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Optimal Reconfiguration of Power Distribution Network Using Hybrid Firefly and Particle Swarm Optimization Algorithm

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***Abstract*- Electrical energy has become the most essential requirement for working of today's modern world. Power distribution networks (PDN) are required for providing power from distribution substations to consumers but are subjected to power loss and voltage drop problems. These problems greatly affect the operational cost and voltage stability level of a PDN. Network reconfiguration (NR) is a cost effective approach to optimize PDN for reduction of power loss and improvement of voltage profile (VP). This paper presents an effective meta-heuristic, population-based algorithm for finding optimal configuration of a PDN. In particular Hybrid Firefly and Particle Swarm Optimization (HFPSO) algorithm is used. The HFPSO algorithm has enhanced exploration and exploitation strategies, and fast convergence rate. MATLAB software is used to implement the algorithm and IEEE 33-bus radial distribution system (RDS) is considered for NR. The results obtained show that active power loss is reduced by 46.35% from original value of power loss and minimum voltage is improved to 0.9572p.u. The comparison of obtained results with literature show that HFPSO algorithm has efficiently reduced active power loss and improved VP of the network.**

***Index Terms*-- Hybrid firefly and particle swarm optimization, Network reconfiguration, Power distribution network, Voltage profile.**

I. INTRODUCTION

PDN is an essential component of electrical power system which provides power from substations to final consumers [1]. There are several problems associated with these networks, such as power loss and voltage drop. The main reason for these problems are the resistance and reactance current present in feeders which are greatly affected by configuration of PDN [2]. Therefore, configuration of PDN is very important for optimal planning of power system. Poor configuration results in high power loss, poor VP and low power factor [3]. These problems leads to extra charges for power distribution companies. To reduce these losses, various methods are used, such as incorporating distributed generation (DG), installation of capacitor banks, network voltage raising and distribution system network reconfiguration [4]. Among these techniques, NR requires least investment as it utilizes the resources already available in the distribution network [5].

The NR is processed by changing the status (close/open) of tie-lines and sectionalizers present in PDN [5] while meeting the network constraints which includes limits of bus voltages, and line currents [6]. Sectionalizers are normally closed and tie-lines are normally open. Objective function determines the configuration of these lines [7]. Hence, to employ an efficient algorithm for NR is necessary. The main aim of NR is reduction of active power loss (APL) to improve system performance [7, 8]. Other objectives includes improving VP, reducing equipment overload and balancing the load between feeders. However, minimizing losses will lead to achievement of other objectives as well.

Merlin and Back proposed the first NR problem in 1975 and determined the optimal solution for minimum power loss [9]. In last two decades, through the advancement in computer sciences, researchers have developed several techniques for optimization of PDNs through NR which can be categorized to analytical, meta-heuristic and artificial intelligence (AI) techniques [10]. The analytical techniques have high computational efficiency but they cannot deal with multi-objectives. Analytical techniques are usually applied for NR having unique switching approaches such as interchange switch strategy [11]; close-all switch strategy [12], open-all switch strategy [13]; and sensitivities computation method [14]. Meta-heuristic and AI techniques have less computational efficiency than analytical techniques [15]. These are population based stochastic methods that do not require objective function to be continuous and convex and thus can efficiently handle the constrained optimization problems [16]. Various meta-heuristic techniques for NR namely Genetic algorithm (GA) considering power loss [17-19], harmony search algorithm (HSA) [20], cuckoo search algorithm (CSA) [21], self-adaptive differential evolutionary algorithm (SADE) [22], stochastic fractal search algorithm (SFSA) [23], fireworks algorithm (FWA) [24], grey wolf optimization [25], particle swarm optimization (PSO) [26-28], firefly algorithm (FA) [29], and improved adaptive imperialist competitive algorithm (IAICA) [30], evolutionary algorithm [31] are present in literature. So far, these have been the most popular and effective techniques to solve the problems related to optimization of power distribution systems generally and NR problem particularly. However, these approaches are more likely to converge on local optima. As a result, main goal of researchers is to solve the problem of local convergence of meta-heuristic approaches. For global optimization, some of these methods do not generate effective results. Such population-based algorithms are useful for local optimal solution. However the trajectory techniques are good at finding global optimal solution. So, advantages of both techniques can be utilized by combining these methods [32]. The main goals of hybridization of PSO algorithm are to balance the exploitation and exploration rates [33]. In comparison with PSO, FA does not have local best variable and thus it is free from problem of local convergence [34]. Furthermore, FA does not have velocity vector, so it is also free from the problems of velocity variations [35]. Hybrid Firefly and Particle Swarm Optimization (HFPSO) algorithm is one of the most recent hybrid meta-heuristic technique [36], which have been used to solve some engineering problems and the results showed that HFPSO algorithm has the ability to produce successful results that were never seen earlier [36].

The application of HFPSO algorithm to NR problem has never been studied previously and using a powerful optimization algorithm can effectively solve NR problem. This paper presents HFPSO to solve NR problem in the field of Electrical Power Engineering. Following are the main contributions of this paper:

1) HFPSO algorithm is used in this paper to solve the problem of NR.
2) The algorithm is applied for reducing power loss and improving VP of standard IEEE 33-bus RDS.
3) Comparison between the findings and results of other simulations using different algorithms found in literature.
4) It is noted from statistical analysis that reliability of HFPSO algorithm is very high for solving NR problem.

The structure of the paper is as follows: Mathematical problem formulation is presented in section 2. A brief overview of FA, PSO and HFPSO algorithms, respectively is presented in section 3. Section 4 describes the implementation of HFPSO to NR problem. Results and comparison of different algorithms are explained in Section 5. Section 6 briefly concludes the article.

II. PROBLEM FORMULATION

The main objective is to find the optimal configuration of RDS. Since many switching combinations are possible, finding the optimal combination is a complex constrained optimization problem. To minimize active power loss (APL), reactive power loss (RPL) and deviation of voltage from the standard value 1p.u. are the three main objectives considered. So if these objective functions with their individual weight factors are considered, then mathematical expression of multi-objective function (MOF) is given by (1).

$$FF = MOF = \min(FF_1,\ FF_2, FF_3) \tag{1}$$

Therefore

$$FF = \min(W_r * P_L,\ W_x * Q_L, W_v * CVD) \tag{2}$$

where:
FF = fitness function,
P_L = function of APL,
Q_L = function of RPL,
CVD = function of cumulative voltage deviation.
The CVD is equal to sum of voltage deviation from desired value (1 p.u.) at every bus as given in (3).

$$CVD = \sum_{i=1}^{nb} |1 - V_i| \tag{3}$$

where:
nb = total number of buses;
V_i = ith bus voltage.
In FF, W_L, W_x, W_v are weight factors with respect to P_L, Q_L and CVD, respectively. Generally, the sum of absolute value of weight factors is 1 as given in (4).

$$|W_L| + |W_X| + |W_V| = 1 \tag{4}$$

In a PDN, the losses are always in the form of P_L, Q_L, and CVD for problems like NR. These losses can be calculated using the weight factors. Each loss is assigned a weight factor according to its significance and impact on system losses. Thus, we have considered these objective functions as their weighted sum, as shown in (2). The constraints are described as follows:

A. VOLTAGE LIMIT

The voltage of each bus (V_i) should be within permissible limits of minimum ($V_{\min}$) and maximum (V_{min}) as given in (5).

$$V_{min} \le V_i \le V_{min} \tag{5}$$

where: i=1, 2, 3… n,

B. LINE LOADING

The apparent power of the lines (S_k) should be less than or equal to maximum allowable power S_k^{max} as given by (6).

$$S_k \le S_k^{max} \tag{6}$$

C. LOAD CONNECTIVITY

Every bus must be connected to the substation.

D. RADIAL STRUCTURE

The PDN should be radially connected such that the number of lines should be less than the number of buses by one.

III. HYBRID FIREFLY AND PARTICLE SWARM OPTIMIZATION (HFPSO)

A. FIREFLY OPTIMIZATION ALGORITHM

It is a bio-inspired algorithm on the basis of flashing patterns and behaviors of fireflies at night. For the sake of survival, these fireflies emit a distinct flashing light [34, 37]. The method depends on the absorption of medium and intensity of flashing light. Light intensity from a light source decreases with increase in distance as defined by inverse square law. Furthermore, the light is also absorbed by the medium through which it passes. Its position (X) and velocity (V) are mathematically expressed as the following equations [38].

$$X_i(t+1) = X_i B_o e^{n^2 ij} - (X)i - g^{best^{t-1}} + \alpha\epsilon \quad (7)$$

$$V_i(t+1) = X_i(t+1) + X_{i_{temp}} \quad (8)$$

B. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

In 1995, Kennedy and Eberhart created PSO algorithm and it is a meta-heuristic method [39]. Living organism's behavior such as a flock of birds or swarm of fish is the base of this method. The advantages of this algorithm includes easy implementation, fast convergence and less calculating variables but this method offers slow convergence when populations are close to one another and get stuck in local optima [40]. Its position (X) and velocity (V) vectors are mathematically expressed as given below [39]:

$$V_i(t+1) = wV_i(t) + c_1 r_1 \left(P_{best_i}(t) - X_i(t)\right) + c_2 r_2 \left(g_{best_i}(t) - X_i(t)\right) \quad (9)$$

$$X_i(t+1) = X_i + V_i(t+1) \quad (10)$$

where w is inertia weight, acceleration coefficients are c_1 and c_2, two random numbers are r_1 and r_2 in the range [1, 0]. Based on the number of iterations, inertia weight is estimated in a linearly decreasing sequence. The following is a mathematical formula for calculating inertia weight [41, 42]:

$$w = w^{max} - \frac{(w^{max} - w^{min}) * iteration}{Max-iteration} \quad (11)$$

C. HYBRID FIREFLY AND PARTICLE SWARM OPTIMIZATION (HFPSO) ALGORITHM

In [36], Ibrahim Berkan Aydilek developed HFPSO algorithm. Objective functions including continuous and discrete functions can be minimized or maximized with optimization algorithms with numerous constraints to get most practicable solution for an optimization problem. In order to get benefits of both algorithms (FA and PSO), there is a need to maintain equilibrium between exploitation and exploration [43, 44]. In FA, terms of personal best(P_{best}) and velocity (V) are not included. Fast convergence is offered by PSO method in terms of local optimal solution for global search whereas in region of local search, FA is more beneficial. Fine global optimal solution is offered by it.

IV. IMPLEMETATION OF HFPSO TO NR PROBLEM

For finding optimal configuration, the load flow analysis technique is used. HFPSO is used for power loss reduction and to place lines in an appropriate condition. The first step of simulation is to input data of distribution system (Data of buses, Data of lines, Data of loads). Then randomly initialize initial configuration by predefining sectionalizers and tie-line switches. Iteratively change the sectionalizers and tie-line switches. Then run the load flow program for RDS. Calculate branch currents, power loss and voltage profile. Check the criteria for feeder reconfiguration. If yes print the results shown on output window otherwise go to step 3. Fig. 1 shows flowchart of HFPSO algorithm.

IEEE 33-bus RDS data and load flow analysis method is used to calculate system losses. HFPSO algorithm is used to reduce system losses by applying a selection to the current population to create an intermediate distribution population. In the beginning, input parameters are entered. Both population-based techniques then utilize these parameters in a step-by-step fashion. After that, constant swarm vectors in ranges of velocity and space of search are initiated. Allocation of individual best (P_{best}) and global best (g_{best}) swarms is mathematically done. In final iteration, comparison of calculated values is performed. Furthermore, record the current location, and determine location and new velocity afterwards [36].

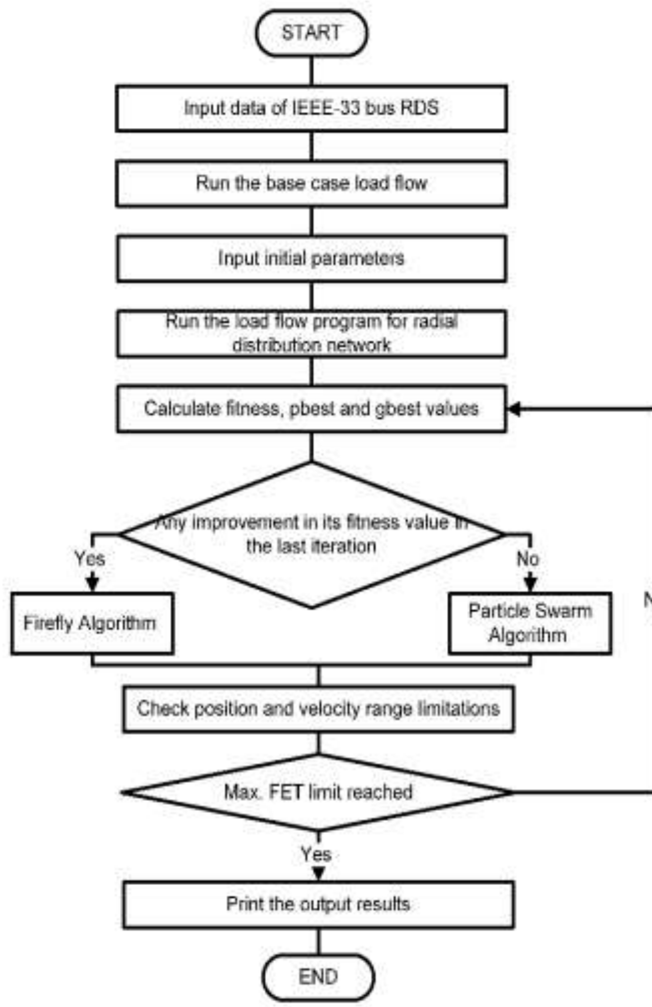

FIGURE 1. Flowchart of HFPSO algorithm for NR problem

If the value of particle's fitness is equal or good than preceding global best, FA will pick it in accordance to (7) and (8); otherwise, it will be calculated by the PSO according to (9) and (10). The particles fitness conditions can be mathematically expressed as:

$$FF(i,t) = \begin{cases} true, fitness - value(particle_i^t \leq g^{best^{t-1}} \\ false, fitness - value(particle_i^t > g^{best^{t-1}} \end{cases} \quad (12)$$

V. RESULTS AND DISCUSSION

The code of this algorithm is executed in MATLAB environment in an Intel core i7 Laptop with CPU of 2.6 GHz and RAM of 16 GB. Initially, the lines 33, 34, 35, 36, and 37 are considered as tie-lines (normally open).

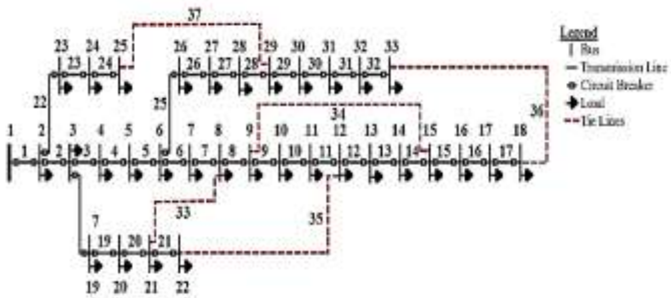

FIGURE 2. IEEE 33-bus RDS before NR

A. RESULTS BEFORE RECONFIGURATION

From load flow analysis of the base network presented in Fig. 2, the VP of each bus, APL and RPL were computed. The VP before reconfiguration is shown in Fig. 4. and 0.9108p.u. is the minimum voltage level.

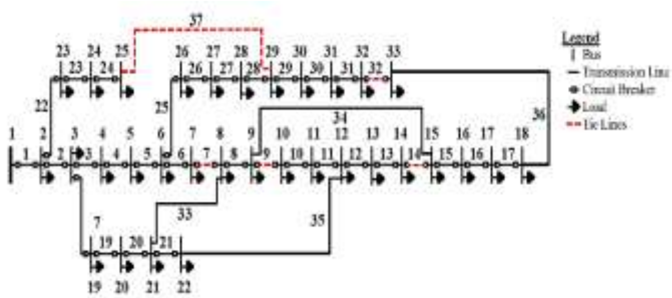

FIGURE 3. IEEE 33-bus RDS after NR

B. RESULTS AFTER RECONFIGURATION

The results show that APL after NR is 109.69 kW as compared with base value of 204.46 kW. This tells that 94.766 kW of active power can be saved. The APL percentage reduction is 46.35%. NR using HFPSO algorithm caused closing of four tie-lines, namely: 33, 34, 35, and 36, while opening of sectionalizes namely: 7, 9, 14, and 32 as shown in Fig. 3. Results are summarized in table 1. The voltages before and after NR of each bus are given in Table 2 and plotted in Fig. 4. The value of minimum voltage after NR is 0.9572 p.u.

TABLE I
RESULTS

Parameter	Before Reconfiguration	After Reconfiguration
Switch to be opended	33,34,35,36,37	7,9,14,32,37
P_L (kw)	204.4592	109.6932
Total P_L reduction (kw)	-	94.766
P_L Reduction Percentage	-	46.35%
Q_L (kvar)	110	90
Min. Voltage (p.u.)	0.9108(at 18-bus)	0.9572(at 31-bus)

TABLE II
COMPARISON OF VOLTAGE PROFILE

Bus No.	Voltage Before Reconfiguration	Voltage After Reconfiguration
1	1	1.0014
2	0.9970	0.9985
3	0.9829	0.9884
4	0.9755	0.9839
5	0.9681	0.9796
6	0.9561	0.9731
7	0.9526	0.9725
8	0.9390	0.9641
9	0.9328	0.9639
10	0.927	0.9675
11	0.9261	0.9676
12	0.9246	0.9679
13	0.9185	0.9653
14	0.9162	0.9645
15	0.9148	0.9613
16	0.9134	0.9609
17	0.9114	0.9588
18	0.9108	0.9575
19	0.9965	0.9999
20	0.9929	0.9830
21	0.9922	0.9784
22	0.9916	0.9749
23	0.9794	0.9882
24	0.9727	0.9816
25	0.9694	0.9783
26	0.9542	0.9747
27	0.9516	0.9724
28	0.9403	0.9713
29	0.9321	0.9638
30	0.9286	0.9606
31	0.9245	0.9572
32	0.9236	0.9579
33	0.9233	0.9614

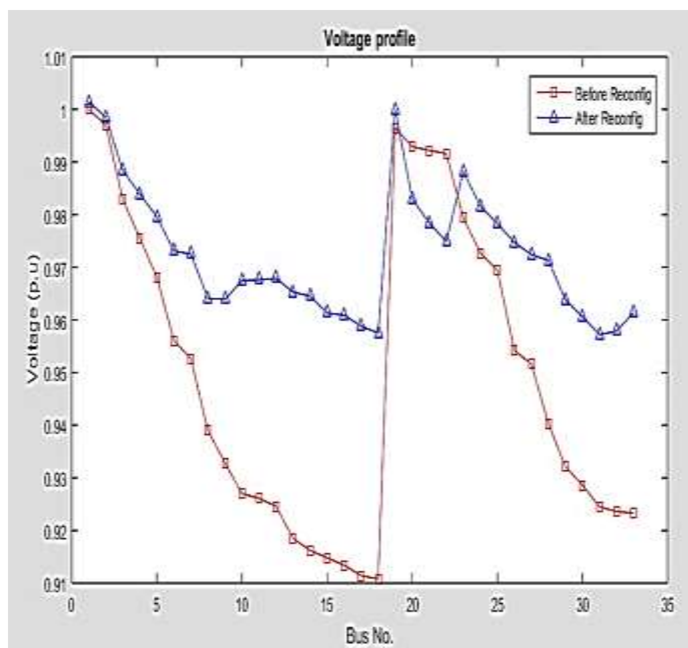

FIGURE 4. Before and after NR voltage profile

C. COMPARISON OF RESULTS WITH OTHER TECHNIQUES

Table 3 presents the comparison of HSPSO algorithm with other techniques which used IEEE 33 bus RDS for NR. It is proved by the overall results that the algorithm of HFPSO gave optimal results as compared to other existing algorithms for NR.

TABLE III
COMPARISON OF RESULTS WITH OTHER TECHNIQUES

Method	APL (kw)	APL reduction (kw)	Min. Voltage	Opened Switches
HFPSO	109.69	94.76	0.9572	7,9,14,32,37
HSA[20]	142.68	60.01	0.9342	7,10,14,36,37
SPSO[26]	139.79	63.01	-	7,9,14,32,37
SFA[29]	139.55	63.13	0.9378	7,9,14,32,37
IAICA[30]	139.6	63.19	0.9380	7,9,14,32,37
FWA[24]	139.98	62.70	0.9412	7,9,14,28,32

VI. CONCLUSION

This paper solved NR problem using HFPSO algorithm for reducing power loss and improving VP of PDN. A constrained multi-objective function was considered. Load flow analysis technique and HFPSO algorithm has been used for analysis. The results achieved present that reduction in the value of APL is of 94.76 kW (46.35%) from the original value of 204.46kw and improvement in the value of minimum voltage is 0.0464p.u and exact value is 0.9572p.u. The comparison of results with various other optimization techniques revealed that optimizing PDN using HFPSO algorithm contributed significantly in improving the bus voltages, and power loss.

REFERENCES

[1] A. L. Rojas, S. Koziel, M. F. Abdel-Fattah, and G. Gutiérrez-Alcaraz, "Distribution Network Reconfiguration for Voltage Stability Enhancement via Feasibility-Preserving Evolutionary Optimization," in *2018 IEEE Electrical Power and Energy Conference (EPEC)*, 2018, pp. 1-8.

[2] M. E. Baran and F. F. J. I. P. E. R. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," vol. 9, no. 4, pp. 101-102, 1989.

[3] M. Y. J. I. J. o. s. e. Mon and t. research, "Design and Calculation of 5 MVAR Shunt Capacitor Bank at 33 kV Bus in Distribution Substation," vol. 3, no. 15, pp. 3259-3263, 2014.

[4] L. Ramesh, S. Chowdhury, S. Chowdhury, A. Natarajan, C. J. I. J. o. E. P. Gaunt, and E. S. Engineering, "Minimization of power loss in distribution networks by different techniques," vol. 2, no. 1, pp. 1-6, 2009.

[5] R. Syahputra, I. Soesanti, and M. J. J. o. E. S. Ashari, "Performance Enhancement of Distribution Network with DG Integration Using Modified PSO Algorithm," vol. 12, no. 1, 2016.

[6] B. Venkatesh, R. Ranjan, and H. J. I. T. o. p. s. Gooi, "Optimal reconfiguration of radial distribution systems to maximize loadability," vol. 19, no. 1, pp. 260-266, 2004.

[7] D. B. Aeggegn, A. O. Salau, and Y. J. A. o. E. E. Gebru, "Load flow and contingency analysis for transmission line outage," pp. 581-594-581-594, 2020.

[8] A. E. Abu-Elanien, M. Salama, and K. B. J. A. e. j. Shaban, "Modern network reconfiguration techniques for service restoration in distribution systems: A step to a smarter grid," vol. 57, no. 4, pp. 3959-3967, 2018.

[9] A. J. P. o. t. P. Merlin, "Search for a minimal-loss operating spanning tree configuration for an urban power distribution system," vol. 1, pp. 1-18, 1975.

[10] U. Raut and S. J. R. E. F. Mishra, "An improved Elitist–Jaya algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems," vol. 30, pp. 92-106, 2019.

[11] M. Kashem, G. Jasmon, V. J. I. J. o. E. P. Ganapathy, and E. Systems, "A new approach of distribution system reconfiguration for loss minimization," vol. 22, no. 4, pp. 269-276, 2000.

[12] F. V. Gomes, S. Carneiro, J. L. R. Pereira, M. P. Vinagre, P. A. N. Garcia, and L. R. J. I. T. o. P. s. Araujo, "A new heuristic reconfiguration algorithm for large distribution systems," vol. 20, no. 3, pp. 1373-1378, 2005.

[13] T. E. McDermott, I. Drezga, and R. P. J. I. T. o. P. S. Broadwater, "A heuristic nonlinear constructive method for distribution system reconfiguration," vol. 14, no. 2, pp. 478-483, 1999.

[14] A. Gonzalez, F. M. Echavarren, L. Rouco, and T. J. I. T. o. P. S. Gomez, "A sensitivities computation method for reconfiguration of radial networks," vol. 27, no. 3, pp. 1294-1301, 2012.

[15] I. A. Quadri, S. Bhowmick, D. J. I. G. Joshi, Transmission, and Distribution, "Multi-objective approach to maximise loadability of distribution networks by simultaneous reconfiguration and allocation of distributed energy resources," vol. 12, no. 21, pp. 5700-5712, 2018.

[16] A. R. Jordehi, "Optimisation of electric distribution systems: A review," *Renewable and Sustainable Energy Reviews,* vol. 51, pp. 1088-1100, 2015/11/01/ 2015.

[17] J. Z. J. E. P. S. R. Zhu, "Optimal reconfiguration of electrical distribution network using the refined genetic algorithm," vol. 62, no. 1, pp. 37-42, 2002.

[18] H. De Faria, M. G. Resende, and D. J. J. o. H. Ernst, "A biased random key genetic algorithm applied to the electric distribution network reconfiguration problem," vol. 23, no. 6, pp. 533-550, 2017.

[19] M. J. E. P. S. R. Abdelaziz, "Distribution network reconfiguration using a genetic algorithm with varying population size," vol. 142, pp. 9-11, 2017.

[20] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. J. I. T. o. p. s. Rao, "Optimal network reconfiguration of large-scale distribution system using harmony search algorithm," vol. 26, no. 3, pp. 1080-1088, 2010.

[21] T. T. Nguyen, A. V. J. I. J. o. E. P. Truong, and E. Systems, "Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm," vol. 68, pp. 233-242, 2015.

[22] P. J. A. M. Acharjee and Computation, "Application of efficient self-adaptive differential evolutionary algorithm for voltage stability analysis under practical security constraints," vol. 219, no. 23, pp. 10882-10897, 2013.

[23] T. P. Nguyen and D. N. J. A. S. C. Vo, "A novel stochastic fractal search algorithm for optimal allocation of distributed generators in radial distribution systems," vol. 70, pp. 773-796, 2018.

[24] A. M. Imran, M. J. I. J. o. E. P. Kowsalya, and E. Systems, "A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using fireworks algorithm," vol. 62, pp. 312-322, 2014.

[25] A. M. Shaheen and R. A. J. I. S. J. El-Sehiemy, "Optimal coordinated allocation of distributed generation units/capacitor banks/voltage regulators by EGWA," vol. 15, no. 1, pp. 257-264, 2020.

[26] T. Khalil and A. Gorpinich, "Tamer M. Khalil and Alexander V. Gorpinich, "Reconfiguration for loss reduction of distribution systems using selective particle swarm optimization", International Journal of Multidisciplinary Sciences and Engineering (IJMSE), Vol. 3, No. 6, pp. 16-21, June 2012," *International Journal of Multidisciplinary Sciences and Engineering (IJMSE),* vol. 3, pp. 2045-7057, 06/01 2012.

[27] A. M. Elsayed, M. M. Mishref, and S. M. J. I. T. o. E. E. S. Farrag, "Distribution system performance enhancement (Egyptian distribution system real case study)," vol. 28, no. 6, p. e2545, 2018.

[28] A. M. Othman, A. A. El-Fergany, A. Y. J. E. p. c. Abdelaziz, and systems, "Optimal reconfiguration comprising voltage stability aspect using enhanced binary particle swarm optimization algorithm," vol. 43, no. 14, pp. 1656-1666, 2015.

[29] C. Gerez, L. I. Silva, E. A. Belati, A. J. Sguarezi Filho, and E. C. J. I. A. Costa, "Distribution network reconfiguration using selective firefly algorithm and a load flow analysis criterion for reducing the search space," vol. 7, pp. 67874-67888, 2019.

[30] S. H. Mirhoseini, S. M. Hosseini, M. Ghanbari, M. J. I. J. o. E. P. Ahmadi, and E. Systems, "A new improved adaptive imperialist competitive algorithm to solve the reconfiguration problem of

distribution systems for loss reduction and voltage profile improvement," vol. 55, pp. 128-143, 2014.
[31] L. Khalil *et al.*, "Optimal Network Reconfiguration in Presence of Renewable Distributed Generation Using Evolutionary Algorithm," vol. 4, no. 2, pp. 38-43, 2021.
[32] C. Blum, A. Roli, and M. Sampels, *Hybrid metaheuristics: an emerging approach to optimization*. Springer, 2008.
[33] R. Thangaraj, M. Pant, A. Abraham, P. J. A. M. Bouvry, and Computation, "Particle swarm optimization: hybridization perspectives and experimental illustrations," vol. 217, no. 12, pp. 5208-5226, 2011.
[34] X.-S. Yang, "Firefly algorithms for multimodal optimization," in *International symposium on stochastic algorithms*, 2009, pp. 169-178: Springer.
[35] I. Fister, I. Fister Jr, X.-S. Yang, J. J. S. Brest, and E. Computation, "A comprehensive review of firefly algorithms," vol. 13, pp. 34-46, 2013.
[36] I. B. J. A. S. C. Aydilek, "A hybrid firefly and particle swarm optimization algorithm for computationally expensive numerical problems," vol. 66, pp. 232-249, 2018.
[37] X.-S. Yang, "Firefly algorithm, Levy flights and global optimization," in *Research and development in intelligent systems XXVI*: Springer, 2010, pp. 209-218.
[38] X.-S. J. I. j. o. b.-i. c. Yang, "Firefly algorithm, stochastic test functions and design optimisation," vol. 2, no. 2, pp. 78-84, 2010.
[39] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, 1995, vol. 4, pp. 1942-1948: IEEE.
[40] T. T. Ngo, A. Sadollah, and J. H. J. J. o. C. S. Kim, "A cooperative particle swarm optimizer with stochastic movements for computationally expensive numerical optimization problems," vol. 13, pp. 68-82, 2016.
[41] R. C. Eberhart and Y. Shi, "Comparing inertia weights and constriction factors in particle swarm optimization," in *Proceedings of the 2000 Congress on Evolutionary Computation. CEC00 (Cat. No.00TH8512)*, 2000, vol. 1, pp. 84-88 vol.1.
[42] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, 1999, vol. 3, pp. 1945-1950: IEEE.
[43] P. Kora and K. S. R. Krishna, "Hybrid firefly and particle swarm optimization algorithm for the detection of bundle branch block," *International Journal of the Cardiovascular Academy*, vol. 2, no. 1, pp. 44-48, 2016.
[44] S. Abd-Elazim, E. J. I. J. o. E. P. Ali, and E. Systems, "A hybrid particle swarm optimization and bacterial foraging for optimal power system stabilizers design," vol. 46, pp. 334-341, 2013.