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OPTIMAL DISTRIBUTION NETWORK RECONFIGURATION FOR LOSS MINIMIZATION AND VOLTAGE PROFILE IMPROVEMENT BASED ON ARTIFICIAL INTELLIGENCE

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ABSTRACT

Optimal reconfiguration is a significant alternative technique of increasing the efficacy of Radial Distribution Networks (RDNs). Reconfiguration is carried out by adjusting the status of RDN switches in such manner that the system's radiality is kept, energized wholly loads and other restrictions are fulfilled. The original version of the Dolphin Echolocation Optimization (DEO) algorithm is designed for solving continuous optimization issues only. As the reconfiguration problem is a discrete issue, the original DEO algorithm cannot deal with this problem. Fortunately, a Binary DEO (BDEO) algorithm was presented for solving discrete optimization issues which is utilized for adapting the reconfiguration issue. This approach is a powerful tool for rearranging systems by altering the status of the RDN switches in a way that minimizes power loss and enhances voltage profile. The BDEO algorithm is evaluated on an IEEE 33 bus RDN under three case studies in MATLAB to validate its performance. By comparing the simulation results with those from previously published work, it is possible to conclude that the suggested strategy is efficient in achieving the optimal outcome because it enhances the system voltage profile while minimizing losses. The comparison results showed that, in instance two, the BDEO for the test RDN greatly increased the minimum voltage from 0.9131 to 0.9431 P.U. and reduced the power loss by 34.2%, from 202.67 to 133.17 KW.

KEYWORDS

Binary Dolphin Echolocation Optimization (BDEO), Radial Distribution Networks (RDNs), MATLAB, Power loss, Voltage profile.

1. INTRODUCTION

1.1. Research Background

Every feeder in the distribution network has a common mix of load styles, including residential, commercial, and industrial. It has also recently grown larger and more complex, with variations in daily load, which leads to poor voltage regulation, lower power factor, higher system losses, and poor power efficiency (Chidanandappa et al., 2015, Al-Jabari et al., 2022). Because of distributed networks' radial architecture and the growing need for electricity, ensuring optimal performance has become more difficult. The surge in power consumption over the past few decades has forced distribution networks to run substantially closer to their maximum limits. During times of high demand, the Radial Distribution Network (RDN), which is distinguished by a higher resistance-to-reactance ratio in comparison to the transmission network, causes notable power losses and voltage drops (Mhawesh et al., 2020). Research indicates that approximately 10-13% of the total power generated is lost owing to distribution grid losses, resulting in increased energy expenses and an unfavorable voltage profile near the distribution line (Ng et al., 2000, Abed, 2024).

So, these losses should be minimized for enhancing the stability and efficiency of the power network, the power factor and the profile of the voltage. Therefore, improving the quality of power transfer within distribution networks has become essential (Neda, 2024). Owing to the hourly fluctuations in network loads across several feeders and the constant escalation in demand, the operation and control of distribution systems are considerably more complex, particularly in regions with elevated load densities (Jumaa et al., 2021). The literature has developed a number of solution methodologies during the last few decades, including optimal reconfiguration. So, the network reconfiguration is the most effective and economic method used for refining voltage profile and diminishing loss in power distribution system that it's not needed any operating cost (De Oliveira et al., 2014, Al-Mamoori et al., 2019). For maximizing the merits and dropping their impact on the power system, network configuration must be optimal. Thus, the optimal reconfiguration problem has become a critical and complicated problem (Mam et al., 2016).

1.2. Literature Review

Over the last 2 decades, several researchers have addressed the network reconfiguration problems utilizing various Artificial Intelligence (AI) and mathematical and heuristics optimization methods. In (Sarfi et al., 1994, Salkuti and Battu, 2021) offers a review of the latest technology in the reconfiguration for reducing network losses. These strategies can be divided into two types: (1) Mathematical and Heuristics optimization methods (Su et al., 2005, Kumar and Rudramoorthy, 2021, Nguyen et al., 2022, Fadhil et al., 2021). Use of the heuristics was motivated because of the need for reducing the issue of reconfiguration search space; (2) Meta-heuristic or Artificial Intelligence (AI) techniques (De Oliveira et al., 2014, Neda, 2020a). Earliest reconfiguration approaches are based on heuristic methodologies. Later on, a large number of optimization methods (meta-heuristic algorithms) were developed for either loss elimination or voltage profile augmentation.

In (Aman et al., 2014) utilized a Discrete Artificial Bee Colony (DABC) to evaluate the maximum load capacity through optimizing distribution grid and then utilized continuous load flow together with graph theory for calculating load flow. Particle Swarm Optimization (PSO) has also been effectively utilized to address the issue of reconfiguration for multi-objective functions (Andervazh et al., 2013). Mohamed Imran and Kowsalya have been used Fireworks Algorithm (FWA) for tackling reconfiguration of the RDN in orders to diminish power loss and improve voltage levels (Imran and Kowsalya, 2014).

Verma and Singh presented in 2018 a Modified Culture Algorithm (MCA) for tackling reconfiguration problem (Verma and Singh, 2018). This algorithm is tested on two standards RDN for diminishing actual power loss. Most of the previous work focused on solving reconfiguration problem with constant loads only and ignoring the variability of the loads and also suffer from the problem of the premature convergence which leads to poor convergence rate and its make difficult for these techniques to reach accurate solutions in short time. In addition, many of these studies using a conventional load flow algorithm which are not appropriate for solving RDN problems because of limitations in the distribution system.

1.3. Research Gap and Contributions

The reconfiguration is a discrete optimization problem while the Dolphin Echolocation Optimization (DEO) and Particle Swarm Optimization (PSO) are a continuous optimization algorithm. So, this work presents a method for modifying the original version of the PSO and DEO from continuous optimization algorithms to a Binary PSO (BPSO) and Binary DEO (BDEO) algorithms so as to solve the discrete reconfiguration problem. The BPSO and BDEO algorithms are proposed as a tool for solving reconfiguration individually. The objective function in this paper is power loss minimization and revamp the voltage. This objective can be accomplished by altering the state of the system switches optimally by using the BDEO algorithm in parallel with Forward/Backward Sweep Power Flow (FBSPF) algorithm. The presented algorithm was verified on IEEE 33 bus RDN under three loading demands (50%, 100% and 160%) utilizing MATLAB program and the outcomes obtained are compared with BPSO and other methods in the literature for assessing the ability and flexibility of the BDEO algorithm. The competitive results of the simulation highlighted that the suggested BDEO can effectively search for the best problem solutions and outperform the BPSO algorithm and other techniques in the literature.

2. METHODOLOGY

2.1. Power Flow

The performance of any optimization algorithm relies on the efficiency of the load flow algorithm. So, the advanced algorithm called Forward/Backward Sweep Power Flow (FBSPF) is being used for achieving power flow analysis in the RDN in this paper. The additional features of this algorithm include low memory requests, computational efficacy and strong convergence (Bai et al., 2024). Fig.1 shows a simple RDN with two nodes. Actual power loss ($P_{loss(K,K+1)}$) of a line linked among sending bus (K) and receiving bus $(K+1)$ can be considered by using Eq. 1 as shown below (Neda and Ma'arif, 2022) (Al-Tameemi et al., 2019):

$$P_{loss(K,K+1)} = R_K \times |I_K|^2 \tag{1}$$

where, R_K denote resistance of the branch k and I_K represent current flow in the branch k.

The total actual power loss (P_{Tloss}) in the system for a number of lines N_b is calculated by using Eq. (2) as shown below (Neda, 2022):

$$P_{Tloss} = \sum_{K=0}^{n_b} P_{loss(K,K+1)} \tag{2}$$

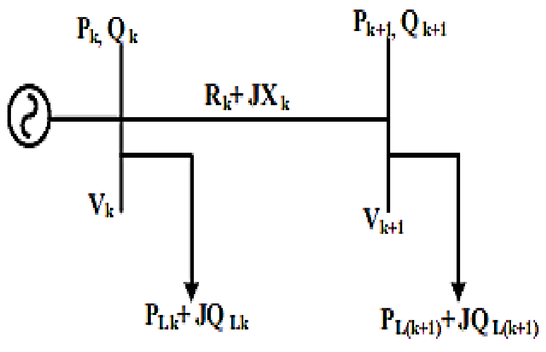


Fig. 1. Simple two buses RDN.

2.2. Objective Function

The main objective of this work's optimal reconfiguration is to identify the best RDN configuration that minimizes power loss, enhances the voltage profile, and satisfies all operating constraints. The following is a description of the primary Objective Function (O. Fun.) of this paper, which aims to minimize the overall actual power loss, along with associated mathematical calculations:

$$\mathrm{O.Fun.}(x) = \text{ Minimize } (P_{Tloss}) \tag{3}$$

$$x = [s_{w1}\ s_{w2}\ s_{w3}\ s_{w4}\ s_{w5}] \tag{4}$$

where, x is control variables which it representing the tie switches vector.

The above $\mathrm{O.Fun.}(x)$ is subjected to:

1. Operational (Equality) constrains

These restrictions contain:

- Radiality restriction:

The system must be kept in radial in nature as displayed in Eq. 5.

$$\left.\begin{array}{l}\det(A) = 1 \text{ or } -1 \text{ (Radial Network)}\\ \det(A) = 0 \text{ (Not Radial)}\end{array}\right\} \tag{5}$$

where, A is the incidence matrix of node.

- Connectivity of load restriction:

The wholly loads have to be covered and no one out of service in the distribution networks.

2. Technical (Inequality) restrictions

These constraints are:

- Voltage restriction:

The voltage in the RDN (V_K) must be kept with their operating limits i.e. minimum (V_{min}) and maximum (V_{max}) limits as demonstrate in Eq. 6. The Max. and Min. limits in this study are 0.9 and 1.05 P.U.

$$V_{min} \le V_K \le V_{max}, \tag{6}$$

- Branch current restriction:

For preventing the over load of the feeders, the current of each line ($I_{K,K+1}$) should be kept under or equal maximum limit ($I_{K,K+1,max}$) as shown in Eq. 7.

$$|I_{K,K+1}| \le |I_{K,K+1,max}| \tag{7}$$

3. BDEO ALGORITHM

In order to mimic the echo of clicks that dolphins make as they search for food and learn about their surroundings, Kaveh and Farhoudi developed a novel technique in 2013 (Neda, 2021, Neda, 2020b, Kaveh and Farhoudi, 2013). So, the DEO optimization is made based on the ability of Dolphins when hunting and catching the preys. Also, the original version of the DEO algorithm is designed for solving continuous optimization issues only and it does not aimed for solving discrete optimization issues.

To investigate the performance of recently developed meta-heuristic techniques in terms of convergence rate improvement, the optimal reconfiguration problem has been solved in this study utilizing the modified dolphin echolocation method known as BDEO (Saedi Daryan et al., 2021). For adapting the DEO algorithm to the problem of reconfiguration and also for preventing the poorer performance due to differ nature of DEO so that easily slip in the local minima, a BDEO is utilized in this work. The following are the chief stages of dolphin echolocation for discrete optimization (Daryan et al., 2019):

Step 1: Choosing the BDEO parameters for example, maximum number of iterations/loops ($\mathrm{Max.Loop.N}$), No. of Locations (NL) and Number of Variables (NV). The NV dependent on the optimization variables.

Step 2: This algorithm modifies the Convergence Factor (CF) according to a function that is established for the convergence rate. Selecting CF of the first loop (Loop_1) randomly equal to ($\mathrm{CF}_1 = 0.1$) to calculate the Predefined Possibility (PP) as:

$$\mathrm{PP} = \mathrm{CF}_1 + (1 - \mathrm{CF}_1) * \frac{\mathrm{Loop}_1}{\mathrm{Max.Loop.N}} \quad (8)$$

Step 3: Computing the Objective Function ($\mathrm{Obj.F.}$), as displayed in below:

$$\mathrm{O.Fun.} = \text{ Minimize } (\mathrm{P_{Tloss}}) \quad (9)$$

Step 4: Defining Suitability ($\mathrm{S_u}$) for each Location (L).

Step 5: Outlining bounds of factor (K) which depends on active radius ($\mathrm{R_{ac}}$) as:

$$\mathrm{K} = -\mathrm{R_{ac}} \text{ to } \mathrm{R_{ac}} \quad (10)$$

Step 6: Defining Incremental Function (IF) for each L based on K rate:

- If $|\mathrm{K}| \neq \mathrm{R_{ac}}$ then,

$$\mathrm{IF(L)} = (1/\mathrm{R_{ac}}) \times (\mathrm{R_{ac}} - |\mathrm{K}|) \times \mathrm{S_u(L)} + \mathrm{IF(L)} \quad (11)$$

- If $|\mathrm{K}| = \mathrm{R_{ac}}$ which denote the top/best L is developed then,

$$\mathrm{IF} = 0 \quad (12)$$

Step 7: Taking into account a partial value of ε to the IF of all alternatives (ideally, the value of ε is smaller than any ftting number): This is the likelihood that a choice would exist in the event that there was no chance during the random procedure.

$$\mathrm{IF} = \mathrm{IF} + \varepsilon \quad (13)$$

Step 8: Determine where this loop is most effective, then zero the IF variables at that precise location.

Step 9: Calculating Probability (P) of select IF for Variable (V) for best L as:

$$P_{Cho_V} = \frac{IF(L)_V}{\sum_{V=1}^{NV} IF(L)_V} \quad (14)$$

where, P_{Cho_V} denote selection probability.

Step 10: Distributing P_{Cho_V} in to:

$$P_{Chov} = \begin{cases} PP \ for \ better \ location \\ (1 - PP) * \ P_{Chov} \ else \end{cases} \quad (15)$$

Step 11: Calculating the following places based on the likelihood that is given to each alternative.

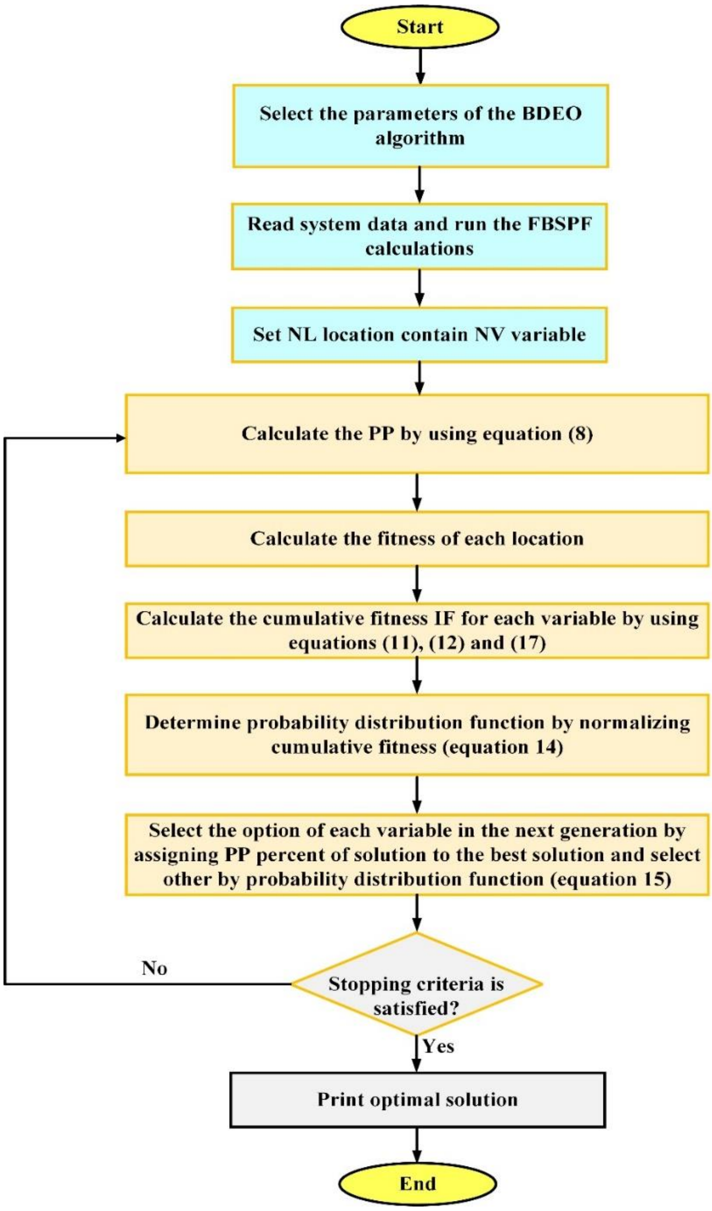
Step 12: Repeat step (2) to (10) till gotten Max. Loop/Iterations (N).

Step 13: End.

Finally, the BDEO's flowchart is shown in Fig.2 and the control parameters of the BDEO and BPSO algorithms were recorded in Table 1.

Table 1. Optimization control parameters.

BPSO	**Value**	**BDEO**	**Value**
Population No.	20	Population No.	20
and $W_{min}W_{min}$	(0.4-0.9)	CF_1	0.1
and C_2C_1	(2-2)	R_{ac}	2



Max. iterations	150	Max. iterations	501

Fig. 2. Flowchart of the BDEO technique-based reconfiguration problem.

4. RESULTS AND DISCUSSION

To validate the efficacy of the current approach to issue solving, the BDEO is applied on IEEE 33 bus RDN (Gautam et al., 2024) under three different types of load. The IEEE 33 RDN basic configuration, which is used to assess the recommended BDEO method, is shown in Fig.3.

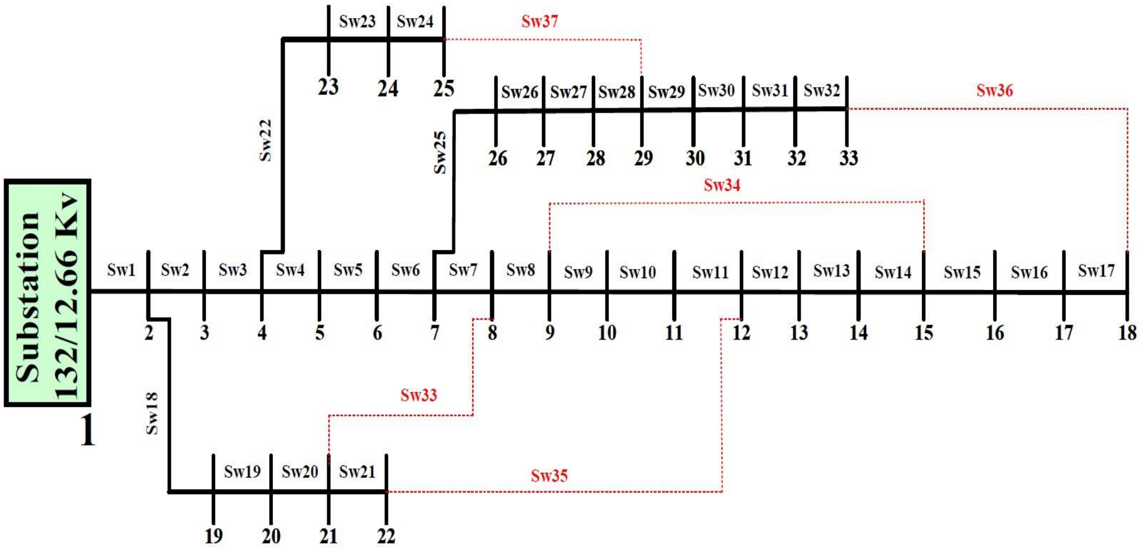


Fig. 3. IEEE 33 base reconfiguration.

The results of the BDEO are then compared to those gathered by using BPSO and other methodologies found in the literature. In reconfiguration algorithm, the BDEO algorithm was programmed by MATLAB R2013b and performed for three cases of load. This system includes 33 bus, 37 lines, 32 sectionalizing switches and five tie switches. The total actual and reactive power consumption, losses, minimum voltage as well as other parameters at base case before reconfiguration are exposed in Table 2.

Table 2. Parameters for IEEE 33 bus RDN at base case.

Parameters	Value
Total load demand (KW)	2300
Total load demand (KVAR)	3715
Total real power loss (KW)	202.67
Minimum voltage (V_{min}) in P.U.	0.9131
Voltage limit (V_{min} and V_{max})	[0.9-1.05]
Base Voltage in Kv	12.66
S Base in MVA	100
Sectionalizing Switches	[S_W 1 *to* S_W32]
Tie Switches	[S_W 33 *to* S_W37]

This study examines the superiority and resilience of the BDEO methodology when the load is changed using three load case studies. The outcomes of the BDEO are compared to those of the BPSO algorithm and other methods that have been published in the literature.

Case 1: light load (50%).

Case 2: nominal load (100%).

Case 3: heavy load (160%).

These scenarios are used to evaluate and verify the BDEO algorithm's capability, potential, and effectiveness in resolving reconfiguration problems at any load shift. The load demand at all buses is changes within the range $(\mu^{min} \leq \mu \leq \mu^{max})$ where $(\mu^{min} = 0.5)$ at light and $(\mu^{max} = 1.6)$ at heavy loads. The load is varied through multiplying μ with load at base case.

$$P_{Li} = \mu \times P_{Li0} \tag{16}$$

$$Q_{Li} = \mu \times Q_{Li0} \tag{17}$$

where, μ represent the magnitude of the load variation ratio and P_{Li0}, Q_{Li0} denote the initial powers at load nodes. After reconfiguration, the optimal configuration of the tie attained by BDEO algorithm are S_W 7, S_W 9, S_W 14, S_W 32, S_W 37 as display in Figure 4 at all three case studies.

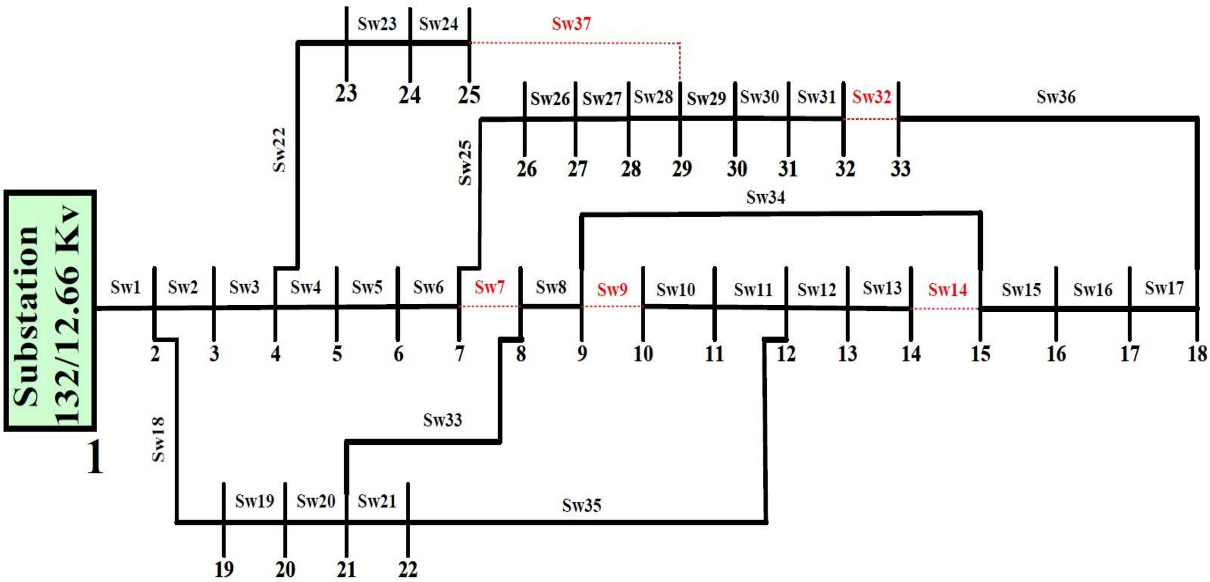


Fig. 4. IEEE 33 after reconfiguration using BDEO algorithm at all cases.

4.1. At Light Load

In this case, the BDEO can be offered for solving reconfiguration at light load. In light load, the RDN active and reactive power loads are P_L= 1.83 MW and Q_L= 1.14 MVAR, as well as, the power loss before reconfiguration P_{Tloss} = 47.06 KW and the poorest voltage V_{min} = 0.9583 P.U. at bus 18 acquired utilizing a factor of 0.5 which it's multiplied by constant actual and reactive power loads. For comparing BDEO efficiency, the results of the light load case with other algorithms, BPSO, Harmony Search Algorithm (HSA) (Rao et al., 2012), FWA (Imran et al., 2014), Sine-Cosine Algorithm (SCA) (Raut and Mishra, 2020), Salp Swarm Algorithm (SSA) (Sambaiah and Jayabarathi, 2021), Heap-Based Optimizer (HBO) (Otuo-Acheampong et al., 2023) and presented algorithm results are providing in Table 3. Clearly, from Table 3, after reconfiguration using BDEO algorithm, [S_W 7, S_W 9, S_W 14, S_W 32, S_W 37] at light load are opened and the total RDN power loss was diminished from 47.06 to 32.32 KW, whilst the structure remains radial. Also, from this table, it was obvious that BDEO achieved 34.7% power loss reduction (P_{Tloss} (%) which is more than the power loss reduction ((P_{Tloss} (%)) at BPSO that achieves only 33.09%, HSA achieves only 29.3%, FWA achieves only 29%, SCA achieves only 29.3%, SSA achieves only 29.3% and HBO achieves only 29.45%. Obviously, after reconfiguration using BDEO algorithm, Table 3 also reveals that the lowest voltage amplitude (P.U.) after reconfiguration using BDEO algorithm is boosted from 0.9583 to 0.9723 at light load. The results display that the BDEO algorithm is attain less power loss and also the lowest voltage is boost impressively in comparisons with other algorithms at light load case. So, the BDEO algorithm is superior among all rival algorithms. Figures 5 and 6 compare and illustrates the voltage profile that was attained at light load using the BPSO and BDEO algorithms, and it is clear that the voltage profile obtained with BDEO is superior to that obtained with BPSO. The results obtained indicated that BDEO is superior than BPSO and other algorithms in the literature in improving the system's voltage profile significantly.

Table 3. Outcomes after and before reconfiguration of 33−bus RDN at case 1.

Approach	Year	Open Switches	(KW)P_{Tloss}	(%)P_{Tloss}	V_{min}(p.u.)	V_{max}(p.u.)
Base case	-	33,34,35,36,37	47.06	-	0.9583	1
BDEO	2024	7,9,14,32,37	32.32	34.7%	0.9723	1
BPSO	2024	7,9,13,32,37	33.09	29.6%	0.9713	1
HSA	2013	7,9,14,32,37	33.27	29.3%	0.9698	1
FWA	2014	7,9,14,28,32	33.39	29.0%	0.9714	1
SCA	2020	37,32,9,14,7	33.26	29.3%	0.9698	1
SSA	2021	7,14,9,32,37	33.27	29.3%	0.9698	1
HBO	2023	7,9,14,32,37	33.20	29.45%	0.9719	1

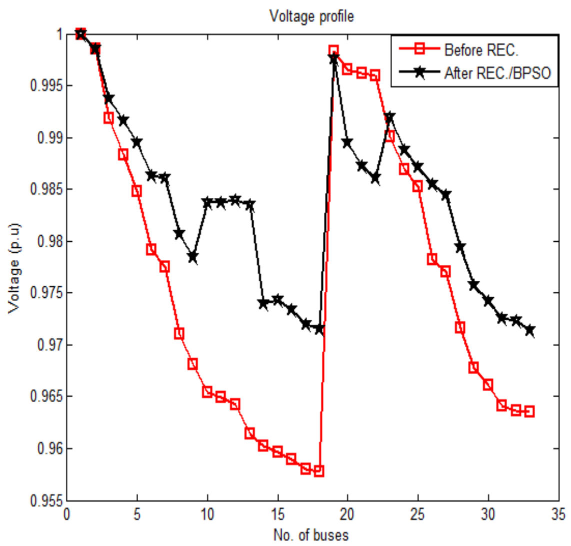


Fig. 5. Voltage profile after and before reconfiguration of 33−bus RDN using BPSO at case 1.

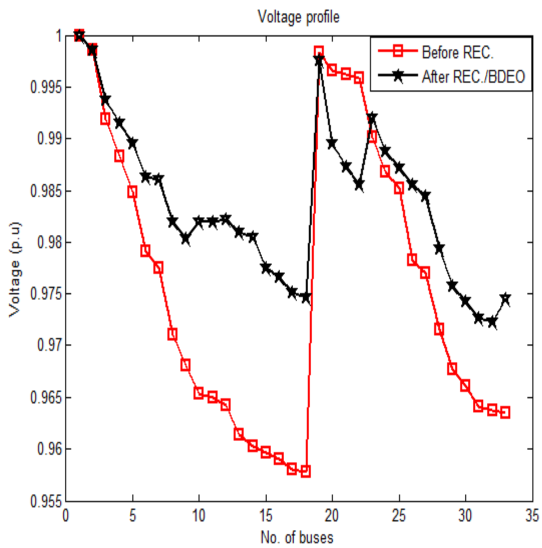


Fig. 6. Voltage profile after and before reconfiguration of 33−bus RDN using BDEO at case 1.

4.2. At Nominal Load

In this case, the BDEO can be offered for solving reconfiguration at light load. In light load, the RDN active and reactive power loads are P_L= 3.715 MW and Q_L= 2.300 MVAR, as well as, the power loss before reconfiguration P_{Tloss} = 202.67 KW and the poorest voltage V_{min} = 0.9131 P.U. at bus 18. For comparing BDEO efficiency, the results of the light load case with other algorithms, BPSO, HSA, FWA, SCA, SSA, HBO and presented algorithm results are listing in Table 4. Clearly, from Table 4, after network reconfiguration using BDEO algorithm, [S_W 7, S_W 9, S_W 14, S_W 32, S_W 37] at nominal load are opened and the entire RDN power loss was diminished from 202.67 to 133.17 KW, whilst the structure remains radial. Also, from this table, it was obvious that BDEO achieved 342% power loss reduction ((P_{Tloss} (%)) which is more than the power loss reduction (P_{Tloss} (%) at BPSO that achieves only 31.6%, HSA achieves only 31.8%, FWA achieves only 30.9%, SCA achieves only 31.14%, SSA achieves only 31.14% and HBO achieves only 31.9%. Obviously, Table 4 also reveals that the lowest voltage amplitude (P.U.) after reconfiguration using BDEO algorithm is boosted from 0.9131 to 0.9431 at nominal load. The results display that the BDEO algorithm is attain less power loss and also the lowest voltage is boost impressively in comparisons with other algorithms at light load case. So, the BDEO algorithm is superior among all rival algorithms. The attained voltage profile at nominal load after and before reconfiguration using BPSO and BDEO algorithms is compared and demonstrated in Figures 7 and 8. The results obtained indicated that BDEO is superior than BPSO and other algorithms in the literature in improving the system's voltage profile significantly.

Table 4. Outcomes after and before reconfiguration of 33−bus RDN at case 2.

Approach	Year	Open Switches	P_{Tloss} (KW)	P_{Tloss} (%)	V_{min} (P.U.)	V_{max} (P.U.)
Base case	-	33,34,35,36,37	202.67	-	0.9131	1
BDEO	2024	7,9,14,32,37	133.17	34.2%	0.9431	1
BPSO	2024	7,9,13,32,37	138.61	31.6%	0.9412	1
HSA	2013	7,9,14,32,37	138.06	31.8%	0.9342	1
FWA	2014	7,9,14,28,32	139.98	30.9%	0.9413	1
SCA	2020	7,9,14,32,37	139.55	31.14%	0.9378	1
SSA	2021	7,14,9,32,37	139.55	31.14%	0.9378	1
HBO	2023	7,9,14,32,37	138.01	31.9%	0.9423	1

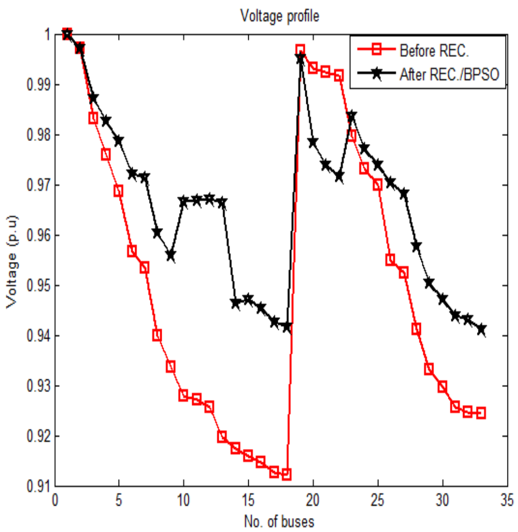


Fig. 7. Voltage profile after and before reconfiguration of 33−bus RDN using BPSO at case 2.

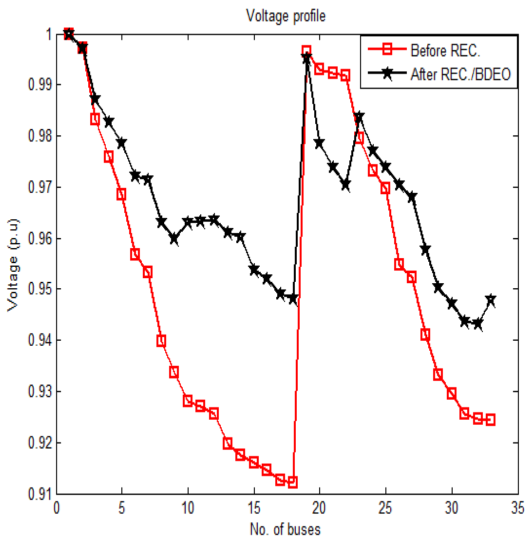


Fig. 8. Voltage profile after and before reconfiguration of 33−bus RDN using BDEO at case 2.

4.3. At Heavy Load

In the last case, BDEO can be offered for solving reconfiguration at light load. In light load, the RDN active and reactive power loads are P_L= 5.87 MW and Q_L= 3.63 MVAR, as well as, the power loss before reconfiguration P_{Tloss} = 575.31 KW and the poorest voltage V_{min} = 0.8529 P.U. at bus 18 acquired utilizing a factor of 1.6 which it's multiplied by constant actual and reactive power loads. For comparing BDEO efficiency, the results of the heavy load case with other algorithms, BPSO, HSA, FWA, SCA, SSA, HBO and presented algorithm results are providing in Table 5. Clearly, from Table 5, after reconfiguration using BDEO algorithm, [S_W 7, S_W 9, S_W 14, S_W 32, S_W 37] at heavy load are opened and the total RDN power loss was diminished from 575.31 to 353.79 KW, whilst the structure remains radial. Also, from this table, it was obvious that BDEO achieved 38.5% power loss reduction ((P_{Tloss} (%)) which is more than the power loss reduction (P_{Tloss} (%) at BPSO that achieves only 34.2%, HSA achieves only 33.8%, FWA achieves only 33.7%, SCA achieves only 33.87%, SSA achieves only 33.47% and HBO achieves only 38.31%. Obviously after DNR using BDEO algorithm, Table 5 also reveals that the lowest voltage amplitude (P.U.) after reconfiguration using BDEO algorithm is boosted from 0.8529 to 0.9158 at heavy load. The results display that the BDEO algorithm is attain less power loss and also the lowest voltage is boost impressively in comparisons with other algorithms at light load case. So, the BDEO algorithm is superior among all rival algorithms. The voltage profile achieved at heavy load using the BPSO and BDEO algorithms is compared and illustrated in Figures 9 and 10, where it is evident that the voltage profile obtained with BDEO is better than that obtained with BPSO. The results obtained indicated that BDEO is superior than BPSO and other algorithms in the literature in improving the system's voltage profile significantly.

Table 5. Outcomes after and before reconfiguration of 33−bus RDN at case 3.

Approach	Year	Open Switches	P_{Tloss} (KW)	P_{Tloss} (%)	V_{min}(p.u.)	V_{max}(p.u.)
Base case	-	33,34,35,36,37	575.31	-	0.8529	1
BDEO	2024	7,9,14,32,37	353.79	38.5%	0.9158	1
BPSO	2024	12,17,20,28,35	378.24	34.2%	0.8820	1
HSA	2013	7,9,14,32,37	380.43	33.8%	0.8697	1
FWA	2014	7,9,13,28,32	381.24	33.7%	0.9027	1
SCA	2020	7,9,14,32,37	380.44	33.87%	0.8967	1
SSA	2021	7,14,9,32,37	380.45	33.47%	0.8967	1
HBO	2023	2,10,12,28,31	354.9	38.31%	0.9115	1

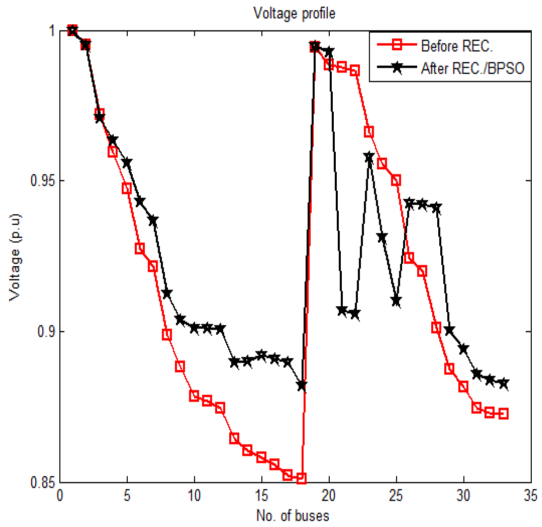


Fig. 9. Voltage profile after and before reconfiguration of 33−bus RDN using BPSO at case 3.

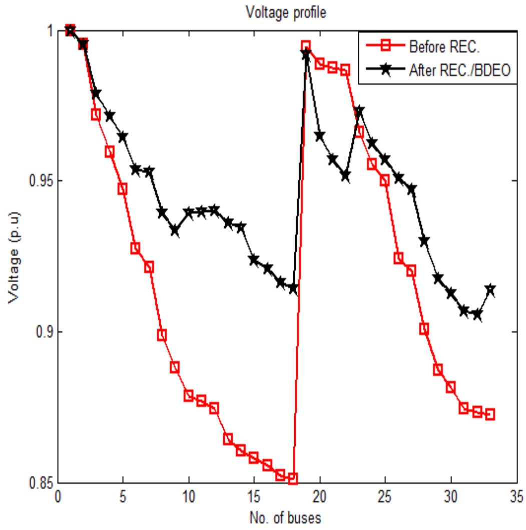


Fig. 10. Voltage profile after and before reconfiguration of 33−bus RDN using BDEO at case 3.

5. CONCLUSION

This article describes how the BDEO method was effectively applied as an optimization tool on the medium-scale RDN to address the reconfiguration issue. By utilizing the dependable BDEO algorithm to reduce power loss and improve voltage profile, an optimal RDN configuration may be obtained by varying the on/off states of the switches while still adhering to all operating restrictions. The supremacy of the presented algorithm is achieved by testing on IEEE 33 bus RDN at three loading conditions. Additionally, a comparison was made between the overall outcomes of the given BDEO algorithm and the outcomes of BPSO and other techniques that were found in the literature. The comparison results clearly demonstrate that the BDEO is a superior tool for attaining a minimum power system loss and enhancing the voltage profile when compared to the BPSO, HSA, FWA, SCA, SSA, and HBO algorithms at all case studies.

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