



Optimizing Radial Distribution System for Minimizing Loss Reduction and Voltage Deviation Indices Using Modified Grey Wolf's Algorithm

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Abstract: A novel metaheuristic optimization procedure for optimizing electrical distribution system is proposed that may help the system planners to know the minimum and maximum objective values. In which the optimal distribution network reconfiguration (DNR) framework and implementation of modified grey wolf optimization (mGWO) algorithm to minimize power loss reduction and node voltage deviation indices have delineated. The DNR involves nonlinear and multimodal function that has been optimized under practical constraints. For the purpose, mGWO algorithm is employed for ascertaining optimum switching position while reconfiguring the distribution system at a minimum fitness value. In fact grey wolf's update its position linearly from a higher value to zero in the search vicinity that provides perfect balance among intensification and diversification to ascertain the best fitness function and exhibits quick and steady convergence. Moreover, the proposed method seems to be a promising optimization tool for the electrical utilities, thereby modifying their operating strategy of distribution system under steady state conditions. This study is conducted on standard IEEE 33-bus and 69-bus distribution systems, the simulated results have analyzed and compared with several recent methods. It shows that the numerical results have provided, by mGWO is superior among the contestant algorithms.

Keywords: Metaheuristic optimization, Modified grey wolf optimization, Radial distribution system, Network reconfiguration, Power loss reduction index, Node voltage deviation index.

1. Introduction

Optimization is an art of acquiring the best solution under the given conditions that give the base or most extreme value of a function, where the function represents the effort required or the preferred benefit. Several optimization techniques have evolved in the past decades that involves in the design, construction and maintenance of engineering system for decision making both at the managerial and the technological level [1]. Particularly, in power system engineering the optimization is aimed to improve not only cost benefits but also reliability, efficiency, economics, environmental friendliness and security. In fact, optimizing distribution system is an imperative task that facilitates to distribute

power at the primary voltage level; thereby the length of the low-voltage feeders is kept to a minimum, reducing cable cost and energy losses and improving voltage regulation. Optimization of the distribution system (DS) is the process of restructuring the existing distribution network by optimally selecting the open/closed status of sectionalizing and tie switches while satisfying system constraints so as to minimize the operator's objectives [2].

In the early stage, classical optimization techniques have been used for optimizing DS such as a simple search method with the objective of minimization of power loss and load balancing index [3], heuristic search strategies for reconfiguring DS [4], artificial neural network with the aim of loss reduction [5], exhaustive search

method for determining minimal-loss [6] and fuzzy embedded heuristic search rule so as to minimize the loss in a radial distribution network [7].

The classical methods hitherto are being discussed in deterministic nature. Despite, these methods holding solid mathematical foundation it uses single path search based on the deterministic transition rule while searching the optimum solution in the search space. Hence, these methods have taken the most computational time and have occupied more memory space.

Later stage, a metaheuristic optimization technique based on either population or nature inspired algorithms have been employed for minimizing power loss and maximizing node voltage magnitude of the DS were presented, such as: genetic algorithm (GA) [8], ant colony search algorithm (ACSA)[9], a new codification with genetic operators [10], artificial bee colony algorithm (ABC) [11], evolutionary algorithms [12], plant growth simulation algorithm (PGSA) [13], bacterial foraging optimization algorithm (BFOA) [14], artificial immune system (AIS) [15], fireworks algorithm (FA) [16], a cuckoo search algorithm (CSA) [17] and runner-root algorithm (RRA) [18].

It is well known that the convergence characteristics of a metaheuristic optimization depends proper balance between exploration and exploitation behavior of the algorithm has employed which tune the control variable of the metaheuristic algorithms towards global optimum whereas, mathematical methods suffered to find a precise solution. For the purpose, either a stochastic technique is incorporated to modify the heuristic operator or a hybrid optimization technique has developed by combining two heuristic tools or with knowledge elements, as well as more traditional approaches. In line with the discussion, Swarnkar [19] and Gupta [20] have adapted graph theory with conventional ant colony optimization and particle swarm optimization algorithms respectively that maneuvers the conventional algorithms as an adaptive ant colony optimization (AACO) and adaptive particle swarm optimization (APSO). These modified algorithms engender feasible individuals in the space and moreover override mesh check.

Likewise, a mapping strategy is incorporated with the imperialist competitive algorithm and it becomes an improved adaptive imperialist competitive algorithm (IAICA) which adapts ICA into discrete nonlinear optimization problem [21], the step size of the E-coli of modified bacterial foraging optimization (MBFOA) has varied in each iteration [22], in case of theta-modified bat

algorithm (T-BA) the Cartesian form is transformed into polar form results the velocity and position of each bat is updated using the phase angle vectors thus increases the convergence speed [23], as the genetic operator has augmented in an enhanced genetic algorithm (EGA), generating superior solutions for electrical distribution reconfiguration problem [24] and the inertia weight is adaptively varied in adaptive weighted improved discrete particle swarm optimization (AWIDPSO) for minimizing power loss [25] and load balancing index [26].

Conversely, in mixed-integer hybrid differential evolution (MIHDE) [27] a common mixed-integer nonlinear programming is embedded through a hybrid differential evolution algorithm that performs migration and acceleration operations to upgrade the exploration of the search space and to improve the fitness. Similarly, hybrid particle swarm optimization (HPSO) was proposed which exploits the benefits of PSO and ant colony optimization [28].

From the extensive literature survey, it is found that DNR is a complex and non-linear optimization problem which aims to minimize either power loss, load balancing among branches, load balancing among feeders, node voltage deviation and number of switching operations alone or through multiobjective. Namely, GA [8], ACSA [9], ABC [11], EP [12], PGSA [13], BFOA [14] and AIS [15] algorithms have nicely reconfigured the DS for minimizing power loss. On the other hand FA [16], CSA [17] and RRA [18] have competently minimized power loss and improving the voltage profile of the distribution network; the first two simultaneously minimize both net real power loss reduction and voltage deviation index and later has exercised in performing single objective and multiobjective optimization.

Similarly, modified algorithms such as AACO [19], APSO [20], IAICA [21], MBFOA [22] T-BA [23] and AWIDPSO [25-26], hybrid algorithms MIHDE [27] and HPSO [28] have applied to ascertain optimal distribution reconfiguration under steady state condition.

Additionally, it is comprehended that power loss, node voltage deviation, load balancing in the branches and number of opening/closing switches are the objective functions of distribution optimization problem. Generally, the combined objective function is expressed in terms of the weighted sum of the normalized membership function. In which all the performance indices have given equal weightage, but the effect of an individual index is not accounted.

In this paper, it is motivated to perform distribution network optimization with the objective of minimization of net power loss reduction and node voltage deviation indices. Wherein, the aggregate sum of power loss reduction and node voltage deviation indices is an objective function. It is minimized collectively using a prudent optimization tool for determining the best and worst fitness value of the objective function to ensure the effective distribution planning and operation.

It is comprehended that finding the best possible solution depends the perfect adjustment of global and local search ability of a metaheuristic algorithms. Nevertheless, the listed optimization methods had identified optimum result and they outperform each other's which seems to be considered as local optima with respect to one another and these are not an end optimum reconfiguration. The present scenario, a novel, talented optimization tool, i.e., grey wolf's optimizer (GWO) has emerged in the optimization environment. First, it has benchmarked on twenty-nine standard test functions, and the results are validated by comparing with other methods [29]. Later, it was applied for solving economic load dispatch problem [30], and followed its convergence characteristic and performance has been investigated while solving the unit commitment problem [31].

It has demonstrated that the GWO uses encircling, hunting and attacking processes for discovering the superior solution while solving various standard test functions, complex engineering and the unit commitment problems, and economic load dispatch. Wherein the acceleration set (a) of the coefficient vector (A) in the grey wolf's position update equation decreases from a higher value to zero linearly.

Moreover, it provides equal opportunity to both global and local optima as the trade-off between exploration and exploitation happens linearly. In this paper a modified grey wolf's optimizer (mGWO) is proposed to increase the diversity of global optimum solution for DNR problem. Wherein, an exponential function is employed to obtain trade-off between exploration and exploitation over the course of iterations. Increasing the exploration in comparison to exploitation increases the convergence speed and avoids the local minima trapping effect. The features of this paper are:

- Successful problem formulation.
- mGWO is exercised for solving DNR problem as a first time.
- The IEEE 33-bus and 69-bus systems, data are nicely integrated with mGWO.

- The global optimum solution is obtained very quickly.
- Numerical solutions are validated in comparison with latest optimization techniques.

The rest of the paper is organized as follows. The suggested mGWO algorithm is articulated in section 2. Section 3 describes DNR problem. The implementation of mGWO is demonstrated in section 4. The simulation results are illustrated in Section 5. Finally, section 6 concludes the research work.

2. Modified grey wolf optimization

The basic grey wolf optimizer (GWO) algorithm has developed by Seyedali Mirjalili that mimics the leadership hierarchy and the hunting mechanism of grey wolves in nature. In their population, grey wolves are categorized as alpha (α), beta (β), delta (δ) and omega (ω) in which first one is most commanded and later two wolves control the rest of the wolves. The vital behavior of GWO are encircling, hunting and attacking the prey, these are analytically modeled as an optimization tool to achieve the best possible solution for any kind of problem. Then, hunting mechanism of grey wolves is described as follows:

Encircling: It is a behavior of the grey wolves and is modeled like Eqs. (1) and (2).

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (2)$$

Where, t specifies the current iteration, A and C are coefficient vectors, vectors X_p and X denotes the position vector of the prey and grey wolf respectively. Then vectors A and C are determined as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

Where, r_1 and r_2 are random vectors between 0 and 1 and vector a is set to decrease linearly from 2 to 0 over the course of iterations.

Hunting: Generally, alpha wolf has presided the hunting in association with beta and delta wolves. In order to mimic the hunting behavior first three best candidate solutions are considered as alpha, beta and delta wolves during the course of the iteration. The

other search agents (omega wolves) update their positions according to the position of three best search agents. It can be modeled mathematically as follows:

$$\bar{X}(t+1) = \frac{\bar{X}_1(t) + \bar{X}_2(t) + \bar{X}_3(t)}{3} \quad (5)$$

Where,

$$\begin{aligned} \bar{X}_1 &= \bar{X}_\alpha - \bar{A}_1 \cdot (\bar{D}_\alpha) \\ \bar{X}_2 &= \bar{X}_\beta - \bar{A}_2 \cdot (\bar{D}_\beta) \\ \bar{X}_3 &= \bar{X}_\delta - \bar{A}_3 \cdot (\bar{D}_\delta) \end{aligned} \quad (6)$$

$$\begin{aligned} \bar{D}_\alpha &= |\bar{C}_1 \cdot \bar{X}_\alpha - \bar{X}| \\ \bar{D}_\beta &= |\bar{C}_2 \cdot \bar{X}_\beta - \bar{X}| \\ \bar{D}_\delta &= |\bar{C}_3 \cdot \bar{X}_\delta - \bar{X}| \end{aligned} \quad (7)$$

Attacking: In this phase the wolves are driving to assault the prey. While mathematically modeling for approaching the prey, coefficient vector ‘A’ plays a vital role and its oscillation range is also decreased by vector ‘a’. Moreover, vector ‘A’ is a random value in the interval $[-a, a]$ where, ‘a’ is decreased linearly from 2 to 0 over the course of iterations. At the point when random generations of vector ‘A’ being in $[-1, 1]$, the subsequent position of a candidate solution can be in any position between its present location and the location of the prey. In which the candidate solution converges if the magnitude of vector ‘A’ satisfies Eq. (8) alternatively it diverges from the prey if the magnitude of vector ‘A’ is accordingly Eq. (9) and hopefully find a fitter prey.

$$|\bar{A}| \leq 1 \quad (8)$$

$$|\bar{A}| \geq 1 \quad (9)$$

2.1 Adaptive acceleration coefficient

It is worthy to note that the acceleration coefficient vector (*a*) balances the process of exploration and exploitation. Predominantly, an escalating exploration area in a search contour results in lower likelihood of local optima stagnation. In order to enhance the exploration rate the linear function is to be replaced an exponential function. In which the acceleration coefficient has varied

adaptively over the course of the iteration and given by Eq. (8).

$$a = 2 \left(1 - \frac{t^2}{T^2} \right) \quad (10)$$

Where, *t* and *T* are current iteration and the maximum number of iterations respectively.

3. Distribution system optimization problem

The DNR is an intricate combinatorial, non-differentiable delimited optimization problem and has devised to minimize net power loss reduction and node voltage deviation indices.

3.1 Distribution power flow model

Power flow in a distribution system can be computed from a simplified distribution system model shown in Fig. 1 using a recursive procedure. The active and reactive power flows through a branch *k* from the bus *p* to bus *q* is written as Eqs. (11) and (12). These can be conveniently abridged as like Eqs. (13) and (14).

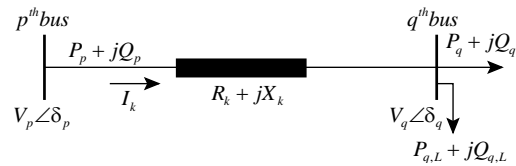


Figure. 1 Simplified distribution network model

$$P_p = P_q + P_{q,L} + P_{k,loss} \quad (11)$$

$$Q_p = Q_q + Q_{q,L} + Q_{k,loss} \quad (12)$$

Where, P_q and Q_q real and reactive power flow out of bus *q*. $P_{k,loss}$ and $Q_{k,loss}$ are real and reactive power loss occur in the branch *k*. $P_{q,L}$ and $Q_{q,L}$ are real and reactive power load at bus *q*.

$$P_p = P_{q,eff} + P_{k,loss} \quad (13)$$

$$Q_p = Q_{q,eff} + Q_{k,loss} \quad (14)$$

Where,

$$P_{q,eff} = P_p + P_{q,L} \text{ and } Q_{q,eff} = Q_p + Q_{q,L}$$

The current flowing through branch *k* between the buses *p* and *q* can be calculated using either Eq. (15) or (16).

$$I_k = \frac{P_p - jQ_p}{V_p \angle -\delta_p} \quad (15)$$

$$I_k = \frac{V_p \angle \delta_p - V_q \angle \delta_q}{R_k + jX_k} \quad (16)$$

To compute the power loss in the distribution system, it is required to calculate voltage at bus q . For the purpose, first it would have compared the equations (15) and (16); second the real and imaginary parts were separated. Followed, both real and imaginary parts have squared and were added together. Thus, the bus voltage is obtained as:

$$V_q^2 = V_p^2 - 2 * (P_p R_k + Q_p X_k) + (R_k^2 + X_k^2) \left\{ \frac{P_p^2 + Q_p^2}{V_p^2} \right\} \quad (17)$$

The power loss in a line segment that connects buses p and q might be figured using (16).

$$P_{k,loss} = I_k^2 * R_k = \left\{ \frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right\} * R_k \quad (18)$$

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

$$P_{Loss} = \sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left\{ \frac{P_{q,eff}^2 + Q_{q,eff}^2}{|V_q|^2} \right\} * R_k \quad (19)$$

The power loss of a line segment connecting buses between p and q after reconfiguration of the network can be computed using Eq. (20).

$$P'_k = I_k'^2 * R_k = \left\{ \frac{P_{q,eff}'^2 + Q_{q,eff}'^2}{|V_q'|^2} \right\} * R_k \quad (20)$$

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

$$P'_{Loss} = \sum_{q=2}^{N_{bus}} \sum_{k=1}^{N_{bus}-1} \left\{ \frac{P_{q,eff}'^2 + Q_{q,eff}'^2}{|V_q'|^2} \right\} * R_k \quad (21)$$

The power loss reduction index is defined as the ratio between the net power loss in the base case and after reconfiguration, and expressed as follows:

$$\Delta P'_{Loss}^{inex} = \frac{P'_{Loss}}{P_{Loss}} \quad (22)$$

The node voltage deviation index is defined as follows:

$$\Delta V^{inex} = \max \left(\frac{V_1 - V_q}{V_1} \right); \forall q = 1, 2, \dots, N_{bus} \quad (23)$$

Where, V_q is voltage magnitude at bus q .

3.2 Objective function

This objective function of the optimization is the net power loss reduction index plus node voltage deviation index, and expressed mathematically as follows:

$$\text{Objective function } (f) = \text{Minimize } (\Delta P'_{Loss}^{inex} + \Delta V^{inex}) \quad (24)$$

3.3 Constraints

Node voltage should be between its lower and upper limits.

$$V_{min} \leq V_q \leq V_{max}; q \in N_{bus} \quad (25)$$

Where, V_{min} and V_{max} are minimum and a maximum node voltage of the node in pu.

The branch current capacity is specified by the manufacturer as.

$$|I_k| \leq I_k^{max}; k \in N_{br} \quad (26)$$

Where, $|I_k|$ and I_k^{max} are k^{th} branch current and its maximum current carrying capacity in ampere.

4. Implementation of mGWO for DS optimization

Rapid convergence and accuracy of an optimization method depends control variables setting and initialization of an algorithm parameter. The control variable is a discrete nature that represents the number of switches (branches) should be opened to maintain a feasible radial topology. Thus, the control variable numbers of mGWO has

equal to the tie-switch numbers of the system. To structure an individual loop, information about the fundamental loops and the switch number in each fundamental loop is required. The implementation of mGWO consists two phases and has described as follows.

4.1 Identifying loop vector

Step-1: Close all regularly open switches.

Step-2: Determine number of fundamental loops (N_L) by Eq. (27).

$$N_L = N_{br} - (N_{bus} - N_{ss}) \quad (27)$$

Where, N_{ss} is a number of sub-station.

Step-3: Decide loop vectors (L)

The distribution system has a regular pattern of tie switches (open switches) which are equal to fundamental loops. Each loop includes possible number of branches (closed switches) forming the j^{th} loop without repeating common branches in between any two loops. Additionally, zeros can be added to make the loop vector matrix as rectangular matrix and the structure is represented as like Eq. (28).

$$L = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_j \end{bmatrix} = \begin{bmatrix} SW_{1,1} & SW_{1,2} & \dots & SW_{1,d} \\ SW_{2,1} & SW_{2,2} & \dots & SW_{2,d} \\ \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \dots & \cdot \\ SW_{j,1} & SW_{j,2} & \dots & SW_{j,d} \end{bmatrix}; j \in N_L \quad (28)$$

Where, L_j is j^{th} loop and $SW_{j,d}$ is d^{th} branch or closed switch in j^{th} loop.

4.2 Application of GWO algorithm

The triumph well ordered strategy of executing mGWO for DNR problem is depicted as takes after:

Step-1: Define input data

Wherein, the initial network configuration, line impedance, a 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.

Step-2: Initialize population

The tie switches are considered as a control variable and it should be selected optimally from each loop to maintain a feasible radial configuration. The control variables are integer numbers and only one switch has to be selected randomly from each loop using Eq. (29).

$$X_{i,j} = \phi \{1, LSW(j)\}; j \in N_L \text{ and } i \in NP \quad (29)$$

Where, LSW is the total number of closed switch in j^{th} loop at loop vector matrix. NP is number of the population and ϕ is pseudorandom integer values drawn from the discrete uniform distribution between any two intervals.

$$X = \begin{bmatrix} SW_1^1 & SW_2^1 & \dots & SW_{N_L-1}^1 & SW_{N_L}^1 \\ SW_1^2 & SW_2^2 & \dots & SW_{N_L-1}^2 & SW_{N_L}^2 \\ \cdot & \cdot & \dots & \cdot & \cdot \\ \cdot & \cdot & \dots & \cdot & \cdot \\ SW_1^{NP} & SW_2^{NP} & \dots & SW_{N_L-1}^{NP} & SW_{N_L}^{NP} \end{bmatrix} \quad (30)$$

Further, the initial population in terms of switch position is represented by Eq. (30); corresponding switch from each fundamental loop is selected for further procedure.

Step-3: Calculate the objective value

For each trial solution, the radial topology has been checked through an efficient algorithm [9], and after the distribution power flow is executed to compute the objective value.

Step-4: Evaluation of objective value and finding best position

The robustness value of all individuals of the present candidate solution matrix (X^o) is computed by Eq. (31). The robustness of i^{th} individual represents its (wolf's) distance from the prey. Sort the population based on the robustness from minimum to maximum, an individual having the minimum robustness is imitated as the alpha; second and third minimum is beta and delta respectively.

$$fit_i = \text{objective value} \quad (31)$$

Step 5: Modifying agent position for optimal solution

The position of i^{th} wolf is updated using Eq. (5), if the mutant solution violates its limit which should be fixed at that level.

Step 6: Fitness re-estimation

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

Step 7: Stopping criterion

If the maximum number of cycles is reached terminate the iteration; otherwise repeat steps from 3 to 6.

5. Simulation result 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 12.66kV and 10MVA. There are 32 and 68 normally closed switches, and five normally open switches specifically [33, 34, 35, 36 and 37] and [69, 70, 71, 72 and 73] in test systems-I and II respectively. The real and reactive power loads of the test systems are 3.72MW and 3.802MW, and 2.3MVar and 3.69MVar. The real power loss and node's minimum voltage at the initial state is found as 202.67kW and 224.95kW, and 0.9130pu and 0.9092pu 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. Then, mGWO based distribution reconfiguration problem is performed for minimizing power loss reduction and node voltage deviation of small and medium distribution systems. For each case, fifty independent trials have been attempted to find the best, average and worst values. The simulated results of test systems are distinguished with the other techniques so as to validate the robustness of the mGWO.

5.3 Optimum solution

The viability of the mGWO technique for tackling the DNR issue has been investigated by minimizing the fitness function through the optimum determination of a new open switch. Therefore, the various optimal tie-switches that have been selected using the mGWO algorithm, The net power loss reduction and node voltage deviation indices, and computational times are exhibited in Table 1 and Table 2 for test system-I and test system-II respectively. The open switches [7, 9, 14, 28, and 32] of test system-I and [69, 70, 14, 55, and 61] of test system-II have identified as global optimum switch because analogous power loss reduction index (PLRI) and node voltage deviation index (NVDI) are at the minimum level. In this scenario, the corresponding optimal DNR is shown in Figs. 2 and 3, respectively, that reveals the radiality of the network.

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

Optimal Tie-switches	PLRI	NVDI	Comp. Time (s)
7, 9, 14, 28, 32	0.6532	0.0552	6.17
7,9,14,32,37	0.6562	0.0560	6.18
7, 9, 14, 28, 36	0.6562	0.0562	6.21
7, 14, 10, 32, 37	0.6606	0.0586	6.23
7, 14, 9, 36, 37	0.6614	0.0601	6.40

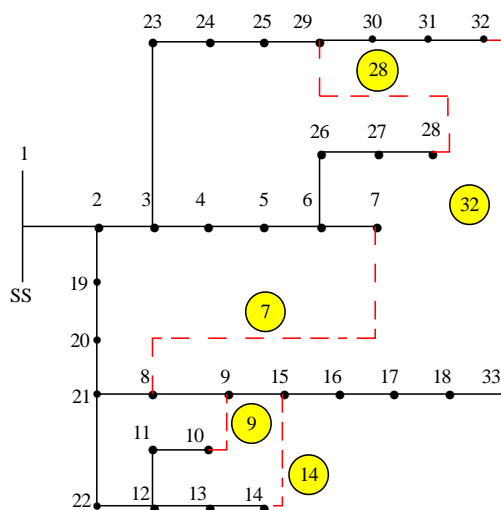


Figure. 2 Optimal reconfiguration of 33-bus for minimum PLRI by mGWO

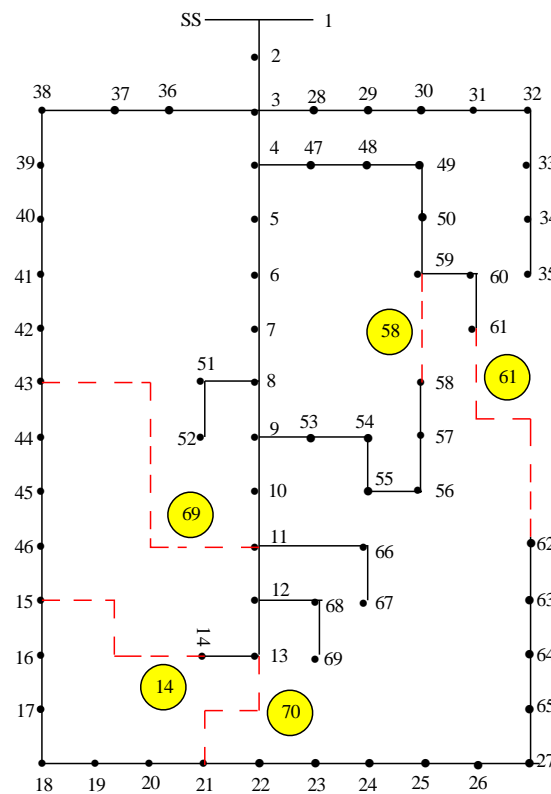


Figure. 3 Optimal reconfiguration of 69-bus for minimum PLRI by mGWO

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

Optimal Tie-switches	PLRI	NVDI	Comp. Time (s)
69,70,14,58,61	0.4308	0.0401	17.25
69,70,13,58,61	0.4349	0.0458	17.26
69,18,14,57,61	0.4356	0.0478	17.31
69,19,13,56,62	0.4361	0.0489	17.33
69,19,14,55,63	0.4361	0.0490	17.41

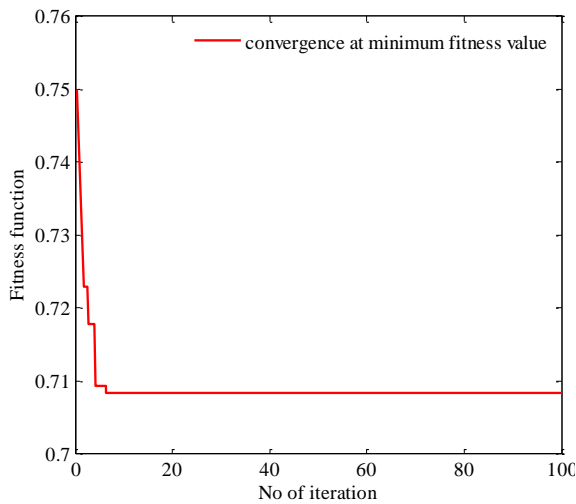


Figure. 4 Convergence characteristics of mGWO for 33-bus system

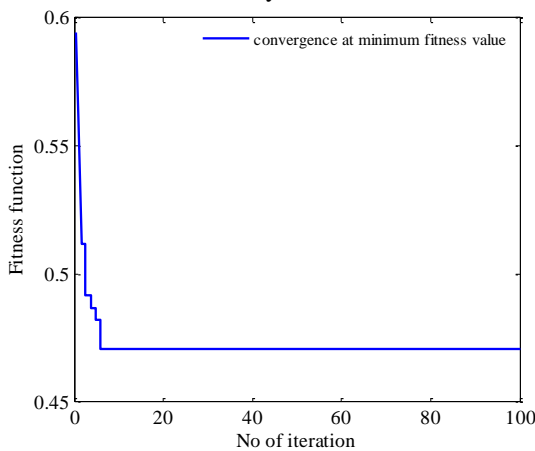


Figure. 5 Convergence characteristics of mGWO for 69-bus system

Furthermore, Figs. 4 and 5 shows the convergence characteristics of mGWO algorithm; where the fitness value is drastically dropped and has been attained the optimal solution within lesser iteration. Therefore, the proposed method has obtained best optimal DNR.

5.4 Comparison of viable solution

In an attempt to expose the predominance of mGWO algorithm in tackling DNR problem, the viable indices that have obtained by FWA [16],

CSA [17], RRA [18], IAICA [21], MBFOA [22] and AWIDPSO [25] techniques for test systems-I, and CSA [17], IAICA [21], MBFOA [22] and AWIDPSO [25] for test systems-II including mGWO were contrasted in Tables 3 and 4 respectively. The improvement in PLRI of mGWO over FWA [16], CSA [17], RRA [18], IAICA [21], MBFOA [22] and AWIDPSO [25] is 0.0375, 0.0286, 0.0353, 0.0357, 0.0104 and 0.0065 respectively in case of test system-I. Similarly, the PLRI has minimized by mGWO over CSA [17], IAICA [21], MBFOA [22], AWIDPSO [25] is 0.0074, 0.008, 0.0072 and 0.0048 respectively in case of test system-II.

Likewise, enhancement in NVDI of mGWO over FWA [16], CSA [17], RRA [18], IAICA [21] and AWIDPSO [25] is 0.0035, 0.0024, 0.0036, 0.007 and 0.0006 respectively in case of test system-I. At the same time, the NVDI has improved by mGWO is 0.0104, 0.0099 and 0.0077 higher than CSA [17], IAICA [21] and AWIDPSO [25] respectively in case of test system-II. Further, mGWO has minimized the power loss of 34.68%, 56.92% of test system-I and test system-II, respectively therefore, the proposed method offered the least network losses. Similarly, mGWO directs the node voltage by 5.84%, 4.18% of test system-I and test system-II respectively.

5.5 Solution quality improvement

The algorithms potentiality of finding minimum power loss and node voltage optimally is compared with well-known optimization techniques that have already proven their ability in solving DNR problem in Figs. 6 and 7 for test systems-I and II correspondingly. It is experienced that the mGWO is diminishing the power loss as well, augmenting node voltage in huge sum in contrast with the other competing methods for both test cases.

The power loss reduction rate is 7.56kW, 6.45kW, 7.13kW, 7.09kW, 2.1kW and 1.31kW greater than FWA [16], CSA [17], RRA [18], IAICA [21], MBFOA [22] and AWIDPSO [25] respectively, of test system-I. As well, the power loss reduction rate is 1.4483kW, 1.45kW, 1.44kW and 1.08kW greater than CSA [17], IAICA [21], MBFOA [22] and AWIDPSO [25] respectively, of test system-II.

The nodal pu minimum voltage obtained by mGWO is 0.0035, 0.0024, 0.007 and 0.0006 higher than FWA [16], CSA [17], both RRA [18] and IAICA [21], and AWIDPSO [25] respectively, of test system-I while in the case of test system-II the pu minimum nodal voltage is 0.0104 and 0.0077

higher than both CSA [17] and IAICA [21], and AWIDPSO [25] respectively. Figs. 8 and 9 shows voltage profiles of test systems-I and II, respectively, in which the node voltages when reconfiguring

network is looked at and it is construed that the voltage profile is enhanced significantly after reconfiguration by the proposed method for the majority of the node.

Table 3. Comparison of performance indices value for 33 bus systems

Methods	Optimal Tie-switches	Fitness value	Indices		% of loss reduction	% of Voltage regulation
			PLRI	NVDI		
Initial condition	33, 34, 35, 36, 37	---	---	---	---	8.70
FWA [16]	7, 14, 09, 32, 28	0.7494	0.6907	0.0587	30.93	6.24
CSA [17]	7, 9, 14, 32, 37	0.7394	0.6818	0.0576	31.82	6.63
RRA [18]	7, 14, 9, 32, 37	0.7473	0.6885	0.0588	31.15	6.63
IAICA [21]	7, 9, 14, 32, 37	0.7511	0.6889	0.0622	31.11	6.75
MBFOA [22]	7, 14, 28, 32, 36	---	0.6636	---	33.64	---
AWIDPSO [25]	7, 14, 11, 32, 28	0.7155	0.6597	0.0558	34.03	6.24
mGWO	7, 9, 14, 28, 32	0.7084	0.6532	0.0552	34.68	5.84

Table 4. Comparison of performance indices value for 69 bus systems

Methods	Optimal Tie-switches	Fitness value	Indices		% of loss reduction	% of Voltage regulation
			PLRI	NVDI		
Initial condition	69, 70, 71, 72, 73					9.17
CSA [17]	14, 57, 61, 69, 70	0.4888	0.4382	0.0505	56.28	5.32
IAICA [21]	14, 57, 61, 69, 70	0.4888	0.4388	0.0500	56.12	5.43
MBFOA [22]	18, 43, 56, 61, 69	---	0.4380	---	56.28	---
AWIDPSO [25]	69, 18, 14, 57, 61	0.4834	0.4356	0.0478	56.44	5.02
mGWO	69, 70, 14, 58, 61	0.4709	0.4308	0.0401	56.92	4.18

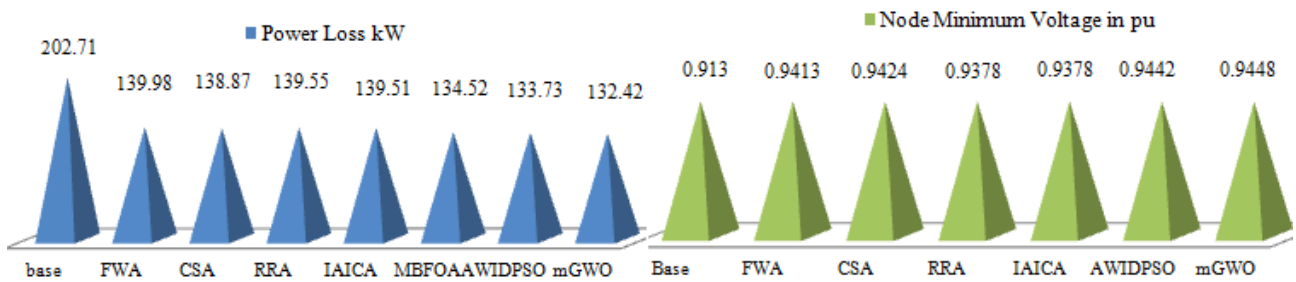


Figure. 6 Comparison of minimum power loss and node voltage for 33 bus systems

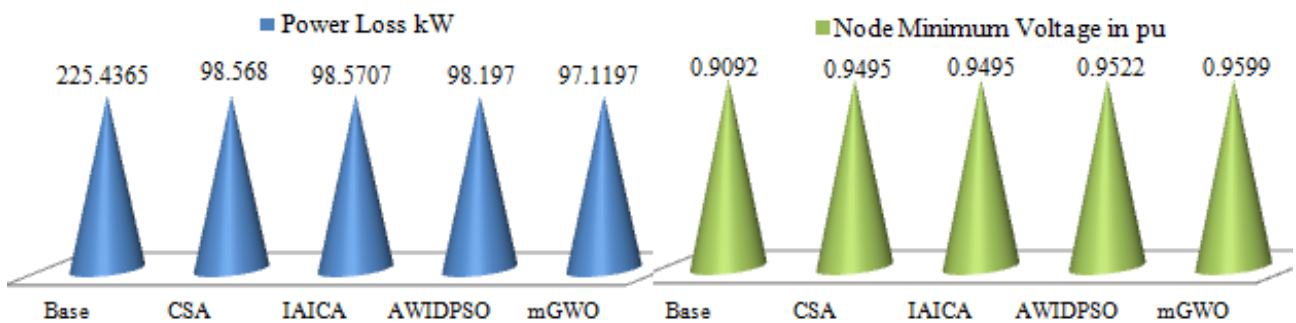


Figure. 7 Comparison of minimum power loss and node voltage for 69 bus systems

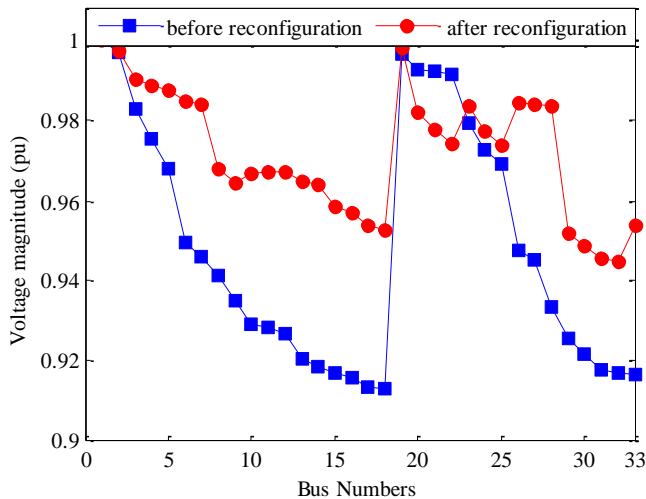


Figure. 8 Voltage profile of 33 bus systems

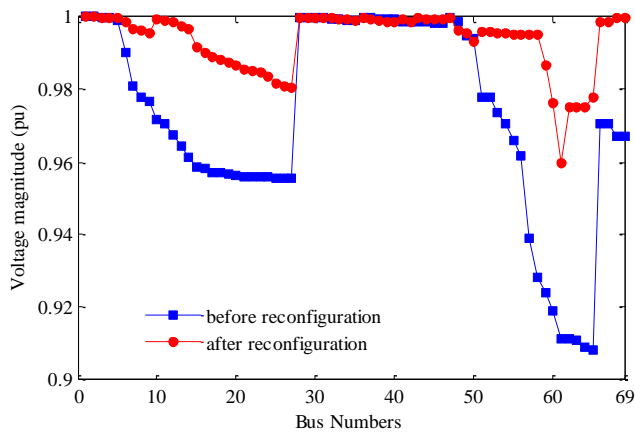


Figure. 9 Voltage profile of 69 bus systems

5.6 Statistical comparison

Any evolutionary and swarm intelligence algorithm can provide an optimal solution for engineering problems. In this scenario, a standard statistical procedure has been employed to know whether it is global optimum, or not. Therefore, the solution that was obtained over fifty trials by FWA [16], RRA [18], IAICA [21], MBFOA [22], AWIDPSO [25] and mGWO algorithms for test system-I and IAICA [21], MBFOA [22], AWIDPSO [25] and mGWO algorithms for Test system-II have been statistically analyzed, and the best, average and the worst values among the final solutions are presented in Table 5 and Table 6 respectively. It is identified that the proposed algorithm has found the best global fitness function and average value of the fitness function is smaller than the best value of other algorithms for both test systems.

Moreover, RRA [18] algorithm has exercised on test system-I only and the final fitness function seems to be struck at premature solution as the best, average and worst values have stayed sane. Finally, the mGWO algorithm is ranked first while reconfiguring distribution system since it has the lowest standard deviation. During the procedure, it is observed that 48 and 46 good quality fitness functions of test system-I and test system-II out of fifty have relatively fallen between the best and average solution. It seems that the mGWO algorithm has a success rate of 93.33% and 86.67%, while optimizing test system-I and II, respectively.

Table 5. Statistical indices of the test results of 33-bus system

Methods	Power Loss (kW)			Std Dev.	Rank
	Best	Average	Worst		
Initial State	202.7060	---	---	--	---
FWA [16]	139.9800	145.63	155.75	5.49	4
RRA [18]	139.5500	139.5500	139.5500	0.00	---
IAICA [21]	139.5100	140.5700	142.3800	1.44	3
MBFOA [22]	134.5200	150.5800	165.4000	15.44	5
AWIDPSO [25]	133.7281	134.5154	135.8254	1.05	2
mGWO	132.4199	133.4344	134.4368	1.01	1

Table 6. Statistical indices of the test results of 69-bus test system

Methods	Power Loss (kW)			Std Dev.	Rank
	Best	Average	Worst		
Initial State	225.4365	---	---	---	---
IAICA [21]	98.5707	100.1577	103.8273	2.6283	3
MBFOA [22]	98.5600	110.3033	155.58	28.51	4
AWIDPSO [25]	98.1970	98.5885	100.0045	0.9038	2
mGWO	97.1197	97.7793	98.7800	0.8302	1

6. Conclusion

In this paper, a powerful metaheuristic modified grey wolf optimization (mGWO) algorithm is successfully employed to minimize the power loss reduction index and node voltage deviation index in a DS through network reconfiguration. It is a complicated combinatorial, non-differentiable constrained optimization problem and the ratio of power loss of all branch sections of the feeder as well as due to network reconfiguration plus node deviation index is deemed as an objective function. Simulation is carried on 33 and 69 bus DS and the simulated results have compared with earlier research work. It is exposed that the optimal determination of tie-switch [7, 9, 14, 28, 32] for 33-bus system and [69, 70, 14, 58, 61] for 69-bus system demonstrates its uniqueness and the acquired configuration is autonomous of the initial state of DS. Moreover, it gives solution at the greatest power loss reduction 132.42kW for 33-bus system and 97.1197kW for 69-bus system, minimal node voltage deviation 0.9448 pu and 0.9599 pu in 33-bus and 69-bus RDS respectively.

Further, it is appreciated that the proposed mGWO algorithm has outperformed FWA [16], CSA [17], RRA [18], IAICA [21], MBFOA [22] and AWIDPSO [25] while optimizing 33-bus system, CSA [17], IAICA [21], MBFOA [22] and AWIDPSO [25] while optimizing 69-bus system. It is substantiated that the mGWO emulates the inherent behavior of grey wolf such as, encircling, hunting and attacking processes while foraging food. In fact, the strategic ration amongst global and local search of the algorithm, varies linearly from a higher value to zero in the basic GWO. It may be decreased the diversity of global optima. To trap the best fitness value from local optima the strategic balance between global and local search is varied exponentially from a higher value to zero in the mGWO method.

The proposed approach has the following advantages:

- Ability to produce highly optimal reconfiguration in a more efficient manner without the computational burden than the previous approaches
- Offers considerable amount of loss reduction and voltage profile improvement in all cases
- Has competitive performance in algorithm convergence

Hence, it is reasoned that the proposed mGWO has the robustness and viable option for discovering global optimum DS reconfiguration and ultimately,

the numerical outcomes would be helpful for power distribution companies.

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