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Optimal Reconfiguration and Optimal Allocation of Distributed Generation Using Different Optimization Techniques

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ABSTRACT

Voltage drop and power losses are existing problems in radial distribution networks. Reconfiguration in distribution network aims to find the best switching combination of system branches that optimize a certain objective function while satisfying some specified constraints, which improves the quality of electrical power and used to increase the distribution network's performance. This paper presents optimal methods for optimizing of the distribution system reconfiguration and installation of DG units in distribution system for minimizing the losses of active power and improving bus voltage profile based on different optimization techniques such as a binary particle swarm optimization (BPSO) algorithm, binary Jaya (BJA) algorithm and Grasshopper Optimization algorithm (GOA). The load flow calculations are carried out using the backward/forward sweep method. The proposed methods are put to the test in the distribution system for the 33-bus test system. The simulation results find that the proposed algorithms reduced the losses of active power and increasing of system bus voltage, and solve the system reconfiguration problem and enhance the distribution system performance after adding of DG. The comparative results prove the efficiency of these methods compared to the other reported algorithms. The results further indicate the superiority of BJA technology over proposed technology's improved system performance.

Keywords*: Distribution network; Reconfiguration; DG; Optimization Techniques; Backward/forward sweep method; active losses reduction ;voltage improvement*

1 .Introduction

The distribution networks play an important role in connecting transmission systems and customers. They are the most visible part of the power system network, so they are the most exposed to the critical observations of the system consumers [1].The distribution networks suffer from voltage drop and power loss problems. However, the power losses in an electric system should be around 3 to 6% in the ideal state. The voltage drop problem distorts the entire network's voltage profile. The main cause of system voltage reduction is due to the huge amount of the load reactive power requirement as a most of load are inductive. About 13% transmitted power is wasted as active losses, so improving bus voltage profile and increasing system efficiency are necessary [2-3]. To solve these problems, many techniques are used such as network reconfiguration, optimal capacitor placement, and distributed generation integration [4]. Network reconfiguration is often used compared to the other techniques due to its cost-effectiveness [5]. This is accomplished by sectionalizing and adjusting the close/open status of tie switches [6]. The main goal of the reconfiguration is to determine the optimal topology of system to minimize active power losses, improve voltage profile, meet the energy demand and maintain system reliability to enhance distribution system performance [7-8]. Different methods have been proposed to solve these problems, which can be divided into traditional and modern methods a reconfiguration is a large-scale, non-linear, and constrained optimization problem with a single objective and multi-objective functions. In [9-17] showed reconfiguration benefits based on improving performance of radial distribution network (RDN). And optimal power flow model for losses reduction and improving voltage profile by different optimization techniques. Secondly distributed generation technologies, (DG) are popular in the distribution system, it is the electrical power source directly connected to the distribution network. The DG can work separately or integrated with the network. The technologies for DG are used in many applications; it can be classified into conventional and renewable distributed generators. In [18] DG is used to solve distribution network problems using sensitivity analysis. The need to feed loads requires increased electricity; this in turn made increasing power losses and decreasing voltage profile. In [19] these problems were solved using distributed generator (DG) for best allocation of DG sources is presented in [20], presented an analytical algorithm. For best location of DG in distribution systems, using different optimization techniques. The proposed methods for finding of optimal allocation of DG and ensure the optimal reconfiguration for distribution system are presented in [21-24]. The goal in this paper simulate the different methods of system reconfiguration and DG optimal allocation, which are based on minimizing active power losses and increasing bus voltage based on the BPSO, BJA and GOA algorithms. The radial distribution system power flow calculation is carried out using BFS. The BPSO, BJA and GOA algorithms are tested on the 33-bus distribution system, and the obtained results are discussed. The other parts of the paper are arranged as follows: The distribution system problems are presented in part 2. Part 3 explains the backward/forward sweep method; the description of the proposed BPSO, BJA and GOA algorithms are given in part 4. The simulation results are discussed in part 5, part 6 shows final conclusion of the paper.

2 . Problem Formulation

The goal of this section is to determine the best possible reconfiguration system for a 33-bus 12.66-kV RDN with DG installation utilizing given optimization techniques to obtain the best possible distribution system operation while meeting network restrictions.

2.1. Objective Functions of Reconfiguration State

2.1. a. Minimizing the losses of active power

The active power losses through RDN reconfiguration can be minimized as follows [20]:

$$\min f_1 = \sum_{\mathrm{i}=1}^{\mathrm{n}} R_i \frac{P_i^2+Q_i^2}{V_i^2} \qquad (1)$$

Where;

f_1 is active power losses, the branch number is i, the total number of branches is n, the branch resistance is R_i, the active and reactive power of branch i is P_i and Q_i respectively, and the up-layer node voltage of branch i is v_i .

2.1.b Improving voltage profile

One of the most critical security and service quality indicators is bus voltage. The load bus voltage variations from 1.0 Pu can be minimized to improve the voltage profile. The objective function can be written as follows [4]:

$$\min\ f_2 = \sum_{i=1}^{nb} |V_i - 1.0| \qquad (2)$$

where:

f_2 is improvement voltage profile and *nb* is the total number of buses.

2.2 Constraints in the System

All the objective functions are solving under the following system constraints:

1. Network topological constrain: The network topology of the distribution network is radial.

2. Constraint on line flow

The power flow in $\mathrm{k^{th}}$ branch ($Flow^k$) should be less than ($Flow^{kmax}$) limits.

$$Flow^k < Flow^{kmax}$$

3. System bus voltage constraints:

$$\mathrm{v_{min}} < \mathrm{v}_i < \mathrm{v_{max}}$$

Where;

$\mathrm{v_{min}}$, $\mathrm{v_{max}}$ are the minimum voltage and the maximum voltage at bus *i*.

4. System bus current constraints [5]:

$$\mathrm{I_{min}} < \mathrm{I}_i < \mathrm{I_{max}}$$

Where; I_i is the magnitude of current at branch *i*; $\mathrm{I_{min}}$ and $\mathrm{I_{max}}$ are the lower and upper current limits at branch *i*, respectively

5. Number of DG

Where:

$$N_{max} < n$$

Where:

$\mathrm{N_{max}}$: Max No of DG

3. Back-Forward Sweep (BFS) Method

The BFS method is one of the most effective methods for calculating RDN load flow because it has a high level of convergence and requires little memory for processing [25]. For each feeder and bus, the BFS approach is utilized to determine power losses and voltage magnitudes. In [26] uses two sets of recursive equations generated from the single-line schematic of the distribution system illustrated in Fig. 1 to solve the load flow of a single source network iteratively.

The power flow through the feeders is computed using the first set of equations, which begin at the end of the last feeder and work backwards to the transmitting side (sending bus). The other set of equations, on the other hand, calculate the voltage magnitude and angle of each bus as it progresses forward from the sending bus to the receiving bus.

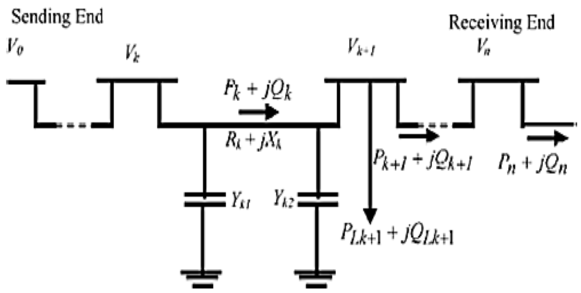

Figure.1. Single line diagram of the RDN

From Figure. 1, the active power (P_k) and the reactive power (Q_k) that are flowing through the feeder from bus 'k' to node 'k+1' can be calculated backwards from the last bus and is given as follows:

$$P_k = P_{k+1} + P_{Lk+1} + P_{Loss}(k, k+1) \quad (3)$$

$$Q_k = Q_{k+1} + Q_{Lk+1} + Q_{Loss}(k, k+1) \quad (4)$$

$$I_k = \frac{V_k < \delta_k - V_{k+1} < \delta_{k+1}}{R_k + jX_k} \quad (5)$$

Where;

P_{k+1}, Q_{k+1} are the active and reactive power flows from bus k+1; P_{Lk+1}, Q_{Lk+1} are active and reactive loads that are connected at bus k+1; $\mathrm{P_{Loss}}(\mathrm{k}, \mathrm{k}+1)$, $\mathrm{Q_{Loss}}(\mathrm{k}, \mathrm{k}+1)$ are active and reactive losses in the feeder from bus k to bus k+1. The magnitude and the angle of voltage at each bus are computed in the forward direction. If the voltage at bus k is$V_k < \delta_k$, and the voltage at bus k+1 is $V_{k+1} < \delta_{k+1}$, then the current flows in the feeder from k to k+1 .

4. Optimization Techniques

In this paper, three optimization techniques are applied to solve the RDN reconfiguration problem and to find the optimal allocation of DG namely BPSO, BJA and GOA.

4.1 Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is a swarm algorithm that simulates the behavior of the bird or fish foraging process [27]. The continuous form of PSO can be expressed as in (6) and (7) [28]. Like other evolutionary algorithms, PSO starts with a random population of particle positions, and then evaluates each particle at its present location in the objective function. The present position x_i , the prior best positionP_i, and the velocity v_i are three n-dimensional vectors that each individual in the population has, where n is the dimension of the search space.

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t) \quad (6)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (7)$$

Where;

w Stands for inertia weight; c_1 and c_2 stand for individual and social learning components, respectively; r_1 and r_2 are random variables with values between 0 and 1; g is a combination of switches derived from the best location of all existing populations; P_i is a combination of switches derived from the best position of the particle.

4.2 Binary Particle Swarm Optimization Algorithm (BPSO)

PSO distinguishes that is simple, fast and can find out the optimum solution efficiently and quickly. Despite its advantages, it sometimes falls into local solutions. Falling into local solutions impedes finding the optimum solution. PSO still applied to different applications and demonstrated efficiency.

The continuous PSO cannot be used to optimize the pure discrete binary combinational problem. Kennedy and Eberhart proposed a BPSO algorithm to handle this kind of problem [29]. In this paper, the combination of the positive integers is known as switches. As a result, the PSO algorithm requires the following steps to convert the velocity (6) and position (7) determined values into positive integers [6, 17, and 23]:

$$v_i^{t+1} = sig(v_i^{t+1}) = \frac{1}{\exp(-v_i^{t+1})} \quad (8)$$

$$x_i^{t+1} = \begin{cases} 1, & rand() < v_i^{t+1} \\ 0, & others \end{cases} \quad (9)$$

4.3 Binary Jaya Algorithm (BJA)

Jaya is a population-based optimization algorithm developed by R. Venkata Roa in 2015 [24]. It is simply predicated on the idea that the best solution for a given situation should be pursued, while the wo rst solution should be avoided. . Requires very small controlling parameters for its work this makes very simple and has gained wide acceptance in the optimization field. The BJA does not require any tuning of parameters The JA does not require any tuning of parameters [30-32]. Let us assume that f(x) is the function to be minimized.

The best candidate is obtained for the best value of f(x) and the worst candidate is obtained for the worst value of f(x). If $X_{n,m,i}$ is the value of the n[th] variable for the m^{th} candidate during the i^{th} iteration [33-34].

$$X_{n,m,i}^{updated} = X_{n,m,l} + r_{1n,i}\left(X_{n,best,l} - \left|X_{n,m,i}\right|\right) - r_{2n,i}\left(X_{n,worst,i} - \left|X_{n,m,i}\right|\right) \quad (10)$$

Where;

$r_{1n,l}$ and $r_{2n,l}$ are two random numbers in the range [0, 1] for the variable *n* during iteration *i*; $X_{n,best,i}$ and $X_{n,worst,i}$ are the values of the variable *n* for the best and worst candidates respectively. The updated value is acceptable if it gives a better function value. All better function values become the input for the next iteration.

4.4. Grasshopper Optimization Algorithm (GOA)

GOA is an optimization approach developed in 2017 by Saremi, Mirjalili, and Lewis. The swarming behavior of grasshoppers is present in both nymphs and adults. In nature, grasshoppers are normally observed alone; nonetheless, they form one of the greatest swarms of all organisms. The swarm's size might be on a continental scale, creating a nightmare for farmers; the life cycle grasshopper is a set of nature-inspired algorithms. The life cycle grasshopper is a set of nature-inspired algorithms that divide the search process logically into two tendencies: exploration and exploitation. The search agents are urged to move suddenly during exploration, whereas they tend to move locally during exploitation. These functions, as well as target searching, are accomplished by grasshoppers, and the mathematical model used to represent grasshoppers swarming behavior is stated as [35]

$$X_i = r_1 S_i + r_2\, G_i + r_3\, A_i \quad (12)$$

Where:

X_i The i^{th} grass hopper's position is defined by this variable grass hopper.

S_i Is social interaction important

G_i Is the i^{th} grass hopper affected by gravity

A_i The advection of the wind is depicted

r_1, r_2 *and* r_3 Are random numbers in [0, 1].

It is important to note that gravity is not taken into account (there is no G_i component) and that the wind direction (A_i component) is always directed towards a target (T_d).

$$S_i = \sum_{\substack{j=1 \\ j\neq 1}}^{N} s(d_{ij})\, \widehat{d_{ij}} \quad (13)$$

Where:

d_{ij} Is the distance between the i^{th} and the j^{th} grasshopper, calculated as, s is a function to define the strength of social forces, as shown in Eq (14),

$\widehat{d_{ij}} = \frac{x_i - x_j}{d_{ij}}$ And is a unit vector from the i^{th} grasshopper to the j^{th}grasshopper. The s function, Which defines the social forces, is calculated as

$$S(r) = f\, e^{\frac{-r}{l}} - e^{-r} \quad (14)$$

Because nymph grasshoppers lack wings, their movements are largely dependent on wind direction. Substituting S, A, and G in Eq (12) yields the following equation:

$$x_i = \sum_{\substack{j=1 \\ i\neq 1}}^{N} s\left(\left|x_j - x_i\right|\right) \frac{x_i - x_j}{d_{ij}} + \widehat{T_d} \quad (15)$$

Because the grasshoppers soon find their comfort zone and the swarm does not converge to a specific location, this mathematical model cannot be utilized directly to solve optimization issues. To tackle optimization difficulties, a modified form of this equation is proposed as follows.

$$X_i^d = c\left(\sum_{\substack{j=1 \\ i\neq 1}}^{N} c\, \frac{Ub_d - Lb_d}{2}\, s\left(\left|x_j^d - x_i^d\right|\right) \frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d}$$

(16)

To balance exploration and exploitation, the parameter c must be reduced according to the number of iterations. The coefficient c, which is proportional to the number of iterations, is computed as follows:

$$c = cmax - l\, \frac{cmax - cmin}{L} \quad (17)$$

Where

cmax is the maximum value, *cmin* is the minimum value, *l* indicates the current iteration, and *L* is the maximum number of iterations. This trend is visible in unimodal, multimodal and composite test functions. [36-39] demonstrated how the GOA algorithm balances exploration and exploitation to move grasshoppers to the global optimum. The attraction and repulsion rates in the pie charts illustrate that the grasshoppers interact differently on the test functions. GOA is used to simulate the reconfiguration of a distribution network in order to discover the ideal network for minimizing power losses and improving voltage profile while taking system architectural restrictions into consideration. The suggested approach mathematically replicates a feeder reconfiguration network based on grasshopper behavior in nature, and it is then utilized to determine the ideal network design. The suggested technique is evaluated on a 33-bus RDN and produced the best solution in an acceptable amount of time. The search agents are represented by grasshoppers, and the food source represents the grasshopper's best position in the swarm thus far. The suggested method can be divided into the following phases.

Step1: Initialize the swarm, initial values of the losses and voltage $X_i(i-1,2,\ldots\ldots,n)$.

Step2: Initialization of maximum, minimum values of c and maximum numbers of iteration.

Step3: Grasshopper selects the best fitness T (the best search agent).

Step4: update c using Eq (16).

Step5: Eq (15) is used to determine the distance between grasshoppers $\left|x_j^d - x_i^d\right|$, update the location of the target search agent, and return the current search agent if it moves outside the bounds.
Step6: Steps 5 and 6 should be repeated until the current iteration count reaches its maximum.
Step7: Print the goal position, which indicates the best opening switches after reconfiguration, as well as the target fitness, which represents the least amount of power loss and voltage drop in the system.
5. Discussion and Simulation Results
Different optimization techniques have been proposed to solve multidisciplinary electrical applications. In this paper, three optimization techniques are applied to solve the RDN reconfiguration problem and to find the optimal allocation of DG. The applied optimization techniques are a binary particle swarm optimization (BPSO) algorithm, binary Jaya (BJA) algorithm, and grasshopper optimization algorithm (GOA). The three applied optimization techniques belong to advanced optimization algorithms that are very proper for multidisc ciplinary applications and have demonstrated efficiency to solve many electrical applications. Advanced optimization algorithms differ from other optimization algorithms. It need only the objective function and is not dependent on the gradient or any differential form of the objective. It also has a few parameters. These advantages make these algorithms easy and practical for different applications.

5.1 Test system

The proposed algorithms are tested using the 33-bus RDN. On branches 33, 34, 35, 36, and 37, the system consists of one feeder, three laterals, 32 normally closed tie lines, and five normally open tie lines. The load on the system is expected to be constant. The system total load is 3.715 MW and 2.226 MVAR [24]. The system base is 12.66 kV and 10 MVA.

5.2 Reconfiguration Case studies.

This study objects to minimize the active power losses and improve the voltage profile by determining the optimal network reconfiguration using the BPSO, BJA and GOA algorithms. The algorithms are implemented in Matlab (R2018b).The number of particles in the network simulation is set to 20, the maximum inertia weight w is set to 0.9, the lowest inertia weight is set to 0.4 the maximum number of iterations is set to 60, and the acceleration constants c_1, c_2 are set to 2.
The standard's initial configuration 33-bus RDN is seen in Figure. 2 after optimal reconfiguration of the RDN. The initial active power loss of the system is 202.67 kW, and the minimum voltage is 0.9131 pu at node 18.
After the system reconfiguration. It can be observed that the reconfiguration of the test system using BPSO, BJA and GOA gives active power losses of 138.93 kW. The percentage of power losses reduction is 31.45%. The base voltage is 0.9423pu, which improved by 3.2%. Figure. 3 shows the voltage profile of the 33 – bus RDN before and after reconfiguration. It can be noticed that, for active power losses, there is a slight improvement obtained by the proposed algorithms in the paper compared to BPSO [22], TLBO [27], HAS [27], refined GA [27]. The proposed BPSO, BJA and GOA give the same result obtained by ANN [28], and they give better results compared to GA [23]. The results obtained for voltage profile improvement are better than the other algorithms listed in table 1.

5.3 DG Case studies

The DG models that we employed in this study were used to examine the impact of prospective DG integration to RDN's 33-bus. As many as five DGs have been placed. That are on buses of 8, 12, 16, 25and 30. As shown in Figure 4, a distribution network with the inclusion of five DGs after optimal reconfiguration network. In order to investigate the impact of projected DG integration in the initial setup of a 33 bus RDN as a base scenario, the total active power losses is 202.67 Kw. After installing up to five DGs on buses the total active power losses decrease of 133 kW, 126 Kw and 128 Kw using BPSO, BJA and GOA, while the total active power loss after network reconfiguration optimization with DG integration is 128 Kw, 118 Kw and 126 Kw using BPSO, BJA and GOA. Power loss reduction after installing the DGs using BPSO, BJA and GOA are 34.46%, 37.44% and 36.7% in percentage while power loss after reconfiguration optimization of network with DG integration are 36.93%, 41.86% and 37.8% in percentage respectively. These results show that network reconfiguration optimization and installation of DG utilizing the BJA has a significant impact on reducing active power loss in the distribution system.

Figure. 5 depict the distribution of active power loss after reconfiguration, after installing 5 DGs, and after reconfiguration with integration of 5 DGs, it's interesting to note that, as shown in Figure. 6, DG integration on a 33bus RDN improved the voltage profile for each bus. By optimizing the RDN's configuration, the voltage profile will be improved even more than before. It should be noticed that in the results, just the voltage magnitude along the bus main feeder is shown. Convergence characteristics of the proposed algorithms shown in Figure 7 are observed that the proposed BJA reach to much less total system power losses than BPSO and GOA, It is method able to find the optimal state and converge after few of iterations.

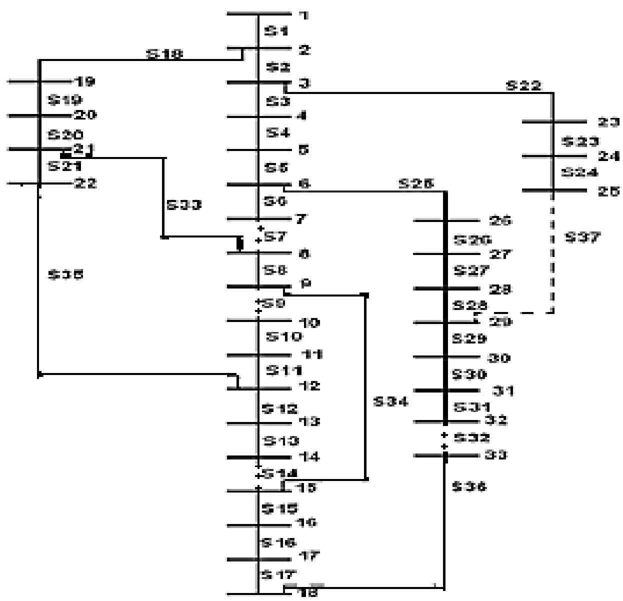

Figure 2. 33-buses test system after optimal reconfiguration

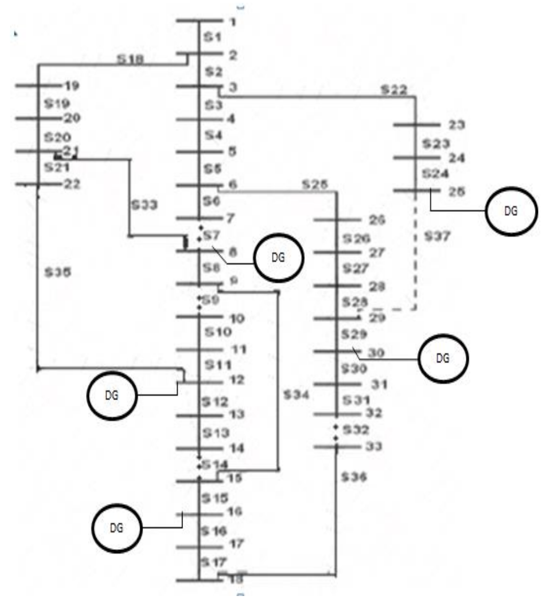

Figure.4. IEEE 33-bus test system with integration of 5 DGs after reconfiguratio

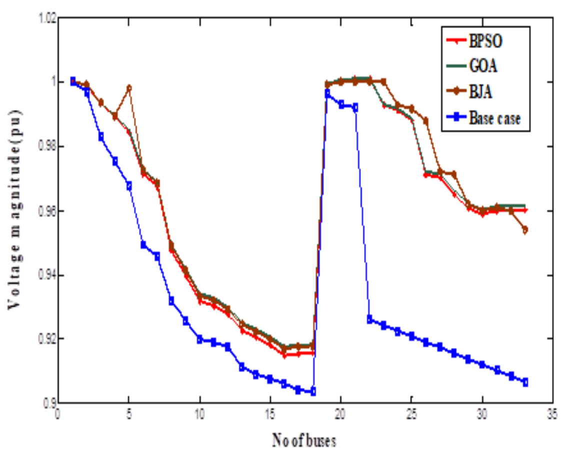

Figure .3. Voltage profile at each bus before and after optimal reconfiguration using different optimization techniques

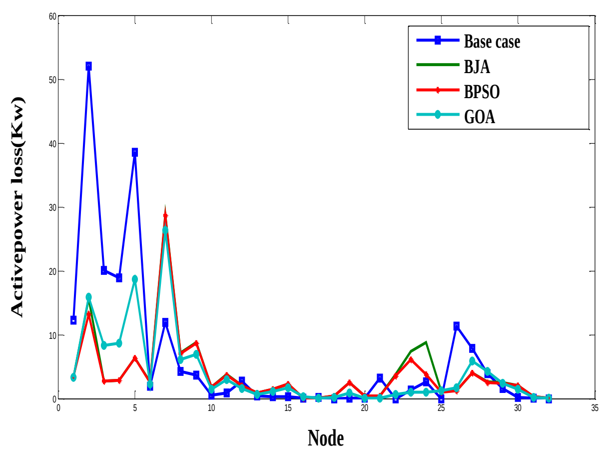

Figure.5. Losses of active Power of 33-bus RDN

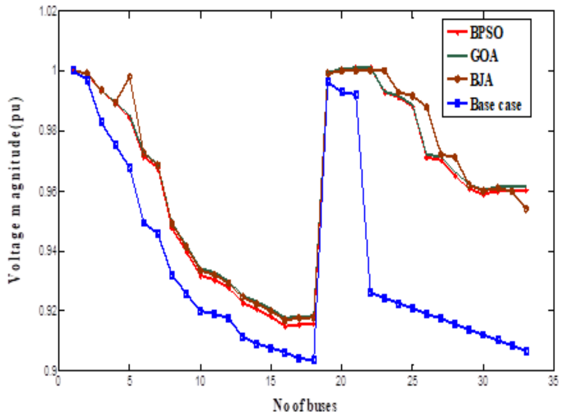

Figure.6 . Optimal voltage profile reconfiguration and integration DG units of 33-bus RDN

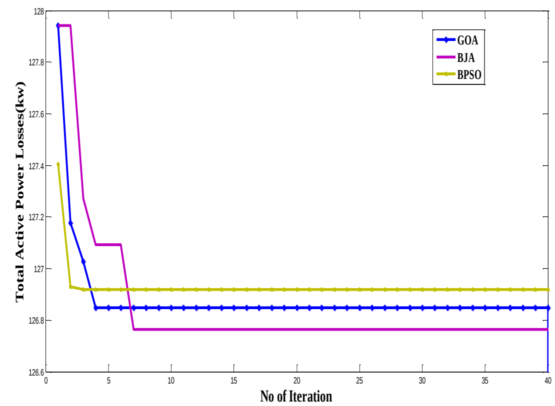

Figure . 7. Convergence characteristics of proposed methods

Table.1. Comparative analysis of reconfiguration methods for the IEEE 33-bus system

Method	GOA	BPSO	BJA	GA [23]	BPSO [23]	TLBO [26]	HAS [26]	Refined GA [27]	ANN [28]
Open Switch	7 9 14 32 37	7 9 14 32 37	7 9 14 32 37	9 28 33 34 36	7 9 14 32 37	7 9 14 28 32	7 9 14 32 37	7 9 14 32 37	7 9 14 32 37
Active Power Loss (KW)	138.93	138.93	138.93	146.4	139.22	139.98	139.6	139.5	138.9
Loss Reduction, %	31.45	31.45	31.45	27.76	31.30	30.93	31.14	3.2	31.45
Minimum Voltage (pu)	0.9432	0.9423	0.9423	0.9370	0.9378	0.941	0.938	-	0.94

6. Conclusions

1. Using the BPSO, BJA, and GOA algorithms, the research provided a methodology for optimal RDN reconfiguration in the presence of DG to improve distribution system performance, the methodology was based on decreasing active power losses and enhancing voltage quality. A conventional 33bus RDN test system was used to validate the methodology. The reconfiguration process is successfully conducted by using BPSO, BJA and GOA. The optimal reconfiguration is obtained when switches 7, 9, 14, 32, and 37 are opened. The comparative results show that the BPSO,
2. BJA and GOA provide lower active power losses and a better voltage profile compared to the other reported algorithms. The integration of DG in the test radial networks resulted in a voltage profile of the network after the integration of five DGs network reconfiguration. Reconfiguring the networks improved the situation even further. The results further indicate the superiority of BJA technology Over BPSO and GOA technology after achieving the perfect network configuration and DG unit integration by reducing active losses and improving the voltage profile, resulting in improved system performance. Continuity of work we will do Improving system performance and stability for conventional and non-conventional power sources,
3. Improving distribution network performance using reconfiguration using another optimization techniques and using renewable energy sources instead of traditional energy sources to reduce energy loss and improve the voltage profile.

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