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Optimal Distribution Network Reconfiguration Using Firefly Algorithm (A Case Study of Doma 33 kV Feeder in Gombe)

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ABSTRACT: Electric power distribution loss and voltage profile improvement are the primary concerns in the power system as customers' demand for electrical energy keeps increasing daily. One of the methods to minimize these problems is by carrying out a reconfiguration process to an existing distribution network. This is achieved by opening or closing the sectionalizing switches and maintaining the feeder in the radial network. This paper presents distribution network reconfiguration (DNR) using the firefly algorithm (FA) to minimize power losses and voltage profile improvement. The method's performance has been investigated on a standard IEEE 33-bus radial distribution network and compared with results using other optimization techniques. The algorithm was finally applied to the Doma 33 kV distribution network in Gombe, where the power loss reduction was obtained to be from 208.4259 kW to 138.9275 kW which was 33.33 % from 128.0027 kW to 106.125 kW which was also 17.09 % for the IEEE 33 Bus network and Doma 69 Bus distribution network respectively. The voltage deviation was obtained as1.1074 p.u equivalent to 33.31 % for the Standard IEEE 33-Bus network and 0.7777 p.u which is 20.38 % for the Doma 69 Bus distribution network. Considering the above positive results losses mitigated will reduce technical losses, which directly impact aggregated technical and commercial losses (AT&C) losses.

Keywords: Voltage profile, network reconfiguration, sectionalizing switches, optimization techniques and loss reduction.

I. INTRODUCTION

The distribution system is the biggest component of the electrical power system. It can be considered as one of the components for energy transportation to different customers in a form that is usable and acceptable at their locations of consumption (Ramesh *et. al.,* 2016). Every person has a right to access to high-quality electricity as it has become a basic necessity in our daily lives. However, most third-world countries continue to face difficulties due to the current state of their weak power infrastructure, which needs to be improved and maintained. Transformers and lines that are primarily heavily loaded are characteristics of the degrading transmission and distribution systems. Power flow analysis is the process of identifying a power system's steady state parameters for a given set of power generation sources and load demand. The resolution of a number of nonlinear power flow equations is required (Ashokumar *et. al*., 2014).

Power system optimization and distribution network automation both call for recurrently quick power flow fixes (Gerez *et al.,* 2019). The size and complexity of today's power systems have significantly increased as a result of the numerous interconnections and consistently high demand (Gomez *et al.,* 2019). Power system operation, metering, control, and planning have all been greatly benefited in recent years by the development of sufficient, efficient, and dependable power flow approaches like fast decoupled power flow (FDPF), Gauss-Seidel (GS), and Newton-Raphson (NR). However, it has been stated time and time again that the following factors may cause such approaches to be ineffective in the analysis and quantification of distribution systems (Hizarci *et al*., 2022).

Majority of the distribution networks are made up of rigid radial feeders that are prone to failure due to overload in various system components. Studies have shown that technical power losses at the distribution level account for about 13% of the total energy generated. Poor, unstable, and unreliable power supply results from the majority of low voltage distribution networks that serve the load centers being heavily loaded and operating outside of their statutory voltage

level. The distribution system's lines carry a range of commercial, residential, and industrial types of loads, and it is undeniably true that these loads vary daily in terms of load. Regarding this, there won't be a constant ratio of power loss across all feeders connected to the network. The distribution network must be reconfigured in order to maximize network efficiency and deliver the best performance to the network's radiality. This is simply accomplished by altering the network switches' states, which minimizes power loss.
When power losses are reduced, the network's reliability and improved power quality will lengthen the equipment's lifespan. When network reconfiguration is used in the power system, the system is more likely to operate under stable conditions with very little loss and is less stressed due to this. The network suffers as a result of the radial distribution system's detrimental operation, which results in increased voltage drop and power losses. The network must then be redesigned and optimized in a way that preserves network integrity while producing the best and most productive outcomes. This paper proposed a method on how to reduce power losses, which primarily happen in the distribution network.

II. LITERATURE REVIEW

This reviewed literature contains basic fundamental concepts and reviews of similar works carried out by different authors using different techniques in the optimal distribution network reconfiguration in power distribution systems.

2.1 Theoretical Background

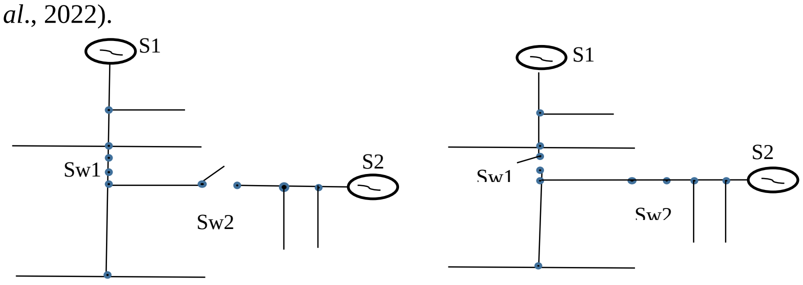
The process of reconfiguring a RDN involves looking for a new and improved system topology in order to distribute power as efficiently as possible. In power system, there are two distinct types of switches that are used for network configuration and protection. The first are tie switches, which are normally open, and the second are normally closed switches referred to as sectionalizing switches. The configuration of the distribution network is impacted by changing the state of these switches, which means that loads are transferred between the lines and the network's radial configuration is preserved. The distribution system's network reconfiguration is described in this implementation method (Dursun, *et. al*., 2017).

2.1.2 Network Reconfiguration Technique

Since there are many operational constraints to take into account, the reconfiguration problem of distribution systems is essentially an optimization combinatorial problem. As a result, finding an accurate and timely solution for a real system is challenging (Liu *et al*., 2018).

For flexibility and configuration management, primary distribution systems use two types of switches: normally open switches (tie switches) and normally closed switches (sectionalizing switches) (Merzoug *et al*., 2020). Closing tie switches (which are typically open) and opening sectionalizing switches (which are typically closed) in the network results in the reconfiguration of the distribution network. All loads are energized and the distribution network's radial structure is maintained while switching operations are being carried out. Naturally, the likelihood of network reconfiguration increases with the number of switches. A straightforward system, as depicted in Figure 4, serves as an illustration of the network reconfiguration.

As shown in Figure 1(a), two sources, S1 and S2, two switches, SW1 (sectionalized) and SW2 (tie), are being considered (Dias Santos *et al*., 2022). By changing the topology of the system, as shown in Figure 1(b), a reconfiguration to reduce system losses can be obtained. When reconfiguring the system, it is advised to open SW1 and close SW2. Before making changes to the fundamental configuration, the impact of constraints on reconfiguration must be carefully examined. This is illustrated in Figure 1. The network's requirement for radial structure is one of the main restrictions to be taken into account. Some general optimization algorithms are unable to directly satisfy this radial constraint. The radial constraint is broken, but a meshed network with all switches closed will have fewer losses (Dias *et al*., 2022).



(a) *(b)*

Figure 1: simple illustration of a network reconfiguration. (Dias *et al*., 2022)

2.1.3 Power Flow Analysis for Distribution Networks

Power system operation, control, and planning now make use of effective and dependable load flow solution techniques like Gauss-Seidel, Newton-Raphson, and Fast decoupled load flow. The analysis of distribution systems with high R/X ratios or unique network structures, however, has repeatedly demonstrated that these methods may become ineffective. As a result, numerous studies have been reported in the literature that were specifically created to address the issue of power flow in radial distribution networks. Methods created to fix radial distribution systems with poor conditions can be categorized into two groups. The Forward-Backward Sweep process is the foundation of the first category of methods for solving ladder networks. The second group of methods, on the other hand, makes proper modifications to already-used techniques like Newton-Raphson.

The calculation of power flows and voltages in a network under specified terminal or bus conditions constitutes the load flow problem. Since power systems are typically balanced, a single-phase representation is sufficient. Four values—the real and reactive power, the magnitude of the voltage, and the phase angle—are connected to each bus. The load flow calculation includes three different bus types, and each bus has two of the four specified quantities. To supply the extra real and reactive power needed to cover the transmission losses, one bus, known as the slack bus, must be chosen. The voltage magnitude and phase angle are specified at this bus. The system's remaining buses are either designated as load buses or voltage-controlled buses. At a voltage-controlled bus, the actual power and voltage magnitudes are specified (Mulyana and Yoakim 2022).

2.1.4 The Concept of Firefly Algorithm

In late 2007 and early 2008 at Cambridge College, Xin-She Yang developed the Firefly Algorithm (FA), which was based on the brilliant behavior and examples of fireflies. The calculation can also be classified as stochastic or deterministic. Calculations that follow similar computational steps on specified inputs and produce similar results are said to be deterministic. Given its ability to conduct nearby searches, deterministic calculation is very effective at locating neighborhood optima.

The value of the objective function of a particular problem determines the brightness or light intensity of a firefly. The light intensity for maximization issues is inversely proportional to the value of the objective function (Yang X 2012).

a) Attractiveness

The following monotonically decreasing function represents a firefly's attractiveness in the firefly algorithm:

$$\beta_r = \beta_o * \exp(-\gamma r_{ij}^m), \quad \text{with m} \geq 1 \qquad \dots (1)$$

Where, r is the distance between any two fireflies, β_o is the initial attractiveness at r = 0, and γ is an absorption coefficient which controls the decrease of the light intensity.

b) Distance

The distance between any two fireflies i and j, at positions xi and xj, respectively, can be defined as a Cartesian or Euclidean distance as follows:

$$r_{ij} = \| x_i - x_j \| = \sqrt{\sum_{k-1}^{d} (x_i k - x_j k)^2} \qquad \dots (2)$$

Where x_i, k is the k^{th} component of the spatial coordinate x_i of the i^{th} firefly and d is the number of dimensions, for d = 2, we have:

$$r_{ij} = \sqrt{x_i - x_j)^2 + (y_i - y_j)^2} \qquad \dots (3)$$

Depending on the nature of the issue, other distance metrics, such as the Manhattan distance or the Mahalanobis distance, may be used to define the calculation of distance r.

c) Movement

The movement of a firefly i which is attracted by a more attractive (brighter) firefly j is given by the following equation:

$$r_{ij} = x_i + \beta_o * \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (rand - \tfrac{1}{2}) \qquad \dots (4)$$

Whereas the first term refers to a firefly's permanent location, the second term considers a firefly's attractive quality to light power seen by nearby fireflies, and the third term refers to a firefly's erratic development in the event that there could be no more magnificent ones.

The coefficient α is a not entirely set in stone by the issue of interest, while rand is an irregular number generator consistently conveyed in the Space [0,1]. Figure 9 shows a flowchart that presents the FA.

Figure 2 is the flowchart presentation used for the realization of the Firefly Algorithm.

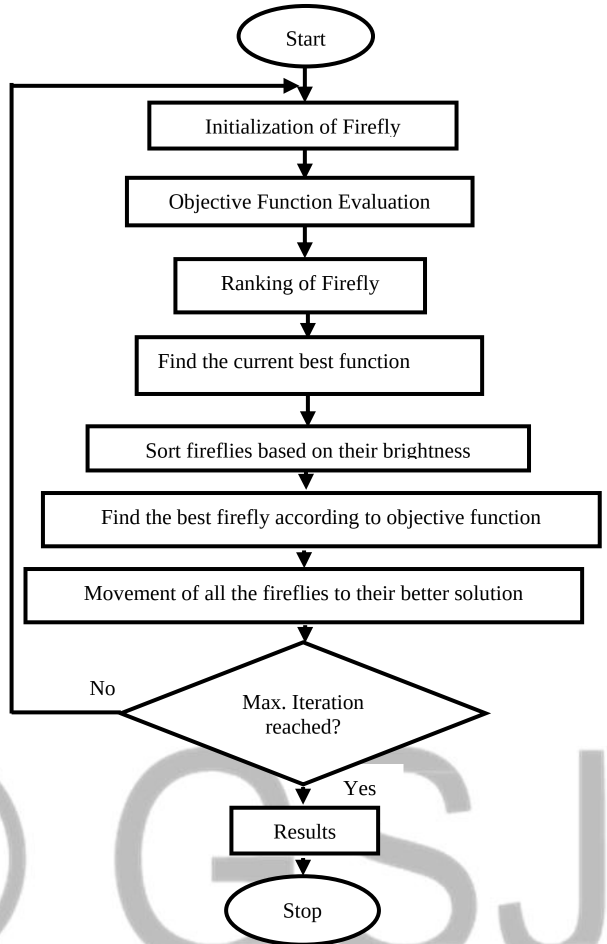


Figure 2: Flowchart for the Firefly Algorithm

2.2 Review of Existing Literature

On the various facets of power distribution network reconfiguration, numerous publications have been made. Power system engineers are tasked with coming up with various methods of reducing these losses and also improving the power quality, thereby minimizing cost, according to numerous studies that have been conducted on the challenges of power loss in distribution systems. Numerous publications that serve as the beam light for achieving the research's goals and objectives have been consulted. The following are some of the publications that were examined:

Schmidt *et. al.,* (2015) modeled a network based on the available distribution paths to present a reconfiguration method. A 33-bus network was taken into account in the work. We gathered and tabulated the available distribution routes (path table). The nonlinear load flow equations were then modified using a mixed integer linear model. The 33-bus test network's power flow was then solved using the resulting linear load flow equations. The results of the power flow were then shown and discussed. Although a linear approach was developed, this might be straightforward and manageable. A linear approach might not be able to simulate or optimize a real distribution network.

Wu & Tsai, (2016) presented a technique for feeder reconfiguration using particle swamp optimization with binary coding. The work used binary codes to represent a collection of potential configurations. Based on the optimization of the particle swamp in binary coding, a network reconfiguration algorithm was created. A 35-bus network's possible coded configurations were reconfigured using the developed algorithm. The ideal arrangement was discovered. The overall network loss was decreased by 7%. The fact that only a limited number of potential solutions were taken into account is one of the work's limitations. The random search method used in particle swamp optimization makes it possible to become stuck in a local minimum.

Sulaima *et. al.*, (2017) for improved power loss minimization in the distribution network and its improvements in the computational time, the modified evolutionary particle swarm optimization (MEPSO) algorithm was proposed. The ranking concept was introduced to improve the EPSO, with the most qualified position being taken in accordance with the least values of power losses which are sorted from the combination of a new and old set of positions. The Newton Raphson Power flow approach was used to calculate the power loss across each switch. The MATLAB environment was used to program the MEPSO algorithm, and simulations were run on a genuine 69-bus IEEE test system. The (EPSO) techniques validated the results. The outcomes showed that MEPSO algorithm had the highest percentage of power loss minimization performance.

III. METHODOLOGY

3.1 Multi-objective algorithm formulation

The goal of this research is to redesign the path of power flow at the distribution level in order to achieve a set of optimal trade-offs between a number of competing objectives.

Consider a multi-objective problem with m decision variables (parameters) and n objectives:

$$Minimize \ y = \left\{ f_1(x), f_2(x), ..., f_n(x) \right\} \quad \dots (5)$$

$$\chi = \left[x_1, x_2, ..., x_m \right] \quad \dots (6)$$

Where;

x_1 and x_2 the decision and objective vectors respectively.

3.1.1 Problem Formulation

The reconfiguration problem can be formulated as follows:

$$\text{Min } f = \sum_{I=1}^{NR} R_i \ |i^2| \quad \dots (7)$$

Subject to the following constraints:

1. The voltage magnitude

$$V_{min} \leq |V_i| \leq V_{max} \quad \forall_i \in N_b \quad \dots (8)$$

2. The current limit of branches

$$|I_i| \leq I_{imax} \quad \forall_i \in N_R \quad \dots (9)$$

3. Radial Topology:

Without meshes, the distribution system should be radial. Normally, no loads will be disconnected while being served.

$$Tie_{sw} = (N_R - N_b) + 1 \quad \dots (10)$$

$$Sec_{sw} = N_b - 1 \quad \dots (11)$$

Where, f is the fitness function to be minimized, *R* is the resistance of the branch *i*, Ii is the magnitude of the current flowing through the branch *i*, V_i is the voltage on bus *i*, V_{min} and V_{max} are minimum and maximum bus voltage limits respectively, I_i and I_{imax} are current magnitude and maximum current limit of branch *i* and N_b and N_R are the total number of buses and branches in the system.

3.1.2 Implementation of Optimal Distribution Network Reconfiguration Using Firefly Algorithm

The following is a description of the steps that were taken to implement the firefly algorithm-based distribution network reconfiguration, and figure 17 illustrates them. These steps are part of the network reconfiguration process:

Initialization: The solution starts with encoding parameters by defining

- S: group of supply substations.
- NB: number of buses.
- NR: number of branches (switches), where each switch has two possible states either '0'for an opened switch (tie switch) or '1'for a closed switch (sectionalizing switch).
- (Pload, Qload): load data; (Rb, Xb): branch data.
- f (0): base configuration defined as a set of states (open/closed) assumed by the switches.
- N: number of fireflies in each iteration and initially located on N randomly chosen open switches.

Once all fireflies finish their tour, the configuration corresponding to each firefly is evaluated in three steps:

Step 1: Check the radiality of the constraints. If radial go to next step otherwise this trial configuration is discarded.
Step 2: Run the load flow and check for voltage and loading limits. If either limit is violated, the configuration is discarded; if no violations are there go to next step.
Step 3: Compute the objective function-minimization of the line losses.

Termination of the algorithm: The solution process continues until maximum number of iterations reached or until no improvement of the objective function has been detected after specified number of iterations. The firefly-based network reconfiguration flow chart is shown in Figure 3.

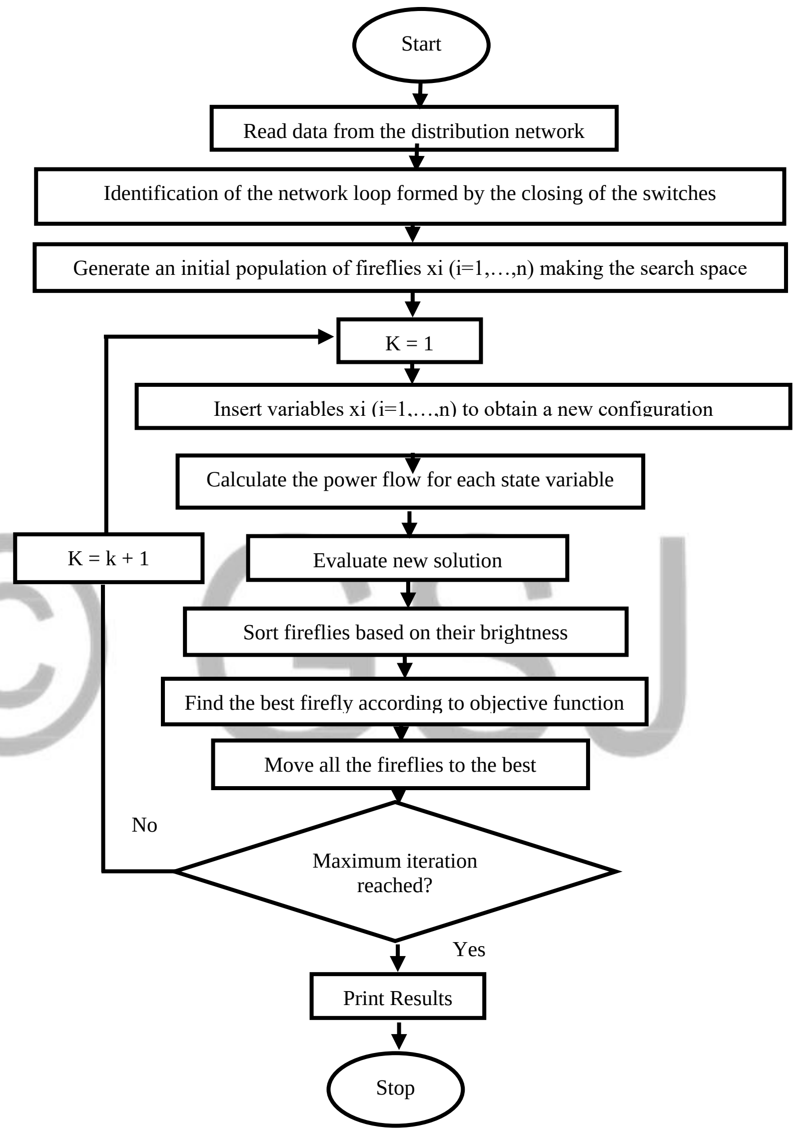


Figure 3: Realization of Firefly based distribution network reconfiguration

IV. RESULTS AND DISCUSSIONS

The research was realized in line with the following procedures:

1. Acquisition of relevant data and carrying out the base-case power flow analysis in MATLAB.
2. Formulation of multi-objective function comprising of total power loss and bus voltage deviations
3. Implementation of the optimal distribution network reconfiguration using Firefly Algorithm.

The realization of the distribution network reconfiguration of the standard IEEE 33 Bus system for both before the reconfiguration scenario and the after reconfiguration are shown in Figures 4 & 5 respectively. The network topology is seen to have obviously changed as a result of the opening and closing of some new switches.

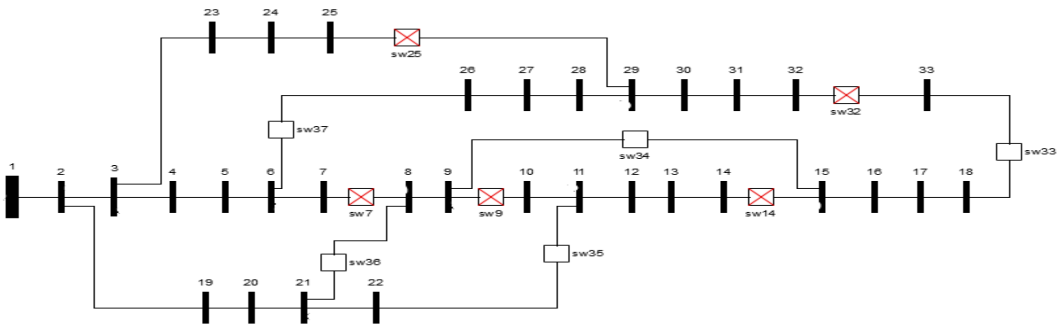


Figure 4: IEEE 33-Bus Distribution Network before Reconfiguration

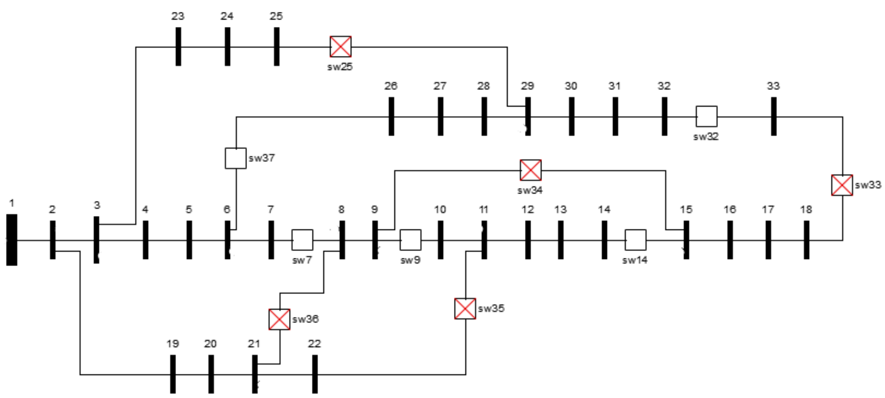


Figure 5: IEEE 33-Bus Distribution Network after Reconfiguration

Parameters obtained on carrying out power flows for the two cases that is the analysis on the IEEE 33 Bus system before the application of the metaheuristic technique and after the application of the Firefly Algorithm are summarized in Table 1.

Table 1: Summary of Performance Indices for IEEE 33-bus System

Parameter	**Before Reconfiguration**	**After Reconfiguration**
Tie switches	33 34 35 36 37	7 9 14 32 37
Active Power Loss (kW)	208.4259	138.9275
Reduction in Active Power Loss (%)	-----	33.33
Reactive Power Loss (kVAR)	*147.203*	*101.325*
Reduction in Reactive Power Loss (%)	-----	31.16
Voltage deviation V_D (p.u)	1.6606	1.1074
Voltage deviation V_D (%)	-----	33.31

The response characteristics of the real and reactive powers for both before and after reconfigurations of the *33-Bus IEEE Radial Distribution Network* indicating the various loss minimization are shown in Figures 6 & 7.

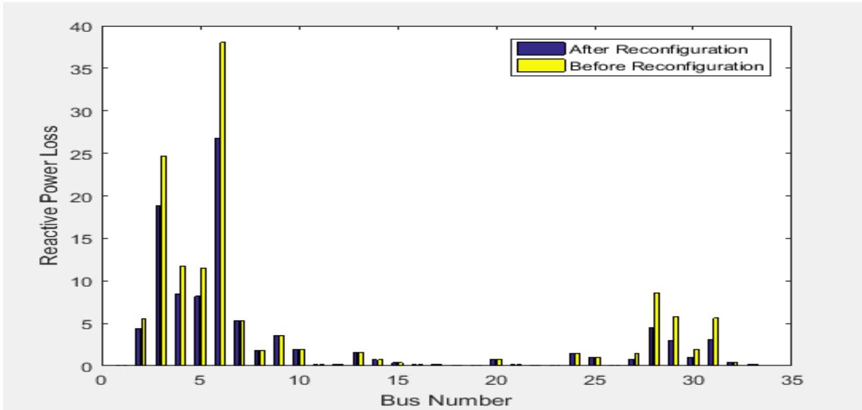


Figure 6: Reactive Power Loss for 33-Bus IEEE Radial Distribution Network before and after Reconfiguration using Firefly Algorithm

It can be deduced that after the application of the Firefly Algorithm, Reactive power loss was significantly reduced as depicted by the yellow and blue chart bars.

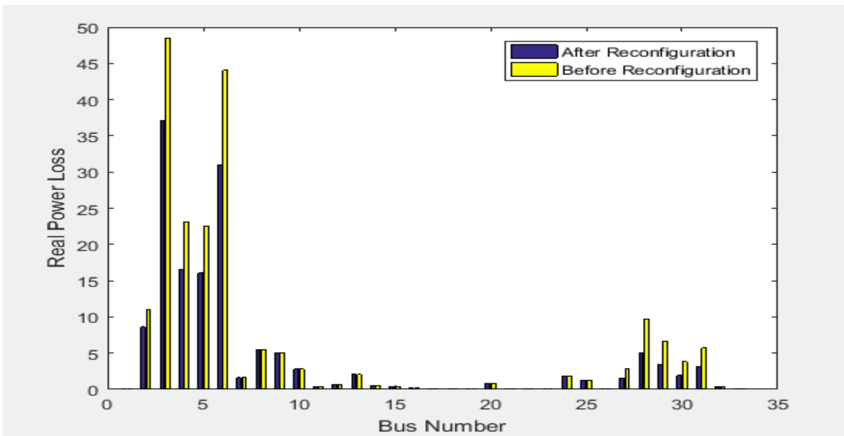


Figure 7: Real Power Loss for 33-Bus IEEE Radial Distribution Network before and after Reconfiguration using Firefly Algorithm.

It has been realized that after the application of the Firefly Algorithm, Real power loss was minimized as shown in figure 7 where the yellow and blue chart bars shows the variations.

The voltage profile curves showing the drastic bus Voltage improvement on the standard IEEE 33Bus system after the application of the firefly Algorithm is shown in Figure 8.

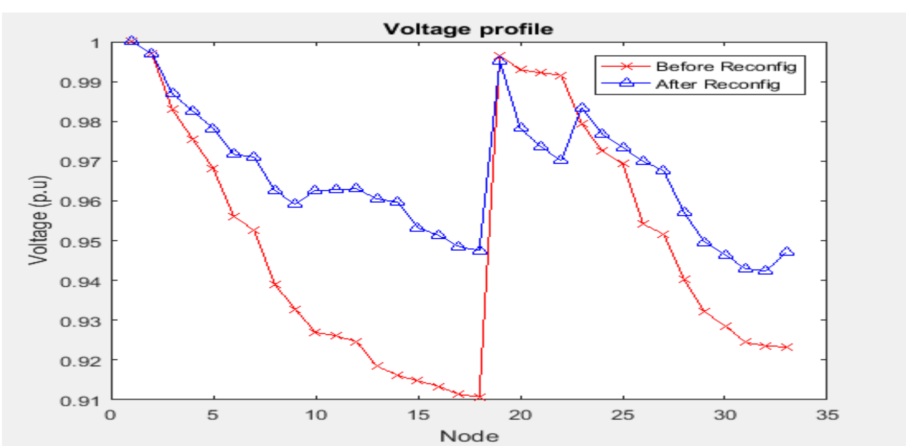


Figure 8: Voltage Profile Improvement for 33-Bus IEEE Radial Distribution Network after Reconfiguration using Firefly Algorithm

Voltage profile improvement is shown in Figure 8 showing the various voltage deviation at all buses which in turn depicts the voltage correction at most of the buses.

The performance of the Firefly Algorithm on the IEEE 33 Bus system is validated with results obtained from literature using Genetic Algorithm GA and Particle Swarm Optimization PSO, the indices are compared and tabulated in Table 2.

Table 2: Performance Validation of FA with GA and PSO

Parameter	**Original Network**	**Firefly**	**GA**	**PSO**
*(**Tie switches**) Before Reconfiguration* *After Reconfiguration*	- -	33 34 35 36 37 7 9 14 32 37	33 34 35 36 37 7 9 14 32 37	33 34 35 36 37 7 9 14 25 32
Active Power Loss (kW) *Reduction in Active Power Loss (%)*	208.4259 -	138.9275 33.33	140.650 32.51	166.5328 20.10
Reactive Power Loss (kVAR) *Reduction in Reactive Power Loss (%)*	*147.20* -	*101.325* 31.16	109.320 25.73	117.854 19.94
Voltage Deviation V_D (p.u) *Voltage Deviation V_D (%)*	1.6606 -	1.1074 33.31	1.2312 25.85	1.1002 33.37

Table 2 illustrates how Firefly Algorithm performed excellently well in the reduction of the Active power loss with 33.33% as against 32.51% by Genetic Algorithm and 20.10% by Particle Swarm Optimization, it also did 31.16% for the Reactive power loss reduction while GA did 32.51%, PSO did 19.94% and also FA did well on the Voltage Improvement with a Voltage Deviation of 33.31% as against 25.85% by GA and 33.37% by PSO.

After acertaining the robustness of the Firefly Algorithm on the IEEE 33 Bus system the same technique was applied on the existing *DOMA -69 Bus Radial Distribution Network*. The network topology of Doma distribution network showing the status of the switches for both before and after application of the Firefly Algorithm are shown in Figures 9 &10.

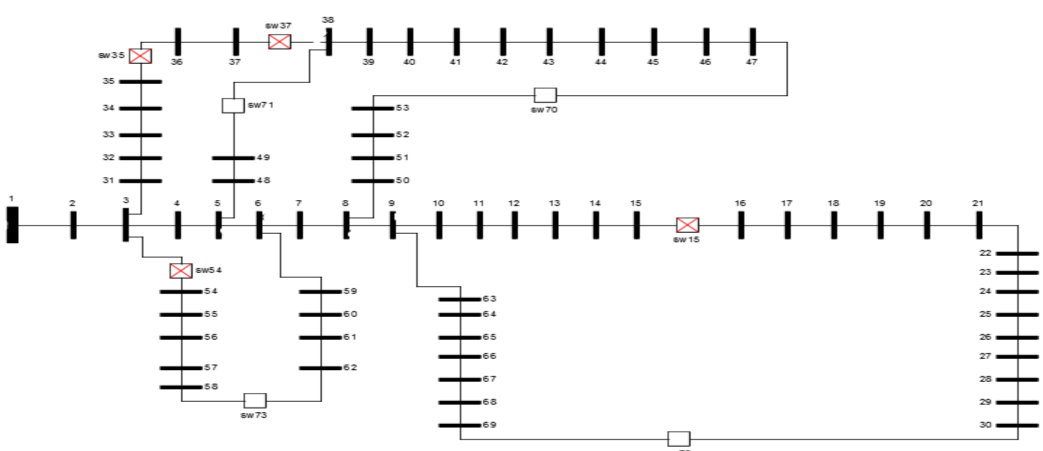


Figure 9: Doma 69-Bus Distribution Network before Reconfiguration.

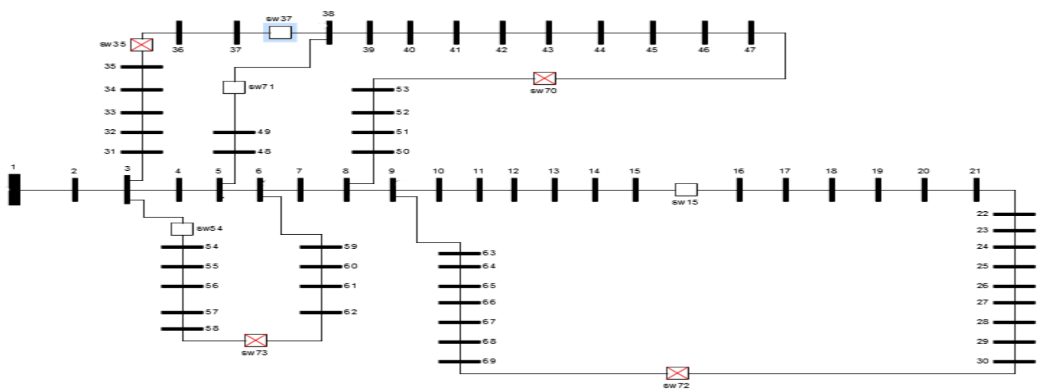


Figure 10: Doma 69-Bus Distribution Network after Reconfiguration

Parameters realized when performing the power flows for the two cases on *DOMA -69 Bus Radial Distribution Network* considering the before and after the application of the Firefly Algorithm are summarized in Table 3.

Table 3: Summary of DOMA -69 Bus Radial Distribution Network

Parameter	**Before Reconfiguration**	**After Reconfiguration**
Tie switches	70 71 72 73	15 37 54 71
Active Power Loss (kW)	128.0027	106.125
Reduction in Active Power Loss (%)	-----	17.09
Reactive Power Loss (kVAR)	138.5527	97.887
Reduction in Reactive Power Loss (%)	-----	29.35
Voltage deviation V_D (p.u)	0.9768	0.7777
Voltage deviation V_D (%)	-----	20.38

Table 3 indicates how Firefly Algorithm performed DOMA -69 Bus Radial Distribution Network where in the reduction of the Active power loss with 17.09%, for the Reactive power loss reduction it did 29.35%, the FA also did well on the Voltage Improvement with a Voltage Deviation of 20.38%.

The response characteristics of the real and reactive powers for both before and after reconfigurations of *DOMA -69 Bus Radial Distribution Network* indicating the various loss minimization are shown in Figures 11 & 12.

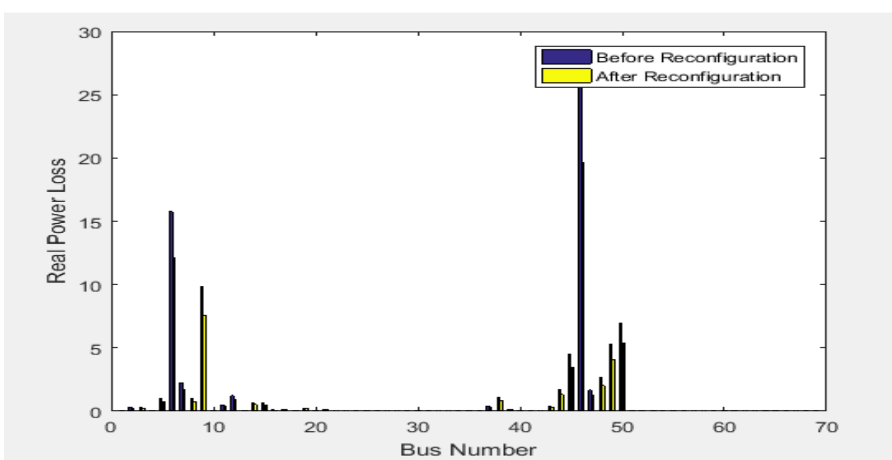


Figure 11: Real Power Loss for DOMA -69 Bus Radial Distribution Network after Reconfiguration using Firefly Algorithm

Real Power Loss on DOMA -69 Bus Radial Distribution Network of each bus in Figure 11 shows the distinct variation between the before and after the application of the FA with blue bars showing the Before the application of the FA and the yellow bars showing the After the application of the FA.

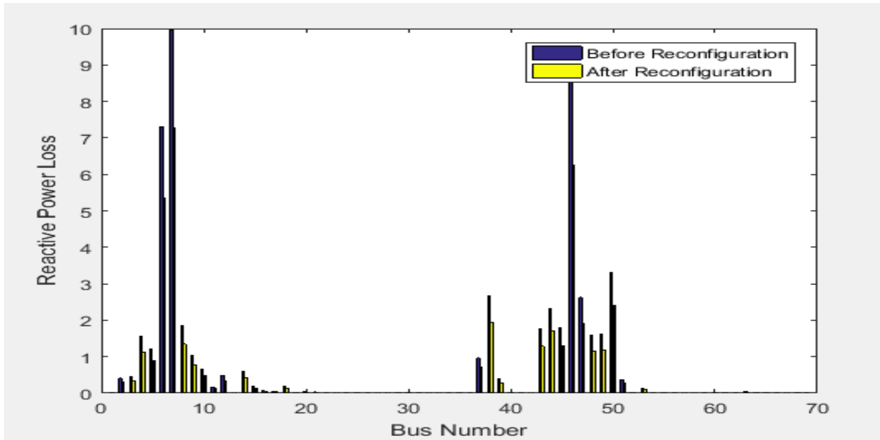


Figure 12: Reactive Power Loss for DOMA -69 Bus Radial Distribution Network after Reconfiguration using Firefly Algorithm.

Reactive Power Loss on DOMA -69 Bus Radial Distribution Network of each bus in Figure 12 shows the distinct variation between the before and after the application of the FA with blue bars showing the Before the application of the FA and the yellow bars showing the After the application of the FA.

The voltage profile curves showing the drastic bus Voltage improvement on the DOMA -69 Bus Radial Distribution Network after the application of the firefly Algorithm is shown in Figure 13.

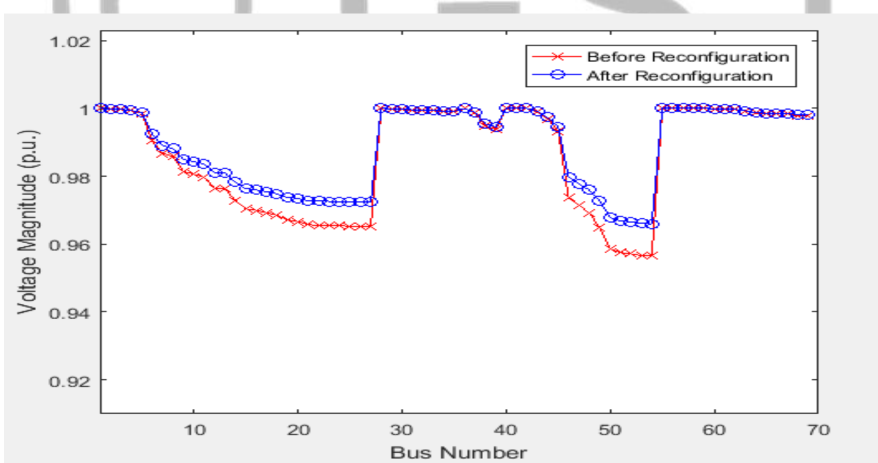


Figure 13: Voltage Profile Improvement for DOMA -69 Bus Radial Distribution Network after Reconfiguration using Firefly Algorithm

Voltage profile improvement is shown in Figure 13 showing the various voltage deviation at all buses with the red lines showing the voltage profile before the application of the FA while the blue lines shows the voltage profile after the application of the FA.

V. **CONCLUSION**

The efficiency and applicability of the method was demonstrated for steady-state constant load analysis using the developed model of the 69-bus Doma Feeder in the Gombe distribution network and the standard IEEE 33-bus radial distribution network. Prior to reconfiguration, the ideal tie switches for the common IEEE 33-bus test network were discovered to be 33, 34, 35, 36, and 37. After applying the FA, the new tie switches were obtained as 7, 9, 14 32, and

37. The tie switches on the Doma 69 Bus distribution network were 70, 71, 72, and 73 before the reconfiguration, and after applying the FA, the new tie switches were obtained as 15, 37, 54, and 71, respectively. The outcome for the IEEE 33-bus network's base case demonstrates a total loss of 280.4259KW but after application of the FA, the losses was reduced to 138.92kW with the percentage reduction in both the active and reactive power loss of 33.33% and 31.16% respectively. The firefly approach causes a Voltage deviation V_D improvement when compared to the network base-case scenario. The voltage deviation V_D was obtained to be 33.31% for the Standard IEEE 33 Bus network and 20.38% for the Doma 69 Bus distribution network.

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