OPTIMAL FEEDER RECONFIGURATION OF RADIAL DISTRIBUTION SYSTEMS USING IMPROVED PARTICLE SWARM OPTIMISATION

R. Karthikeyan

Lecturer (Assistant Professor, Deputated from Annamalai University)

Department of Electrical and Electronics Engineering,

Alagappa Polytechnic College, Karaikudi, India.

ABSTRACT

The optimum feeder reconfiguration issue in a radial power distribution system is addressed in this research using a unique approach guided by an improved particle swarm optimisation algorithm. The financial component of an electrical power system is often determined mainly by the losses in the conductor lines. The improved particle swarm optimisation technique is used to reduce network active power loss in radial power distribution systems, which is the focus of the proposed research in this section. System power loss is included in the calculation as a cost function for each particle in the swarm. The MATLAB software is used to investigate the proposed approach for the radial distribution system. A significant level of system loss reduction and an appealing bus voltage profile can be shown in the case studies compared to earlier methodologies, such as genetic algorithm and particle swarm optimisation.

Keywords: Feeder reconfiguration, Improved particle swarm optimisation, Power loss, Radial power distribution system.

1. INTRODUCTION

Transmission and distribution systems distribute the electricity produced at the power plant to the different loads they serve [1]–[3]. As a result of the small amount of energy loss that occurs during the transmission of electrical power to end consumers, the electrical power generated at producing stations does not match the load consumed by customers. Transmission and distribution line losses account for most of an electric grid's total energy loss. Complex form $I^2*(R+jX)$ represents the apparent power loss in an AC transmission and distribution line [2], [3]. The RDS has a high resistance-to-reactance (R/X) ratio, making actual power loss the principal cause of perceived power loss in an AC distribution line. The resistive loss in an AC system is similar to active power loss since it is an active part of the AC distribution line impedance. The AC distribution system's power line resistive loss reduction is critical to the system's efficient operation and long-term planning. Thus, the study aims to decrease RDS's actual power loss [3].

Feeder reconfiguration is a method for reducing the actual power loss in the power distribution network [4]. In several countries, feeder reconfiguration in the RDS is on the rise. The radial power distribution network's feeder reconfiguration is a complex engineering challenge that aims to find the ideal radial architecture that decreases line losses while fulfilling system criteria. Changing the switch position of the tie lines is used to reconfigure a system structure, either by opening or shutting them. An RDS has a wide variety of tie-line switching combinations, making it difficult to choose the ideal feeding arrangement. The loss reduction issue in an electrical power network is often one of the most crucial and hardest to address. Optimal feeder reconfiguration may minimise power loss in the AC distribution network due to this suggested research [5]. Optimal feeder reconfiguration may lower the system loss since the active power loss is directly proportional to the actual component of the line current [3].

RDS optimisation has been more popular in recent years due to its installation simplicity and improved network performance [6]. Given the numerous advantages of redesigned radial power distribution networks, the use of naturally propelled artificial algorithms to optimise feeder configurations in distribution systems has emerged as a more energising and popular trend in radial distribution network optimisation and improvement. Rajaram and co-authors proposed a feeder reconfiguration to reduce active power loss in the distribution network using a mix of optimisation and heuristic techniques [3]. An autonomous switch position shows effectiveness for the best possible feeder design. To ensure that the planned reconfiguration is dependable, secure, and capable of meeting the load requirement, different customers' load profile is considered during the feeder reconfiguration planning phase. In order to limit distribution line losses and strains on the feeder section, the tie lines switch should be configured optimally. The quality of the system's voltage may also be improved by rearranging the feeders.

It is possible to decrease system power losses by determining the optimal feeder reconfiguration in radial distribution networks using heuristic approaches [3]–[6]. In [3], a method was proposed to retain the radial structure of the distribution system by balancing the closure of a tie line switch with the opening of an analogous tie line switch. Even while this method works well for small RDS, the computations needed to fix the feeder reconfiguration issue make it inefficient for larger power distribution systems. According to [7], an optimisation model for the feeder design issue is used to estimate conductor loss as a piecewise linear function. Using this method, even very tiny power distribution networks may quickly and efficiently converge. When solved using this technique, large-scale distribution systems with more than 1000 nodes might result in unreasonably tough computing challenges for live execution.

The poorly meshed RDS has been modelled using a compensation-based load flow approach [8]. However, compensation-based reconfiguration is only successful for single-phase systems and is inappropriate for complex multi-phase systems. It also has the drawback of requiring more time to find the optimal configuration. Distribution network losses may be reduced using genetic algorithms (GA) that apply optimum network reconfiguration [9]. GA-based optimum feeder reconfiguration in RDS offers several advantages over traditional techniques. It addresses the most critical issue restrictions, such as voltage limits, security and generation limitations. These genes reflect the open state of the RDS line switch, the fitness function consisting of RDS line loss, and weighted parameters for bus voltage limitations and line thermal limits in the chromosomes. According to test results, even though the 97-bus RDS lost less than fifteen minutes, the calculation time was still relatively high.

To find an acceptable non-substandard optimum outcome for feeder reconfiguration, several studies proposed using the SA, GA and ant colony search (ACS) algorithms [10]. When it comes to solving dimensional optimisation issues, although technically sound, the approach takes an unusually long time. The distribution feeder reconfiguration was made more efficient using heuristic principles and a fuzzy multi-objective method. Four multi-objective considerations were considered in this technique, including balancing feeders, distribution line loss, bus voltage profile, and thermal restrictions. Even if the simulation's results are encouraging, there is not enough information provided to make an informed decision on which membership function to use for the goals. Because they only need a modest amount of computing to achieve optimum solutions for small distribution networks, the approaches listed above are often used even though they do not have better convergence characteristics. In order to handle the feeder reconfiguration difficulties in more extensive distribution networks, these solutions need enormous amounts of processing time. They are thus not suitable for online or real-time applications.

The differential evolution method has been used to discover the best network reconfiguration for reducing power loss and balancing demand in the power distribution system. Power losses, node voltage variation, and line current restrictions were all considered in this technique. A single optimisation problem with weighted parameters included these several goals, and the tie line switch location was optimised using the reconfiguration with the lowest fitness function. To find the best possible feeder reconfiguration, a multi-objective particle swarm optimisation (MPSO) approach has been developed to minimise system losses, tie line switch locations, and node voltage variation [11]. Stochastic heuristics and graph theory approaches are used to improve the probabilistic random search of the self-tuning procedure during the minimisation stage. It is now possible to find the optimal distribution system reconfiguration and DG in a power system with active power loss reduction as the cost function.

Artificial intelligence (AI) algorithms have been used to handle a number of power system optimisation challenges during the last two decades [12]. Using AI approaches, RDS active power loss may be reduced by implementing optimum feeder reconfiguration [12], [13]. Real power loss reduction was explored as an objective function for reconfiguring the large-scale RDS using an enhanced tabu search algorithm (TSA) [14]. Reconfiguring radial networks using the ACO approach aims to reduce power losses [10]. In order to decrease network loss and improve bus voltage quality, a unique two-stage approach based on fuzzy logic and harmony search algorithm (HSA) was suggested for the optimum placement of capacitors in RDS with a fitness function [15]. In this study, the author used particle swarm optimisation and weight improved particle swarm optimisation to determine where the best DGs should go and how much power they should be rated. The minimisation problem also considers power balance constraints, DG generation limits, and node voltage limits. The PSO and its variant algorithms have been shown to offer more significant loss reduction and faster convergence qualities for optimal feeder reconfiguration in power distribution systems [16]. There has been much interest in PSO owing to its effectiveness and simplicity. Many academics have turned to the PSO algorithm to tackle technical challenges and a variety of power system issues, which takes inspiration from natural phenomena such as flocks of birds and schools of fish. PSO's various benefits and utility in tackling engineering optimisation issues have been shown in several studies.

Using an improved version of the PSO algorithm called improved particle swarm optimisation (IPSO) [17] and considering the benefits of feeder reconfiguration in distribution systems as well as the application of intelligent PSO technique in engineering optimisation, this paper aims to find the most desirable feeder reconfiguration in 33-bus and 69-bus power distribution systems. By combining their discovery and development talents without demanding additional obligations while calculating fitness functions, the IPSO is a specific form of the PSO method. The proposed IPSO technique based feeder reconfiguration is formulated for the real power loss minimization problem in the power distribution system, and the obtained results are compared to that of the GA and PSO algorithms, providing valuable conclusions about the effectiveness and efficiency of the proposed improved method. The remainder the paper is organised as, section 2 provides an overview of the feeder reconfiguration problem and its mathematical formulation. In contrast, Section 3 describes the standard PSO, the proposed IPSO, and algorithmic steps to find the optimal feeder reconfiguration in radial power distribution systems. Section 4 includes simulation studies. Section 5 concludes the discussion.

2. PROBLEM FORMULATION

The optimum feeder reconfiguration is shown to decrease the active power loss of an RDS sufficiently. Along these lines, the goal of this study is to minimise the active power loss of the distribution system, which is given as,

$$\text{Minimize} P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} \left[\alpha_{ij}\left(P_i P_j + Q_i Q_j\right) + \beta_{ij}\left(Q_i P_j - P_i Q_j\right)\right] \tag{1}$$

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j}\cos\left(\delta_i - \delta_j\right) \tag{2}$$

$$\beta_{ij} = \frac{r_{ij}}{V_i V_j}\sin\left(\delta_i - \delta_j\right) \tag{3}$$

$$Z_{ij} = r_{ij} + jx_{ij} \tag{4}$$

where, the resistance and reactance of the power line connecting nodes i and j, are represented by the variables r_{ij} and x_{ij}, respectively; the impendence of the power line connecting nodes i and j is represented by Z_{ij}; the magnitude and angle of the bus voltage at node i is V_i & δ_i, respectively; the magnitude and angle of the bus voltage at node j is V_j & δ_j, respectively; the real and reactive power injected at node i is P_j & Q_j, respectively; and the number of nodes in the RDS is n.

2.1 Real and reactive power balance

$$P_i = \sum_{j=1}^{n} V_i V_j \left[G_{ij} \cos\left(\delta_i - \delta_j\right) + B_{ij} \sin\left(\delta_i - \delta_j\right) \right] \quad (5)$$

$$Q_i = \sum_{j=1}^{n} V_i V_j \left[G_{ij} \sin\left(\delta_i - \delta_j\right) - B_{ij} \cos\left(\delta_i - \delta_j\right) \right] \quad (6)$$

where, the conductance and susceptibility of the power line between nodes i and j are referred to as G_{ij} and B_{ij}, respectively.

2.2 Bus voltage limits

$$V_{i\min} \le V_i \le V_{i\max} \quad (7)$$

where V_{imin} & V_{imax} are the bus i's minimum & maximum voltage limitations, respectively.

3. PROPOSED APPROACH FOR FEEDER RECONFIGURATION

This section introduces a new method for finding the best RDS feeder setup. To reduce radial power system losses, this method makes use of IPSO, a newly developed typically invigorated optimisation algorithm, to determine the most optimal feeder arrangement. For the feeder reconfiguration of the radial power system, a backwards-forward sweep power flow computation was utilised to predict line power flows and bus voltage. The successive parts illustrate the IPSO's genesis and algorithmic stages for active power loss reduction in radial power systems equipped with optimum feeder reconfiguration.

3.1 Improved Particle Swarm Optimization Algorithm

Individuals in flocking or schooling behaviours, such as birds or fish, provide the inspiration for the PSO algorithm. In 1995, Eberhart and Kennedy devised the PSO method for solving optimisation issues [18].

The PSO method uses a swarm of particles to search for a globally optimal solution to a given N-dimensional issue. The location and velocity of each particle or person in a swarm are distinct. It is possible to describe the location and velocity of a particle as a possible solution to the issue and its next iteration's step length in mathematics. The i^{th} particle's location and velocity are indicated as xi = [xi1, xi2, …, xiN] and vi = [vi1, vi2, …, viN] for an N-dimensional mathematical problem with 'm' particles. The i^{th} particle's best location relative to previous iterations is recorded as the local best solution and indicated by the expression $p_i = [p_{i1}, p_{i2}, \ldots, p_{iN}]$ after each iteration. In a population, the best overall position is called the global best position $p_g = [p_{g1}, p_{g2}, \ldots, p_{gN}]$. For the following iteration, the i^{th} particle's velocity and position updates may be estimated by utilising the particle's current velocity and distance from the local best position to the global best position.

$$v_{id}^{t+1} = \omega . v_{id}^{t} + \varphi_1 (p_{gd} - x_{id}^{t}) + \varphi_2 (p_{id} - x_{id}^{t}) \quad (8)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad (9)$$

where, t is the iteration index; d is the dimension index; ω is the inertia weight; $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$; c_1 is the social acceleration coefficient, c_2 is the cognitive acceleration coefficient; both r_1 and r_2 are random values that are evenly distributed between 0 and 1.

Using PSO factors such as inertia weight, social and cognitive agents, and others, the IPSO method was created [17]. Both local and global solutions are enhanced by this updated version of the PSO algorithm, which converges in the shortest time for global optimum solutions. The following equations may be used to get the values of the parameters c1 and c2 in the below equations.

$$\omega_1 = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \times t \quad (10)$$

$$\omega = \omega_{\min} + \omega_1 \times r_3 \quad (11)$$

$$c_1 = c_{1\max} - \frac{c_{1\max} - c_{1\min}}{t_{\max}} \times t, \quad (12)$$

$$c_2 = c_{2\max} - \frac{c_{2\max} - c_{2\min}}{t_{\max}} \times t, \quad (13)$$

where, minimal and maximum weights are represented by the $\omega_{\min}$ and $\omega_{\max}$; c_{1min} and c_{1max} represent the corresponding minimum and maximum social weights. The maximum iteration number is denoted by t_{max}, and r_3 is a uniformly distributed random number.

The goal of this study is to find the best RDS feeder arrangement with the help of IPSO. The detailed instructions for implementing the suggested approach may be found in the next section.

3.2 Implementation

The algorithmic steps to find the optimal feeder reconfiguration in the distribution system are detailed in this section. Give 'm' be the population size and 'N' be the number of variables in an optimisation problem. For optimal feeder reconfiguration, the number of open switches in a radial system is 'N'.

The described here are the algorithmic procedures for discovering the best distribution system feeder reconfiguration. Suppose the population size is m and the number of variables in the optimisation problem is N. In that case, the problem has m variables. N is the number of open switches required for a radial system's best possible feeder reconfiguration.

Step 1: Analyse the RDS load and line data.

Step 2: Set the iteration index to 1 and suitable values for the IPSO coefficients.

Step 3: In the vector $x_i = [x_{i1}, x_{i2},\ldots., x_{iN}]$, i = 1 to m, randomly arrange a feasible solution for all of the 'm' particles, where x_{i1} to x_{iN} represent the open switch position of feeder lines on the intermediate [2, n].

Step 4: Turn on the power distribution system's switch position x_i for particle i.

Step 5: Calculate the line power flows, node voltage, and active power loss using Eq. (1) for particle i, a radial distribution with an open switch position. The i^{th} particle's fitness value should be based on the computed active power loss. For every one of those particles, repeat step 4.

Step 6: Determine the i^{th} particle's local optimal p_i and the global optimal position p_g among all particles based on the least cost function.

Step 7: Using Eq. (10) to Eq. (13), change the IPSO weight and social parameters.

Step 8: Using Eq. (8) and Eq. (9) independently, update the particle's velocity and location.

Step 9: As in step 3, if any particles break the requirements, assign the random solution for the violated position randomly; otherwise, go to Step 10. Verify that the revised particle's location satisfies the system constraints Eq. (5) to Eq. (7).

Step 10: Whether or not all of the necessary requirements are satisfied, i.e., is t equal to t_{max} or not? The load flow solutions are reached; if not, increase the number of iterations and go to step 4 as necessary.

The IEEE-33 bus RDS is studied, and the findings are described in the next part to illustrate the proposed work's skill and competence.

4. SIMULATION RESULTS

IEEE-33 bus RDS has tested the approach, and the results have been compared to those of other methods like GA, PSO, and PIPSO. The proposed IPSO algorithm is applied to the 33-bus IEEE RDS test network, with a total active power load of 3.72 MW and 2.3 MVAR of reactive power.

Parameters used in simulation studies include ten numbers of population, 100 iterations, the inertia weight ω is chosen at random from a range of 0.4 to 0.9, it is possible to have two social agents, one with c1 = 2 and the other with c2 = 2.

4.1 33-Bus Distribution System

The suggested technique is tested and analysed to determine the optimal feeder reconfiguration using a 33-bus radial distribution network and the algorithm described in the previous section. Table 1 displays the MATLAB software's simulation results. The provided solution clearly outperforms earlier techniques when it comes to active power loss reduction, voltage profile improvement, and simulation time. Fig. 1 depicts the bus voltage correlation between the radial distribution network with and without feeder reconfiguration. As shown in Fig. 2, the suggested IPSO may achieve convergence in a 33-bus radial distribution network.

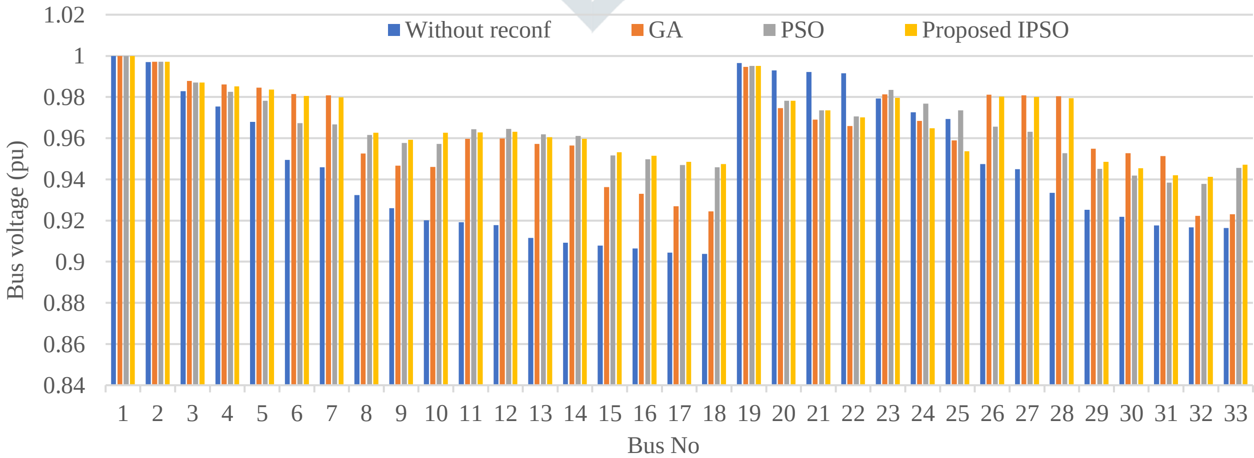

Fig.1 Comparison of bus voltage after reconfiguration using GA, PSO and the proposed IPSO algorithms

Table 1. Comparison result - GA, PSO and the proposed IPSO algorithms

Algorithm	Switch - open state	Real loss (kW)	Reduction in real loss (%)	Reactive loss (kVAR)	Reduction in reactive loss (%)	Simulation time (s)
GA	7,10,14,28,31	145.69	30.95	115.25	19.48	5.67
PSO	7,10,14,32,37	140.28	33.51	102.93	28.09	4.96
IPSO	7,9,14,28,32	139.98	33.65	104.98	26.65	4.72
Base case	33,34,35,36,37	210.99	-	143.13	-	-

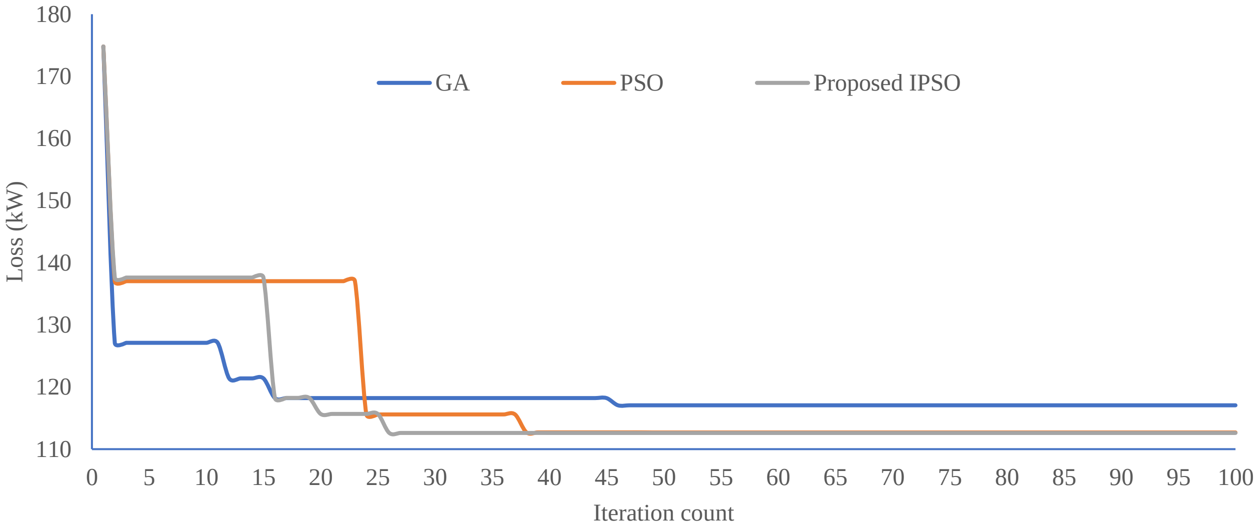

Fig. 2 Convergence characteristics of GA, PSO and the proposed IPSO algorithms

In the IPSO technique, there has been an increase in local and global positions after each cycle. In this way, the proposed method takes an exceptionally least number of iterations counts to achieve the optimal feeder reconfiguration in 33-bus distribution systems. Furthermore, from Table 1, it is evident that the IPSO strategy's calculation time is substantially quicker than that of the current approaches, such as GA and PSO. Comparing the suggested IPSO methodology to currently used techniques, the actual power loss for the 33-bus test system is also decreased substantially. The suggested IPSO approach additionally improves the system's bus voltage profile.

5. CONCLUSION

Using IPSO as a guide, a method has been presented for figuring out the best way to reconfigure IEEE radial power distribution systems with 33-bus feeders. The MATLAB software was used to create and test the m-script. According to the case study, the new technique has been the most effective in increasing node voltage and reducing active power loss. The IPSO algorithm has been shown to have superior quality and benefits over earlier existing computations, such as GA and PSO in terms of active power loss reduction, voltage improvement, and computing time. A larger power distribution network may be scanned for optimal feeder reconfigurations using this approach. It is also possible to combine the location of the DG and feeder reconfiguration with this strategy to get an even higher loss reduction.

REFERENCES

[1] R. Bhoyar and S. Bharatkar, "Potential of MicroSources, Renewable Energy sources and Application of Microgrids in Rural areas of Maharashtra State India," *Energy Procedia*, vol. 14, pp. 2012–2018, Jan. 2012, doi: 10.1016/j.egypro.2011.12.1202.

[2] V. V. Murty and A. Kumar, "Optimal placement of DG in radial distribution systems based on new voltage stability index under load growth," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 246–256, 2015.

[3] R. Rajaram, K. Sathish Kumar, and N. Rajasekar, "Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with Distributed Generation (DG)," *Energy Rep.*, vol. 1, pp. 116–122, Nov. 2015, doi: 10.1016/j.egyr.2015.03.002.

[4] C.-T. Su and C.-S. Lee, "Feeder reconfiguration and capacitor setting for loss reduction of distribution systems," *Electr. Power Syst. Res.*, vol. 58, no. 2, pp. 97–102, 2001.

[5] B. Esmailnezhad and H. Shayeghi, "Simultaneous Distribution Network Reconfiguration and DG allocation for loss reduction by Invasive Weed Optimization algorithm," in *2013 Smart Grid Conference (SGC)*, 2013, pp. 166–172.

[6] J. Zhu, *Optimization of Power System Operation*. John Wiley & Sons, 2009.

[7] E. R. Ramos, J. Martinez-Ramos, A. G. Expósito, and A. U. Salado, "Optimal reconfiguration of distribution networks for power loss reduction," in *2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502)*, 2001, vol. 3, pp. 5-pp.

[8] K. Nagaraju, S. Sivanagaraju, T. Ramana, and P. Prasad, "A novel load flow method for radial distribution systems for realistic loads," *Electr. Power Compon. Syst.*, vol. 39, no. 2, pp. 128–141, 2011.

[9] M. Abdelaziz, “Distribution network reconfiguration using a genetic algorithm with varying population size,” *Electr. Power Syst. Res.*, vol. 142, pp. 9–11, 2017.
[10] C.-T. Su, C.-F. Chang, and J.-P. Chiou, “Distribution network reconfiguration for loss reduction by ant colony search algorithm,” *Electr. Power Syst. Res.*, vol. 75, no. 2–3, pp. 190–199, 2005.
[11] M.-R. Andervazh, J. Olamaei, and M.-R. Haghifam, “Adaptive multi-objective distribution network reconfiguration using multi-objective discrete particles swarm optimisation algorithm and graph theory,” *IET Gener. Transm. Distrib.*, vol. 7, no. 12, pp. 1367–1382, 2013.
[12] K.-H. Jung, H. Kim, and Y. Ko, “Network reconfiguration algorithm for automated distribution systems based on artificial intelligence approach,” *IEEE Trans. Power Deliv.*, vol. 8, no. 4, pp. 1933–1941, 1993.
[13] R. Qiu, X. Lv, and S. Chen, “A survey on artificial intelligence algorithm for distribution network reconfiguration,” in *Robotic Welding, Intelligence and Automation*, Springer, 2011, pp. 497–504.
[14] A. Y. Abdelaziz, F. Mohamed, S. Mekhamer, and M. Badr, “Distribution system reconfiguration using a modified Tabu Search algorithm,” *Electr. Power Syst. Res.*, vol. 80, no. 8, pp. 943–953, 2010.
[15] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. Rao, “Optimal network reconfiguration of large-scale distribution system using harmony search algorithm,” *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1080–1088, 2010.
[16] X. Jin, J. Zhao, Y. Sun, K. Li, and B. Zhang, “Distribution network reconfiguration for load balancing using binary particle swarm optimization,” in *2004 International Conference on Power System Technology, 2004. PowerCon 2004.*, 2004, vol. 1, pp. 507–510.
[17] T. Niknam, M. Narimani, J. Aghaei, and R. Azizipanah-Abarghooee, “Improved particle swarm optimisation for multi-objective optimal power flow considering the cost, loss, emission and voltage stability index,” *IET Gener. Transm. Distrib.*, vol. 6, no. 6, pp. 515–527, 2012.
[18] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95 - International Conference on Neural Networks*, Nov. 1995, vol. 4, pp. 1942–1948 vol.4. doi: 10.1109/ICNN.1995.488968.