Improved Gorilla Troop Optimization Algorithm Distribution Network Reconfiguration with Power Loss Reduction and Voltage Profile Enhancement

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ABSTRACT

Reconfiguration of distribution system is a combinational complex optimization method that seeks to find a radial structure that reduces system power loss and increases system reliability simultaneously satisfying operational constraints. Improved Gorilla troops optimization algorithm (IGTOA) is a meta-heuristic algorithm developed from Gorilla troops optimization algorithm which was developed recently and it was inspired by their intelligent behavioral nature and also the grouped lifestyle of gorillas. Improvisation is done in initialization of position of gorillas by using a new mapping technique known as Circle chaotic mapping. This technique eases the population diversity and paves the way for global search. With this improvement the basic GTO is greatly enhanced. This algorithm is analyzed and evaluated on 16-, 33- & 69- bus systems. Graphical and numerical results illustrate that IGTOA provides good solution quality, optimal avoidance also the robustness compared with the GTO and other known algorithms. The test results demonstrate that IGTOA explores competitive performance in real-world scenario.

Keywords: *Distribution System Reconfiguration, IGTOA, Circle Chaotic Mapping, Power Loss Minimization, Voltage Stability, Metaheuristic Optimization.*

1.INTRODUCTION

The distribution system supplies power to the distribution networks, but more power loss occurs on the grid and the voltage regulation is low. Many ways are there to minimize power loss and to improve voltage profiles in distribution systems, such as operating voltage can be increased, compensating reactive power and balancing loads. These methods are technically feasible but require huge investment costs. Grid reconfiguration is considered as a best technique for reducing power loss and significantly enhances profile voltage with low investment in distribution networks. Generally, reconfiguration refers to altering the network's topology by opening or closing switches, with the objective of minimizing losses while ensuring the system operates within its permissible limits.

In order to reduce power losses, Olamaei et al. [1] suggested a modified honey bee mating optimization algorithm for distribution feeder reconfiguration. The technique finds appropriate network configurations by using honey bee mating behavior as an optimization tool. The Harmony Search algorithm was used by Srinivasa Rao et al. [2] to reconfigure large-scale distribution systems optimally. Their research showed how to find efficient switching configurations for loss reduction using population-based search strategies. Binary particle swarm optimization (BPSO) was used by Firdaus et al. [3] to reduce distribution network losses and raise the voltage stability index.

An adaptive cuckoo search-based technique for distributed generation allocation and efficient network reconfiguration was created by Nguyen et al. [4]. In order to enhance distribution system performance, the study focused on the joint optimization of switching configurations and DG placements. In the context of a remotely voltage-controlled bus, Das et al. [5] examined distribution network reconfiguration with optimal distributed generator placement. Their research took into account how voltage regulation, DG location, and network topology interact. An adaptive multi-objective distribution network reconfiguration method utilizing graph theory and multi-objective discrete particle swarm optimization was introduced by Haghifam et al. [6]. The strategy took into consideration the structural limitations of distribution networks while addressing a number of operational goals. A hybrid Big Bang–Big Crunch algorithm for multi-objective network reconfiguration and capacitor placement inside a fuzzy context was presented by Sedighizadeh and Bakhtiary [7]. Their method took into account both reactive power compensation and network switching optimization at the same time. Verma and Singh [8] investigated an evolutionary search technique for finding better network configurations by applying a modified culture algorithm to distribution network reconfiguration. A modified bacterial foraging optimization technique for loss minimization and distribution system reconfiguration was presented by Naveen et al. [9]. The potential of bacterial foraging behavior to enhance the search for effective distribution network configurations was investigated in their work.

The Artificial Gorilla Troops Optimizer (GTO), a nature-inspired metaheuristic method for global optimization problems, was first presented by Abdollahzadeh et al. [10]. The method offers a different optimization framework that may be applied to electrical power system issues, even if it is not restricted to distribution networks. In the Virunga region, McNeilage [11] examined the food and habitat utilization of two mountain gorilla populations in disparate settings. This work's significance to DNR is indirect and primarily contextual to gorilla-inspired optimization approaches because it relates to biological habitat study rather than electrical network reconfiguration. Sathish Kumar and Jayabarathi [12] used the bacterial foraging optimization technique to study power system reconfiguration and loss minimization. Their efforts helped to apply bio-inspired optimization techniques to the functioning of distribution systems. A sophisticated genetic algorithm for the best reconfiguration of electric distribution networks was put forth by Zhu [13]. To find efficient network designs under discrete switching limitations, genetic algorithms use selection, crossover, and mutation processes.

Power loss minimization through network reconfiguration in the presence of distributed generation was examined by Srinivasa Rao et al. [14], emphasizing the significance of taking DG into account when choosing an ideal network design. A heuristic method for lowering losses in distribution networks was introduced by Martín and Gil [15]. Their efforts aided in the creation of useful search-based methods for enhancing network performance. In order to overcome the computational difficulties involved in choosing appropriate switch combinations in big networks, Gomes et al. [16] presented a novel heuristic reconfiguration technique intended for large distribution systems. In their study on distribution system reconfiguration in the presence of distributed generators, Wu et al. [17] emphasized the importance of taking DG integration into consideration when choosing suitable network designs. An enhanced mixed-integer hybrid differential evolution technique for distribution network reconfiguration was created by Su and Lee [18]. The technique addresses the discrete nature of switching decisions by combining differential evolution with a mixed-integer formulation. A variable-scaling hybrid differential evolution technique was presented by Chiou et al. [19] to address distribution network reconfiguration issues. To enhance the optimization procedure, the approach investigated variable scaling and hybrid evolutionary search. With a focus on the applicability of adaptive evolutionary techniques to large networks, Swarnkar et al. [20] examined adaptive genetic algorithms for identifying minimum-loss configurations in large-scale radial distribution systems.

Ayasu et al. [21] used an adaptive simulated gorilla troop optimization approach to study how to improve power distribution efficiency through optimal capacitor placement. Their research is pertinent to voltage enhancement and reactive power compensation, which support the goals of network reconfiguration. Gacem et al. [22] used a hybrid gorilla troops optimization–genetic method for a real-case study to investigate multi-objective sizing and location of dispersed generation. A framework for handling DG planning issues with conflicting goals is provided by the combination of two optimization techniques. A Hyperbolic Tangent Particle Swarm Optimization (HT-PSO) technique for distribution network reconfiguration was presented by Puma Ttito et al. [23]. In order to find optimal network designs, this work expands the use of particle swarm-based techniques. A

distribution network reconfiguration optimization technique based on the whale optimization algorithm and undirected-graph isolation group detection was presented by Hu et al. [24]. Finding workable configurations while taking network connectivity into account is relevant when graph-based structural analysis and metaheuristic search are combined. In a distribution network that supplies electric vehicle charging stations, Pratap et al. [25] examined the best distribution of controlled power-factor distributed generation in conjunction with network reconfiguration. Their research is especially pertinent to contemporary distribution systems, when additional operational limitations are brought about by controllable DG and rising charging demand. DG power factor and network topology optimization together provide a means of addressing the evolving needs of distribution systems with new electrical loads.

PROBLEM STATEMENT

This paper focuses power loss reduction without disturbing the radial structure and also to improve voltage profile of the network. The function can be expressed by

$$\Delta P = Re\left\{2\sum I_i(E_m - E_n) + R_{line}\sum |I_i|^2\right\} \quad (1)$$

ΔP represents total power loss of the system,

I_i represents the current flowing in the i^{th} branch, R_{line} represents line resistance, E_m, E_n represents the voltage in m^{th} and n^{th} branch.

The constraints for this distributed system reconfiguration problem can be developed as,

2.1. Voltage Constraints

The voltage in the nodes should not exceed its upper and lower limit and it is expressed as

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (2)$$

V_i – node voltage at 'i^{th}' branch

V_i^{min} – minimum voltage at 'ith' branch

V_i^{max} - maximum voltage at 'ith' branch

2.1. Current Constraints

The currents flowing through all the branches should be within the steady-state thresholds. It can be expressed as,

$$I_{ij} \leq I_{ij}^{max_adm} \quad (3)$$

I_{ij} - represents $_{current}$ flowing from ith branch to jth branch $I_{ij}^{max_adm}$ – represents maximum current flowing from ith branch to jth branch.

2.3. Topological Constraints

Distribution system reconfiguration must adhere to topological limitations to retain the radial structure. Security criteria need be met in addition to this topological structure. The radial topology should resemble a spanning tree that represents the network's structure. Topological network should have (N − 1) edges, N represents total vertices in the system and should include all the vertices in the system.

2.3. Power Flow Constraints

The loads real and reactive powers should constantly be in balance. This is considered as N_b represents number of lines, P_i and Q_i represents real power and reactive power for link 'ith' *branch* P_{Gi} and Q_{Gi} represents real and reactive power at 'ith' *branch* P_{Di} and Q_{Di} represents real and reactive load demand at 'ith' *branch* G_{ij} and B_{ij} represents real and imaginary parts of element Y_{ij} in the Y_{bus} admittance matrix δ_i and δ_j represents voltage angles at branches *i* and *j* respectively.

1. Gorilla Troop Optimization

The natural behavior of gorillas matches humans. Gorillas, like many other animals, are known to display human-like emotions, particularly in the areas of empathy, grief, joy, compassion, and fear, however the degree to which they feel and show these emotions may be different from that of humans. They develop close relationships with their relatives and even consider their futures. Lifespan of gorilla is 30 to 40 years. Their diet includes leaves, fruits, shoots and stalks. Gorillas live in group called as gorilla groups. This troop consists of 6 to 30 sometimes more than 50 gorillas. Group leader is silverback male gorilla. Group members consist of 1 to 4 male gorillas, female gorillas, young adult male gorillas (blackbacks) and infant gorillas. Entire group is led by

this leader silver back. When gorilla reaches puberty, growth of silver hair is noted and then it is named as silverback gorilla.

In addition, the silverback is the captain of the entire army, it takes all decisions, sorts out all disputes, guides other gorillas for food sources, determines group activities and also it is responsible for security. Gorillas between the ages of 8 to12 are known as black-backed gori because they do not have silver hair on their backs. They will always be with the captain and they work as protectors for their group. Generally, male and female gorillas will migrate to the new groups. In addition, adult male gorillas are also capable of breaking away from their family groups, migrate to other groups, attracts the female in that groups and finally build their own armies. Some young male gorillas stay with the original herd and follows their leader. If the leader dies, then these male gorillas will fight the battle brutally for the post of group leader and to mate with the adult females.

These are the behavioral nature of gorillas based on this nature; a mathematical model has been developed known as Gorilla Troop Optimization (GTO) algorithm. This GTO has three main phases; they are initialization phase, global discovery phase, and local mining phase they are explained below in detail.

3.1. Initialization Phase

In this phase Initialization of population, maximum iteration, variables and the migration mechanism are initialized. Assuming that there be P number of gorillas in the search space(Q). Let j^{th} position of the gorillas in their search space be expressed as

$$Xj = (Xj,1, Xj,2, \ldots..Xj,D), \qquad i = 1,2,3, \ldots.P.$$

Initialization phase of gorillas can be written as,

$$X_{P.Q} = rand(P,Q) \times (UB - LB) + LB \tag{4}$$

where UB and LB are the upper boundary and lower boundary in the Q-space respectively, $rand(P,Q)$ is the matrix with P number of rows and Q number of columns, and its entries will have a value of 0 to 1in eq(4).

3.2. Exploration Phase

In this phase, the gorillas are separated from their own group to different environments which may be known or not known to them. Let all gorillas be assumed as competent solutions and considered as optimal for every optimization process and noted as the silverback. For the migration nature of gorillas and for their position updates this exploration phase were developed with three different approaches they are i) migration to unknown places, ii) migration to known places and iii) move to different gorilla troops. These approaches are given below as Eq. (5),

$$GX(t+1) = \begin{cases} (ub - lb) \times r_2 + lb, r_1 k \ (r_2 - C) \times X_A(t) \\ + L \times Z \times X(t), r_1 \ 0.5 \ X(t) L \left(L \times \left(X(t) - X_B(t)\right) - r_4 \times \left(X(t) - X_B(t)\right)\right), r_1 \\ < 0.5 \end{cases} \tag{5}$$

$GX(t+1)$ represents the candidate position of gorilla in the upcoming iteration. t represents the current value of iteration, X(t) refers to the current position of single gorilla. The random numbers are denoted as $r1, r2, r3$ and $r4$, their values range from 0 to1. Let $X_A(t)$& $X_B(t)$ are the positions for two gorillas which has been selected randomly from its population. Let Z represents a row vector in the search space and their values have been generated randomly in $[c, -c]$. K is constant. The variable C can be calculated using Eq. (6)

$$C = (cos\ cos\ (2 \times r_5) + 1) \times \left(1 - \frac{1}{Maxiter}\right) \tag{6}$$

r_5 denotes a random number from 0 and 1, and Maxiter represents maximum number of iterations. The Variable L can be calculated using Eq. (7).

$$L = C \times l \tag{7}$$

Where l is a random number and lies between [-1, 1]. Using Eq. (6) and Eq. (7), C and L are calculated with large interval of optimization operation. This interval reduces in the last stages. The fitness is calculated for new candidate $GX(t+1)$, fitness GX is better than X and $here$ $F(GX) < F(X)$. The functions $F()$ indicates fitness with specific problem, this is retained and it replaces the old solution $X(t)$. Let $X_{Silverback}$ be the optimal solution for this case.

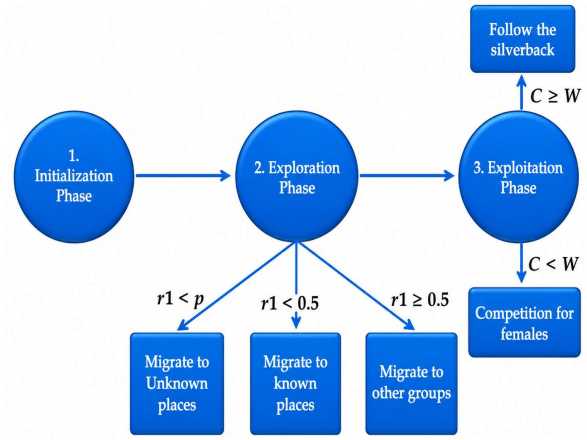


Figure 1. Three phases of GTO

3.3. Exploitation Phase

Generally, in the troop silverback gorilla will be healthy and powerful compared to the other male gorillas which are still young. So, these young male gorillas will always obey the decisions taken by their leader. When Silverback gorilla grows older or if dies, then new leader has to be selected from the younger black back gorillas. These young male gorillas will fight among them for the female gorillas and also for the leadership. These two conflicts of gorillas are involved in this phase. The new variable W is introduced for controlling the switch between them. From these two behaviors the value of C and W are considered. The C value is computed using Eq. (3), if C value is greater than the value of W, then the first behavior (conflict for female gorillas) is chosen. It is expressed as

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \quad (8)$$

where the value of L is computed using Eq. (7), $X_{Silverback}$ denotes the best result, and X(t) represents the position vector for the current value. The variable M is calculated using Eq. (9)

$$M = \left(\left|\sum_{i=1}^{N} X_i(t)/P\right|^{2^L}\right)^{\frac{1}{2^L}} \quad (9)$$

From the above expression P is the size of gorilla's population, and $X_{i(t)}$ represents the i^{th} iteration of position vector of the gorilla. If C value is less than the value of W, then this behavior (conflict for leadership) is chosen. The gorilla's location is calculated using the following expressions,

$$X(t+1) = X_{silverback} - \{(X_{silverback} \times Q) - (X(t) \times G)\} \quad (10)$$

$$G = 2 \times r_6 - 1 \quad (11)$$

$$A = \varphi \times E = \{N_1, r_7 \geq 0.5 \quad (12)$$

$$N_2, r_7 < 0.5 \quad (13)$$

The position of gorillas is denoted by eq. (10) and impact force(G) is calculated using Eq. (11), r_6 is a random variable from 0 to 1. In Eq. (12), A represents the intensity of violence in the conflict of gorillas φ is a constant. In Eq. (13), r_7 is random variable between 0 and 1, E is defined as 1D array of random numbers in normal distribution and its values are assigned in Eq. (13) and Q is the search space dimension. After calculations, the new fitness value is generated and candidate GX(t+1) is calculated. If the fitness F(GX)<F(X), the solution GX will be saved and continues for the next process, and the optimal solution is defined as the $X_{Silverback}$. Figure 1 shows the different phases of Gorilla Troop Optimization algorithm.

2. FORMULATION OF IGTOA FOR SOLVING RECONFIGURATION PROBLEM

Table 1. Algorithm for population initialization using Circle chaos mapping

Algorithm 1: Pseudo-code for circle chaos mapping method	
1	Initialize the size of population as P and the search space Q
2	Z is randomly generated with the values ranging from [0,1]
3	For $j = 1\ to\ P$
4	For $k = 1\ to\ Q$
5	The chaotic variable Z_n is generated using equation (11)
6	$S_{j,n} = Z_n$

7	End For
8	$S_{i,}$ Sequence is mapped in the gorilla's search space $X_j = S_i \times (ub - lb) + lb$
9	End For
10	Return X_j $(j = 1,2, \ldots., P)$ as initial population matrix.

Table 2. Algorithm for IGTOA

Algorithm 2: Pseudo-code for IGTO algorithm	
1	Let P be the size of gorilla population initialized and higher iterations number as Maxiter
2	Using circle chaos mapping, the chaotic group X_j is initialized
3	Fitness value of all individual gorillas is calculated
4	While $t < Maxiter$
5	Parameter C is updated using equation (3)
6	Parameter L is updated using equation (4)
7	For every gorilla X_j do
8	The current gorilla position is updated using equation (2
9	End For loop
10	Calculate the Candidate position of each gorilla
11	Optimal solution is taken as silverback ($X_{Silverback}$)
12	For every gorilla X_i do
13	If $C \geq W$ then
14	Gorillas Position is updated using equation (5)
15	Else
16	Gorillas Position is updated using equation (7)
17	End If loop
18	End For loop
19	Fitness values are updated for gorillas
20	The best solution is updated as $X_{Silverback}$
21	$t = t + 1$
22	End While loop
23	Best solution is $X_{Silverback}$ and update its fitness.

The performance of the Gorilla Troop Optimization algorithm is improved and that a new algorithm is formed as Improved Gorilla Troop Optimization Algorithm (IGTOA). For population initialization of gorillas, Circle Chaotic mapping is used, which is believed to increase population diversity. Then an efficient learning strategy based on the lens opposition is applied to extend the search area and also to prevent this method to fall into a local optimum. The specific process is defined as follows. The circle chaotic mapping has been shown to have a significant impact on the quality of individuals in the original population and on the performance of metaheuristic algorithms. Both the algorithms are shown in Table 1 and 2. When using this GTO method for solving this optimization problem, the population size is initiated with a random search. Although this is feasible it lacks flexibility and relies on probability distributions and this has not been guaranteed that the starting set is evenly spread in the search model, reducing the accuracy and speed of the convergence.

Chaos mapping is a complex technique used for nonlinear approach and it is characterized by unpredictability, flexibility and randomness. Comparing this technique with other method such as random distribution, chaos method allows individual gorillas to deeply examine the search space with higher sensitivity and convergence speed, hence this mapping improvise this algorithm. The result showed that this circular chaos mapping gives better probing results than other mapping techniques such as tent chaotic mapping and logistic mapping. To increase diversity of population and to utilize the data in search space, circular chaotic mapping is implemented in this research work for initialization of gorillas. Mathematically, the Circle chaotic mapping is expressed as,

$$z_{k+1} = z_k + b - \frac{a}{2\pi} sin\ sin\ (2\pi z_k)\ mod(1), z_k \epsilon (0,1) \quad (14)$$

where a and b are constants with a = 0.5 and b = 0.2 in eq(14). The circular chaos mappings were chosen to run independently. It has been observed that the transmission path of circular chaos mapping is widely spread and more uniformly distributed in the search space [0, 1] than in the search domain. where a and b are constants with a = 0.5 and b = 0.2. The circular chaos mappings were chosen to run independently. It has been observed that the transmission path of circular chaos mapping is widely spread and more uniformly distributed in the search space [0, 1] than in the search domain.

With these improvement mechanisms mentioned in the above algorithm, the proposed IGTO flowchart is shown in Figure 2.

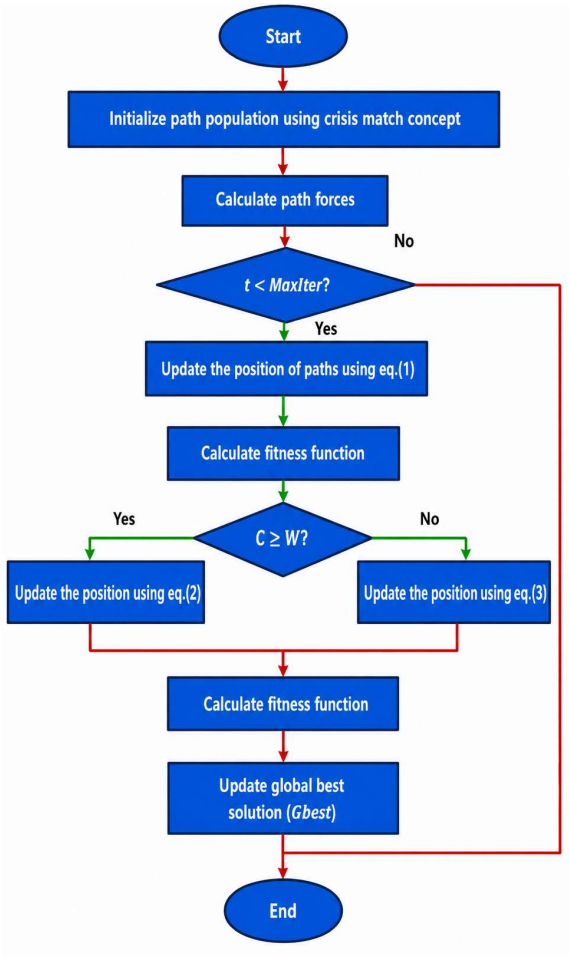


Figure 2. Flowchart of IGTO algorithm

3. RESULT AND DISCUSSION

The developed IGTO algorithm is tested using standard IEEE standard buses such as 16, 33, and 69 bus. The network diagrams are shown in Figures. 3(a)-(c). From Table 3, when these switches are open [7, 8, 16] for 16-Bus then the loss is less. Table 4 clearly shows when the switches [7, 14, 28, 32, 37] are open then the loss is reduced for 33 bus system and Table 5 explains when the switches [13, 43, 56, 61, 69] are at open then the loss is reduced for 69 bus system. Similarly, different status of switches using IGTOA are shown in Tables 3-5. For 16-Bus, the loss for base configuration is 511.4 kW and after using the proposed IGTOA loss is found to be 418.12 kW. For 33 bus network, base configuration loss is 202.71 kW, using IGTOA, reconfiguration was carried out and the loss was reduced to 131.43 kW. The base configuration for 69 bus system is 225 kW, using proposed method reconfiguration is done and power loss was decreased to 94.37 kW. The power loss for 16, 33 and 69 buses are reduced by 18.24%, 35.16%, and 58.12% respectively.

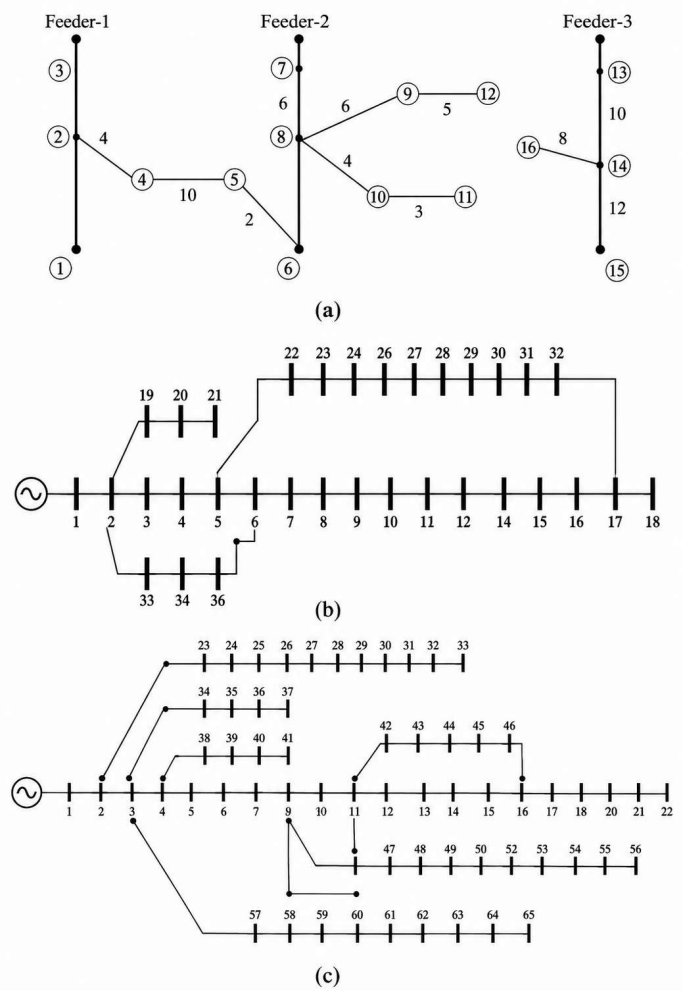


Figure 3. Network Diagram for (a) 16-Bus, (b) 33-Bus, (c) 69-Bus

Table 3. Loss Analysis of 16 Bus Using IGTOA Under Different Conditions of Switching

Switches that are closed	Sw	Loss(kW)
1,2,3,4,5,6,9,10,11,12,13,14,15	7,8	418.12
1,3.4,5,6,7,8,9,10,11,12,14,16	2,1	427.40
1,3,4,5,6,8,9,10,11,12,13,14,15	2,7	430.51
1,2,3,5,6,7,8,9,10,11,12,13,16	4,1	432.28
1,3,4,5,6,7,8,9,10,11,12,13,14	2,1	459.67

Table 4. Loss Analysis of 33 Bus Using IGTOA Under Different Conditions of Switching

Switches that are closed	Switches	Loss(kW)
1,2,3,4,5,6,8,9,10,11,12,13,15, 16,17,18,19,20,21, 22,23,24,25,26,27,29,30,31,33,34,35,36	7, 14, 28, 32, 37	131.43
1,2,3,4,5,6,7,8,9,10,12,15,16,17,18,19,20,21,22,23,24,25, 26,27,29,30,32,33,34,35,36,37	11, 13, 14, 28, 31	144.86
1,2,3,4,5,6,8,10,11,12,13,15,16,17,18,19,20,21,22,23,24,25, 26,27,28, 29,30,31,33,34,35,36	7, 9, 14, 32, 37	147.22
1,2,3,4,5,7,8,10,11,12,13,15,6,17,18,19,20,21,22,23,24,25, 26,27,28,29,30,31,33,34,35,36	6, 9, 14, 32, 37	154.63
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,19,20,21,22,23, 24,25,26,27,28,29,30,31,32,33	18, 34, 35, 36, 37	157.45
1,2,3,4,5,6,8,9,11,12,15,16,17,18,19,20,21,22,23,24,25,26, 27,28,29,30,31,33,34,35,36,37	7, 10, 13, 14, 32	165.48

Table 5. Loss Analysis of 69 Bus Using IGTOA Under Different Conditions of Switching

Switches that are closed	Switches	Loss
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,19,20,21,22,23,24,25,26,27,28,29, 30,31,32,33,34,35,36,37,38,39,40,41,42,44,45,46,47,48,49,50,51,52,53,54,5 5,57,58,59,60,62,63,64,65,66,67,68	7, 14, 28, 32, 37	131.43
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,19,20,21,22,23,24,25,26,27,28,29, 30,31,32,33,34,35,36,37,38,39,40,41,2,43,44,45,46,47,48,50,51,52,53,54, 55,56,57,58,59,60,62,63,64,65,66,68	11, 13, 14, 28, 31	144.86
1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29, 30,31,32,33,34,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,5 6,57,58,59,60,61,62,63, 64,65,66,68,69	7, 9, 14, 32, 37	147.22
1,2,3,4,5,6,7,8,9,10,12,13,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30, 31,33,34,36,37,38,39,40,41,42,44,45,46,47,48,49,50,51,52,53,54,56, 57,58,59,60,61,63,64,65,66,68,69	6, 9, 14, 32, 37	154.63
1,2,3,4,5,6,7,8,9,10,11,13,15,16,18,19,20,21,22,23,24,25,26,27,28,29,30,31, 33,34,35,36,37,38,40,41,42,43,44, 45,46,47,48,49,50,51,52,53,54,56,57,58,59,60,61,63,64,65,66,67,68	18, 34, 35, 36, 37	157.45
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,20,21,22,23,24,25,26,27,28,29, 30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,48,49,50,51,52,53,54,5 6,57, 58,59,60,62,64,65,66,67,68,69	7, 10, 13, 14, 32	165.48

4. COMPARATIVE ASSESMENT

This Proposed IGTOA is evaluated with other relevant algorithms like Modified Bacterial Foraging Optimization Algorithm, Bacterial Foraging Optimization Algorithm, Harmony search Algorithm, Hybrid Differential Evolution, Variable Scaling Hybrid Differential Evolution, Refined Genetic Algorithm, Ant colony, and other popular methods. Table 6-8 shows the comparison of power loss results with various algorithms for 16, 33 and 69 buses. So, the developed IGTO algorithm is a strong fit for distributed frameworks. Figure 4 shows the graph of convergence for 16, 33 and 69 bus systems using IGTOA respectively. This modified algorithm converges at the faster rate and so this proposed algorithm reflects the higher convergence accuracy.

It is tested using 25 individual runs and with different initializations. Minimum loss occurs when (7,8,16), (7,14,28,32,37) and (13,43,56,61,69) switches are in open positions for the test system of 16 bus, 33 bus and 69 bus systems with less computational time. Loss in the power is minimized approximately by 18%, 35%, 58% for 16, 33 and 69 buses respectively. Graph of convergence shows that this proposed method converges better. The profile voltage is also improved significantly in comparison with base reconfiguration.

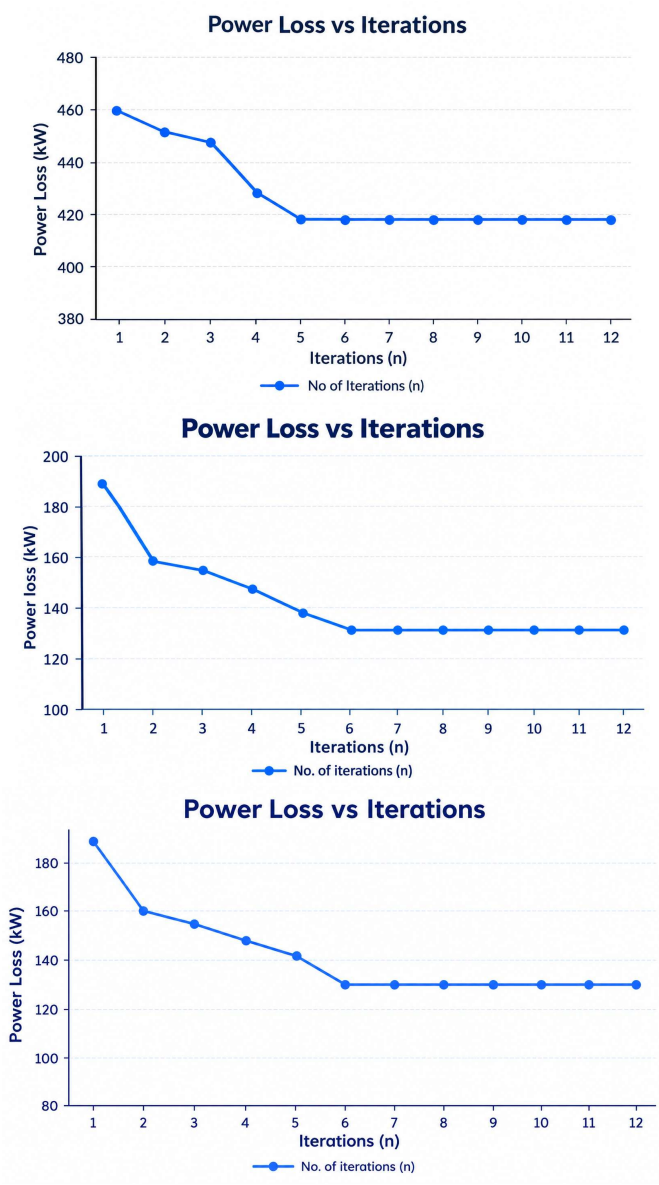


Figure 4. Convergence characteristics for distribution loss using IGTOA for (a) 16-Bus test system, (b) 33-Bus test system, (c) 69-Bus test system

Table 6. Comparison of proposed IGTOA for 16-Bus with different algorithms

Algorithms	Open Switches	Loss (kW)
IGTOA (proposed)	7, 8, 16	418.12
MBFOA [9]	7, 9, 14	424.23
BFOA [13]	7, 9, 16	454.23
RGA [14]	7, 9, 16	466.11
HDE [20]	8, 9, 16	466.1
VHDE [21]	7, 9, 16	466.1

Table 7. Comparison of proposed IGTOA for 33-Bus with different algorithms

Algorithms	Open Switches	Loss (kW)
IGTOA (proposed)	7, 14, 28, 32, 37	131.43
MBFOA [9]	7, 14, 28, 32, 36	134.52
BFOA [13]	7, 9, 13, 14, 32	135.78
HAS [15]	7, 9, 14, 32, 37	138.06
RGA [14]	7, 9, 14, 32, 37	139.55
ACS & GA [19]	7, 9, 14, 28, 32	137.00

Table 8. Comparison of proposed IGTOA for 69-Bus with different algorithms

Algorithms	Open Switches	Loss(kW)
IGTOA (proposed)	13, 43, 56, 61, 69	94.37
MBFOA [9]	18, 43, 56, 61, 69	98.56
HAS [15]	13, 18, 56, 61, 69	99.3

5. CONCLUSION

IGTO algorithm has been successfully applied for the distribution network reconfiguration for power loss minimization and profile voltage enhancement. Implementation of circle chaos mapping with the GTOA has boosted the search ability and so the efficiency is increased. This proposed method has faster convergence rate over the metaheuristic methods. This proposed IGTOA is tested using the 16, 33 and 69bus test systems, results shows that the real power loss has been reduced to greater extent and voltage profile of the feeder has also improved than existing methods. The obtained results using this proposed algorithm confirmed the robustness and effectiveness of this method for solving this DNR problem. This method can be used for larger scale reconfiguration problems and also for real time applications. This algorithm is best suitable for distribution automation framework service restoration procedures due to its effective convergence nature.

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