Chapter 2

PLACEMENT OF MULTI-DISTRIBUTED GENERATIONS THROUGH MODIFIED GWO FOR LOSS MINIMIZATION

2.1 INTRODUCTION

Distributed Generations (DGs) employing renewable energy resources have emerged as an environment friendly solution for meeting consumer demands locally, without posing much burden on transmission network. Optimal placement of multiple distributed generations helps in minimizing transmission losses, and thus improves voltage profile and reduces loss of revenue as a result of energy wastage.

Though many researchers have addressed the issue of loss minimization and voltage profile improvement in distribution networks, effort is required to be made in further reduction of power loss and improvement of bus voltage profile in order to improve efficiency of power distribution, and in delivering quality power to consumers. In this chapter, optimal placement of multiple DGs using modified Grey Wolf Optimization (GWO) algorithm has been proposed. DG locations have been considered as discrete variables whereas, DG size and power factor (in case of Type-3 DGs injecting real as well as reactive power) have been considered as continuous variables in proposed modified GWO algorithm. DGs have been optimally placed to minimize real power loss in the distribution network and improve bus voltage profile as a result of loss reduction. Backward-forward sweep load flow [184] has been used to calculate bus voltages and power loss. Case studies have been performed on a standard 33-bus radial distribution test system. Efficiency of proposed approach of multiple DG placements in loss reduction and voltage profile improvement has been tested by comparing power loss computed under multiple DGs placed in the system by proposed approach with loss when DGs are placed by IA method [65] and hybrid method [93]. Bus voltage profile obtained under optimally placed DGs by proposed approach has been compared with profile obtained when DGs are optimally placed by IA method [65]. The following section describes the general concept of GWO and its mathematical background.

2.2 GREY WOLF OPTIMIZATION SEARCH ALGORITHM: AN OVERVIEW

Over the last few decades, meta-heuristic optimization algorithms have grown in popularity. Interestingly, some of these, such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), are popular among researchers of different areas.

The grey wolf (Canis lupus) is a member of the Canidae family. Grey wolves are natural predators, which mean these lies on the top of the food supply chain. These wolves, in general, live in a group. The average group size is 3 to10. Like other swarm based optimization techniques, this algorithm model considers the hunting behaviour of grey wolves and starts with an initial population of these hunting wolves. Population individuals called wolves are subdivided into alpha beta, delta, and omega wolf. These wolves attack the prey based on their location and distance from the prey. Encircling, hunting, and attacking the prey are the three important steps for prey hunting [185]. The wolves follow a hierarchy of strict social dominance, as can be seen in Figure 2.1. Based on these hierarchy alpha wolves is superior in terms of managing the other wolf by its discipline and skilled leadership quality.

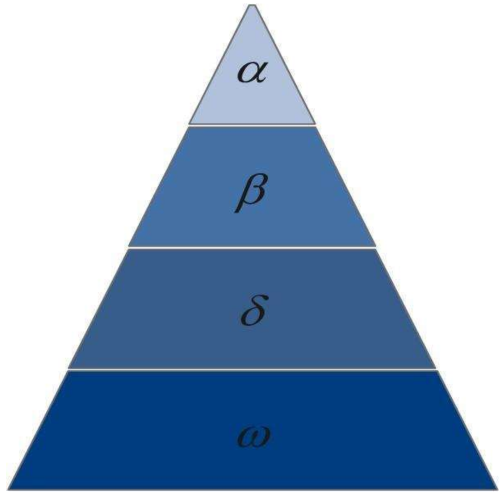

Figure 2.1: Dominating Hierarchy of Grey wolf decreasing from top to down

2.2.1 Encircling

Encircling of the prey by the grey wolf is modelled as;

$$\vec{D} = |\vec{C}.\vec{P}_{prey}(t) - \vec{P}_{wolf}(t)| \quad (2.1)$$

$$\vec{P}_{wolf}(t+1) = \vec{P}_{prey}(t) - \vec{A}.\vec{D} \;| \quad (2.2)$$

where, $\vec{D}$ is the distance between grey wolf and prey, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{P}_{prey}$ is the position vector of the prey, and $\vec{P}_{wolf}$ indicates the position vector of a grey wolf, t and $t+1$ represent the current and updated iteration count respectively during the optimization process.

The coefficient vectors $\vec{A}$ and $\vec{C}$ are given by;

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (2.3)$$

$$\vec{C} = 2\vec{r}_2 \quad (2.4)$$

where, coefficient of acceleration $\vec{a}$ is decreased linearly from 2 to 0 throughout the iterations. $\vec{r}_1$ and $\vec{r}_2$ are random vectors in [0 1]. During the encircling the prey changes its position and try to get away from the wolves, vectors $\vec{A}$ and $\vec{C}$ update the position of a wolf according to change in the position of the prey [185] and brings the position of the wolf closer to prey.

2.2.2 Hunting

The alpha wolf is superior to the entire wolves and leads the hunting of prey in association with beta and delta wolves. The beta and delta wolf follow the alpha wolf in hunting. To represent the hunting phenomena during the iteration process, the best candidates considered first as solutions are alpha, beta, and delta wolves. The fourth search agent i.e. omega wolves update their positions in association with and according to the best search solution obtained from alpha, beta, and delta wolves. Mathematically this can be modelled as:

$$\vec{P}_{wolf}(t+1) = \frac{\left(\vec{P}_1 + \vec{P}_2 + \vec{P}_3\right)}{3} \tag{2.5}$$

$$\left.\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1.\vec{P}_\alpha - \vec{P}_{wolf}\right|; \\ \vec{D}_\beta &= \left|\vec{C}_2.\vec{P}_\beta - \vec{P}_{wolf}\right|; \\ \vec{D}_\delta &= \left|\vec{C}_3.\vec{P}_\delta - \vec{P}_{wolf}\right| \end{aligned}\right\} \tag{2.6}$$

$$\left.\begin{aligned} \vec{P}_1 &= \vec{P}_\alpha - \vec{A}_1.\vec{D}_\alpha; \\ \vec{P}_2 &= \vec{P}_\beta - \vec{A}_2.\vec{D}_\beta; \\ \vec{P}_3 &= \vec{P}_\delta - \vec{A}_3.\vec{D}_\delta \end{aligned}\right\} \tag{2.7}$$

where, $\vec{P}_\alpha, \vec{P}_\beta$ and $\vec{P}_\delta$ are present position of alpha, beta and delta wolf, respectively, and $\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$ represent the distance between the prey and alpha wolf, beta wolf, and delta wolf, respectively.

2.2.3 Attacking

In this phase, the wolves take the position of prey without letting the prey to change its position and assault it. The vector coefficient $\vec{A}$ in mathematical modelling depicts the approach of the victim and plays a key role and its vacillation range gradually reduces by acceleration coefficient vector $\vec{a}$ as the wolf moves closer to the prey. In general, vector $\vec{A}$ changes its value in the interval [-a a] randomly, and is governed by decreasing the value of the vector $\vec{a}$ from 2 to 0 linearly throughout the iterative process. During the attack modelling the position of a solution candidate, the succeeding location of a candidate solution/wolf will be somewhere in between its current location and the location of prey, if the random value of the vector $\vec{A}$ lies in the range [-1 1]. The absolute value of the vector $\vec{A}$ ensures the convergence of the solution candidate if it satisfies (2.8); otherwise, there is no solution as the candidate diverges away from the prey if the absolute value follows (2.9), and definitely, an optimally best prey will be evolved as a final solution with this algorithm.

$$\text{Solution converges if} \quad |A| < 1 \tag{2.8}$$

$$\text{Solution diverges if} \quad |A| \geq 1 \tag{2.9}$$

2.2.4 Acceleration coefficient

2.2.4.1 *Linear acceleration coefficient*

The acceleration coefficient vector $\vec{a}$ controls the exploration and exploitation process and balances it with adequate value. A larger surface area for exploration results in sluggishness and the increased chance of stagnation to be trapped in local optima, and hence an enhanced rate of exploration can be achieved by decreasing the acceleration coefficient vector linearly with increasing iterations, where the acceleration coefficient is varied adaptively throughout the iterations and is given as;

$$a = 2(1 - \frac{t}{T}) \quad (2.10)$$

where, t and T are current and maximum iterations count respectively, during the optimization process adopted.

2.3 MODIFICATION IN THE GWO ALGORITHM

As mentioned above the grey wolves attack the prey after hunt process is finished i.e. when the prey stops changing its position. In order to mathematically model approaching the prey the value of $\vec{a}$ is being decreased. And hence, the fluctuation range of $\vec{A}$ decreases by $\vec{a}$. In other words, $\vec{A}$ is a random value in the interval $[-a, a]$ where a is decreased from 2 to 0. The rate of the exploration and exploitation may be controlled by controlling the rate of decrease of value a as the iterations reach to final value. A higher rate of decreasing the value of a may cause the exploration to stagnation into local optima.

2.3.1 Adaptive acceleration coefficient

The acceleration coefficient vector $\vec{a}$ controls the exploration and exploitation process and balances it with adequate value. A larger surface area for exploration results in sluggishness and increased chance of stagnation i.e. be trapped in a local optima, and hence an enhanced rate of exploration can be achieved by decreasing the acceleration coefficient vector exponentially rather than linearly with increasing iterations. Though decreasing the acceleration coefficient with high value of exponent may result in solution to be trapped at local optima, and hence an adequately suitable value must be chosen to avoid the solution to be trapped in local minima. And hence an adequate value of exponent as 2 is chosen in this work to increase the iteration process and to obtain the global minima. The acceleration coefficient is varied adaptively throughout the iterations and is given as;

$$a = 2\left(1 - \frac{t^2}{T^2}\right) \tag{2.11}$$

2.3.2 Pseudo code for modified GWO algorithm

The procedure as pseudo code for execution of modified GWO algorithm is presented in Figure 2.2. Each and every step of GWO algorithm is demonstrated in this pseudo code.

Pseudo code for modified GWO algorithm
Initialize the population of search agent i.e. grey wolf $\boldsymbol{P_i}$
Initialize with modified $\boldsymbol{a}, \boldsymbol{A}$ and $\boldsymbol{C}$
Obtain the fitness function corresponding to each search agents
Obtain search agent for best fitness $\boldsymbol{P_\alpha}$
Obtain search agent for 2nd best fitness $\boldsymbol{P_\beta}$
Obtain search agent for 3rd best fitness $\boldsymbol{P_\delta}$
while $\boldsymbol{t} < \boldsymbol{T}$
for each search agent
Update the position of current search agent using (2.5)
end for
Update $\boldsymbol{a}, \boldsymbol{A}$ and $\boldsymbol{C}$
Obtain the fitness function corresponding to each search agents
Update $\boldsymbol{P_\alpha}, \boldsymbol{P_\beta}$ and $\boldsymbol{P_\delta}$
Increase the iteration
end while
Obtain $\boldsymbol{P_\alpha}$ and corresponding fitness function as the final solution

Figure 2.2: Pseudo code for modified GWO algorithm

2.4 DG MODEL

Renewable energy resources may be modelled as DG sources. They can be classified into two categories: dispatchable and non-dispatchable generation as far as their power injection to the system is concerned. DG units are considered as a dispatchable source, if its output power can be regulated to the desired output values automatically, typically by controlling the rate of fuel consumption. This includes generation technologies such as small-scale hydro plants and biomass-based gas turbines. However, DG units are considered as a non-dispatchable source, if its output power are intermittent in nature i.e. totally depends on weather conditions and thus cannot be controlled (e.g., wind plants and photovoltaic solar plants speed and solar irradiance).

Active power injection and reactive power injection/absorption by DGs are dynamic in nature and depend upon different variables. Dynamic model of DGs have been suggested in literature, accordingly. This thesis has considered static model of DGs representing these as source of constant real power and source/load of constant reactive power. Current work has considered placement of Type-1, Type-2 and Type-3 DG only, and these have been modelled as constant real/reactive power source as stated above. Placements of Type-4 DG haven't been considered in this thesis.

2.5 PROBLEM FORMULATION

The work in this chapter proposes an approach that considers modified Grey Wolf Optimization (GWO) to find optimal location, size and power factor of multiple DGs placed in a radial distribution network with the objective to minimize real power loss (P_L), and to improve bus voltage profile as a result of loss reduction. The optimization problem is stated as,

$$\min_{DG} P_L \tag{2.12}$$

Subjected to equality and inequality constraints presented below.

2.5.1 Power losses

The total real (P_L) and reactive (Q_L) power losses in a distribution system with b branches can be determined as below:

$$P_L = \sum_{i=1}^{b} I_i^2 R_i \tag{2.13}$$

$$Q_L = \sum_{i=1}^{b} I_i^2 X_i \tag{2.14}$$

where, R_i and X_i represent the resistance and the reactance, respectively, of branch i. $\overline{I}_i$ is the complex current flowing through branch i that can be obtained from the backward-forward load flow solution [184] considering a suitable algorithm. The branch current $\overline{I}_i$ for a radial distribution network can be given by;

$$\overline{I}_i = \sum_n \overline{I}_{load,n} \ \forall\ n \text{ beyond branch } i \text{ towards the receiving end of the feeder} \tag{2.15}$$

where, $\overline{I}_{load,n}$ represents load current at bus-n and is given by;

$$\overline{I}_{load,n} = \frac{P_{load,n} - jQ_{load,n}}{\overline{V}_n^*} \tag{2.16}$$

where, $P_{load,n}$ and $Q_{load,n}$ are real and reactive power load demand at bus-n and V_n^* is conjugate of complex voltage $\overline{V}$ at bus-n.

The complex current $\overline{I}_i$ has two components: real (I_{ri}) and reactive (I_{qi}). Hence, Equations (2.13) and (2.14) can be rewritten as [186]:

$$P_L = \sum_{i=1}^{b} [I_{ri}^2 R_i + I_{qi}^2 R_i] \tag{2.17}$$

$$Q_L = \sum_{i=1}^{b} [I_{ri}^2 X_i + I_{qi}^2 X_i] \tag{2.18}$$

When the active and reactive currents (i.e., I_{rk} and I_{qk}) of a DG unit are injected at bus-k, Equations (2.17) and (2.18) can be rewritten as:

$$P_{LDG} = \sum_{i=1}^{k-1} (I_{ri} - I_{rk})^2 R_i + \sum_{i=k}^{b} I_{ri}^2 R_i + \sum_{i=1}^{k-1} \left(I_{qi} - I_{qk}\right)^2 R_i + \sum_{i=k}^{b} I_{qi}^2 R_i \tag{2.19}$$

$$Q_{LDG} = \sum_{i=1}^{k-1} (I_{ri} - I_{rk})^2 X_i + \sum_{i=k}^{b} I_{ri}^2 X_i + \sum_{i=1}^{k-1} \left(I_{qi} - I_{qk}\right)^2 X_i + \sum_{i=k}^{b} I_{qi}^2 X_i \tag{2.20}$$

where, P_{LDG} and Q_{LDG} represent real and reactive power loss, respectively, in a feeder of radial distribution network after DG placement at bus-k. Buses and branches have been numbered in increasing order from substation to remote end of the feeder as shown in Figure 2.3. It is observed from Figure 2.3 that total number of buses (represented as nb) is equal to total number of branches plus one in case of radial distribution feeder. In (2.19) and (2.20), I_{ri} and I_{qi} represent real and reactive component of branch current $\overline{I}_i$ in the absence of DG in the system.

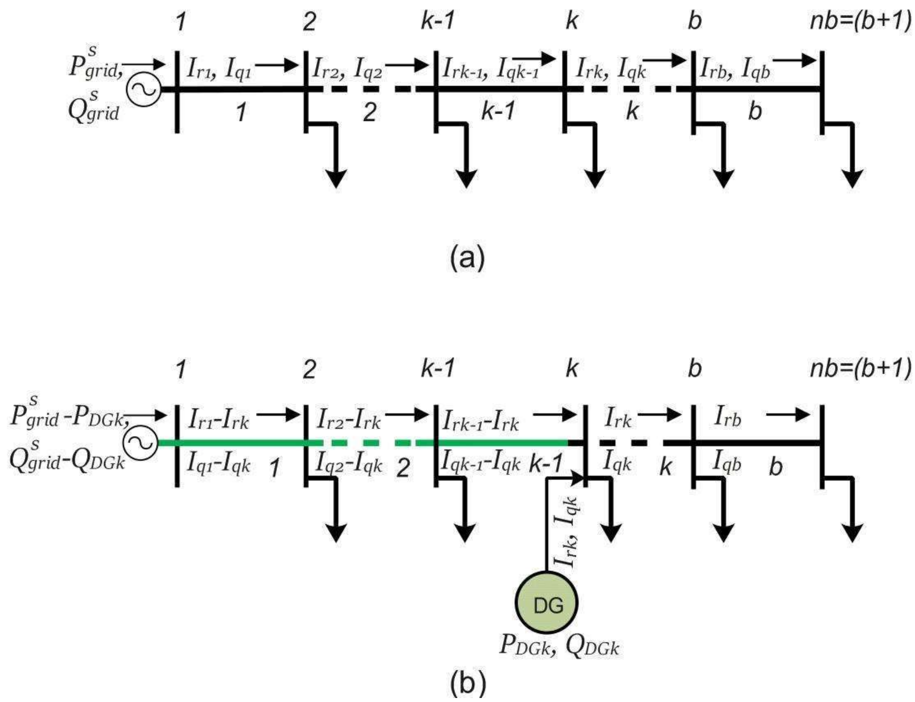

Figure 2.3: A radial distribution system: (a) without a DG unit and (b) with a DG unit

Let $a_k = (sign)\tan(\cos^{-1}(DG_{pf}^{k}))$, where $sign = +1$ for the DG unit injecting reactive power; $sign = -1$ for the DG unit consuming reactive power. The symbol DG_{pf}^{k} represent the power factor of DG unit placed at bus-k.The relationship between I_{qk} and I_{rk} at bus-k can be expressed as below:

$$I_{qk} = a_k I_{rk} \tag{2.21}$$

Substituting Equation (2.21) into Equations (2.19) and (2.20), we obtain:

$$P_{LDG} = \sum_{i=1}^{k-1}(I_{ri} - I_{rk})^2 R_i + \sum_{i=k}^{b} I_{ri}^2 R_i + \sum_{i=1}^{k-1}\left(I_{qi} - a_k I_{rk}\right)^2 R_i + \sum_{i=k}^{b} I_{qi}^2 R_i \tag{2.22}$$

$$Q_{LDG} = \sum_{i=1}^{k-1}(I_{ri} - I_{rk})^2 X_i + \sum_{i=1}^{b} I_{ri}^2 X_i + \sum_{i=1}^{k-1}\left(I_{qi} - a_k I_{rk}\right)^2 X_i + \sum_{i=k}^{b} I_{qi}^2 X_i \tag{2.23}$$

In case of placement of multiple DGs, (2.22) and (2.23) get modified, accordingly. Present work minimizes real power loss P_L using optimally placed DGs subjected to following constraints. As Type-4 DG has not been considered in this work, *sign* has been taken as +1, only.

2.5.2 Equality constraints

Following power balance as equality constraints must be satisfied while integrating DG power to cope up with the load demand and system losses incurred

$$P_{grid}^{S} + \sum_{i \in [ndg]} P_{DG,i} = \sum_{i=1}^{nb} P_{load,i} + P_{LDG} \tag{2.24}$$

$$Q_{grid}^{S} + \sum_{i \in [ndg]} Q_{DG,i} = \sum_{i=1}^{nb} Q_{load,i} + Q_{LDG} \tag{2.25}$$

where, $P_{grid}^{S}, Q_{grid}^{S}$ are real and reactive power supplied by the grid, respectively. $P_{DG,i}$ and $Q_{DG,i}$ are real and reactive power, respectively, supplied by DG connected at bus i. $[ndg]$ represents the set of buses where DGs are connected.

2.5.3 Inequality constraints of DG size and system operation

$$\sum_{i \in [ndg]} P_{DG,i} \leq \left[\sum_{i=1}^{nb} P_{load,i} + \sum_{i=1}^{b} I_i^2 R_i \right] \tag{2.26}$$

$$\sum_{i \in [ndg]} Q_{DG,i} \leq \left[\sum_{i=1}^{nb} Q_{load,i} + \sum_{i=1}^{b} I_i^2 X_i \right] \tag{2.27}$$

$$\sum_{i \in [ndg]} DG_{size}^{i} \leq DG_{size}^{max} \tag{2.28}$$

$$DG_{loc}^{1} \neq DG_{loc}^{2} \neq \cdots DG_{loc}^{n} \tag{2.29}$$

$$DG_{pf}^{min} \leq DG_{pf}^{k} \leq DG_{pf}^{max} \; k \in [ndg] \tag{2.30}$$

$$V_{L,min} \leq V_i \leq V_{L,max} \; \forall \; \mathrm{i} = 1, 2, \dots, \mathrm{nb} \tag{2.31}$$

$$I_k \leq I_{k,max} \,\forall\, \mathrm{k} = 1, 2, \dots, \mathrm{b} \tag{2.32}$$

where,

V_i = Magnitude of voltage at bus-i

$V_{L,min}$ = Minimum limit of bus voltage magnitude

$V_{L,max}$ = Maximum limit of bus voltage magnitude

$I_{k,max}$ = Maximum limit of current magnitude in branch-k

DG_{size}^{i} = Size of DG to be placed at bus-i

DG_{size}^{max}= Maximum limit of DG size to be placed at bus-i

DG_{loc}^{1}= Location of first DG to be placed in the system

DG_{loc}^{2}= Location of second DG to be placed in the system

DG_{loc}^{n}= Location of nth DG to be placed in the system

DG_{pf}^{min}= Minimum limit of power factor for Type-3 DG

DG_{pf}^{max}= Maximum limit of power factor for Type-3 DG

DG_{pf}^{k}= power factor of k$^{\text{th}}$ Type-3 DG

Due to high capital cost involved in installation of multiple DGs, present work has considered placement of a maximum number of three DGs in the system though the proposed approach may be used for placement of higher number of DGs, too. In this work, placement of Type-1 DGs (injecting only real power to the bus), Type-2 DGs (injecting only reactive power to the bus) and Type-3 DGs (injecting real as well as reactive power at optimal power factor) has been considered. Optimal location, size and power factor of DGs have been obtained based on application of modified GWO algorithm which is described in the next section.

2.6 APPLICATION OF MODIFIED GWO FOR DG PLACEMENT

DG sizing and allocation includes discrete and continuous variables, as the location of installation of DG is discrete in nature while size and power factor are continuous. Implementation of modified GWO algorithm is evolutionary population-based algorithm inspired by the social behaviour of grey wolf. The optimization algorithm starts with random generation of wolf (DG location, size, and power factor) initial population and as the process goes on based on the prey's location, these population further get subdivided in to alpha, beta and delta wolves. Different steps involved are as per following:

Step 1: Input the system data line impedances and load data, network configuration, optimization parameter such as initial search agents and population, number of maximum iterations etc. Each search agent consists the following:

$$\left[DG_{loc}^{1} \quad DG_{size}^{1} \quad DG_{pf}^{1} \quad DG_{loc}^{2} \quad DG_{size}^{2} \quad DG_{pf}^{2} \cdots \quad DG_{loc}^{n} \quad DG_{size}^{n} \quad DG_{pf}^{n}\right] \quad (2.33)$$

Step 2: Start the iteration, find the fitness value corresponding to i^{th}search agents and based on its position assign it as alpha, beta or delta wolf and update the corresponding fitness.

Step 3: Update the position of each search agent taking the average of position of three best agent wolves obtained so far.

Step 4: Repeat steps 2 to 3 for all other search agents till the final iteration.

Step 5: Store the final search agent as the optimal solution and terminate the search process.

Applying the above procedure, single and multiple DG placement for different types viz. Type-1 (injecting only real power), Type-2 (injecting only reactive power) and Type-3 (injecting both real and reactive power), have been obtained. Present work has taken the number of search agents and maximum number of iterations as 50 and 100, respectively, considering these values to be sufficiently high.

2.7 RESULTS AND DISCUSSION

Proposed approach of optimal placement of multiple DGs is tested on a 33 bus, 32 branch radial distribution network [51] consisting of real and reactive power demand of 3.715 MW and 2.3 MVAr, respectively. The details of the system are given in Appendix A. Present work has considered only constant power loads. The lower and upper voltage thresholds are set at 0.9 pu and 1.1 pu, respectively.

It is assumed that dispatchable DG units can be allocated at all buses in the system. As their sites are unspecified in the test system, these sources are assumed to be available at all buses.

Simulations are carried out in MATLAB R2018a environment. Optimal location, size and power factor (in case of Type-3 DGs) were obtained based on results of modified GWO algorithm. Optimal location, size and power factor of DGs were also obtained using Improved Analytical (IA) method proposed in [65] and Hybrid method proposed in [93]. Bus voltages and real power loss in the network for the without DG case, and with Type-1, Type-2, Type-3 DGs at one, two and three locations were calculated using load flow with backward-forward sweep algorithm [184], for the proposed method as well as two existing methods considered (viz. IA method [65] and Hybrid method [93]).

Real power loss in the network in the absence of DGs, and optimal location (the bus number where DG is to be placed), size (in MW, MVAr, MVA for Type-1, Type-2, Type-3 DG, respectively) and power factor (in case of Type-3 DGs) along with real power loss in the network with one, two and three numbers of Type-1, Type-2 and Type-3 DGs have been shown in Table 2.1 for the proposed method, IA method [65] and Hybrid method [93]. Table 2.1 also shows percentage loss reduction for each case of DG placement. It is observed from Table 2.1 that DG placement by proposed approach results in higher reduction in real power loss compared to two existing methods except in the case of three numbers of Type-3 DGs that has highest loss reduction by Hybrid method [93]. Though, loss reduction by proposed method has slightly better results compared to Hybrid method proposed in [93] for most of the cases of DG placement, it may lead to considerable saving in revenue if considered for the whole year.

Table 2.1: Real power loss reduction by single/multiple DG placement

Type and No of DG		**Proposed Approach**			**IA Method** [65]			**Hybrid Method** [93]		
		Size (loc/ loc, pf) in MVA/ MW/ MVAr	**Loss (kW)**	**% Loss Reduction**	**Size (loc /loc, pf) in MVA/ MW/ MVAr**	**Loss (kW)**	**% Loss Reduction**	**Size (loc/ loc, pf) in MVA/ MW/ MVAr**	**Loss (kW)**	**% Loss Reduction**
Without DG		NA	211	NA	NA	211.2	NA	NA	211	NA
Type-1	**1 DG**	2.5902 (6)	111.01	**47.40**	2.601 (6)	111.1	47.39	2.49 (6)	111.17	47.31
	2 DG	0.8522 (13), 1.1581 (30)	87.16	**58.70**	1.80 (6), 0.72 (14)	91.63	56.61	0.83 (30), 1.11 (13)	87.28	58.64
	3 DG	07698 (14), 1.0677 (30), 1.0948 (24)	72.78	**65.50**	0.90 (6), 0.90 (12), 0.72 (31)	81.05	61.62	0.079 (13), 1.07 (24), 1.01 (30)	72.89	65.45
Type-2	**1 DG**	1.25 (30)	151.36	**28.26**	*	*	*	1.23 (30)	151.41	28.24
	2 DG	0.4655 (12), 1.0636 (30)	141.82	**32.78**	*	*	*	0.43 (12), 1.04 (30)	141.94	32.73
	3 DG	0.358 (13), 0.55 (24), 1.05 (30)	138.3	**34.45**	*	*	*	0.36 (13), 0.51 (24), 1.02 (30)	138.37	34.42

Type-3	1 DG	3.1079 (6, 0.82)	67.85	**67.85**	3.107 (6, 0.82)	67.9	67.82	3.107 (6, 0.82)	67.9	67.81
	2 DG	0.9328 (13,0.73), 1.559 (30, 0.90)	28.5	**86.50**	2.195 (6, 0.82), 1.098 (30, 0.82)	44.39	78.98	1.039(13, 0.91), 1.508 (30, 0.72)	28.6	86.44
	3 DG	0.849 (14, 0.90), 1.4501 (30, 0.71), 1.1869 (24, 0.89)	11.75	**94.43**	1.098 (6, 0.82), 1.098 (30, 0.82), 0.768 (14, 0.82)	22.29	89.45	0.873(13, 0.90), 1.186(24, 0.89), 1.439 (30, 0.71)	11.7	94.45

NA - not applicable, * - not considered

Table 2.2 shows minimum and maximum bus voltage magnitudes with corresponding bus numbers in case of DG placement by proposed method as well as IA method [65]. The difference between maximum bus voltage and minimum bus voltage (i.e. range of voltage variations among buses) has also been shown for different cases of DG placement. It is observed from Table 2.2 that DG placement by proposed approach yields better voltage profile for most of the cases. It is observed from Table 2.1 and Table 2.2 that Type-2 DGs (injecting only reactive power) are least effective in power loss reduction as well as in voltage profile improvement, whereas, Type-3 DGs at optimal power factor are most effective. This may be due to high R/X ratio of distribution lines where real power injection is required in addition to reactive power injection to minimize power loss in the network and improve voltage profile.

Voltage profile of buses with DG placement by proposed approach has been shown in Figure 2.4, Figure 2.5 and Figure 2.6 for Type-1, Type-2 and Type-3 DGs, respectively. It is observed from Figure 2.4, Figure 2.5 and Figure 2.6 that placement of three number of DGs results in better voltage profile compared to single DG and two DGs for all the three types of DGs. Figure 2.7 shows voltage profile of buses for all the three types of DGs placed by proposed approach. It is observed from Figure 2.7 that optimal placement of Type-3 DGs at three locations leads to best voltage profile compared to other cases.

Table 2.2: Voltage profile improvement by single/multiple DG placement

Cases		Proposed Approach			IA Method [65]		
		V_{min} in pu (at bus no.)	V_{max} in pu (at bus no.)	(V_{max}-V_{min}) in p.u.	V_{min} in pu (at bus no.)	V_{max} in pu (at bus no.)	(V_{max}-V_{min}) in p.u.
Base Case		0.9037 (18)	1 (1)	0.0963	0.9037 (18)	1 (1)	**0.0963**
Type-1	1 DG	0.9424 (18)	1 (1)	0.0576	0.9425 (18)	1 (1)	0.0575
	2 DG	0.9685 (33)	1 (1)	**0.0315**	0.9539 (33)	1 (1)	**0.0461**
	3 DG	0.9687 (33)	1 (1)	0.0313	0.9690 (18)	1 (1)	0.0310
Type-2	1 DG	0.9165 (18)	1 (1)	0.0835	*	*	*
	2 DG	0.9304 (18)	1 (1)	0.0696	*	*	*
	3 DG	0.9306 (18)	1 (1)	0.0694	*	*	*
Type-3	1 DG	0.9584 (18)	1.0015 (6)	**0.0431**	0.9575 (18)	1.0007 (6)	0.0432
	2 DG	0.9803 (25)	1.0010 (30)	**0.0207**	0.9600 (18)	1.0031 (6)	0.0431
	3 DG	0.9914 (8)	1.006 (30)	**0.0146**	0.9821 (25)	1.0006 (14)	0.0185

* - not considered

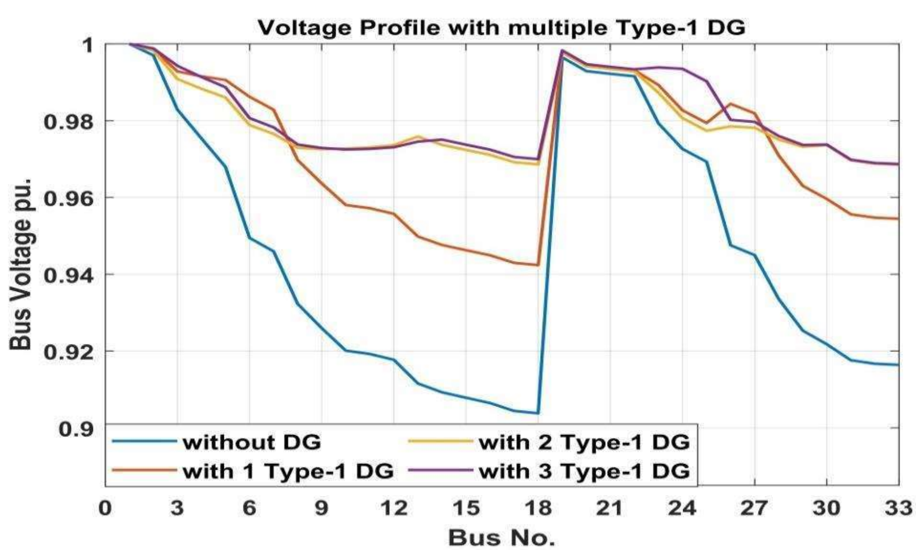

Figure 2.4: Voltage Profile for multiple Type-1 DG placement by proposed approach

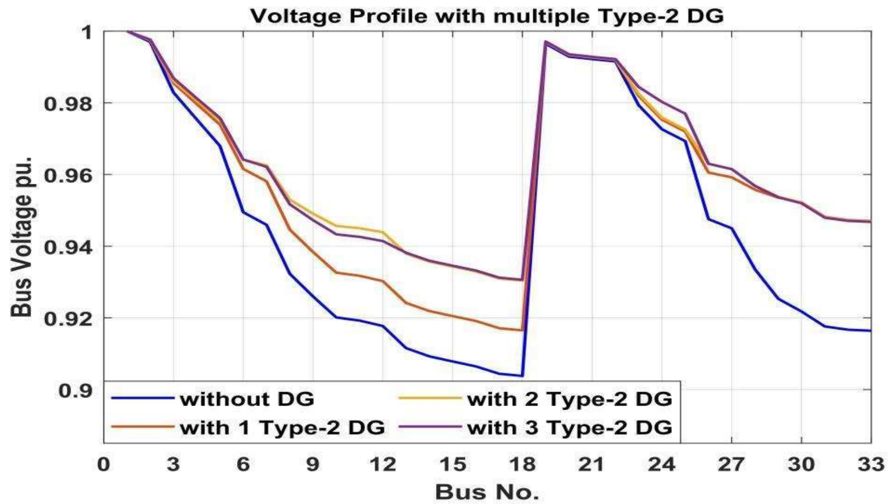

Figure 2.5: Voltage Profile for multiple Type-2 DG placement by proposed approach

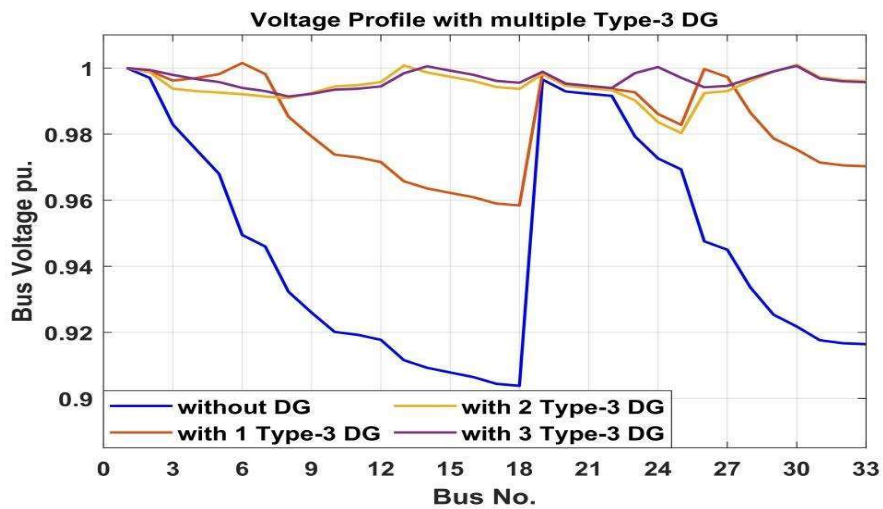

Figure 2.6: Voltage Profile for multiple Type-3 DG placement by proposed approach

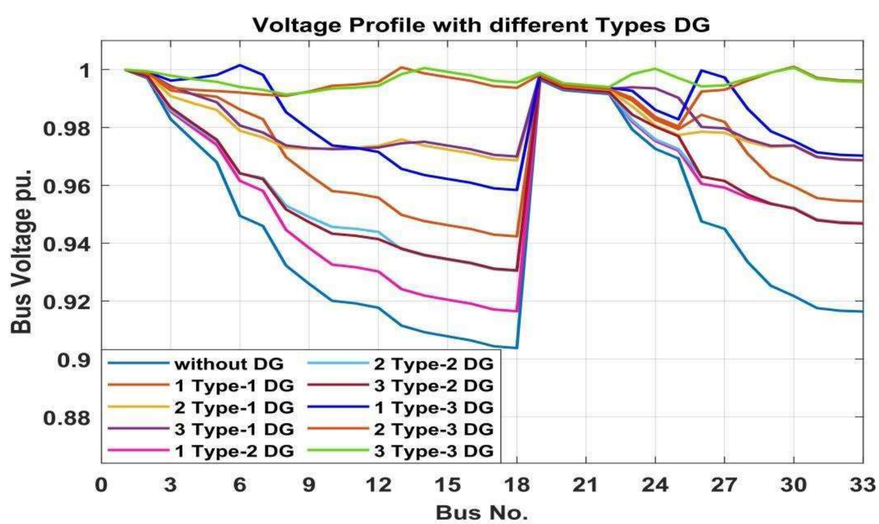

Figure 2.7: Comparative Voltage Profile for different types of multiple DG placement

In Figure 2.8 to Figure 2.15 convergence characteristics of different cases under study has been shown. The characteristic depicts that the modified GWO approach have performed well as compared to traditional GWO approach for the application of DG location and sizing. The proposed method converges well and achieves the objective function value in lesser number of iterations as compared with the original GWO algorithm.

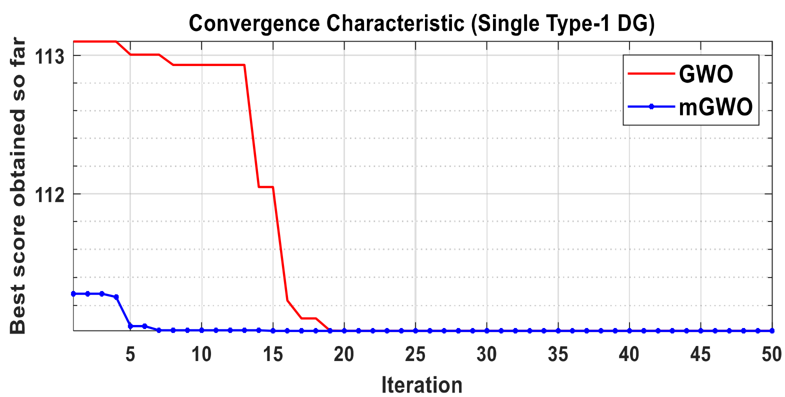

Figure 2.8: Convergence Characteristic for single Type-1 DG

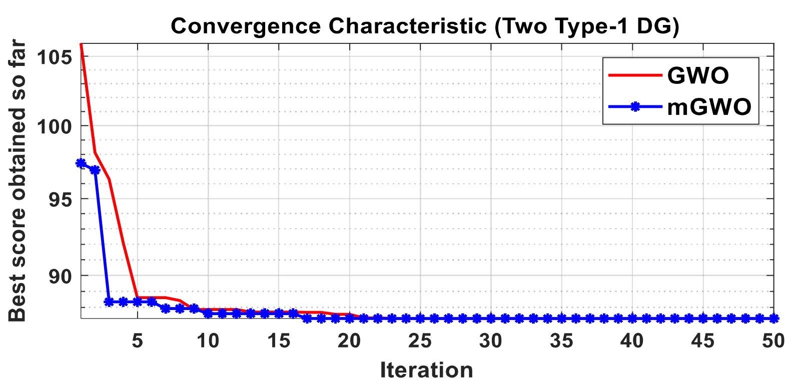

Figure 2.9: Convergence Characteristic for Two Type-1 DG

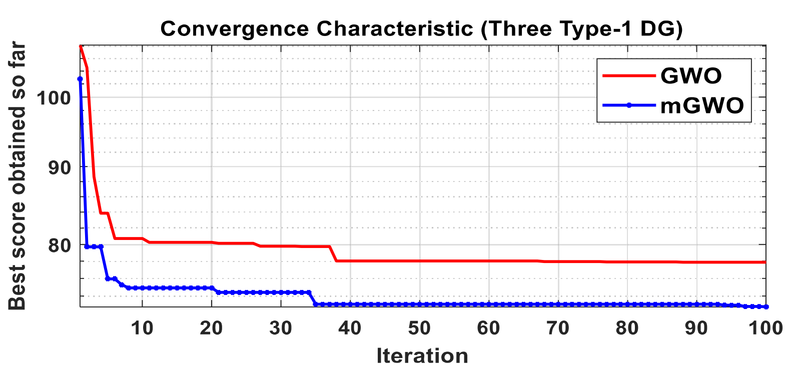

Figure 2.10: Convergence Characteristic for Three Type-1 DG

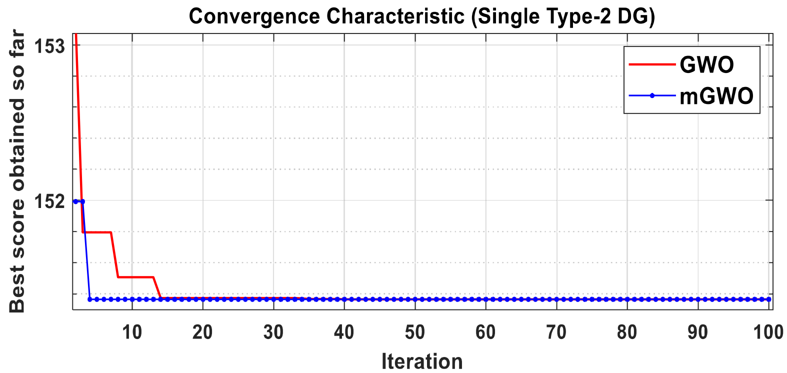

Figure 2.11: Convergence Characteristic for single Type-2 DG

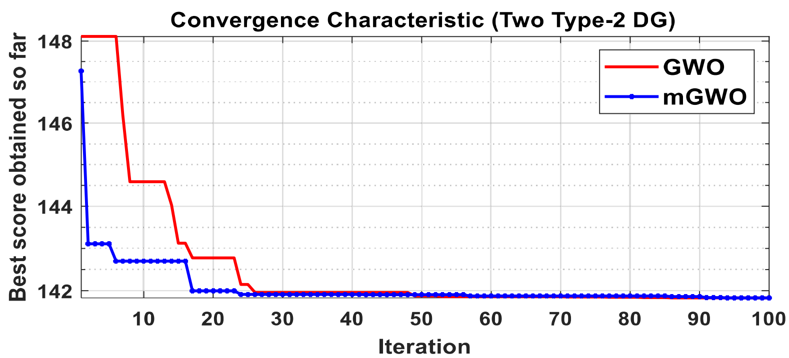

Figure 2.12: Convergence Characteristic for Two Type-2 DG

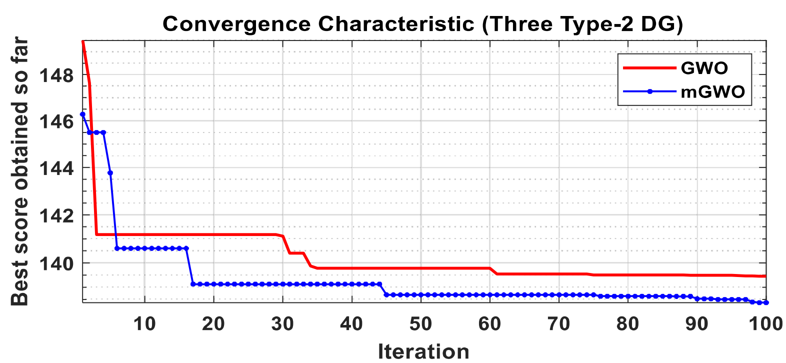

Figure 2.13: Convergence Characteristic for Three Type-2 DG

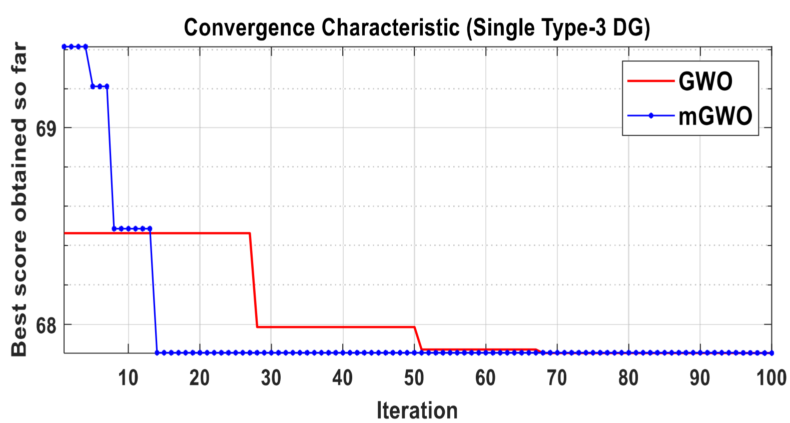

Figure 2.14: Convergence Characteristic for Single Type-3 DG

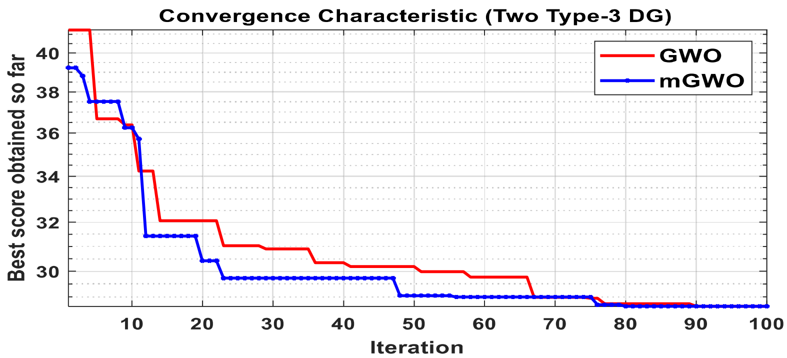

Figure 2.15: Convergence Characteristic for Two Type-3 DG

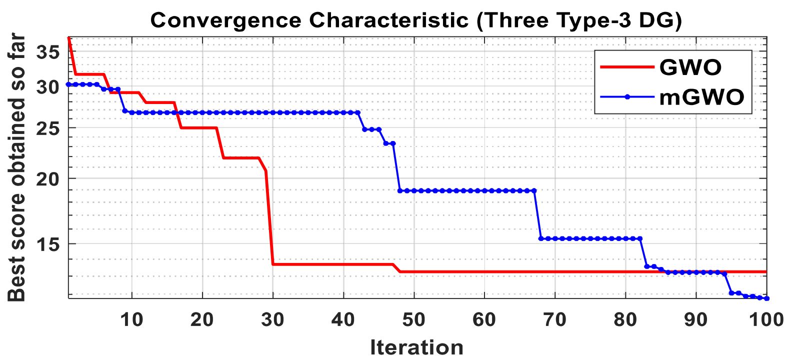

Figure 2.16: Convergence Characteristic for Three Type-3 DG

2.8 SUMMARY

This chapter has presented a modified GWO based approach for optimal placement of Type-1, Type-2 and Type-3 multiple DGs to minimize real power loss and improve voltage profile (as a result of loss reduction) in a distribution network. Present work has considered optimal placement of DGs up to a maximum of three locations considering capital cost involved though the approach may be utilized for placement of higher number of DGs. Power loss and voltage profile obtained by proposed approach has been compared with results obtained by two existing approaches. Case studies performed through MATLAB simulations on IEEE 33-bus radial distribution system show that proposed approach of optimal placement of multiple DGs by modified GWO method is quite effective in loss minimization and voltage profile improvement. Out of all the three types of DGs considered, Type-3 DGs placed at three optimal locations produces maximum reduction in power loss and best improvement in voltage profile. It has been found that the proposed modified GWO based approach gives the better results in lesser number of iterations as compared to existing GWO method.