Chapter 2

Optimal Sizing and Siting of Multiple Dispersed Generation System Using PSO-GWO Algorithm

2.1 Introduction

In this chapter a hybrid Particle Swarm Optimization-Grey Wolf Optimization (PSO-GWO) based methodology is proposed for optimal placement of Distributed Generation (DG) units in the distribution network. A multi-objective function is framed utilizing a weighted sum of voltage stability index, real power loss, and voltage deviation at the buses from the desired value, with weights optimized using Genetic Algorithm (GA). The proposed methodology is tested on IEEE 33-bus Radial Distribution System (RDS) for placement of Type-1 DGs. The effectiveness of the proposed approach in loss minimization, voltage profile improvement, and voltage stability enhancement has been established over existing metaheuristic approaches.

2.2 Problem Formulation

A multi-objective function is formulated below that represents the weighted sum of active power loss, voltage stability index, and voltage deviation from the desired value. The formulated objective function has been optimized in this work using the PSO-GWO algorithm under a set of operating constraints.

2.2.1 Active Power Loss

Active power loss (P_{Loss}) in the distribution network may be expressed as [12]:

$$P_{Loss} = \sum_{a=1}^{n}\sum_{b=1}^{n}(\alpha_{ab}(P_aP_b + Q_aQ_b) + \beta_{ab}(Q_aP_b - P_aQ_b)) \tag{2.1}$$

where,

$$\alpha_{ab} = \frac{R_{ab}}{V_aV_b}cos(\delta_a - \delta_b) \tag{2.2}$$

$$\beta_{ab} = \frac{R_{ab}}{V_aV_b}sin(\delta_a - \delta_b) \tag{2.3}$$

and

$$\bar{Z}_{ab} = R_{ab} + jX_{ab} \tag{2.4}$$

where, $\bar{Z}_{ab}$, R_{ab}, and X_{ab}: represent impedance, resistance and reactance, respectively, of the line connecting buses a and b.

V_i = Voltage magnitude at bus-i

δ_i = Voltage angle at bus-i

P_i= Real power injection at bus-i

Q_i = Reactive power injection at bus-i

n = Total number of buses present in the system.

The active power loss given by (2.1) has been considered as the first objective function (OF_1) that is being minimized as presented below [12]:

$$OF_1 = minimization(P_{Loss}) \tag{2.5}$$

2.2.2 Voltage Deviation

Voltage deviation from the reference voltage can be expressed as the squared sum of voltage deviation from desired voltage for all the buses.

$$\Delta VD = \sum_{i=1}^{n} (V_i - V_{ref,i})^2 \tag{2.6}$$

where, $V_{ref,i}$ = Reference (desired) voltage at bus i. In this work, reference voltage has been taken as 1.0 p.u. for all the buses.

The voltage deviation from the desired value given by (2.6) has been considered as the second objective function (OF_2) that has been minimized as presented below [97]:

$$OF_2 = minimization(\Delta VD) \tag{2.7}$$

2.2.3 Voltage Stability Index

Voltage stability is the ability of a power system to maintain bus voltages within acceptable limits. Remote end buses of radial distribution networks are prone to significantly low voltage profile as a result of cumulative voltage drops in different sections of the feeder. Voltage stability margin of a network may be examined in terms of distance of current operating point to maximum loadability point (which is considered as the critical point). Several indices have been proposed in literature to determine voltage stability of a network. One such existing index has been used in this work to determine voltage stability of a radial distribution network and is presented below:

A branch of a radial distribution network connecting buses n_1 and n_2 is shown in Fig. 2.1, where, bus n_1 is towards the substation side, whereas, bus n_2 is towards receiving end side. In this figure, P_{n2} and Q_{n2} represent net real power consumption and net reactive power consumption, respectively, for buses n_2 onward toward receiving end side. The Voltage Stability Index (VSI) for this system may be given as [98].

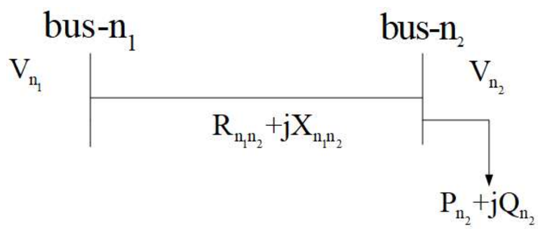

Fig. 2.1 Diagram for the line connecting n_1 and n_2 buses.

$$VSI(n_2) = |\bar{V_{n1}}|^4 - 4.0P_{n2}X_{n1n2} - Q_{n2}R^2_{n1n2} - 4.0P_{n2}R_{n1n2} - Q_{n2}X_{n1n2}|\bar{V_{n1}}|^2 \qquad (2.8)$$

where,

$VSI(n_2)$ =Voltage Stability Index (VSI) for receiving end bus n_2. It is used for static voltage stability analysis of the distribution system. VSI value ranges between 0 and 1 with 0 representing its critical value. Thus, if certain bus of a distribution network is having VSI=0, it means that bus has reached its maximum loadability limit (viz. voltage stability limit). Further loading on this bus may cause progressive decrease of its voltage leading to its voltage collapse. The buses having lower VSI values are prone to threat of voltage instability. Typical value of $VSI(n_2)$ without DG integration ranges between 0.65 pu to 0.70 pu for constant power load in 33-bus IEEE network [99]. VSI value must be greater than zero for all the buses from bus-2 onward in order to have voltage stability in the system [98].

The most critical bus is the one that has the lowest value of VSI. The higher VSI value for all the buses ensures a higher voltage stability margin. Therefore, the third objective function (OF_3) that considers maximization of voltage stability margin has been considered as,

$$OF_3 = minimization(\frac{1}{VSI(n_2)}); \quad (n_2 = 2, 3..., n) \qquad (2.9)$$

Minimization of the reciprocal of $VSI(n_2)$ ensures maximization of voltage stability margin.

2.2.4 Proposed Multi-Objective Function

The proposed multi-objective function considers the weighted sum of OF_1, OF_2 and OF_3 given by (2.5), (2.7), and (2.9) as presented below:

$$OF_{fun} = minimization(\lambda_1 OF_1 + \lambda_2 OF_2 + \lambda_3 OF_3) \tag{2.10}$$

where, OF_{fun} = Proposed multi-objective function
λ_1 = Multiplier representing weightage for OF_1
λ_2 = Multiplier representing weightage for OF_2
λ_3 = Multiplier representing weightage for OF_3.

Weightage multipliers λ_1, λ_2, λ_3 have been optimized using Genetic Algorithm (GA). Initially, the random values are generated between 0.1 and 1. To avoid the ineffectiveness of any weightage multiplier the lower limit of all lambdas is selected as 0.1 instead of 0. The set of λs producing minimum value of OF_{fun} resulted in λ_1 = 0.17, λ_2 = 0.7, and λ_3 = 0.17, which were considered as optimal λ values. OF_{fun} formulated with optimal λ values was optimized further using the PSO-GWO algorithm under a set of equality and inequality constraints presented in Subsection 2.2.5 below.

2.2.5 System Constraints

Power Balance Equation

Each bus must satisfy real and reactive power balance equation as presented below:

$$P_{Ga} - P_{Da} = \sum_{b=1}^{n} V_a V_b [G_{ab} cos(\delta_a - \delta_b) + B_{ab} sin(\delta_a - \delta_b)]; \quad a = 1, 2, ..., n. \tag{2.11}$$

$$Q_{Ga} - Q_{Da} = \sum_{b=1}^{n} V_a V_b [G_{ab} sin(\delta_a - \delta_b) + B_{ab} cos(\delta_a - \delta_b)]; \quad a = 1, 2, ..., n. \quad (2.12)$$

where, P_{Gi} = Real power generation at bus-i

Q_{Gi} = Reactive power generation at bus-i

P_{Di} = Real power demand at bus-i

Q_{Di} = Reactive power demand at bus-i

$Y_{ij} = G_{ij} + jB_{ij}$ = Off diagonal elements in i^{th} row and j^{th} column of the bus admittance matrix.

Voltage Constraints

Voltages at all the buses must be within permissible limits as given below:

$$V_{a,min} \leq V_a \leq V_{a,max}; \qquad a = 1, 2, ..., n. \quad (2.13)$$

DG Size constraint

For Type-1 DG, the active power injected by DG to the bus must be within permissible limits as given below:

$$P^{T-1DG} \leq (P^{T}_{D,load} + P_{Loss}) \quad (2.14)$$

where, P^{T-1DG} is the maximum permissible size of Type-1 DG and $P^{T}_{D,load}$ is total active power demand by the connected loads.

2.3 Proposed Approach of DG Placement

In this work, the optimal location and size of multiple DGs have been obtained using a hybrid approach consisting of a combination of PSO and GWO. Present work has considered placement of Type-1 DGs, only. However, the methodology may be extended to the placement of other types of DGs, too. The existing PSO and GWO techniques alongwith the proposed hybrid PSO-GWO approach to DG placement are presented below.

2.3.1 Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) [100] algorithm is inspired by flocks. It gives optimal solutions based on population. The population of particles searches for the better solutions through their own experience and also by that of others.

Particle Swarm Optimization (PSO) is a nature-inspired evolutionary and stochastic optimization technique to solve a computationally hard optimization problem. In the algorithm, the swarm with n number of particles communicates with each other directly or indirectly using search direction. Each particle has two characteristics: a position and a velocity. Each particle updates its position according to its previous experience and the experience from the neighbor. The Particle Swarm Optimization (PSO) algorithm is described in the following steps:

Step 1. Initialization of random position and velocity of n particles

The initial population is generated in the specified range, randomly. Initial velocity is assumed to be a zero vector. For convenience, we may consider the position and velocity of j^{th} particles for i^{th} iteration as x_j^i and v_j^i, respectively. The particles generated initially with position are $x_1(0), x_2(0), x_3(0), \ldots. x_n(0)$. Evaluate the objective function value corresponding to the particles as $f[x_1(0)]$, $f[x_2(0)]$, $f[x_3(0)]$ ....$f[x_n(0)]$.

Step 2. p_{best} and g_{best} calculation

In the i^{th} iteration, the two important parameters (i.e. p_{best} and g_{best}) used by j^{th} particle are calculated as:

1) p_{best}: The historical best value of x_j^i (position of j^{th} particle in the current iteration i), with the highest value of objective function $f[x_j^i]$, encountered by particle j in all previous iterations.

2) g_{best}: The historical best value of x_j^i (positions of all particles up to that iteration), with the highest value of objective function $f[x_j^i]$, encountered in all the previous iterations by any of the n particles.

Step 3. Velocity and position updating

With the help of p_{best} and g_{best}, update the velocity and position of each particle for the respective iteration as:

$$v_j^{(i+1)} = \omega v_j^i + c_1 rand_1 (p_{best_i} - x_j^i) + c_2 rand_2 (g_{best_i} - x_j^i) \tag{2.15}$$

$$x_j^{(i+1)} = x_j^i + v_j^{(i+1)} \tag{2.16}$$

where, The weight function is given as:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Itr_{max}}.i \tag{2.17}$$

c_1 and c_2 are the cognitive (individual) and social (group) learning rates, respectively, and $rand_1$ and $rand_2$ are uniformly distributed random numbers in the range 0 and 1. ω_{max} and ω_{min} are the initial and final values of the inertia weight, respectively and Itr_{max} is maximum iterations. The values of ω_{max} = 0.9 and ω_{min} = 0.4 [100].

Step 4. Check the convergence criterion.

Step 5. Increase iteration count (Itr) by one.

Step 6. Check the stopping criterion.

If it is satisfied, stop otherwise move to step 2.

The flowchart for optimal siting and sizing of DGs using PSO is shown in Fig. 2.2. In this flowchart x_{loc} and x_{size} correspond location and size of DG, with $[X_{par}]$ representing the set consisting of the location and size of all the DGs to be placed in the system.

2.3.2 Grey Wolf Optimization (GWO)

Grey wolf [101] (Canis lupus) belongs to the canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. The group size is 5–12 on average. They have a very disciplined social dominance hierarchy as shown in Fig. 2.3.

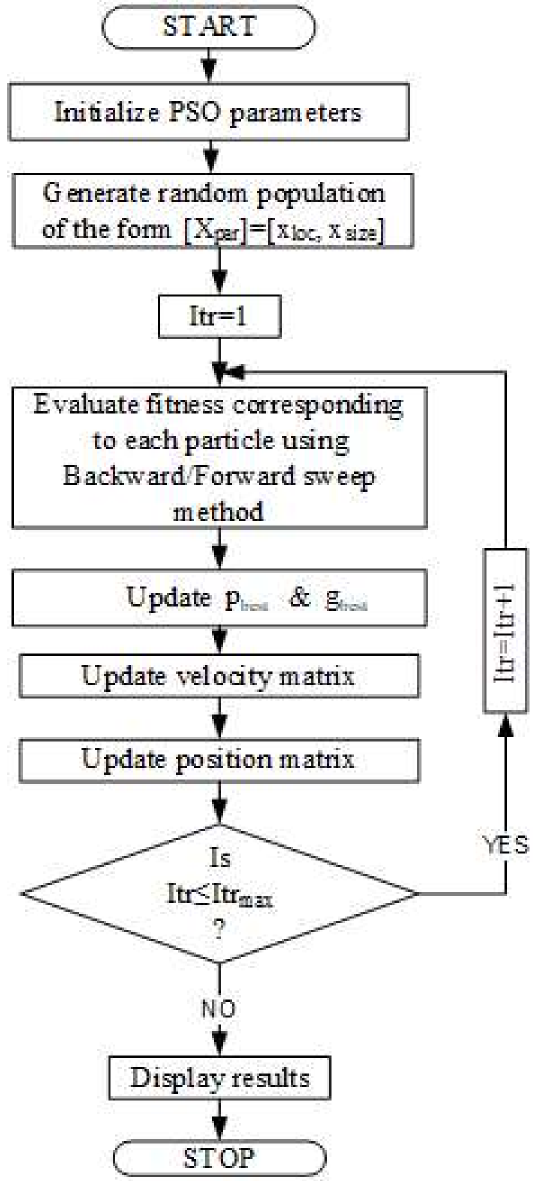

Fig. 2.2 Flowchart for optimal siting and sizing of DGs using PSO

The leaders are called alpha. The alpha is mostly responsible for making decisions about hunting. The alpha's decisions are dictated to the pack.

The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. It plays the role of an advisor to the alpha and discipliner for the pack. The beta reinforces the alpha's commands throughout the pack and gives feedback to the alpha.

The lowest-ranking grey wolf is omega. The omega plays the role of a scapegoat. Omega wolves always have to submit to all the other dominant wolves.

If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category.

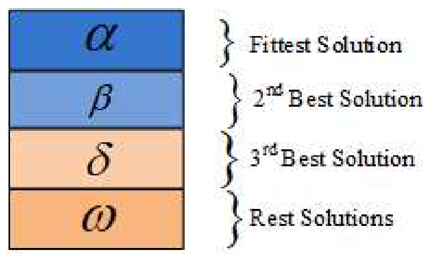

Fig. 2.3 Social order of grey wolf.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. The various phases of grey wolf hunting are shown in Fig 2.4.

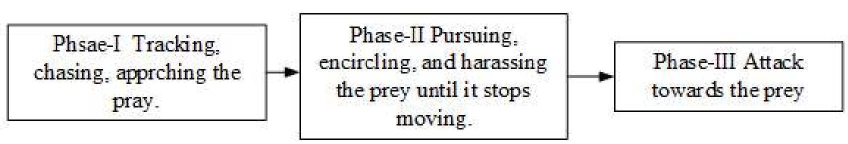

Fig. 2.4 Phases of grey wolves hunting.

Mathematical Model

In this subsection, the mathematical models of the social hierarchy, tracking, encircling, and attacking prey are provided.

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha (α). Consequently, the second and third best solutions are named beta (β) and delta (δ), respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm, the hunting (optimization) is guided

by α, β, and δ. The ω wolves follow these three wolves.
A mathematical representation of the encircling behavior of grey wolves to pray is given below.

$$\bar{D} = |\bar{E} \cdot P\bar{O}S_{prey}(t) - PO\bar{S}(t)| \tag{2.18}$$

$$P\bar{O}S(t+1) = P\bar{O}S_{prey}(t) - \bar{B} \cdot \bar{D} \tag{2.19}$$

where, t indicates the current iteration, $\bar{B}$ and $\bar{E}$ are coefficient vectors, $P\bar{O}S_{prey}$ is the position vector of the prey, and $P\bar{O}S$ indicates the position vector of a grey wolf.

The vectors $\bar{B}$ and $\bar{E}$ are calculated as follows:

$$\bar{B} = 2br_1 - b \tag{2.20}$$

$$\bar{E} = 2r_2 \tag{2.21}$$

where components of b are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0,1].

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space, we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution), beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The mathematical equation for finding the position of prey by α, β and δ wolves is given here.

$$\begin{aligned} \bar{D}_{\alpha} &= |\bar{E}_1 \cdot P\bar{O}S_{\alpha} - P\bar{O}S| \\ \bar{D}_{\beta} &= |\bar{E}_2 \cdot P\bar{O}S_{\beta} - P\bar{O}S| \\ \bar{D}_{\delta} &= |\bar{E}_3 \cdot P\bar{O}S_{\delta} - P\bar{O}S| \end{aligned} \tag{2.22}$$

$$\begin{aligned} P\bar{O}S_1 &= P\bar{O}S_{\alpha} - \bar{B}_1 \cdot (\bar{D}_{\alpha}) \\ P\bar{O}S_2 &= P\bar{O}S_{\beta} - \bar{B}_2 \cdot (\bar{D}_{\beta}) \\ P\bar{O}S_3 &= P\bar{O}S_{\delta} - \bar{B}_3 \cdot (\bar{D}_{\delta}) \end{aligned} \tag{2.23}$$

$$P\bar{O}S = \frac{P\bar{O}S_1 + P\bar{O}S_2 + P\bar{O}S_3}{3} \tag{2.24}$$

According to (2.23) and (2.24) (i.e. the best three positions) remaining wolves update their position.

2.3.3 Proposed Hybrid PSO-GWO-based Approach

All real-world problems are optimally solved by the PSO algorithm, easily. But there is always a possibility in the PSO algorithm that the solution may be trapped in local minima. The hybrid PSO-GWO algorithm is formed in order to utilize the better exploitation capability of PSO and the good exploration capability of GWO [102]. Random positions are given by PSO with a small possibility of some particles to avoid local minima. The exploration capability of GWO is used to prevent the risk of movement of particles away from global minima by directing some particles' positions instead of random positioning. Therefore, the present work has considered a hybrid metaheuristic approach that combines PSO and GWO to determine the optimal position and size of multiple DGs. The objective function defined by (2.10) has been minimized through the PSO-GWO algorithm taking DG location and size as decision variables. The weightage of three components of the proposed multi-objective function has been assigned using Genetic Algorithm (GA) as discussed in the section 2.2. To have the values of P, Q, V & δ at various stages, backward/forward load flow has been applied. The results of the backward/forward load flow have been used to calculate P_{Los}, ΔVD and $VSI(n_2)$ to determine the proposed multi-objective function at each iteration of the PSO-GWO algorithm. The flow chart to determine the optimal position and size of multiple DGs using the proposed PSO-GWO algorithm is shown in Fig. 2.5.

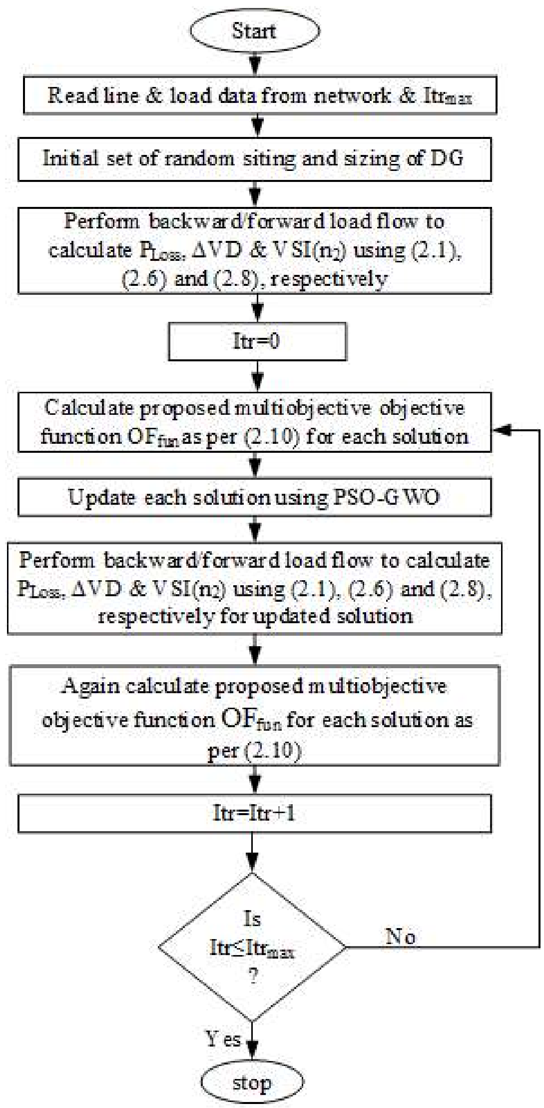

Fig. 2.5 Flow chart for hybrid PSO-GWO for obtaining optimal location and size of DGs

2.4 Results and Discussion

The effectiveness and validation of the PSO-GWO technique is tested on IEEE 33-bus radial distribution system to determine the optimal siting and sizing of Type-1 DGs in order to minimize active power loss and voltage deviation and maximize Voltage Stability Index $(VSI(n_2))$. The details of the IEEE 33-bus radial distribution system are given in Appendix A. The population size and iterations are taken as 50 and 100, respectively, to find the best results. Maximum and minimum voltage limits have been taken 1.05 p.u. and 1 p.u., respectively, for all buses considering $\pm 5\%$ permissible voltage variations.

The simulation results obtained by the proposed hybrid PSO-GWO approach along with a few existing metaheuristic approaches are shown in Table 2.1. Table 2.1 also present results obtained by Mixed Integer Non-Linear Programming (MINLP) approach which is a conventional method. MINLP results are obtained by GAMS software using DICOPT solver. It is observed from Table 2.1 that active power loss and voltage deviation are minimum, whereas, the voltage stability index is maximum compared to existing metaheuristic approaches and MINLP approach if DG location and size are obtained by the proposed PSO-GWO algorithm. It is also observed from Table 2.1 that all the metaheuristic approaches produce higher VSI value compared to MINLP method out of which highest VSI value is obtained if DG size and location are obtained by proposed PSO-GWO algorithm. Hence, placement of multiple DGs through the proposed PSO-GWO algorithm is more effective in loss minimization, and voltage profile, as well as voltage stability margin enhancement compared to the existing metaheuristic, approaches. The exact value of the maximum capacity of Type-1 DG is calculated as 3.931 MW for IEEE 33-bus system. Considering practical considerations, the maximum capacity of Type-1 DG is taken as 4 MW for IEEE 33-bus system. The minimum permissible DG size is taken as 0.1 MW in this work. Though the DG size shown in Table 2.1 are not representing practical values, these have been used to compare the results of PSO-GWO with existing approaches.

The voltage profile of the system in absence of DG and after DG placement by the proposed approach are shown in Fig.2.6. It can be clearly observed from Fig.2.6 that the

Table 2.1 Simulation results of different optimization techniques for IEEE 33-bus RDS

GA[103]		PSO[103]		GA-PSO[103]		MINLP		PSO-GWO	
ODGL*	**ODGS***	**ODGL***	**ODGS***	**ODGL***	**ODGS***	**ODGL***	**ODGS***	**ODGL***	**ODGS***
11	1.5	8	1.1768	11	0.925	9	0.98	31	0.9343
29	0.4228	13	0.9816	16	0.863	16	0.425	26	0.8663
30	1.0714	32	0.8297	32	1.2	25	0.946	12	1.2252

	GA[103]	**PSO[103]**	**GA-PSO[103]**	**MINLP**	**PSO-GWO**
P_{Loss} **(kW)**	106.3	105.30	103.40	97.7883	**92.7686**
VD (pu)	0.0407	0.0335	0.0124	0.0289	**0.0034**
VSI (pu)	0.9490	0.9256	0.9508	0.7869	**0.9560**

*ODGL-Optimal DG Location, *ODGS-Optimal DG Size

voltage of each bus has improved significantly if DGs are placed by the proposed approach. The voltage magnitudes at each bus without DG and with DG, placed at the optimal location using the proposed PSO-GWO algorithm are shown in Table 2.2. It is observed from Table 2.2 that the minimum value of voltages with and without DG are 0.9811 pu and 0.9131 pu at buses 26 and 18, respectively. This shows considerable enhancement in the voltage profile of the network if DGs are placed using the proposed PSO-GWO algorithm.

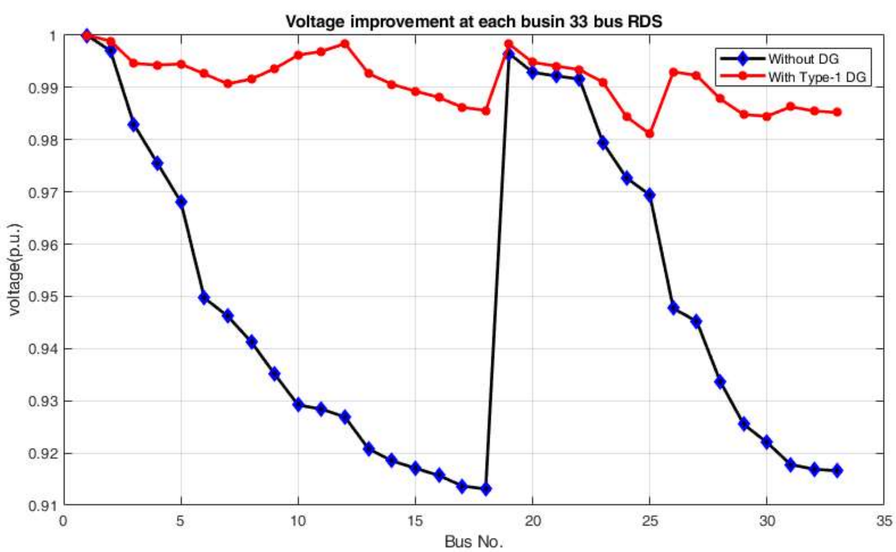

Fig. 2.6 Voltage profile improvement corresponding to optimal solution by PSO-GWO algorithm (IEEE 33-bus RDS)

Table 2.2 Voltages magnitude at each bus without DG and with DG placed using PSO-GWO algorithm (IEEE 33-bus RDS)

Bus No.	Without DG	With DG	Bus No.	Without DG	With DG
1	1.000	1.000	18	**0.9131**	0.9856
2	0.9970	0.9989	19	0.9965	0.9983
3	0.9829	0.9946	20	0.9929	0.9948
4	0.9755	0.9943	21	0.9941	0.9922
5	0.9681	0.9945	22	0.9922	0.9941
6	0.9497	0.9926	23	0.9916	0.9936
7	0.9462	0.9907	24	0.9794	0.9910
8	0.9413	0.9916	25	0.9727	0.9844
9	0.9351	0.9936	26	0.9694	**0.9811**
10	0.9292	0.9962	27	0.9477	0.9930
11	0.9284	0.9969	28	0.9452	0.9923
12	0.9269	0.9984	29	0.9337	0.9878
13	0.9208	0.9927	30	0.9255	0.9848
14	0.9187	0.9906	31	0.9220	0.9845
15	0.9171	0.9893	32	0.9178	0.9867
16	0.9157	0.9881	33	0.9169	0.9855
17	0.9137	0.9862			

2.5 Summary

In this chapter, a hybrid PSO-GWO algorithm was proposed for determining the optimal location and size of multiple DGs for loss minimization, voltage profile improvement, and voltage stability enhancement. A multi-objective function comprising the weighted sum of power loss, voltage deviation of buses from desired value, and voltage stability index was proposed. The optimal weighting factors were obtained using Genetic Algorithm (GA), whereas, the proposed multi-objective function was optimized using the PSO-GWO algorithm with DG size and location taken as decision variables. Simulations were carried out in MATLAB environment on IEEE 33-bus radial distribution system. Simulation results show that the proposed approach of multiple DG placement is more effective in loss minimization and voltage profile together with voltage stability enhancement compared to a few other existing metaheuristic approaches. Present work has considered placement of Type-1 DGs only, though the work can be extended to the placement of other types of DGs, too.

****