Engineering Science and Technology, an International Journal 35 (2022) 101230

HOSTED BY

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

Distribution network reconfiguration using time-varying acceleration coefficient assisted binary particle swarm optimization

Halime Hizarci [a,*], Onur Demirel [b], Belgin Emre Turkay [c]

[a] Dept. of Electrical and Electronic Engineering, Faculty of Engineering, Sakarya University, Sakarya, Turkey
[b] Dept. of Electronic and Automation, Kirsehir Ahi Evran University, Kirsehir, Turkey
[c] Dept. of Electrical Engineering, Faculty of Electrical and Electronics Engineering, Istanbul Technical University, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 4 January 2022
Revised 23 July 2022
Accepted 8 August 2022
Available online 24 August 2022

Keywords:
Radial network
Distribution network reconfiguration
Power loss
Acceleration coefficient
Particle swarm optimization

ABSTRACT

The particle swarm optimization (PSO) algorithm is widely used to solve a variety of complicated engineering problems. However, PSO may suffer from an effective balance between local and global search ability in the solution search process. This study proposes a new acceleration coefficient for the PSO algorithm to overcome this issue. The proposed coefficient is implemented on the distribution network reconfiguration (DNR) problem to reduce power loss. The lowest power loss is obtained while problem constraints (maintain radial structure, voltage limits, and power flow balance) are satisfied with the proposed method. The validity of the proposed acceleration coefficient-based binary particle swarm optimization (BPSO) in handling the DNR problem is examined through simulation studies on IEEE 33-bus, P&G 69-bus, and 84-bus Taiwan Power Company (TPC) practical distribution networks. Furthermore, the DNR problem is evaluated regarding energy cost and environmental issues. Finally, the average computational times of the different acceleration coefficient-based PSO methods are compared. The solution speed of the proposed acceleration coefficient-based method is faster than the other methods in the DNR problem.

1. Introduction

Reducing power losses in the power distribution network is important due to the high resistance value compared to the transmission network. Furthermore, as the power losses increase the operational cost of the system, power loss minimization is necessary for efficient usage of the distribution networks. Network reconfiguration, distributed generation (DG), and capacitor placement are the approaches for reducing power loss in distribution networks. Network reconfiguration is preferable because the DG and capacitor placement are costly methods to minimize power losses.*.

Distribution network reconfiguration (DNR) is an operation based on changing the status of the tie (normally open) and sectionalizing (normally closed) switches to reduce power losses in the distribution network. Finding an optimal solution is important because the DNR is a combinatorial problem with complex search space because of voltage, current, and radiality constraints. Moreover, a large number of switch is considered in the DNR problem, and there are 2^n possible changes (where n represents branch number). Therefore, evaluating all candidate-switching combinations takes much time, especially in large distribution networks. So, it is not easy to find the optimal solution quickly. Therefore, there are three categories of the DNR problem solution: the optimal flow pattern-based method, branch exchange method, and intelligent optimization method [1].

DNR was first presented by Merlin and Back for power loss reduction in 1975 [2]. Since then, several comprehensive research has been done to improve the performance of distribution networks. For example, Civanlar et al. solve the DNR problem using the branch exchange method, and they greatly effort to develop a power loss formulation [3]. Nevertheless, as the DNR result depends on the initial structure of the network, solution searching efficiency will be lower in the branch exchange method, especially in large-scale networks. In [4], Baran and Wu present a general formulation of DNR for load balancing and power loss reduction. In [5], improved mixed-integer hybrid differential evolution (IMI-DE) is presented to solve the DNR problem, and the objective function is to reduce power loss. A heuristic method is presented for the DNR problem, and the method is based on minimum branch current [6]. In [7] and [8], genetic algorithm (GA) and harmony search algorithm (HSA) are used for the solution of DNR. Also,

* Corresponding author.
E-mail address: hhizarci@sakarya.edu.tr (H. Hizarci).
Peer review under responsibility of Karabuk University.

https://doi.org/10.1016/j.jestch.2022.101230
2215-0986/

another GA-based solution is presented in [9]. A hybrid big bang–big crunch algorithm (BB-BCA) [10] is used to solve the DNR problem with power loss, voltage deviation minimization, and load balancing objectives. The fireworks algorithm (FWA) [11] is used for DNR, considering different load levels (heavy, normal, and light) for voltage stability enhancement and power loss minimization.

Selective bat algorithm (SBAT) and selective PSO (SPSO) [12] are presented to find an optimal solution for DNR based on a two-step solution (mesh vector and search space determination) to avoid sticking to non-feasible solutions. A similar approach (called selective binary PSO) that alternates the transfer function of PSO is presented for the DNR problem solution in [13]. In addition, the authors proposed a two-step approach based on an analysis of the network meshes to reduce the search space of BPSO. An improved version of selective BPSO is presented in [14], and the sigmoid function is changed with a parameter in a wide range. A three-dimensional group search optimization (3D-GSO) [15] is proposed for the DNR problem with the aim of power loss reduction, and 3D-GSO is implemented for different load levels. Ant colony optimization (ACO) is another method presented to find the optimal switch pattern to minimize power loss in the distribution network [16,17].

In [18], a salp swarm algorithm (SSA), an improved version of SSA (called ISSA), and information gap decision theory (IGDT) are used for optimal DNR based on power loss and energy cost reduction. A new swarm-based approach entitled improved whale optimization (IWOA) [19] is presented for the DNR problem to minimize power losses. In [20], a chaotic stochastic fractal search (CSFSA) algorithm is developed to overcome the weakness of the SFSA, and it is implemented on the DNR problem. A switch opening and exchange (SOE) method consisting of three steps is used in DNR [21]. In the first step, the switches open sequentially until all the loops are open. Then, the branch statuses obtained in the first step are modified to find better radial topologies in the second and third steps. In [22], the harris hawks optimization (HHO) algorithm is proposed as a four-step solution procedure for the DNR, and the objective function is the reduction of power loss.

In [23], a hybrid of binary particle swarm optimization and gravity search algorithm (BPSO-GSA) is used for the optimal DNR. The loss minimization and reliability indices are considered the study's objective function. Artificial ecosystem-based optimization (AEO) is used to solve the DNR problem to reduce power loss [24]. Statistical analysis is performed based on the minimum, mean, and maximum adaptive function values in the study. In [25], an improved coyote optimization algorithm (ICOA) is performed for the reconfiguration of the balanced and unbalanced power distribution networks to minimize power loss. The most important advantage of ICOA is that it only updates the optimal solution so far without creating a new population.

PSO is used for different complex problems due to its ease of implementation and has fewer parameters to adjust. For example, PSO-based algorithms are used to delete transactions [26], and mine high-utility item sets [27] in the data mining research field. Another variant of PSO, named adaptive PSO, is proposed for the balanced allocation of resources in resource leveling problems [28].

Generally, power loss reduction, voltage deviation, voltage stability index, and system reliability are considered as the objective function of the DNR in the literature. Nevertheless, less attention is paid to reducing greenhouse gas emissions (GHG). As power losses decrease the efficiency of the power system, efforts to minimize the power losses in the distribution network (which is responsible for the large proportion of the power losses) have a positive environmental impact.

This paper proposes a new time-varying acceleration coefficient-assisted BPSO algorithm to solve the feeder reconfiguration problem. An exponential-based acceleration coefficient is proposed to adaptively adjust the balance between local and global search. With the proposed acceleration coefficient, the particles in the swarm can rapidly reach the global optimal solution without falling into the local optimal. Also, the convergence speed is improved compared to the constant acceleration coefficient.

Furthermore, the proposed algorithm gives an optimal and robust solution to the DNR problem. In addition to power loss reduction, the cost of energy and GHG emissions (CO_2, NO_x, and SO_x) are considered in this study. Three case studies are examined to test the effectiveness and robustness of the proposed BPSO. Furthermore, the proposed approach is compared with the other studies based on the coefficient modification. As a result of the simulation study, the proposed BPSO gives better power loss reduction and convergence results.

This paper is organized as follows. First, the proposed acceleration coefficient of BPSO is introduced in Section 2. The proposed BPSO is implemented considering the DNR problem's objective function and constraints in Section 3. Next, case studies are given in Section 4. Finally, the conclusion is presented in Section 5.

2. Binary PSO

PSO algorithm is firstly introduced by social psychologist J. Kennedy and electrical engineer R. Eberhart in 1995 [29]. Then, the same authors also proposed a binary version of the PSO after two years [30]. The inspiration source of the PSO algorithm is the food search of the animals that move in a swarm. Each individual in the swarm is defined as a particle. PSO grounds on the share of social information in the swarm.

The movement of the particles in a swarm is presented in Fig. 1. Each particle in the swarm adjusts its position using its previous experience towards to best position. The fitness function is a criterion to determine how close a particle is to the solution. The best solution of a particle, which is closest to the optimal solution, is called p_{best} (personal best). Moreover, g_{best} (global best) is by far the best solution among all particles in the swarm. The search process of the algorithm continues until the target is reached.

In Fig. 1, the velocity of the particle i is mathematically modeled as in (1).

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{1}$$

where ω is inertia weight and scale velocity of the particle i. d defines the dimension of the search space. c_1 is the cognitive (or personal) acceleration coefficient, and c_2 is the social one. r_1 and r_2 are the random numbers between $[0 - 1]$.

The positions of each particle are updated based on (2).

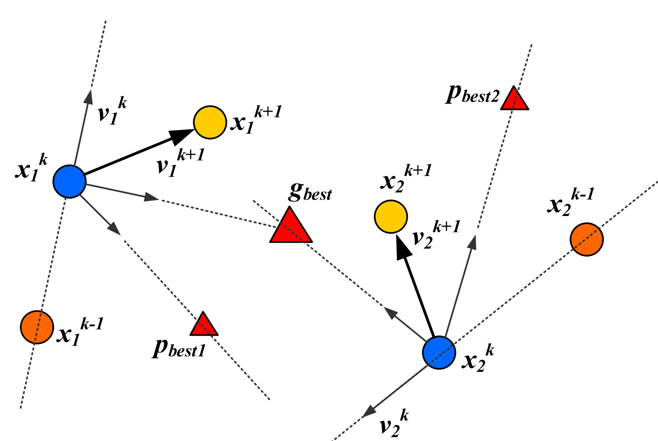

Fig. 1. Particle movement in PSO algorithm.

$$x_{id} = x_{id} + v_{id} \tag{2}$$

Changing the position of a particle in BPSO is defined below:

$$if\ (rand\,( ) < S(v_{id})) \quad \begin{matrix} then & x_{id} = 1 \\ else & x_{id} = 0 \end{matrix}$$

$$S(v) = \frac{1}{1 + e^{-v}} \tag{3}$$

$S(v)$ is the sigmoid transfer function, and $rand()$ is a quasi-random number selected between $[0 - 1]$. Eventually, the velocity and direction of a particle in each dimension in a solution space will change based on a combination of the best coordinates of its neighbors and its own p_{best} coordinates at each iteration.

PSO algorithm has many advantages, such as ease of implementation, fast convergence, short computational time, wide adaptivity to different problems, and the requirement of fewer control parameters. However, when PSO is faced with complex functions, it can be trapped into the local optimum point, or premature convergence occurs. Therefore, researchers propose various improvements to overcome these problems. The improvements focus on swarm adaptation, position updating mechanism, control parameters, neighborhood topology, and fitness landscape analysis [31].

2.1. Improved time-varying acceleration coefficient assisted BPSO

The acceleration coefficients are important control parameters of the PSO algorithm, leading to particles flying to desirable solution regions. Generally, c_1 and c_2 are set as 2 in the PSO algorithm. However, the coefficients are the key component in the searching, and a constant value may be harmful in searching for optimal solutions [6,32]. Therefore, except for the coefficients with constant values, there are several strategies of acceleration coefficients based on dynamically changing with the iteration [33,34]. For example, Ratnaveera et al. proposed a linear time-varying accelerated coefficient (TVAC) to enhance the search for the optimal solution [35]. In their study, while the cognitive acceleration coefficient (c_1) of PSO is linearly decreased from 2.5 to 0.5, the social acceleration coefficient (c_2) is linearly increased from 0.5 to 2.5 during the iteration.

In [36], a variant of PSO, called randomised PSO, is proposed to search for problem space more comprehensively. In the paper, TVAC presented in [35] is used as the acceleration coefficients, and the acceleration coefficients are randomly perturbed using Gaussian white noise. A tangent chaotic acceleration coefficient is presented in [37] to solve stuck in local minima and premature convergence problems.

A sine–cosine acceleration coefficient (SCAC) based PSO is proposed in [38], and the range of the c_1 and c_2 is changing from 2.5 to 0.5 and 0.5 to 2.5, respectively. The authors claimed that the SCAC gives better balance at the early stages of the global search and later global convergence stages than TVAC. Another coefficient entitled nonlinear dynamic acceleration coefficient (NDAC) is presented in [39], and the coefficients range is used as in [35]. A sigmoid-based acceleration coefficient (SBAC) [40] is proposed, and the increasing/decreasing of the coefficients is relatively slow compared to others. Lin et al. propose piecewise nonlinear acceleration coefficients (PNAC) [41]. The approach is different from others in appearance due to its piecewise form. A summary of the time-varying coefficients is given in Table 1.

In this study, a new exponential-based acceleration coefficient (EBAC) is proposed. The proposed coefficient-based BPSO effectively balances local and global search capabilities. The EBAC is represented mathematically as follows:

$$c_1 = c_{1i} + 2e^{-(2.2iter/max_{iter})^2} \tag{4}$$

$$c_2 = c_{1f} - 2e^{-(2.2iter/max_{iter})^2} \tag{5}$$

where $c_{1i} = 0.5$ and $c_{1f} = 2.5$, respectively. *iter* and *maxiter* represent the current iteration and maximum iteration number. To see the changes in the coefficients better, iteration $-c_1/c_2$ is illustrated in Fig. 2 for the acceleration coefficients, which are listed in Table 1.

The averages of the best-so-far solution in the last iteration of each algorithm are given in Fig. 3a and Fig. 3b. The simulation results are obtained based on two traditional benchmark test functions (Sphere and Rastrigin). Population size (N) and iteration number for the compared algorithms are set to 30 and 500, respectively. It is seen from Fig. 3a that the proposed acceleration coefficient converges faster than others for the f_1 function. In Fig. 3b, the proposed EBAC is the sole algorithm that reaches optimal solution at the end of the iteration.

The pseudocode of the proposed BPSO algorithm is presented in Fig. 4. Furthermore, the implementation of the proposed BPSO steps is given in Section 3.

3. DNR problem formulation

The objective function of the DNR problem is minimizing the total real power losses, and it is calculated as follows:

$$P_{loss} = \sum_{i}^{N_{br}} R_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{6}$$

where N_{br} is the total branch number, P_i and Q_i are real and reactive power of branch i, R_i is the resistance of the i^{th} branch and finally V_i is voltage magnitude at bus i.

Constraints of the DNR problem are given below.

Power flow balance: The power flow constraint may be calculated by (7) and (8).

$$P_{Gi} - P_{Di} = P_i = |V_i| \sum_{j=1}^{N_{bus}} |V_j| \left[G_{ij} \cos\left(\delta_i - \delta_j\right) + B_{ij} \sin\left(\delta_i - \delta_j\right) \right] \tag{7}$$

$$Q_{Gi} - Q_{Di} = Q_i = |V_i| \sum_{j=1}^{N_{bus}} |V_j| \left[G_{ij} \sin\left(\delta_i - \delta_j\right) - B_{ij} \cos\left(\delta_i - \delta_j\right) \right] \tag{8}$$

where $i = 1, 2, \cdots, N_{bus}$ (N_{bus} is the bus number); P_{Gi}, Q_{Gi}: active and reactive power generation at bus i; P_{Di}, Q_{Di}: active and reactive load demand at bus i; $|V_i|$, $|V_i|$: voltage magnitude at buses i and j; G_{ij}; B_{ij}: real and imaginary part of the bus admittance matrix (Y_{ij}); δ_i, δ_j: voltage angle at buses i and j.

Voltage limits: The voltage magnitude of the bus i must lie within the permissible range given in (9). This constraint is important for power quality; generally, permissible values are 10 % for voltage drop and over-voltage.

$$V_{i,\,min} \le V_i \le V_{i,max} \tag{9}$$

where the minimum and maximum bus voltages are $V_{i,min} = 0.9$ and $V_{i,max} = 1.1$ pu, respectively.

Line loading: Line loading constraint limits the maximum current of bus i. Currents passing through for each branch must lie within the permissible ranges given in (10).

$$I_i \le I_{i,max} \tag{10}$$

Radiality and connectivity of the network: This constraint specifies maintaining the radial structure of the distribution network. Continuity of the power flow to the loads is necessary for the DNR problem. So, it is required to maintain the radial form of the network. After the reconfiguration, all buses must be energized, and there must be no isolated bus in the distribution network.

The branch node incidence matrix is used to verify the radiality of the network in the study.

Table 1
Review of the acceleration coefficients.

Reference	Expression	Parameters
TVAC [35]	$c_1=(c_{1f}-c_{1i})\frac{iter}{max_{iter}}+c_{1i}$ and $c_2=(c_{2f}-c_{2i})\frac{iter}{max_{iter}}+c_{2i}$	$c_{1f}=0.5, c_{1i}=2.5$ $c_{2f}=2.5, c_{2i}=0.5$
SCAC [38]	$c_1=\partial\times\sin\left(\left(1-\frac{iter}{max_{iter}}\right)\times\frac{\pi}{2}\right)+\delta$ and $c_2=\partial\times\cos\left(\left(1-\frac{iter}{max_{iter}}\right)\times\frac{\pi}{2}\right)+\delta$	$\partial=2\delta=0.5$
NDAC [39]	$c_1=-(c_{1f}-c_{1i})\left(\frac{iter}{max_{iter}}\right)^2+c_{1f}$ and $c_2=-c_{1i}\times\left(1-\frac{iter}{max_{iter}}\right)^2+c_{1f}\times\frac{iter}{max_{iter}}$	$c_{1f}=2.5c_{1i}=0.5$
SBAC [40]	$c_1=\frac{1}{1+e^{(-\lambda iter/max_{iter})}}+2(c_{1f}-c_{1i})\left(\frac{iter}{max_{iter}}-1\right)^2$ $c_2=\frac{1}{1+e^{(-\lambda iter/max_{iter})}}+(c_{1f}-c_{1i})\left(\frac{iter}{max_{iter}}\right)^2$	$\lambda=0.0001c_{1f}=2.5c_{1i}=0.5$
PNAC [41]	$c_1=\begin{cases}4\times\left(\frac{iter}{max_{iter}}-\frac{1}{2}\right)^2+\frac{3}{2}, & if\ 0<\frac{iter}{max_{iter}}<\frac{1}{2}\\ -4\times\left(\frac{iter}{max_{iter}}-\frac{1}{2}\right)^2+\frac{3}{2}, & if\ \frac{1}{2}\le\frac{iter}{max_{iter}}\le 1\end{cases}$ $c_2=\begin{cases}-4\times\left(\frac{iter}{max_{iter}}-\frac{1}{2}\right)^2+\frac{3}{2}, & if\ 0<\frac{iter}{max_{iter}}<\frac{1}{2}\\ 4\times\left(\frac{iter}{max_{iter}}-\frac{1}{2}\right)^2+\frac{3}{2}, & if\ \frac{1}{2}\le\frac{iter}{max_{iter}}\le 1\end{cases}$	

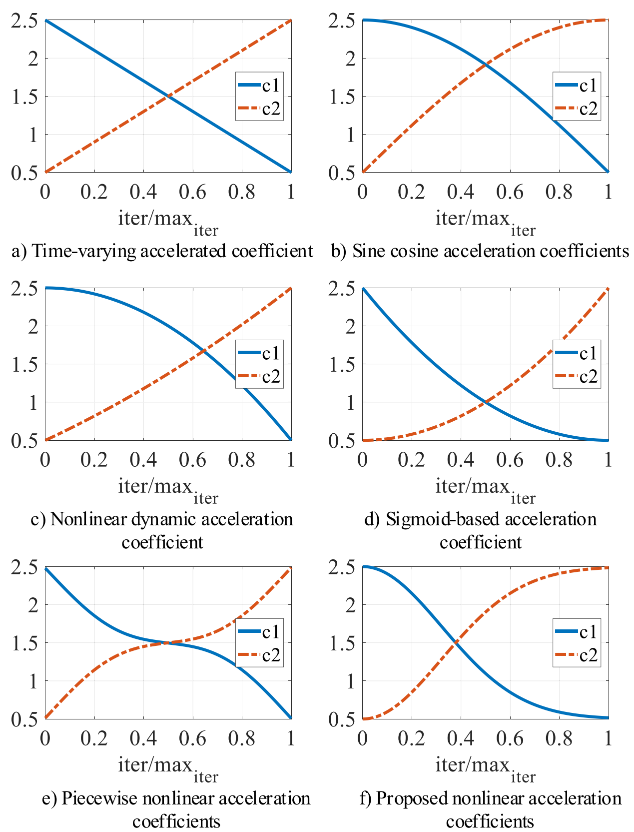

Fig. 2. Comparison of different acceleration coefficients.

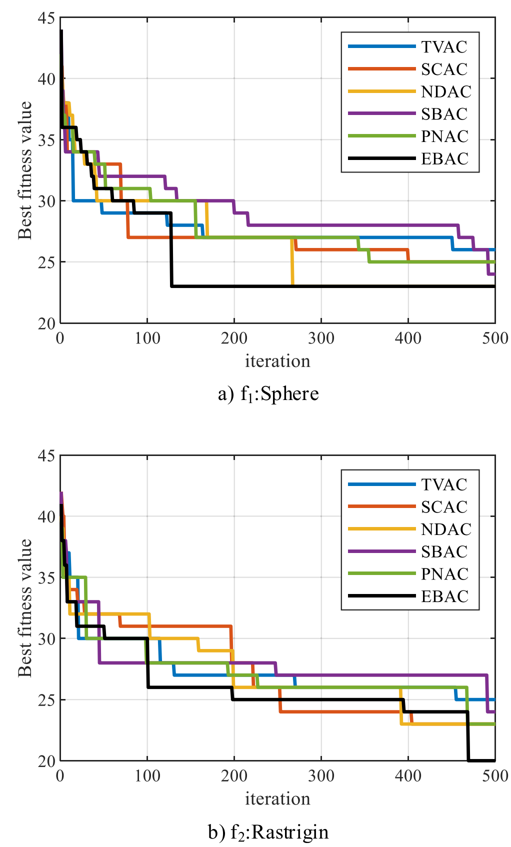

Fig. 3. The convergence characteristic for different acceleration coefficients.

$$A_{ij}=\begin{cases}1 & if\ \ branch\ \ start\ \ at\ \ bus\ \ i\\ -1 & if\ \ branch\ \ start\ \ at\ \ bus\ \ j\\ 0 & \quad\quad otherwise\end{cases}\tag{11}$$

where $i=1,2,3,\cdots,N_{br}$ and $j=1,2,3,\cdots,N_{bus}$.

The radiality of the network is checked with the determinant of the A matrix and $|det(A)|=1$ should be satisfied [42].

Cost and Environmental Benefits of DNR: Although the main objective is the power loss minimization in the DNR problem, the DNR also affects energy cost and environmental issues. Especially due to the high resistance of the distribution networks, power loss increases. Increasing power loss corresponds to an increase in the energy cost. Moreover, more energy production is needed to distribute the same energy to the consumers. This situation means producing more emission gases per MWh to generate the same energy in a power plant.

Power cost: The annual cost from the active power losses is calculated as follows:

$$C_{loss}=K_{loss}\times P_{loss}\times T_s\tag{12}$$

where K_{loss} represents the cost per kilowatt-hour equal to 0.06 $/kW [18,19] and T_s is the time in hours equal to 8760.

Energy loss: Annual energy loss is calculated as in (13):

$$Energy\ \ losses=8760\times Power\ \ losses\times L_F\tag{13}$$

L_F is the loss factor [43], and it is considered 0.3 for residential loads in (13).

Emissions reduction: Conventional power plants generate emissions equal to 0.0036 kg SO_2, 0.1 kg NO_x, and 720 kg CO_2 per MWh [43]. Therefore, CO_2, NO_x, and SO_2 are calculated as follows:

$$CO_2\ \text{reduction}=720\times E_{loss}\tag{14}$$

$$NO_x\ \text{reduction}=0.1\times E_{loss}\tag{15}$$

$$SO_2\ \text{reduction}=0.0036\times E_{loss}\tag{16}$$

Pseudocode for EBAC BPSO

Input: *N: swarm size, d: dimension, iter: iteration,* max_{iter}*: maximum iteration,* ω_{max} , ω_{min} *: maximum and minimum inertia weights*
Output: P_{gbest}

```
Initialize the BPSO parameters
Randomly and uniformly initialize the position of each particle in the swarm
Randomly generate the initial velocities for each particle
Evaluate the fitness values of each particle using objective function
Set the personel best and global best of the swarm
while iter < max_iter do
  Update ineratia weight according to ω(iter) = (ω_max − ω_max)/max_iter × iter
  for i=N do
    Update the velocity of each particle according to Eq. (1)
    where c_1 and c_2 given in Eqs. (4) and (5)
    Update the position of each particle according to Eq. (2)
    Calculate the fitness values of the new particle x_i using obj. func.
    if value (x_i) < value (p_best) then
      Set x_i = p_i
      if value(x_i)<value (g_best) then
        Set x_i=p_g
      end
    end
  end
end
```

Fig. 4. Implementation of proposed BPSO algorithm.

The cost and environmental benefits assessment are given for three cases in Section 4.

The steps of the proposed algorithm for the DNR problem are given below:

Step 1: The population size and dimension of the search space of the PSO algorithm are determined. The inertia weight decreases from 0.9 to 0.4 during the iteration. The maximum iteration number is 100 for the DNR problem.

Step 2: A random population consisting of switch combinations is initialized, and matrixes with the dimension $N \times d$ are built for initial velocity and positions.

Step 3: Distribution network data is loaded for power flow, and connectivity of the buses is checked with the branch incidence matrix. Also, the branch incidence matrix helps to trace closed loops in the network.

Step 4: The algorithm's main loop is given in this step. Each particle's positions and velocities are determined based on the iteration number. In order to search for a wider search space, the inertia weight defined in step 1 is decreased with the iteration number. Velocities and positions are calculated using (15) and stored in the matrix form for each particle. As the algorithm is called binary PSO, the sigmoid function is used to scale the positions of particles between 0 and 1. Thus, statues of the switches are converted to 1 for open and 0 for closed.

Step 5: The objective function is calculated by realizing the power flow for the radial network formed according to the switching combination obtained from the swarm.

Step 6: Fitness function and constraints of the problem are checked for the particle i. The best position of particle i is updated. If the position is better than the previous position, this position is selected as p_{best}. If the position is better than the global best position of the swarm, then it is assigned as g_{best}.

Step 7: The stopping criterion is checked, and if it meets then g_{best} is chosen as the optimal solution to the problem. Otherwise, it is returned to Step 4 in the algorithm. Finally, the algorithm is terminated when the iteration number reaches its maximum value.

4. Case studies for DNR problem

In this paper, the DNR problem is solved by a proposed exponential-based acceleration coefficient assisted binary PSO. The proposed BPSO algorithm is implemented in three distribution networks in MATLAB R2021a environment. For the power flow, MATPOWER [44] tool is used. The algorithm is run on a PC with a 2.40-GHz CPU and 12-GB RAM. Results for all cases are obtained after ten independent runs of the algorithm.

The population size of the PSO algorithm is selected as 20. Tie switches specify the dimension of the problem, and the dimension is 5 for 33 and 69-bus distribution networks and 13 for the 84-bus distribution network. The inertia weight is linearly decreased during the iteration, from 0.9 to 0.4. The maximum iteration number is 100 for the DNR problem.

4.1. IEEE 33-bus distribution network

The 33-bus distribution network has 32 sectionalizing and 5 tie lines, as seen in Fig. 5. The base voltage of the system is 12.66 kV. The network's total active and reactive powers are 3715 kW and 2300 kVAr, respectively [4]. The initial total active power loss of the system is 202.68 kW.

After ten independent runs, obtained results are given in Table 2. Moreover, implementing the proposed method is compared with other studies available in the literature. As indicated in Table 2, it can be noted that in the base case, the total real power losses of the 33-bus test system were 202.68 kW. After the reconfiguration, power loss reduction is 31.45 % in the proposed method. The proposed BPSO algorithm gives lower power loss than SSA, ISSA, and IGDT algorithms and equal power loss with the 3D-GSO algorithm. The optimal switch configuration obtained in 3D-GSO and proposed BPSO are the same. There is a small difference between the power loss due to the load flow method used in the simulation.

Table 2 also gives the annual net saving, amount of CO_2, NO_x, and SO_2 reductions due to reducing power losses using distribution networks network reconfiguration. Total cost is saved 33507.940$ after the DNR in the 33-bus distribution network. Furthermore, the positive impact of the power loss reduction using the DNR on the environmental issue is examined. It is clear from Table 2 that the amount of environmentally harmful gases significantly decreased after the reconfiguration.

The voltage profile of the 33-bus network before and after DNR is depicted in Fig. 6. Minimum voltage is seen at bus 18 with 0.9131 pu and at bus 32 with 0.9378 pu before and after DNR. Especially, the voltage profile at buses 6–18 is improved significantly after the reconfiguration.

The initial case and optimum case of the system seen in Fig. 6 are examined, as bus 18 is the furthest bus to the main substation, and the minimum voltage is seen at bus 18 before the reconfiguration. After the reconfiguration, the network's topology is changed; in this case, the furthest bus is 32. Loads are transferred from over-

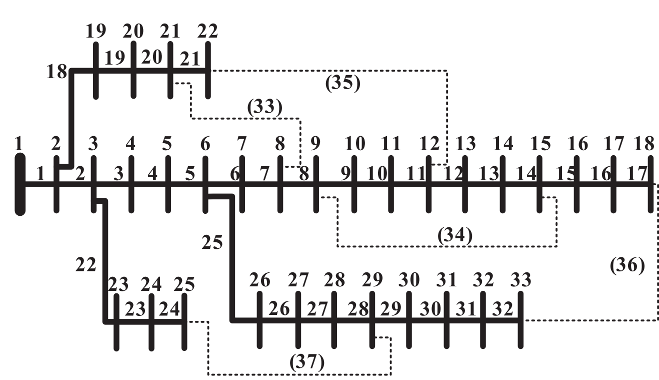

Fig. 5. Single line diagram of 33-bus distribution network.

Table 2
Result comparison of different algorithms for the 33-bus test system.

	Base case	SSA [18]	ISSA [18]	IGDT [18]	3D-GSO [15]	ACO [17]	Proposed BPSO
Power losses (kW)	202.68	142.16	141.99	170.5027	139.26	139.55	138.928
Power loss cost ($)	106528.26	74721.99	74589.38	89616.2349	73195.056	73347.48	73020.3198
Net saving ($/yr)	–	31809.312 (29.86 %)	31938.880 (29.98 %)	16912.025 (15.88 %)	33333.204 (31.29 %)	33181.128 (31.15 %)	33507.940 (% 31.45)
CO_2 reduction (kg)	–	268989.466	268667.798	322618.389	263502.202	264050.928	262873.151
NO_x reduction (kg)	–	37.360	37.315	44.808	36.598	36.674	36.510
SO_2 reduction (kg)	–	1.345	1.343	1.613	1.318	1.320	1.314
Open switches	33-34-35-36-37	7-9-14-36-37	7-9-14-28-36	8-32-33–34-37	7-9-14-28-32	7-9-14-32-37	7-9-14-32-37

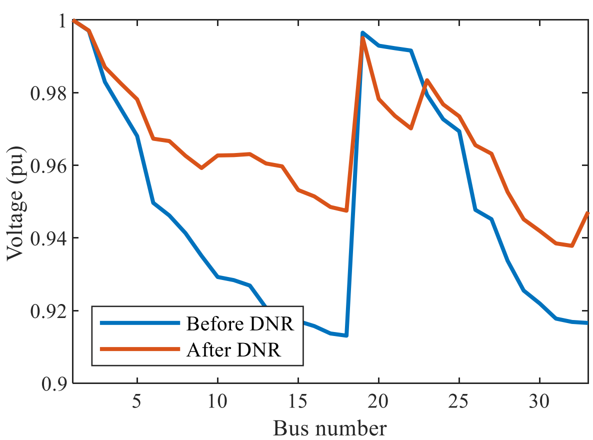

Fig. 6. Voltage profile of 33-bus test system.

loaded lines to fewer loaded lines by changing the status of the switches. Thus, the voltage profile is improved.

4.2. PG&E 69-bus distribution network

The single-line diagram of the 69-bus distribution network is presented in Fig. 7, and the network has 68 sectionalizing switches and 5 tie lines. The base voltage of the system is 12.66 kV [45]. The total active and reactive powers of the network are 3802 kW and 2695 kVAr, respectively. Power loss in the base case is 224.97 kW.

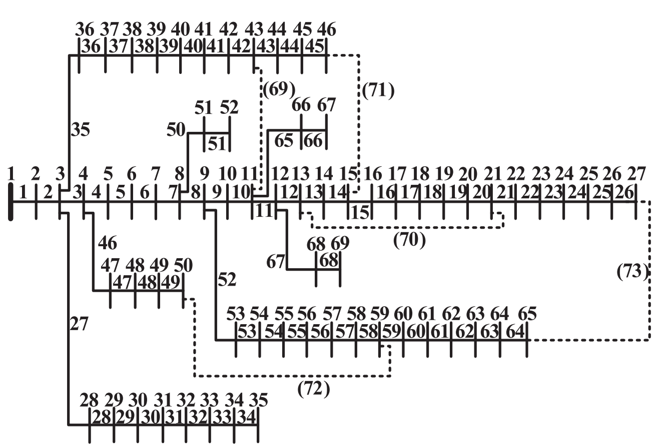

Fig. 7. Single line diagram of 69-bus distribution network.

After the reconfiguration, the best switch combination which gives the minimum power loss is obtained as 14-57-61-69-70. When the power loss results are compared with other methods, it is seen that the proposed BPSO is better than GA and HSA. Although the switch combination is different in the methods, the proposed method gives the same power loss reduction with FWA, 3D-GSO, and IWOA. When switches 56, 57, and 58 are open, they give the same power loss. This situation is related to the connected load to these buses. There are no loads in buses 56, 57, and 58, so opening the switches gives equal power loss.

According to Table 3, power loss reduction is 56.18 % after the reconfiguration. Net cost saving with the reconfiguration using the proposed method is 66425.790$. Also, the reduction of the power losses shows an impact on GHG reduction. Both cost and environmental benefits are obtained with the DNR.

The influence of the power loss reduction is also seen in the voltage profile of the 69-bus network. Voltage levels at the buses before and after feeder reconfiguration is shown in Fig. 8. The minimum voltage is 0.9092 pu at bus 65, and after the DNR voltage profile is improved, and minimum voltage level is seen at bus 61 with 0.9495 pu.

4.3. 84-bus Taiwan power Company (TPC) distribution network

84-bus TPC (seen in Fig. 9) is used in the study as a real case study. In the network, there are 83 sectionalizing and 13 tie lines [5]. The base voltage of the system is 11.4 kV. The total active and reactive powers of the network are 28350 kW and 20,700 kVAr, respectively. In the base case, the total power loss is 531.994 kW.

In the 84-bus network, voltage constraints are $V_{i,min} = 0.95$ and $V_{i,max} = 1.05$ pu, respectively. Feeder A has heavy loads; thus, most of the buses at this feeder violate the voltage constraints before the DNR. After the DNR using the proposed BPSO, the best switch combination that gives the minimum losses is obtained as 7-13-34-39-42-55-63-72-83-86-89-90-92. The number of buses that violate the voltage limits is ten, and after the DNR, all violated buses are improved.

A comparison is given in.

Table 4, and the minimum power loss is obtained as 469.337 kW. Proposed BPSO gives better results than IMI-DE, CSFSA, SBAT, BB-BCA, and GA. Power loss cost and GHG are reduced using the DNR without additional DG or capacitor placement. Hence the DNR is the proper solution that does not require additional cost.

The voltage profile of the 84-bus network before and after DNR is shown in Fig. 10. The minimum voltage is 0.9285 pu at bus 10

Table 3
Result comparison of different algorithms for the 69-bus test system.

	Base case	FWA [11]	HSA [7]	GA [7]	3D-GSO [15]	IWOA [19]	Proposed BPSO
Power losses (kW)	224.97	98.59	99.35	103.29	98.59	98.5952	98.595
Power loss cost ($)	118247.42	51821.63	52218.360	54289.224	51821.63	51821.63	51821.63
Net saving ($/yr)	–	66425.790 (56.18 %)	66025.872 (55.84 %)	63955.008 (54.09 %)	66425.790 (56.18 %)	66425.790 (56.18 %)	66425.790 (56.18 %)
CO_2 reduction (kg)	–	186557.894	187986.096	195441.206	186557.894	186557.894	186557.894
NO_x reduction (kg)	–	25.911	26.109	27.145	25.911	25.911	25.911
SO_2 reduction (kg)	–	0.933	0.940	0.977	0.933	0.933	0.933
Open switches	69-70-71-72-73	14-56-61-69-70	13-18-56-61-69	14-53-61-69-70	14-56-61-69-70	14-58-61-69-70	14-57-61-69-70

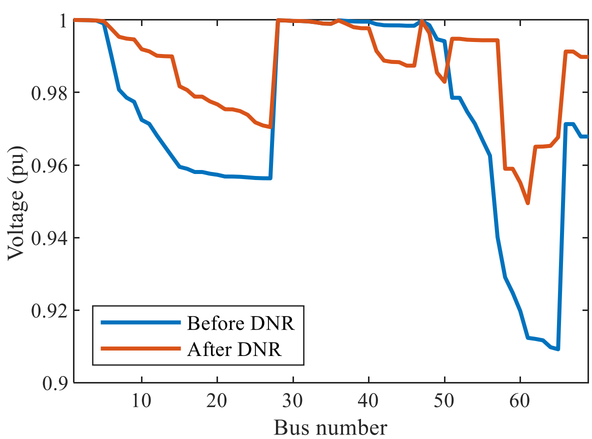

Fig. 8. Voltage profile of 69-bus test system.

and after the DNR voltage profile is improved. As a result, the minimum voltage level is seen at bus 72 with 0.9532 pu.

The proposed acceleration coefficient is compared with other coefficients available in the literature. According to the results presented in Table 5, the proposed coefficient gives the minimum average running time of 32.058 s. Thus, it gives better performance compared to other coefficients available in the literature.

As a result, the proposed algorithm gives the best switching pattern that provides minimum power loss as well as minimum voltage deviation while satisfying the constraints of the DNR problem for these three distribution networks.

Convergence assessment is shown in Fig. 11, and it is obvious that the proposed acceleration coefficient-based BPSO is more robust than others in the DNR problem solution.

Eventually, the proposed acceleration coefficient-based BPSO algorithm for the DNR problem converges to an optimal solution better than other methods. Also, computational times show that the method given in this study is less time-consuming than others.

The limitation of the proposed algorithm is using the sigmoid function as the classical transfer function for transforming the velocity to the probability. Newly introduced transfer functions such as v-shaped, x shaped, and z-shaped in the literature can be used to improve the performance of the BPSO as well as the proposed EBAC BPSO.

To verify the performance of the proposed algorithm, statistical details are listed in Table 6. Results are obtained after 20 independent runs with 250 iterations. The smallest standard deviation signifies a near-optimal solution, and the proposed algorithm that has

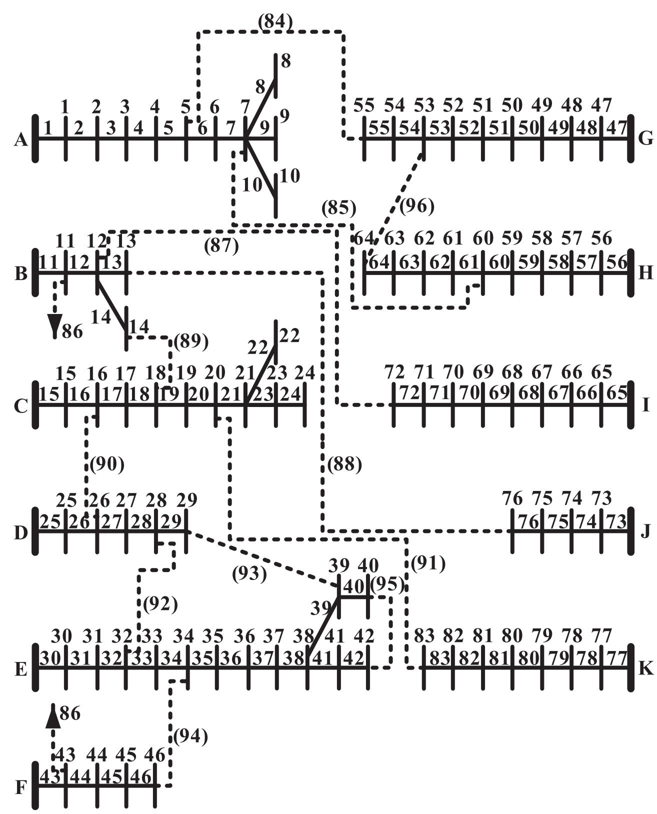

Fig. 9. Single line diagram of 84-bus distribution network.

the smallest standard deviation with 2.51 is satisfied better than other algorithms, according to the results seen in Table 6.

4.4. Wilcoxon test

Wilcoxon signed-rank sum test is a non-parametric test used in outcome comparations between two independent groups [46,47]. The test is used when the position of one of the variables is compared with the positions of the other. The null hypothesis is tested using the Wilcoxon test against the alternative hypothesis. Let the null hypothesis and alternate hypothesis [48]:

$$H_0 : \mu_o = \mu_a$$

$$H_1 : \mu_o \neq \mu_a$$

Table 4
Result comparison of the different algorithms for the 84-bus TPC system.

	Base case	IMI-DE [5]	SBAT [12]	CSFSA [20]	Heuristic method [6]	BB-BCA [10]	GA [9]	SOE [21]	ACO [16]	Proposed BPSO
Power losses (kW)	531.994	469.88	469.88	469.878	470.89	471.62	469.878	470.06	469.88	469.337
Power loss cost ($)	279616.046	246968.928	246968.928	246967.877	247499.784	247883.472	246967.877	247063.536	246968.928	246683.527
Net saving ($/yr)	–	32647.1184 (11.68 %)	32647.1184 (11.68 %)	32648.170 (11.68 %)	32116.262 (11.49 %)	31732.574 (11.35 %)	32648.170 (11.68 %)	32552.510 (11.64 %)	32647.1184 (11.68 %)	32932.519 (11.78 %)
CO_2 reduction (kg)	888060.698	–	889088.141	889088.141	889084.356	890999.222	892380.499	889084.356	889428.730	889088.141
NO_x reduction (kg)	123.342	–	123.484	123.484	123.484	123.750	123.942	123.484	123.532	123.484
SO_2 reduction (kg)	4.440	–	4.445	4.445	4.445	4.455	4.462	4.445	4.447	4.445
Open switches	84-85-86-87-88-89-90-91-92-93-94-95-96	7-13-34-39-41-55-62-72 -83-86-89-90-92	7-13-34-39-42-55-62-72-83-86-89-90-92	7-13-34-39-42-55-62-72-83-86-89-90-92	7-34-39-42-55-63-72-82-86-88-89-90-92	7-33-38-55-62-72-83-86-88-89-90-92-95	7-13-34-39-42-55-62-72-83-86-89-90-92	7-13-34-39-42-55-63-72-83-86-89-90-92	7-13-34-39-41-55-62-72-83-86-89-90-92	7-13-34-39-42-55-63-72-83-86-89-90-92

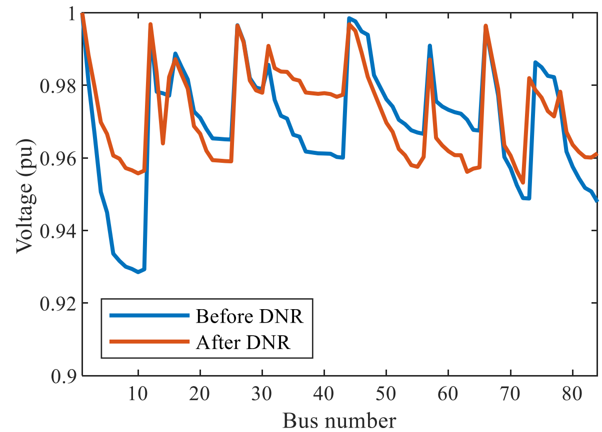

Fig. 10. Voltage profile of 84-bus TPC test system.

Table 5
Comparison of acceleration coefficients based on the computational effort (maximum iteration number is 100).

	Average iteration times (s)
Fixed c (c_1=c_2 = 2)	32.705
TVAC [35]	33.236
SCAC [38]	34.714
NDAC [39]	33.451
SBAC [40]	32.895
PNAC [41]	33.461
Proposed BPSO	32.058

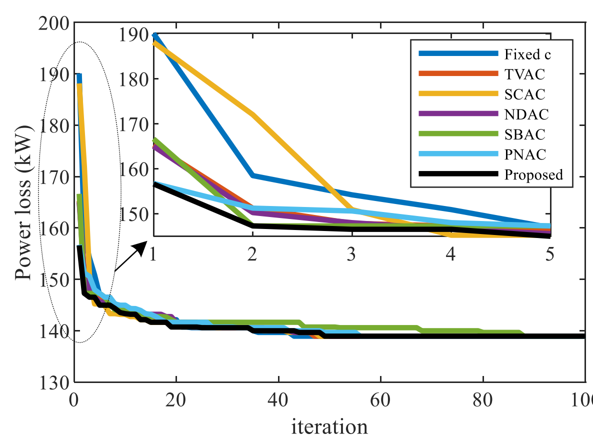

Fig. 11. Convergence of different acceleration coefficients.

μ_o: the value of bus voltages for the base case of the distribution network before network reconfiguration.

μ_a: the value of bus voltages after network reconfiguration.

The significance level (α) is determined as 0.05. The probability (p) of the Wilcoxon signed-rank sum test for the 33-bus distribution network after reconfiguration is calculated, and the results are given in Table 7.

For the proposed BPSO, $p = 4.2204e - 05$. As the p-value is less than the significance level ($\alpha = 0.05$), the null hypothesis can be rejected, and it is concluded that the proposed method is statistically significant. The p-values of the proposed BPSO and IGDT methods are the smallest compared to other methods.

Table 6
Statistical details for 33-bus network.

Algorithm	Best (kW)	Average (kW)	Worst (kW)	Standard deviation	Open switches
Proposed BPSO	138.928	140.3251	156.6013	2.51	7-9-14-32-37
FWA [11]	140.335	147.02	157.243	5.39	7-9-14-28-32
HSA [8]	138.06	152.33	195.10	11.28	7-10-14-36-37
RGA [8]	139.5	164.9	198.4	13.34	7-9-14-32-37
ITS [8]	139.28	163.5	196.3	12.11	7-9-14-36-37
GA [8]	141.6	166.2	202.7	14.53	7-9-14-32-37

Table 7
Wilcoxon signed-rank sum test probability of different algorithms for the 33-bus network.

Algorithm	SSA [18]	ISSA [18]	IGDT [18]	3D-GSO [15]	Proposed BPSO
p	6.8087e-05	4.9565e-05	4.2204e-05	4.5744e-05	4.2204e-05

5. Conclusion

This paper deals with the DNR problem for power loss minimization using the exponential-based acceleration coefficient-assisted BPSO algorithm. Simulation results of different distribution networks based on the proposed accelerated coefficient-based BPSO are presented in the study.

The contributions of this paper are summarized as below:

- An exponential-based acceleration coefficient-assisted BPSO algorithm is proposed to find optimal switch combinations that minimize the power losses while providing the problem constraints such as network radiality, bus voltage limits, and connectivity of all loads.

- The superiority of the proposed EBAC BPSO is successfully confirmed on three distribution networks.

- After the distribution network reconfiguration using EBAC BPSO, power loss is reduced without DG or capacitor placement which requires an extra cost.

- The effectiveness of EBAC PSO in reducing environmentally harmful gases such as CO_2, NO_x, and SO_2 is also considered in this paper.

- The proposed acceleration coefficient is compared with the other time-varying coefficients in terms of computing time and convergence speed. As a result of the study, it is seen that the proposed method gives less computational time and faster convergence speed than other studies available in the literature.

Moreover, it is possible to extend the proposed algorithm for unbalanced and large power distribution networks as the future scope of this paper. The proposed algorithm can also be used for other power system problems such as load balancing, and optimal DG/capacitor placement.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] H. Li, W. Mao, A. Zhang, C. Li, An improved distribution network reconfiguration method based on minimum spanning tree algorithm and heuristic rules, Int. J. Electr. Power Energy Syst. 82 (Nov. 2016) 466–473, https://doi.org/10.1016/j.ijepes.2016.04.017.
[2] A. Merlin, H. Back, Search for a Minimal-Loss Operating Spanning Tree Configuration in an Urban Power Distribution System, 1975.
[3] S. Civanlar, J.J. Grainger, H. Yin, S.S.H. Lee, Distribution feeder reconfiguration for loss reduction, IEEE Trans. Power Deliv. 3 (3) (1988) 1217–1223, https://doi.org/10.1109/61.193906.
[4] M.E. Baran, F.F. Wu, Network reconfiguration in distribution systems for loss reduction and load balancing, IEEE Trans. Power Deliv. 4 (2) (1989) 1401–1407, https://doi.org/10.1109/61.25627.
[5] S.u. Ching-Tzong, C.-S. Lee, Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution, IEEE Trans. Power Deliv. 18 (3) (2003) 1022–1027, https://doi.org/10.1109/TPWRD.2003.813641.
[6] A.A. Mohd Zin, A.K. Ferdavani, A.B. Khairuddin, M.M. Naeini, Reconfiguration of radial electrical distribution network through minimum-current circular-updating-mechanism method, IEEE Trans. Power Syst. 27 (2) (2012) 968–974.
[7] R.S. Rao, K. Ravindra, K. Satish, S.V.L. Narasimham, Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation, IEEE Trans. Power Syst. 28 (1) (2013) 317–325, https://doi.org/10.1109/TPWRS.2012.2197227.
[8] R.S. Rao, S.V.L. Narasimham, M.R. Raju, A.S. Rao, Optimal network reconfiguration of large-scale distribution system using, IEEE Trans. POWER Syst. 26 (3) (2011) 1080–1088.
[9] B. Tomoiagă, M. Chindriş, A. Sumper, R. Villafafila-Robles, A. Sudria-Andreu, Distribution system reconfiguration using genetic algorithm based on connected graphs, Electr. Power Syst. Res. 104 (2013) 216–225, https://doi.org/10.1016/j.epsr.2013.06.021.
[10] M. Sedighizadeh, S. Ahmadi, M. Sarvi, An efficient hybrid big bang-big crunch algorithm for multi-objective reconfiguration of balanced and unbalanced distribution systems in fuzzy framework, Electr. Power Components Syst. 41 (1) (2013) 75–99, https://doi.org/10.1080/15325008.2012.732658.
[11] A. Mohamed Imran, M. Kowsalya, D.P. Kothari, A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks, Int. J. Electr. Power Energy Syst. 63 (2014) 461–472.
[12] C. Gerez, L.I. Silva, E.A. Belati, A.J. Sguarezi Filho, E.C.M. Costa, Distribution network reconfiguration using selective firefly algorithm and a load flow analysis criterion for reducing the search space, IEEE Access 7 (2019) 67874–67888, https://doi.org/10.1109/ACCESS.2019.2918480.
[13] L.I. Silva, E.A. Belati, C. Gerez, I.C. Silva Junior, Reduced search space combined with particle swarm optimization for distribution system reconfiguration, Electr. Eng. 103 (2) (2021) 1127–1139, https://doi.org/10.1007/s00202-020-01150-z.
[14] R. Pegado, Z. Ñaupari, Y. Molina, C. Castillo, Radial distribution network reconfiguration for power losses reduction based on improved selective BPSO, *Electr. Power Syst. Res.*, vol. 169, no. 2018, pp. 206–213, 2019, doi: 10.1016/j.epsr.2018.12.030.
[15] H. Teimourzadeh, B. Mohammadi-Ivatloo, A three-dimensional group search optimization approach for simultaneous planning of distributed generation units and distribution network reconfiguration, Appl. Soft Comput. 88 (2020), https://doi.org/10.1016/j.asoc.2019.106012 106012.
[16] C. Su, C. Chang, J. Chiou, Distribution network reconfiguration for loss reduction by ant colony search algorithm, Electr. Power Syst. Res. 75 (2005) 190–199, https://doi.org/10.1016/j.epsr.2005.03.002.
[17] A. Swarnkar, N. Gupta, K.R. Niazi, Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization, Swarm Evol. Comput. 1 (3) (2011) 129–137, https://doi.org/10.1016/j.swevo.2011.05.004.
[18] R. Fathi, B. Tousi, S. Galvani, A new approach for optimal allocation of photovoltaic and wind clean energy resources in distribution networks with reconfiguration considering uncertainty based on info-gap decision theory with risk aversion strategy, J. Clean. Prod. 295 (2021), https://doi.org/10.1016/j.jclepro.2021.125984 125984.
[19] S.M. Abd Elazim, E.S. Ali, Optimal network restructure via improved whale optimization approach, Int. J. Commun. Syst. 34 (1) (2021) 1–15, https://doi.org/10.1002/dac.4617.
[20] T. Tran The, D. Vo Ngoc, N. Tran Anh, Distribution network reconfiguration for power loss reduction and voltage profile improvement using chaotic stochastic fractal search algorithm, Complexity 2020 (2020) 1–15.

[21] J. Zhan, W. Liu, C.Y. Chung, J. Yang, Switch opening and exchange method for stochastic distribution network reconfiguration, IEEE Trans. Smart Grid 11 (4) (2020) 2995–3007, https://doi.org/10.1109/TSG.2020.2974922.
[22] A.M. Helmi, R. Carli, M. Dotoli, H.S. Ramadan, Efficient and sustainable reconfiguration of distribution networks via metaheuristic optimization, IEEE Trans. Automat. Sci. Eng. 19 (1) (2022) 82–98.
[23] A. Fathy, M. El-Arini, O. El-Baksawy, An efficient methodology for optimal reconfiguration of electric distribution network considering reliability indices via binary particle swarm gravity search algorithm, Neural Comput. Appl. 30 (9) (2018) 2843–2858, https://doi.org/10.1007/s00521-017-2877-z.
[24] T.T. Nguyen, A novel metaheuristic method based on artificial ecosystem-based optimization for optimization of network reconfiguration to reduce power loss, Soft Comput. 25 (23) (2021) 14729–14740, https://doi.org/10.1007/s00500-021-06346-4.
[25] T.T. Nguyen, Q.T. Nguyen, T.T. Nguyen, Optimal radial topology of electric unbalanced and balanced distribution system using improved coyote optimization algorithm for power loss reduction, Neural Comput. Appl. 33 (18) (2021) 12209–12236, https://doi.org/10.1007/s00521-021-06175-4.
[26] J.C. Lin, Q. Liu, P. Fournier-viger, T. Hong, M. Voznak, J. Zhan, A sanitization approach for hiding sensitive itemsets based on particle swarm optimization, Eng. Appl. Artif. Intell. 53 (2016) 1–18, https://doi.org/10.1016/j.engappai.2016.03.007.
[27] J.-W. Lin, L.u. Yang, P. Fournier-Viger, J.-T. Wu, T.-P. Hong, L.-L. Wang, J. Zhan, Mining high-utility itemsets based on particle swarm optimization, Eng. Appl. Artif. Intell. 55 (2016) 320–330.
[28] J. Chun, W. Lin, Q. Lv, D. Yu, G. Srivastava, C.H. Chen, Adaptive particle swarm optimization model for resource leveling, Evol. Syst. (2022), https://doi.org/10.1007/s12530-022-09420-w.
[29] J. Kennedy, R. Eberhart, Particle swarm optimization, in *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, vol. 4, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.
[30] J. Kennedy, R. C. Eberhart, A discrete binary version of the particle swarm algorithm, in *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, 1997, vol. 5, pp. 4104–4108, doi: 10.1109/ICSMC.1997.637339.
[31] E.H. Houssein, A.G. Gad, K. Hussain, P.N. Suganthan, Major advances in particle swarm optimization: theory, analysis, and application, Swarm Evol. Comput. 63 (2021) 100868.
[32] P.N. Suganthan, Particle swarm optimiser with neighbourhood operator, in *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*, 1999, pp. 1958–1962, doi: 10.1109/CEC.1999.785514.
[33] M. Ghasemi, E. Akbari, A. Rahimnejad, S.E. Razavi, S. Ghavidel, L. Li, Phasor particle swarm optimization : a simple and efficient variant of PSO, Methodol. Appl. 23 (2019) 9701–9718.
[34] M. Ghasemi, J. Aghaei, M. Hadipour, New self-organising hierarchical PSO with jumping time-varying acceleration coefficients, Electron. Lett. 53 (20) (2017) 1360–1362, https://doi.org/10.1049/el.2017.2112.
[35] A. Ratnaweera, S.K. Halgamuge, H.C. Watson, Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients, IEEE Trans. Evol. Comput. 8 (3) (Jun. 2004) 240–255, https://doi.org/10.1109/TEVC.2004.826071.
[36] W. Liu, Z. Wang, N. Zeng, Y. Yuan, F.E. Alsaadi, X. Liu, A novel randomised particle swarm optimizer, Int. J. Mach. Learn. Cybern. 12 (2) (2021) 529–540.
[37] A.T. Kiani, M.F. Nadeem, A. Ahmed, I.A. Khan, H.I. Alkhammash, I.A. Sajjad, B. Hussain, An improved particle swarm optimization with chaotic inertia weight and acceleration coefficients for optimal extraction of PV models parameters, Energies 14 (11) (2021) 2980.
[38] K. Chen, F. Zhou, L. Yin, S. Wang, Y. Wang, F. Wan, A hybrid particle swarm optimizer with sine cosine acceleration coefficients, Inf. Sci. (Ny) 422 (2018) 218–241, https://doi.org/10.1016/j.ins.2017.09.015.
[39] K. Chen, F. Zhou, Y. Wang, L. Yin, An ameliorated particle swarm optimizer for solving numerical optimization problems, Appl. Soft Comput. 73 (2018) 482–496, https://doi.org/10.1016/j.asoc.2018.09.007.
[40] D. Tian, X. Zhao, Z. Shi, Chaotic particle swarm optimization with sigmoid-based acceleration coefficients for numerical function optimization, Swarm Evol. Comput. 51 (March) (2019), https://doi.org/10.1016/j.swevo.2019.100573 100573.
[41] M. Lin, Z. Wang, F. Wang, D. Chen, Improved simplified particle swarm optimization based on piecewise nonlinear acceleration coefficients and mean differential mutation strategy, IEEE Access 8 (2020) 92842–92860, https://doi.org/10.1109/ACCESS.2020.2994984.
[42] A.Y. Abdelaziz, F.M. Mohamed, S.F. Mekhamer, M.A.L. Badr, Distribution system reconfiguration using a modified Tabu Search algorithm, Electr. Power Syst. Res. 80 (8) (2010) 943–953, https://doi.org/10.1016/j.epsr.2010.01.001.
[43] M. Sedighizadeh, M. Dakhem, M. Sarvi, H.H. Kordkheili, Optimal reconfiguration and capacitor placement for power loss reduction of distribution system using improved binary particle swarm optimization, Int. J. Energy Environ. Eng. 5 (1) (2014) 73, https://doi.org/10.1007/s40095-014-0073-9.
[44] R.D. Zimmerman, C.E. Murillo-Sanchez, R.J. Thomas, MATPOWER: steady-state operations, planning, and analysis tools for power systems research and education, IEEE Trans. Power Syst. 26 (1) (2011) 12–19, https://doi.org/10.1109/TPWRS.2010.2051168.
[45] M.E. Baran, F.F. Wu, Optimal capacitor placement on radial distribution systems, IEEE Trans. Power Deliv. 4 (1) (1989) 725–734, https://doi.org/10.1109/61.19265.
[46] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Swarm Evol. Comput. 1 (1) (2011) 3–18, https://doi.org/10.1016/j.swevo.2011.02.002.
[47] E.R. Ziegel, Nonparametric Statistical Inference, Technometrics 35 (2) (1993) 239–240.
[48] E.S. Ali, S.M. Abd Elazim, A.Y. Abdelaziz, Ant lion optimization algorithm for renewable distributed generations, Energy 116 (2016) 445–458, https://doi.org/10.1016/j.energy.2016.09.104.