 is for without DG. Figure 7 and 8 are for 118 bus distribution system where Figure 7 shows the voltage profile without DG and Figure 8 displays the improved voltage profile after allocating DGs in the system.

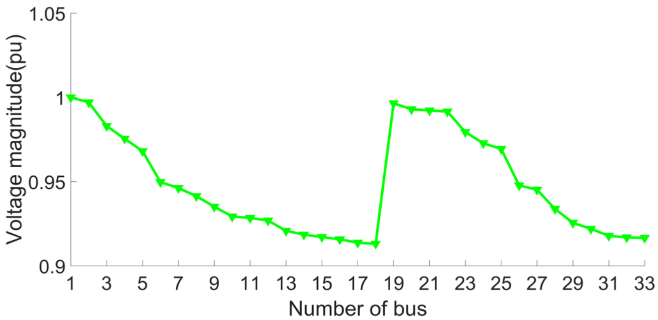

Figure 3. Bus voltages without DG of IEEE 33 bus system

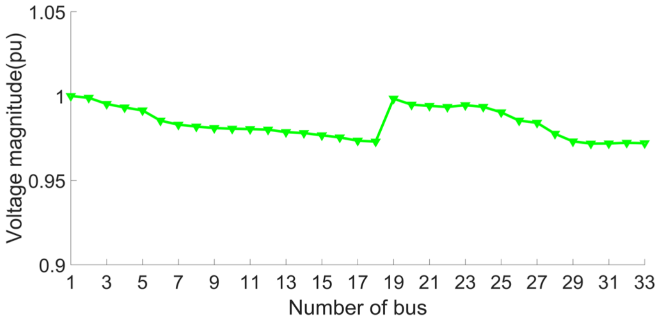

Figure 4. Bus voltages with 5 DG of IEEE 33 bus system using MFO

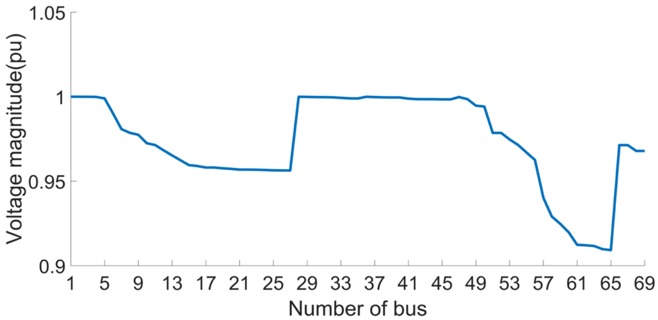

Figure 5. Bus voltages without DG of IEEE 69 bus system

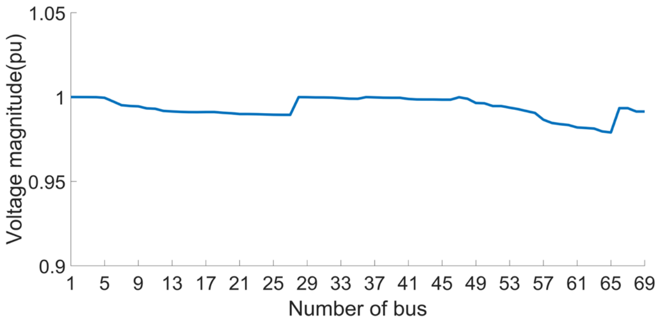

Figure 6. Bus voltages with 5 DG of IEEE 69 bus system using MFO

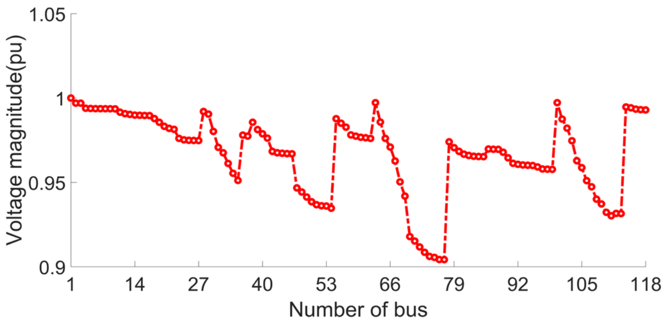

Figure 7. Bus voltages without DG of 118 bus system

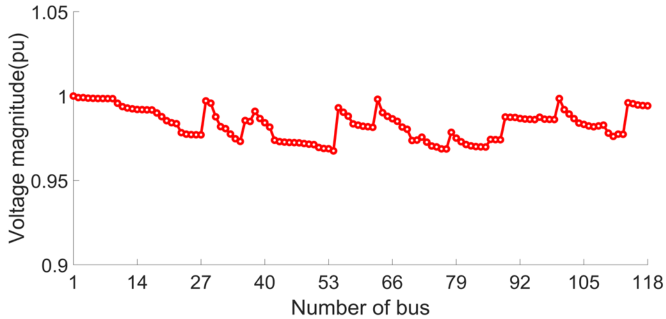

Figure 8. Bus voltages with 5 DG of 118 bus system using MFO

Table 17. Comparison table for optimal locations and sizes of DGs on IEEE 33 bus System

| Method | DG Location | DG size (kW) | Loss (kW) | Method | DG Location | DG size (kW) | Loss (kW) |
|---|---|---|---|---|---|---|---|
| GA/PSO [65] | 32 | 1200 | 103.4 | GWO[52] | 13 | 754 | 73.06 |
| | 16 | 863 | | | 24 | 850 | |
| | 11 | 925 | | | 30 | 1109 | |
| GA [65] | 11 | 1500 | 106.3 | WOA | 25 | 1101 | 72.5409 |
| | 29 | 422.8 | | | 12 | 912 | |
| | 30 | 1071.4 | | | 30 | 1034 | |
| PSO [65] | 13 | 981.6 | 105.3 | SSA | 24 | 912.68779 | 71.9386 |
| | 32 | 981.6 | | | 13 | 867.04192 | |
| | 8 | 981.6 | | | 30 | 1008.7476 | |
| TLBO [66] | 12 | 1182.6 | 124.7 | MFO | 24 | 1100 | 71.2696 |
| | 28 | 1191.3 | | | 14 | 754 | |
| | 30 | 1186.3 | | | 30 | 1071 | |
| QOTLBO [66] | 13 | 1083.4 | 103.4 | MOBOSA | 30 | 973 | 72.2 |
| | 26 | 1187.6 | | | 12 | 973 | |
| | 30 | 1199.2 | | | 24 | 973 | |

Table 18. Comparison table for optimal locations and sizes of DGs in 69 bus System

| Method | IEEE Bus System | DG locations | DG sizes | Loss |
|---|---|---|---|---|
| GWO [52] | 69 | 11, 18, 61 | 541, 406, 1751 | 69.51 |
| MFO | 69 | 11, 61, 18 | 527, 1719, 380 | 69.41 |

The comparisons with existing literature have been presented in Table 17 for IEEE 33 bus system. All the applied techniques in this work have performed better, and MFO has given the best result among all. Table 18 presents the comparison between MFO and GWO (from existing literature), where both have been used to allocate 3 DGs on IEEE 69 bus system. In this case, the performance of MFO is better than GWO. Figure 9 - 11 have been shown to describe the performances of each technique by the percentage of loss reduction for applied distribution systems. Figure 9, 10 and 11 are for IEEE 33, IEEE 69 and 118 distribution system respectively. It can be seen that the more number of DG helps to reduce more loss.

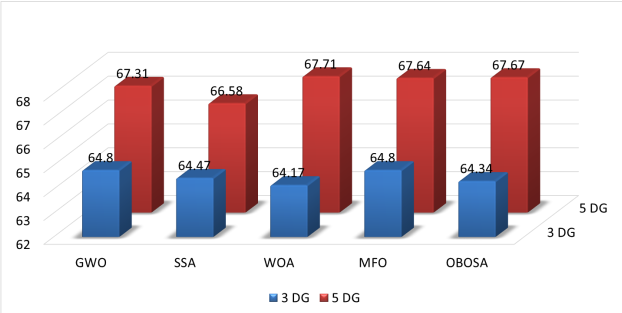


Figure 9. Percentage of loss reduction of IEEE 33 bus system

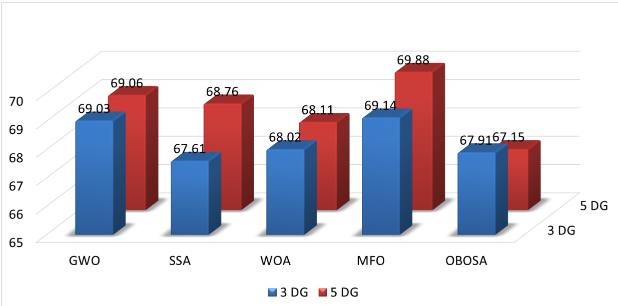


Figure 10. Percentage of loss reduction of IEEE 69 bus system

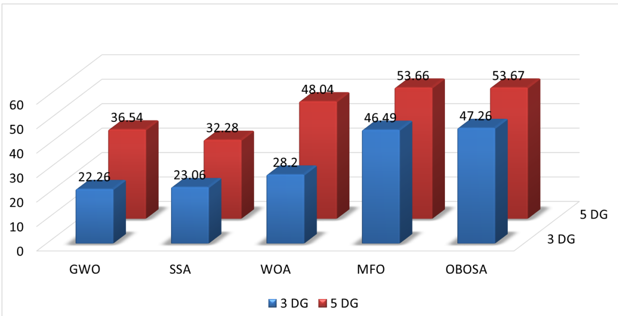


Figure 11. Percentage of loss reduction of IEEE 118 bus system

*B. Optimal Locations of DG for Energy Loss Minimization*

The energy loss minimization has been performed using the proposed MOBOSA considering the variations of DG output and load. This has been tested on IEEE 33, IEEE 69 and 118 bus system. 3 and 5 DGs have been allocated in the 33 system. But, as the 69 and 118 bus systems are large, therefore, more number of DG has been incorporated. For 69 distribution system 5 and 10 DGs, and for 118 system 10 and 20 number of DGs have been allocated. For each distribution system different PV, wind and load profile of 24 hours have been considered. The input data and respective results for different test system have been discussed below.

- DG Allocation on IEEE 33 Radial Network for Energy Loss Minimization:

The annual average variation of the PV power generation throughout the day for 33 bus system has been shown in Figure 12. Figure 13 shows the average wind variation of 24 hours in per unit for the same system. The load variation of 33 bus system also has been taken into account which has been presented in Figure 14.

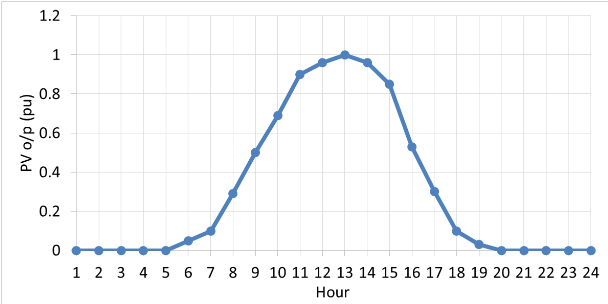

Figure 12. Annual daily average PV variation for IEEE 33 bus system

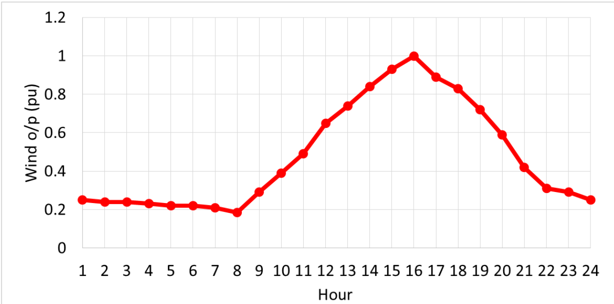

Figure 13. Annual daily average wind variation for IEEE 33 bus system

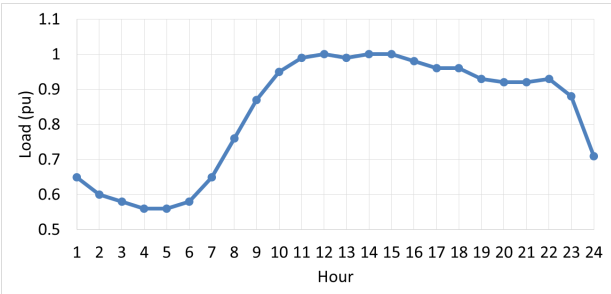

Figure 14. Annual daily average load variation for IEEE 33 bus system

Considering the above factors, the DGs have been allocated in 33 bus distribution system. Table 19 presents the optimal DG locations on IEEE 33 bus system with 3 DGs as well as 5 DGs and minimum/maximum bus voltages have been shown. It is found that the energy loss is minimized with the DG allocation and 5 number of DGs provide more loss reduction.

Table 19. DG allocation on 33 bus system for energy loss minimization

| Number of DG | Type | Optimal Locations | Energy Loss (kWh) | Min bus Voltage (pu) | Max bus Voltage (pu) |
|---|---|---|---|---|---|
| Without DG | … | ….. | 3427.2 | 0.9151 | 1 |
| 3 DG | PV | 32,30,25 | 3022.3 | 0.9151 | 1 |
| | Wind | 32,30,25 | 2848.1 | 0.9412 | 1 |
| 5 DG | PV | 32,30,25,8,31 | 2843.4 | 0.9398 | 1 |
| | Wind | 32,30,25,8,31 | 2584.8 | 0.9423 | 1 |

This solution is for energy loss minimization which provides the optimal locations for minimization of power losses of 24 hours. The voltage profiles of each hour of IEEE 33 bus system have been presented in Figure 15 when no DG is connected in the network. The differences between hourly voltage profiles can be seen due to hourly load variation in the system. Figure 16 shows the 24 hours voltage profile when 5 DGs are connected at the optimal nodes. The remarkable voltage improvement in each hour can be noticed in Figure 16 compared to Figure 15.

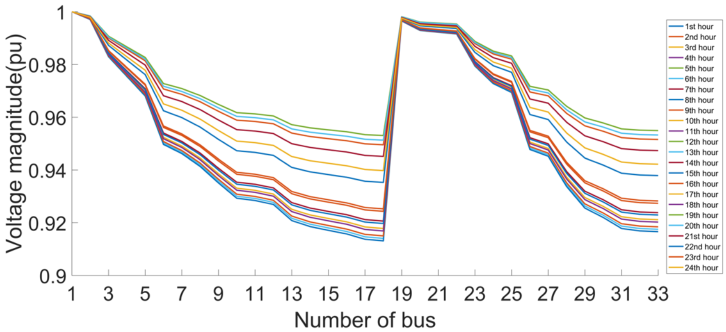


Figure 15. Bus voltages of 24 hours of IEEE 33 bus system without DG

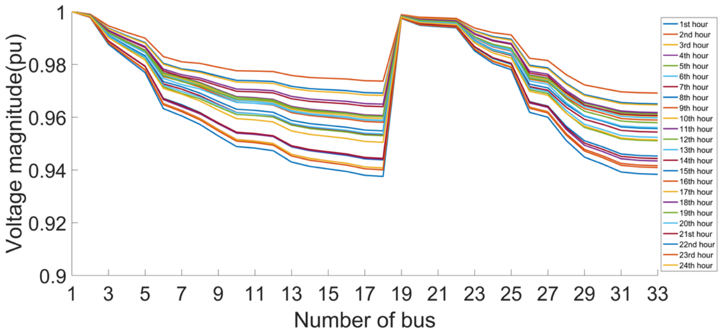


Figure 16. Bus voltages of 24 hours of IEEE 33 bus system with 5 DG (wind generation)

- DG Allocation on IEEE 69 Radial Network for Energy Loss Minimization:

The PV and wind variations of 24 hours have been shown in Figure 17 and Figure 18 respectively, which have been considered for the IEEE 69 system to allocate the DGs. The daily load variation for the same system has been taken as Figure 19 on hourly basis.

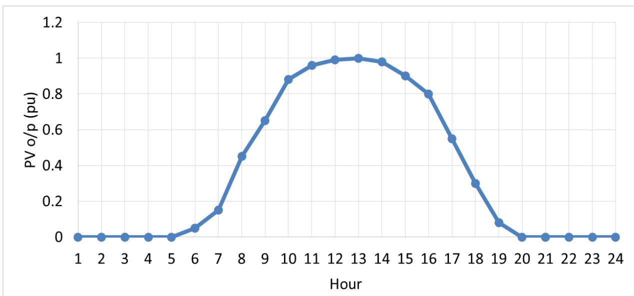


Figure 17. Annual daily average PV variation for IEEE 69 bus system

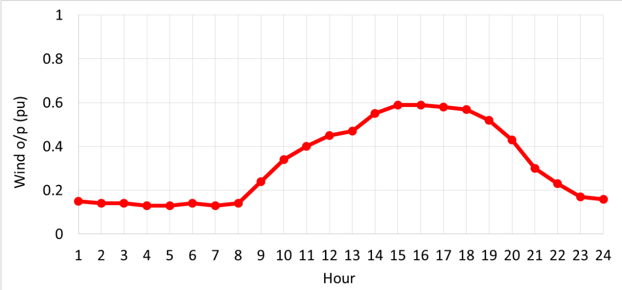


Figure 18. Annual daily average wind variation for IEEE 69 bus system

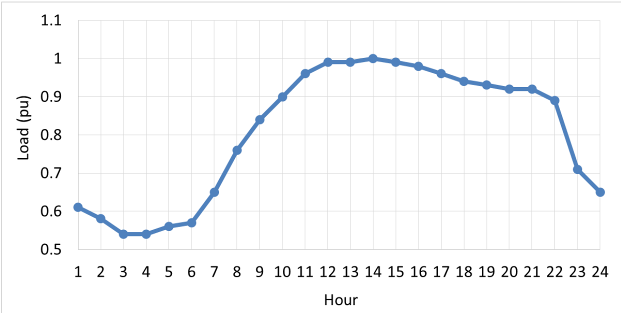


Figure 19. Annual daily average load variation for IEEE 69 bus system

Table 20 presents the optimal locations of the DG in IEEE 69 bus system considering the variations of DG power and loads. 5 and 10 DGs have been allocated and it has been found that the energy loss is significantly less for any cases when DGs are connected. The energy loss is lesser with 10 DGs compare to 5 DG allocation and the minimum bus voltage of the system has also improved.

Table 20. DG allocation on 69 bus system for energy loss minimization

| Number of DG | Type | Optimal Locations | Energy Loss (kWh) | Min bus Voltage (pu) | Max bus Voltage (pu) |
|---|---|---|---|---|---|
| Without DG | … | …….. | 3597.80 | 0.9091 | 1 |
| 5 DG | PV | 61,64,59,65,21 | 2330.90 | 0.9091 | 1 |
| | Wind | 61,64,59,65,21 | 2304.50 | 0.9495 | 1 |
| 10 DG | PV | 61,64,59,65,21,12,11,62,18,17 | 2241.50 | 0.9429 | 1 |
| | Wind | 61,64,59,65,21,12,11,62,18,17 | 2188.70 | 0.95 | 1 |

The hourly voltage improvement of IEEE 69 bus system can be compared between Figure 20 and Figure 21, where Figure 20 represents the voltage profiles without DG and Figure 21 is when 10 DGs are allocated optimally in the network. In Figure 21, the node voltages of 24 hours duration have improved upto a remarkable level with the optimally allocated DGs.

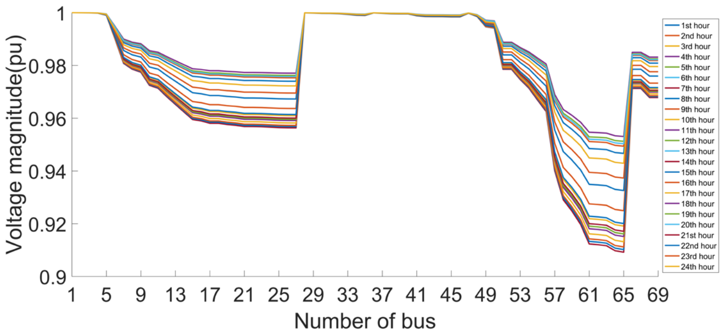


Figure 20. Bus voltages of 24 hours of IEEE 69 bus system without DG

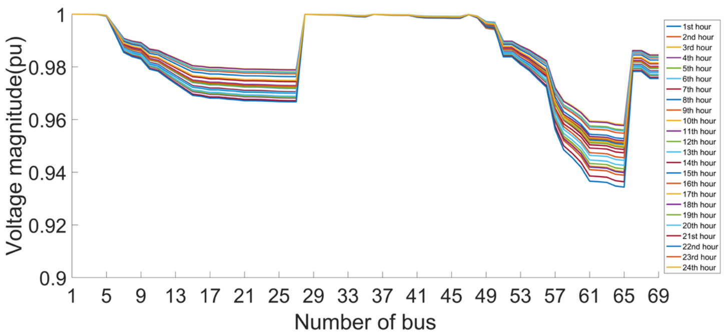


Figure 21. Bus voltages of 24 hours of IEEE 69 bus system with 10 DG (wind generation)

- DG Allocation on 118 Radial Network for Energy Loss Minimization:

Figure 22 – 24 have been considered as input of DG power and load for the 118 bus system. Where Figure 22 shows the 24 hours variation of PV power in pu and Figure 23 present the hourly variation of wind power. The load variation of 24 hours duration has been shown in Figure 24.

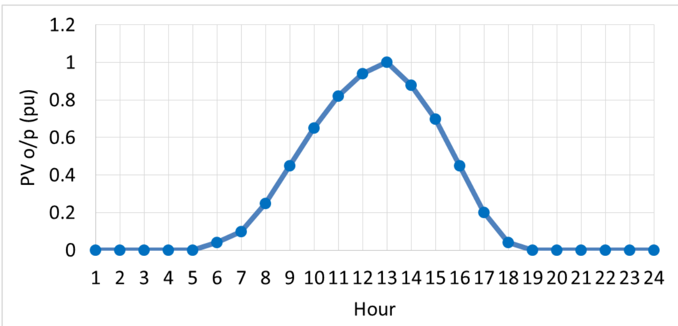


Figure 22. Annual daily average PV variation for 118 bus system

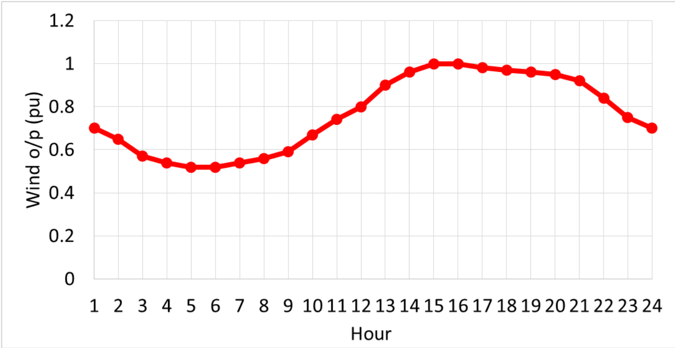


Figure 23. Annual daily average wind variation for 118 bus system

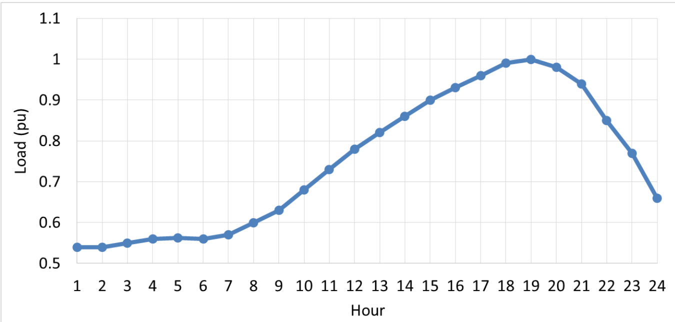


Figure 24. Annual daily average load variation for 118 bus system

The optimal allocations of 10 and 20 DGs in the 118 bus system have been presented in Table 21 considering the above variation. It has been found that without DG the energy loss of the system is high and it gets reduced with the allocation of DGs. The loss reduction is more with 20 DGs compare to 10 DGs. The minimum bus voltage of the system also has been improved by the DGs.

Table 21. DG allocation on 118 bus system for energy loss minimization

| Number of DG | Type | Optimal Locations | Energy Loss (kWh) | Min bus Voltage (pu) | Max bus Voltage (pu) |
|---|---|---|---|---|---|
| Without DG | … | …….. | 12892.00 | 0.9053 | 1 |
| 10 DG | PV | 74,111,71,70,50,109,107,112,54,96 | 10992.00 | 0.9053 | 1 |
| | Wind | 74,111,71,70,50,109,107,112,54,96 | 7764.40 | 0.9598 | 1 |
| 20 DG | PV | 74,111,71,70,50,109,107,112,54,96,76,97, 42,108,110,72,80,32,66,31 | 10502.00 | 0.9338 | 1 |
| | Wind | 74,111,71,70,50,109,107,112,54,96,76,97, 42,108,110,72,80,32,66,31 | 6542.90 | 0.9654 | 1 |

Figure 25 shows the hourly voltage profiles of the 118 bus system without DG and Figure 26 presents the same with 20 DGs which are allocated optimally. The improvement of the voltage profile for every hour can be noticed easily by comparing both the figures.

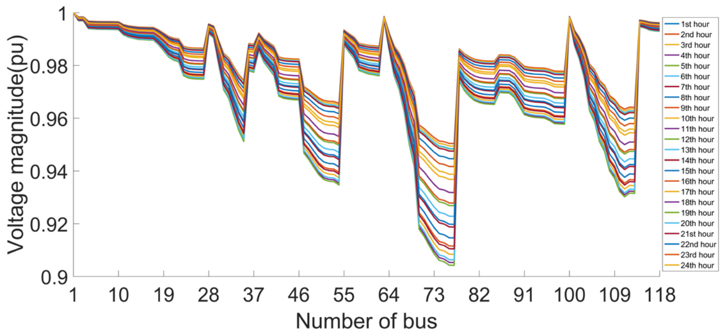


Figure 25. Bus voltages of 24 hours of 118 bus system without DG

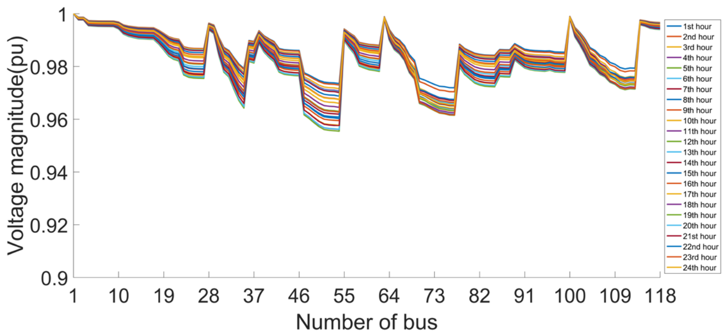


Figure 26. Bus voltages of 24 hours of 118 bus system with 20 DG (wind generation)

Therefore, Figure 15 - 16, 20 - 21, and 25 – 26 have been presented for the of bus voltages during 24 hours for IEEE 33, IEEE 69 and 118 bus systems respectively. The voltage profiles have been shown with 24 different colors for 24 hours. From those figures, the improvement of bus voltages can be noticed by comparing the voltage profiles between DG and without DG. The improvement of voltage profiles has been shown considering the wind generator as DGs. Voltage profile improvements due to PV have not been shown here because, PV generation is zero at night, hence, the node voltages would be the same as without DG.

## 5. Conclusion and Future Work

In this work, the DGs have been placed at optimal nodes considering the variation of PV/wind power generation and load variation in the distribution network. The proper locations of the DG with optimal sizes have been found out such a way for which the energy loss in a day will be minimum which is more realistic and sustainable.

Newly developed soft computing techniques (GWO, SSA, WOA, and MFO) and proposed algorithm (MOBOSA) have been used to solve the problems. It has been found that no specific technique is good for all types of problems. However, Modified OBOSA has achieved minimum loss with optimal DG's power injection to the system and it also takes the least computational time to solve the problems. This technique arises to a situation where the equal DG capacity is being installed in a particular system and the total penetration of DGs is less to achieve the same loss minimization compare to others. Moreover, the identical DG sizes in the system can lead to cost benefit and easy maintenance. All the techniques have been implemented on IEEE 33, IEEE 69 and 118 radial distribution systems.

For future work, artificial intelligence, machine learning and mixed-integer linear programming can be accommodated for more variability. Uncertainty of renewable energy sources is present and forecasting may be required for this study. Hybrid power generations like wind, PV hybrid and battery energy storage can be used to fulfil the power demand at any time. The optimal number of DG can be found out by considering cost optimization.

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systems," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 534-545, 2014.

**Appendix – A**

| From bus | To bus | r(Ω) | x(Ω) | Bus No | P (kW) | Q (kvar) | From bus | To bus | r(Ω) | x(Ω) | Bus No | P (kW) | Q (kvar) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 0.036 | 0.01296 | 1 | 0 | 0 | 60 | 61 | 0.207 | 0.0747 | 60 | 80.551 | 49.156 |
| 2 | 3 | 0.033 | 0.01188 | 2 | 133.84 | 101.14 | 61 | 62 | 0.247 | 0.8922 | 61 | 95.86 | 90.758 |
| 2 | 4 | 0.045 | 0.0162 | 3 | 16.214 | 11.292 | 1 | 63 | 0.028 | 0.0418 | 62 | 62.92 | 47.7 |
| 4 | 5 | 0.015 | 0.054 | 4 | 34.315 | 21.845 | 63 | 64 | 0.117 | 0.2016 | 63 | 478.8 | 463.74 |
| 5 | 6 | 0.015 | 0.054 | 5 | 73.016 | 63.602 | 64 | 65 | 0.255 | 0.0918 | 64 | 120.94 | 52.006 |
| 6 | 7 | 0.015 | 0.0125 | 6 | 144.2 | 68.604 | 65 | 66 | 0.21 | 0.0759 | 65 | 139.11 | 100.34 |
| 7 | 8 | 0.018 | 0.014 | 7 | 104.47 | 61.725 | 66 | 67 | 0.383 | 0.138 | 66 | 391.78 | 193.5 |
| 8 | 9 | 0.021 | 0.063 | 8 | 28.547 | 11.503 | 67 | 68 | 0.504 | 0.3303 | 67 | 27.741 | 26.713 |
| 2 | 10 | 0.166 | 0.1344 | 9 | 87.56 | 51.073 | 68 | 69 | 0.406 | 0.1461 | 68 | 52.814 | 25.257 |
| 10 | 11 | 0.112 | 0.0789 | 10 | 198.2 | 106.77 | 69 | 70 | 0.962 | 0.761 | 69 | 66.89 | 38.713 |
| 11 | 12 | 0.187 | 0.313 | 11 | 146.8 | 75.995 | 70 | 71 | 0.165 | 0.06 | 70 | 467.5 | 395.14 |
| 12 | 13 | 0.142 | 0.1512 | 12 | 26.04 | 18.687 | 71 | 72 | 0.303 | 0.1092 | 71 | 594.85 | 239.74 |
| 13 | 14 | 0.18 | 0.118 | 13 | 52.1 | 23.22 | 72 | 73 | 0.303 | 0.1092 | 72 | 132.5 | 84.363 |
| 14 | 15 | 0.15 | 0.045 | 14 | 141.9 | 117.5 | 73 | 74 | 0.206 | 0.144 | 73 | 52.699 | 22.482 |
| 15 | 16 | 0.16 | 0.18 | 15 | 21.87 | 28.79 | 74 | 75 | 0.233 | 0.084 | 74 | 869.79 | 614.775 |
| 16 | 17 | 0.157 | 0.171 | 16 | 33.37 | 26.45 | 75 | 76 | 0.591 | 0.1773 | 75 | 31.349 | 29.817 |
| 11 | 18 | 0.218 | 0.285 | 17 | 32.43 | 25.23 | 76 | 77 | 0.126 | 0.0453 | 76 | 192.39 | 122.43 |
| 18 | 19 | 0.118 | 0.185 | 18 | 20.234 | 11.906 | 64 | 78 | 0.559 | 0.3687 | 77 | 65.75 | 45.37 |
| 19 | 20 | 0.16 | 0.196 | 19 | 156.94 | 78.523 | 78 | 79 | 0.186 | 0.1227 | 78 | 238.15 | 223.22 |
| 20 | 21 | 0.12 | 0.189 | 20 | 546.29 | 351.4 | 79 | 80 | 0.186 | 0.1227 | 79 | 294.55 | 162.47 |
| 21 | 22 | 0.12 | 0.0789 | 21 | 180.31 | 164.2 | 80 | 81 | 0.26 | 0.139 | 80 | 485.57 | 437.92 |
| 22 | 23 | 1.41 | 0.723 | 22 | 93.167 | 54.594 | 81 | 82 | 0.154 | 0.148 | 81 | 243.53 | 183.03 |
| 23 | 24 | 0.293 | 0.1348 | 23 | 85.18 | 39.65 | 82 | 83 | 0.23 | 0.128 | 82 | 243.53 | 183.03 |
| 24 | 25 | 0.133 | 0.104 | 24 | 168.1 | 95.178 | 83 | 84 | 0.252 | 0.106 | 83 | 134.25 | 119.29 |
| 25 | 26 | 0.178 | 0.134 | 25 | 125.11 | 150.22 | 84 | 85 | 0.18 | 0.148 | 84 | 22.71 | 27.96 |
| 26 | 27 | 0.178 | 0.134 | 26 | 16.03 | 24.62 | 79 | 86 | 0.16 | 0.182 | 85 | 49.513 | 26.515 |
| 4 | 28 | 0.015 | 0.0296 | 27 | 26.03 | 24.62 | 86 | 87 | 0.2 | 0.23 | 86 | 383.78 | 257.16 |
| 28 | 29 | 0.012 | 0.0276 | 28 | 594.56 | 522.62 | 87 | 88 | 0.16 | 0.393 | 87 | 49.64 | 20.6 |
| 29 | 30 | 0.12 | 0.2766 | 29 | 120.62 | 59.117 | 65 | 89 | 0.669 | 0.2412 | 88 | 22.473 | 11.806 |
| 30 | 31 | 0.21 | 0.243 | 30 | 102.38 | 99.554 | 89 | 90 | 0.266 | 0.1227 | 89 | 62.93 | 42.96 |
| 31 | 32 | 0.12 | 0.054 | 31 | 513.4 | 318.5 | 90 | 91 | 0.266 | 0.1227 | 90 | 30.67 | 34.93 |
| 32 | 33 | 0.178 | 0.234 | 32 | 475.25 | 456.14 | 91 | 92 | 0.266 | 0.1227 | 91 | 62.53 | 66.79 |
| 33 | 34 | 0.178 | 0.234 | 33 | 151.43 | 136.79 | 92 | 93 | 0.266 | 0.1227 | 92 | 114.57 | 81.748 |
| 34 | 35 | 0.154 | 0.162 | 34 | 205.38 | 83.302 | 93 | 94 | 0.233 | 0.115 | 93 | 81.292 | 66.526 |
| 30 | 36 | 0.187 | 0.261 | 35 | 131.6 | 93.082 | 94 | 95 | 0.496 | 0.138 | 94 | 31.733 | 15.96 |
| 36 | 37 | 0.133 | 0.099 | 36 | 448.4 | 369.79 | 91 | 96 | 0.196 | 0.18 | 95 | 33.32 | 60.48 |
| 29 | 38 | 0.33 | 0.194 | 37 | 440.52 | 321.64 | 96 | 97 | 0.196 | 0.18 | 96 | 531.28 | 224.85 |
| 38 | 39 | 0.31 | 0.194 | 38 | 112.54 | 55.134 | 97 | 98 | 0.1866 | 0.122 | 97 | 507.03 | 367.42 |
| 39 | 40 | 0.13 | 0.194 | 39 | 53.963 | 38.998 | 98 | 99 | 0.0746 | 0.318 | 98 | 26.39 | 11.7 |
| 40 | 41 | 0.28 | 0.15 | 40 | 393.05 | 342.6 | 1 | 100 | 0.0625 | 0.0265 | 99 | 45.99 | 30.392 |
| 41 | 42 | 1.18 | 0.85 | 41 | 326.74 | 278.56 | 100 | 101 | 0.1501 | 0.234 | 100 | 100.66 | 47.572 |
| 42 | 43 | 0.42 | 0.2436 | 42 | 536.26 | 240.24 | 101 | 102 | 0.1347 | 0.0888 | 101 | 456.48 | 350.3 |
| 43 | 44 | 0.27 | 0.0972 | 43 | 76.247 | 66.562 | 102 | 103 | 0.2307 | 0.1203 | 102 | 522.56 | 449.29 |
| 44 | 45 | 0.339 | 0.1221 | 44 | 53.52 | 39.76 | 103 | 104 | 0.447 | 0.1608 | 103 | 408.43 | 168.46 |
| 45 | 46 | 0.27 | 0.1779 | 45 | 40.328 | 31.964 | 104 | 105 | 0.1632 | 0.0588 | 104 | 141.48 | 134.25 |
| 35 | 47 | 0.21 | 0.1383 | 46 | 39.653 | 20.758 | 105 | 106 | 0.33 | 0.099 | 105 | 104.43 | 66.024 |
| 47 | 48 | 0.12 | 0.0789 | 47 | 66.195 | 42.361 | 106 | 107 | 0.156 | 0.0561 | 106 | 96.793 | 83.647 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 48 | 49 | 0.15 | 0.0987 | 48 | 73.904 | 51.653 | 107 | 108 | 0.3819 | 0.1374 | 107 | 493.92 | 419.34 |
| 49 | 50 | 0.15 | 0.0987 | 49 | 114.77 | 57.965 | 108 | 109 | 0.1626 | 0.0585 | 108 | 225.38 | 135.88 |
| 50 | 51 | 0.24 | 0.1581 | 50 | 918.37 | 1205.1 | 109 | 110 | 0.3819 | 0.1374 | 109 | 509.21 | 387.21 |
| 51 | 52 | 0.12 | 0.0789 | 51 | 210.3 | 146.66 | 110 | 111 | 0.2445 | 0.0879 | 110 | 188.5 | 173.46 |
| 52 | 53 | 0.405 | 0.1458 | 52 | 66.68 | 56.608 | 110 | 112 | 0.2088 | 0.0753 | 111 | 918.03 | 898.55 |
| 52 | 54 | 0.405 | 0.1458 | 53 | 42.207 | 40.184 | 112 | 113 | 0.2301 | 0.0828 | 112 | 305.08 | 215.37 |
| 29 | 55 | 0.391 | 0.141 | 54 | 433.74 | 283.41 | 100 | 114 | 0.6102 | 0.2196 | 113 | 54.38 | 40.97 |
| 55 | 56 | 0.406 | 0.1461 | 55 | 62.1 | 26.86 | 114 | 115 | 0.1866 | 0.127 | 114 | 211.14 | 192.9 |
| 56 | 57 | 0.406 | 0.1461 | 56 | 92.46 | 88.38 | 115 | 116 | 0.3732 | 0.246 | 115 | 67.009 | 53.336 |
| 57 | 58 | 0.706 | 0.5461 | 57 | 85.188 | 55.436 | 116 | 117 | 0.405 | 0.367 | 116 | 162.07 | 90.321 |
| 58 | 59 | 0.338 | 0.1218 | 58 | 345.3 | 332.4 | 117 | 118 | 0.489 | 0.438 | 117 | 48.785 | 29.156 |
| 59 | 60 | 0.338 | 0.1218 | 59 | 22.5 | 16.83 | | | | | 118 | 33.9 | 18.98 |

**Arnab Pal** has received the B.Tech degree in Electrical Engineering from the MAKAUT, WB, India in 2016 and M.Tech degree in Power System specialization from the NIT Agartala, India in 2018. He is now a PhD research scholar in the Department of Electrical Engineering at NIT Agartala. His area of interest is Distribution Network, Distributed Generation, Microgrid, Electric Vehicle and Application of Optimization Techniques.

**Ajoy Kumar Chakraborty** has completed his B.E.E (Hons) from Jadavpur University, M. Tech in Power System from IIT Kharagpur and Ph.D in Electrical Engineering from Jadavpur University. He has more than 100 publications in national and international journals and conferences. Author is currently serving as Professor in NIT Agartala. His area of interest is Power System, Distributed Generation, Smart Grid, Electric Vehicle and Optimization.

**Arup Ratan Bhowmik** has obtained his B.Tech in Electronics and Communication Engineering from West Bengal University of Technology, M.Tech degree in Electrical Engineering from Tripura University (A Central University), India in 2011 and Ph.D in Engg. from NIT Agartala in 2015 respectively. His areas of interest include Application of Soft Computing techniques to different Power System problems, Power Quality, FACTS, Optimal Power flow, Economic load dispatch and Power system Operation & Control. He has published more than 30 research papers in various national and international journals and conferences. He is reviewer of different reputed journals including IEEE Transaction of Power System, IEEE Transaction on Industrial Application.