

Maximizing Power Loss Reduction in Radial Distribution Systems by Using Modified Gray Wolf Optimization

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Abstract

This paper presents an optimal Distribution Network Reconfiguration (DNR) framework and solution procedure that employ a novel modified Gray Wolf Optimization (mGWO) algorithm to maximize the power loss reduction in a Distribution System (DS). Distributed Generation (DG) is integrated optimally in the DS to maximize the power loss reduction. DNR is an optimization problem that involves a nonlinear and multimodal function optimized under practical constraints. The mGWO algorithm is employed for ascertaining the optimal switching position when reconfiguring the DS to facilitate the maximum power loss reduction. The position of the gray wolf is updated exponentially from a high value to zero in the search vicinity, providing the perfect balance between intensification and diversification to ascertain the fittest function and exhibiting rapid and steady convergence. The proposed method appears to be a promising optimization tool for electrical utility companies, thereby modifying their operating DS strategy under steady-state conditions. It provides a solution for integrating more DG optimally in the existing distribution network. In this study, IEEE 33-bus and 69-bus DSs are analyzed for maximizing the power loss reduction through reconfiguration, and the integration of DG is exercised in the 33-bus test system alone. The simulation results are examined and compared with those of several recent methods. The numerical results reveal that mGWO outperforms other contestant algorithms.

Keywords: radial distribution system, network reconfiguration, power loss reduction, modified gray wolf optimization, distributed generation

1. Introduction

In an electrical utility system, a Distribution System (DS) is an extensive part that usually supplies the consumer demand for electricity at an acceptable voltage magnitude. Generally, a DS operates in a radial structure to facilitate efficient protection and coordination schemes that can be re-structured for optimizing the controllable parameter. Distribution Network Reconfiguration (DNR) is the procedure for changing the topology of distribution feeders by changing the open / closed status of sectionalizing and tie switches while satisfying system constraints to satisfy the operator's objectives. This has been mathematically devised as an optimization problem subjected to various operational restrictions for ascertaining an optimal radial structure that reduces the power loss and load-balancing index [1-2] or maximizes the benefits under normal operation

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conditions [3]. In this context, some metaheuristic algorithms for minimizing power loss and maximizing node voltage magnitude of the DS have been presented, such as the Genetic Algorithm (GA) [4], the ant colony search algorithm [5], evolutionary algorithms [6], the plant growth simulation algorithm [7], the bacterial foraging optimization algorithm [8], and the cuckoo search algorithm [9]. These algorithms competently reconfigure the DS for minimizing power loss, improving the voltage profile of the distribution network. The convergence characteristic of a metaheuristic algorithm is dependent on an appropriate balance between exploration and exploitation behaviors. Therefore, researchers are attempting to tune the control variable of metaheuristic algorithms toward a global optimum, whereas mathematical methods have failed to find a correct solution. For this purpose, either a stochastic technique is incorporated to modify the heuristic operator or a hybrid optimization technique is developed by combining two heuristic tools or knowledge elements, as well as more traditional approaches being employed.

In line with this discussion, Swarnkar adopted graph theory with the conventional ant colony optimization algorithm, modifying the standard algorithm to perform Adaptive Ant Colony Optimization (AACO) [10]. This modified algorithm places feasible individuals in the space and overrides the mesh check. Likewise, in the Improved Adaptive Imperialist Competitive Algorithm (IAICA), a mapping strategy is incorporated, which adapts the imperialist competitive algorithm into a discrete nonlinear optimization problem [11]; the step size of the *E. coli* of the Modified Bacterial Foraging Optimization Algorithm (MBFOA) varies in each iteration [12]; and in Adaptive Weighted Improved Discrete Particle Swarm Optimization (AWIDPSO), the inertia weight is adaptively varied [13]. Conversely, in Mixed-Integer Hybrid Differential Evolution (MIHDE) [14], common mixed-integer nonlinear programming is embedded in a hybrid differential evolution algorithm. This algorithm performs migration and acceleration operations, which result in upgrades of the exploration tendency of the algorithm in the search space to improve fitness.

An extensive literature survey has revealed that DNR is a complex and nonlinear optimization problem that aims to minimize power loss, load balancing among branches, load balancing among feeders, node voltage deviation, and the number of switching operations either alone or through multiple objectives. Namely, AACO, MBFOA, AWIDPSO, and MIHDE have been devised solely for minimizing power loss, whereas IAICA was devised to reduce power loss and node voltage deviation separately. Similarly, hybrid particle swarm optimization [15] and the runner-root algorithm [16] have been employed to ascertain the optimal distribution reconfiguration in a multiobjective environment, wherein the norm 2 and max-min methods are incorporated, respectively, to obtain a compromised membership function between the best and worst objective functions. Similarly, AWIDPSO has been used for determining the optimal distribution restructure in a multiobjective scenario wherein the compromised objective function is obtained through a fuzzy membership function [17]. Power loss reduction of the current DS through physical restructuring is known to be possible to a certain level. To reduce the power loss and improve the voltage profile, a capacitor bank can be placed in the existing DS. The capacitor size and location are optimized using the flower pollination algorithm of Abdelaziz [18] and improved harmony algorithm of Ali [19]. Subsequently, Distributed Generation (DG) in the DS is optimized using the ant lion optimization algorithm [20].

Placement of either a capacitor or DG device in the existing DS without reconfiguration is known to yield only a modest benefit. This paper aims to perform DNR using a prudent optimization tool for determining the best and worst fitness values of the objective function to ensure effective distribution planning and operation. Furthermore, DG in the existing DS is optimized. Identifying the best solution is known to be dependent on the perfect adjustment of the global and local searchability of a metaheuristic algorithm. Nevertheless, the optimization methods mentioned herein have obtained optimal results and outperformed each other. It can be stated that the solution obtained using these methods are not an optimal end solution. A novel and valuable optimization tool, the Gray Wolf Optimizer (GWO), has emerged in this field. GWO has been benchmarked using 29 standard test functions, and the results have been validated by comparing with other methods [21]. The convergence and performance of GWO have also been investigated for solving the unit commitment problem [22].

GWO uses encircling, hunting, and attacking processes for discovering a superior solution when solving various standard test functions, performing sophisticated engineering, solving unit commitment problems, and dispatching economic loads. The acceleration set (a) of the coefficient vector (A) in the GWO position update equation decreases linearly from a higher value to zero. Equal opportunity is provided to both global and local optima because the trade-off between exploration and exploitation occurs linearly. In this paper, modified GWO (mGWO) is proposed, and this method increases the diversity of global optimum solution for a DNR problem. An exponential function is employed to obtain a trade-off between exploration and exploitation throughout the iterations. Increasing the degree of exploration in comparison to exploitation increases the convergence speed and avoids local minima trapping. When mGWO is used for solving a DNR problem for the first time, it provides practical solutions for IEEE 33 and 69 buses, and the global optimum solution is obtained quickly.

The rest of this paper is organized as follows. Section 2 describes the DNR problem. The mGWO algorithm is proposed in Section 3. The implementation of mGWO is demonstrated in Section 4. The simulation results are presented in Section 5. Finally, the study is concluded in Section 6.

2. Articulation Of The DNR Problem

2.1. Distribution network model for loss reduction

The power flow in a DS can be computed from the simplified DS model illustrated in Fig. 1 by using a recursive procedure. Active power flows through branch k from bus p to bus q , which is expressed as Eq. (1) and can be conveniently abridged as in Eq. (2).

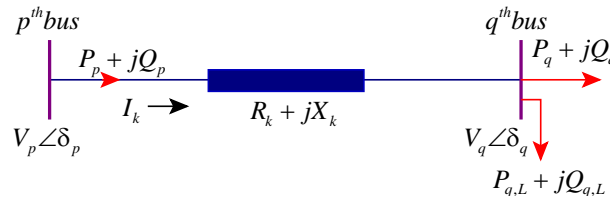


Fig. 1 Simplified DS model

$$P_p = P_{q,eff} + P_{k,loss} \tag{1}$$

where

$$P_{q,eff} = P_p + P_{q,L} \tag{2}$$

The current flowing through branch k between buses p and q can be calculated using either Eq. (3) or Eq. (4):

$$I_k = \frac{P_p - jQ_p}{V_p \angle -\delta_p} \tag{3}$$

$$I_k = \frac{V_p \angle \delta_p - V_q \angle \delta_q}{R_k + jX_k} \tag{4}$$

When computing the power loss in the DS, the voltage at bus q must be calculated. For this purpose, first, Eqs. (3) and (4) are compared. Second, the real and imaginary parts are separated. Third, the real and imaginary parts are squared and summed. Thus, the bus voltage is obtained as

$$V_q^2 = V_p^2 - 2*(P_p R_k + Q_p X_k) + (R_k^2 + X_k^2) \left(\frac{P_p^2 + Q_p^2}{V_p^2} \right) \tag{5}$$

The power loss in a line segment that connects buses p and q can be determined using Eq. (6).

$$P_{k,loss} = I_k^2 * R_k = \left(\frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right) * R_k \quad (6)$$

The aggregate power loss of the feeder can then be calculated by summing the losses of all line segments of the feeder, which is given as

$$P_{Loss} = \sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left(\frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right) * R_k \quad (7)$$

The power loss of a line segment connecting buses p and q after network reconfiguration can be computed as

$$P_k' = I_k'^2 * R_k = \left(\frac{P_{q,eff}'^2 + Q_{q,eff}'^2}{|V_q'|^2} \right) * R_k \quad (8)$$

The aggregate power loss of the feeder can then be determined by summing the losses of all line segments of the feeder, which is given as

$$P_{Loss}' = \sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left(\frac{P_{q,eff}'^2 + Q_{q,eff}'^2}{|V_q'|^2} \right) * R_k \quad (9)$$

The net power loss reduction, in the system, is difference in power loss before, after reconfiguration, and is given as

$$\Delta P_{Loss} = \left(\sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left(\frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right) * R_k \right) - \left(\sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left(\frac{P_{q,eff}'^2 + Q_{q,eff}'^2}{|V_q'|^2} \right) * R_k \right) \quad (10)$$

2.2. Power loss reduction due to DG

If DG is optimally located in a weak node of the DS using the loss sensitivity factor approach, technical, economic and environmental benefits are obtained. The effect on power loss in the line segment between buses p and q is computed using

$$P_{k,loss}^{DG} = \left(\frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right) * R_k + \frac{R_k}{V_q^2} (P_g^2 + Q_g^2 - 2P_{q,eff}P_g - 2Q_{q,eff}Q_g) \left(\frac{D}{L} \right) \quad (11)$$

The net power loss reduction in a DS is the difference between the power loss that occurs in the system without and with DG and is calculated as

$$\Delta P_{Loss}^{DG} = \sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left(\frac{R_k}{V_q^2} (P_g^2 + Q_g^2 - 2P_{q,eff}P_g - 2Q_{q,eff}Q_g) \left(\frac{D}{L} \right) \right) \quad (12)$$

2.3. Objective functions

2.3.1. Network reconfiguration

The objective function is formulated by taking the difference in the power loss of all line sections of the feeder as well as the network reconfiguration. For this purpose, an appropriate candidate open-switch position, the power loss reduction of a branch segment, is computed and should be maximized; the objective function is defined mathematically as

$$\text{Objective function}(f) = \text{Maximize}(\Delta P_{Loss}) \quad (13)$$

2.3.2. DG integration

The objective function for maximizing the net power loss reduction computed using Eq. (12) is expressed as

$$\text{Objective function}(f) = \text{Maximize}(\Delta P_{Loss}^{DG}) \quad (14)$$

2.4. Constraints

The node voltage should be between its lower and upper limits:

$$V_{\min} \leq V_q \leq V_{\max}; q \in N_{bus} \quad (15)$$

The branch current should be less than or equal to its maximum capacity, as specified by the manufacturer [1]:

$$|I_k| \leq I_k^{\max}; k \in N_{br} \quad (16)$$

The total size of DG is always less than or equal to the total load and active power loss of the network. The minimum and maximum DG kW ratings are selected as 10 % and 80 % of the entire system's real power demand, respectively.

$$\sum_{k=1}^{N_{DG}} P_{g,k} < (P_{Load} + P_{Loss}) \quad (17)$$

3. Modified Gray Wolf Optimization

The basic GWO algorithm, developed by Seyedali Mirjalili, mimics the leadership hierarchy, and hunting mechanism of gray wolves in nature [21]. In their population, gray wolves are categorized as alpha (α), beta (β), delta (δ), or omega (ω); the alpha is most dominant, whereas deltas and omegas control the rest of the wolves. The critical behavior in GWO is encircling, hunting, and attacking the prey, analytically modeled as an optimization tool for obtaining the optimal solution for any problem. The hunting mechanism of gray wolves is described in the following.

3.1. Encircling

This gray wolf behavior is modeled by

$$\vec{D} = |\vec{C} \cdot \vec{X}_{prey}(t) - \vec{X}_{wolf}(t)| \quad (18)$$

$$\vec{X}_{wolf}(t+1) = \vec{X}_{prey}(t) - \vec{A} \cdot \vec{D} \quad (19)$$

The vectors "A" and "C" play a crucial role in updating the position of a wolf according to that of the prey [21], considering a two-dimensional position vector and some of the possible neighbors. These coefficients are determined using Eqs. (20) and (21), where coefficient "a" is decreased linearly from 2 to 0 throughout the iterations.

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (20)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (21)$$

3.2. Hunting

Generally, the alpha wolf, in association with beta and delta wolves, presides over the hunting. To mimic hunting behavior, three of the best candidate solutions are alpha, beta, and delta wolves, which are first considered during the iteration. The other search agents (omega wolves) update their positions according to those of the three best search agents. This can be mathematically modeled as [21]

$$\vec{X}(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3} \quad (22)$$

where

$$\bar{X}_1 = \bar{X}_{alpha} - \bar{A}_1 \cdot (\bar{D}_{alpha}); \bar{X}_2 = \bar{X}_{beta} - \bar{A}_2 \cdot (\bar{D}_{beta}); \bar{X}_3 = \bar{X}_{delta} - \bar{A}_3 \cdot (\bar{D}_{delta}) \quad (23)$$

$$\bar{D}_{alpha} = |\bar{C}_1 \cdot \bar{X}_{alpha} - \bar{X}|; \bar{D}_{beta} = |\bar{C}_2 \cdot \bar{X}_{beta} - \bar{X}|; \bar{D}_{delta} = |\bar{C}_3 \cdot \bar{X}_{delta} - \bar{X}| \quad (24)$$

3.3. Attacking

In this phase, the wolves move in to assault the prey. In the mathematical model indicating the approaching of the victim, coefficient vector “A” plays a vital role and its oscillation range decreases by vector “a.” Moreover, vector “A” has a random value in the interval $[-a, a]$, where “a” is decreased linearly from 2 to 0 throughout the iterations. At the point where random generations of vector “A” are in the range $[-1, 1]$, the subsequent position of a candidate solution can be anywhere between its present location and the prey’s location. The candidate solution converges if the magnitude of vector “A” satisfies Eq. (25); alternatively, it diverges from the prey if the magnitude satisfies Eq. (26) and hopefully a fitter prey is found.

$$|\bar{A}| \leq 1 \quad (25)$$

$$|\bar{A}| \geq 1 \quad (26)$$

3.4. Adaptive acceleration coefficient

The acceleration coefficient vector “a” balances the processes of exploration and exploitation. A larger exploration area in a search contour results in a lower likelihood of stagnation in a local optimum. To enhance the exploration rate, the linear function should be replaced by an exponential function [23], where the acceleration coefficient is varied adaptively throughout the iterations and is given as

$$a = 2 \left(1 - \frac{t^2}{T^2} \right) \quad (27)$$

4. Computational Flow of mGWO Based DNR Problem

Rapid convergence and accuracy of an optimization method depend on control variables setting and initialization of an algorithm parameter. The control variable is a discrete nature that represents the number of switches (branches) to be opened to maintain a feasible radial topology. The control variable of mGWO is equal to the open switch of the system. When structuring an individual loop, information about the fundamental loops and the switch number in each primary loop are required. The computational flow consists of two phases and is described as follows.

4.1. Identifying loop vector

Step 1: Close all regularly open switches.

Step 2: Determine the number of fundamental loops (N_L) by Eq. (28).

$$N_L = N_{br} - (N_{bus} - N_{ss}) \quad (28)$$

Step 3: Decide loop vectors

The distribution system has a regular pattern of tie switches (open switches) which are equal to fundamental loops. Each loop includes the possible number of branches (closed switches) forming a j^{th} loop without repeating common branches in between any two loops. Moreover, infeasible topologies emerge during the iterative process, which builds the computational burden. Therefore, a few rules are framed to create just possible radial topologies.

Rule 1: The d^{th} member of the individual must belong to the loop vector L_j .

Rule 2: Only one member from a common branch vector can be selected to form an individual.

Rule 3: All the common branch vectors of any prohibited group vector cannot participate simultaneously to form an individual.

Rules 1 and 2 prevent islanding of exterior and interior nodes respectively, whereas Rule 3 prevents the islanding of principal interior nodes of the distribution network graph. Additionally, zeros can be added to make the loop vector matrix as a rectangular matrix, and the structure is represented by Eq. (29):

$$\text{Loop vectors}(L) = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_j \end{bmatrix} = \begin{bmatrix} SW_{1,1} & SW_{1,2} & \dots & SW_{1,d} \\ SW_{2,1} & SW_{2,2} & \dots & SW_{2,d} \\ \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \dots & \cdot \\ SW_{j,1} & SW_{j,2} & \dots & SW_{j,d} \end{bmatrix}; j \in N_L \quad (29)$$

4.2. Implementation of GWO algorithm

The well-ordered triumph strategy of executing mGWO for DNR problem is depicted in this section:

4.2.1. Define input data

Wherein, the initial network configuration, line impedance, possible number of fundamental loops, branches in each loop, number of tie switches in each loop, population size, algorithm parameters and the number of iterations are defined.

4.2.2. Initialize population

As, the tie switches are considered a control variable, and it should be selected optimally from each loop to maintain a possible radial configuration. The control variables are integer numbers, and only one switch is chosen randomly from each loop using Eq. (30):

$$X_{i,j} = \phi\{1, LSW(j)\}; j \in N_L \text{ and } i \in NP \quad (30)$$

Further, the initial population concerning switch position and DG size is represented by Eq. (31); the corresponding switch from each fundamental loop and DG is selected for the further procedure.

$$X = \begin{bmatrix} SW_1^1 & SW_2^1 & \cdot & \cdot & SW_{N_L-1}^1 & SW_{N_L}^1 & P_{g1}^1 & P_{g2}^1 & P_g^3 \\ SW_1^2 & SW_2^2 & \cdot & \cdot & SW_{N_L-1}^2 & SW_{N_L}^2 & P_{g1}^2 & P_{g2}^2 & P_{g3}^2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ SW_1^{NP} & SW_2^{NP} & \cdot & \cdot & SW_{N_L-1}^{NP} & SW_{N_L}^{NP} & P_{g1}^{NP} & P_{g2}^{NP} & P_{g3}^{NP} \end{bmatrix} \quad (31)$$

4.2.3. Calculate the objective value

For each trial solution, the radial topology is checked through the following sequential procedures [9], and after, the distribution power flow is executed to compute the objective value.

- i. Initialize a connected matrix of the loop distribution network A (b, b) with b is the number of buses of the network system and a set of feeders $S = [feeder1, feeder2, \dots, feeder k]$. Each entry in matrix A is defined as follows:
 - $A(i, j) = 1$ and $A(j, i) = 1$ if node i is connected to node j .
 - $A(i, j) = 0$ and $A(j, i) = 0$ if node i is not connected to node j .
- ii. Read the trial solution which is a set of tie-switches, and need to check and modify $A(i, j) = 0$ and $A(j, i) = 0$ if the switch on the branch from node i to node j is a tie-switch.

- iii. Evaluate all load nodes as follows: If node $n \notin S$ and $A(m, n) = 1$, with $m = 1, 2, \dots, \text{length}(S)$ and $n = k + 1, k + 2, \dots, b$ then the node n is moved to S , $S = S + [\text{node } n]$ and $A(m, n) = 0$, $A(n, m) = 0$.
- iv. If matrix A is a zero matrix and length of array S is equal to the number of buses, then the trial solution is a radial network configuration.

4.2.4. Identifying sensitivity node

The loss sensitivity factors (LSF) are computed from load flow using Eq. (32), and values are arranged in descending order for all buses to form a priority list. A bus with the highest priority is placed DG device.

$$\frac{\partial P_{\text{Line Loss}}}{\partial P_{q,\text{effective}}} = \frac{2 * P_{q,\text{effective}} * R_k}{V_q^2} \quad (32)$$

4.2.5. Evaluation of objective value and finding the best position

The robustness value of all individuals of the present candidate solution matrix (X^0) is computed using Eq. (33). The robustness of i^{th} individual represents the wolf's distance from the prey. Based on the robustness the populations are sorted in ascending order, a solution with minimum fittest value is imitated the alpha wolf; second and third minimum fittest values are beta and delta wolves respectively.

$$fit_i = \text{objective value} \quad (33)$$

4.2.6. Modifying agent position for an optimal solution

The position of an i^{th} wolf is updated using Eq. (22) if the mutant solution violates its limit which is fixed at that level.

4.2.7. Fitness re-estimation

The power flow is executed with the updated position of the solution vector to ascertain objective value. Then, its robustness is estimated to distinguish the best global solution.

4.2.8. Stopping criterion

If the maximum number of cycles is reached, terminate the iteration; otherwise, repeat steps from 3 to 8.

5. Simulation Results and Discussion

5.1. Particulars of the test system

A standard IEEE 33-bus (Test system-I) and 69-bus (Test system-II) radial distribution systems are considered for investigating the effectiveness of the mGWO. The base kV and MVA of both the systems are 12.66 kV and 10 MVA. There are 32, 68 normally closed switches, 5 normally open switches specifically 33-37 and 69-73 in test systems-I and II respectively. The real and reactive power loads of the test systems are 3.72 MW and 3.802 MW, and 2.3 MVar and 3.69 MVar. The real power loss and the node's minimum voltage at the initial state are found as 202.67 kW and 224.95 kW, and 0.9130 p.u. and 0.9092 p.u. respectively. The remaining data's are referred from [1].

5.2. Simulation environment

The mGWO algorithm is coded in the MATLAB, version 8.1 and is executed in an Intel @ Core™ i5-4210C CPU, 1.70GHz, 4 GB RAM personal computer. Two case studies were conducted using mGWO algorithm; one is performing distribution reconfiguration to maximize power loss reduction of small and medium distribution systems and the second is maximizing power loss reduction in the presence of DG in the existing DS. In the first case, thirty independent trials are attempted to find the best, average and worst values. The simulated results of test systems are distinguished with the other techniques to validate the robustness of the mGWO.

5.3. Case Study-I: Maximizing loss reduction through NR

5.3.1. Optimal reconfiguration

The viability of the mGWO technique for tackling the DNR is investigated by maximizing the objective function through the optimal determination of a new open switch. Therefore, various optimal tie switches are selected using the mGWO algorithm. The power loss, node least voltage and computational times are exhibited in Table 1 and Table 2 for test system-I and test system-II respectively.

Table 1 Possible optimal tie-switch position in 33-bus by mGWO

Optimal Tie-switches	Power Loss (k W)	V _{Min} (pu)	Comp Time (s)
7, 9, 14, 28, 32	132.9939	0.9447	6.61
7, 9, 14, 32, 37	133.0082	0.9440	6.51
7, 9, 14, 28, 36	133.0194	0.9438	6.52
7, 14, 10, 32, 37	133.9202	0.9414	6.57
7, 14, 9, 36, 37	134.0765	0.9399	6.58

Table 2 Possible optimal tie-switch position in 69-bus by mGWO

Optimal Tie-switches	Power Loss (k W)	V _{Min} (pu)	Comp Time (s)
69,70,14,55,61	97.9889	0.9596	17.62
69,70,13,58,61	98.0451	0.9542	17.62
69,18,14,57,61	98.1970	0.9522	26.02
69,19,13,56,62	98.3112	0.9511	26.24
69,19,14,55,63	98.3181	0.9510	26.26

It is identified that the power loss is reduced and node voltage is improved when the switches 7, 9, 14, 28, 32 are opened in test system-I whereas, the switches 69, 70, 14, 55, 61 are opened in test system-II. In this scenario, the corresponding optimal DNR is shown in Fig. 2 and 3 respectively that reveals the radial topology of the network. Furthermore, Fig. 4 shows the convergence characteristics of the mGWO algorithm; where the fitness value drastically dropped from a high value, and the mGWO can be attained optimal solution within the lesser iteration.

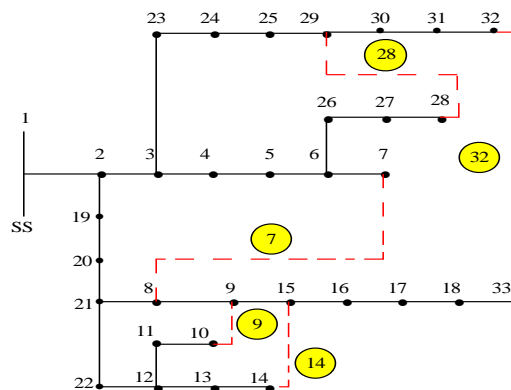


Fig. 2 Optimal reconfiguration of 33-bus for minimum power loss by mGWO

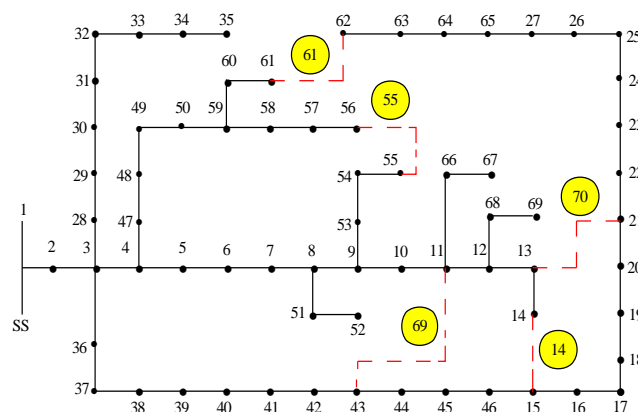


Fig. 3 Optimal reconfiguration of 69-bus for minimum power loss by mGWO

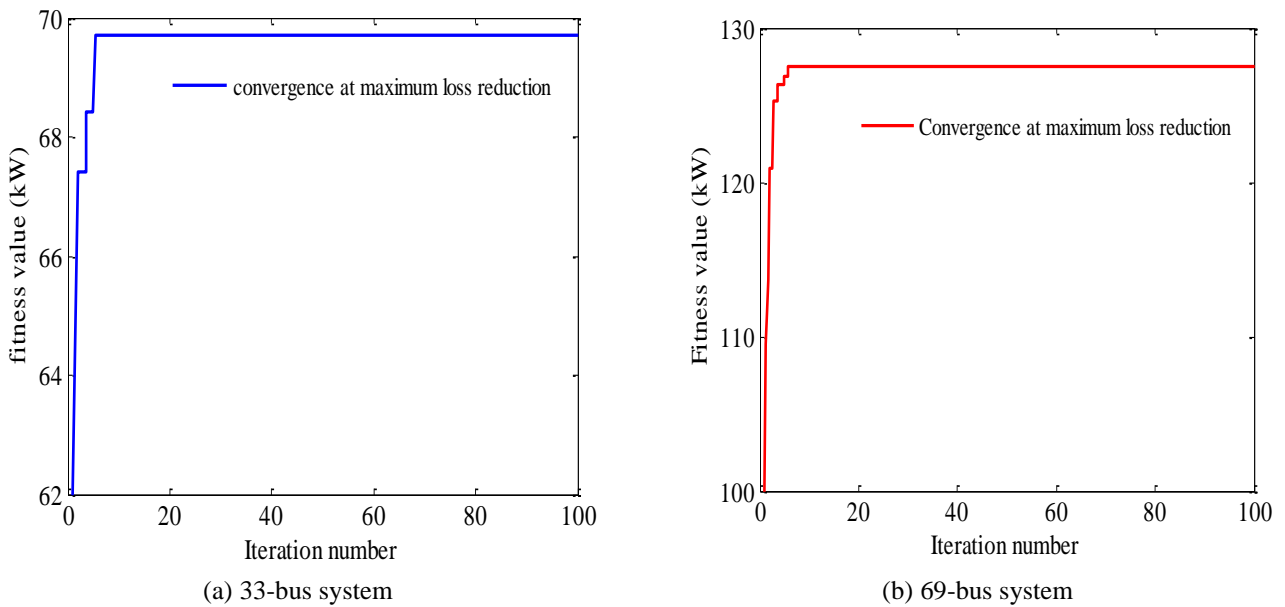


Fig. 4 Convergence characteristics of mGWO

5.3.2. Comparison of a viable solution

In an attempt to expose the predominance of mGWO algorithm in tackling DNR problem, the viable solution is obtained using CSA, IAICA, MBFOA, AWIDPSO, and RRA, and techniques including mGWO are contrasted in Tables 3 and 4 for test systems-I and II respectively. The improvement in power loss reduction of CSA, IAICA, MBFOA, AWIDPSO, and RRA, and mGWO from primary pattern is 63.84, 63.20, 68.19, 63.16, 69.72 and 68.95 kW respectively for test system-I. Similarly, CSA, IAICA, MBFOA, AWIDPSO, and mGWO are reduced the power loss from the initial configuration as 126.8685, 126.8658, 126.8765, 127.2395, and 127.4476 kW respectively for test system-II. Further, the algorithms’ potentiality of power loss reduction is illustrated in Fig. 5 for two test systems. It is experienced that the mGWO augmented the power loss diminishment massively in contrasted with the other competing methods in both test cases. Certainly, mGWO maximized the power loss reduction of 34.39 %, 56.53 % of test system-I and test system-II respectively. The mGWO method offered the least power losses, and similarly, regulated the node voltage by 5.85 %, 4.21 % of test system-I and test system-II respectively.

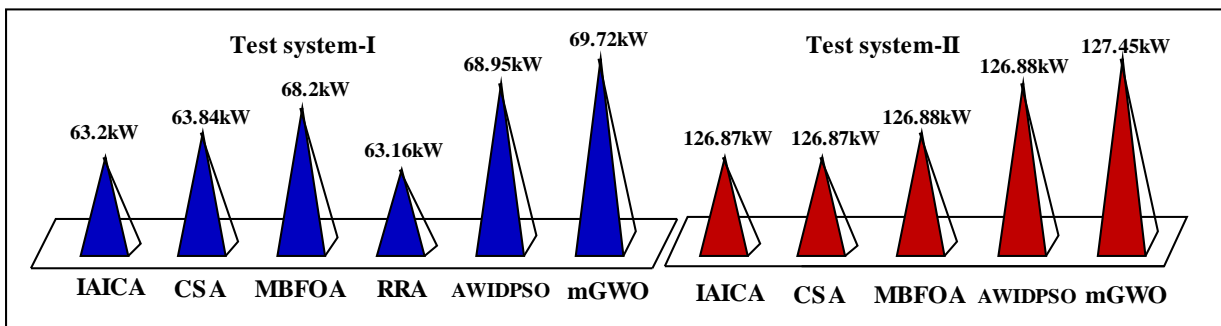


Fig. 5 Comparisons of maximization of power loss reduction

Table 3 Comparison of minimum power loss for 33 bus systems

Methods	Optimal Tie-switches	Power Loss (kW)	% of Power loss reduction	No. of Switches changed	% of Voltage regulation at V^{min}
Initial condition	33, 34, 35, 36, 37	202.7100	---	---	8.70
CSA	7, 9, 14, 32, 37	138.8700	31.49	4	6.63
IAICA	7, 9, 14, 32, 37	139.5100	31.18	4	6.75
MBFOA	7, 14, 28, 32, 36	134.5200	33.64	4	---
AWIDPSO	7, 14, 11, 32, 28	133.7281	34.03	5	6.24
RRA	7, 14, 9, 32, 37	139.5500	31.16	4	6.63
mGWO	7, 9, 14, 28, 32	132.9939	34.39	5	5.85

Table 4 Comparison of minimum power loss for 69 bus systems

Methods	Optimal Tie-switches	Power Loss (kW)	% of Power loss reduction	No .of Switches changed	% of Voltage regulation at V^{min}
Initial condition	69, 70, 71, 72, 73	225.4365	---	---	9.17
CS	14, 57, 61, 69, 70	98.5680	56.28	3	5.32
IAICA	14, 57, 61, 69, 70	98.5707	56.12	3	5.43
MBFOA	18, 43, 56, 61, 69	98.5600	56.28	4	---
AWIDPSO	69, 18, 14, 57, 61	98.1970	56.44	4	5.02
mGWO	69, 70, 14, 55, 61	97.9889	56.53	3	4.21

5.3.3. Solution quality improvement

The performance of the mGWO algorithm while, performing stated objective is compared in Table 5 with well-known optimization techniques that are already proven their ability in solving the DNR problem. The power loss reduction rate is 5.8761, 6.5161, 1.5261, 0.7342 and 6.5561 kW greater than CSA, IAICA, MBFOA, AWIDPSO, and RRA respectively, of test system-I. Likewise, the power loss reduction rate is 0.5791, 0.5818, 0.5711, and 0.2081 kW greater than CSA, IAICA, MBFOA, and AWIDPSO respectively, of test system-II. The nodal pu minimum voltage obtained using mGWO is 0.0024, 0.0069, 0.0005 and 0.0069 higher than CSA, IAICA, AWIDPSO, and RRA respectively, of test system-I while in the case of test system-II the pu minimum nodal voltage is 0.010, 0.0096, and 0.0074 higher than CSA, IAICA, and AWIDPSO respectively. Fig. 6 shows the voltage profile of test systems-I and II, and the voltage profile is enhanced significantly after reconfiguration for the majority of the node.

Table 5 Solution quality improvement by mGWO over the state-of-the-art methods

Methods	Power Loss (kW)		Node's minimum voltage (pu)	
	33-bus	69-bus	33-bus	69-bus
CSA	5.8761	0.5791	0.0024	0.0101
IAICA	6.5161	0.5818	0.0069	0.0096
MBFOA	1.5261	0.5711	---	---
AWIDPSO	0.7342	0.2081	0.0005	0.0074
RRA	6.5561	---	0.0069	---

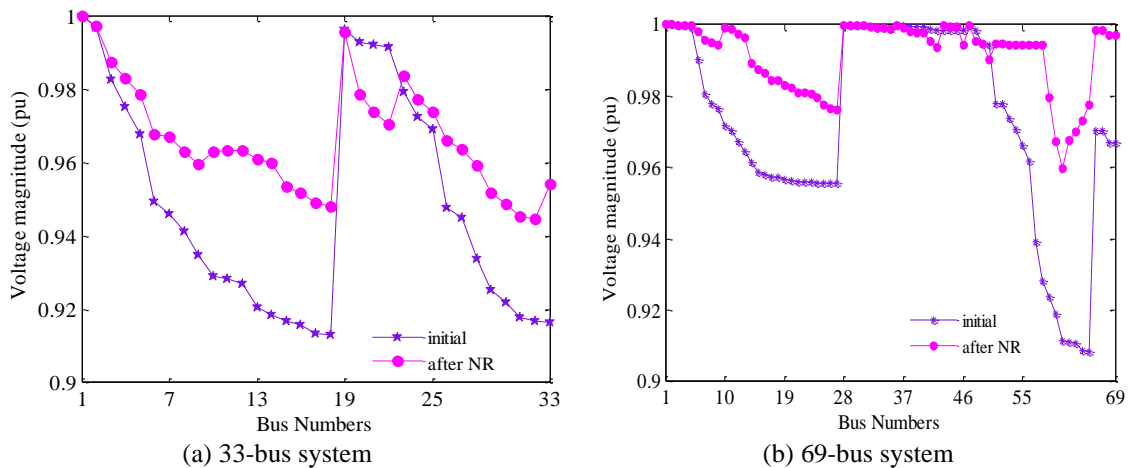


Fig. 6 Voltage profile improvement by mGWO

Power flow at a node and power loss in the branch are analyzed in Figs. 7 to 10 are for test systems I and II respectively to investigate the solution quality improvement while reconfiguring the distribution network. It observed that the power flow at all nodes in test system-I are reduced after reconfiguration. Conversely, the power flow at nodes 5-22, 41-45, 47, 48, 51-54, 57, 61 are increased. The investigation shows that the existing DS operates without overloading the feeder conductors after reconfiguration and also capable of supply extendable load. Consequently, power loss also streamlined among the branches. The power loss decreased some of the branches and is increased the remaining branches. Ultimately, the net power loss is reduced in the optimally restructured distribution network.

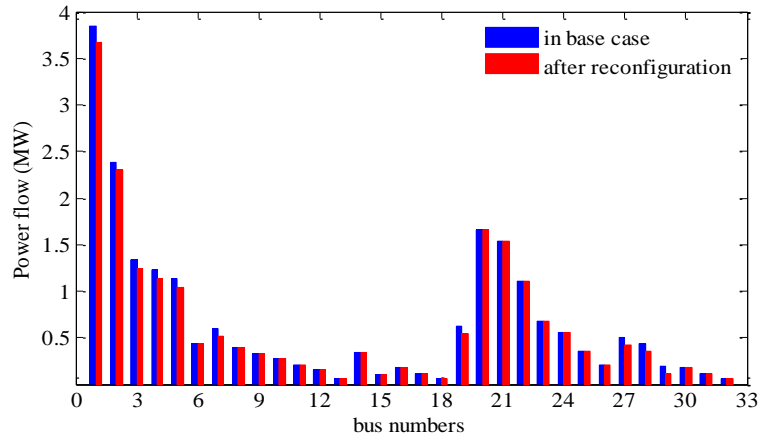


Fig. 7 Power flow at various nodes of a 33 bus system

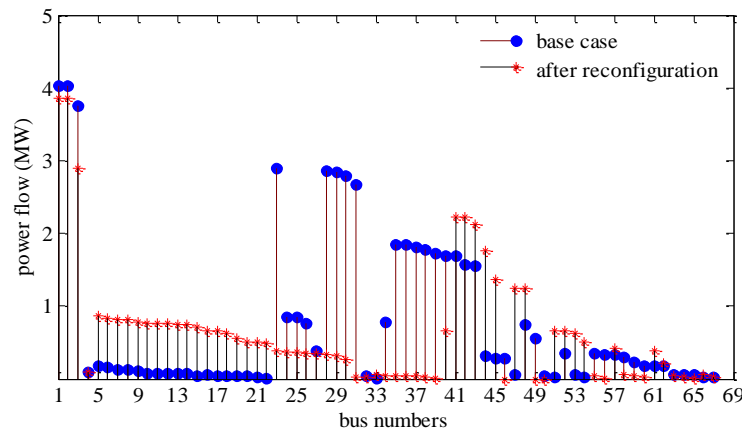


Fig. 8 Power flow at various nodes of a 69 bus system

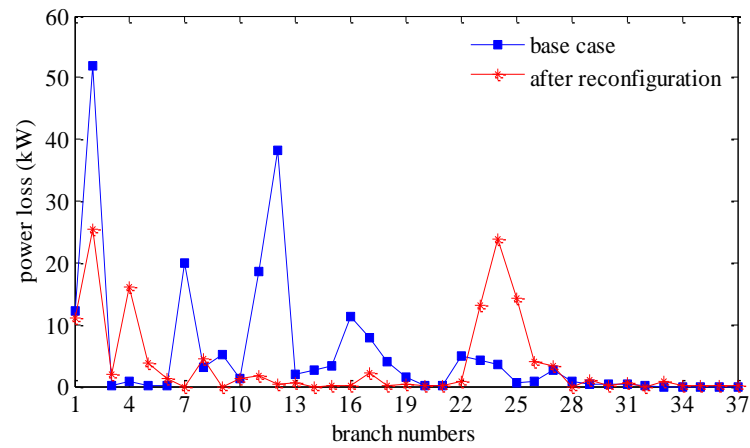


Fig. 9 Power loss at various branches of a 33 bus system

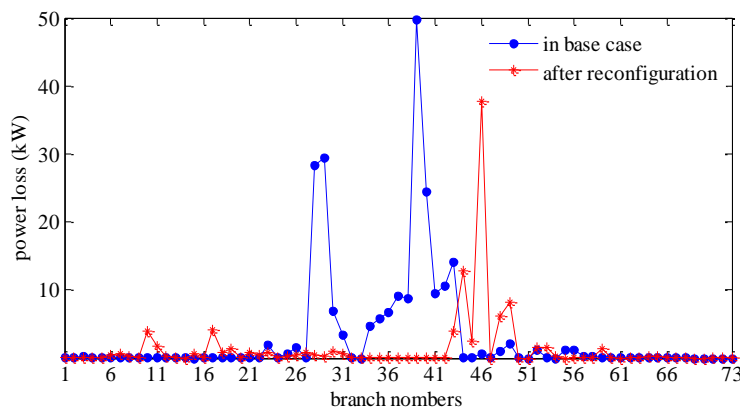


Fig. 10 Power loss at various branches of a 69 bus system

5.3.4. Statistical comparison

Any evolutionary and swarm intelligence algorithm can provide an optimal solution for engineering problems. In this scenario, a standard analytical procedure has been employed to know whether it is a global optimum, or not. Therefore, the best solutions of the objective function that was obtained over 50 trials by IAICA, MBFOA, AWIDPSO, RRA, and mGWO algorithms for test system-I and Test system-II are statistically analyzed, and the best, average and the worst values among the final solutions are presented in Table 6 and Table 7 respectively. The mGWO algorithm found the best global fitness function and the average value of the fitness function smaller than the best value of other algorithms for both test systems.

Moreover, the RRA algorithm is exercised on test system-I only, and the final fitness function seems to strike at the premature solution as the best, average and worst values which are stayed same. Finally, the mGWO algorithm is ranked first while reconfiguring distribution system since it has the lowest standard deviation. During the procedure, it observed that 46 and 48 good quality fitness functions of test system-I, and test system-II out of 50 are relatively fallen between the best and average solution. The success rate is found to be 93.33 % and 86.67 % for test system-I and II, respectively while optimizing using the mGWO algorithm.

Table 6 Statistical indices of the test results of a 33-bus system

Methods	Power Loss (kW)			Std Dev.	Rank
	Best	Average	Worst		
Initial State	202.7060	---	---	--	---
CSA	138.8700	---	---	---	---
IAIC	139.5100	140.5700	142.3800	1.44	3
MBFOA	134.5200	150.5800	165.4000	15.44	4
AWIDPSO	133.7281	134.5154	135.8254	1.05	2
RRA	139.5500	139.5500	139.5500	0.00	---
mGWO	132.9939	133.6423	135.0000	1.00	1

Table 7 Statistical indices of the test results of a 69-bus test system

Methods	Power Loss (kW)			Std Dev.	Rank
	Best	Average	Worst		
Initial State	225.4365	---	---	---	---
CSA	98.5680	---	---	---	---
IAICA	98.5707	100.1577	103.8273	2.6283	3
MBFOA	98.5600	110.3033	155.58	28.51	4
AWIDPSO	98.1970	98.5885	100.0045	0.9038	2
mGWO	97.9889	98.1419	99.6200	0.8156	1

5.4. Case Study-II: Maximizing loss reduction in the presence of DG

5.4.1. Optimal location and size of DG

This case study is conducted under three circumstances. First, the system of the initial configuration is considered and standard load flow is employed to identify sensitive nodes; the most sensitive node is identified for DG placement, and the optimal size of DG is determined using the proposed algorithm for minimizing power loss. Second, the two most sensitive nodes are identified, and the optimal DG size is established using the proposed algorithm, again for maximizing the loss reduction. Conversely, in the third scenario, the three most sensitive nodes are preferred as the optimal locations and sizing of DG, which are determined using mGWO. Table 8 shows the optimal tie switch, DG sizes, and locations for all three circumstances.

Nodes 28, 23, and 3 are identified as the three most sensitive nodes; in the first scenario, the DG size is 2.619 MW and is optimally located at node 28; the power loss is reduced by 51.81 %, and the minimum node voltage is increased to 0.9589 p.u. In the second scenario, nodes 28 and 23 are identified as highly sensitive nodes. Therefore, the optimal DG sizes are 1.232 and 1.470 MW; as a result, power loss is decreased by 60.48 %, and voltage profile is improved by 0.9781 p.u. In the third scenario, DG sizes of 0.858, 1.033, and 1.268 MW are integrated optimally by the proposed algorithm at nodes 28, 23, and 3, respectively. Hence, the power loss is decreased by 64.64 %, and the node minimum voltage magnitude is enhanced by 0.9852 p.u.

Table 8 Feasible solutions obtained using mGWO for a 33-bus system

Particulars	Without DG	With DG		
		Single	Two	Three
Power Loss (KW)	202.7069	97.6793	80.1161	71.68
% Loss Reduction	---	51.81	60.48	64.64
Min Voltage (p.u)	0.9131	0.9589	0.9781	0.9852
Location of DG	---	28	28, 23	28,23,3
DG's Size (MW)	---	2.6190	1.232(28) 1.470(23)	0.858 (28) 1.033(23) 1.268(3)

5.4.2. Feasible solution

In Table 9, the feasible solution obtained using mGWO for the three circumstances at the maximum loss reduction is compared with those obtained using other methods. The proposed method achieves 51.81 % loss reduction from the initial state when integrating a single DG device, which is higher than that obtained using other methods; that is, 5.21%, 7.40%, 30.32%, 28.57 %, 25.68 %, 24.59 %, 23.19 %, 31.38 %, and 17.31 % for ALOA, GA, EVPSO, PSOPC, ADPSO, DAPSO, ANALYTICAL, and BSOA, respectively. Regarding the placement of two DG device, mGWO results in a loss reduction of 60.48 % from the fundamental configuration, which is superior to the values obtained using other algorithms: 3.01%, 3.12%, 25.85%, 28.11%, 24.69%, 24.59%, 16.48%, and 10.32% for ALOA, GA, EVPSO, PSOPC, AEPSO, ADPSO, DAPSO, and BSOA, respectively. For three DG devices, mGWO results in a loss reduction of 71.68% with regards to the initial configuration, higher than that obtained using other contestant algorithms: 10.37 %, 1.43%, and 3.33 % for BSOA, PSO, and ANALYTICAL, respectively.

Table 9 Comparison of feasible solutions obtained using various methods for the 33-bus system

Cases	Methods	Power Loss without DG=202.7069kW				
		Power Loss (KW)	% Loss Reduction	Min Voltage (p.u)	Location of DG	Total DG Size (MW)
Single DG	mGWO	97.679	51.81	0.9589	28	2.619
	ALOA[20]	103.053	49.16	0.9503	6	2.450
	GA[20]	105.481	47.96	---	6	2.580
	EVPSO[20]	140.190	30.84	0.9284	11	0.763
	PSOPC[20]	136.750	32.54	0.9318	15	1.000
	AEPSO[20]	131.430	35.16	0.9347	14	1.200
	ADPSO[20]	129.530	36.10	0.9348	13	1.210
	DAPSO[20]	127.170	37.26	0.9349	8	1.212
	Analytical[20]	142.340	29.78	0.9331	18	1.000
BSOA[20]	118.120	41.73	0.9441	8	1.858	
Two DG	mGWO	80.116	60.48	0.9781	28, 23	2.702
	ALOA[20]	82.600	59.25	0.9732	13, 30	2.041
	GA[20]	82.700	59.20	0.9685	13, 29	2.050
	EVPSO[20]	108.050	46.70	0.9457	14, 31	1.109
	PSOPC[20]	111.450	45.02	0.9418	8, 12	1.683
	AEPSO[20]	106.380	47.52	0.9447	14, 29	1.200
	ADPSO[20]	106.240	47.59	0.9467	15, 30	1.171
	DAPSO[20]	95.930	52.68	0.9651	13, 32	1.965
	BSOA[20]	89.340	55.93	0.9665	13, 31	1.804
Three DG	mGWO	71.68	64.64	0.9852	28, 23, 3	3.159
	BSOA[20]	79.97	61.50	---	3,13,29	2.943
	PSO[20]	72.72	64.13	---	24,30,14	2.916
	Analytical[20]	74.15	64.30	---	13,30,24	2.700

Voltage profile improvement is another useful index and is analyzed through the percentage voltage regulation at the node at which the voltage is lowest. The proposed method outperforms other contestant algorithms because it achieves the least percentage of voltage regulation-4.29 %, 2.24%, and 1.50 %-for placement of one, two, and three DG devices, respectively, in

the existing DS. The effect of DG on voltage profile improvement is analyzed in Fig. 11, which compares the node voltage improvements without and with DG for all three scenarios. The voltage magnitude at all nodes is favorably altered.

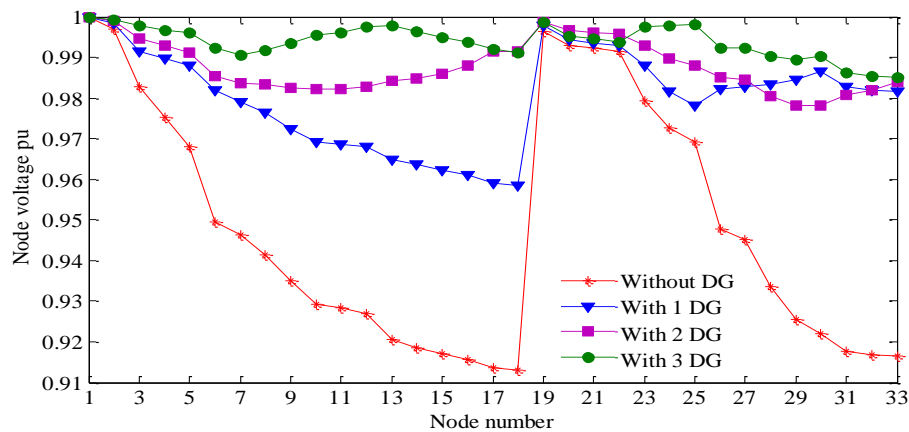


Fig. 11 Power loss at various branches of a 33 bus system

6. Conclusions

In this paper, a powerful metaheuristic algorithm, mGWO, is successfully employed to maximize power loss reduction in a DS through two methods. In the first method, the network reconfiguration is optimized, whereas in the second method, the penetration of DG in the existing DS and the selection of the required DG size are performed optimally, which results in voltage profile improvement. This is a complicated combinatorial, nondifferentiable, constrained optimization problem. In the first approach, the difference in a power loss of all branch sections of the feeder, as well as the network reconfiguration is deemed an objective function. In the second approach, the difference between the power loss that occurs in the system without and with DG is considered the objective function. To identify a weak node, the loss sensitivity factor approach is incorporated in the forward/backward-sweep distribution load flow algorithm.

The mGWO algorithm is used to solve this problem; this algorithm emulates the inherent behavior of gray wolves, which encircle, hunt, and attack their prey. The strategic ratio between the global and local searches of the algorithm varies linearly from a high value to zero in the basic GWO. This may decrease the diversity of global optima. When obtaining the best fitness value from local optima, the strategic balance between global and local search is varied exponentially from a high value to zero in the mGWO method. Simulation is performed on 33- and 69-bus DSs for network reconfiguration and a 33-bus system for DG implementation. The simulation results are compared with those of previous studies; the optimal determination of a tie switch is unique, and the acquired configuration is autonomous of the initial state of the DS. Moreover, this paper provides a solution to reduce massive power loss in radial DSs, and the improvement brought about by this solution is analyzed in detail. Hence, the proposed mGWO is a robust and viable algorithm for discovering the global optimum DS reconfiguration, and ultimately, the numerical outcomes are helpful for power distribution companies wishing to inject real power into a DS through PV-type DG. The penetration of a different type of DG, placement of DG after reconfiguration, and performing network reconfiguration in the presence of DG are topics for future research.

Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

I_k	k^{th} branch current	t	Current iteration
I_k^{max}	k^{th} branch maximum current	\vec{A}, \vec{C}	Coefficient vectors
R_k, X_k	Resistance and reactance of the line section between buses p and q	\vec{a}	Acceleration vector
P_k, Q_k	Real and reactive power is flowing out of bus p	\vec{r}_1	Random vectors in [0 1]
P_q, Q_q	Real and reactive power is flowing out of bus q	T	Maximum iteration
$P_{q,L}, Q_{q,L}$	Real and reactive power load at bus q	N_L	Number of fundamental loops
$V_p \angle \delta_p$	Voltage magnitude and the angle at bus p	L_j	j^{th} loop vector
$V_q \angle \delta_q$	Voltage magnitude and the angle at bus q	$SW_{j,d}$	d^{th} branch or closed switch in the j^{th} loop
$P_{k,\text{loss}}$	Real power loss in the branch segment k	NP	Population size
$P_{q,\text{eff}}, Q_{q,\text{eff}}$	Effective active and reactive power supplied beyond the bus q	LSW	Total number of the closed switch in the j^{th} loop at loop vector matrix
N_{ss}	Number of substations	$P_{g1}^i \dots P_{g3}^{NP}$	Size of distributed generation
$P'_{q,\text{eff}}, Q'_{q,\text{eff}}$	Effective active and reactive power supplied beyond the bus q after reconfiguration	ϕ_j	Pseudorandom integer values are drawn from the discrete uniform distribution between any two intervals.
N_{bus}, N_{br}, N_{DG}	Number of bus, branch and distributed generation	List of abbreviations	
P_g, Q_g	Real and reactive power supplied by DG	CSA	Cuckoo search algorithm
D	Distance from source to the DG location in km	GA	Genetic Algorithm
L	The total length of the feeder from source to bus k in km	PSO	Particle Swarm Optimization
ΔP_{Loss}	Net power loss after reconfiguration	RRA	Runner-root algorithm
$\Delta P_{\text{Loss}}^{DG}$	Net power loss after DG placed	EVPSO	Escape Velocity PSO
\vec{D}	Position vector of each hunter from any other hunters	PSOPC	PSO with Passive Congregation
\vec{X}_{prey}	Position vector of the prey	AEPSO	PSO with Area Extension
\vec{X}_{wolf}	Position vector of the gray wolf	ADPSO	Adaptive Dissipative PSO
		DAPSO	Dynamic Adaptation of PSO
		BSOA	Backtracking search optimization algorithm

Appendix

Algorithm parameter	Population size (NP)	:	30
	Maximum number of iteration	:	100
System voltage limits	$V\text{-Min}$:	0.95pu
	$V\text{-Max}$:	1.05pu

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